

Economic Analysis of Using Cornell Decision Support System for Tomato Production

Yangxuan Liu

liu430@purdue.edu

Department of Agricultural Economics

Purdue University

Michael Langemeier

Department of Agricultural Economics

Purdue University

Ian Small

Department of Plant Pathology

Cornell University

Laura Joseph

Department of Plant Pathology

Cornell University

William Fry

Department of Plant Pathology

Cornell University

Selected Paper prepared for Presentation at the International Food and Agribusiness Management Association's 2015 Annual Meeting, Saint Paul, Minnesota, June 14 - 17, 2015

Copyright 2015 by Yangxuan Liu, Michael Langemeier, Ian Small, Laura Joseph, and William Fry. All rights reserved. Readers may make verbatim copies of this document for non-commercial purposes by any means, provided that this copyright notice appears on all such copies.

Economic Analysis of Using Cornell Decision Support System for Tomato Production

Abstract

Stochastic efficiency with respect to a function is used to compare late blight management strategies between a calendar spray schedule and a spray schedule forecasted using the Potato/Tomato Late Blight Decision Support System (DSS). Results show that in terms of disease control, the DSS recommended spray schedule is more effective. Average net income over fungicide cost and average risk-adjusted net income for the DSS recommended spray schedule is lower for susceptible cultivars and higher for moderately susceptible cultivars and moderately resistant cultivars. The value added by DSS ranges from -\$17.69 to \$48.33 per acre. Our research contributes to the literature by providing a method to evaluate the economic benefit of adopting DSS.

Key Words: Stochastic efficiency with respect to a function, precision farming, disease management

Introduction

The United States is the world's second leading producer of tomatoes, after China. Annually, U.S. fresh and processed tomatoes contribute more than \$2 billion to cash farm income. California and Florida represent almost two thirds of total U.S. fresh tomato acreage. Ohio, Virginia, Georgia, Tennessee, North Carolina, New Jersey, and Michigan are also major tomato production states. Late blight infection is a persistent problem faced by tomato growers. It is highly contagious, and can be easily dispersed (Wale, Platt, and Nigel 2008). Every year, a tremendous amount of fungicide is applied to control late blight. Reducing the amount of fungicides applied to control late blight has both environmental and economic benefits. The emergence of precision farming technology can increase farming efficiency and reduce the environmental impact of input usage. However, the decision to adopt precision farming depends on the cost and return of the precision farming technology. In this study, a new potential application of precision agriculture to tomato plant disease control for late blight are examined.

The precision agriculture technology examined in this study is called the Potato/Tomato Late Blight Decision Support System (DSS). It uses precision farming technology to recommend precise and timely use of fungicide in accordance with weather conditions and pathogen inoculum. This system could potentially increase farm net returns and reduce risks (Fohner, Fry, and White 1984). The traditional management of late blight depends highly on preventative weekly fungicide application during the planting season (Song et al. 2003). However, late blight epidemics and thus the need for fungicide depends heavily on weather and the source of pathogen inoculum (Fohner, Fry, and White 1984). Consequently, a calendar based schedule may not be the most efficient or cost-effective method of applying fungicide to control late blight.

The efficacy of DSS in disease suppression and fungicide reduction has been an important topic of previous biology and pathology research (Fry, Apple, and Bruhn 1983; Fohner, Fry, and White 1984). Economic research in the area of late blight management is limited (Guenther, Michael, and Nolte 2001; Johnson et al. 1997). Risk analyses in agriculture have been adopted to a wide range of individual decision making processes taking grower's behavior in face of income uncertainties into consideration (Parcell and Langemeier 1997; Harris and Mapp 1986; Llata et al. 1999; Ritchie et al. 2004; Zacharias and Grube 1984; Musser, Tew, and Epperson 1981; Cochran, Robison, and Lodwick 1985; Greene et al. 1985; Williams et al. 2014). However, risk analysis has not yet been applied in the area of late blight precision farming adoption.

The intent of this paper is to contribute to the understanding of the economic incentives facing a grower choosing to adopt or not to adopt DSS through the analysis of net income over fungicide cost. This paper will examine the economic impact of using DSS to mitigate the impact of late blight. Specifically, the overall objective of this paper is to compare the economic benefits of scheduling fungicide applications with DSS with a 7-day spray schedule by taking into account the risk attitudes of tomato growers.

Our analyses require the integration of different models covering DSS, pathology models, and economic components. DSS is used to develop a weather-based spray schedule. The LATEBLIGHT model (Andrade-Piedra et al. 2005), a pathology model, is used to simulate disease severity under different weather scenarios. Net income over fungicide cost distributions are developed for alternative fungicide application schedules from 2000 to 2009 in 12 locations in North Carolina. Three tomato cultivar resistance levels for late blight (susceptible, moderately susceptible and moderately resistant) are examined in this study. Stochastic efficiency with

respect to a function (Hardaker et al. 2004; Hardaker and Lien 2010; Meyer, Richardson, and Schumann 2009) is used to identify the risk adjusted value of DSS.

Methods

Late blight creates a highly uncertain decision making environment. Recognizing this, this paper incorporates uncertainty and producers' risk attitudes into the decision making framework. Alternative decisions can be ranked with risk attitudes of each individual (Schumann 2011). In this paper, mutually exclusive alternative fungicide spray decisions faced by tomato growers (i.e., a calendar spray schedule and the DSS recommended spray schedule) are compared. Weather conditions in different years creates a distribution of net income. Computer simulation programs using historical weather data can generate an empirical probability distribution function for net income between alternative spray schedules. The probability distribution functions can then be ranked using stochastic efficiency procedures. Stochastic efficiency with respect to a function (Hardaker et al. 2004; Meyer, Richardson, and Schumann 2009; Hardaker and Lien 2010) are used to identify risk efficient fungicide application strategies and to compute the certainty equivalent of net income for each spray schedule.

Stochastic efficiency with respect to a function is first used to calculate certainty equivalents, which is the risk adjusted value of net income over fungicide cost. Risky alternatives with higher CEs are preferred to alternatives with lower CEs (Hardaker et al. 2004; Meyer, Richardson, and Schumann 2009; Hardaker and Lien 2010). Stochastic efficiency with respect to a function is also used to identify the utility weighted risk premium (RP) or the value

of information provided by DSS. The power utility function¹ was used to calculate the certainty equivalents. Relative risk aversion levels used for stochastic efficiency with respect to a function include 0, 1, 3, and 5.

Given a risk aversion level, the utility weighted risk premium (RP) can be calculated for the DSS spray schedule and the 7-day spray schedule using the following equation:

$$RP_{DSS,Calendar,R_a} = CE_{DSS,R_a(w)} - CE_{Calendar,R_a(w)} \quad (1)$$

where RP reflects the minimum amount of money (\$/acre) that a decision maker is willing to pay for the new technology (Hardaker et al. 2004), which could also be viewed as the value of the information provided by DSS for tomato growers. When RP is positive, the DSS spray schedule is preferred to the 7-day spray schedule.

Data

Data generating process requires the use of DSS (Forbes et al. 2008), the LATEBLIGHT pathology model (Andrade-Piedra et al. 2005), and economic components. Two computer programs, PythonTM and SAS®, are used to obtain the distribution of net income over fungicide cost for both 7-day and DSS spray schedules. The 7-day spray schedule is the most commonly adopted calendar spray schedule for fungicide application by tomato growers. Growers are also assumed to be able to initiate fungicide application based on the DSS recommendation. The PythonTM program is used to generate data for disease severity, and the number of fungicide applications by Ian Small and Laura Joseph from the Fry Lab at Cornell University. A SAS® program is then used to add economic components (tomato price, yield, fungicide cost) to construct net income over fungicide cost.

¹ The power utility function exhibits decreasing absolute risk aversion and constant relative risk aversion. The functional form of power utility is as follows: $U(x) = \frac{x^{1-r}}{1-r}$ for $r \neq 1$; $U(x) = \ln(x)$ for $r = 1$.

Disease severity and the number of fungicide applications are generated for three different levels of cultivar resistance (susceptible, moderately susceptible, and moderately resistant) in 12 locations from 2000 to 2013 in North Carolina. Two basic components of the simulation programs are DSS (Forbes et al. 2008), and the LATEBLIGHT model (Andrade-Piedra et al. 2005). These components are presented in detail elsewhere (Forbes et al. 2008; Andrade-Piedra et al. 2005) and will not be discussed in detail in this paper.

A description of the generation of disease severity and the number of fungicide applications used in the DSS model is as follows. Historical weather data (rainfall, temperature, and humidity) for 12 locations in North Carolina was used to forecast the incidence of late blight and the number of fungicide applications. The plant growth season was assumed to be from 3/26 to 7/27. A fungicide rate of 1.5 pints per acre of Bravo WeatherStik was assumed for each application and cultivar. DSS was used to generate DSS spray schedules for each year. The 7-day and DSS spray schedules were then incorporated into the LATEBLIGHT model (Andrade-Piedra, Hijmans, Juarez, et al. 2005). This model is used to simulate the disease epidemic for schedules involving each resistance category and season. The start time for late blight was randomly selected after the Blitecast forecast reached the severity value of 18.

The number of fungicide applications for each schedule were used to compute net income over fungicide cost for each weather scenario. A yield function that relates tomato production to late blight infection is currently not available. Because of this, yield losses are not incorporated into the analysis. Net income over fungicide cost is computed as follows:

$$\text{Net income over fungicide cost}_{l,y,c,i} \quad (2)$$

$$\begin{aligned} &= \text{Tomato price}_{l,y} * \text{average tomato yield}_{l,y} \\ &- (\text{Fungicide cost} + \text{application cost}) \\ &* \text{number of application}_{l,y,c,i} \end{aligned}$$

where l stands for the each of the 12 locations; y stands for the specific year; c stands for each cultivar (susceptible, moderately susceptible, and moderately resistant); and i refers to the 7-day or the DSS recommended spray schedule. Tomato prices and average yields from 2000 to 2009 for North Carolina were obtained from USDA Tomato Statistics for fresh tomatoes

<http://usda.mannlib.cornell.edu/MannUsda/viewDocumentInfo.do?documentID=1210>).

Average yield and price were assumed to be the same among different cultivar resistance levels. As indicated above, Bravo WeatherStik (chlorothalonil) was used for each fungicide application. Application costs are listed in Table 1. Data pertaining to the number of fungicide applications were provided by Ian Small and Laura Joseph from the Fry Lab at Cornell University.

Analysis and Results

The Simulation and Econometrics to Analyze Risk (SIMETAR©) model developed by Richardson, Schumann and Feldman (2006) is used to conduct the stochastic efficiency analysis. Analysis is conducted for 12 locations in North Carolina. Three cultivar resistant levels (susceptible, moderately susceptible, and moderately resistant) for tomatoes are examined at each location. Microsoft Visual Basic for Applications (VBA) language was used to facilitate the computations obtained from SIMETAR.

Table 2 shows the summary of statistics for tomato revenue, late blight disease rating, and fungicide applications. For the susceptible cultivar, DSS requires a higher number of fungicide applications than the 7-day spray schedule, but also exhibits better disease control. For

the moderately susceptible cultivars and the moderate resistant cultivars, DSS requires less fungicide applications than the 7-day spray schedule, and has better disease control. These results suggest that the timing of fungicide application is important in controlling late blight. Efficiently applying fungicide helps reduce fungicide applications and allows for more effective control of the disease. The average net income over fungicide cost for DSS is smaller than that for the 7-day spray schedule for the susceptible cultivars, but is relatively higher for the moderately susceptible and moderately resistant cultivars.

Table 3 summarizes the average certainty equivalents for the 12 locations in North Carolina for each cultivar. Four different relative risk aversion levels were evaluated. DSS generates a lower certainty equivalent for each risk aversion level for susceptible cultivars and a higher certainty equivalent for each risk aversion level for moderately susceptible cultivars and moderately resistant cultivars. The risk premium ranges from -\$17.69 to -\$16.89 per acre for the susceptible cultivars, from \$25.46 to \$25.95 for the moderately susceptible cultivars, and from \$48.09 to \$48.33 for the moderately resistant cultivars.

Conclusions

This study used computer generated data from North Carolina to examine the economic benefits of adopting precision farming technology to tomato production. In summary, DSS requires a higher number of fungicide applications for susceptible cultivars, and less fungicide applications for moderately susceptible cultivars and moderately resistant cultivars. For all the cultivars, DSS is more effective in controlling disease than the calendar spray schedule. For the susceptible cultivars, the calendar spray schedule was preferred. Conversely, DSS was the preferred risk strategy for moderately susceptible cultivars and moderately resistant cultivars. The value of DSS ranged from -\$17.69 to \$48.33 per acre.

Our research contributes to the literature by providing a method to evaluate the economic benefits of adopting DSS. Knowing the value of the information provided by DSS can help to promote DSS to tomato growers for adoption. This would help improve late blight management actions taken by growers to control the spread of the disease and limit potential loss. The improvement in productivity will help to ensure food security for the growing population.

Further study will involve incorporating the relationship between disease severity and tomato yields into our analysis. This will enable us to more accurately measure the value of the precision farming technology.

References

- Andrade-Piedra, J. L., R. J. Hijmans, H. S. Juarez, G. A. Forbes, D. Shtienberg, and W. E. Fry. 2005. Simulation of potato late blight in the Andes. II: Validation of the LATEBLIGHT model. *Phytopathology* 95 (10):1200-1208.
- Cochran, M. J., L. J. Robison, and W. Lodwick. 1985. Improving the efficiency of stochastic dominance techniques using convex set stochastic dominance. *American Journal of Agricultural Economics* 67 (2):289-295.
- Fohner, G. R., W. E. Fry, and G. B. White. 1984. Computer-simulation raises question about timing protectant fungicide application frequency according to a potato late blight forecast. *Phytopathology* 74 (10):1145-1147.
- Forbes, G. A., W. E. Fry, J. L. Andrade-Piedra, and D. Shtienberg. 2008. Simulation models for potato late blight management and ecology. *Integrated Management of Diseases Caused by Fungi, Phytoplasma and Bacteria* 3:161-177.
- Fry, W. E., A. E. Apple, and J. A. Bruhn. 1983. Evaluation of potato late blight forecasts modified to incorporate host-resistance and fungicide weathering. *Phytopathology* 73 (7):1054-1059.
- Greene, C. R., R. A. Kramer, G. W. Norton, E. G. Rajotte, and R. M. McPherson. 1985. An economic analysis of soybean integrated pest management. *American Journal of Agricultural Economics* 67 (3):567-572.
- Guenther, J. F., K. C. Michael, and P. Nolte. 2001. The economic impact of potato late blight on US growers. *Potato Research* 44 (2):121-125.
- Hardaker, J. B., and Gudbrand Lien. 2010. Stochastic efficiency analysis with risk aversion bounds: a comment. *Australian Journal of Agricultural and Resource Economics* 54 (3):379-383.
- Hardaker, J. B., J. W. Richardson, G. Lien, and K. D. Schumann. 2004. Stochastic efficiency analysis with risk aversion bounds: a simplified approach. *Australian Journal of Agricultural and Resource Economics* 48 (2):253-270.
- Harris, T. R., and H. P. Mapp. 1986. A stochastic dominance comparison of water-conserving irrigation strategies. *American Journal of Agricultural Economics* 68 (2):298-305.
- Johnson, D. A., T. F. Cummings, P. B. Hamm, R. C. Rowe, J. S. Miller, R. E. Thornton, G. Q. Pelter, and E. J. Sorensen. 1997. Potato late blight in the Columbia Basin: An economic analysis of the 1995 epidemic. *Plant Disease* 81 (1):103-106.
- Llata, M. de la, M. Langemeier, S. S. Dritz, M. D. Tokach, R. D. Goodband, J. L. Nelssen, and M. de la Llata. 1999. Economics of adding fat and increasing lysine:calorie ratio in diets for growing-finishing gilts. *Kansas State University Swine Day 1999. Report of Progress* 84I:113-116.
- Meyer, Jack, James W. Richardson, and Keith D. Schumann. 2009. Stochastic efficiency analysis with risk aversion bounds: a correction. *Australian Journal of Agricultural and Resource Economics* 53 (4):521-525.
- Musser, W. N., B. V. Tew, and J. E. Epperson. 1981. An economic examination of an integrated pest management production system with a contrast between E-V and stochastic dominance analysis. *Southern Journal of Agricultural Economics* 13 (1):119-124.
- Parcell, J. L., and M. R. Langemeier. 1997. Feeder-pig producers and finishers: Who should contract? *Canadian Journal of Agricultural Economics-Revue Canadienne D Agroeconomie* 45 (3):317-327.

- Ritchie, J. W., G. Y. Abawi, S. C. Dutta, T. R. Harris, and M. Bange. 2004. Risk management strategies using seasonal climate forecasting in irrigated cotton production: a tale of stochastic dominance. *Australian Journal of Agricultural and Resource Economics* 48 (1):65-93.
- Schumann, Keith D. 2011. Semi-nonparametric test of second degree stochastic dominance with respect to a function. *Journal of Econometrics* 162 (1):71-78.
- Song, J. Q., J. M. Bradeen, S. K. Naess, J. A. Raasch, S. M. Wielgus, G. T. Haberlach, J. Liu, H. H. Kuang, S. Austin-Phillips, C. R. Buell, J. P. Helgeson, and J. M. Jiang. 2003. Gene RB cloned from *Solanum bulbocastanum* confers broad spectrum resistance to potato late blight. *Proceedings of the National Academy of Sciences of the United States of America* 100 (16):9128-9133.
- Wale, Stuart, Harold William Platt, and Cattlin Nigel. 2008. *Diseases, pests and disorders of potatoes: a color handbook*. Burlington, MA, USA: Academic Press.
- Williams, Jeffery R., Andrew T. Saffert, G. Barnaby, Richard V. Llewelyn, and Michael R. Langemeier. 2014. A Risk Analysis of Adjusted Gross Revenue-Lite on Beef Farms. *Journal of Agricultural and Applied Economics* 46:227-244.
- Zacharias, T. P., and A. H. Grube. 1984. An economic evaluation of weed control methods used in combination with crop rotation: a stochastic dominance approach. *North Central Journal of Agricultural Economics* 6 (1):113-120.

Table 1. Fungicide application cost in 2013.

Name	Quantity	Fungicide Cost	Application Cost	Total fungicide application cost
Bravo	1.5	\$8.63	\$6.58	\$15.21
WeatherStik	pints	/acre/application	/acre/application	acre/application

*Fungicide price is obtained from local agricultural chemical distributor on Long Island by Dr. M. T. McGrath in April 2013. Application cost (\$6.58/acre/application) comes from Lazarus (2013). USDA Prices Paid Indices (Ag Chem & mach) are used to adjust the fungicide price and application cost in 2013 to nominal prices in previous years.

Table 2. Summary Statistics for Tomato Revenue, Late Blight Disease Rating, and Fungicide. No. of observations is 112.

Item	Spray Schedule			
	7-Day		DSS	
	Mean	S.D	Mean	S.D.
<u>Susceptible Cultivars</u>				
Number of Fungicide Applications*	11.00	0	12.6	2.6
Disease Rating (RAUDPC)***	0.1023	0.1210	0.0048	0.0165
Cost of Fungicide Applications*	\$ 124.02	13.25	\$ 141.56	29.30
Net Income over Fungicide Cost per Acre	\$ 9,230.62	658.81	\$ 9,213.08	656.82
<u>Moderately Susceptible Cultivars</u>				
Number of Fungicide Applications*	11.0	0.0	8.8	1.9
Disease Rating (RAUDPC)	0.00734	0.0445	0.00340	0.0160
Cost of Fungicide Applications*	\$ 124.02	13.25	\$ 98.72	21.5
Net Income over Fungicide Cost per Acre	\$ 9,230.62	658.81	\$ 9,255.92	658.8
<u>Moderately Resistant Cultivars</u>				
Number of Fungicide Applications*	11.0	0.0	6.8	1.4
Disease Rating (RAUDPC)	0.000654	0.00491	0.000216	0.00071
Cost of Fungicide Applications*	\$ 124.02	13.25	\$ 76.00	16.4
Net Income over Fungicide Cost per Acre	\$ 9,230.62	658.81	\$ 9,278.64	660.74

* , **, ***Mean difference is statistically significant at 1% , 5%, and 10% significant level.

Table 3. Certainty Equivalent of Net Income over Fungicide Costs per Acre for Randomly Selected Start Date Scenario.

Item	Spray Schedule		Difference DSS over 7- Day
	7-Day	DSS	
<u>Susceptible Cultivars</u>			
r=0	\$ 9,251.42	\$ 9,233.73	\$ (17.69)
r=1	\$ 9,227.88	\$ 9,210.34	\$ (17.54)
r=3	\$ 9,183.29	\$ 9,166.06	\$ (17.23)
r=5	\$ 9,142.28	\$ 9,125.39	\$ (16.89)
<u>Moderately Susceptible Cultivars</u>			
r=0	\$ 9,251.42	\$ 9,276.88	\$ 25.46
r=1	\$ 9,227.88	\$ 9,253.42	\$ 25.54
r=3	\$ 9,183.29	\$ 9,209.02	\$ 25.73
r=5	\$ 9,142.28	\$ 9,168.23	\$ 25.95
<u>Moderately Resistant Cultivars</u>			
r=0	\$ 9,251.42	\$ 9,299.51	\$ 48.09
r=1	\$ 9,227.88	\$ 9,276.00	\$ 48.12
r=3	\$ 9,183.29	\$ 9,231.50	\$ 48.21
r=5	\$ 9,142.28	\$ 9,190.61	\$ 48.33

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