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Risk Management Strategies using Precision Agriculture Technology to Manage Potato Late Blight

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ABSTRACT

Precision agriculture has emerged as a revolutionary technology, which transforms farming related data into useful information for agricultural decision-making. This paper compares precision farming technology with calendar-based approach in scheduling fungicide applications to manage potato (*Solanum tuberosum* L.) late blight disease. Three fungicide scheduling strategies were evaluated: calendar-based strategy, BlightPro decision support system based strategy (DSS-based strategy), and unsprayed control. Using results from 14 yr of computer simulation experiments for 59 locations in the United States, we constructed distributions of net return to all costs excluding fungicide cost and application cost per 0.41 ha (net return per 0.41 ha) for the calendar-based and DSS-based strategies at each location. These distributions were then compared using three risk management methods: stochastic dominance, stochastic dominance with respect to a function, and stochastic efficiency with respect to a function. The DSS-based strategy was identified as the most effective approach to manage late blight in terms of disease suppression, net return per 0.41 ha, and risk-adjusted net return. Results indicate that the DSS-based strategy is the preferred method to schedule fungicide applications. Under high disease pressure circumstances, the economic benefits to potato growers of adopting the precision agriculture technology ranged from US$30 to $573 per 0.41 ha. For risk neutral individuals, who are concerned about the difference between average net return per 0.41 ha, the benefits ranged from $30 to $305 per 0.41 ha. Except for growers raising the moderately resistant potato cultivars, more risk averse individuals tended to benefit more from adopting the precision agriculture technology, with benefits ranging from $38 to $573 per 0.41 ha.

Core Ideas

- The benefits of adopting precision farming technology was investivated in scheduling fungicide applications to manage potato late blight.
- The precision farming technology is the preferred method to schedule fungicide applications in terms of disease suppression, net return per 0.41 ha, and risk-adjusted net return.
- The increased adoption of the precision farming technology would help manage late blight, limit potential crop losses, and improve net returns.

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Precision agriculture relies on information systems to optimize agricultural production decisions by accounting for variability and uncertainties (Gebbers and Adamchuk, 2010). Based on the information provided, growers can make informed farming decisions (e.g., planting, harvesting, crop protection) and use farm resources wisely (Cooke et al., 2011; Lowenberg-DeBoer, 2015). This approach identifies site-specific differences and adjusts management actions accordingly (Auernhammer, 2001; Schimmelpfennig and Ebel, 2011). Precision agriculture technology has been on the market since the 1990s, but questions remain about its profitability and future (Griffin and Lowenberg-DeBoer, 2005). Economic studies that assess the impacts of precision farming technologies can reveal the advantages and potential barriers to adoption, and can significantly increase the adoption rate of precision farming technology (Vorotnikova et al., 2014).

The majority of precision agriculture studies focus on corn (*Zea mays* L.), soybean [*Glycine max* (L.) Merr.], and other major cereal crops, whereas vegetable crops have historically received less attention (Griffin and Lowenberg-DeBoer, 2005). Few studies examine the economic benefit of precision agriculture for potato production. Potato is the fourth largest crop in the world, exceeded only by maize, wheat (*Triticum aestivum* L.), and rice (*Oryza sativa* L.) (FAO, 2009). The United States is among the world's largest potato-producing countries (FAO, 2016), with $3.66 billion worth of potato sold and 425 thousand harvested hectares in 2014 (USDA, 2015). As technology for precision agriculture continues to evolve, new potential applications of precision agriculture are becoming possible. These include the integration of location-specific weather forecasts into plant disease models as part of crop protection strategies for the management of late blight disease on potato and tomato (*Lycopersicon esculentum* Mill.) crops (Small et al., 2015a). This research will examine the benefits provided by one of the weather-related precision agriculture technologies, named the BlightPro DSS, in managing late

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Abbreviations: AUDPC, area under disease progress curve; CE, certainty equivalent; DSS, decision support system; FSD, first-degree stochastic dominance; RP, risk premium; net return per 0.41 ha, net return to all costs excluding fungicide cost and application cost per 0.41 ha; SERF, stochastic efficiency with respect to a function; SSD, second-degree stochastic dominance; SDRF, stochastic dominance with respect to a function.

blight disease. Late blight disease, caused by the *Phytophthora infestans* (Mont.) de Bary, may be considered the most economically damaging potato pathogen (Fry and Goodwin, 1997b; Guenthner et al., 1999; Johnson, 2008; Niederhauser and Mills, 1953; Wale et al., 2008). Worldwide, a conservative estimate of the annual cost of the disease to potato production is US$6.7 billion in yield losses and costs of late blight management measures (Haverkort et al., 2008). In the United States, the annual cost of late blight to potato production is estimated to be US$287.8 million, of which fungicide expenses constitute a substantial proportion of the cost (Guenthner et al., 2001). In practice, the traditional management of late blight depends highly on preventative fungicide applications on a regualr calendar basis (e.g., weekly) during the growing season.

The use of precision farming technology as a guidance to schedule fungicide applications mitigates production risk, improves fungicide use efficiency, and can reduce the potential environmental impact of fungicide usage in managing late blight (Small et al., 2015b). The BlightPro DSS recommends precise and timely use of fungicide in accordance with weather conditions, pathogen characteristics, host resistance, as well as fungicide characteristics and efficacy (Small et al., 2015a). It is a good example of how precision farming technology transforms weather data into accessible information to help farmers make decisions. The efficacy of disease forecasting systems, such as Blitecast, for late blight disease management has been an important topic of previous plant pathology research (Fohner et al., 1984; Fry et al., 1983; Small et al., 2015b). Fohner et al. (1984) found that fungicide scheduling according to Blitecast did not suppress diseases any more effectively than the application of a calendar-based strategy. Subsequently, Blitecast has been integrated with other forecasting systems and technologies into the BlightPro DSS (Small et al., 2015a). Small et al. (2015b) examined the benefits of adopting BlightPro DSS in terms of late blight disease suppression and fungicide usage efficiency. They concluded that the DSS-based strategy maintained or improved disease suppression and average fungicide use efficiency relative to the calendar-based strategy. However, these studies did not evaluate the economic effects of the BlightPro DSS on potato production costs, revenues, and risks associated with income volatility.

We advance the study conducted by Small et al. (2015b) and introduce risk analysis to evaluate the benefit of adopting precision agriculture in managing late blight. Net return to all costs excluding fungicide cost and application cost per 0.41 ha (net return per 0.41 ha) distributions are developed using 14 yr of historical weather data (2000–2013) from 59 locations (five states, include Massachusetts, Maine, North Carolina, North Dakota, New York, Wisconsin). Three categories of late blight resistant potato cultivars (susceptible, moderately susceptible, and moderately resistant) are evaluated under two late blight initiation scenarios: a worst case scenario and a randomly selected disease initiation scenario. The former scenario represents the earliest theoretically possible disease initiation, and the later scenario represents the potential variability in late blight initiation over the course of a production season, for a field that starts the season disease-free. By comparing the BlightPro DSS-based strategy with a calendar-based disease management strategy, we evaluate the benefit of using BlightPro DSS on potato yield, cost, revenue, and risk-adjusted net return. Stochastic dominance (Hadar and Russell, 1969) and stochastic dominance with respect to a function (Meyer, 1977) are used to compare pairwise late blight management choices between a calendar-based strategy and the DSS-based strategy. Stochastic efficiency with respect to a function (Hardaker and Lien, 2010; Hardaker et al., 2004; Meyer et al., 2009) is used to determine the risk adjusted value of BlightPro DSS. The overall objective of this paper is to identify the most risk-efficient fungicide scheduling strategy. More specifically, we evaluate the economic value of fungicide scheduling strategies, when taking producers' risk aversion level into consideration.

MATERIALS AND METHODS

Decision Support System and Precision Fungicide Application for Potato Production

Late blight poses a special challenge for potato growers in humid (Olanya et al., 2007) and cool (16–21°C) climates (Krause et al., 1975; Wallin, 1962). For unprotected crops, late blight epidemics can cause significant crop losses and economic failure for potato growers (Fry and Goodwin, 1997b). If incorrectly managed, the disease has the potential to completely destroy the entire field within 2 to 3 wk after the appearance of visible symptoms (Johnson, 2008). Late blight can be dispersed aerially by wind currents or in splashing water droplets (Fry and Goodwin, 1997a), and can spread long distances through infected potato tubers, tomato seedlings, or tomato fruits (Fry and Goodwin, 1997b). Growers commonly utilize fungicides with protectant activity to manage late blight (Song et al., 2003), applying these fungicides on a calendar-based, weekly schedule. However, calendar-based scheduling strategies have drawbacks (Vorotnikova et al., 2014). First, if weather conditions are unfavorable for disease development, unnecessary applications are at best inefficient, wasting both chemicals and labor and entailing extra costs (Fohner et al., 1984; Fry, 1982). Second, the repeated use of certain fungicides can lead to the emergence of late blight strains that are resistant to these fungicides (Deahl et al., 1991, Deahl et al., 1993, Fry et al., 1979, Goodwin et al., 1996). Third, the interaction among several factors influencing disease progress increases the complexity of late blight management (Small et al., 2015b). These factors include the influence of weather on the pathogen, level of potato cultivar resistance to late blight, fungicide residue on the crop, and potential pathogen resistance to fungicide. Finally, rising public concern regarding the potential health and environmental effects of pesticides is motivating judicious use of fungicide (Gustavsson et al., 2011). These drawbacks create an opportunity for a decision support system to provide scientific-based information to guide decision-making.

The BlightPro DSS is an an internet-based platform available at the USAblight website (http://usablight.org) (Small et al., 2015a, 2015b). The BlightPro DSS was developed by Cornell University researchers to improve late blight disease suppression and fungicide use efficiency, by providing real-time support for late blight management (Small et al., 2015a). The BlightPro DSS provides free service for its users to manage late blight. The BlightPro DSS links several models (Andrade-Piedra et al., 2005a; Fry et al., 1983, Krause et al., 1975) into a system that enables predictions of disease and fungicide dynamics based on location-specific weather conditions, host resistance, pathogen inoculum, and fungicide usage. When conditions are favorable for late blight, an integrated alert system in the BlightPro DSS issues notifications about upcoming critical thresholds for fungicide intervention via e-mail and/or text message.

Small et al. (2015b) examined the potential benefits of the BlightPro DSS in terms of disease supression and fungicide use efficiency. However, their study did not evaluate the economic effects of the DSS-based strategy on potato production costs, revenues, and risks in net return variability. Risk associated with income fluctuations are key determinants of the adoption of new technology by growers. In this study, we compare the net return after adjusting for cost of applying fungicide between the DSS-based strategy and the calendar-based strategy, while considering the risks associated with weather conditions, yields, and input and output prices.

Data

Infection by late blight influences the photosynthesis process of potato leaves and reduces the bulking rate of potato tuber, which results in potato yield loss. The higher the disease severity of late blight, the more impact on the photosynthetic process. Fungicide application impacts the disease progress by hindering the development of late blight disease on potato plants. The data related to number of fungicide applications and AUDPC (area under disease progress curve, which is a quantitative summary of disease severity over time) were generated and discussed in Small et al. (2015b). We have used the datasets generated in computer simulation experiments by Small et al. (2015b), and expanded the analysis to include potato yield loss percentage data based on the model developed by Shtienberg et al. (1990). Shtienberg et al. (1990) developed and parameterized a general model to estimate late blight induced yield loss for potato. The model estimates potato yield loss percentage due to foliar late blight. Shtienberg's yield loss model has been extensively tested and has been shown to provide accurate yield loss predictions under different soil and weather conditions, and for various cultivars (Rakotonindraina et al., 2012; Shtienberg et al., 1990). Many researchers have used computer simulation models to evaluate farming practices, including integrated pest management strategies for corn and pea (*Pisum sativum* L.) (Musser et al., 1981), multi-species insect management strategies for soybean (Boggess et al., 1985), and soybean aphid management using natural enemies (Zhang and Swinton, 2009).

The simulation experiments in our research used 14 yr of meteorological data (2000–2013), recorded from 59 locations in 6 potato-producing states, including 6 locations from Maine, 5 locations from Massachusetts, 13 locations from New York, 12 locations from North Carolina, 9 locations from North Dakota, and 14 locations from Wisconsin. Each year's weather conditions at one certain location creates a unique potato growth environment. In total, 771[1] potato growth environments were included in the simulation analyses after removing those years with more than 2% missing weather data. The simulation experiments were generated using three categories of late blight resistant potato cultivars, including susceptible cultivars, moderately susceptible cultivars, and moderately resistant cultivars. For the simulation analyses only one representative cultivar was used for each category of disease resistance. For the BlightPro DSS analyses each disease-resistance category includes several different potato cultivars.

Two disease initiation scenarios were investigated for each disease-resistance category and each potato growth environment: (i) a worst case scenario representing the earliest theoretically possible disease initiation, which could start from infected potato tubers planted in the current season or from infected volunteer potatoes sprouting in the field; and (ii) a randomly-selected disease initiation scenario which represents the potential variability in late blight initiation over the course of a production season, for a field that starts the season disease-free. This scenario is a closer representation of reality, where a crop becomes infected by inoculum from external sources (e.g., infected farms/vegetable gardens) in the surrounding environment. Three methods of fungicide scheduling throughout the production season are compared, including a calendar-based (7-d spray schedule), DSS-based (BlightPro DSS-recommended spray schedule), and unsprayed control (no fungicide application). In total, 13,878 simulations (771 environments × three disease-resistance categories × three methods of fungicide scheduling × two scenarios) were generated to compare DSS-based with the calendar-based strategy. Figure 1 illustrates the difference between the DSS-based strategy and the calendar-based strategy. The calendar-based strategy involved with routine fungicide applications every 7 d. Weekly sprays were initiated 35 d after planting and continued until the end of the season. In contrast, the DSS-based strategy was influenced by the resistance of the potato cultivar, the favorability of the weather for late blight progress, and the influence of prevailing weather on fungicide residue on potato crops (Small et al., 2015a). For the DSS-based strategy, sprays were initiated when 18 Blitecast severity values (Krause et al., 1975) had accumulated since median emergence and plants were at least 0.15 to 0.20 m in height (for field experiments). Subsequent applications were scheduled according to Simcast (Fry et al., 1983), based on the effect of weather on the pathogen (accumulation of blight units) and on fungicide weathering (accumulation of fungicide units).

A representation of the data generating process is shown in Fig. 2. The LATEBLIGHT 2004 disease model integrated with fungicide sub-models (Andrade-Piedra et al., 2005a) was used in conjunction with a potato yield loss model (Shtienberg et al., 1990) to evaluate the efficacy of fungicide scheduling methods. These models have been widely tested and validated to simulate late blight disease progress (Andrade-Piedra et al., 2005b) and the yield loss percentage caused by the disease (Rakotonindraina et al., 2012). The calendar-based, DSS-based, and unsprayed control schedules were incorporated into the LATEBLIGHT 2004 disease model (Andrade-Piedra et al., 2005b) to determine the disease severity and the percentage of defoliation. For a comprehensive description of the data generating process see Small et al. (2015b). The potato yield loss percentage for the calendar-based, DSS-based, and unsprayed control strategies were obtained by incorporating the percentage of defoliation from the LATEBLIGHT 2004 disease model into the potato yield loss model (Shtienberg et al., 1990).

[1] Small et al. (2015b) identify 768 environments. The discrepancy between the numbers is due to the difference in handling of three environments. In these three environments, the late blight epidemic started around the end of the season (<6 d from the end of the season). In this paper, these environments were included in the analysis, and it was assumed that the yield was not impacted by the disease.

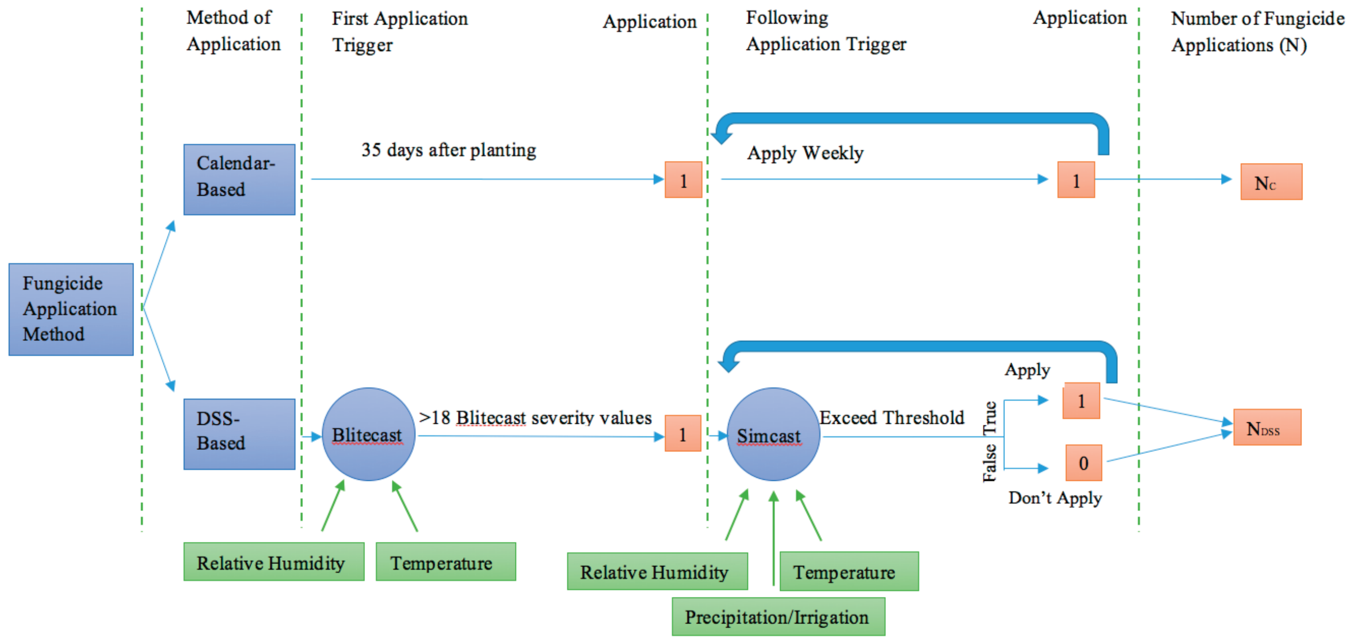

Fig. 1. Difference between the calendar-based strategy and the BlightPro decision support system (DSS)-based strategy. The Blitecast system reports daily severity values, which are calculated using relative humidity and temperature data as inputs (Krause et al., 1975). The Simcast system reports Blight Units and Fungicide Units, which are calculated using relative humidity and temperature, as well as precipitation/irrigation data as inputs (Fry et al., 1983). N_c stands for the number of applications for the calendar-based strategy per season per 0.41 ha and N_{DSS} stands for the number of applications for the DSS-based strategy per season per 0.41 ha. Note: This figure is a conceptual extension of Fig. 2 in Vorotnikova et al. (2014).

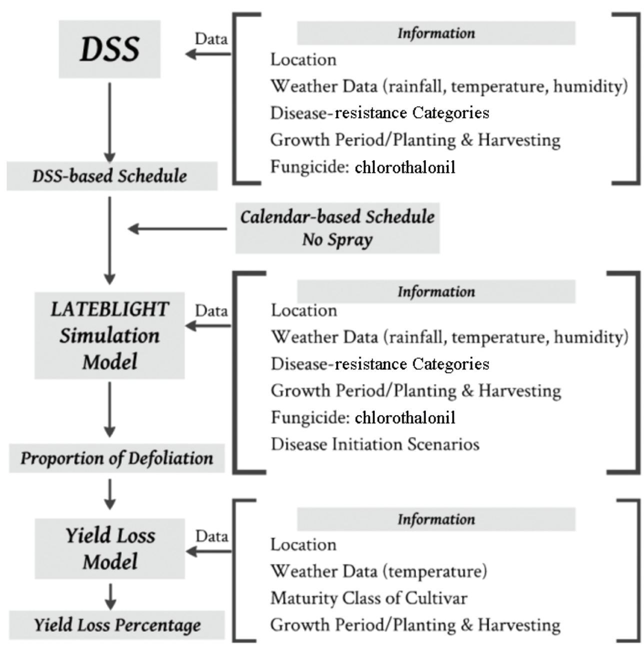

Fig. 2. Data generating process for 59 locations from 2000 to 2013. The simulation experiments were generated for three categories of disease-resistance to late blight: susceptible cultivars, moderately susceptible cultivars, and moderately resistant cultivars. Two scenarios were examined for each disease-resistance category: worst case scenario and the randomly selected disease initiation scenario.

The following common parameters were used (Small et al., 2015b). The length of the season was 110 d (Table 1). Late blight was initiated with 0.001% disease severity (one lesion per 10 plants). A protectant fungicide with active ingredient chlorothalonil was applied at a rate of 1.34 kg a.i./ha (equivalent to 1.5 pints per acre) for each application. Our study was limited to locations in rainfed production regions and temperate climates where the cold winter eliminates host plants between growing seasons (Small et al., 2015b). All diseases other than late blight, and the effects of pests, weeds, nutrients, and heat or frost shock were not modeled and assumed not to influence this study. Growers are also assumed to be able to initiate fungicide applications according to the DSS-based strategy. We did not attempt to estimate the loss due to tuber infections. Only yield loss at harvest was considered.

Net Return per 0.41 Hectare

To estimate the economic benefits of switching to the DSS-based strategy, we compared each of the 59 locations' distributions of the net return to all costs excluding fungicide cost and application cost per 0.41 ha (net return per 0.41 ha) within a 14-yr period for three fungicide application scheduling strategies, including calendar-based, DSS-based, and unsprayed control as a base comparision. Potato yield is first calculated to estimate net return per 0.41 ha. Potato yield per 0.41 ha was estimated using historical state-level average potato yield data obtained from the Potatoes Annual Summary (USDA, various issues) adjusted by potato yield loss percentage from the

Table 1. Potato growth period.

State	Plant date	Emergence date	Harvest date
North Carolina	26 March	10 April	27 July
Other states	15 May	30 May	15 September

computer simulation results. Specifically, the potato yield per 0.41 ha is calculated for each production season y, each state s, and each location l as follows:

$$\text{Potato yield}_{l,y} = \text{average potato yield}_{s,y} \times (1 - \frac{\text{yield loss percentage}_{l,y}}{100}) \quad [1]$$

The fungicide cost per 0.41 ha for each application in 2013 is \$8.63. We applied at a rate of 1.34 kg a.i./ha (equivalent to 1.5 pints per acre) for each application. Fungicide price was obtained from a local agricultural chemical distributor on Long Island by Dr. M. T. McGrath in April 2013 (M.T. McGrath, personal communication, 29 Dec. 2013). Application cost (\$6.58/0.41 ha/application) comes from Lazarus (2013), the total cost per 0.41 ha of a self-propelled boom sprayer, and includes fuel, lubricants, repairs and maintenance, labor, power, implement depreciation (depreciation is both time-related and use-related) and overhead costs (interest, insurance, and housing). We assumed that the fungicide cost and application cost were the same for all 59 locations. United States Department of Agriculture Prices Paid Indices (agricultural chemical and machinery indices) were used to adjust the fungicide price and application cost in 2013 to nominal prices in previous years. In turn, cost of fungicide applications were calculated as a product of fungicide application cost and number of fungicide applications:

$$\text{Cost of fungicide applications}_{l,y} = (\text{fungicide cost}_{y} + \text{application cost}_{y}) \times \text{no. of applications}_{l,y} \quad [2]$$

Historical state-level potato price data was obtained from the Potatoes Annual Summary (USDA, various issues). Ideally, yield and price data for each potato cultivar should be used when calculating yield and revenue. The potato processing cost related to different quality of potato tuber should also be considered in calculations. Due to limitations relating to availability of public data, we assumed average yield and price to be the same among potato cultivars in each of the disease-resistance categories. Revenue per 0.41 ha was calculated for each production season and each location as a product of yield and price:

$$\text{Revenue}_{l,y} = \text{potato price}_{s,y} \times \text{potato yield}_{l,y} \quad [3]$$

For each production season and each location, net return to all costs excluding fungicide cost and application cost per 0.41 ha (net return per 0.41 ha) was equal to cost of fungicide applications (Eq. [2]) subtracted from revenue (Eq. [3]):

$$\text{Net return per 0.41 ha}_{l,y} = \text{revenue}_{l,y} - \text{cost of fungicide applications}_{l,y} \quad [4]$$

There was no additional cost associated with using the DSS-based strategy in the analysis. Currently, the BlightPro DSS provides a free service for its users. An integrated alert system in the BlightPro DSS issues notifications to its user about upcoming critical thresholds for intervention (fungicide application) via e-mail and/or text message to limit the time cost of the users using the system.

Risk Aversion

The risk of late blight infection creates uncertainties for decision makers. Recognizing this, we incorporated the uncertainty caused by income volatility due to late blight infection and the producers' risk attitudes into the decision-making framework. Alternative decisions can be ranked with individual risk attitudes (Schumann, 2011). Producers with different degrees of risk-aversion are likely to have different preferences for alternative strategies (Monjardino et al., 2015). In this paper, we compare mutually exclusive decisions faced by potato growers for alternative fungicide spray strategies (i.e., the calendar-based strategy or the DSS-based strategy).

We used stochastic dominance and stochastic efficiency with respect to a function (SERF) procedures to rank the entire probability distribution functions of net return per 0.41 ha for each location and alternative fungicide spray strategy. Stochastic dominance methods (Hadar and Russell, 1969; Hanoch and Levy, 1969; Meyer, 1977; Rothschild and Stiglitz, 1970) were used to identify the most risk efficient strategy between the DSS-based and calendar-based strategies. These methods compare the cumulative distribution functions of the net return per 0.41 ha for decision makers with different risk aversion levels. Stochastic efficiency with respect to a function (Hardaker and Lien, 2010; Hardaker et al., 2004; Meyer et al., 2009) was used to compute the certainty equivalents (CEs) of the net return per 0.41 ha for each spray strategy. Stochastic efficiency with respect to a function evaluated the economic benefits of adopting BlightPro DSS under different risk aversion assumptions.

The Simulation and Econometrics to Analyze Risk (SIMETAR) software was used to conduct the stochastic dominance and SERF analysis. The stochastic dominance and SERF analysis were done separately for each location to compare the net return per 0.41 ha distributions between DSS-based strategy and calendar-based strategy. The same analyses were repeated and conducted 354 times by using 354 Excel files (59 locations × 3 disease-resistance categories × 2 scenarios). Each excel file summarizes the distributions of net return per 0.41 ha for DSS-based and calendar-based strategies for a specific location, category, and scenario.

Stochastic Dominance

Stochastic dominance approaches use the cumulative distribution functions to identify the risk efficient set of risky alternatives in a manner consistent with expected utility theory. Stochastic dominance (Hadar and Russell, 1969; Hanoch and Levy, 1969; Quirk and Saposnik, 1962; Rothschild and Stiglitz, 1970) is a method used to find necessary and sufficient conditions for cumulative distribution $F(x)$ to be preferred or indifferent to cumulative distribution $G(x)$ by all agents in a particular group (Meyer, 1977). Stochastic dominance makes general assumptions and places limited restrictions on the utility function. As a result of these underlying assumptions, stochastic dominance can be characteristic of a wide range of individuals and utility functions (Hadar and Russell, 1969; Quirk and Saposnik, 1962). These approaches can be used to predict decision makers' preferences between given pairs of uncertain alternatives without having any knowledge of the decision makers' utility function (Hadar and Russell, 1969; Harris and Mapp, 1986).

Hadar and Russell (1969) developed the concept of first-degree stochastic dominance (FSD) and second-degree stochastic dominance (SSD). In essence, FSD holds when one cumulative distribution lies entirely above the other (Hadar and Russell, 1969). First-degree stochastic dominance allows us to compare the choices faced by all decision makers who have positive marginal utility (Hadar and Russell, 1969). There is no restriction on decision makers' preferences other than assuming the utility function is increasing and twice differentiable (Hadar and Russell, 1969), which implies decision makers prefer more wealth to less. Second-degree stochastic dominance holds when the area under one cumulative distribution is equal to, or larger than that under the other cumulative distribution (Hadar and Russell, 1969). Second-degree stochastic dominance requires a concave utility function or a non-increasing marginal utility function, which means decision makers are risk averse (Hadar and Russell, 1969). Holding average income constant, risk averse decision makers prefer lower variance and less downside risk.

Developed by Meyer (1977), stochastic dominance with respect to a function (SDRF) ranks uncertain choices on the basis of the lower and upper bounds of decision makers' absolute risk aversion levels (Harris and Mapp, 1986; King and Robison, 1981). In other words, SDRF establishes necessary and sufficient conditions for the cumulative distribution function of $F(y)$ to be preferred to the cumulative distribution function of $G(y)$ by all individuals whose absolute risk aversion functions lie between lower $r_1(y)$ and upper bounds $r_2(y)$ (Harris and Mapp, 1986). Stochastic dominance with respect to a function has been implemented by many empirical studies (Barham et al., 2011; Cochran et al., 1985; Greene et al., 1985; Harris and Mapp, 1986; King and Robison, 1981; de la Llata et al., 1999; Musser et al., 1981; Parcell and Langemeier, 1997; Ritchie et al., 2004; Zacharias and Grube, 1984). It is a practical tool to help farmers better understand their risk preferences and choices under price, yield, or weather uncertainty (King and Robison, 1981). The major advantage of SDRF is that it imposes no restrictions on the width of the relevant absolute risk aversion interval (King and Robison, 1981). It allows the lower and upper bounds on absolute risk aversion interval to vary among studies (King and Robison, 1981). First- and second-degree stochastic dominance can be viewed as special cases of SDRF (King and Robison, 1981).

Stochastic dominance with respect to a function analysis requires information pertaining to absolute risk aversion coefficients. According to Raskin and Cochran (1986), this information can be obtained by transforming relative risk aversion coefficients to absolute risk aversion coefficients. Relative risk aversion levels used in this study include slightly risk averse (0–1.0), moderately risk averse (1.0–5.0), and strongly risk averse (5.0–10.0) (Hardaker et al., 2015). The risk attitudes from Hardaker et al. (2015) were transformed for each location l as follows:

$$r_{a,l} = r_r / w_l \quad [5]$$

where $r_{a,l}$ stands for absolute risk aversion[2] for a specific location, r_r stands for relative risk aversion, and w_l stands for the average net return per 0.41 ha for each location of both DSS-based and calendar-based strategies.

Stochastic Efficiency

According to Hardaker et al. (2004), SERF uses CEs to rank risky alternatives for a specified risk aversion level. The CE of a risky alternative is the guaranteed amount of money at which a decision maker would be willing to accept, instead of taking the risky alternative (Williams et al., 2014). Thus, risky alternatives with higher CEs are preferred to those with lower CEs (Hardaker and Lien, 2010; Hardaker et al., 2004; Meyer et al., 2009). For a risk averse decision maker, the CE is less than the expected value of the risky alternative. To calculate CE, the utility function needs to be specified. Schumann et al. (2004) compared six different utility functions and conclude that the overall efficient set can be similar across different utility functions. In this analysis, the power utility function[3] was used. The power utility function has been widely used for modeling risk aversion (Wakker, 2008). The power utility function is often referred to as the constant relative risk aversion utility function. In addition to constant relative risk aversion, this utility function exhibits decreasing absolute risk aversion as an individual's wealth increases, which is a commonly assumed risk preference characteristic. Relative risk aversion levels (r_r) used to generate the stochastic efficiency results ranged from 0 (risk neutral) to 10 (strongly risk averse) (Hardaker et al., 2015).

Given a risk aversion level, the utility weighted risk premium (RP) can be calculated using CEs of DSS-based and calendar-based strategies as follows.

$$\mathrm{RP}_{\mathrm{DSS,Calendar},\, r_r} = \mathrm{CE}_{\mathrm{DSS},\, r_r} - \mathrm{CE}_{\mathrm{Calendar},\, r_r} \quad [6]$$

A positive RP means that if the potato growers are informed about the availability of the DSS-based strategy, they would prefer to switch to this precision agriculture technology. The RP reflects the minimum amount of money ($/0.41 ha) that would have to be paid to a potato grower to make them continue using calendar-based strategy instead of switching to the DSS-based strategy. The RP could also be viewed as the value of the information provided by BlightPro DSS for potato growers. Stochastic efficiency with respect to a function methods can be adopted to a wide range of individual decision making processes. It has been applied to evaluate various alternative decisions, such as beef farms' insurance policies (Williams et al., 2014), and sustainability of crop farming systems (Lien et al., 2007).

[2] Given a twice-differentiable Bernoulli utility function U, Arrow-Pratt measures of absolute risk aversion coefficient r_a is defined as

$$r_a = -\frac{U''(x)}{U'(x)},$$

and the relative risk aversion coefficient r_r is defined as

$$r_r = -x\frac{U''(x)}{U'(x)},$$

where x is income or wealth.

[3] The functional form of the power utility is as follows:

$$U(x) = \frac{x^{1-r_r}}{1-r_r}$$

for $r_r \neq 1$; $U(x) = \ln(x)$ for $r_r = 1$, where r_r is the relative risk aversion coefficient, and x is income or wealth.

RESULTS AND DISCUSSION

Fungicide Applications and Disease Rating

The summary statistics for the number of fungicide applications and AUDPC for the worst case scenario and the randomly selected disease initiation scenario are provided in Tables 2 and 3, respectively. For the susceptible cultivars, BlightPro DSS recommended a higher number of fungicide applications than the calendar-based strategy, but also exhibited higher levels of disease suppression. For the moderately susceptible cultivars, BlightPro DSS recommended fewer fungicide applications and had higher disease suppression, which suggested that BlightPro DSS improved the efficiency of fungicide usage and allowed for more effective disease suppression. As expected for moderately resistant cultivars, the calendar-based strategy achieved high levels of disease suppression but with lower fungicide use efficiency, relative to the DSS-based strategy (Small et al., 2015b).

The BlightPro DSS issues notifications about fungicide application based on favorable weather conditions. The two scenarios (Tables 2 and 3) were investigated using the same weather data. The difference between the two scenarios relates to the assumption pertaining to the starting date of the disease. As a result, the BlightPro DSS recommended fungicide application schedules for both scenarios were the same. The average number of fungicide applications for the DSS-based strategy decreased, when the disease-resistance level increased. The average number of fungicide applications for the DSS-based strategy was 14, 9, and 7 applications, for the susceptible cultivars, the moderately susceptible cultivars, and the moderately resistant cultivars, respectively. The DSS-based strategy resulted in a 23% increase, a 15% decrease, and a 35% decrease in average number of fungicide applications relative to the calendar-based strategy (11 sprays) for the susceptible cultivars, the moderately susceptible cultivars, and the moderately resistant cultivars, respectively. The favorability of prevailing weather for late blight also influenced the number of recommended sprays by BlightPro DSS (Small et al., 2015b). Higher application rates were associated with years where more favorable disease development environments were observed (Small et al., 2015b). In addition, variation in the average number of fungicide applications among states were observed. For susceptible cultivars, the average number of fungicide applications ranged from 11 to 16 applications per season among the six states. The average number of fungicide applications ranged from 8 to 11, and 6 to 8 for moderately susceptible cultivars and moderately resistant cultivars, respectively. Massachusetts and Maine had the highest average number of fungicide applications, and North Dakota had the lowest average number of fungicide applications for all three categories of cultivars.

For the worst case scenario (Table 2), the average AUDPC for the unsprayed control was 4662 for the susceptible cultivars, 4359 for the moderately susceptible cultivars, and 2428 for the moderately resistant cultivars. The use of fungicide reduced late blight disease severity dramatically. The average AUDPC for the DSS-based strategy was 319 for susceptible cultivars, 926 for moderately susceptible cultivars, and 144 for moderately resistant cultivars. The average AUDPC for the calendar-based strategy was 2061 for susceptible cultivars, 1357 for moderately susceptible cultivars, and 89 for moderately resistant cultivars. The DSS-based method decreased the average level of disease as well as the variance in disease severity for susceptible cultivars and moderately susceptible cultivars.

Table 2. Summary statistics for potato revenue, late blight disease rating, and fungicide applications for the worst case scenario. The number of observations is 771.

	Control				Calendar				DSS			
Item	Mean	SD	Min.	Max.	Mean	SD	Min.	Max.	Mean	SD	Min.	Max.
Susceptible cultivars												
No. of fungicide applications	0	0	0	0	11	0	11	11	13.6	3.3	1	21
AUDPC†	4662	1865	0	7365	2061	1872	0	7335	319	567	0	3965
Yield loss percentage	39.5	20.9	0.0	79.4	12.7	15.8	0.0	72.5	0.5	1.8	0.0	23.5
Potato yield, cwt/0.41 ha	176.6	81.8	62.0	459.9	255.3	87.4	79.0	459.9	291.3	81.7	148.6	459.9
Cost of fungicide applications, $/0.41 ha	0	0	0	0	134	19	111	167	165	46	13	287
Net return per 0.41 ha, $/0.41 ha	1638	928	363	5184	2194	985	348	5043	2492	1000	806	5171
Moderately susceptible cultivars												
No. of fungicide applications	0	0	0	0	11	0	11	11	9.4	2.4	1	15
AUDPC	4359	1777	0	7196	1357	1531	0	6536	926	984	0	4534
Yield loss percentage	33.8	19.2	0.0	73.4	7.3	11.0	0.0	57.0	1.8	3.6	0.0	28.2
Potato yield, cwt/0.41 ha	193.1	80.2	72.3	459.9	271.8	84.8	96.2	459.9	287.4	81.4	150.7	459.9
Cost of fungicide applications, $/0.41 ha	0	0	0	0	134	19	111	167	114	33	13	205
Net return per 0.41 ha, $/0.41 ha	1786	921	423	5184	2343	986	448	5043	2507	992	746	5171
Moderately resistant cultivars												
No. of fungicide applications	0	0	0	0	11	0	11	11	7.1	1.7	1	11
AUDPC	2428	1618	0	5509	89	275	0	2513	144	273	0	1799
Yield loss percentage	9.3	10.2	0.0	43.4	0.3	0.8	0.0	8.5	0.1	0.3	0.0	6.0
Potato yield, cwt/0.41 ha	265.2	80.8	121.0	459.9	292.1	81.9	166.1	459.9	292.5	81.8	169.8	459.9
Cost of fungicide applications, $/0.41 ha	0	0	0	0	134	19	111	167	86	24	13	152
Net return per 0.41 ha, $/0.41 ha	2434	1008	708	5184	2531	1010	857	5043	2582	1013	916	5171

† AUDPC is area under disease progress curve, which is a quantitative summary of disease severity over time.

For the randomly selected disease initiation scenario (Table 3), the average AUDPC for the unsprayed control was 1865 for susceptible cultivars, 1632 for moderately susceptible cultivars, and 758 for the moderately resistant cultivars. Fungicide applications reduced these numbers dramatically. The average AUDPC for the DSS-based strategy was 79 for susceptible cultivars, 245 for moderately susceptible cultivars, and 36 for moderately resistant cultivars. The average AUDPC for the calendar-based strategy was 457 for susceptible cultivars, 264 for moderately susceptible cultivars, and 14 for the moderately resistant cultivars.

Yield

Using the potato yield loss model (Shtienberg et al., 1990), we were able to evaluate the impact of the BlightPro DSS on potato yield and advance the research conducted by Small et al. (2015b). Tables 2 and 3 present the summary statistics for average potato yield loss percentage and average potato yield for the unsprayed control and two fungicide application strategies. The DSS-based strategy achieved higher average yield than calendar-based strategy for susceptible cultivars and moderately susceptible cultivars. For moderately resistant cultivars, average yield was very similar for both strategies.

For the worst case scenario (Table 2), fungicide applications reduced the average potato yield loss percentage of susceptible cultivars from 39.5% for the unsprayed control to 12.7% for the calendar-based strategy and 0.5% for the DSS-based strategy. This was equivalent to an increase in the average potato yield from 176.6 cwt/0.41 ha (unsprayed control) to 255.3 cwt/0.41 ha (calendar-based) and 291.3 cwt/0.41 ha (DSS-based). The average yield loss percentage for the moderately susceptible cultivars were reduced from 33.8% for the unsprayed control to 7.3% for the calendar-based strategy and 1.8% for the DSS-based strategy. Consequently, average potato yield for the moderately susceptible cultivars increased from 193.1 cwt/0.41 ha (unsprayed control) to 271.8 cwt/0.41 ha (calendar-based) and 287.4 cwt/0.41 ha (DSS-based). For the moderately resistant cultivars, average yield loss percentage was 9.3% for the unsprayed control, and 0.3 and 0.1% for the calendar-based and DSS-based strategies, respectively. Average potato yield for the moderately resistant cultivars increased from 265.2 cwt/0.41 ha (unsprayed control) to 292.1 cwt/0.41 ha (calendar-based) and 292.5 cwt/0.41 ha (DSS-based).

The trends in results with respect to potato yields for the randomly selected disease initiation scenario (Table 3) are very similar to those for the worst case scenario. Fungicide applications reduced average potato yield loss percentage of susceptible cultivars from 10.5% for the unsprayed control to 2.2% for the calendar-based stategy and 0.1% for the DSS-based strategy. This was equivalent to an increase in the average potato yield from 261.9 cwt/0.41 ha (unsprayed control) to 286.2 cwt/0.41 ha (calendar-based) and 292.5 cwt/0.41 ha (DSS-based). The average yield loss percentage for the moderately susceptible cultivars was reduced from 8.2% for the unsprayed control to 1.2% for the calendar-based strategy and 0.4% for the DSS-based strategy. Consequently, average potato yield for the moderately susceptible cultivars increased from 268.6 cwt/0.41 ha (unsprayed control) to 289.2 cwt/0.41 ha (calendar-based) and 291.6 cwt/0.41 ha (DSS-based). For the moderately resistant cultivars, average yield loss percentage was

Table 3. Summary statistics for potato revenue, late blight disease rating, and fungicide applications for the randomly selected disease initiation scenario. The number of observations is 771.

	Control				Calendar				DSS†			
Item	Mean	SD	Min.	Max.	Mean	SD	Min.	Max.	Mean	SD	Min.	Max.
Susceptible cultivars												
No. of fungicide applications	0	0	0	0	11	0	11	11	13.6	3.3	1	21
AUDPC‡	1865	2029	0	6869	457	1126	0	6739	79	276	0	2613
Yield loss percentage	10.5	17.9	0.0	69.8	2.2	8.3	0.0	63.3	0.1	0.6	0.0	10.9
Potato yield, cwt/0.41 ha	261.9	91.0	67.3	460.0	286.2	84.1	88.2	460.0	292.5	81.8	167.3	460.0
Cost of fungicide applications, $/0.41 ha	0	0	0	0	134	19	111	167	165	46	13	287
Net return per 0.41 ha, $/0.41 ha	2392	1039	394	5184	2475	1005	379	5043	2504	1005	825	5171
Moderately susceptible cultivars												
No. of fungicide applications	0	0	0	0	11	0	11	11	9.4	2.4	1	15
AUDPC	1632	1902	0	6532	264	800	0	6124	245	569	0	4013
Yield loss percentage	8.2	15.4	0.0	64.6	1.2	5.4	0.0	48.9	0.4	1.9	0.0	27.8
Potato yield, cwt/0.41 ha	268.6	88.3	78.2	460.0	289.2	82.6	112.8	460.0	291.6	81.8	161.7	460.0
Cost of fungicide applications, $/0.41 ha	0	0	0	0	134	19	111	167	114	33	13	205
Net return per 0.41 ha, $/0.41 ha	2454	1031	457	5184	2504	1005	590	5043	2547	1008	847	5171
Moderately resistant cultivars												
No. of fungicide applications	0	0	0	0	11	0	11	11	7.1	1.7	1	11
AUDPC	758	1230	0	4968	14	102	0	1517	36	146	0	1754
Yield loss percentage	1.8	5.5	0.0	38.9	0.1	0.3	0.0	5.6	0.03	0.2	0.0	4.1
Potato yield, cwt/0.41 ha	287.5	82.7	127.1	460.0	292.6	81.8	169.8	460.0	292.7	81.8	169.7	460.0
Cost of fungicide applications, $/0.41 ha	0	0	0	0	134	19	111	167	86	24	13	152
Net return per 0.41 ha, $/0.41 ha	2625	1020	832	5184	2536	1011	894	5043	2584	1014	919	5171

† DSS is decision support system.

‡ AUDPC is area under disease progress curve, which is a quantitative summary of disease severity over time.

1.8% for the unsprayed control, 0.1% for the calendar-based strategy, and 0.03% for the DSS-based strategy. Average potato yield for the moderately resistant cultivars increased from 287.5 cwt/0.41 ha (unsprayed control) to 292.6 cwt/0.41 ha (calendar-based) and 292.7 cwt/0.41 ha (DSS-based).

Net Return per 0.41 Hectare

Summary statistics for the cost of fungicide applications, and the potato net return per 0.41 ha are also shown in Tables 2 and 3. For both the worst case and randomly selected disease initiation scenarios, the cost of fungicide applications for the DSS-based strategy decreases with increasing disease-resistance level.

For the susceptible cultivars, the number of fungicide applications and thus the fungicide application cost was higher for the DSS-based strategy than it was for the calendar-based strategy. However, there was a strong payoff from the extra fungicide applications. Both the potato yield and net return per 0.41 ha was relatively higher for the DSS-based strategy when compared to the calendar-based strategy.

For the moderately susceptible and moderately resistant cultivars, the number of fungicide applications and the fungicide application cost was lower for the DSS-based strategy than it was for the calendar-based strategy. For the moderately susceptible cultivars, the more timely fungicide applications associated with the DSS-based strategy improved potato yields. This increase in potato yield, along with the cost savings associated with fewer fungicide applications for the DSS-based strategy, resulted in a relatively higher net return per 0.41 ha. For the moderately resistant cultivars, the relatively higher net return per 0.41 ha associated with the DSS-based strategy resulted from fungicide application cost savings rather than higher potato yields.

Stochastic Dominance Results

The results of the stochastic dominance analysis are presented in Tables 4 and 5 for the calendar-based and DSS-based strategies. These tables summarize the percentage of locations that appeared in each of the three possible efficient sets among the 59 locations: calendar-based, DSS-based, or both. For stochastic dominance analysis, the preferred or dominant strategy was defined to be in the efficient set. To illustrate this, for a certain location, if the DSS-based strategy dominates the calendar-based strategy, DSS is in the efficient set for this location, and vice versa for the calendar-based strategy. If neither strategy dominates the other, then both strategies were in the risk efficient set for that location. In summary, DSS-based strategy was the preferred fungicide application strategy for numerous locations. The results showed that less risk averse growers were more willing to adopt the precision farming technology, and growers who grew more late blight resistant potato cultivars would be more willing to adopt.

For the worst case scenario, the BlightPro DSS was strongly preferred for all three disease-resistance categories based on FSD, SSD, and SDRF. For both the susceptible and moderately resistant cultivars, stochastic dominance with respect to a function showed that the DSS-based strategy was preferred over the calendar-based strategy in all 59 locations for all risk aversion levels. For the moderately susceptible cultivar, 98.3% of the 59 locations preferred the DSS-based strategy over the

Table 4. Percentage of locations in risk efficient set for the worst case scenario.

Item	Calendar	DSS†	Both
	Unit %		
Susceptible cultivars			
FSD	0.0	44.1	55.9
SSD	0.0	94.9	5.1
SDRF			
Slightly risk averse	0.0	100.0	0.0
Moderately risk averse	0.0	100.0	0.0
Strongly risk averse	0.0	100.0	0.0
Moderately susceptible cultivars			
FSD	0.0	50.8	49.2
SSD	0.0	94.9	5.1
SDRF			
Slightly risk averse	0.0	98.3	1.7
Moderately risk averse	1.7	98.3	0.0
Strongly risk averse	1.7	98.3	0.0
Moderately resistant cultivars			
FSD	0.0	93.2	6.8
SSD	0.0	98.3	1.7
SDRF			
Slightly risk averse	0.0	100.0	0.0
Moderately risk averse	0.0	100.0	0.0
Strongly risk averse	0.0	100.0	0.0

† DSS is decision support system. FSD stands for first-degree stochastic dominance. SSD stands for second-degree stochastic dominance. SDRF stands for stochastic dominance with respect to a function.

Table 5. Percentage of locations in risk efficient set for the randomly selected disease initiation scenario.†

Item	Calendar	DSS	Both
	Unit %		
Susceptible cultivars			
FSD‡	1.7	1.7	96.6
SSD	32.2	32.2	35.6
SDRF			
Slightly risk averse	39.0	59.3	1.7
Moderately risk averse	39.0	49.2	11.9
Strongly risk averse	50.8	39.0	10.2
Moderately susceptible cultivars			
FSD	0.0	22.0	78.0
SSD	1.7	54.2	44.1
SDRF			
Slightly risk averse	5.1	93.2	1.7
Moderately risk averse	6.8	84.7	8.5
Strongly risk averse	15.3	74.6	10.2
Moderately resistant cultivars			
FSD	0.0	94.9	5.1
SSD	0.0	100.0	0.0
SDRF			
Slightly risk averse	0.0	100.0	0.0
Moderately risk averse	0.0	100.0	0.0
Strongly risk averse	0.0	100.0	0.0

† Due to rounding, for some cases the sum of the efficient sets for calendar, decision support system (DSS), and both columns are not equal to 100.0%.

‡ FSD stands for first-degree stochastic dominance. SSD stands for second-degree stochastic dominance. SDRF stands for stochastic dominance with respect to a function.

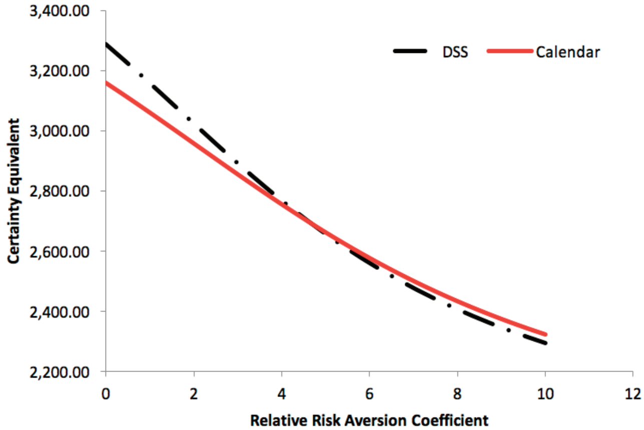

Fig. 3. Certainty equivalent as a function of risk aversion for alternative strategies at one location in Wisconsin (susceptible cultivars and the randomly selected disease initiation scenario).

calendar-based strategy. For one location, in Wisconsin, the dominated preference switched from being indifferent between the two spray strategies to the calendar-based strategy as the risk aversion level increased.

For the randomly selected disease initiation scenario, DSS-based strategy was still preferred over the calendar-based strategy for a large proportion of the locations. For the slightly risk averse growers, a higher percentage of the locations preferred the DSS-based strategy over the calendar-based strategy. 59.3% of the 59 locations preferred the DSS-based strategy for the susceptible cultivars, 93.2% of the 59 locations preferred the DSS-based strategy for the moderately susceptible cultivars, and all of the 59 locations preferred the DSS-based strategy for the moderately resistant cultivars. Maine, New York, North Dakota, and Wisconsin had the highest percentage of locations for which the DSS-based strategy was preferred for the susceptible cultivars.

Table 6. Average certainty equivalent of net return per 0.41 ha for the worst case scenario.

Item†	Certainty equivalent		Risk premium
	Calendar	DSS‡	DSS over calendar
Susceptible cultivars			
r = 0	$2212	$2516	$305
r = 1	$2082	$2422	$340
r = 5	$1542	$2086	$544
r = 10	$1273	$1846	$573
Moderately susceptible cultivars			
r = 0	$2363	$2530	$167
r = 1	$2254	$2436	$182
r = 5	$1812	$2104	$292
r = 10	$1538	$1870	$333
Moderately resistant cultivars			
r = 0	$2554	$2605	$51
r = 1	$2461	$2512	$51
r = 5	$2129	$2179	$50
r = 10	$1892	$1940	$48

† r is the relative risk aversion coefficient. A power utility function is assumed.

‡ DSS is decision support system.

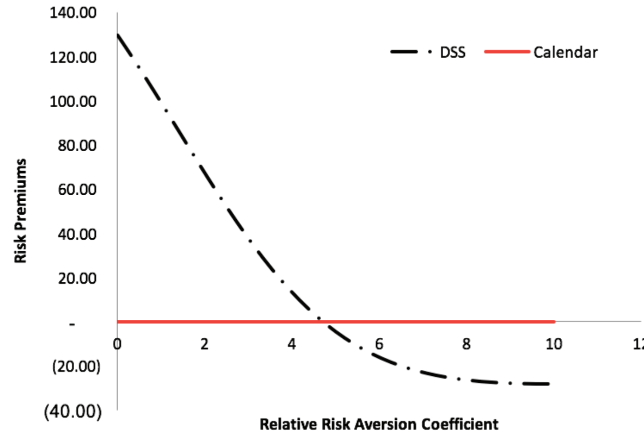

Fig. 4. Risk premium as a function of risk aversion for alternative strategies at one location in Wisconsin (susceptible cultivars and the randomly selected disease initiation scenario).

For the moderately risk averse growers, DSS-based strategy was still preferred over the calendar-based strategy for a large proportion of the locations. 49.2% of the 59 locations preferred the DSS-based strategy for the susceptible cultivars, 84.7% of the 59 locations preferred the DSS-based strategy for the moderately susceptible cultivars, and all of the 59 locations preferred the DSS-based strategy for the moderately resistant cultivars. Maine and North Dakota had the highest percentage of locations for which the DSS-based strategy was preferred for the susceptible cultivars.

For strongly risk averse growers, DSS-based strategy was preferred over the calendar-based strategy for a vast majority of the locations. 39.0% of the 59 locations preferred the DSS-based strategy for the susceptible cultivars, 74.6% of the 59 locations preferred the DSS-based strategy for the moderately susceptible cultivars, and all of the 59 locations preferred the DSS-based

Table 7. Average certainty equivalent of net return per 0.41 ha for the randomly selected disease initiation scenario.

Item†	Certainty equivalent		Risk premium
	Calendar	DSS‡	DSS over calendar
Susceptible cultivars			
r = 0	$2492	$2523	$30
r = 1	$2391	$2429	$38
r = 5	$2008	$2094	$86
r = 10	$1763	$1853	$90
Moderately susceptible cultivars			
r = 0	$2521	$2565	$43
r = 1	$2425	$2471	$46
r = 5	$2068	$2139	$71
r = 10	$1825	$1901	$76
Moderately resistant cultivars			
r = 0	$2555	$2602	$48
r = 1	$2462	$2510	$47
r = 5	$2135	$2179	$44
r = 10	$1901	$1940	$39

† r is the relative risk aversion coefficient. A power utility function is assumed.

‡ DSS is decision support system.

strategy for the moderately resistant cultivars. Maine and North Dakota had a higher percentage of the locations that prefer the DSS-based strategy for the susceptible cultivars.

Stochastic Efficiency Results

To find the value of the BlightPro DSS, we compared the average CEs and RPs of the DSS-based and calendar-based strategies using SERF analysis. Figures 3 and 4 illustrate an example of SERF analysis, which compared the CEs and RPs between the calendar-based and the DSS-based strategies. In this example, the DSS-based strategy was preferred for less risk averse individuals. As the risk aversion level increased, the calendar-based strategy was preferred. The crossover point, the point for which preferences switched from the DSS-based strategy to the calendar-based strategy, occurred at a relative risk aversion level of approximately 4.6. The stochastic efficiency with respect to a function results varied among the 59 locations. Tables 6 and 7 summarize the results for the average CE and RP of relative risk aversion level 0, 1, 5, and 10 for each disease-resistance categories at the 59 locations. Regardless of the risk aversion level and disease-resistance category, BlightPro DSS generated higher average CEs than that of the calendar-based strategy.

The value of information created by the BlightPro DSS varies by scenario, disease-resistance category of the potato cultivar, producer risk aversion level, and location. For the worst case scenario, the average risk premium ranged from $305 to $573 per 0.41 ha for the susceptible cultivars, $167 to $333 per 0.41 ha for the moderately susceptible cultivars, and $48 to $51 per 0.41 ha for the moderately resistant cultivars. These values for the worst case scenario represents the value created by the BlightPro DSS if the disease starts at the earliest potential disease outbreak point, either through infected potato tubers planted in the current season, or through infected volunteer potato. The randomly selected disease initiation scenario is closer aligned with reality, where the initiation of the late blight epidemic depends on influx of inoculum from surrounding environment (e.g., infected neighbor farm) throughout the production season. The risk premiums were lower for the randomly selected disease initiation scenario. Average risk premiums ranged from $30 to $90 per 0.41 ha for susceptible cultivars, from $43 to $76 per 0.41 ha for moderately susceptible cultivars, and from $39 to $48 per 0.41 ha for moderately resistant cultivars. It was also important to note that the benefit of less risk averse growers was mostly smaller than that for more risk averse growers, except for moderately resistant cultivars. Also, for growers who produced more late blight resistant potatoes, the benefit was generally less than it was for growers who produced more susceptible cultivars. The value of adoption also depended on the location of the farm as illustrated in Fig. 5 and 6. There was more variation among states for susceptible cultivars and moderately susceptible cultivars than there was for moderately resistant cultivars.

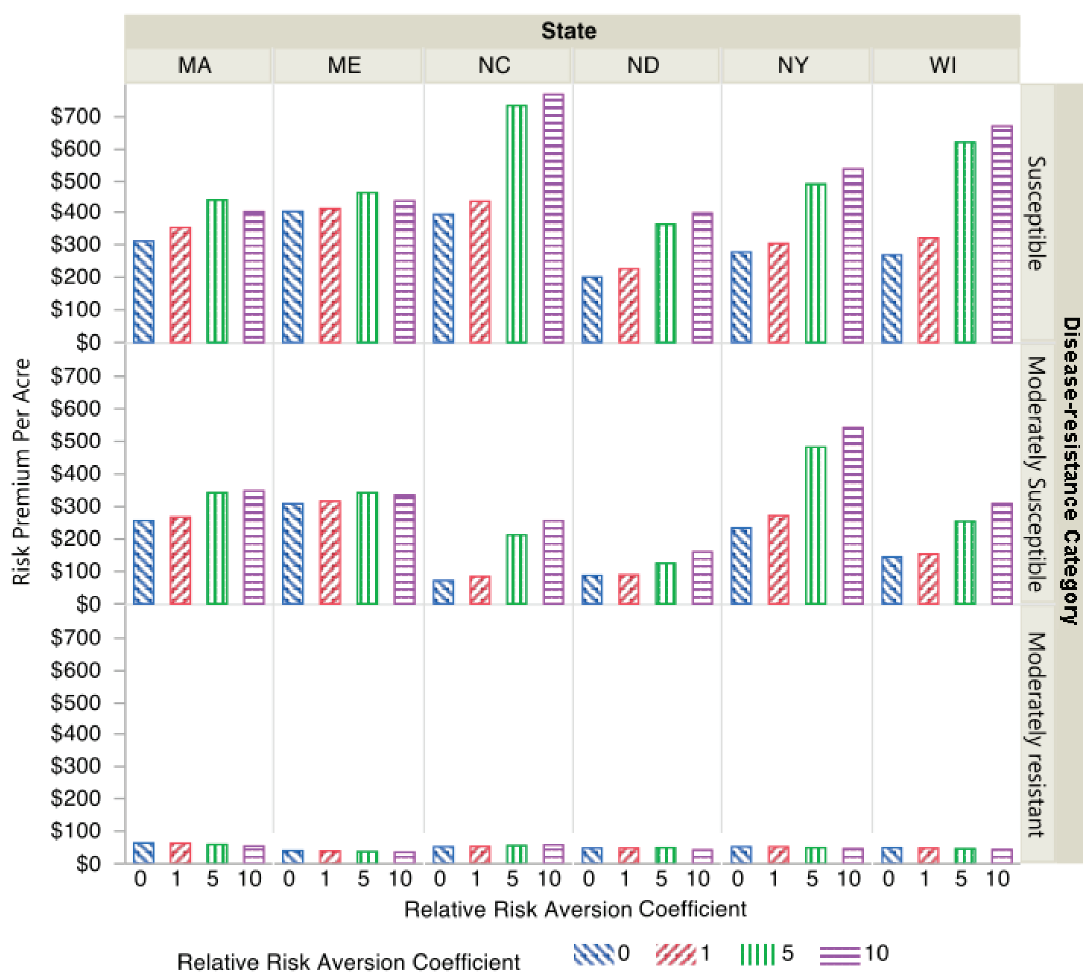

Fig. 5. State average risk premiums ($/per 0.41 ha) for for the worst case scenario.

CONCLUSIONS

This paper discusses how new technologies and practices are being harnessed to help potato growers manage risk, and improve food production and profitability. Our study builds on the work conducted by Small et al. (2015b). By overlaying economic and risk analyses onto their results, we demonstrate the benefits of adopting precision agriculture. In particular, by using economic models along with plant pathology models, we were able to demonstrate the role of precision agriculture technology in improving disease management, yield, and net return given a range of possible weather and price risks. We identified the risk-efficient fungicide scheduling strategy by using stochastic dominance methods. In addition, we also evaluated the economic benefit to scheduling fungicide applications with the precision agriculture technology using the stochastic efficiency with respect to a function method. The analysis in this article used the same average yield and seed cost among potato cultivars. Future analysis will explore the sensitivity of the results to varying yield and seed cost assumptions.

Overall, our study shows that precision agriculture technology can improve input usage efficiency, boost productivity, and increase net return; while compensating the grower for the additional risk associated with net return variability. The DSS-based strategy was identified as the most effective approach to manage late blight in terms of disease suppression, potato productivity, net return, and risk-adjusted net return. Results indicated that the DSS-based strategy was the preferred risk mitigating method to schedule fungicide applications. Less risk-averse growers and growers with susceptible potato cultivars are more willing to adopt the precision agriculture technology. Under high disease pressure circumstances, the economic benefits to potato growers who adopt the precision agriculture technology ranged from \$30 to \$573 per 0.41 ha.

By quantifying the benefits associated with adopting the BlightPro decision support system (DSS) strategy to improve late blight management for potato production, our research has important implications for technology adoption and future work. Knowing the value of the information provided by the BlightPro DSS can help improve the adoption rate of this precision agriculture technology, as well as help plant pathologists make further improvements to the potato production systems. Increased adoption of the BlightPro DSS would help manage late blight, limit potential crop losses, and improve the net return of potato growers.

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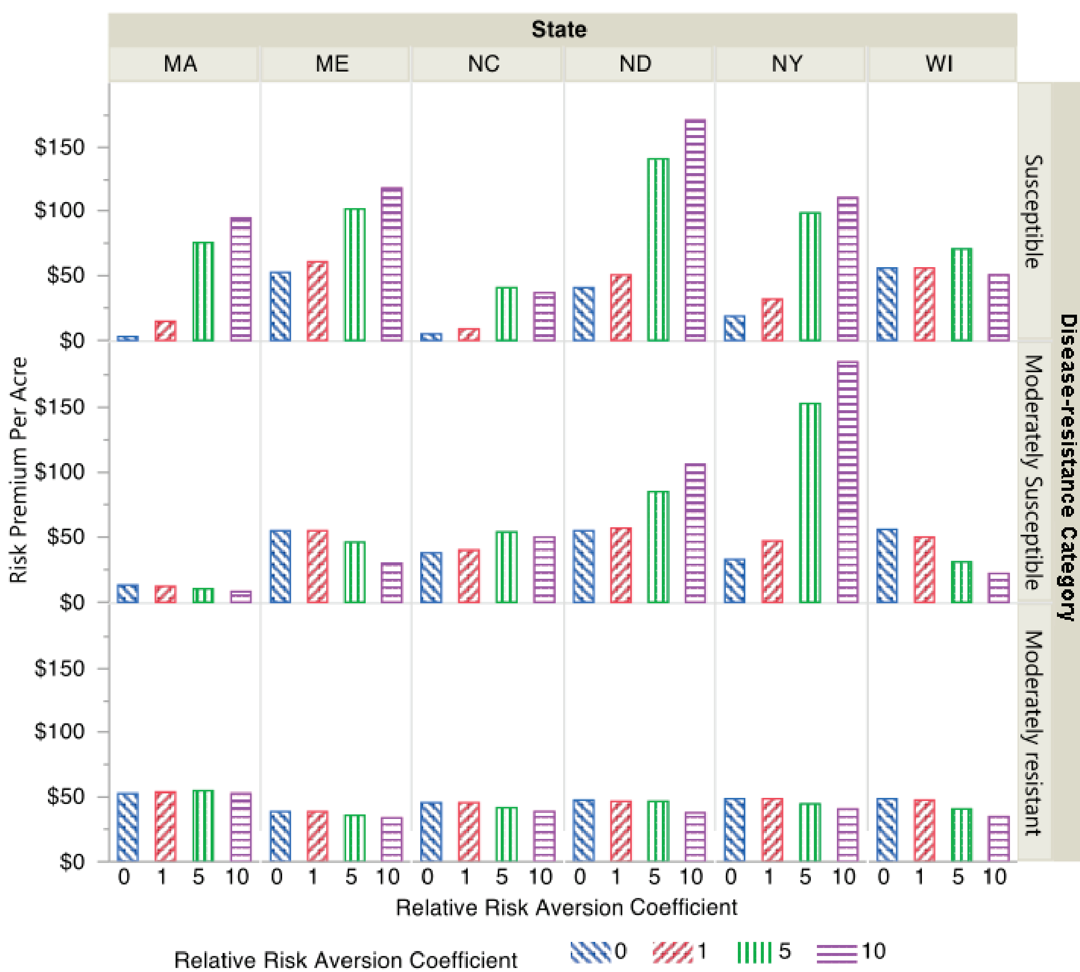

Fig. 6. State average risk premiums (\$/per 0.41 ha) for the randomly selected disease initiation scenario.

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