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SPATIAL AND TEMPORAL MODELING FOR RISK ASSESSMENT
AND MANAGEMENT OF POTATO LATE BLIGHT
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SPATIAL AND TEMPORAL MODELING FOR RISK ASSESSMENT AND MANAGEMENT OF POTATO LATE BLIGHT (*PHYTOPHTHORA INFESTANS*) IN MICHIGAN

By

Kathleen Marie Baker

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ABSTRACT

SPATIAL AND TEMPORAL MODELING FOR RISK ASSESSMENT AND MANAGEMENT OF POTATO LATE BLIGHT (*PHYTOPHTHORA INFESTANS*) IN MICHIGAN

By

Kathleen Marie Baker

In the Midwestern United States, potato late blight (*Phytophthora infestans*) is a temporally sporadic disease, occurring only when microclimate conditions within the canopy are favorable and inoculum is present. Favorable environmental conditions include air temperatures between 7 and 27 degrees C and relatively long periods (10 hours or more) of leaf wetness. Increasing concern in the agricultural community over observed and projected climate change has prompted numerous studies on the possible implications for crop yields. However, relatively little work has focused on disease management.

Historical trends in hourly weather variables and potato late blight risk as expressed by a modified Wallin Disease Severity Value index were analyzed at 7 stations in Wisconsin, Michigan, and Ohio from 1948-1999. All sites showed significant trends in at least one of the risk estimates. While late blight risk was greatest at all stations in August, periods of increasing risk occurred across the region particularly during July. The increases in disease risk appeared to be associated with upward trends in dry bulb and dew point temperature at nearly all of the stations, particularly during July and August. These results correspond with historical climatological trends in the Upper Great Lakes that point to warmer and wetter growing season conditions. Significant trends in

precipitation totals and in the frequency of days with precipitation have also been documented.

Because potato late blight spreads rapidly, limited options are available to growers once the crop canopy has become infected. Spatial and temporal dynamics of the leading edge of a late blight field infection with respect to weather-based explanatory vaiables were characterized using regression models. To improve management decisions, desiccation zone parameters were identified by exploring spatial consistency of localized late blight infection spread in experimental plots both between replicates and between years. Time in days since inoculation was the variable most strongly related to distance of lesion farthest from the point of initial inoculation. The best linear model that did not include time in days used both the hours above 90 percent relative humidity and hours between 70 and 80 percent relative humidity.

Ever to my parents, who continue to impress upon me the importance of dedication, simplicity, love and vegetables.

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Love and gratitude to everyone who smiled tolerantly at vegetable geography and supported my constant department hopping, especially my committee: Drs. Jeff Andresen, Willie Kirk, Jay Harman and Ray Hammerschmidt, and to the folks at MSU GREEEN for funding the project.

To all of my potato boys (and the occasional itinerant spud babe), may there always be someone to pull you out of the muck, may your plates never know contamination, and may you never be without a pie when you really need one.

As always, extra special thanks to: scum-of-the-earth-cat, who learned to speak English; Laura, the strong-wristed, who was more than a sister; Tom, who replenished my stock of honey-roasted macadamia nuts; Ilya, who used the unusual theme of landmines to inspire and admonish me; Gregory, who shared his cows and snuck in as quietly as possible; and Grandma, who made some mean banana bread. To my circle of friends and neighbors (who are often both at once!), I appreciate your smiles and support so much. And, of course, to the girls who tried to burn down my garage – I'll *never* forget you.

In our lives and our research, let us follow the advice of Sergei Chesnokov and try to reconcile 'the gap between the truth of science and the truth embodied in the soul of the artist'.

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CHAPTER 1

INTRODUCTION

Late blight of potato, caused by *Phytophthora infestans* (Mont. De Bary), has recently re-emerged as a major factor in potato (*Solonum tuberosum*) production in North America (Fry & Goodwin, 1997). Potato late blight is the most important potato disease throughout the potato growing regions of the world (Inglis et al., 1996) and is considered one of the most important plant diseases relative to global food production in the future (Agrios, 1997). Prior to 1992, North American populations of *P. infestans* (A_1 mating type) were easily controlled by metalaxyl-based fungicide applications. A new aggressive genotype of *P. infestans* (US8, A2 mating type, metalaxyl-insensitive) has replaced the previous clonal lineage and the foliage of all currently available commercial varieties is highly susceptible to current populations (Inglis et al., 1996; Douches et al., 1997).

No fungicides currently in use completely arrest epidemic development, and even plants protected with five-day fungicide applications at a maximum rate of active ingredient became infected when environmental conditions were conducive to late blight development and inoculum was plentiful (Kirk et al., 2000; Mayton et al., 2001). Even plants protected with five-day fungicide applications at a maximum rate of active ingredient become infected when environmental conditions are conducive to late blight development and inoculum is plentiful (Kirk et al., 2000). In Michigan, the Michigan Potato Industry Commission Pest Survey estimated that 7 - 18 protective applications were made during a typical growing season depending on length of growing season and end use of crop. These fungicide applications reduce the profitability of the industry and could have attracted criticism from environmental groups seeking to reduce reliance on pesticides (MPIC, 2000).

The increasing economic impact of potato late blight, in terms of both yield loss and increased fungicide use, makes understanding disease dynamics in space and time important for estimation of risk. Since epidemics occur only when environmental conditions are conducive and inoculum is present in the potato canopy, potato late blight is a suitable disease for geographically-based epidemiological research at a wide range of spatial and temporal scales. Two geographically-based research topics, varying in scale, follow, including: a) the quantification of historical trends in late blight conducive climate conditions; and b) the characterization of the spatial and temporal dynamics of an epidemic within a single field to enhance the effectiveness of grower late blight management techniques after a canopy has become infected.

The following sections focus on the background of potato production, the canopy microclimate conditions necessary for foliar infection by late blight, and the estimation procedure for late blight risk. Specific research questions and objectives follow.

GLOBAL AND LOCAL POTATO PRODUCTION

The potato is generally considered to be the fourth most important global food crop behind rice, wheat and maize, and is grown throughout the world in a wider range of latitudes than any other agricultural crop (Hijmans et al., 2000). About seven percent of the total global potato production (NPC, 2001) occurs in the United States; close to 550,000 hectares were grown annually in the U.S. between 1959 and 1998. During this same time, however, average yield nearly doubled from 3 to 6 metric tons per hectare (NPC, 1999). Major potato growing regions of the U.S. include the Northwest, Upper Midwest, Northeast and Southeast. The states of Washington and Idaho led in revenue from potato production during 2000 (Figure 1a). When production value is standardized by state area (dollars per 1000 hectares), North Dakota, Wisconsin, Michigan, Maine, Delaware and Florida are also important producers (Figure 1b).

In Michigan, production in the last several years has remained relatively steady at 680,000 metric tons which is just over three percent of the nation's production (NPC, 1999; MASS, 1999-2000). Approximately 80 percent of that production, as of 2000, was dedicated to varieties particularly used for chipping and the snack-food industry. In terms of farmgate value, the state's crop is worth nearly 90 million dollars annually (MPIC, 2000). Michigan's production by county is shown in Figure 2. Montcalm County has consistently grown twice the area of any other Michigan county, reporting 5,300 harvested hectares in 1999. Production zones in Michigan are linked to soil texture, with most potatoes in the state grown in well-drained loamy-sand and sandy-loam soils. A high percentage of the state's production is located in the central lower Peninsula, but the southwest and northern Lower Peninsula and the central Upper Peninsula also have substantial potato production.

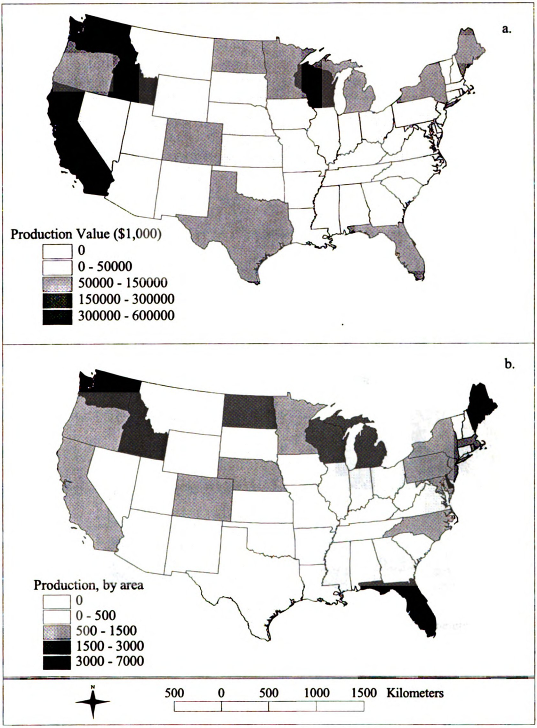


Figure 1. Value of state potato production in the coterminous United States (National Potato Council, 2000), a. Production value in thousands of dollars. b. Production value standardized by area in dollars per thousand hectares.

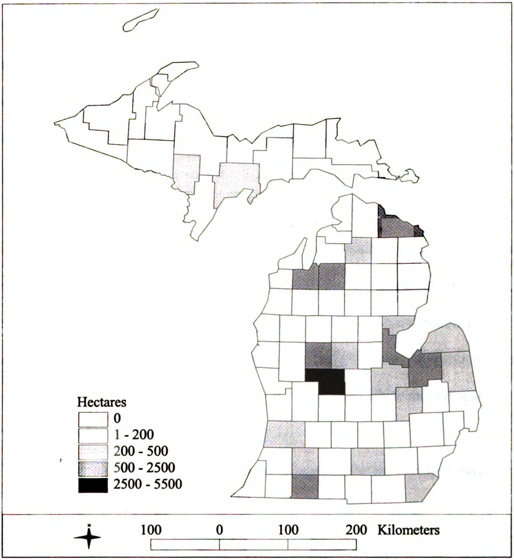


Figure 2. Potato acreage by Michigan county (Michigan Agricultural Statistics, 1999-2000; MPIC 2001; unpublished MSU Extension data).

CANOPY MICROCLIMATE

Leaf Wetness

Canopy wetness and air temperature affect the initiation and rate of late blight spread once inoculum is present in the canopy. The wetness period or wetness duration of a leaf generally refers to the length of time that liquid water is present on the leaf surface. As an agricultural variable, leaf wetness has many beneficial aspects, such as temperature regulation, soil water conservation and leaf turgor enhancement, which aids in photosynthesis (Armstrong et al., 1993). In contrast to these positive effects, leaf wetness duration is the most important factor for a large number of crop diseases including potato late blight (Fry et al., 1997; Wilks et al., 1991); apple scab (Penrose and Nicol, 1996); bacterial spot of peach; (Zehr and Shepard, 1996); Septoria of wheat; Rhynchosporium of barley; Athracnose of watermelon (Monroe et al., 1997); and white mold disease of dry beans (Deshpande et al., 1995).

Water on the leaf surface may be the result of a precipitation event, or may be deposited by dew or fog. Most potato crops in Michigan also receive regular irrigation. Depending on the type of wetting event and the characteristics of the leaf (e.g. wax on cuticle, hair density), the water on the surface may be in the form of droplets, or may cover the leaf in a thin film (Thompson, 1981). In some studies, a microscopic film of water was still detected on grass blades an hour after moisture was no longer visible (Giesler et al., 1996).

Meteorologically, the likelihood and magnitude of infection is correlated strongly with the duration of wetting period and temperature. Fungi and bacteria generally produce secondary inoculum in increasing quantities as duration of wetting period increases within pathogen specific temperature ranges and when the host is in a vulnerable condition, e.g. immature leaf tissue (Kirk, personal communication). The relationship between wetting period and disease has been assessed with various models and sensors.

Leaf Wetness Sensors

The most frequently used leaf wetness sensors are made with electrical resistance grids. Equally spaced fingers of copper or other conductive metal form an alternating circuit over the surface of a fiberglass board and surface moisture is detected by changes in the electrical resistance of the grid (Gillespie and Kidd, 1978). Color, orientation modifications and coverings of absorbent cloth have been tested to more accurately simulate leaf surface conditions, but these changes can cause the measured wetness period to vary by about three hours (Armstrong et al., 1993; Gillespie et al., 1993). In low biomass canopies, such as turfgrass, surface grids do not closely approximate the leaf surface. Instead of resistance grids, small stainless steel pins can be inserted directly into blades of grass. This type of sensor is thought to be sensitive to microscopic water films (Giesler et al., 1996). A beta ray gauge is perhaps the most accurate measure of leaf wetness, but is also costly and sensitive to inclement weather (Armstrong et al., 1993).

The duration of leaf wetness has been shown to be exceedingly variable, even at multiple locations in close proximity to one another within the same field (Andresen and Edson, 2001). Comparisons of different devices for leaf wetness measurement showed that while most sensors accurately modeled shape of the leaf's drying curve , the estimate of leaf wetness duration was inaccurate (Armstrong et al., 1993). However, it is duration of leaf wetness that is critical to pathogen models (Thompson, 1981). Penrose and Nicol (Penrose and Nicol, 1996) advocate the use of at least three wetness sensors per site to improve reliability for disease warning estimates.

Leaf Wetness Algorithms

As sensors vary in method and accuracy, so do models. Mathematical models for estimating leaf wetness differ in both the number of variables used and the complexity of the relationships among those variables. Perhaps the most complete, as well as one of the earliest algorithms was based on the energy balance equation for a surface, and subdivides the canopy into layers approximately 10 cm in depth (Thompson, 1981). For each layer, resistances and energy balance parameters were calculated. Other models have approximated leaf wetness using more easily measurable meteorological variables. Little standardization exists among these models due to the wide range of disciplines in which they originated.

Both climatological and agronomic variables influence duration of leaf wetness. Net radiation, wind speed, vapor pressure and soil moisture are critical climatological components. Although net radiation is difficult to estimate accurately given the number of variables involved in the surface energy budget and the influence of cloud cover, it is essential for estimating the quantity of energy available for evaporation. Ambient vapor pressure and vapor pressure gradients affect the rate and direction of movement of moisture from the leaf surface. Soil moisture and wind speeds also influence the vapor pressure gradient and movement of moisture to and from the canopy, although some studies have specified that leaf movement does not significantly influence drying time, (Armstrong et al., 1993). Canopy structure and density, and leaf orientation, temperature, and surface properties influence interception of precipitation and radiation, as well as aerodynamic resistance.

Due to the difficulty in monitoring or estimating leaf wetness, it has often been approximated using the so-called "90 percent criterion". If relative humidity within the canopy remains above 90 percent, leaves in that canopy are considered wet. Relative humidity is a temperature-dependent proxy for vapor pressure, as a proportion of the saturation vapor pressure of air at the same temperature. Because saturation vapor pressure increases with temperature, relative humidity decreases when vapor pressure remains constant while the air warms. Thompson (1981) found that the 90 percent criterion often underestimated leaf wetness duration, especially on days when dew, as opposed to precipitation, was the primary source of canopy moisture. This was especially true for ground crops, while the criterion may have been a good approximation for tree crops as there is air movement through the canopy, and the canopy is often less dense. The 90 percent criterion was not considered the best leaf wetness estimate for disease alert systems and other applications of leaf wetness, especially in ground crop situations where dew is an integral aspect of wetness duration (Gleason et al., 1994).

Both leaf wetness sensor values and relative humidity approximations are used to quantify moisture in the growing environment for a number of agricultural purposes. Harvest moisture forecasts have been implemented in these types of approximations in wheat and barley (Atzema, 1998), rice (Lu and Siebenmorgen, 1994), cut grass (Atzema, 1998), hay (Barr and Brown, 1995), and alfalfa (Wilks et al., 1993). Predictive epidemiological models have been extensively developed for potato early and late blight (Wallin, 1962; Nutter and MacHardy, 1980; Shtienberg and Fry, 1990a; Shtienberg and Fry, 1990b; Doster and Fry, 1991; Raposo et al., 1993; Johnson, 1998) to optimize the initiation and effectiveness of fungicide applications. Similar strategies have been developed for tomatoes (Gillespie et al., 1993) and *Botrytis* in both greenhouse vegetables (Shtienberg and Elad, 1997) and onions (Vincelli and Lorbeer, 1989), as well as for *Sclerotinia* stem rot in oilseed rape (Twengstrom et al., 1998).

Potato Canopy Characteristics

Under non-limiting conditions of water, nutrients and solar radiation, potato plants increase leaf area very quickly and create a microclimate favorable to late blight (Dorozhkin, 1971; Harris, 1992). Leaf wetness in potato canopies must include auxiliary branches and stems as well as laminar tissue since *P. infestans* can affect all tissue that makes up the potato canopy. The canopy is generally considered closed when the ratio of total leaf area to ground surface area, or leaf area index (LAI), is equal to 3 (Jeffries and Heilbronn, 1995). However, the canopy continues to increase in density, reaching maximum LAI's upwards of 8, depending on growing conditions, approximately two months after planting (Allen and Scott, 1992). The increasing density of the potato canopy increases the duration of leaf wetness by capturing a large percentage of incident radiation but limiting the amount of radiation reaching lower leaves that could evaporate water. Water vapor pressure also remains higher than that of the ambient air as the canopy limits airflow, and shading by upper branches protects lower canopy levels from high temperatures (Thompson, 1981). The importance of leaf wetness to potato late blight and the suitability of the physical environment within the potato canopy to extending leaf wetness duration together create a situation so conducive to disease that potatoes have been considered 'suicidal' (Dorozhkin, 1971).

POTATO LATE BLIGHT

As potato production is global, the re-emergence of late blight has become a worldwide problem (Fry and Goodwin, 1997). The infection of the potato plant occurs only after extended periods of leaf wetness at relatively cool temperatures, although infection can occur even at air temperatures in excess of 30°C (Kirk, personal communication). Late blight is readily transmitted by seed-borne inoculum and, consequently stems and leaves may be exposed to late blight from infected seed pieces and in-field volunteer plants (Lambert et al., 1998).

In the canopy, sporangia can be transported by wind or splash from plant to plant during precipitation or irrigation events. Symptoms appear in the canopy within 5-8 days of inoculation and include necrotic lesions on leaves and stems that appear gray and water soaked (Lacy and Hammerschmidt, 1995).

The influence of canopy air temperature on the development and growth of *P. infestans* has been well documented (Harrison, 1992). Although the optimal temperature for hyphal growth in foliage varies among potato cultivars, it is typically between 15 and 20°C (Harrison and Lowe, 1989; Harrison, 1992). *P. infestans* is an obligate pathogen and the base temperature for late blight development may be related to that for potato leaf and sprout development, i.e., 4°C (Kirk et al., 1985). A decreased rate of sporangial development occurs at temperatures below the optimal temperature of 10°C (Kadish and Cohen, 1992).

Many potato late blight protection strategies depend upon high level inputs of agrochemicals. Estimation of 'current' field conditions that influence late blight development enables growers to apply appropriate fungicides in response. There are currently several types of fungicide applied routinely for prevention of late blight in Michigan and several others with more specific activity that could be used when conditions are more favorable for late blight development or when infection has occurred. In order to effectively advise growers on the appropriate late blight control strategy it is necessary to have information based on knowledge of fungicide efficacy, foliar development, varietal susceptibility to late blight, intended market, and past and current weather records.

The control of potato late blight and estimation of associated field conditions throughout the growing season have continued to be top research priorities for the Michigan potato industry since 1995 (MPIC, 2000). Because conditions are only sporadically favorable and inoculum is not always present, timely and effective management recommendations are crucial to the economics of potato production. The

Upper Great Lakes region is important to the study of late blight field epidemic characteristics as the disease occurs more sporadically than in other U.S. production areas because of the variability of growing season weather conditions. For this reason, 90 percent of Michigan growers incorporate some form of weather monitoring into their disease management practices (MPIC, 2000).

Potato Late Blight Models

The 90 percent relative humidity criterion has been used for potato late blight monitoring since early analyses of canopy based records of the physical environment in relation to disease development (Wallin, 1962). Average air temperatures and duration of wetting period are combined in the daily assignment of Wallin disease severity values, which have become standard in estimating potato late blight risk (MacKenzie, 1981). Microclimate-based late blight models were established originally in the 1940's and fungicide spray programs and other management decisions were based upon the accumulation of 'blight favorable days', or thresholds of the disease severity values (DSV) beginning in the 1960's (Beaumont, 1947; Wallin and Schuster, 1960; Wallin, 1962; MacKenzie, 1981). DSV range from 0 to 4 and are calculated using the average air temperature during extended periods of high relative humidity (Table 1). The severity of late blight risk is estimated by both the number of hours above the relative humidity threshold and the air temperature during that time. Longer leaf wetness durations, approximated by 90 percent relative humidity, and higher air temperatures between the thresholds of 7.2 to 27.0°C are indicative of greater late blight risk (Wallin, 1962). The traditional Blightcast model developed during predominance of the US1 genotype (A1 mating type, metalaxyl-sensitive) recommended initiation of fungicide applications after the accumulation of either ten consecutive favorable days or 18 DSV following emergence (MacKenzie, 1981).

Table 1. Potato canopy air temperature and relative humidity thresholds in the computation of Wallin disease severity values for late blight risk estimation (Wallin, 1962).

	Severity values for the number of hours relative humidity > 90%				
Ave Temp	0 (none)	1 (minimal)	2 (slight)	3 (moderate)	4 (severe)
7.2-11.7	<16 hours	16-18 hours	19-21 hours	22-24 hours	n/a
11.7-15.0	<13 hours	13-15 hours	16-18 hours	19-21 hours	22-24 hours
15.0-27.0	<10 hours	10-12 hours	13-15 hours	16-18 hours	19-21 hours

Michigan State University (MSU) has been using a modified Wallin model for making management recommendations to growers for several years (Baker et al., 2000). The model was adapted for use with hourly temperature and relative humidity data. Each of the hourly values above the relative humidity threshold are assigned to a particular Wallin-based temperature category and totaled for the day. Relative humidity thresholds are set at 80 percent, instead of the traditional 90 percent criterion, to account for the underestimation of the 90 percent threshold especially with respect to the canopy environment. Justification for using an 80 percent relative humidity threshold is described in Chapter 2.

Spatial spread of potato late blight within a field of potatoes by continuous leaf and stem infection is rapid and limited options are available to growers once the crop canopy has become infected. Making appropriate management recommendations in such a situation is, therefore, difficult as symptoms develop latently, up to 7 days after initial infection and spread of mycelium through the foliar tissue. The importance of weather characteristics during the growing season and associated risk estimates are unquestionably linked to development of late blight epidemics, but the spatial and temporal dynamics of infection have not been quantified. Neither has the relationship between those dynamics been understood in relation to weather-based explanatory variables.

RESEARCH QUESTIONS

This research focuses on understanding the influence of weather and climate on potato late blight dynamics in Michigan. Models are developed to further understand the spatial spread of late blight and the increase in magnitude of foliar infection in a field situation with respect to physical, weather-based characteristics of the canopy. In addition, historical analysis quantifies trends in the effects of these weather variables over the long term throughout the Michigan region. The primary research question explored is: In what ways can potato late blight epidemic dynamics and risk be better understood, and recommendations improved, through spatio-temporal modeling of field infections and historical weather data analysis? The main research focus is expanded more specifically at various spatial and temporal scales, as follows:

a) historical assessment of late blight risk in the greater Michigan region

- Historically, how much has potato late blight risk varied spatially and temporally in the greater Michigan region?

- What are the trends in the last 50 years in late blight severity value accumulations?

b) epidemiology of late blight spread within a field during an epidemic

- When and where does the leading edge of late blight expand following introduction of initial inoculum?
- What is the influence of weather on the spread of a late blight within a field?

OBJECTIVES

- Assess the impact of location on late blight risk within Michigan and analyze trends at these locations to determine how risk has changed over time.
- Create an algorithm for estimating the location of the leading edge of late blight including confidence bounds.
- Characterize the spread of potato late blight in a confined (research plot) area as a function of weather related explanatory variables.

This dissertation consists of three chapters. Following this introduction, the second chapter analyzes historical weather conditions in the Upper Great Lakes region and the implications of trends for the severity of potato late blight epidemics in space and time. The third chapter describes the movement of the leading edge of infection following inoculation and quantifies the relationship between this movement and explanatory variables involving time and weather conditions.

CHAPTER 2

HISTORICAL TREND ANALYSIS OF REGIONAL POTATO LATE BLIGHT RISK

INTRODUCTION

Potato late blight is a temporally sporadic disease that occurs only when microclimate conditions within the canopy are favorable and inoculum is present (Lacy and Hammerschmidt, 1995). Leaf wetness duration and in-canopy relative humidity are critical variables in determining the relative risk of late blight development. As a result, changes in meteorological variables throughout the growing season that influence the amount of in-canopy moisture and vapor pressure could significantly impact subsequent disease pressure. Precipitation and dew point temperature are two variables of this nature that can be easily quantified.

This chapter describes the identification of weather-based trends that have influenced potato late blight disease risk in the Upper Great Lakes region of the U.S. Only the influence of climate on disease risk as calculated by modified Wallin disease severity values (Wallin, 1962) is considered, regardless of irrigation, other cultural practices, or pathogen biotype changes that may have impacted late blight risk. This historical perspective for potato late blight risk characterizes temporal trends in the greater Michigan region from 1948-1999. The analyses also explore spatial similarities in trends by statistically comparing the magnitude and timing of late blight risk between locations.

METHODS AND MATERIALS

Data Characteristics

Historical air and dew point temperatures were extracted from the National Climatic Data Center's (NCDC) Surface Airways data-set for seven first order National Weather Service (NWS) stations in the greater Michigan region (Alpena - APN, Grand Rapids - GRR, Green Bay - GRB, Muskegon - MKG, Toledo - TOL, Traverse City - TVC, and Sault Ste Marie - Y62) (EarthInfo, 1948-1999). Throughout this chapter, locations are listed in tables and figures in order of latitude, from northernmost to southernmost. For each location, shown in Figure 3, years with missing values for more than seven days of the growing season (May 1 to September 30) were not used. Station record lengths ranged from 35 to 49 years for the 52-year period from 1948-1999. The initial year in the period of record for each station was as follows: Y62, 1948; APN, 1964; TVC, 1949; GRB, 1950; MKG, 1948; GRR, 1964; TOL, 1955.

Possible discontinuities in the data series were of concern because of the length of the series and the fact that instrument updates, site modifications and location changes occurred at each of the stations independently. The magnitude of change until 1990, as identified in previous studies is low, especially in view of the 20°C temperature window used in this study to derive secondary variables (Robinson, 2000). For example, Robinson (2000) found that pre-1990 changes altered temperature measurements less than 1°C. Therefore, the data series was judged to be appropriate for the study. Of continued concern, however, is the gradual shift beginning in the 1990's to the

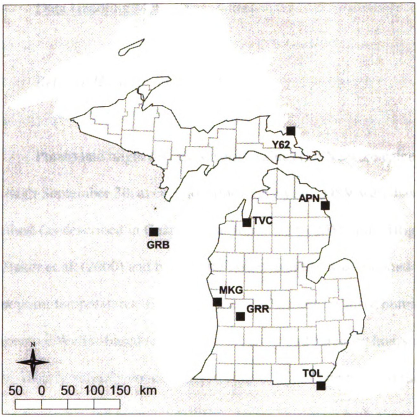


Figure 3. National Weather Service (NWS) stations used in historical trend analysis.

Automated Surface Observing System (ASOS) instrumentation at airports to standardize observational methodology, as the impact on data continuity after this change is unclear.

Data Handling Methods

Relative Humidity Thresholds

Potato late blight disease severity values (DSV) were calculated each day, May 1 through September 30, at each location every year. DSV were based on the Wallin method (as described in Chapter 1) as modified by MSU Late Blight Lab and described in Baker et al. (2000) and below. Relative humidity was obtained with hourly air and dew point temperatures. Each hour above 80 percent relative humidity was assigned to its respective Wallin-based temperature category and category hours were summed for each day. Hourly values were considered conducive for late blight if the associated air temperature ranged from 7.2 to 27°C. Hours that were both above the relative humidity threshold and within temperature ranges from 7.20 –11.69, 11.70-14.99, and 15.00-27.00 for a requisite number of hours (detailed explanation in Table 1) were assigned the corresponding DSV. DSV range from 0 to 4, where 0 were not conducive, and 4 were highly conducive to late blight development. 24-hour daily periods were set at 12:00 noon through 11:59 a.m., to maximize single day estimation of duration of the leaf wetness period.

Although a 90 percent relative humidity ambient air threshold is often used as the best approximation of leaf wetness, an 80 percent relative humidity threshold was used in this study for the following reasons. Given the dense structure of a potato canopy, relative humidity is typically higher in the canopy than the ambient air. Figure 4 shows the relationship between canopy and ambient relative humidity. Hourly relative humidity data were recorded at Entrican, MI during the growing season in 1997, 1998 and 1999 from the time of canopy closure (LAI=3) to beginning of canopy senescence (LAI=2). Mean and standard deviation of the ambient relative humidity per one percent intervals of canopy relative humidity are shown with respect to the 90 percent criterion for estimating leaf wetness and the line of 1:1 relationship between canopy and ambient relative humidity is included for clarity. Approximately 125 ambient relative humidity values were included for each canopy interval. Ambient percent relative humidity values were about 5-7 percent lower than those recorded in the canopy air, with standard deviations ranging from 3-5 percent. At 80 percent ambient relative humidity, the canopy relative humidity was within one standard deviation of 90 percent and at 83 percent ambient relative humidity, the canopy mean relative humidity was 90 percent. Given these results, a large percentage of hours when the canopy relative humidity was near 90 percent would not be counted if the ambient threshold for DSV accumulation was greater than 80 percent.

Comparison of disease severity accumulations in the canopy and ambient air at different relative humidity thresholds also indicate that the 90 percent ambient relative humidity threshold is insufficient for estimating canopy conditions (Figure 5). The 90 percent criterion has been shown in previous studies to underestimate leaf wetness duration in ground crops and to be less than optimal for disease alert systems (Thompson, 1981; Giesler et al., 1996). The 80 percent ambient threshold, however, consistently

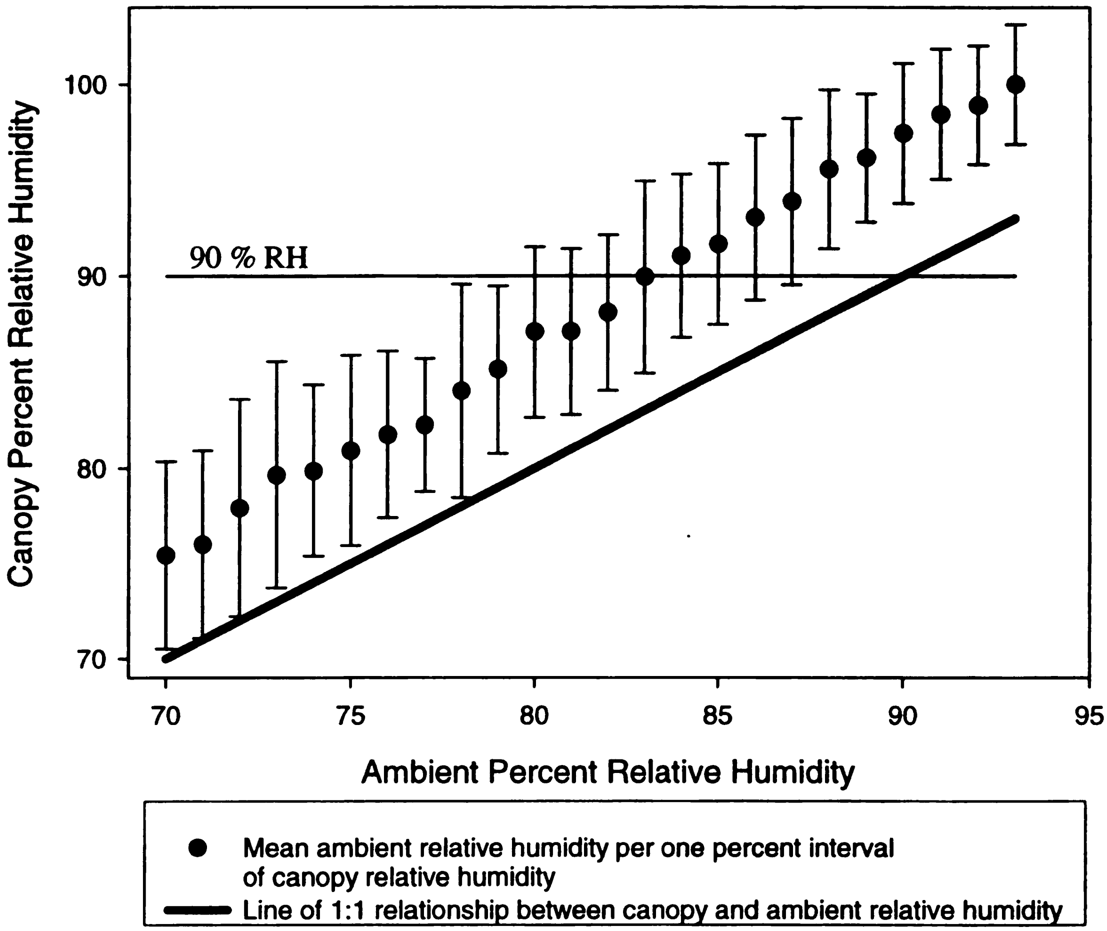


Figure 4. Comparison of in-canopy and ambient air relative humidity from a potato canopy in Entrican, MI during the growing seasons of 1997, 1998, and 1999. Mean and standard deviation of ambient relative humidity are shown for each one percent interval of canopy air relative humidity (approximately 125 ambient values per canopy percentage). The 1:1 relationship line is shown for clarity, and the 90% canopy relative humidity is shown as the common criteria for estimating leaf wetness.

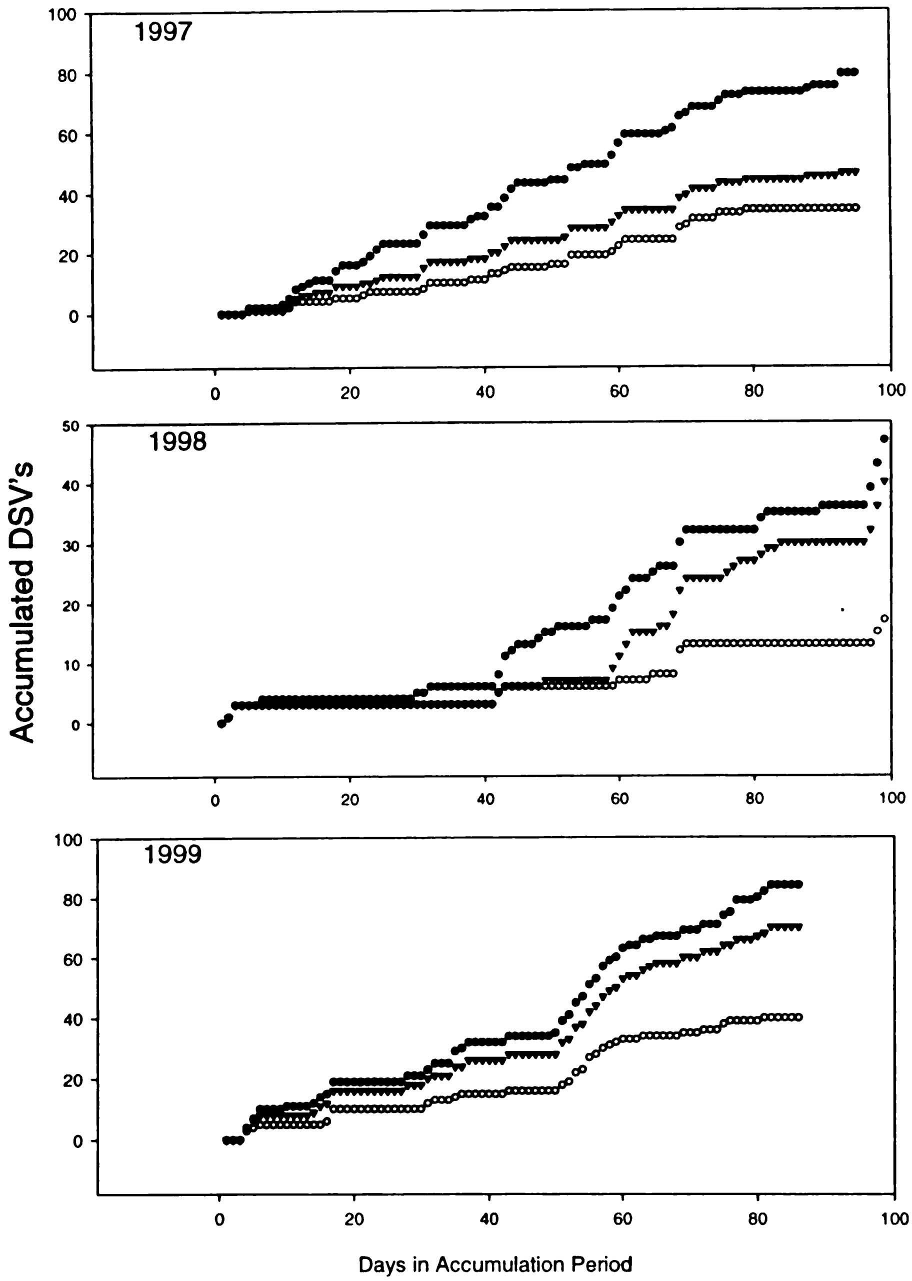


Figure 5. Disease severity value accumulations for 1997, 1998, 1999 at Entrican, Michigan. DSV were based on relative humidity thresholds of 90 percent in the canopy and both 80 and 90 percent in the ambient air. DSV were accumulated in days after potato emergence and hilling, when sensors were placed in the canopy (approximately May 15-30).

- • 80% RH - Ambient
- ○ 90% RH - Ambient
- ▾ 90% RH - Canopy

overestimates the 90 percent canopy threshold in terms of disease risk. Given the closeness of disease severity value accumulations between 80 percent ambient and 90 percent canopy on day 100 in 1998, and day 51 in 1999, a lesser ambient threshold would be prone to occasional but serious underestimation in potato late blight risk, especially during periods of strongly increasing DSV accumulation. Therefore, an 80 percent ambient air relative humidity threshold was used for the calculation of potato late blight disease severity values throughout this analysis.

Hourly and Three-Hour Data

Archived NWS weather data alternated between hourly and three-hour values. Three-hour values were most frequently used from 1965-1972, and from 1978 to 1981. When hourly values were not available, three-hour values were used to estimate hourly values with linear interpolation. Hourly ambient air temperature values, dew point temperature, and relative humidity hourly values were compared with those interpolated from three-hour values and analyzed with respect to the timing and magnitude of differences.

Trend Analysis

Non-parametric statistical methods were appropriate for trend analysis since the underlying distributions of the data were generally unknown. These methods are also not affected by missing values and data errors that resulted from measurement changes and missing hourly values that may have impacted estimation of correlation and slope parameters. The possibility of a large number of outliers in the risk indicators derived as secondary variables from ambient and dew point temperature also made non-parametric statistics a better choice than similar parametric estimates. Trends in the timing and accumulation of disease severity values were quantified using a non-parametric slope estimator (Sen, 1968). Unlike linear regression, the trend magnitude statistic (*B*) is not significantly impacted by lack of normality, missing data values and errors that are unavoidable in derivative data. This method was used in similar studies of hydrological and climatological time series trend analyses (Andresen et al., 2001). When ***n*** is the number of observation in a series, *B* is calculated as:

$$B = median\{D_{ij}\} \qquad \text{Equation 1}$$

where for all possible pairs (x_i, x_j), $1 \le i < j \le n$, D_{ij} is the difference in a risk associated value through time when:

$$D_{ij} = \frac{(x_j - x_i)}{j - i} \qquad \text{Equation 2}$$

and *i* and *j* are years included in the analysis for a single location while *x* is the risk related estimate for that specific year.

The probability of detecting a statistically significant difference between risk indicators, derived as secondary variables from weather data, was estimated at the p=0.05 significance level using Kendall's tau b non-parametric correlation coefficient (SAS statistical software package). Both the magnitude of the correlation coefficient and the number of years (***n***) included for a given location were used in the determination of significance. Kruskall-Wallis one way analysis of variance on ranks was also used at the

p=0.05 level to test for statistically significant differences between potato late blight risk indicator estimates at various locations. Trend analysis was performed using time series of the DSV derived variables for each growing season from 1948-1999 at each location. These risk indicators (Table 2) are described in detail below.

Seasonal DSV Accumulation

The growing season included the 153 days from May 1 through September 30 for each year. The seasonal accumulation of DSV, $\sum_0^{153} v$ or Σv, is the sum of all 153 individual values when v is the individual disease severity value from 0 to 4 of days within a single growing season. Trend analysis was performed on both the $\sum_0^{153} v$ time series including all available years, and on a temporal subset that excluded years (j) after 1990 ($\sum_0^{153} v_{j \le 1990}$). This subset limited the study to pre-ASOS instrumentation in order to assume the 1°C maximum series bias found by Robinson (Robinson, 2000).

DSV Day Type Analysis

Different disease severity values (0,1,2,3,4) indicated different late blight risk related conditions, or a different type of disease risk day. When x_y is a growing season day with a specific DSV, y, $\sum_0^{153} x_y$ (or Σx_y) represents the sum of days of this type in a particular growing season, e.g. Σx_y represents x days in a particular growing season with disease severity value of y. The number of days with each specific DSV value, Σx_y and the number of days with a value greater than zero, $\Sigma x_{y>0}$, were compared to determine if

Table 2. Indicators of potato late blight risk estimated for each growing season and location included in the 1948-1999 analyses and derived as secondary variables from ambient air temperature, dew point temperature, and time in days during the growing season (from May 1 through September 30).

Derived Variables	Simplified	Description
v		the individual DSV[1] per day within a single growing season[2]
x		a growing season day with a particular DSV assigned
y		the DSV assigned to a particular growing season day
$\sum_{0}^{153} v$	Σv	number DSV accumulated per growing season[2]
$\sum_{0}^{153} v_{j\leq 1990}$	$\Sigma v_{j\leq 1990}$	number DSV accumulated per growing season for growing seasons prior to the year 1991, where j is the year
$\sum_{0}^{153} x_{y}$	Σx_y	total number of days with a particular DSV in a single growing season
$t_{(\sum v=18)}$	$t_{\Sigma v=18}$	time in days (t) until the growing season accumulation of DSV is equal to 18
$t_{(\sum v=30)}$	$t_{\Sigma v=30}$	time in days (t) until the growing season accumulation of DSV is equal to 30
$\sum_{t_i}^{t_{i+5}} v \geq 10$	$\Sigma v \geq 10$	number of five day periods ($t_i..t_{i+5}$) in a single growing season when the accumulated DSV (for those five days) is equal to at least 10
$\sum_{Startdate}^{Enddate} v$	30-day Σv	number DSV accumulated during a particular period specified by *start date* and *end date* during a single growing season

[1]Potato late blight disease severity values (DSV) were calculated using the modified Wallin method explained in this chapter.
[2] Growing season included May 1 through September 30 (153 days) in all years (1949 - 1999) in analyses.

trends were related to increasing frequency of a specific type of risk condition. The distribution of $\Sigma x_{y>0}$ and the change in Σx_y distribution were also compared at each station location.

Threshold Analysis

The time, t, in days until the accumulation of DSV, Σv, reached a threshold value, was calculated for fungicide spray triggers at 18 and 30 accumulated DSV. The 18 DSV ($t_{\Sigma v=18}$) accumulation corresponded to the traditional Wallin model threshold initiation of fungicide sprays(Wallin and Schuster, 1960; Wallin, 1962; MacKenzie, 1981), while 30 ($t_{\Sigma v=30}$) was used in the MSU modified system as a key Σv that signaled a point to increase fungicide application rate from minimum to maximum manufacturer's recommended application rate. In the MSU system, applications of fungicides were recommended to start soon after emergence regardless of conditions, or Σv, in order to prevent initiation of epidemics from late blight contaminated seed.

Analysis of Highly Conducive Periods

Consecutive rain days and other relatively short time periods with large increases DSV accumulation are especially important for management decisions related to late blight control. The number of times during each growing season when the accumulated late blight risk, v, during any five day time period, $t_{i..i+5}$, was greater than 10 ($\sum_{t_i}^{t_{i+5}} v \geq 10$

or $\Sigma v \geq 10$) was used to estimate the frequency of canopy conditions that were highly conducive to late blight.

Timing of Change in Risk

To determine the timing in the changes in potato late blight risk accumulation over the 50 year period, trends in 30-day accumulated values ($\sum_{Startdate}^{Enddate} v$) were assessed to determine which periods within the growing season were most influenced by changing weather patterns. Since no previous research has established an optimal time scale within the growing season for late blight risk, or defined the beginning and end of risk periods seasonally, DSV accumulations, v, were started on the first and fifteenth of each month ($\sum_{May1}^{May31} v, \sum_{May15}^{June15} v, .., \sum_{Sept1}^{Sept30} v$) to ensure complete coverage of the entire growing season. These 30-day periods were then associated with potato canopy leaf area index (LAI) estimates for the growing region (Allen and Scott, 1992). LAI monthly estimates were important to the understanding of how canopy conditions relate to those in the ambient air during analyzed time intervals.

Environmental Variable Trends

Similarly, to determine relationships between trends in late blight risk values and the physical environmental variables from which they were derived, monthly dew point temperature(T_d) and ambient temperature (T_a) were also analyzed for the presence of trends ($\sum_{May1}^{May31} T, .., \sum_{Sept1}^{Sept30} T$).

RESULTS

Comparison of Hourly and Three-Hour Data

Differences between hourly and interpolated values in air and dew point temperature and associated relative humidity percentages were greatest at sunrise and sunset, as would be expected given the sinusoidal nature of the diurnal temperature curve, and the linear nature of the interpolation method. In 1985 at Grand Rapids, for example, the greatest difference in both ambient temperatures and relative humidity occurred just after sunrise and before sunset, or 8:00 and 21:00 respectively, and standard deviations were greatest from 21:00 to 8:00. Temperature differences were less than 1°C and the mean difference in relative humidity values was about ±1-2 percent with a mean standard deviation 3.8 percent.

Seasonal DSV Accumulation

Median value lines were overlaid on time series of annual accumulations at each location (Figure 6(a-g)). Across the region, DSV accumulations, Σv, tended to be greater in 1960-62, 1978-79 and 1994-96. Boxplots and accompanying summary statistics were used to visualize the distribution of Σv at each location during the growing seasons from 1948-1999 (Figure 7). The greatest Σv ranges, as well as the highest maximum Σv values, were found at Muskegon, Grand Rapids and Toledo. Alpena, Traverse City, and

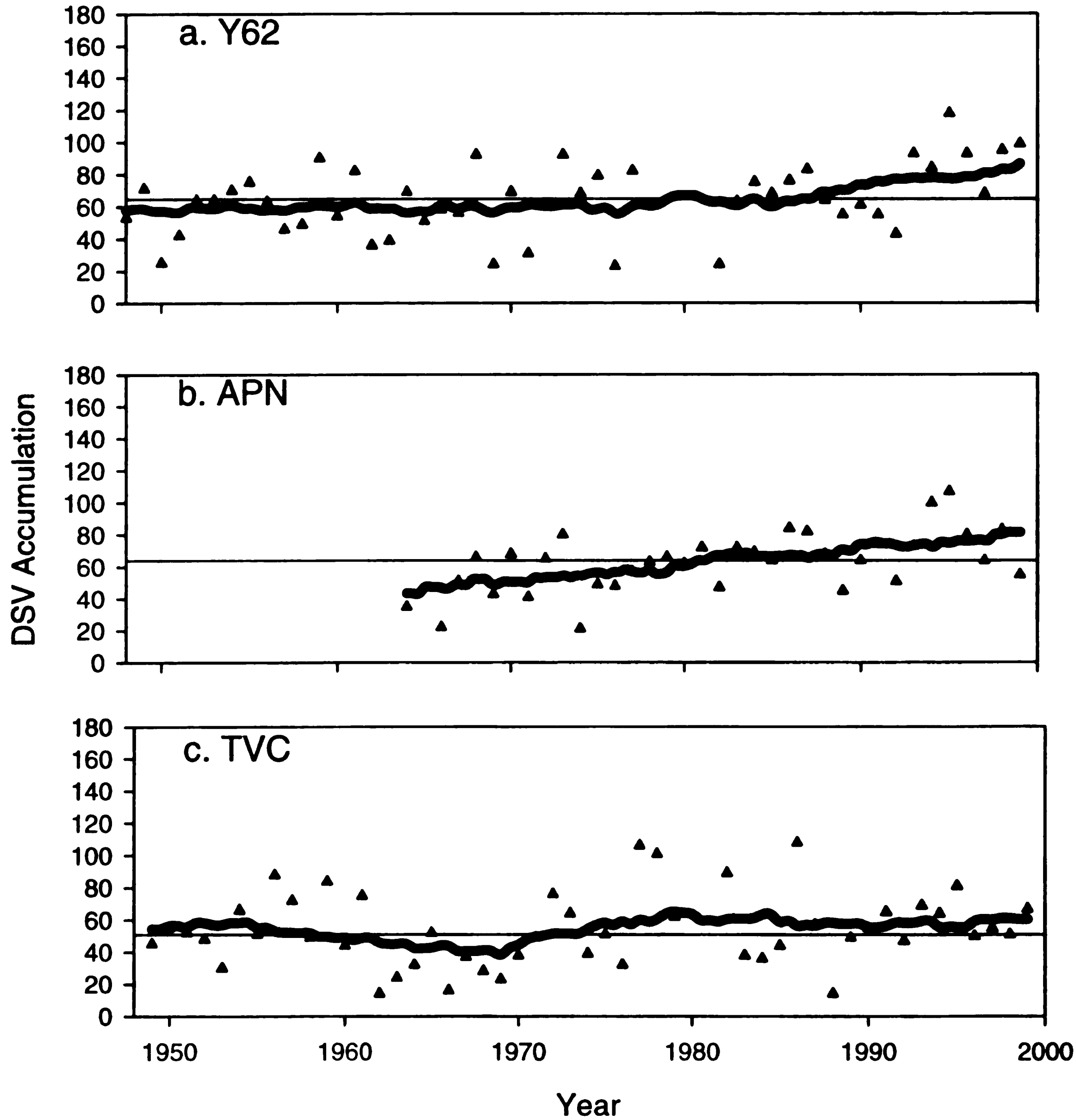
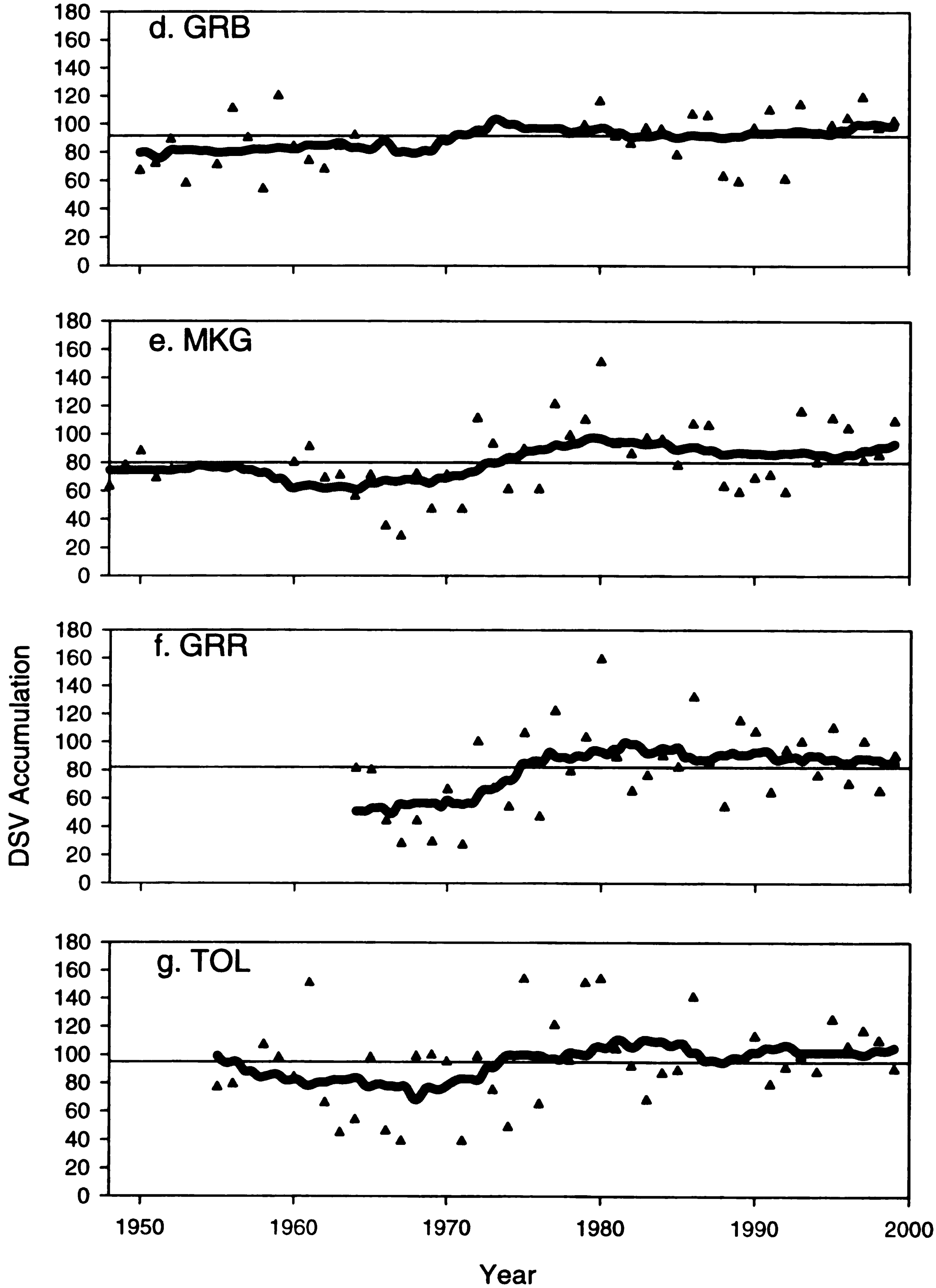


Figure 6 (a-g). DSV accumulation (Σv) by year for: a) Sault Ste Marie (Y62), b) Alpena (APN), c) Traverse City (TVC), d) Green Bay (GRB), e) Muskegon (MKG), f) Grand Rapids (GRR), and g) Toledo (TOL). Values are overlaid with location-specific median value line and smoothed trend line.


d. GRB
e. MKG
f. GRR
g. TOL
DSV Accumulation
Year
0
20
40
60
80
100
120
140
160
180
1950
1960
1970
1980
1990
2000

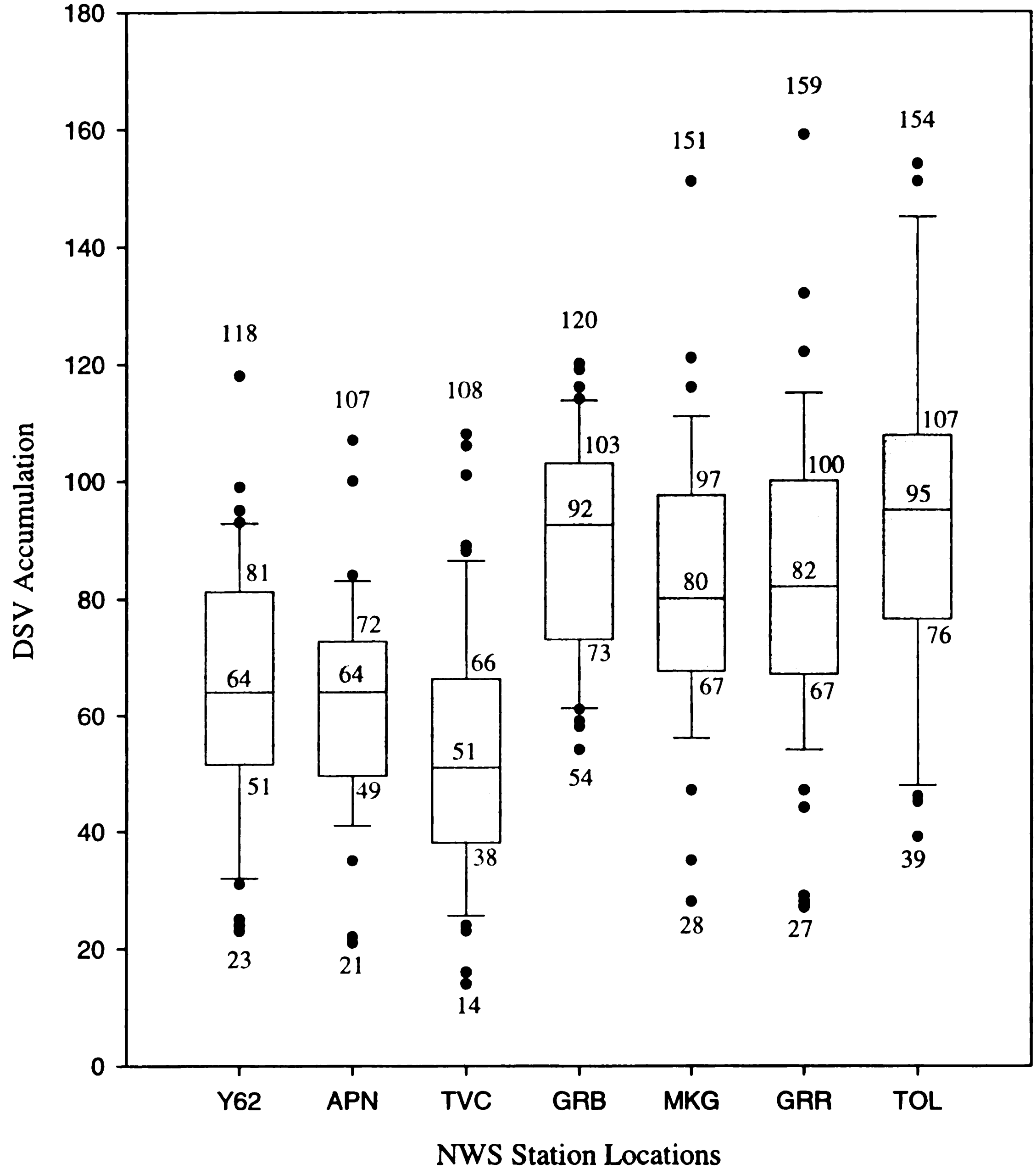


Figure 7. Accumulated potato late blight DSV (Σv) from May 1 to September 30 at seven locations in the Upper Great Lakes region, locations described in Figure 6. Summary statistics, from top to bottom of each boxplot, include maximum (above maximum point), 75% quartile (right of upper whisker), median (box midline), 25% quartile (right of lower whisker) and minimum values (below minimum).

Sault Ste Marie were less variable, and had lower Σv values than the other stations. Green Bay had a similar mean Σv to the southern stations, but fewer outliers.

The results from the analysis of Σv, including the median DSV accumulated and the rate of change in Σv for both the total data set and the pre-ASOS temporal subset are shown in Table 3. The median Σv for the entire 52-year period ranged between 51 at Traverse City to 90 at Toledo. Alpena and Sault Ste Marie were not statistically different from Traverse City. Green Bay, Muskegon and Grand Rapids were not significantly different from Toledo. However, the three northernmost locations were significantly different from the four southernmost locations. All Σv were found to increase between 1948 and 1999 and the increases were significantly greater than zero at all sites except Toledo and Traverse City. Increases in Σv at Sault Ste Marie, Green Bay, Muskegon and Toledo were of similar magnitude, between 0.54 and 0.61 DSV per year from 1948-1999. The magnitude of the increases in Σv at Alpena and Grand Rapids, 1.00 and 1.10 respectively, was nearly double those at the other locations.

When years after 1990 were excluded from the analysis, similarities and differences between locations became more complex. The median $\sum_{0}^{153} v_{j \le 1990}$ at Green Bay and Toledo were greater than stations with a median lower than 65, but not significantly different from Muskegon, Grand Rapid, or one another. The median values of $\Sigma v_{j \le 1990}$ at Muskegon and Grand Rapids were not significantly different from that at Sault Ste Marie. Grand Rapids and Traverse City had median values significantly different from one another. Alpena and Sault Ste Marie median $\Sigma v_{j \le 1990}$ were not significantly different from those at Grand Rapids and Traverse City. The estimated rates of increase over time remained significantly greater than zero after the removal of post-

Table 3. Analysis of accumulated DSV per growing season, May 1 through September 30, at seven locations in the greater Michigan region from 1948-1999 and from 1948-1990 including a) the median DSV accumulated per growing season and b) the rate of change in DSV accumulated per growing season.

	a) Median number DSV accumulated per growing season[1] ($\sum_0^{153} v$)					
	1948-1999			1948-1990		
NWS station[2]	N	Median		N	Median	
Y62	47	64.0	b[3]	38	63.5	bcd
APN	35	64.0	b	26	63.5	cd
TVC	49	51.0	b	40	49.0	d
GRB	36	92.5	a	27	89.0	a
MKG	45	80.0	a	36	76.5	ab
GRR	36	82.0	a	27	80.0	abc
TOL	41	95.0	a	32	93.5	a

	b) Non-paramentric trend (rate of change in v per year) for DSV accumulated per growing season			
NWS station	1948-1999		1948-1990	
Y62	0.55	*[4]	0.23	
APN	1.00	***	1.12	*
TVC	0.25		0.10	
GRB	0.56	**	0.43	
MKG	0.54	*	0.54	
GRR	1.10	*	2.21	*
TOL	0.61		0.86	

[1] Growing season included May 1 through September 30 (153 days).
[2] National Weather Service (NWS) station locations: Y62 - Sault Ste Marie; APN - Alpena; TVC - Traverse City; GRB - Green Bay, WI; MKG - Muskegon, MI; GRR - Grand Rapids, MI; TOL - Toledo, OH.
[3] Within a single column, values followed by the same letter are not significantly different at P = 0.05 (Kruskal-Wallis One Way Analysis of Variance on Ranks).
[4] Rate of change is significantly greater than zero at P = 0.05 (*), P = 0.01 (**), or P = 0.001 (***) (Kendall Tau b).

1990 data at only Alpena and Grand Rapids. In comparison to the analysis of Σv, the rate of change in $\Sigma v_{j \leq 1990}$ increased at Toledo, remained constant at Muskegon, and decreased at all other locations.

DSV Day Type Analysis

Median values and trend statistics for the number of different disease risk day types each growing season are shown in Table 4. The number of days with a DSV of 0, $\sum_0^{153} x_0$, at Alpena and Traverse City were significantly different from the four southernmost locations, but not from one another or from Sault Ste Marie. The median value at Sault Ste Marie was not significantly different from that of Grand Rapids. $\sum_0^{153} x_0$ decreased at all locations over the 50-years in the region. This decrease was statistically significantly at Sault Ste Marie, Alpena, Green Bay and Muskegon.

The number of days that the DSV was greater than zero ($\Sigma x_{y>0}$) are shown in Figure 8 (a-g) for all NWS locations, broken down by specific values of y (Σx_y). The median Σx_1 were more frequent at all stations than Σx_1, Σx_2, or Σx_3 (Table 4). Σx_2 , Σx_3 and Σx_4 were less frequent at all locations, and increased in range as station latitude decreased.

The trends in the number of days with each $\Sigma x_{y>0}$ were not significantly different between one another at the four southernmost stations (Table 4). Neither were $\Sigma x_{y>0}$ significantly different from one another at the three northern stations. Σx_1 at Sault Ste Marie, Traverse City, and Alpena were not significantly different from those at Grand Rapids. Σx_2 at Sault Ste Marie, Alpena, Muskegon and Grand Rapids were not

Table 4. Analysis of specific DSV value day types per growing season, May 1 through September 30, at seven locations in the greater Michigan region from 1948-1999: a) median number of days with each value per growing season and b) rate of change in number of days of each value per growing season.

a) Median number of days per growing season[1] with specific DSV value (y) from 0 - 4 ($\sum_0^{153} x_y$)

NWS station[2]	$\sum_0^{153} x_0$		$\sum_0^{153} x_1$		$\sum_0^{153} x_2$		$\sum_0^{153} x_3$		$\sum_0^{153} x_4$	
Y62	122.0	ab[3]	12.0	bc	9.0	bc	5.0	ab	4.0	bc
APN	123.0	a	12.0	c	8.0	bc	5.0	ab	5.0	abc
TVC	125.0	a	12.0	bc	7.0	c	3.0	b	4.0	c
GRB	109.0	c	18.0	a	13.0	a	6.5	a	7.0	a
MKG	113.0	c	15.0	ab	11.0	ab	6.0	a	5.0	ab
GRR	115.0	bc	14.5	abc	11.0	ab	6.5	a	5.0	abc
TOL	106.0	c	18.0	a	14.0	a	7.0	a	5.0	ab

b) Non-paramentric trend (rate of change in x per year) in number of days per growing season with specific DSV value (y) from 0 through 4

NWS station	$\sum_0^{153} x_0$		$\sum_0^{153} x_1$		$\sum_0^{153} x_2$		$\sum_0^{153} x_3$		$\sum_0^{153} x_4$	
Y62	-0.22	*[4]	0.03		0.08	*	0.02		0.04	*
APN	-0.44	**	0.14		0.16	**	0.11	**	0.07	
TVC	-0.10		0.00		0.00		0.30		0.00	
GRB	-0.19	*	0.00		0.09	*	0.06	**	0.03	
MKG	-0.30	**	0.09		0.09	*	0.04		0.04	
GRR	-0.48		0.15		0.22	**	0.00		0.13	*
TOL	-0.25		0.06		0.13	*	0.00		0.08	

[1] Growing season included May 1 through September 30 (153 days) in all years (1949 - 1999) in analyses.

[2] National Weather Service (NWS) station locations: Y62 - Sault Ste Marie; APN - Alpena; TVC - Traverse City; GRB - Green Bay, WI; MKG - Muskegon, MI; GRR - Grand Rapids, MI; TOL - Toledo, OH.

[3] Within a single column, values followed by the same letter are not significantly different at P = 0.05 (Kruskal-Wallis One Way Analysis of Variance on Ranks).

[4] Rate of change is significantly greater than zero at P = 0.05 (*) or P = 0.01 (**) (Kendall Tau b).

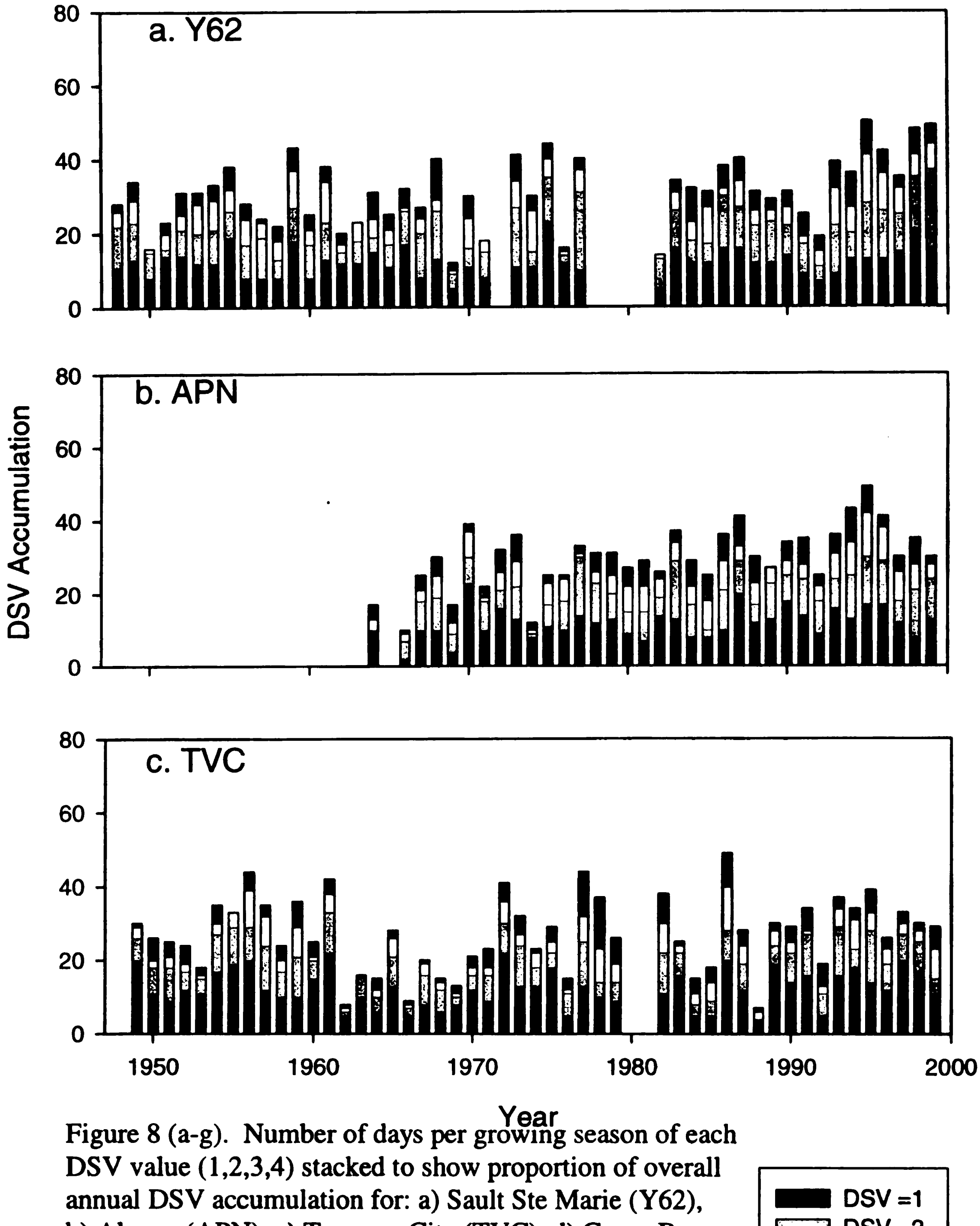
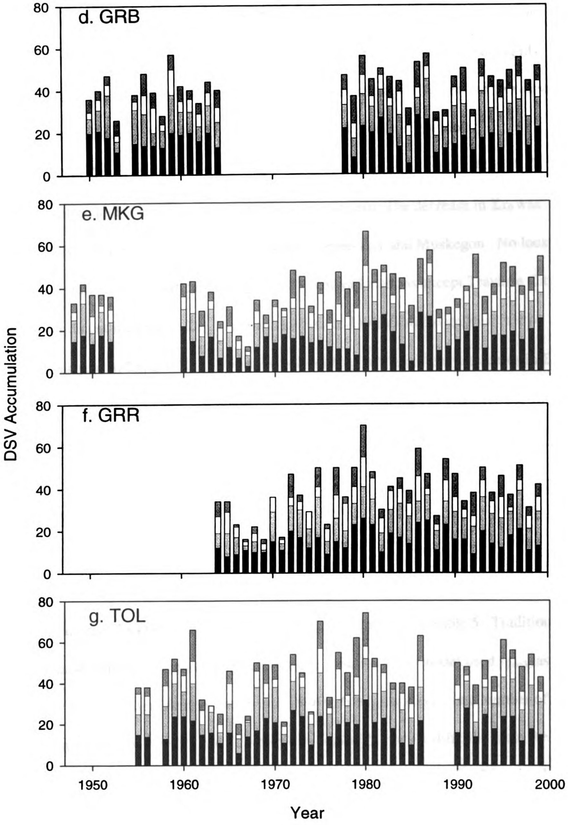


Figure 8 (a-g). Number of days per growing season of each DSV value (1,2,3,4) stacked to show proportion of overall annual DSV accumulation for: a) Sault Ste Marie (Y62), b) Alpena (APN), c) Traverse City (TVC), d) Green Bay (GRB), e) Muskegon (MKG), f) Grand Rapids (GRR), and g) Toledo (TOL). Total growing season days were 153 in this analysis; DSV=0 each year was $153-\Sigma x_{y>0}$.



d. GRB
e. MKG
f. GRR
g. TOL
DSV Accumulation
Year
0
20
40
60
80
1950
1960
1970
1980
1990
2000

significantly different from one another. Σx_3 at Sault Ste Marie and Alpena were not significantly different from the four southern stations. At Muskegon, Grand Rapids, Toledo, Sault Ste Marie, and Alpena, Σx_4 were not statistically different, but Traverse City was significantly different from Green Bay, Muskegon and Toledo.

While Σx_0 decreased from 1948 to 1999 at every location, temporal trends for every location and every $\Sigma x_{y>0}$ were either positive or zero. The decrease in Σx_0 was statistically different at Sault Ste Marie, Alpena, Green Bay and Muskegon. No location showed a statistically significant change in Σx_1, but all locations except Traverse City had a significant increase in Σx_2. Alpena and Grand Rapids had the greatest rate of change per year in Σx_1 and Σx_2. Alpena and Green Bay had significant increases in Σx_3 and Grand Rapids and Sault Ste Marie had a significant increases in Σx_4 over the 50 year time period.

Threshold Analysis

The number of days from the beginning of the growing season until the accumulation of 18 DSV ($t_{\Sigma v=18}$) and 30 DSV ($t_{\Sigma v=30}$) is shown in Table 5. Traditional Wallin models initiated fungicide sprays at $t_{\Sigma x=18}$, and the MSU model used $t_{\Sigma x=30}$ as a point to increase fungicide application rate. For both $t_{\Sigma x=18}$ and $t_{\Sigma x=30}$ the number of days was greatest at Traverse City and Traverse City was significantly different from the four southernmost stations, but not from Sault Ste Marie or Alpena. Sault Ste Marie and Alpena $t_{\Sigma v=18}$ were not significantly different from Muskegon $t_{\Sigma v=18}$. Alpena $t_{\Sigma v=18}$ was also not significantly different from those at Green Bay, Muskegon and Grand Rapids.

Table 5. Analysis of the accumulation of DSV to thresholds of 18 and 30 per growing season, May 1 through September 30, at seven locations in the greater Michigan region from 1948-1999 including a) the median DSV accumulated per growing season and b) the rate of change in DSV accumulated per growing season.

	a) Median number of days (t) to DSV accumulation thresholds ($\sum v$) per growing season[1]			
NWS station[2]	$t_{(\sum v=18)}$		$t_{(\sum v=30)}$	
Y62	81.0	ab[3]	95.0	ab
APN	81.0	abc	99.0	ab
TVC	83.0	a	107.0	a
GRB	69.5	cd	84.0	c
MKG	68.0	bcd	86.0	bc
GRR	61.5	cd	87.0	bc
TOL	57.0	d	76.0	c

	b) Non-paramentric trend in number of days (t) (rate of change in t per year) to DSV accumulation thresholds per growing season			
NWS station	$t_{(\sum v=18)}$		$t_{(\sum v=30)}$	
Y62	-0.48	*[4]	-0.45	*
APN	-0.83		-1.08	**
TVC	-0.08		-0.18	
GRB	-0.14		-0.21	
MKG	-0.32		-0.33	
GRR	-0.64	*	-1.09	***
TOL	-0.39		-0.47	*

[1] Growing season included May 1 through September 30 in all years (1949 - 1999).
[2] National Weather Service (NWS) station locations: Y62 - Sault Ste Marie; APN - Alpena; TVC - Traverse City; GRB - Green Bay, WI; MKG - Muskegon, MI; GRR - Grand Rapids, MI; TOL - Toledo, OH.
[3] Within a single column, values followed by the same letter are not significantly different at P = 0.05 (Kruskal-Wallis One Way Analysis of Variance on Ranks).
[4] Rate of change is significantly greater than zero at P = 0.05 (*), P = 0.01 (**), or P = 0.001 (***) (Kendall Tau b).

Sault Ste Marie, Alpena, Muskegon and Grand Rapids were not significantly different from one another with respect to $t_{\Sigma v=30}$.

The time to these spray thresholds decreased over the 50-year period at all locations (Table 5). The time in days to both thresholds significantly decreased at Grand Rapids and Sault Ste Marie, and $t_{\Sigma v=30}$ decreased significantly at Alpena and Toledo, from 1948-1999. Alpena and Grand Rapids had the greatest decrease over time in the number of days to the thresholds.

Analysis of Highly Conducive Periods

The numbers of periods highly conducive to late blight within a growing season for each location are shown in Figure 9(a-g). Conditions were considered to be highly conducive if 10 DSV or more were accumulated in a five-day period ($\Sigma v \geq 10$). Years when the total number of periods was zero are shown with a black box at the origin, while years without a bar or origin point were not included in the analysis. The peak number of $\Sigma v \geq 10$ occurred from 1978-80 and 1994-99 for most locations. Maximum $\Sigma v \geq 10$ increased with decreasing latitude. A decreasing frequency of zero values over time was noted for Traverse City, Grand Rapids, and Toledo.

Median values of $\Sigma v \geq 10$ and rate of change in the number of periods for each location from 1948-1999 are shown in Table 6. $\Sigma v \geq 10$ at the three northern stations were not significantly different from one another, nor were the southern stations significantly different from one another. At Sault Ste Marie, Alpena, Muskegon, Grand Rapids and Toledo $\Sigma v \geq 10$ was not statistically different between locations. The increase in the

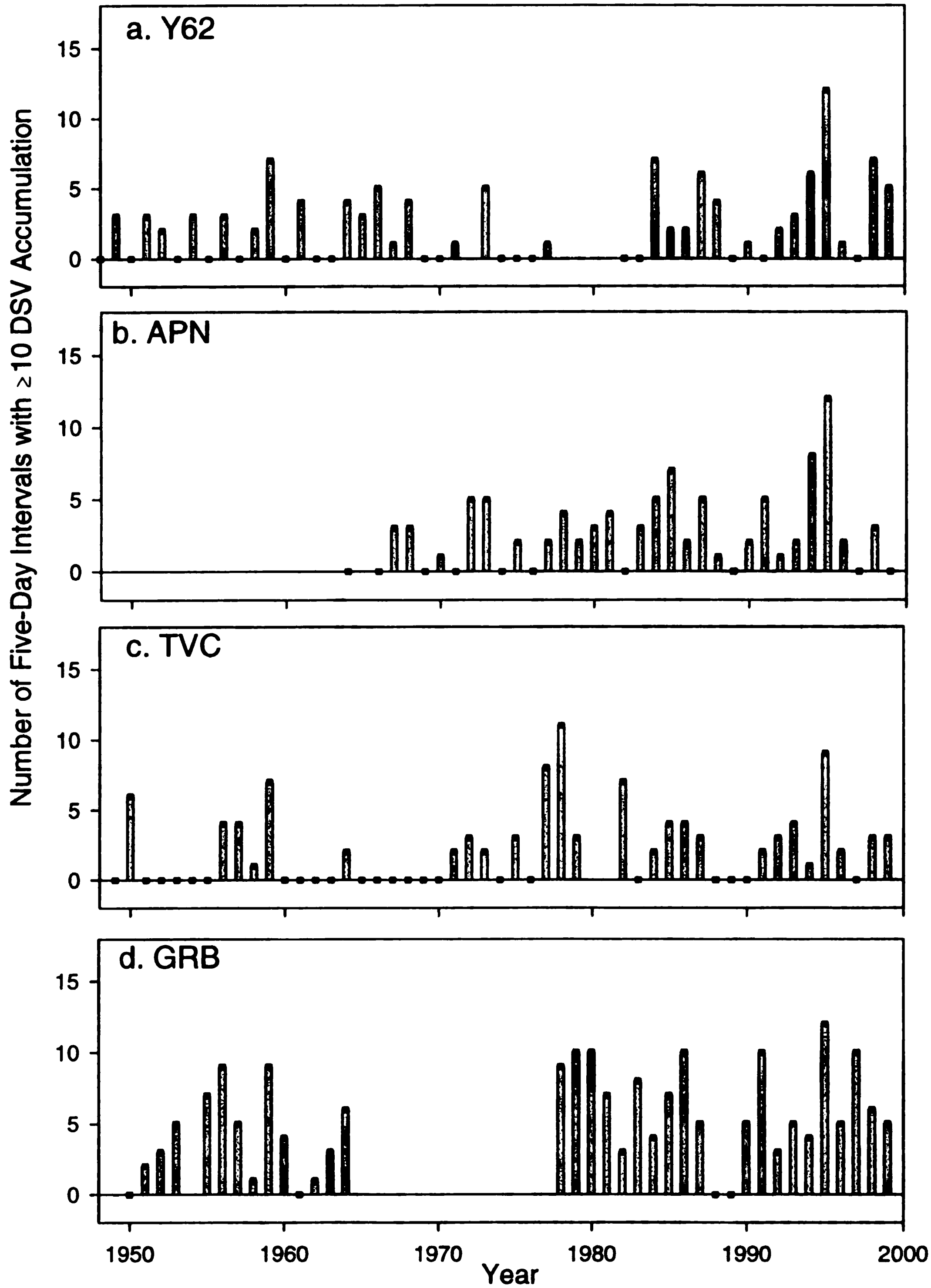


Figure 9 (a-g). Number of five-day intervals with disease severity value accumulation of ten or more per growing season for: a) Sault Ste Marie (Y62), b) Alpena (APN), c) Traverse City (TVC), d) Green Bay (GRB), e) Muskegon (MKG), f) Grand Rapids (GRR), and g) Toledo (TOL). Note change of scale in 9g.Years when the total umber of high accumulation periods was zero are shown with a black box at the origin, while years without a bar or origin point were not included in the analysis.

Table 6. Analysis of the number of five day periods with an accumulation of ten or more DSV per growing season, May 1 through September 30, at seven locations in the greater Michigan region from 1948-1999 and from 1948-1990 including a) the median DSV accumulated per growing season and b) the rate of change in DSV accumulated per growing season.

NWS station[1]	a) Median number of five days periods (t_i to t_{i+5}) with an accumulation of ten DSV or greater ($\sum_{t_i}^{t_{i+5}} v \geq 10$) per growing season[2]	
Y62	2.0	bc
APN	2.0	bc
TVC	1.0	c
GRB	5.0	a
MKG	3.0	ab
GRR	4.0	ab
TOL	4.0	ab

NWS station	b) Non-paramentric trend in the number of five days periods (t_i to t_{i+5}) with an accumulation of ten DSV or greater per growing season (rate of change in periods per year)	
Y62	0.00	
APN	0.00	
TVC	0.25	*[4]
GRB	0.05	
MKG	0.07	
GRR	0.14	*
TOL	0.13	**

[1] National Weather Service (NWS) station locations: Y62 - Sault Ste Marie; APN - Alpena; TVC - Traverse City; GRB - Green Bay, WI; MKG - Muskegon, MI; GRR - Grand Rapids, MI; TOL - Toledo, OH.
[2] Growing season included May 1 through September 30 (153 days) in all years (1949 - 1999) in analyses.
[3] Within a single column, values followed by the same letter are not significantly different at P = 0.05 (Kruskal-Wallis One Way Analysis of Variance on Ranks).
[4] Rate of change is significantly greater than zero at P = 0.05 (*) or P = 0.01 (**) (Kendall Tau b).

number of $\Sigma v \geq 10$ intervals from 1948 to 1999 at Grand Rapids, Toledo and Traverse City was significant statistically. The greatest increase in $\Sigma v \geq 10$ was measured at Traverse City. Increases in $\Sigma v \geq 10$ at Green Bay and Muskegon were also positive, but there was no change in the number of $\Sigma v \geq 10$ intervals at the two northernmost stations, Sault Ste Marie and Alpena (Table 6).

Timing of Change in Risk

The analysis of DSV accumulation during 30-day periods throughout the growing season, $\sum_{Startdate}^{Enddate} v$, started on the first and fifteenth of each month, is shown in Table 7. Median 30-day Σv were consistently lowest at Traverse City, except during the period beginning June 15, when Alpena was slightly lower. Highest median 30-day Σv generally occurred at Toledo for all periods. On only one occasion (July1-July31, Grand Rapids) were the medians of any of the four southernmost locations of Green Bay, Muskegon, Grand Rapids and Toledo statistically different from one another. The three northernmost locations of Sault Ste Marie, Alpena and Traverse City were not statistically different throughout the season. From June 15 onward, the median 30-day Σv at Grand Rapids was not significantly different from the medians at the three northernmost stations.

All trends of 30-day Σv since 1948 were positive with the exception of Muskegon and Grand Rapids during September. Greatest increases occurred during periods that started at June 15 or later. The increase in 30-day Σv was statistically significant at Sault Ste Marie, Alpena, Muskegon and Grand Rapids for periods beginning on both June 15

Table 7. Analysis of DSV accumulation during 30-day periods per growing season, May 1 through September 30, at seven locations in the greater Michigan region from 1948-1999 including: a)the median DSV accumulation (Σv) during 30-day periods per growing season and b) rate of change in DSV accumulation during 30-day periods per growing season.

a) Median DSV accumulation (Σv) during 30-day periods per growing season[1]

NWS station[2]	$\sum_{May1}^{May31} v$	$\sum_{May15}^{June15} v$	$\sum_{June1}^{June30} v$	$\sum_{June15}^{July15} v$	$\sum_{July31}^{July1} v$	$\sum_{Aug15}^{July15} v$	$\sum_{Aug30}^{Aug1} v$	$\sum_{Sept15}^{Aug15} v$	$\sum_{Sept30}^{Sept1} v$
Y62	2.0 c[3]	4.0 c	7.0 bc	11.0 ab	16.0 bc	20.0 abc	20.0 ab	21.0 ab	14.0 ab
APN	3.0 bc	4.0 bc	7.0 c	9.0 b	17.0 bc	18.0 bc	21.0 ab	20.0 ab	13.0 ab
TVC	2.0 c	4.0 bc	7.0 bc	10.0 b	11.0 c	14.0 c	16.0 b	15.0 b	10.0 b
GRB	3.0 ab	9.0 ab	11.5 abc	16.0 a	21.5 a	26.5 a	26.5 a	27.0 a	17.0 ab
MKG	2.0 bc	7.0 abc	11.0 ab	14.0 ab	20.0 ab	27.0 ab	28.0 a	22.0 a	15.0 ab
GRR	4.0 ab	8.5 a	13.5 a	14.5 ab	16.5 bc	22.5 abc	26.0 ab	22.5 ab	17.5 ab
TOL	7.0 a	13.0 a	14.0 a	16.0 a	20.0 ab	28.0 ab	28.0 a	25.0 a	20.0 a

b) Non-parametric trend (rate of change in (Σv) per year) in DSV accumulation (Σv) during 30-day per growing season

NWS station	$\sum_{May31}^{May1} v$	$\sum_{June15}^{May15} v$	$\sum_{June30}^{June1} v$	$\sum_{July15}^{June15} v$	$\sum_{July31}^{July1} v$	$\sum_{Aug15}^{July15} v$	$\sum_{Aug30}^{Aug1} v$	$\sum_{Sept15}^{Aug15} v$	$\sum_{Sept30}^{Sept1} v$
Y62	0.03	0.04	0.06	0.16 *	0.16 *	0.13	0.13	0.07	0.08
APN	0.06	0.00	0.15	0.31 **	0.33 **	0.33	0.27	0.33 *	0.13
TVC	0.00	0.00	0.02	0.06	0.00	0.09	0.12	0.12	0.05
GRB	0.00	0.00	0.08	0.11	0.08	0.00	0.11	0.07	0.11
MKG	0.00	0.08	0.00	0.15 *	0.19 *	0.21	0.27	0.13	-0.08
GRR	0.00	0.14	0.18	0.30 *	0.36 **	0.58 **	0.63 *	0.29	-0.10
TOL	0.05	0.14	0.24 *	0.16	0.08	0.14	0.31	0.32	0.00

[1] Growing season included May 1 through September 30 (153 days) in all years (1949 - 1999) in analyses.

[2] National Weather Service (NWS) station locations: Y62 - Sault Ste Marie; APN - Alpena; TVC - Traverse City; GRB - Green Bay, WI; MKG - Muskegon, MI; GRR - Grand Rapids, MI; TOL - Toledo, OH.

[3] Within a single column, values followed by the same letter are not significantly different at P = 0.05 (Kruskal-Wallis One Way Analysis of Variance on Ranks).

[4] Rate of change is significantly greater than zero at P = 0.05 (*) or P = 0.01 (**) (Kendall Tau b).

and July 1. At Grand Rapids, 30-day $\Sigma\nu$ increases were statistically significant starting on July 15 and August 1. The increase in 30-day $\Sigma\nu$ at Alpena starting August 15 was also significant. Finally, 30-day $\Sigma\nu$ at Toledo increases were significant starting June 1.

Mean 30-day $\Sigma\nu$ for the each location's full growing season are shown in Figure 10. 30-day $\Sigma\nu$ increased at all locations from May until August, then decreased to the end of the season. The change in environmental conditions favorable to late blight closely mirrored the seasonal pattern of potato canopy leaf area index (LAI), also estimated in Figure 10. While the exact timing and magnitude of LAI varied with variety, planting date and growing season, it typically increased from emergence until about August, when the canopy senesced (Allen and Scott, 1992). Mean 30-day $\Sigma\nu$ values circled in Figure 10 increased significantly in 30-day $\Sigma\nu$ from 1948-1999 (extracted from Table 7). In most cases, significant increases in 30-day $\Sigma\nu$ occurred during June and July, earlier in the season than the more typical climatological late blight risk peak in August.

Environmental Variable Trends

Rate of change statistics for monthly mean dew point and ambient air temperature at the seven locations from 1948-1999 are shown in Table 8. For every month, Alpena had the greatest increase in dew point temperature of any station. The 50 year increase in dew point temperature at Alpena was significantly greater than zero during July and August, and also for the growing season as a whole. Increases only slightly less than those at Alpena occurred at the two southernmost stations of Grand Rapids and Toledo during June, July and August. The increase was significantly greater than zero at Grand

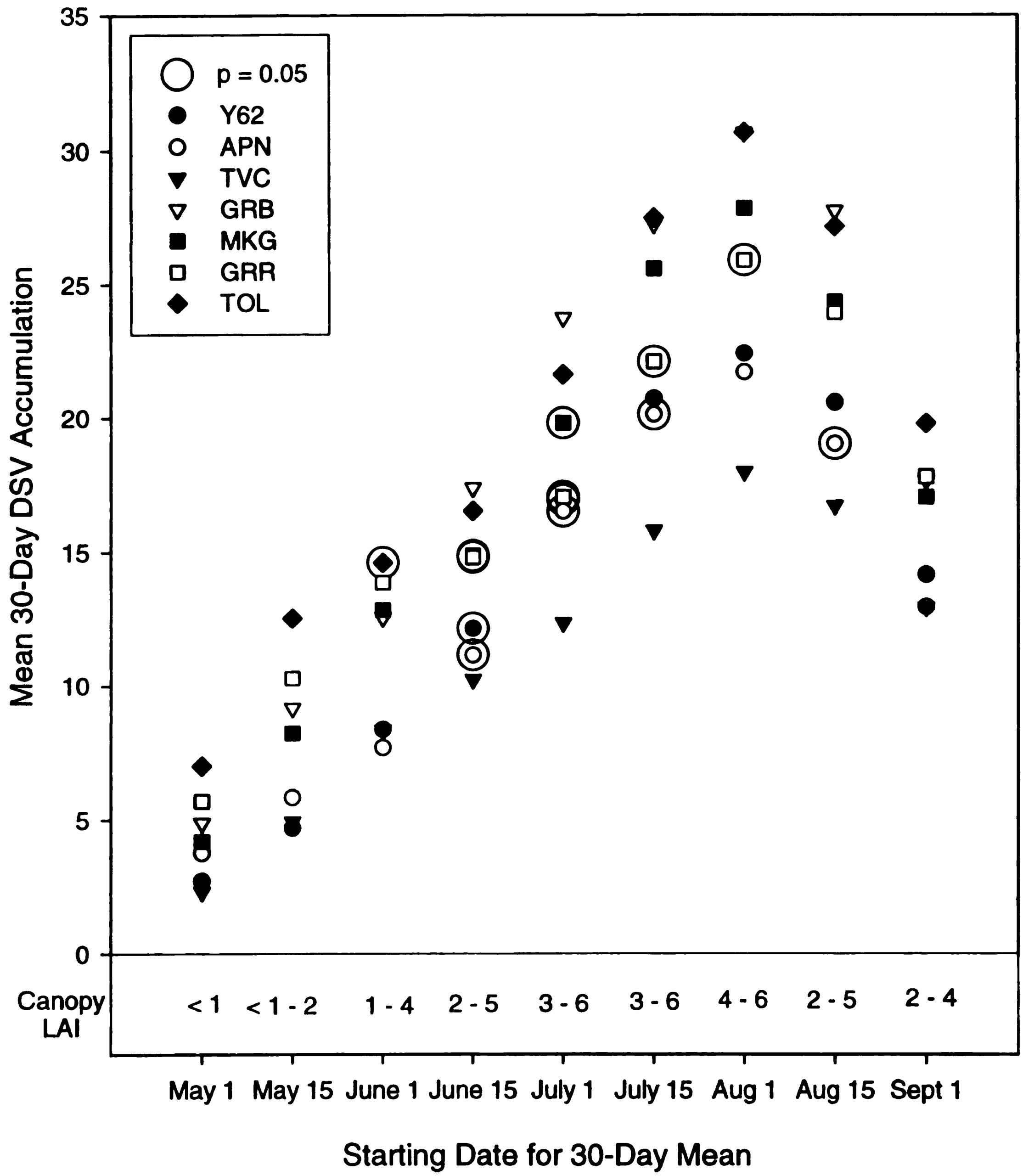


Figure 10. Mean 30-day DSV accumulation with starting dates at 15-day intervals throughout the growing season. Locations where the increase in 30-day DSV accumulation during 1948-1999 was significantly greater than zero at the p=0.05 level are circled. Associated 30-day accumulation rates of change and significantly different were extracted from Table 6. Estimates of potato canopy leaf area index (LAI) for northern growing regions (e.g. latitude 42N+) are included for each 30-day period (Allen and Scott, 1992). LAI = 3 is considered full canopy.

Table 8. Analysis of rate of change per growing season, May 1 through September 30, at seven locations in the greater Michigan region from 1948-1999 for: a) dew point temperature and b) air temperature.

NWS station[2]	a) Non-parametric trend (rate of change) in dew point temperature per growing season[1]					
	May	June	July	August	September	**Season**
Y62	0.02	0.01	0.01	0.01	0.01	**0.01**
APN	0.06	0.05	0.06 **[3]	0.05 *	0.03	**0.05** ***
TVC	0.00	0.00	0.02	0.02	0.02	**0.02**
GRB	0.01	0.02	0.03	0.02	0.03	**0.02** *
MKG	-0.02	0.00	0.01	0.01	-0.01	**0.02**
GRR	0.01	0.03	0.05	0.05 *	-0.01	**0.03**
TOL	0.02	0.04	0.04 *	0.02	0.00	**0.02**

NWS station	b) Non-parametric trend (rate of change) in air temperature by per growing season					
	May	June	July	August	September	**Season**
Y62	0.03	0.02	0.01	0.01	0.01	**0.01**
APN	0.05	0.03	0.02	0.02	0.03	**0.02** *
TVC	0.03	0.01	0.02 *	0.01	0.02	**0.01**
GRB	0.03	0.02	0.02	0.01	0.02	**0.02**
MKG	-0.01	-0.01	0.00	0.00	-0.02	**0.01**
GRR	0.03	0.02	0.02	0.02	0.00	**0.01**
TOL	0.02	0.02	0.03	0.00	0.00	**0.01**

[1] Growing season included May 1 through September 30 (153 days) in all years (1949 - 1999) in analyses.
[2] National Weather Service (NWS) station locations: Y62 - Sault Ste Marie; APN - Alpena; TVC - Traverse City; GRB - Green Bay, WI; MKG - Muskegon, MI; GRR - Grand Rapids, MI; TOL - Toledo, OH.
[3] Rate of change is significantly greater than zero at P = 0.05 (*), P = 0.01 (**), or P=0.001(***) (Kendall Tau b).

Rapids in August and at Toledo in July. The seasonal total increase in dew point temperature was also significantly greater than zero at Green Bay. While the greatest increase in dew point temperature occurred in May at Sault Ste Marie and Alpena, all other locations had higher increases later in the season.

In contrast to the later season dew point increases, the greatest increases in ambient air temperatures occurred in May at most locations. Greatest increases again occurred at Alpena, except in July when the increase was slightly higher at Toledo. The mean air temperature increase was significant at Alpena for the seasonal mean and at Traverse City for July. The only air temperature decreases occurred at Muskegon from 1948-1999 during May, June and September.

DISCUSSION

Environmental conditions between 1948 and 1999 became more conducive for development of potato late blight throughout the Upper Great Lakes region, within the parameters of what is currently known about the influence of temperature and relative humidity on late blight development. Risk of infection has also been increasing with the advent of metalaxyl-insensitive strains of *P. infestans* and tightening fungicide regulations. Host resistance does not seem to be a viable solution to late blight risk in the immediate future. Taken together, these trends may mean that potato production is becoming relatively more difficult through time in the Upper Great Lakes region.

The increase in late blight risk, as measured by at least one of the risk indicators derived from DSV estimates, was significantly greater than zero at every location. For each tested risk indicator, the increase in risk was statistically significant for at least one of the northern locations (Traverse City, Alpena, Sault Ste Marie) and one of the southern locations (Toledo, Grand Rapids, Muskegon, Green Bay).

Conditions at Alpena and Grand Rapids became significantly more conducive for the development of late blight over the period from 1948 to 1999 in the greatest variety of tested indicators used to estimate risk. Risk indicators such as Σv, Σx_2, and 30-day Σv in June and July also showed statistically significant increase at Sault Ste Marie and Muskegon. The lowest rate of change over the 50-year period of any location for nearly all measures of change in risk was found at Traverse City. The only risk related indicator with a trend that increased significantly greater than zero at Traverse City was the number of five-day intervals with an accumulation of at least ten disease severity values.

When 1991 through 1999 were removed from the data set, rates of change were no longer significant for Σv at Sault Ste Marie, Green Bay, or Muskegon. This result could be related to the implementation of ASOS instrumentation, but because these changes most likely would not have such a broad impact, it may point to increasingly conducive meteorological conditions in the 1990's.

Σv per growing season, used in this study as an indicator of overall growing season late blight risk, increased at all stations from 1948-1999. At all locations there was a decrease in the number of days with no late blight risk (Σx_0). In addition, the number of days of each day type indicated that late blight risk from minimal (Σx_1) through severe (Σx_4) levels increased or at least remained constant at each location.

Fungicide applications are often initiated or increased following specific DSV related thresholds. This research has shown that these thresholds corresponded closely to the time of 'full' potato canopy (LAI=3). Environmental conditions that influence late blight risk also closely mirror the estimated LAI of the potato crop. Knowledge of the canopy environment, therefore, may be more valuable for management decision making than Wallin-based DSV systems for monitoring late blight risk in terms of making fungicide recommendations. A DSV-type system may be most useful with respect to identifying extremely conducive periods in the growing season (e.g. five day periods with at least 10 DSV's). However, it is difficult for growers to respond to these periods as high precipitation totals that favor late blight development also make field work (such as spraying) difficult. Because of the high precipitation and humidity during these periods, they would be fairly easily identified without a DSV system. Future research should focus on the usefulness of DSV-type late blight risk systems.

As shown in Figure 10, ambient environmental conditions most favorable for late blight occurred during August coincident with peak leaf area index (LAI) in the potato canopy. This period is crucial because when LAI ≥ 3 canopy conditions are increasingly more conducive to late blight than ambient conditions might suggest. Both air flow and light penetration decrease as LAI increases, resulting in a greater likelihood of late blight development because of higher relative humidity percentages, cooler temperatures and longer leaf drying times in the canopy. Significant increases in conducive conditions as measured by 30-day Σv occurred during June and July, prior to the August peak in late blight risk. This result is important in terms of foliar fungicide spray timing early in the season, e.g. shortly after emergence, especially in June. The period of increasing risk spans the period of canopy development, from just after emergence in June to the August peak in measured late blight risk indicators, indicating that from 1948 to 1999 higher late blight risk occurred more quickly after emergence and remained higher for longer periods of time, e.g. during times of full canopy development.

When 30-day trends in the environmental variables of dew point and ambient air temperature were analyzed, ambient air temperature increased most frequently in May. This result suggests an earlier spring warm up and a possible lengthening of the growing season. Growth of the potato canopy occurs with development and expansion of individual leaves and the rate of development and expansion increases with increasing temperatures. Warmer temperatures in May lead to higher LAI earlier in the season, creating a canopy microclimate more conducive to late blight development at the same time as larger scale weather patterns are also increasing late blight risk.

Dew point temperatures, by contrast, increased less in May than during the rest of the growing season. This result would suggest an increase in growing season moisture throughout the Upper Great Lake region in June, July, August and September. Because the rate of change in late blight risk was strongest in June and July, when dew point temperatures are increasing as opposed to ambient air temperatures, increasing moisture is most likely impacting the accumulation of DSV more than change in temperature. The accumulation of fungicide spray threshold values earlier in the season, is likely also being impacted more by the increase in dew point temperatures in June and July than the earlier spring warm up. Median time to threshold values across locations corresponded to estimates of full canopy conditions.

Increases in dew point and air temperature are supported by the research of Karl and Knight's on trends in precipitation in the United States, which estimated a 10 percent increase in the annual precipitation as a national average in the last 80 years (1998).

During this time, heavy and extreme precipitation events began to contribute a greater portion of the total precipitation in both single and multiple day precipitation events. The increasing frequency of these events is likely one of the factors influencing the increase of highly conducive five-day intervals. The annual number of days with precipitation also increased in the contiguous United States (Karl and Knight, 1998).

In the Great Lakes region, precipitation amounts have risen approximately 0.4 mm yr^{-1} since 1895, with a significantly greater number of wet days following wet day (Andresen et al., 2001). These increases in annual precipitation, number of days with precipitation, and the number of wet days following wet days are each expected to have increased risk of potato late blight infection and subsequent yield and economic losses.

CONCLUSIONS

Throughout the Upper Great Lakes region, the risk of potato late blight has been increasing due to increasingly favorable environmental conditions. The most consistent indicators of change in estimated risk of late blight development across the greater Michigan region were: a) the increase in total DSV (Σv) per growing season, b) the decrease in days with a DSV equal to zero (conditions not conducive to late blight development), and c) the increase in the number of days per season with a DSV equal to 2 (conditions moderately conducive to late blight development). These results may indicate that the resurgence of potato late blight reported in Fry and Goodwin (1997) may be due not only to metalaxyl-insensitive genotypes, but may also be related to an increase in the frequency and duration of environmental conditions conducive to late blight and to earlier canopy development.

Future research should also explore the long-term trends of other weather-based plant pathogen and host systems. Results from this and similar trend analysis can then be used as a baseline to compare the affects of various climate change scenarios on pathogen systems. New data sources, such as NEXRAD precipitation data, also will provide new research opportunities for estimating potato late blight risk on finer spatial scales. With respect to *P. infestans*, the usefulness of DSV-type late blight risk systems should be analyzed and the threshold values for both relative humidity and temperature should be re-evaluated.

CHAPTER 3

CHARACTERIZING THE LEADING EDGE OF A POTATO LATE BLIGHT FIELD INFECTION

INTRODUCTION

Potato late blight, caused by *Phytophthora infestans* Mont. de Bary, is the most important disease of the potato in all potato growing regions throughout the world (GILB, 1999) and, economically, the most important potato disease in North America (Inglis et al., 1996). Late blight spreads in potato canopies by continuous leaf and stem infection when inoculum is present and environmental conditions are favorable, typically moist cool weather (Lacy and Hammerschmidt, 1995). Potato late blight risk has been estimated with for several decades Wallin daily disease severity values, which are calculated based on temperature and relative humidity conditions (Wallin, 1962; MacKenzie, 1981). Disease severity values (DSV) range from 0 to 4, with 0 representing conditions unsuitable for infection and 4 representing extremely conducive conditions (Wallin, 1962).

Cultural practices, such as timing of irrigation and harvest, as well as chemical control through intensive fungicide use in combination with the desiccation of infected plants, are often used to as a means of limiting epidemics. Analyses of spatial and temporal dynamics of late blight and other *Phytophthora* species have not focused specifically on understanding in-field epidemics (Jaime-Garcia, 1998; Zwankhuizen et al., 1998; Ristaino and Gumpertz, 2000). The spread of potato late blight and the percent of the foliage infected through time and space as the epidemic progresses are important to growers who must make management decisions to limit the spread of late blight. No fungicides currently in use completely arrest epidemic development, so desiccation of infected plants is a critical component of risk management (Kirk et al., 2000; Mayton et al., 2001). Early detection and confidence in the desiccation zone is especially important given that infected plants reach 100 percent foliar infection approximately 20 days after initial inoculation (Baker et al., 2000; Mayton et al., 2001).

The research described in this chapter characterizes the spread of the leading edge of a potato late blight field infection after a point source inoculation. Late blight epidemics in Michigan are often initiated from infected seed and infection spreads from this single initial point source. Linear regression techniques that incorporate time and weather-based independent variables are used to empirically describe the rate and magnitude of the spread. These models may then be used within defined confidence bounds in practical, post-infection situations. Although late blight can also spread from outside sources such as cull piles and nearby infected fields, it is not possible to determine exact location of inoculum source for modeling purposes.

Spatial Methods in Plant Pathology

Spatial statistical methods tend to focus on the structure of data sets. Space, time and attribute characteristics then define the applicability of point pattern, zonal or geostatistical methods. The prominence of geostatistics (e.g. semivariogram and kriging analysis) in plant epidemiology spatial applications in recent years no doubt stems from this traditional perspective. With the growing popularity of methodologies that incorporate geographic information systems (GIS), a considerable number of studies have been published recently that both use GIS and spatial analysis for epidemiological research (Headrick and Pataky, 1988; Lecoustre et al., 1989; Lannou and Savary, 1991; Orum et al., 1997) and that advocate its use in epidemiological studies (Chellemi et al., 1988; Rossi et al., 1992; Liebhold et al., 1993; Nelson et al., 1994; Madden and Hughes, 1995).

The methods used in this analysis deviate from traditional methods for determining spatial structure. Chrisman (1997) made the case that of the space, time and attribute aspects of an analysis, one must be fixed, one controlled, and one measured (e.g. time held constant, space divided in consistent blocks, severity of infection estimated). Although this may be true in a traditional multidisciplinary geographic setting, the method and data source used in more non-traditional research ventures should incorporate assumptions of fluidity that are not accounted for in the generally accepted 'fixed, controlled, measured' scheme. Field observations, although occasionally obtained mechanically, are generally gathered by trained field technicians, where human error and bias may result. Time of assessment varies from day to day, placement of initial inoculum varies from plot to plot, and space is controlled very weakly as it is impossible to assess field plots daily in unchanging zones. In addition, confounding variables such as variability in plant density, canopy structure, and differences in fertilization and irrigation at a micro-scale are impossible to be accounted for in a way that would make most traditional methods usable.

In epidemic systems that develop spatially and temporally without the direct impact of physical-based explanatory variables such as weather, a theoretical model of disease progress in space and time can be relatively simply established by combining defined mathematical relationships (Olanya and Campbell, 1990). Straightforward stochastic techniques using neighbor relations have been defined for viruses (Gibson, 1997) and spread of fungal pathogens not linked to weather variables (Goleniewski and Newton, 1994; Xu and Ridout, 1998; Xu and Ridout, 2000).

Objectives

Because potato late blight spreads rapidly, limited options are available to growers once infection occurs. Infected seed tubers often initiate epidemics at a single point in the canopy in regions, such as the Upper Great Lakes region, where *P. infestans* does not typically over-winter as mycelial fragments or spores in the soil. This chapter describes the analysis of late blight spread within an experimental plot and specifically associates the movement of the leading edge of infection outward from the point of initial inoculum introduction.

The analysis follows the movement of late blight symptoms through the potato canopy using the lesion farthest from the point of initial inoculation both along-row and across-row as an indicator of movement through the canopy. Amount and rate of spread of late blight varied due to differences in climate and host susceptibility. Therefore, it was important that this study encompassed several years and was highly replicated within years. The primary objective of this analysis was to measure the movement of the leading edge of a potato late blight field locus in space and time based on prior knowledge of location and time of inoculation. Linear regression models that used: a) time in days after inoculation as the independent variable, b) Wallin's disease severity values estimates, and c) hourly microclimate characteristics of the canopy, to predict location and rate of appearance of lesions distal to the initial point of inoculation (L_D) were calculated.

METHODS

Field plots

Previous experiments at Michigan State University (MSU) have identified potato cultivars and ABL with different responses to foliar late blight. Snowden has consistently been one of the most susceptible (Douches et al., 1997). In all field experiments, cut and whole seed pieces (75-150g) of potatoes, cv. Snowden, were planted with 27 cm between seed in north-south rows 86 cm apart at the Michigan State University Muck Soils Experimental Station, Bath, MI (Houghton Muck; Euic, mesic Typic Haplosaprists). Soils were plowed to 20 cm depth during October following harvest of preceding crops. Soils were prepared for planting with a mechanical cultivator in early May and fertilizer applied during final bed preparation on the day of planting. Fertilizers were applied in accordance with results from soil testing carried out in the spring of each year and about 250 kg N/ha (total N) was applied in two equal doses at planting and hilling. Additional micronutrients were applied according to petiole sampling recommendations and in all years; approximately 0.2, 0.3 and 0.2 kg/ha boron, manganese and magnesium, respectively, were applied as chelated formulations.

Plots were irrigated as necessary to maintain canopy and soil moisture conditions conducive for development of foliar late blight (Madden and Hughes, 1995) with turbine rotary garden sprinklers (Gilmour Group, Somerset, PA, U.S.A.) at 1055 l H_2O ha/hr and managed under standard potato agronomic practices. Weeds were controlled by hilling and with metolachlor at 2.3 l/ha 10 days after planting (DAP), bentazon salt at 2.3 l/ha, 20 and 40 DAP and sethoxydim at 1.8 l/ha, 58 - 60 DAP. Insects were controlled with imidacloprid at 1.4 kg/ha at planting, carbaryl at 1.4 kg/ha, 31 and 55 DAP, endosulfan at 2.7 l/ha, 65 and 87 DAP and permethrin at 0.56 kg/ha, 48 DAP. The dates of application were similar for all years.

Zoospore suspensions were made from *P. infestans* cultures of a single isolate, [MI 95-7, US8 genotype, insensitive to mefenoxam/metalaxyl, A2 mating type], the predominant biotype present in the major potato growing regions of North America (Fry and Goodwin, 1997), grown on rye agar plates for 14 days in the dark at 15°C. Sporangia were harvested from the rye agar plates by rinsing the mycelial/sporangial mat in cold (4°C) sterile, distilled water and scraping the mycelial/sporangial mat from the agar surface with a rubber policeman. The mycelial/sporangial suspension was stirred with a magnetic stirrer for 1 hour. The suspension was strained through four layers of cheesecloth and the concentration of sporangia was adjusted to about 1×10^3 sporangia/ml using a hemacytometer. Sporangial cultures were incubated for 2-3 hours at 4°C to stimulate zoospore release. The suspension was sprayed on greenhouse grown, potted potato plants at a rate intended to expose all potato foliage to inoculum of *P. infestans*. After inoculation, plants were covered in plastic to prolong leaf wetness and moved to growth chambers held at a constant temperature of 15°C. Single inoculated plants were moved to predetermined positions within the research plots after lesions developed and sporangia were visible on leaves and stems. Research plots were untreated with any fungicide during the last week of July in each year of the study. Fourteen research plots were included in the analysis; 8m x 26m plots were inoculated at the center point of their longest edge in 1997 (3 plots) and 1998 (5 plots); 16m x 16m plots were inoculated at their center points (8m from the edge along the ninth row) in 1999 (2 plots) and 2001 (4 plots),

Mean percent blighted foliar area was measured by subjective visual estimation from the time the plots were inoculated until complete defoliation of the canopy. Plots were assessed throughout the epidemic at 2-meter intervals along-row in each row of the plots from 1997-1999. Assessments occurred every 3-5 days. In 2001, daily assessments of percent blighted foliar area were made at 1m intervals along-row in each row from the time lesions could be visually detected until they reached the outer edges of the plot. When lesions reached the outer edge, 1m measurements were continued on a 3-5 day schedule.

Regression Analysis

Following data collection, each plot was subdivided into quadrants from the point of inoculation. Rectangular plots were divided into two quadrants, because the inoculation point was in the center of the longest edges, and square plots were divided into four, because the inoculation point was at the plot's center point. For each year, half of the quadrants were randomly selected for use in model estimation (set A). The other quadrants were used for model testing (set B). The lesion distal to the point of initial inoculation was determined for each quadrant using the percent blighted foliar area estimates and became the derived variable, L_D.

Least squares linear regression and multiple regression were used to quantify the association between independent variables and location of the leading edge of late blight. Variables that were not significant in the regression, or were strongly collinear with other independent variables, were not included in the analyses. Multicollinearity was considered a problem if tolerance [as computed in Statistical Analysis Software (SAS-Institute, 1999)] of the explanatory variable on the other variables was less than 0.1.

Individual variables were tested for association with the dependent variable using the full data set (P=0.05). Regression equations using these variables were then reanalyzed including dummy slope and intercept variables to test for significant differences between data sets A and B. The dummy intercept value was held constant at zero for data set A and 1 for data set B. If the dummy intercept was associated (P=0.05) with L_D, then the intercept of data set A and data set B were significantly different from one another. The dummy slope value was held constant at zero for data set A and given the value of the associated independent variable for data set B. If the dummy slope was associated (P=0.05) with the dependent variable, then the slope of the relationship between data sets A and B were considered significantly different from one another with respect to the dependent variable.

If the dummy variables were not significantly greater than zero for the randomly selected data sets, then the model was considered usable in field situations. If the dummy variables were collinear with one another, only the dummy slope was tested (P=0.05). In order to isolate the movement of late blight following the start of the epidemic, data values equal to zero, representing absence of lesion development, were removed.

For each quadrant and assessment date, the distribution of lesions was analyzed to result in both along-row and across-row parameters. Both splash and aerial dispersal impact the spread of sporangia and late blight of *P. infestans*. Consequently, new foci develop and overlap both within and across rows (Ristaino and Gumpertz, 2000). Therefore, this analysis does not rely strictly on Euclidean distance of disease from inoculation point. Although this change of assumptions is unusual, we feel that incorporating separate along-row and across-row components is justified, as the characteristics of disease spread along and across rows have not been established and may be related to differences in plant canopy structure and density and the interaction of two dispersal mechanisms (Ristaino and Gumpertz, 2000). In addition, recommendations may be implemented in field situations where equipment limitations and ease of use call for a rectangular desiccation zone.

In order to determine if spread was isotropic, the distance of the lesion distal to the initial point of inoculation (L_D) both along-row and across-row was computed not as a standard Euclidean distance, but as the greatest number of 1m assessment units north/south and east/west. For the example quadrant shown in Figure 11, both the along-row and across-row distance were recorded as 5m although standard Euclidean distance measurements would indicate 6.4m as the maximum spread (given *i* as the inoculation point). The resulting model thus describes rectangular disease spread, as opposed to the more traditional circular model of disease expansion.

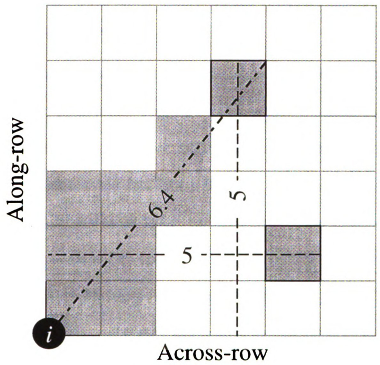


Figure 11. Example of along and across-row distance components using an example quadrant from the analysis. Instead of estimating a circular disease expansion radius in Euclidean distance from the inoculation (*i*) point (6.4 for this quadrant), the leading edge expansion model uses the maximum distance from the inoculation point of both an along-row and across-row component (5, in both cases).

The time dependent regression model included no explanatory variables other than distance from inoculation point (L_D) and days after inoculation (DAI). This model was used with dummy variables to test for a significant difference between across-row and along-row spread for data set A. Specific environmental variables, as well as indicators of potato late blight risk derived as secondary variables from hourly ambient air temperature and dew point temperature from day of initial inoculation to day of assessment are described in Table 9.

Similar to the time dependent approach, two more detailed regression models were also developed using explanatory variables in addition to space and time. The models relied on disease severity value (DSV) and weather characteristics from time of inoculation through assessment date for L_D. Both risk estimates and weather characteristics were derived as secondary variables from hourly weather data from an automated weather station in East Lansing MI, approximately 15 km from the field plots. This station is part of the Michigan Automated Weather Network (MAWN) and is the closest station with hourly temperature and relative humidity data consistent over the five-year period of the study.

An approach that may be described as driven by the physical environment used traditional weather variables that influence risk of late blight spread, specifically temperature (T) and relative humidity (RH). Included in the analysis were the number of hours from initial inoculation with: a) each of the relative humidity/temperature categories used in modified-Wallin DSV calculation (ΣW_1, RH>80% and 7°C≤T<11°C; ΣW_2, RH>80% and 11°C≤T≤15°C ; ΣW_3, RH>80% and T≤15°C; ΣW_{ALL}, RH>80% and 7°C≤T≤15°C); b) each 10 percent humidity category from 50 percent upwards (ΣRH_{50},

Table 9. Environmental variables and indicators of potato late blight risk derived as secondary variables from hourly ambient air temperature and dew point temperature from day of initial inoculation to day of assessment.

Variables	Description
DAI	days after inoculation
DSV	potato late blight disease severity values, calculated for each day after inoculation using the modified Wallin method explained in Chapter 2.
T	temperature in °C
RH	relative humidity
$\Sigma T_{>15}$	sum of hours since inoculation with temperature greater than 15°C
ΣRH_{90}	sum of hours since inoculation with 90% $\leq$RH $\leq$100%
ΣRH_{80}	sum of hours since inoculation with 80% $\leq$RH <90%
ΣRH_{70}	sum of hours since inoculation with 70% $\leq$RH <80%
ΣRH_{60}	sum of hours since inoculation with 60% $\leq$RH <70%
ΣRH_{50}	sum of hours since inoculation with 50% $\leq$RH <60%
$\Sigma RH_{>70}$	sum of hours since inoculation with 70% $\leq$RH $\leq$100%
ΣW_1	sum of hours since inoculation with 80% $\leq$RH $\leq$100% and 7°C $\leq$T<11°C
ΣW_2	sum of hours since inoculation with 80% $\leq$RH $\leq$100% and 11°C $\leq$T<15°C
ΣW_3	sum of hours since inoculation with 80% $\leq$RH $\leq$100% and 15°C $\leq$T $\leq$27°C
ΣW_{ALL}	sum of hours since inoculation with 80% $\leq$RH $\leq$100% and 7°C $\leq$T $\leq$27°C
Σx_1	total number of days with DSV =1 since inoculation
Σx_2	total number of days with DSV =2 since inoculation
Σx_3	total number of days with DSV =3 since inoculation
Σx_4	total number of days with DSV =4 since inoculation
$\Sigma x_{y>0}$	total number of days with DSV>0 since inoculation
Σv	sum of all consecutive DSV per day since inoculation

50%≤RH<60%; ΣRH_{60}, 60%≤RH<70%; ΣRH_{70}, 70%≤RH<80%; ΣRH_{80}, 80%≤RH<90%; ΣRH_{90}, 90%≤RH≤100%); and c) accumulated hours at 15°C and above ($\Sigma T_{>15}$, T≥15°C) and at a relative humidity of 70% and above ($\Sigma RH_{>70}$, RH≥70%) (Table 9).

A risk-based approach utilized DSV estimates and their accumulation by day from inoculation to day of assessment. Derived variables included: total DSV from inoculation to assessment date (Σv), the number of days with late blight risk from inoculation to assessment date ($\Sigma x_{y>0}$), and the number of days with each unique DSV value, 1 through 4, from inoculation to assessment date (Σx_1, Σx_2, Σx_3, Σx_4).

Application of Leading Edge Regression

For the time dependent model, linear regression was used to model the relationship between time in days after inoculation and the expansion of the leading edge from the inoculation point to test for directional differences in data set A. The implications of this model for use in estimating in-field desiccation zone parameters was explored. Predicted values and the 99 percent confidence bound for those values were calculated in SigmaStat (SPSS-Inc, 1997).

RESULTS

Time Dependent Variables

Linear regression results for the time dependent model are shown in Table 10 (Equation 10.01). Distance of farthest infected foliage from inoculation (L_D) was used as the dependent variable, explained only by days after inoculation. Dummy variables were not significant in the regression model, indicating that the slope and intercept of the relationship between time as DAI and distance as L_D were not significantly different between data sets A and B. The adjusted R-squared value was 0.624 with a error mean square (MSE), an unbiased estimator of variance for the regression model, of 3.6.

Adjusted R-squared and MSE were similar for the comparison of along-row and across row spread of late blight using only data set A (Equation 10.02). Predicted distance of along and across row spread were not significantly different from one another. Adjusted R-squared was slightly higher and MSE was slightly lower than those of the regression incorporating the full data set, as would be expected given the smaller data set. Because directional variation was not statistically significantly different at $P=0.05$, the along-row and across-row measured and predicted distances were combined for all further analyses. A scatter plot of DAI (from 0 to 30) and L_D is shown in Figure 12a.

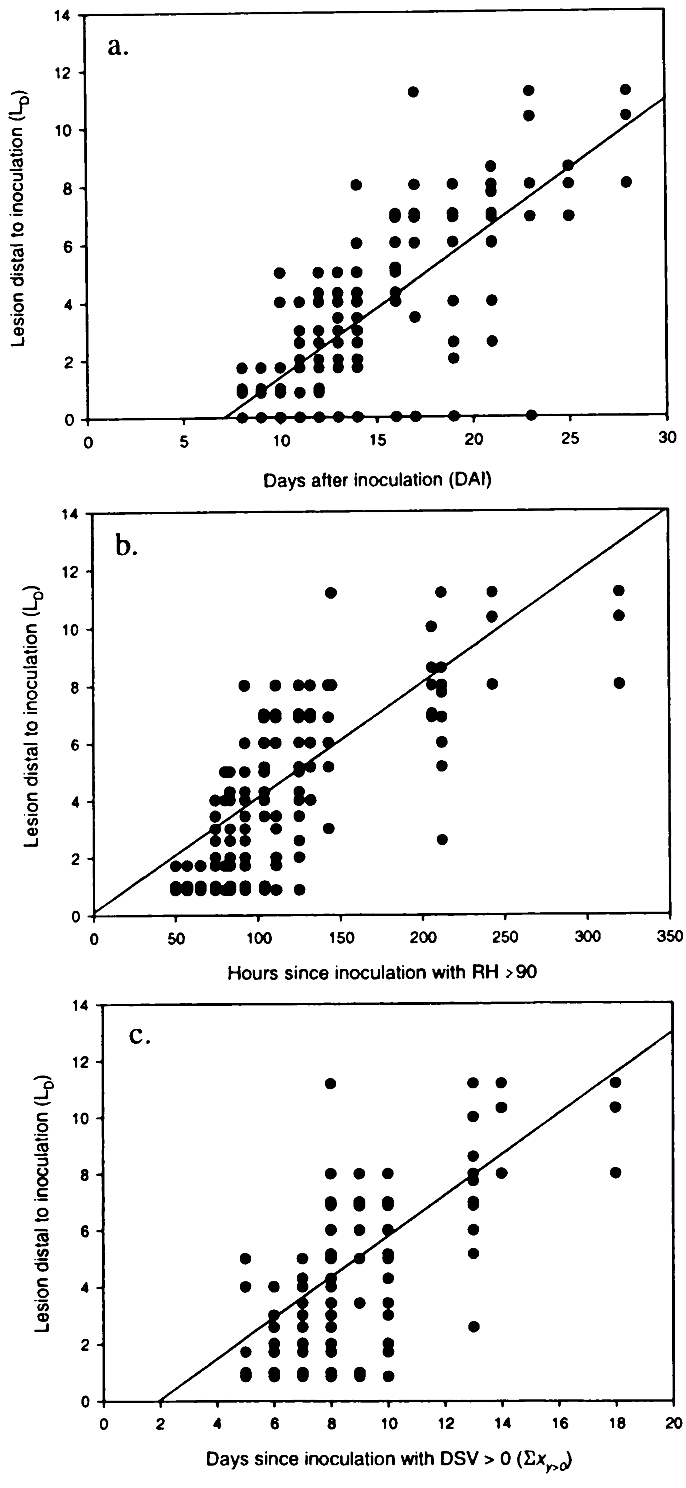


Figure 12. Regression results for lesion distal to inoculation (L_D) and: a) days after inoculation, b) hours since inoculation with relative humidity greater than 90 percent, and c) days since inoculation with DSV > 0.

Weather Variables

Results of linear models incorporating single weather-based independent variables are also shown in Table 10. The number of hours in the lowest two modified-Wallin DSV estimation category (ΣW_1, ΣW_2) were very weakly correlated with L_D (Eq. 10.3 and 10.4). MSE's were nearly twice those of the regressions incorporating days after inoculation, indicating considerably more prediction error. Number of hours in the third modified-Wallin category (ΣW_3) had a stronger relationship with distance from inoculation point, with an adjusted R-squared of 0.558 (Eq. 10.05). The sum of all modified-Wallin hours, ΣW_{ALL}, (Eq. 10.06) had a slightly higher adjusted R-squared and lower MSE than Equation 10.05.

A regression equation with hours of temperature greater than 15°C ($\Sigma T_{>15}$) as the independent variable (Eq. 10.07) had adjusted R-squared and MSE between those of the ΣW_3 (Eq. 10.05) and the sum of all modified-Wallin hours (ΣW_{ALL}).

Adjusted R-squared values of regression models incorporating hours accumulated since inoculation in various relative humidity categories ranged from 0.417-0.603, and MSE ranged from 3.82-5.6. When the independent variable was hours accumulated between 70 and 80 percent relative humidity (ΣRH_{70}) the regression model yielded the highest adjusted R-squared value and the lowest MSE. Hours between 50 and 60, 60 and 70, and 90 and 100 (ΣRH_{50}, ΣRH_{60}, ΣRH_{90}) had slightly weaker relationships. Relative humidity hours between 80 and 90 (ΣRH_{80}) percent had the weakest relationship with distance of the farthest lesion from the inoculation point of any tested relative humidity category. The relationship between ΣRH_{90} and L_D is shown in Figure 12b.

Table 10. Linear regression results for time and weather independent variable models. Dummy slope and intercept variables were included to test significant differences between the models created from two randomly chosen data sets (A and B). Dummy variables were identified as significant (<0.0001) or not significantly different (A=B).

Eq. #	**Regression Model**	**Adjusted R - squared**	**Error Mean Square (MSE)**	**Dummy Intercept**	**Dummy Slope**
		Time Dependent			
		Data sets A and B			
10.01	$y=-2.73 + 0.47(DAI)$	0.624	3.618	A = B	A = B
		Along Row vs Across Row			
10.02	$y = -1.91 + 0.43(DAI)$	0.638	3.010		A = B
		Weather Dependent			
10.03	$y = 1.60 + 0.24(\Sigma W_1)$	0.335	6.390	A = B	A = B
10.04	$y = 3.40 + 0.07(\Sigma W_2)$	0.373	6.027	A = B	A = B
10.05	$y = -3.17 + 0.04(\Sigma W_3)$	0.558	4.250		A = B
10.06	$y = -1.83 + 0.03(\Sigma W_{ALL})$	0.597	3.870		A = B
10.07	$y = -1.23 + 0.03(\Sigma T_{>15})$	0.569	4.150	A = B	A = B
10.08	$y = 0.07 + 0.04(\Sigma RH_{90})$	0.556	4.270	A = B	A = B
10.09	$y = -2.49 + 0.10(\Sigma RH_{80})$	0.417	5.610		A = B
10.10	$y = -1.67 + 0.13(\Sigma RH_{70})$	0.581	4.030	A = B	A = B
10.11	$y = -1.14 + 0.16(\Sigma RH_{60})$	0.549	4.340	A = B	A = B
10.12	$y = -3.49 + 0.18(\Sigma RH_{50})$	0.541	4.410		A = B
10.13	$y = -1.66 + 0.03(\Sigma RH_{<70})$	0.603	3.820	A = B	A = B

Dummy slope and intercept indicated that data sets A and B would not result in statistically different relationships between these weather variables and location of the leading edge of infection.

Disease Severity Value Variables

The DSV based regression models utilized input data derived from the standard meteorological variables in the form of modified-Wallin DSV (Table 11). DSV dependent linear regression models each had considerably lower adjusted R-squared values and higher MSE than the weather or time dependent models. The sum of DSV from inoculation to observation (Σv) as the independent produced a model (Eq. 11.1) with an adjusted R-squared of 0.405. A slightly stronger relationship existed for the sum of days with DSV>0 ($\Sigma x_{y>0}$), and the relationship between $\Sigma x_{y>0}$ and L_D is shown in Figure 12c. Because the dummy slope was statistically significant in this model, the data sets A and B resulted in models with significantly different slopes. Number of days with individual modified-Wallin severity values from 1 through 4 resulted in much lower test statistics. Days with DSV=4 (Σx_4)had the strongest relationship, with adjusted R-squared of 0.337 (Eq. 11.6). The dummy slope variable was significant when DSV=1 was the independent variable, indicating that with this model, data from the sets A and B resulted in significantly different slopes.

Table 11. Linear regression results for DSV independent variable models. Dummy slope and intercept variables were included to test significant differences between the models created from two randomly chosen data sets (A and B). Dummy variables were identified as significant (<0.0001) or not significantly different (A=B).

Eq. #	**Regression Model**	**Adjusted R - squared**	**Error Mean Square (MSE)**	**Dummy Intercept**	**Dummy Slope**
		Weather Dependent			
11.1	$y = 1.60 + 0.24(\Sigma W_1)$	0.405	5.722	A = B	A = B
11.2	$y = 3.40 + 0.07(\Sigma W_2)$	0.419	5.607		<0.0001
11.3	$y = -3.17 + 0.04(\Sigma W_3)$	0.162	8.060		<0.0001
11.4	$y = -1.83 + 0.03(\Sigma W_{ALL})$	0.063	9.015		A = B
11.5	$y = -1.83 + 0.03(\Sigma W_{ALL})$	0.226	7.440	A = B	A = B
11.6	$y = -1.23 + 0.03(\Sigma T_{>15})$	0.337	6.370	A = B	A = B

Combined Variables

Multiple regression models combining variables that were not collinear and retained their significance in combination with one another are shown in Table 12. The model including the hours accumulated in each of the three modified-Wallin categories, ΣW_{ALL} (Eq. 12.1), had similar statistics to those of the time dependent model, *DAI* (Eq. 8.1). A model that included relative humidity over 90 percent ($\Sigma RH_{>90}$) and between 70 and 80 percent (ΣRH_{70}) as independent variables resulted in the only relationship stronger than those including time in days after inoculation (Eq. 12.2). Adjusted R-squared was 0.645 and MSE was 3.416. Even in combination, the days with specific DSV (Eq. 12.3) were not as strongly related to L_D as were the weather dependent variables. The dummy slope was significant when both DSV=1 and DSV=4 were used as independent variables, indicating that the models from data sets A and B resulted in significantly different rates of movement of L_D through time.

The final two combined models (Eq. 12.4 and 12.5) included days after inoculation (DAI) with DSV variables, and these models had the strongest relationship with farthest late blight lesion from initial inoculation point of any models tested and the lowest MSE. Data sets A and B resulted in models that were not significantly different, as the dummy slope and intercepts were not statistically significant in the regression. When DAI as independent variables was combined with: a) DSV=4 (Σx_4,) and b) both DSV>0 and DSV=4 (Σx_4, $\Sigma x_{y>0}$) , the models resulted in adjusted R-squared values of 0.673 and 0.717 respectively.

Table 12. Linear regression results for time, weather and DSV combined independent variable models. Dummy slope and intercept variables were included to test significance between the two halves of the data set (A and B). Dummy variables were identified as significant (<0.0001) or not significantly different (A=B).

Eq. #	Regression Model	Adjusted R - squared	Error Mean Square (MSE)	Dummy Intercept	Dummy Slope
	Weather Dependent				
12.1	$y = -2.00 + -0.12(\Sigma W_1) + 0.05(\Sigma W_2) + 0.04(\Sigma W_3)$	0.627	3.584		A = B
12.2	$y = -1.64 + 0.02(\Sigma RH_{90}) + 0.08(\Sigma RH_{70})$	0.645	3.416	A = B	A = B
	DSV Dependent				
12.3	$y = -2.52 + 1.22(\Sigma x_1) + 1.57(\Sigma x_4)$	0.552	4.310		<0.0001
	Combined Model				
12.4	$y = -2.54 + 0.40(DAI) + 0.61(\Sigma x_4)$	0.673	3.145	A = B	A = B
12.5	y = -1.68 + 0.60(DAI) -0.55(DDAY) + 0.99(D4)	0.717	2.720	A = B	A = B

Application of Regression Model

As a practical application of model results, the time dependent model developed from data set A to test the differences between along and across row distances was used to estimate desiccation zone parameters. The combined data set and resulting regression line (Eq. 10.02), as well as 99 percent confidence bounds for the model, are shown in Figure 13. Predicted values obtained from regression equations for data set A and B were not significantly different (as seen from dummy variable significance results of Equation 10.01) and so the equation estimated from set A was retained for use in the estimation of desiccation zone parameters. The 99 percent upper confidence bound for the model, where days after late blight inoculation is the independent variable, follows the quadratic equation:

$$99\%Confidence = -2.485 + 0.744DAI + 0.00385DAI^2$$

and was used as an approximation of the observable leading edge of potato late blight for desiccation zone recommendations. Because no lesions were found prior to eight days after the introduction of inoculum, the bound of late blight expansion at eight days with 99 percent confidence was considered the distance of non-visible expansion of *P. infestans* infection. From the above equation, calculating for 8 DAI, the 99 percent conficence bound was 3.71m. This result was added to the overall confidence bound for recommendations as a best estimate based on empirical observation for the impact of the eight-day latent period (delay in expression of symptoms) on late blight spread. The

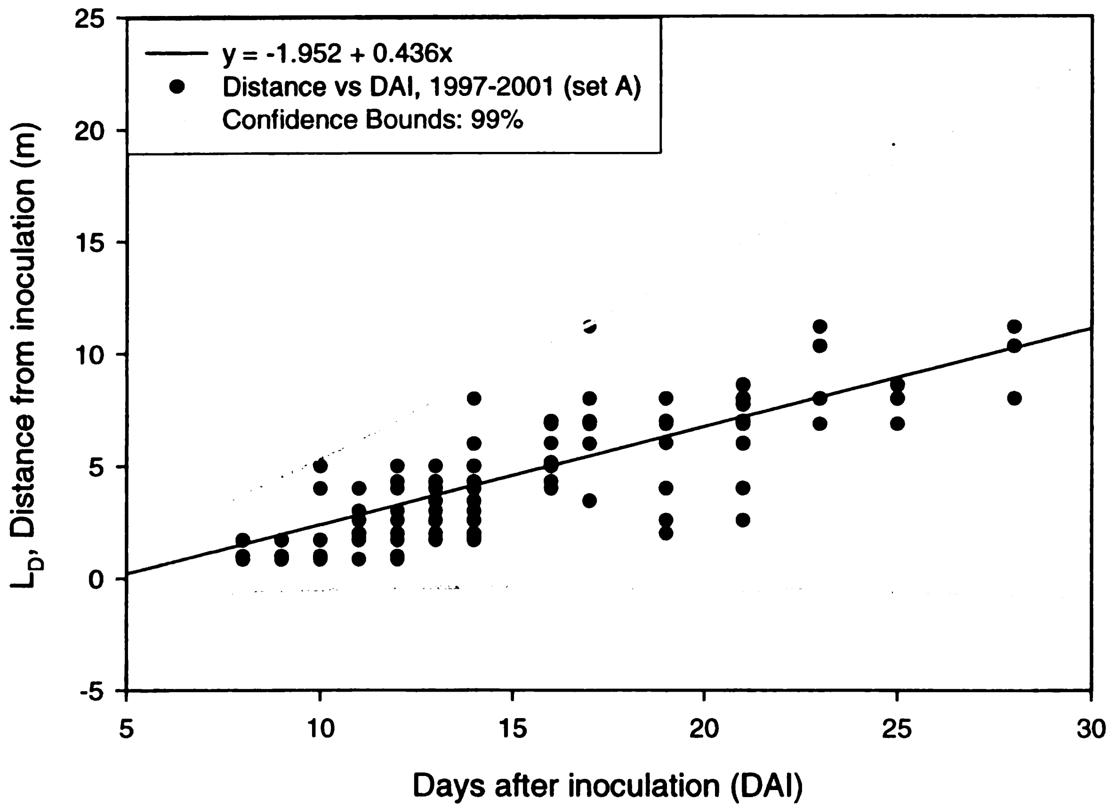


Figure 13. Observed values and predicted linear regression line. Distance from initial inoculation point in meters is predicted using days after inoculation.

formula for the expansion of potato late blight with 99 percent confidence from a point source inoculation both along-row and across-row was therefore estimated as:

$$99\% Confidence = 1.23 + 0.744x + 0.00385x^2$$

Leading edge results from data sets both A and B are shown in relation to this curve in Figure 14. The size in square meters of the recommended desiccation zone with respect to time since inoculation, equal to total area with 99 percent confidence, is shown in Figure 15. Estimated percent foliar infection, interpolated from assessment zone centroids, for a single field plot thirteen days after inoculation in 2001 is shown as an example (Figure 16). Predicted observable infection is 2.41 m from the point of inoculation. Observable infection distance with 99 percent confidence is 7.8 m and total infection distance with 99 percent confidence is 11.5 m from inoculation.

DISCUSSION

Linear regression modeling was used to characterize spread of late blight within a field plot. While this technique is not common within plant pathology literature, linear regression was a straightforward method for determining basic association between spread and independent variables.

The time in days after inoculation (*DAI*) had the strongest relationship with distance of farthest lesion from the point of initial inoculation. Number of hours over 70 percent relative humidity ($\Sigma RH_{>70}$) had the strongest relationship of the weather dependent variables. These two independent variables were also highly correlated with one another, partially because they are both accumulated variables. Although the

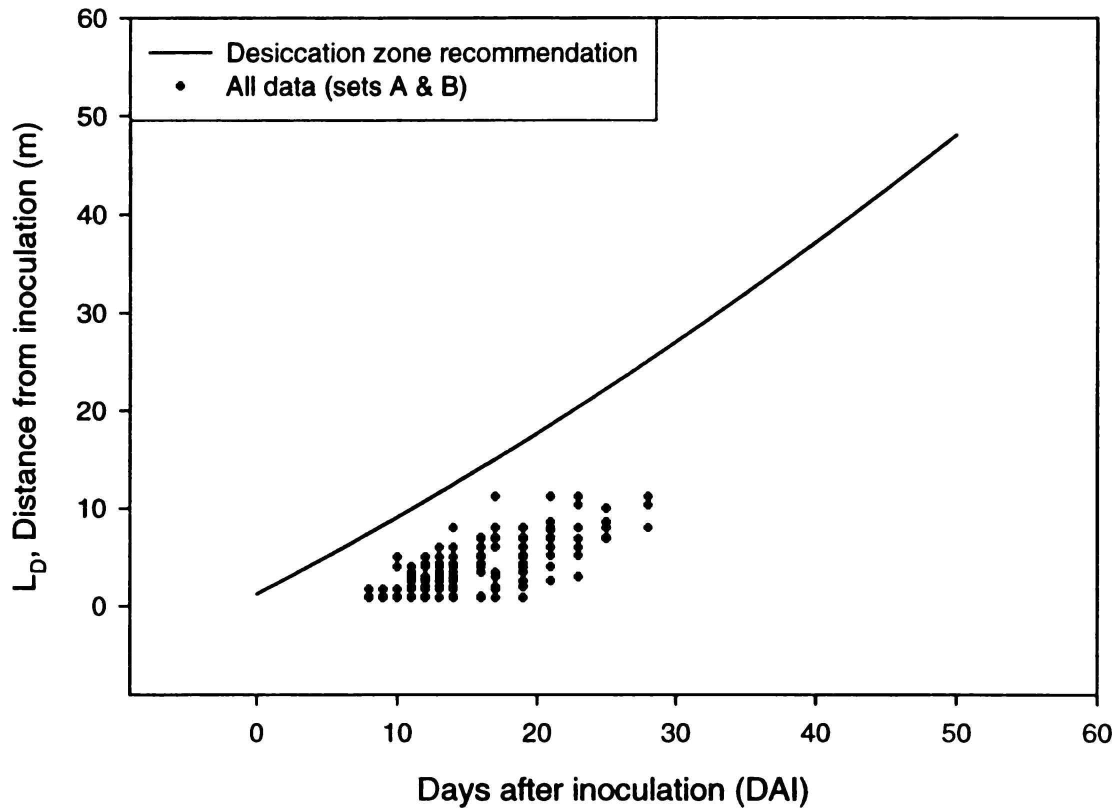


Figure 14. All data from sets A and B and the recommended desiccation zone in meters both along and across-row from the inoculation point in days after inoculation.

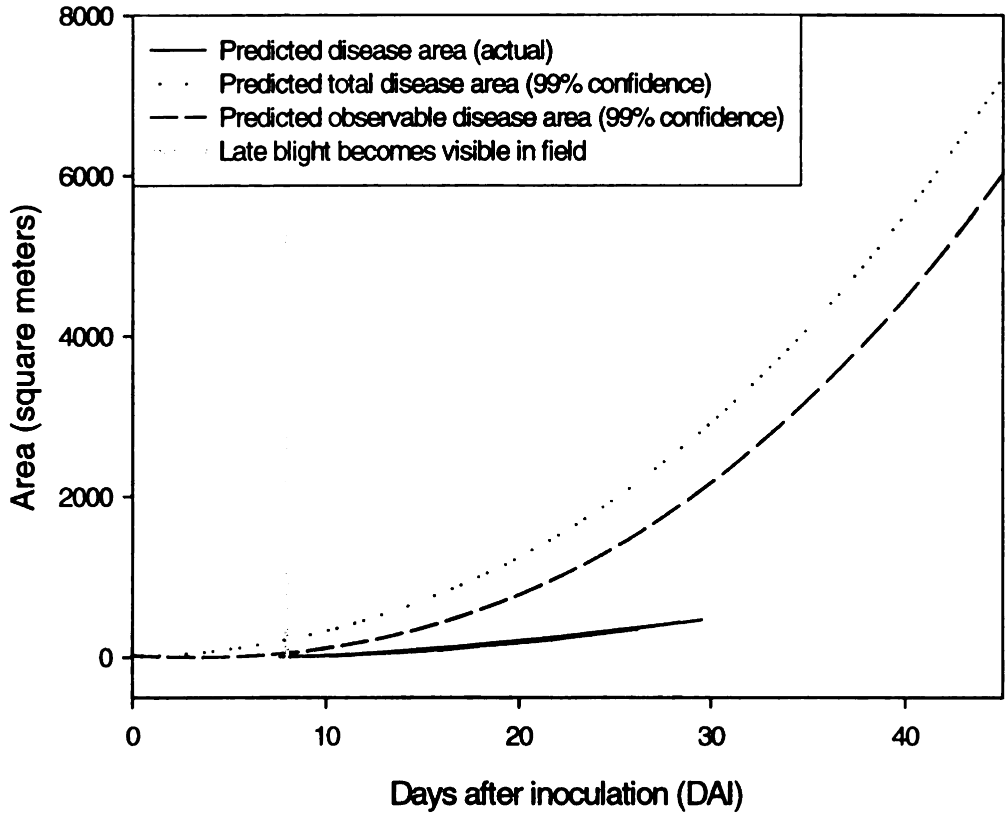


Figure 15. The increase in the area of predicted observable disease, the predicted observable disease, and the total predicted disease. Late blight expansion becomes visible in the field approximately 8 days after inoculation.

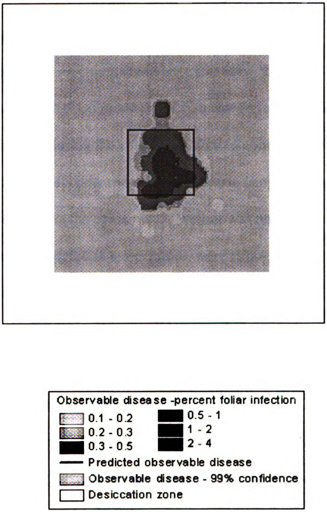


Figure 16. Observable disease from an example 2001 research plot after 13 days after inoculation with the model predicted observable disease, the predicted observable disease 99% confidence bound, and the total predicted diseased area with 99% confidence (recommended desiccation zone).

occurrence of potato late blight epidemics has been associated with conducive canopy weather conditions, the results of this study did not directly support that canopy conditions traditionally thought to promote late blight are strongly related to the spread of the leading edge of late blight lesions in the field. Several aspects of the analysis could have impacted this result. In each year, initial inoculum was placed in the canopy at approximately the same time and canopy conditions, including both canopy development and diurnal temperatures, were highly favorable for epidemic development. This similarity in the time of initial inoculum could have impacted the results from other independent variables. The first two modified-Wallin categories (Eq. 10.03 and 10.04), for instance, were infrequent during the epidemic period in comparison to the other weather variables used for independent variables. Because temperatures were relatively consistent between years during the epidemic, as well, it was not unexpected that relative humidity categories, without regard to temperature, were strongly related to distance from inoculation.

These same factors may have impacted the rate of along and across row late blight spread between replicates and years. While differences in along-row and across-row spread have been noted in the field in some instances (Baker et al., 2000), these differences may relate to plant density and canopy structure that are related to row direction in some years, and plots, but not in others. In general it would be expected that along-row plants would be more likely to have a more similar microclimate and more likely to be in physical contact with one another. However, it was observed in some field seasons during the course of this study that even relatively slight differences in drainage, nutrient availability, and/or soil characteristics could impact the structure and density of the potato canopy. Potato late blight spread was observed to be closely associated with these slight changes in canopy density, which corresponded to row direction in some (but not all) cases. Further research should, perhaps, incorporate some measure of canopy characteristics in the analysis.

The weaker relationship exhibited between L_D and disease severity value variables also may relate to the overall suitability of canopy conditions for epidemic development. These regression results were also impacted by the fact that DSV are not ratio scale data. Σv assumes that DSV is an interval scale, which may or may not be true. The analysis of individual values of DSV assume only nominal scale data. Although the nominal scale is likely a safer assumption with regards to DSV in the independent variable, counts of these day types are also only interval scale data, which does not match standard regression assumptions. Probably for similar reasons, all cases where the dummy slope variable was significantly different between data set A and B occurred in regression models incorporating DSV variables.

Of the combined models, both the combined modified-Wallin category model (Eq. 12.1) and the model including $\Sigma x_{y>0}$ (Eq. 12.5) included negative coefficients. In the former, the negative value probably resulted from the fact that nearly all hours were within one of the three categories. In this case, conducive hours in a lower temperature class represented the inverse of the hours in the higher temperature classes which were more conducive for late blight (less time needed in the category for infection to occur). In the case of the combined model incorporating $\Sigma x_{y>0}$, the negative coefficient for this variable was counterintuitive and was related to interaction between $\Sigma x_{y>0}$ and the other independent variables.

Additionally confounding for all model results was the fact that both the dependent and independent variables were accumulated over time. As yet, the relationship between potato late blight and the number of days prior to infection that are crucial to the understanding of risk remain undefined. Since the course of an epidemic is assumed to be affected to some extent by conditions over the period from inoculation onward, both distance and environmental conditions were accumulated for each date from the day of inoculation. Because each daily and hourly value after inoculation is incorporated into every disease risk estimate, this accumulation results in noise in the regression models.

The increase in area of the desiccation zone with time continues to make management of in-field potato late blight infections challenging. Because this model expresses time as days after inoculation (DAI), inoculation date would need to be estimated using weather conditions, or perhaps highest foliar infection rates. Difficulties may also arise during practical implementation of the model in determining the inoculation point, as this may not be the most blighted region of the field. Canopy characteristics, such as LAI, affected by factors such as nutrient availability, time in the growing season of late blight development, and defoliation as a result of symptoms each could impact the observed location of highest infected foliage. The influence of canopy structure and density is also of utmost importance to field applications of this research.

CONCLUSION

This chapter adds further doubts, in addition to those expressed in Chapter 2, as to the usefulness of Wallin-type risk values in the estimation and prediction of late blight risk. Again it seems that canopy conditions are more strongly associated with late blight infection, as well as epidemic spread in the field. Furthermore, the accumulations of these DSV should be used with caution in any situation, given that they are not clearly defined as an interval scale numeric variable. Instead, the DSV may serve the purpose of a day-typing mechanism. Addition/subtraction and other numerical operations on 'day-types' then become theoretically questionable. Further research is necessary to clarify the relationship between ambient air condition, canopy environment and spread of potato late blight.

Further research should also include verifying spread models through extensive field tests. Modeling the complete late blight epidemic from inoculation to complete canopy defoliation would also be useful from the standpoint of understanding field infection dynamics. Continued research should also focus on the interplay between cultivar resistance and fungicide regimes, in addition to environmental conditions. The implications of this type of research for potato breeders might suggest a focus on slowing disease spread through the production of varieties which decrease sporulation rates.

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