The Economic Value of Precision Management System for Fungicide Application in Florida Strawberry Industry

Ekaterina Vorotnikova
Graduate Student
E-mail: vorotnikova@ufl.edu

John J VanSickle
Professor

Tatiana Borisova
Professor

Food and Resource Economics Department,
University of Florida

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Ekaterina Vorotnikova, John VanSickle and Borisova Tatiana[1]

[1]The authors are (respectively): Graduate Student, Professor, and Assistant Professor, Food and Resource Economics Department, University of Florida

1 Introduction

Precision techniques allow agriculture to cope with the challenges of meeting increasing demand for food and energy while at the same time improving environmental sustainability of food production, managing input costs, and improving the quality of work environment (Gebbers and Adamchuck 2010). Precision agriculture (PA), also referred to as "information-intensive" agriculture (Bramley 2009), is defined as a "set of technologies that combines sensors, information systems, enhanced machinery, and informed management to optimize production by accounting for variability and uncertainties within agricultural systems" (Gebbers and Adamchuck 2010). Numerous studies have been exploring various aspects of PA; however, significant gaps in knowledge remain. Specifically, the majority of studies focus on PA for field crops (such as corn, wheat, soybean, and cotton) while much less attention is paid to application of PA technologies to horticultural crops (Bramley 2009, Griffin and Lowenberg-DeBoer 2005). While some studies deal with citrus and grapes (Whitney et al. 1999 and Stafford 2007), no studies were found that examine PA for small fruit production, such as berries. However, small fruit production comprises a significant share of total US agricultural production. For example, the U.S. is the world's largest strawberry producer, accounting for over a quarter of total world production (NASS 1995). Over the past ten years, U.S. utilized production[1] increased by more than 60% (Figure 1). Most of the U.S. production is consumed domestically, and an increasing amount of strawberries are being produced for fresh-market uses (Boriss et al. 2010). Precision technologies could have a significant impact on strawberry input use and environmental sustainability.

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[1] defined as produced crops that were marketed, and either domestically consumed or exported

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Figure 1. Strawberry Production and Exports Values for the U.S. 1997-2011
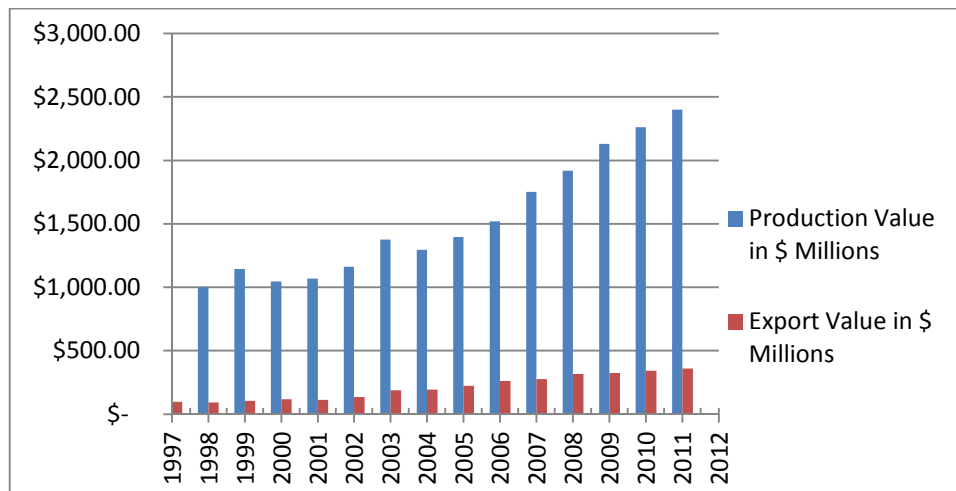
Source: National Agricultural Statistical Services (NASS), 2013 and Foreign Agricultural Service (FAS), 2013

A review of 210 studies that examined the economic benefits and losses of PA technologies (Griffin and Lowenberg-DeBoer 2005) showed that although 68% of the studies reported benefits associated with precision agriculture technologies, some studies showed losses. The profitability of PA depends on the type of technology and its costs, farm size, and the methods used to evaluate the PA costs and benefits (Griffin and Lowenberg-DeBoer 2005, Batte 2000). A key factor affecting the PA profitability is the amount of information PA technologies can provide to the producer about the spatial or temporal variable factors. While the effects of information about spatial factors (e.g., soil fertility and weed pressure) have been extensively studied, the economics of PA technologies addressing the temporal variability is yet to be explored. Insufficient recognition of temporal variations has been identified as one of the critical issues in PA studies (McBratney et al. 2005).

This study examines the profitability of PA technology developed to optimize the timing of fungicide application to control anthracnose fungus disease in Florida strawberry production. Using data from strawberry production experiments, we analyze the potential profitability of the strawberry advisory system (SAS) developed at the University of Florida. SAS uses real-time information about air

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temperature and strawberry leaf wetness to evaluate anthracnose disease risk in strawberry and to allow producers to adjust the timing of fungicide application to the periods conducive to anthracnose development. The background on Florida strawberry production and experiment are described in the next section, followed by the explanation of the data from the production experiments, the methods, results, and conclusion. Overall, we show that SAS can increase the returns of Florida's strawberry producers. Specifically, the in comparison with the conventional calendar method of fungicide application, this precision disease management system reduces the fungicide applications and costs while either leaving strawberry yields unaffected or actually increasing the yield.

2 Study Area

Strawberry is the most significant berry crop by production value in Florida, and during the winter season Florida dominates the national strawberry market. In 2012, a record 300.4 million pounds of strawberry was harvested in Florida from approximately 10,100 acres (NASS, 2013). Almost ninety percent of Florida's strawberry is grown around Plant City in Hillsborough County, west central Florida. The production season starts in November and continues through March of the following year. The heaviest harvesting occurs between the months of February and March, driven by the climatic conditions and the dynamics of the strawberry markets. Specifically, prices for strawberries pick out in February and then experience steady downward pressure until bottoming out in May and June in response to the increasing strawberry supply from California.

Fungal diseases such as anthracnose and Botrytis fruit rots are major challenges for strawberry growers. Even in well-managed fields, losses from fruit rot can exceed 50% when conditions favor disease development (Ellis and Grove 1982). Fungicides are commonly used by the growers to stem off the development of the diseases. Fungicides are applied once a week, and fungicide cost comprises approximately 7% of pre-harvest variable costs, which represents about $690 per acre (IFAS 2010). Main issues facing strawberry industry are increasing costs of fungicides, building resistance to the

fungicides, and rising public concerns about potential health and environmental effects of fungicide use (Peres et al. 2010b). Production methods that can reduce fungicide rates without affecting strawberry yields can provide significant economic and environmental benefits to Florida strawberry industry.

Past research shows that accurate information about weather conditions can be used to tailor fungicide applications to precisely manage the anthracnose disease pressure. Periods with warm and wet weather create especially favorable conditions for the development and spread of anthracnose fruit rot, thus increasing the risk of harvest losses. In contrast, given cool and dry conditions, the risk of the disease development is relatively minor. Bulger et al. (1987) and Wilson et al. (1990) used a logistic regression to model the proportion of immature and mature strawberry fruit infected by anthracnose (%Inf) as a function of temperature, T, and leaf wetness duration, W:

$$\ln\left[\frac{\%Inf}{1-\%Inf}\right] = b_0 + b_1 W + b_2 WT + b_3 WT^2 + b_4 WT^3 \qquad (1)$$

Wilson and Madden (1990) estimated the model parameters, b_0, b_1, b_2, b_3, and b_4:

$$\ln\left[\frac{\%Inf}{1-\%Inf}\right] = -3.7 + 0.33 * W - 0.069 * W * T + 0.005 * W * T^2 - 0.000093 * W * T^3 \quad (2)$$

Finally, denoting the left-hand side of equation (1) as the disease index, or DI, the proportion of strawberry fruit infected by the fungus can be specified as:

$$\%Inf = \frac{EXP(DI)}{1+EXP(DI)} \qquad (3)$$

The relationships (2) and (3) was used by Mackenzie and Peres (2012) to develop an on-line strawberry advisory system (SAS) that indicates the level of anthracnose disease risks and recommends fungicide application if the disease risks is high (Fig. 2). Specifically, using strawberry production experiments, Mackenzie and Peres (2012) identified the critical combinations of temperature and leaf wetness duration at which the disease pressure is high given Florida growing conditions, and at which fungicide application is recommended. When according to (3) there is 15% probability that strawberries are

expected to develop disease ($\%\mathrm{Inf}_{Anthracnose} \geq 0.15$), SAS issues a warning of the "moderate" risk of disease development, and recommends to spray a "preventive" type of fungicide. When model (3) predicts that at least 50% of strawberries were expected to develop disease ($\%\mathrm{Inf}_{Anthracnose} \geq 0.50$), SAS indicates "high" risk of disease, and recommends to spray "a curative" fungicide (Turechek et al., 2006). Producers can also enter their past fungicide application practices into SAS, and the system will modify recommendation based on the manufacturer specifications for specific fungicide used by the growers. For example, the maximum number of sequential applications for Cabrio should be limited to two, and the maximum rate of its application is 70 oz (4.375 pounds) per acre per season.

Figure 2. Strawberry Advisory System (SAS)
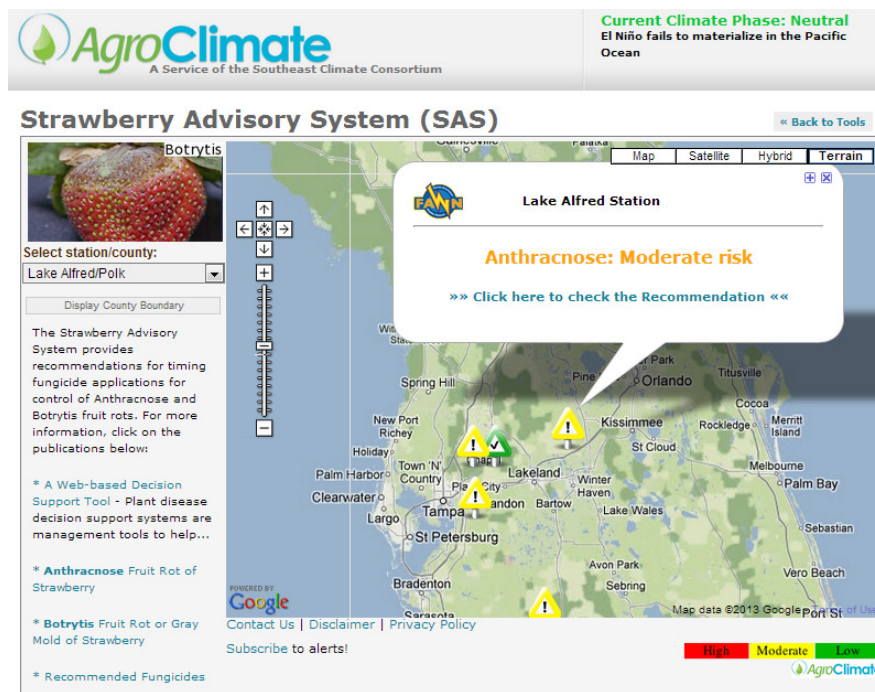
Source: the system can be accessed at **http://agroclimate.org/tools/strawberry/**

The fundamental differences between two fungicide application systems, Calendar and Model, are demonstrated in Figure 3 On one hand, traditionally growers use weekly (Calendar-based) application method to control for disease to maximize the expected payoff. This method does not depend on weather conditions, thus it does not have an application trigger as it is routinely applied on the same day of every

week. Depending on the length of the production season the number of applications accumulates 15 for an average season as shown in Figure 2. On the other hand, if grower chooses to use the precision application system, the final decision about the timing of fungicide treatment depends on the application trigger that is issued by Strawberry Advisory System, SAS. SAS determines if weather conditions are conducive for the disease development from the inputs of the sensors that measure leaf wetness duration and temperature during that wetness period. The sensors record new information about the weather every 15 minutes – wetness duration then is reported in hours while temperature information gets averaged for that timeframe. These measurements are used as independent variables for the Wilson-Madden regression (Equation 2). The final output of the logistic regression is a %Inf that ranges from 0 to 1 and predicts probability of the field getting infected. The specifications, 15%, at which the weather was considered to be conducive for the development of the anthracnose were determined by Peres, MacKinzie, and Seijo (2010b).   If conducive for disease development weather is detected, SAS triggers an application, otherwise no application is recommended. The logic behind the system is that it is optimal for the producer to spray only when conditions are conducive for the disease development. This way the farmer avoids unnecessary treatments reducing fungicide costs while simultaneously decreasing the probability of the fungicide resistance buildup. In addition, targeted applications make their effect more impactful because it stems off the disease right before it has the potential to develop and spread within a significant area of the field.

Figure 3.
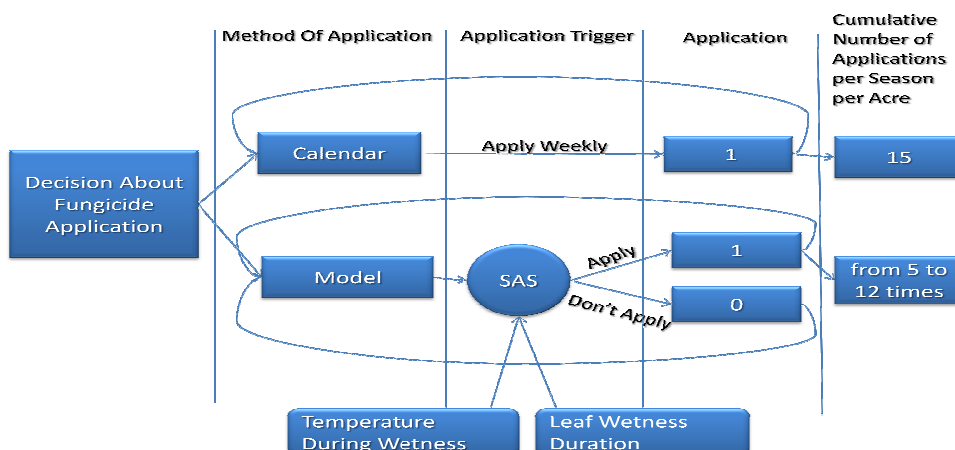
In this study, we examine the potential economic benefits provided by SAS to an average Florida strawberry producer. Specifically, we compare the net present value (NPV) from strawberry production for a 10-year planning horizon given traditional fungicide application system and the precision fungicide application system that follows SAS recommendations.

3 Data

Strawberry Florida state-wide producer prices and yields were obtained from National Agricultural Statistics Service, NASS, for the years 1984 through 2011. The state-wide data were supplemented with the information collected from strawberry production experiments conducted at the University of Florida research farm at the Gulf Coast Research and Education Center, in Wimauma, Florida.

The production experiments were conducted for six production seasons (November – March, 2006 – 2012). The experiments followed a randomized complete block design with four blocks (four plots), each in a separate plastic-mulched, raised bed. Bare-root strawberry transplants were planted into fumigated soil using staggered rows. Each bed was divided into three section according to the fungicide application method used: calendar-based (with weekly fungicide applications), model-based (with fungicide application according to the SAS recommendations), and a control (with no fungicide application). Berries were harvested twice a week starting in December and ending in March. Marketable fruit were counted, weighed, and then cumulated for each production season. Diseased fruits were also counted for anthracnose (AFR) and Bortrytis (BFR) incidences, and also cumulated for each production season. The number of berries tossed for reasons other than anthracnose and Bortrytis diseases (i.e. cull) was also recorded and summed up for each season. To summarize, the information about marketable number of the berries (referred to as "Number"), marketable weight of berries in grams ("Weight"), the number of berries tossed for reasons other than the disease ("Cull"), the number of berries affected by Botrytis ("Botrytis") and Anthracnose ("Anthracnose") is available for four plots, three fungicide application

methods, and six production seasons (2006-07, 2007-08, 2008-09, 2009-10, 2010-11, 2011-12). Thus, the series contained 72 independent sets of observations.

During each season, leaf wetness interval and the temperature during the wetness intervals were recorded with 15-minute intervals. The temperature measurements were then averaged out for a given wetness period. The number of days when the weather conditions were conducive for the development of anthracnose given two different thresholds (%Inf $\geq$ 0.15 and %Inf $\geq$ 0.50) was recorded (Table 1).

Table 1. The Number of Days with Weather Conditions Conducive for the Disease Development

Number of SAS Triggers		
Season	Threshold	
	%Inf $\geq$ 0.15	%Inf $\geq$ 0.15
2006-2007	33	1
2007-2008	34	4
2008-2009	13	4
2009-2010	36	17
2010-2011	14	1
2011-2012	32	4

In turn, the total numbers of fungicide applications for the plots in the calendar-based, model-based, and control groups are summarized in Table 2. Following manufacture's specifications, the number of applications for the model-based treatment is smaller than the number of days conducive for the disease development (compare Tables 1 and 2). Fungicide can be applied at most once a week, and hence, even if there are several triggers for disease development during the week, only one application is administered. On average there were 15 applications for Calendar-based fungicide application system; and only 8 applications for the Model-based system (with the range from 5 to 12 applications depending on the weather during the season). For the six years of experiments the number of applications per one production season diminishes on average to 9 compared to 15 of the Calendar based model, which is 44% lower on average than that of the weekly application system.

Table 2. Number of Fungicide Applications Per Season

Season	Calendar-based system	Model-based system
2006-2007	16	10
2007-2008	16	12
2008-2009	17	5
2009-2010	14	6
2010-2011	10	6
2011-2012	15	8
Average	14.66667	7.833333

4 Methodology

Let *X* denote the set of possible fungicide application options. The producer's decision is a choice of the specific application level $x \in X$ that satisfies profit maximization criteria. The outcome of alternative actions *x*, for example, yield, is affected by various uncontrolled factors (e.g., weather and disease pressure), and is not known precisely. Denote the un-controlled factors by a random variable θ. It is assumed that the producer can identify possible realizations of the random events - possible "states of nature" - $\theta \in \Theta$ (e.g., high or low disease pressure). The decision maker's beliefs about possible states on nature are reflected in the probabilities $p(\theta)$.

Given that payoff function *F(x)* depends on the realization of the random parameter θ, the producer has two alternatives. First, he/she can immediately choose an optimal action x_0 (apply) to maximize the expected payoff function:

$$\Pi_0 = max_x \int_\theta^\infty (r\, F(x, \theta) - w\, x)\, p(\theta)\, d\theta \qquad (4)$$

where *r* refers to the sale price, and *w* denotes the price of the fungicide. Alternatively, the producer can improve his/her knowledge about the random state variable by seeking additional information (e.g., by accessing SAS). Information is defined as any stimulus that influences the probability distribution assigned to states of nature θ. Suppose the producer receives information *y* (e.g., accurate

information about the disease pressure). This message leads the producer to change the beliefs about the probabilities of possible states. This change depends on how accurate the information message is. For example, information can be delivered in the form of a message "low risk" or "high risk", and it would be up to the decision-maker to translate this message into the probability of the specific events.

The decision maker's probability distribution over the possible states of nature after getting the message y can be denoted as conditional probability $p(\theta|y)$. Let x_y denote the optimal action posterior to the receipt of the message y:

$$\Pi_y = max_x \int_\theta^\infty (r\, F(x,\theta) - w\, x)\, p(\theta|y)\, d\theta \qquad (5)$$

For each possible information message, y, *ex post* optimal decision should be chosen. Then, the expected profit given data collection can be estimated as the expectation of the ex post performance:

$$\Pi_1 = \int_\theta^\infty [max_x\, (r\, F(x,\theta) - w\, x)\, p(\theta|y)]\, p(y|\theta)\, d\theta \qquad (6)$$

Then, the value of information, VOI, and hence, the expected benefits from precision agriculture technology, is the difference between expected payoffs with and without information:

$$\text{VOI} = \Pi_1 - \Pi_0 \qquad (7)$$

Value of information depends on the following factors: a) the distribution of θ; b) the accuracy of information, $p(y|\theta)$ and; c) the functional form of F(.) (Lawrence 1999).

In this paper, the objective is to value the effect of the new precision technology on the Florida strawberry production. In other words, we examine the value of information provided by SAS to an average Florida

strawberry producer. To achieve this goal, we compare producer's payoffs given two information collection strategies: no additional information is collected (i.e., the producers follow the traditional, calendar-based fungicide application strategy) and information about the decease pressure is collected through accessing SAS (i.e., the producers follow the model-based fungicide application strategy). Specifically, the value of information is calculated as difference between the 10-year net present values (NPV) of profits for each information collection and fungicide application system. Profits' NPVs are stochastically forecasted using historical yields and prices as well as the results from the six year production experiments. The distribution of the difference between the two models for each respective weather condition determines the final NPV of VOI, and thus quantifies the impact of the new technology. The stochastic framework allows evaluation of a distribution of profits for each fungicide application method given a range of weather conditions typical to Florida. Thus, the final value of the new precision technology is also a stochastically modeled distribution that is weather dependent covering a range from most to least conducive to disease development weather conditions.

$$\pi = Predicted\ Yeild * Projected\ Price - Projected\ Total\ Costs \quad (8)$$

Strawberry Yield Model

Predicted yield is obtained in several steps. First, we project state-wide strawberry yield by employing simple OLS regression using years as independent variable and historical state average yield as dependent variable – this is a deterministic component for the yield.

Next, the deviates from the trend (as a percent of the predicted values, estimated as the ratios of the errors to the predicted values of yield) are obtained from the same OLS regression. Correlation is then found between the time series of yields' and prices' deviates. The projected yield and price are then attuned by now correlated deviates from trend as percentage of the predicted values for yield and price respectively.

These deviates now provide the distribution from which stochastic components for the predicted yield and price are going to be randomly drawn. Second, we calculate deviations from trend as a percent of predicted values from the OLS regression that was obtained from the six year experimental data. This

OLS regression is weather dependent and provides shifts in yields for each of the three models: Control, Calendar-based, and Model-based application methods. Specifically, strawberry yield (pound per acre) is modeled as a function of historical state yield, weather, and weather intensity.

$$Predicted\ Yeild = E\big(f(State\ Yield, Weather, Weather\ Intensity, Control, Model)\big) \quad (9)$$

For the OLS Yield regression calendar model's observations are chosen as a base scenario, i.e. the effect of the calendar treatment is accounted for in the Intercept variable while dummy variables are introduced to distinguish between Control and Model methods. The choice to have Calendar based treatment's data in the intercept is driven by the fact that this method is in fact the traditional method that is currently used and has been used over several decades. Thus, the data for the historical state yield for the years 1984 to 2011 are for calendar based application method. This is important because state yield is used in the regression as an independent variable. The yield regression is actually expressed in terms of calendar method, i.e., calendar method behaves as a base scenario while adjusting other methods by introducing dummy variables, Control and Model (Equation 9).

For Weather variable, the 15% threshold is used to quantify this variable since 15% threshold is more sensitive and indicative of the weather conditions conducive for the disease development than the 50% threshold. Thus, the Weather variable is a summation of days during which 15% threshold was reached.

In model (9), Weather Intensity measures how early in the season and how intensive, i.e. close to each other, the triggers occur. This intensity measure may affect the overall season's production because there a risk of a disease spread, and the earlier it occurs in the season, the more following yield might be affected. The measure is quantified by the following logic: for each trigger issued by the SAS system, we count the number of weeks left in the season respective to that trigger, so the number of weeks left in the season at the time of the trigger is recorded at every occurrence and then cumulated in the Weather Intensity measure for the entire season for every production season (Table 3).

These data points are then used to forecast Weather Intensity as a variable. OLS regression models the relationship between Weather Intensity as the independent and Weather as dependent variable. Thus, Weather Intensity is a function of a coefficient multiplied by the "Weather" variable. From the same OLS regression deviates as a percentage of predicted are calculated by dividing the error term by predicted an then randomly fitting them around the projected values, creating a distribution stochastically.

Table 3.

Weather and Weather Intensity Measures form Production Experiments		
Production Season	Weather	Weather Intensity
2006-2007	33	344
2007-2008	34	289
2008-2009	13	173
2009-2010	36	653
2010-2011	14	46
2011-2012	32	649
Average	27	359

The errors from this OLS Yield regression were tested for normality by conducting Chi-square test with null hypothesis that the errors are normally distributed. The results of the test show that at 5% significance level the test fails to reject the null hypothesis.

Normal distribution with mean and standard deviations that are calculated from 6 year experimental weather data as indicated in Table 3. Thus, the deviates from trend as a percent of predicted values are calculated from this regression specifically for each application method. Then these unique to each method deviates adjust previously projected yields putting another level of stochastic component that incorporates weather and method effect on the yield. The errors were also tested for being normally distributed and results of the chi-square test show that the hypothesis that these errors are from normal distribution cannot be rejected at 5% significance level. The final results are three Yield distributions that

reflect yield as a function of possible weather events. Uniform distribution is used to draw the deviates, which keeps weather conditions relatively consistent amongst all three methods given each set of weather conditions in otherwise a random stochastic forecasting.

The hypothesis is that the regression analysis will confirm that the calendar-based treatment and the model-based treatment result in higher strawberry yields (as compared with the control group). We also expect that the model-based treatment results have higher yields than those of calendar-based treatment. Weather conditions are modeled based on Wilson-Madden weather index, and we expect it to have a negative effect on yield. However, weather conditions can also have a positive effect on yields, since it takes sun and water for the crop to grow.

Table 4. Independent variables used in regression analysis for Strawberry Marketable Weight

Variable	Description	Expected effect on the dependent variable, marketable yield
State Yield	State Yield during the production seasons from 2006 to 2012 as obtained from NASS.	Positive
Control	Dummy Variable, indicating the experimental plots that did not receive any treatment.	Negative, the yield for control is expected to be lower than those of the other two models.
Model	Dummy Variable, indicating the experimental plots treated with the model-based method (i.e., precision disease management) .	Positive since the yield is expected be higher than that of the Calendar based treatment.
Weather	Cumulated number of days that are conducive for the development of the decease according to the Wilson-Madden weather index for the entire season (%Inf > 0.15, Table 2).	Negative
Weather Intensity	Metric that measures how early in the season each trigger occurs. The measure is cumulated for all triggers for the entire production season.	Negative

Strawberry Prices

To forecast strawberry prices, first, projected price was obtained from the OLS regression of historical average strawberry state prices for the years 1984 to 2011 on the year trend (NASS, 2012). Similar to the approach used to forecast the yield, the errors from the regression are tested whether they are from normal distribution, and chi-square test confirms at 5% significance level that the hypothesis that the errors are from normal distribution cannot be rejected. Furthermore, deviation from the trend as a percent of predicted values is then calculated by dividing error term by predicted values of the same OLS regression. As mentioned earlier, correlation is found between price and yield unsorted deviations from the trend as a percent of predicted. Next prices and yields are adjusted for correlation uniform standard deviates, which then result in final stochastic prices for both yield and price. The prices that are correlated with the projected historical state yield reflect proper supply/demand fundamentals.

$$Projected\ Price = E\big(f(Historical\ Florida\ State\ Price), correlation(Price, Yield)\big)\ (10),$$

Strawberry Production Costs

Projected total production cost is a sum of projected total fixed and variable costs:

$$Projected\ Total\ Costs = Projected\ Total\ Fixed\ Costs + Projected\ Total\ Variable\ Costs\ (11),$$

The data for costs was obtained from the Strawberry Production Budget for the year 2011 prepared by Institute of Florida Agricultural Service (IFAS). The data is arranged as cost per acre. The budget contained the following price and quantity data: fertilizer, fumigants, fungicides, insecticides, surfactants, labor, contracted services, machinery use, and miscellaneous other materials. The information used in constructing the budgets were obtained by consultation with, and review by, individual growers, county Extension faculty, and UF/IFAS researchers. Surveys and correspondence with farm suppliers and growers were used to obtain the input prices.

Fixed costs is a sum of land rent, machinery fixed cost and overhead. We project this sum at 2% inflation rate over the 10 Year period. Variable costs are operating costs, harvesting costs, pack and sell costs:

$$Total\ Variable\ Costs$$

$$= E(f(Fungicide\ Costs, Harvest\ Costs(Yield), Pack\ and\ Sell\ Costs(Yield), Operating\ Cost)\ (12)$$

Operating costs include strawberry production operating costs with the exception of fungicide costs (since these costs were modeled differently for the three different models of fungicide application), such as transplants, plastic mulch, scouting, tractor and general farm labor, fumigant, machinery variable costs, transplants, herbicides, insecticide, fertilizer, crop insurance, and interest on operating capital costs per acre. These operating costs are projected at inflation rate of 2% and are the same for all three models of fungicide application.

Fungicide costs depend on the fungicide application method. Specifically, for control group, fungicide costs are zero. For the Calendar method, the number of fungicide applications is equal to the number of weeks in a season (15, on average). Finally, for the Model-based method, the number of fungicide applications depends on SAS-based risk assessment. For all three methods, fungicide costs per season equals to a product of price per fungicide application, the number of applications per season, and the number of acres (26 acres, assuming an average Florida farm). Fungicide price at the year one is $590 per application per acre, it is then projected at 2% for every consequent year for 10 years.

To model the number of applications for the model-based application method, first OLS regression was used to find a relationship between applications and weather. For the OLS regression the dependent variable was the six year data on the number of applications per season as displayed in Table 4 and independent variables were Weather and Weather squared, where Weather as discussed earlier is a normal distribution with mean and standard deviations obtained from the experimental six year data (Table 3).

The errors from the regression were tested for normality using chi-square test. The hypothesis that the error are from normal distribution cannot be rejected at 5% significance level. Second, the estimated number of applications was adjusted by the deviates from the trend. as a percentage of predicted obtained by dividing the errors from the regression by the predicted values making the 10-year projection stochastically distributed and at the same time respective to the range of the weather conditions. Thus, when weather value is randomly drawn from the normal distribution as mentioned above, it enters directly

to the number of application calculation plus gets adjusted for an error distribution around it.

Harvesting costs are yield-dependent and calculated by multiplying the predicted yield for each fungicide application method by harvesting cost (per pound) obtained from the IFAS Strawberry Budget. Similarly, Pack and Sell Costs are also yield dependent and specific to each model of fungicide application. These costs are obtained by multiplying pack and sell costs per pound by yield in pounds. The harvesting cost per pound and pack and sell costs per pound are projected at 2% rate of inflation to the 10 year horizon of the model.

5 Results

5.1 Deterministic Results: OLS Regression Results for Strawberry Marketable Weight

The results of the regression analysis are presented in Table 5. The results were consistent for the two strawberry varieties, and the effects of all the variables on strawberry yield matched the expectations. The only exception is variable Weather Intensity, which appears to have a positive effect on yield. However, this effect is much smaller in absolute terms than the significant and negative effect of variable Weather.

Table 5. Regression Analysis Results for the Marketable Weight of Strawberries

Variable	Estimates	Standard Errors
Intercept	5909.493***	1861.526
Average State Yield	0.467***	0.069
Weather	-736.556***	40.002
Weather Intensity	53.018***	2.218
Control	-2430.243***	476.847
Model	1392.280***	476.847
R^2 = 0.835; R^2 adj = 0.828 *** signifies 0.001 significance level ** - 0.05 significance level * - 0.01 significance level		

Table 6 breaks down the estimates of the results of regression above (Table 5) according to each method of application by configuring dummy variable effect for each estimate in the regression respectively. The errors from this OLS regression were tested for normality using Chi-square test, and the results confirm that at 5% significance level the hypothesis that the errors are normally distributed cannot be rejected.

Table 6.

Method of Application	Estimates For Yield (grams)
Control	3479
Calendar	5909
Model	7301

The results show that Model application method improved yield over Calendar based application by 24%. In other words, while Model application method reduced the number of fungicide applications by 44%, it resulted in the yield higher than the yield in Calendar based application.

4.2 Stochastic Results

Using the results from the OLS regression, Yield is forecasted stochastically as described in the Methodology section using deviates as percentage of trend obtained by dividing errors by predicted values. The final stochastically obtained values for yields are then simulated using Monte Carlo method of simulation by drawing 500 observations from the stochastic Yield distribution for each method of fungicide application. Figure 4 displays the results of the Yield distributions after being stochastically forecasted. These approximations of the probability density functions are weather dependent, thus seasons with disease-conducive weather are reflected on the left hand side (yield is magnitude).
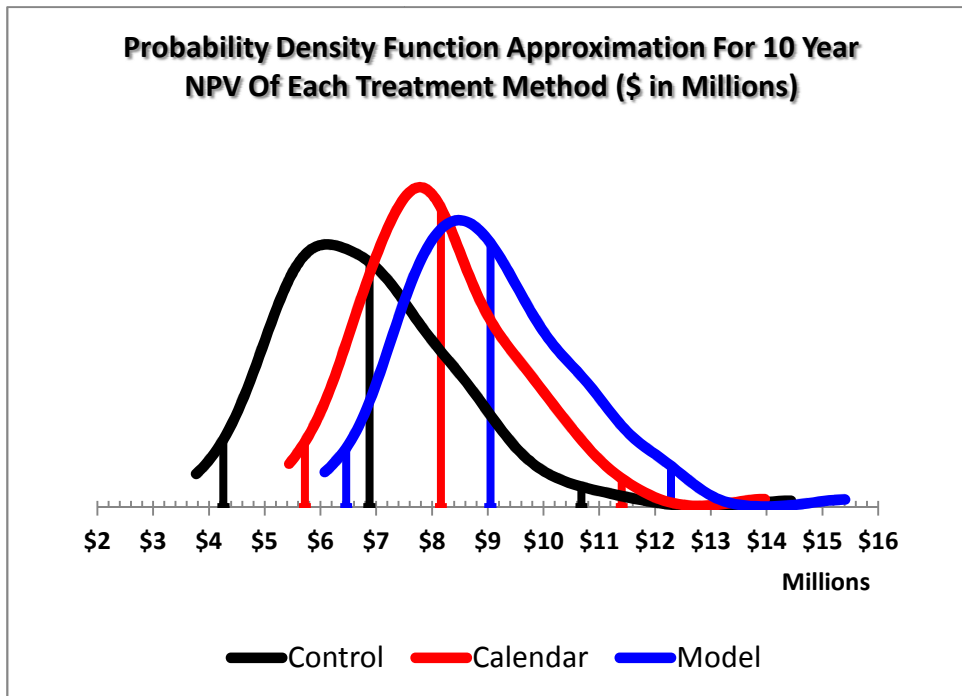
Figure 4.
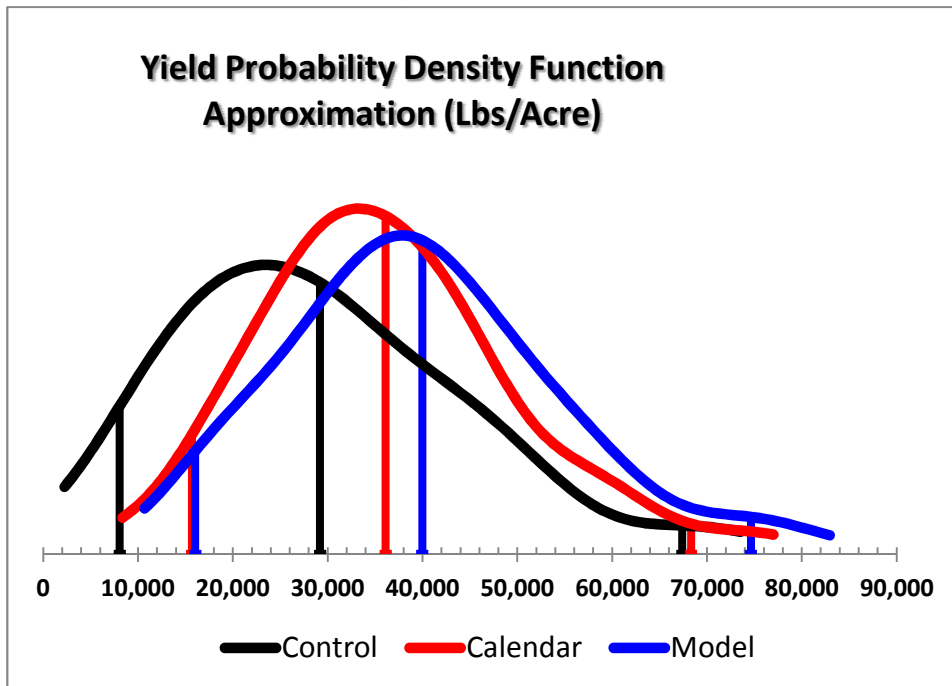
It can be seen that Model based yield is skewed to the right in comparison with the Calendar based yield and Control, implying that at any given weather condition Model based fungicide application system gives the highest yield. The variance, i.e. bandwidth, of the Calendar based system is the smallest by magnitude while that of the Model-based treatment is higher by magnitude than the Calendar based (the variance of Control is the highest). This shows that the Calendar model presents the least risks out of all three methods. Therefore, it is important to realize whether the increase in yield that the Model-based treatment provides is worth the slightly increased risk that is picked up as a function of slightly increased variance.

NPV of 10 year cash flows (CF), referred to also as profits, for each method of fungicide application are found. Monte Carlo simulation is applied to the final formulation of profit presented in the Methodology section in the Equation (8).

Figure 5.

Probability Density Function Approximation For 10 Year NPV Of Each Treatment Method ($ in Millions)
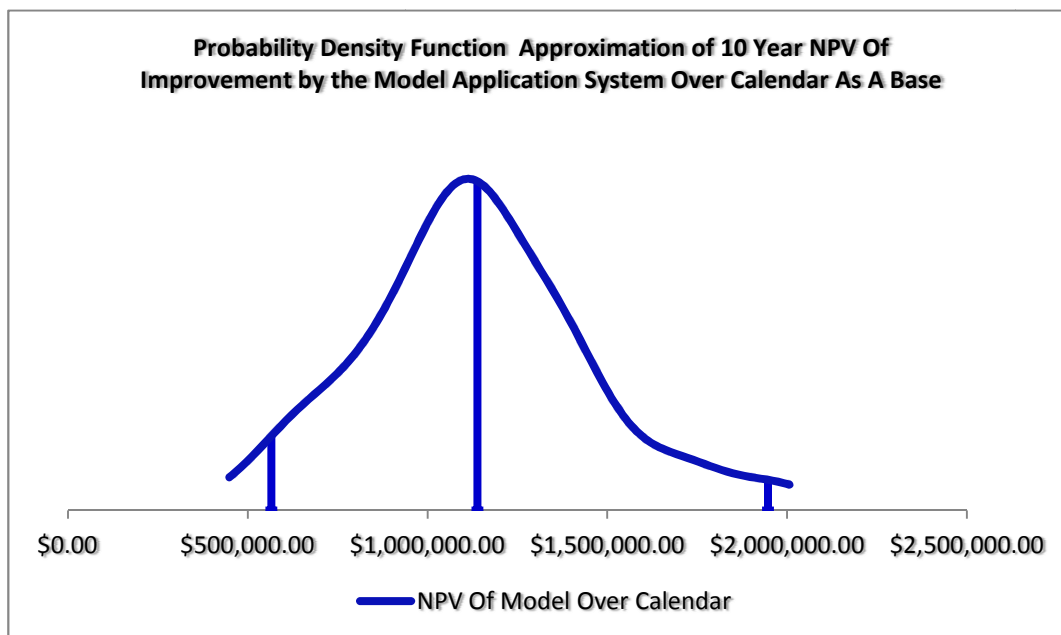
These profits now incorporate the difference in yield between models, which result in difference in Revenues, as well as difference in total costs. Configured for all these variables, Figure 4 demonstrates that Model indeed outperforms the Calendar method and certainly the Control. Given the savings on the fungicide costs as well as increase in yield (and hence revenues), the graphs demonstrate that the gap between Calendar and Model based application systems has in fact widened compared to the gap that was observed in the graphical result of the Yield distributions. This shows that the value that the new fungicide application system provides is increased once costs savings are accounted for.

Finally, the main goal of the paper was to value this new information intensive technology in fungicide application method as improvement over the presently used traditional fungicide application system. To achieve this goal, the difference between NPVs of the two application systems was found and then Monte Carlo simulation was performed, drawing 500 observations from the difference of 10 year profits between two models distribution. The result presented in Figure 6

shows that the simulated difference in NPV is positive, ranging from a little over $450,000 to close to $2,006,000, with an average around $1,139,000. This result confirms that Model based application system outperforms the traditional calendar based application system at any given weather condition. In addition since the NPV of the difference is always positive it means that the reward of higher yields is well worth a slightly increased yield risk.

Figure 6.

Probability Density Function Approximation of 10 Year NPV Of Improvement by the Model Application System Over Calendar As A Base

NPV Of Model Over Calendar

5 Conclusion

The objective of this study was to examine the economic benefits associated with precision fungicide application system for Florida strawberry production. Given the weather and disease forecast system developed by the University of Florida researchers (Pavan et al., 2011), strawberry growers can potentially 1) reduce fungicide application rates during cool and dry conditions without affecting yields, thus reducing production costs; or 2) apply fungicide at the precise time of high disease pressure during warm and wet weather, therefore, decreasing anthracnose disease development and spread, and increasing the yields and profits.

The data from six-year strawberry production experiments were examined using regression analysis techniques. Strawberry harvests given the traditional (calendar-based) and the precision (forecast model- based) fungicide treatment were compared with the control group with no fungicide applications. Stochastic forecasting framework and Monte Carlo simulations were used for the analysis. 10 Year NPV of free cash flows for each fungicide application method were forecasted for a 26 acre Florida Strawberry farm. 4% discount rate was used for the valuation.

Production experiments data showed that for the six production seasons (2006-07, 2007-08, 2008-09, 2009-10, 2010-11, 2011-12), Model based treatment required on average 44% less fungicide applications as compared with the Calendar based treatment while increasing the yield by 26%. Forecasted and simulated results confirmed the preliminary results by demonstrating that indeed a probability density function of Model based yield was outperforming that of Calendar based application system at any given weather condition.

Therefore, precision disease management system while reducing fungicide use and costs, either leaves yields unchanged or actually increases the yields if compared to conventional Calendar application method, thus precision disease management system can increase profits for the grower.

Overall, the precision disease management system is a viable fungicide application system that adds economic value to the Florida strawberry producer because it reduces their fungicide use and costs while potentially increasing the yields, therefore, increasing profits while reducing environmental hazards.

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