

Risk Analysis and Producer Level Impact of the SAS-based

Ekaterina Vorotnikova, Tatiana Borisova, John J. VanSickle, and Natalia A. Peres

The authors are (respectively): Graduate Student, Assistant Professor and Professor in the Food and Resource Economics Department, and Associate Professor in Gulf Coast REC, University of Florida

Selected Paper prepared for presentation at the Southern Agricultural Economics Association Annual Meeting, Dallas, TX, February 1-4, 2014

Copyright 2014 by Ekaterina Vorotnikova, Tatiana Borisova, John J. VanSickle, and Natalia A. Peres. 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.

Risk Analysis and Producer Level Impact of the SAS-based

Ekaterina Vorotnikova, Borisova Tatiana, John J. VanSickle, and Natalia A. Peres

The authors are (respectively): Graduate Student, Assistant Professor and Professor in the Food and Resource Economics Department, and Associate Professor in Gulf Coast REC, University of Florida

1.0 INTRODUCTION

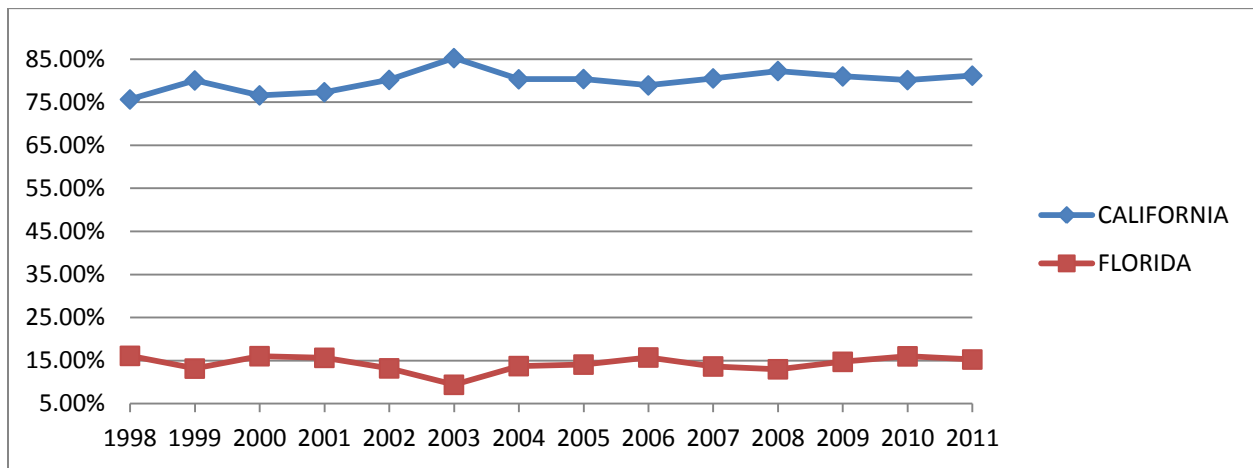
Precision agriculture (PA), also referred to as “information-intensive” agriculture (Bramley 2009), is defined as a “set of technologies that combines sensors, information systems, enhanced machinery, and informed management to optimize inputs and production by accounting for variability and uncertainties within agricultural systems” (Gebbers and Adamchuck 2010). The value of PA “lies in improving the decision making process to increase the efficiency of allocation of productive inputs” (Batte 1999), which in turn can have a significantly positive effect on both profitability of the farm as well as the environmental sustainability.

Numerous studies have been exploring economic viabilities 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 (Swinton and Lowenberg-DeBoer 1998, Godwin *et al.* 2003) while much less attention is paid to application of PA technologies to horticultural crops (Griffin and Lowenberg-DeBoer 2005, Bramley 2009). Even though some studies deal with citrus and grapes (Whitney *et al.* 1999 and Stafford 2007), no studies were found that examine economic viability of PA for small fruit production, such as berries, which are considered high value crop.

This study fills this gap of investigating PA technology for strawberry production as well as comparing its risk profile to that the traditional and new PA. The objective of the study is to conduct comparative risk analysis between the two production technologies that use two distinct fungicide treatment systems for strawberry production in the subtropical weather climate. The study uses experimental production data from trials in the grower fields from nine farms, where growers have

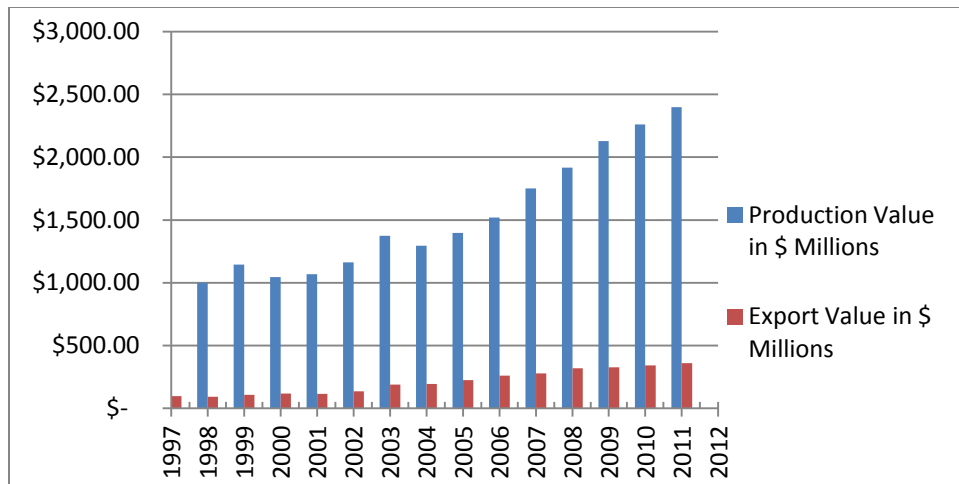
grown strawberries using both production methods simultaneously for three production seasons. Weather is the driver of stochastics in the model. Based on the stochastic dominance criteria and efficiency analysis for risk-adjusted profitability, we conduct a risk, profitability, and feasibility analysis for all possible risk preferences of the farmer. The study analyzes whether the farmer is sufficiently compensated for slightly increased risk in the new method of fungicide application.

The U.S. is the world’s largest strawberry producer accounting for over a quarter of total world production (FAOSTAT 2012). California and Florida are the largest strawberry producing states in the U.S., whose average yearly production value is consistently around 80% and 15%, respectively, of the total U.S. production (Figure 1).



Source: Based on data obtained from National Agricultural Statistical Services (NASS), 2013 Figure 1. The Percentages of Total Yearly Production Value of Two Top Strawberry Producing States, 1998-2011

In the past ten years, total production value increased by more than 60% (Figure 2). 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, production costs, and environmental sustainability.



Source: National Agricultural Statistical Services (NASS), 2013 and Foreign Agricultural Service (FAS), 2013

Figure 2. Strawberry Production and Exports Values for the U.S. 1997-2011

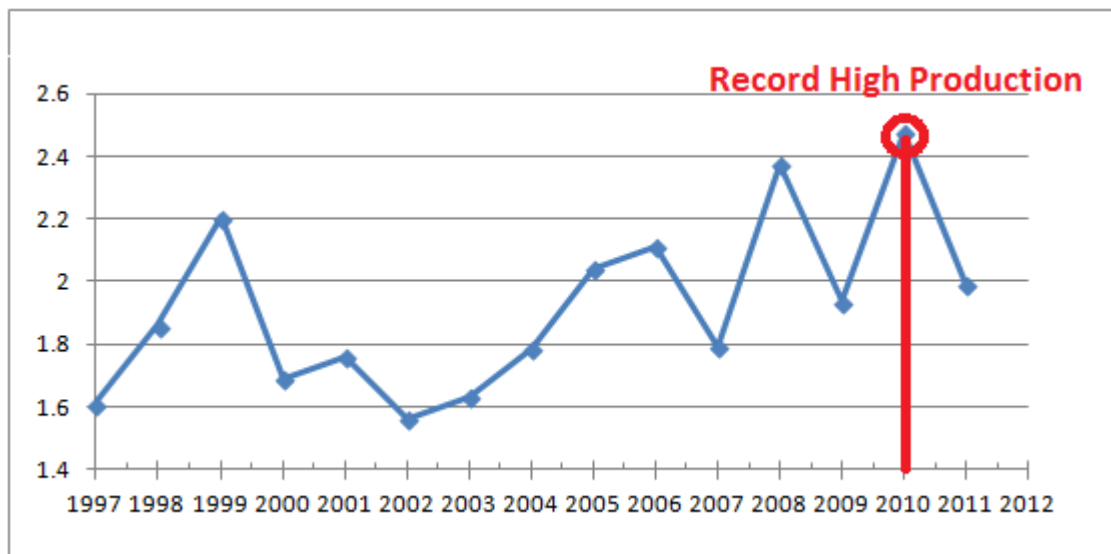
While the effects of information about spatial factors (e.g., planting patterns, plant diversity, weed pressure, and soil type) have been extensively studied (Brophy and Mundt 1991, Mundt et al. 1997, Waller et al. 1997, Mitchell et al. 2002, and Oliver and Robertson 2009), the economics of PA technologies addressing the temporal variability was addressed in only a few studies (e.g., Goodwin *et al.* 2003). Insufficient recognition of temporal variations has been identified as one of the critical issues in PA studies (McBratney et al. 2005).

Difficulties in predicting profitability of PA technologies were elaborated extensively in existing studies (Atherton et al., 1999); however, PA profitability is found to be the main driver behind the adoption of PA technologies (Batte 2003). Thus, conducting profitability studies can be timely and urgent and can significantly increase the adoption rate of PAs. This study evaluates the profitability of one PA technology, Strawberry Advisory System (SAS), developed to assist agricultural producers in the southeastern U.S. in managing weather- and climate-related risks. SAS was developed to optimize the fungicide application timing in Florida strawberry production (Pavan *et al.* 2009). Specifically, SAS uses real-time information about air temperature and strawberry leaf wetness duration to tailor fungicide applications to the periods of high risks for anthracnose and *Botrytis* fruit rot developments.

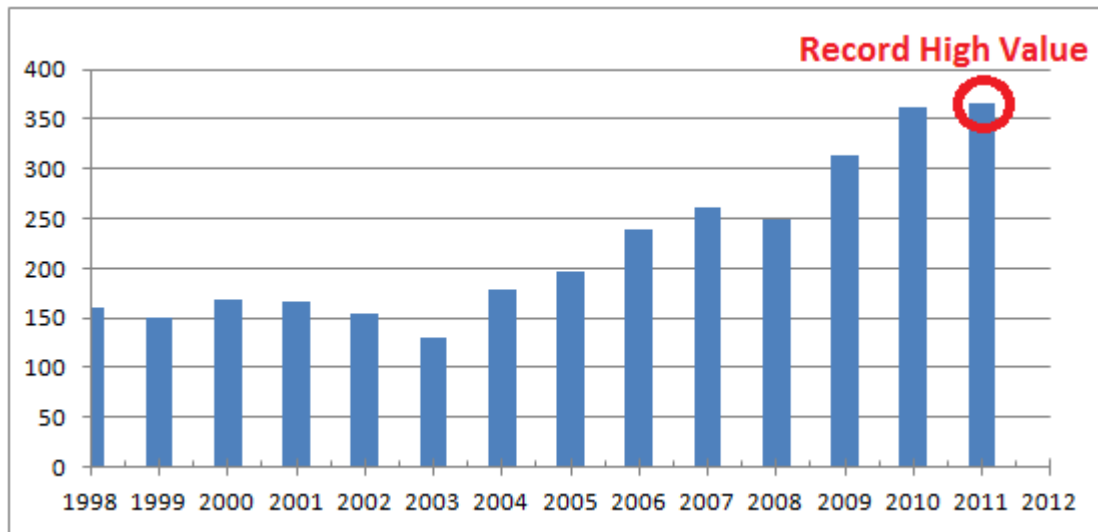
SAS can be accessed on-line through the *AgroClimate.org* website, which is developed and maintained jointly by the Southeast Climate Consortium (SECC), Florida Climate Institute, and Florida Cooperative State Extension Service. Currently, there are 45 grower subscribers for SAS electronic alerts (including instant text messaging); and in 2012 the web-site was accessed 3,099 times by 617 people (interview Natalia Peres, 2013).

2.0 STUDY AREA

Strawberry is the most significant berry crop by production value in Florida. During the winter season Florida dominates the national strawberry market. In 2010, total production *volume* (in pounds) reached a record high of 2.5 million pounds (Figure 3). A year earlier, in 2011, the total *value* of production reached a record of \$366.3 Million (Figure 4), and in 2012, a record of 10,100 acres was under strawberry production (NASS 2013).



Source: Based on data from National Agricultural Statistical Services (NASS), 2013
Figure 3. Florida Production in Millions of Pounds (1997-2012)



Source: Based on data obtained from the National Agricultural Statistical Services (NASS), 2013
 Figure 4. Strawberry Production Value in \$ Millions

Almost ninety percent of Florida’s strawberries are grown near Plant City in Hillsborough County, west central Florida. The production season starts in November and continues through March of the following year (Figure 5). The heaviest harvesting occurs between the months of February and March, driven by the climatic conditions and the dynamics of the strawberry market. Specifically, prices for strawberries generally peak in December or January and then experience steady downward pressure until bottoming out in May or June in response to the increasing strawberry supplies from California.

Fungal diseases such as anthracnose (*AFR*) and Botrytis (*BFR*) fruit rots are major challenges for strawberry growers (Pavan et al. 2009). Even in carefully managed fields, losses from fruit rot can exceed 50% when conditions favor disease development (Ellis and Grove 1982, Turechek et al. 2006).

Fungicides are commonly used by the growers to stem off the development of these diseases. Currently fungicides are applied on a calendar based schedule, following a once a week program (Mertely et al. 2009a; 2009b). Fungicide costs comprise approximately 7% of pre-harvest variable costs, which represents about \$690 per acre (IFAS 2010). Significant issues facing the 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 negatively affecting strawberry yields and quality can provide significant economic and environmental benefits to Florida strawberry industry.

3.0 STRAWBERRY ADVISORY SYSTEM

Past research shows that accurate information about weather conditions can be used to tailor the fungicide applications to manage the anthracnose and Botrytis disease pressure (Wilson 1990, Mackenzie and Peres 2012, more on Botrytis). Periods with warm and wet weather create favorable conditions for the development and spread of anthracnose and botrytis fruit rots increasing the risk of harvest losses. In contrast, given cool and dry conditions, the risk of this disease development is relatively minor.

Bulger et al. (1987) and Wilson et al. (1990) developed a system that predicts the spread of anthracnose and Botrytis disease on berries based on the duration of leaf wetness and the average temperature during the wetness period. They found that the most conducive temperature for anthracnose disease development for both immature and mature fruit is between 25 and 30 C, while for Botrytis disease development the most conducive temperature is between 15C and 25C with the absolute optimal temperature being 20 C (Bulger et al. 1987). Guided by this research, UF scientists conducted strawberry field experiments (Pavan et al 2006, 2011, Fraisse et al. 2006, Turecheck et al. 2006, Merteley et al. 2009) and in 2009 launched the on-line Strawberry Advisory System (SAS) (Pavan, 2011). SAS was designed to predict disease-conducive conditions by processing leaf wetness duration and average temperature during the wetness period, and to issue alerts for fungicide applications when conditions for disease development are favorable.

In this study, we compare simulated yields for a 10-year planning horizon given a traditional fungicide application method and the precision fungicide application method that follows SAS recommendations. In the analysis the effect of two diseases, anthracnose and Botrytis, are accounted by the model as well as two type of different cultivars, more- and less-resistant ones, separately.

3.1 The Difference between SAS- and Calendar-Based Fungicide Application Methods

The fundamental differences between the two fungicide application methods, Calendar-based and

SAS-based, are demonstrated in Figure 5. The calendar-based application method involves routine fungicide application on the same day of every week during the production season. Since the Florida production season is on average 15 weeks, the average total number of applications for the entire season, N_C , is equal to 15 (Figure 5). In contrast, for the SAS-based method, the timing of the fungicide application depends on the trigger from SAS. SAS determines the probability of disease development based on the leaf wetness duration (W) and an average temperature during the wetness period (T). If the probability exceeds the thresholds of 15% (for Anthracnose, p_{SAS}^{AFR}) or 50% (for Botrytis, p_{SAS}^{BFR}), then SAS issues a trigger alert for fungicide application respectively for each disease. The total number of applications sums up to N_{SAS} . The fewer disease conducive days there are throughout the season, the lower is the number of applications under SAS-based method. Conversely, the more disease conducive days there are, the higher is the number of applications, N_{SAS} . In the worst case scenario N_{SAS} is equal to N_C .

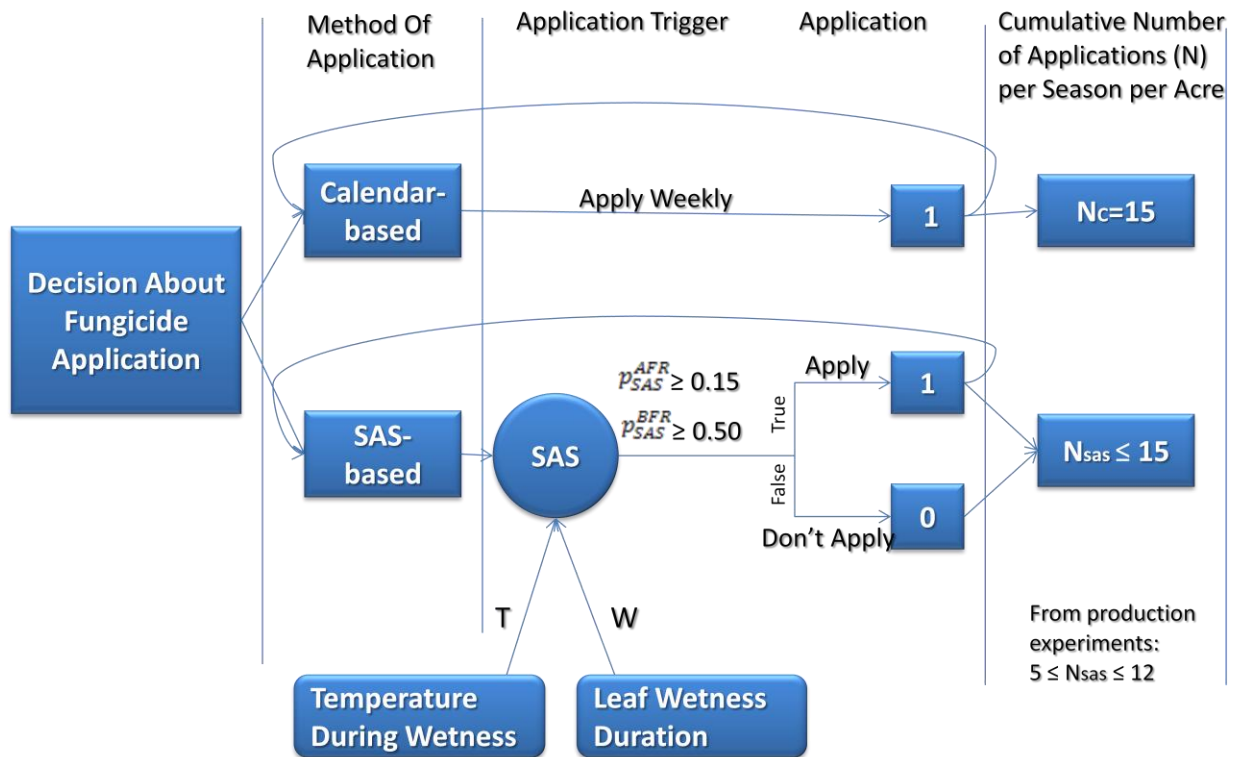


Figure 5. Difference in Calendar and SAS-based Application Methods

3.2 SAS Operation

SAS predicts the probability of disease infection based on the relationship between the wetness duration and temperature during the wet period, originally proposed by Wilson et al. (1990) and Bulger et al. (1987) for the Anthracnose and Botrytis diseases, respectively. They used a logit regression model, where the infection level of the disease was accurately described as a function of wetness duration (W) and temperature during the wet period (T). Equation (1) describes the relationship, where percentage of infection of ripe fruit and flowers, $\%Inf$, is the dependent variables within logit equation.

$$\ln\left(\frac{\%Inf}{1 - \%Inf}\right) = f(T, W) \quad (1)$$

Two factors had to be taken into account in the regression analysis. First, the functional form of the model had to accurately represent the observed relationship between $\%Inf$ and T , such that $\%Inf$ increases to a maximum and then decreases. Second, in the regression model, $\%Inf$ had to increase with increases in W , but should not exceed 1.0 or fall below 0.0 for any value of W . Wilson et al. (1990) and Bulger et al. (1987) used a logistic regression to model the proportion of immature and mature strawberry fruit infected by anthracnose ($\%Inf^{AFR}$, Equation 2) and by Botrytis ($\%Inf^{BFR}$, Equation 3), respectively, as a function of temperature, T , and leaf wetness duration, W :

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

$$\ln\left[\frac{\%Inf^{BFR}}{1 - \%Inf^{BFR}}\right] = -4.367 + 0.0127WT - 0.0703W - 0.0000068WT^3 \quad (3)$$

Models (2) and (3) are referred to as the Wilson-Madden weather index for each of the diseases respectively.

Denoting the left-hand side of equations (2) and (3) as the disease index, or DI , the proportion of strawberry fruit infected by the fungus can be specified as:

$$\%Inf^D = \frac{EXP(DI^D)}{1 + EXP(DI^D)} \quad (4)$$

where $D \in [1:AFR, 2:BFR]$ to distinguish between two fungi diseases. The relationships (2), (3), and (4) were used by Mackenzie and Peres (2012) to develop the on-line Strawberry Advisory System (SAS) that indicates the level of anthracnose and Botrytis disease risks. SAS recommends fungicide application if the disease risk is high (Figure 5). Specifically, using strawberry production experiments and the knowledge of critical combinations of temperature and leaf wetness duration at which the disease pressure becomes critical (Wilson 1990), Mackenzie and Peres (2012) identified that given Florida growing conditions, an Anthracnose $\%Inf^{AFR} = 0.15$ should be considered as a threshold to trigger the fungicide application. Thus, when equation (4) estimates a 15% probability for anthracnose development in strawberries, SAS issues a warning of the “moderate” risk of disease development, and recommends spraying a “preventive” type of fungicide such as Captan (Captan 80WDG; Micro Flo Company LLC, Memphis, TN, Peres 2010a). Furthermore, when equation (4) estimates at least a 50% probability of strawberries developing the disease ($\%Inf^{AFR} = 0.50$), SAS indicates “high” risk of disease, and recommends spraying “a curative” fungicide such as Cabrio (Cabrio 20EG; BASF Corporation, Research Triangle Park, NC, Peres 2010a). For Botrytis there is only one threshold ($\%Inf^{BFR} = 0.50$) to trigger a fungicide application. The label restrictions on the maximum rate and frequency of fungicide applications are also accounted for in the SAS recommendations. Specifically, the maximum number of sequential applications for Cabrio is limited to two, and the maximum rate of its application is 70 oz (4.375 pounds) per acre per season (Cabrio Fungicide 2011). In turn, Captan can only be applied at the rate of one ounce per one gallon of water per 100 square feet of land; and sequential applications should be separated by at least seven days (Captan Fungicide 1998). To account for these restrictions, producers are asked to enter their past fungicide application practices into SAS, and the system modifies the recommendation based on the label specifications for each fungicide used by the growers.

4.0 DATA

The data span four production seasons: 2010-2011 through 2012-2013. The data are collected by Professor Natalia Peres from the University of Florida research farm at the Gulf Coast Research and

Education Center in Wimauma, Florida. The data are collected from seven different farms located throughout Balm region: Fancy Farms, Pacific Farm, BBI, Simmons Farm, Berry Bay, Ferry Farm, and Austin Farm. Seven different locations make it possible to conduct a large scale experiment that captures various growing conditions in the region. Each grower's field was divided into two areas. The grower uses standard fungicide application practices in one area and SAS based applications - in the other. To replicate all possible harvest outcomes, five different cultivars are used, which come from ten different nurseries. The cultivars divide into more disease resistant such as Festival, Alafia, and Sanibel as well as less-disease resistant ones such as Treasure and Albion. The data consists of marketable weight, disease instances, and the number of triggers generated by SAS. Historical data for yearly state average strawberry prices and yields were collected from NASS. Third, strawberry production budget data was obtained from VanSickle et al. (2009) available from the University of Florida (UF).

Marketable fruit were counted, weighed, and then cumulated for each production season. Diseased fruits were also counted for anthracnose (AFR) and Botrytis (BFR) incidences, and also cumulated for each production season. The number of berries tossed for reasons other than anthracnose and Botrytis diseases (i.e., cull) was also recorded and summed up for each season.

During each season, leaf wetness interval (W) and the temperature during the wetness period (T) were recorded every 15 minutes by sensors at the Balm weather station. Then, the temperature measures were averaged over all temperature readings during the wetness period. These measures were used as independent variables for the Wilson-Madden regression (Equations 2 and 3, respectively for each disease). If weather was conducive for disease development, SAS triggered a recommendation for a fungicide application.

Thus, *Weather Anthracnose* and *Weather Botrytis* variables are constructed for Anthracnose and Botrytis diseases, respectively to capture the overall risk of disease development during the production season for each disease. Each data point is a summation of days for each production season, during which the 15% threshold ($\%Inf^{AFR} \geq 0.15$) for anthracnose and 50% threshold ($\%Inf^{BFR} \geq 0.50$) for

Botrytis is reached (Table 1).

Table 1. The Number of Days with Weather Conditions Conducive for Anthracnose and Botrytis, Derived Weather Variables, and Number of Fungicide Applications

Season	Farm	Cultivar	Weather Anthracnose	Weather Botrytis	Model Application	Calendar Application	Percentage Change in Application Rate
12/13	Ferry Farm	Albion	22.0	14.0	6	15	60%
12/13	Ferry Farm	Festival	14.0	7.0	2	10	80%
12/13	Austin Farms	Festival	30.0	17.0	9	18	50%
12/13	Fancy Farm	Festival	22.0	13.0	9	18	50%
12/13	Fancy Farm	RH	21.0	16.0	7	11	36%
12/13	Fancy Farm	RP	21.0	16.0	7	11	36%
12/13	Pacific Farm	Alafia	41.0	26.0	9	16	44%
Average			24.4	15.6	7.0	14.1	51%
11/12	Fancy Farm	Festival	22	17	6	14	57%
11/12	Fancy Farm	Radiance	24	19	6	14	57%
11/12	Simmons	Radiance	24	19	7	11	36%
11/12	Pacific Farm	Sanibel	32	25	9	13	31%
11/12	Berry Bay	Radiance	13	7	3	12	75%
11/12	Ferry Farm	Albion	22	14	9	15	40%
11/12	Ferry Farm	Festival	24	19	7	13	46%
Average			23.0	17.1	6.7	13.1	49%
10/11	Fancy Farms	Festival	13	11	4	9	56%
10/11	Fancy Farms	Festival	13	11	3	8	63%
10/11	Fancy Farms	Festival	13	11	4	11	64%
10/11	Simmons	Festival	22	17	6	11	45%
10/11	Pacific	Alafia	21	17	4	11	64%
Average			16.4	13.4	4.2	10	58%

Lastly, *Application* variable is quantified by the number of total fungicide applications for the entire season combined for both diseases and two application methods, respectively (Table 1). Under the Calendar-based application method 8 to 18 applications are administered each production season, averaging around 15. Under the SAS-based method 5 to 9 fungicide treatments are applied each season, averaging around 6 applications per season, which is about 50% decrease compared to that of the Calendar based method.

Manufactures' specifications limit fungicide application rate to once a week. Thus, even if there are several triggers for disease development during a week, only one application is administered.

Therefore, for each given season the number of applications is smaller than the number of days conducive for the disease development.

5.0 MODEL

Weather conditions (i.e., a combination of temperature and leaf wetness) can be denoted by a random weather variable $\theta \in \Theta$, where Θ represents all possible states of weather conditions. Yield is affected by random weather conditions, and fungicide application: $Y(\theta, x)$. The variability of revenue is a result of yield variability, that depends on the random weather events, and strawberry prices variability, that depends on the market, which in turn is a function of the supply and demand dynamics. Assuming inelastic demand, an increase in supply depresses prices. To reflect this dependence, the correlation between historical strawberry prices, s_t , and historical yields, Y_t , $correl(s_t, Y_t)$, is used.

Alternatively, the producer can improve his/her knowledge about the random state variable, weather, by seeking additional information from SAS. For the SAS-based production practice, let X denote the set of possible number of fungicide applications, $X \in [0,18]^1$. SAS predicts the probability of disease development-conducive weather, $p_{SAS}(\theta)$. Given predicted probability, SAS also issues a trigger alert for fungicide application, thus, it determines the number of applications $x(p_{SAS}(\theta)) \in X$ for the entire season. For a 15-week long production season, SAS will result in zero applications if during the season, none of the 15 weeks had days conducive for disease development. The number of applications will be the maximum and equal to the number of applications of the traditional method if the season had days with disease development-conducive weather conditions in each week of the season:

Since weather, θ , and sale price, s , vary from season to season, calendar-based and SAS-based fungicide applications result in a distribution of profits for each application method.

¹ For anthracnose trials the experiments continues for an average of 15 weeks, and the maximum fungicide application rate is once a week, the maximum number of fungicide applications is fifteen.

6.0 SIMULATING KEY VARIABLES

The weather, θ , is represented through two variables in the model, *Weather Anthracnose* and *Weather Botrytis*. The *Weather* variable is randomly drawn from a normal distribution with mean and variance obtained from the data collected from the field trials:

$$Weather\ Anthracnose \sim Normal(23.5, 5.54) \quad (5)$$

Since there are only six *Weather* variable observations from the experiment, these data cannot be tested for normality. To understand whether normal distribution can be used, historical data for temperature and humidity provided by Florida Automated Weather Network (FAWN) system (<http://fawn.ifas.ufl.edu/>) was tested for normality. The data included 14 production seasons starting in 1998 and continuing to 2013. The hypothesis that the weather follows normal distribution could not be rejected at 5% significance level using Chi-Square test.

The *Weather Intensity* variable is obtained by using a simple OLS regression with *Weather* as an independent variable:

$$Weather\ Botrytis = \mu * Weather + \delta * Weather^2 + u_{WI} \quad (6)$$

where u_{WI} is the error term. Following the methodology of Richardson et al. (2000) we generate stochastic predicted values from the OLS regression (Equation 6). First, the deviates from the trend are generated by dividing the error term by the predicted value of *Weather Intensity* measure as follows:

$\frac{u_{WI}}{Weather\ Botrytis}$. The deviates are then sorted and arranged from minimum to maximum in a vector,

$S_{WI,t}$. Next, a probability is assigned to each of the sorted deviates as having an equal chance of being observed ($1/T$) in history, where T is the number of historical observations, which are used in the regression. The distribution of these deviates based on each deviate's assigned probability is represented by $F(S_{WI,t})$. Finally, we define stochastically predicted *Weather Intensity* as:

$$Weather\ Botrytis^n = Mean\ Weather\ Botrytis * [1 + MVE(S_{WI,t}, F(S_{WI,t}))] \quad (7)$$

where $t = 1, 2, 3, \dots, T$ historical years, and $n = 1, 2, 3, \dots, N$ simulated years, $S_{WI,t}$ is a vector of deviates from trend as a percentage of predicted, and $F(S_{WI,t})$ represents distribution of deviates in the

$S_{WI,t}$ vector of sorted deviates, and MVE stands for Multivariate Empirical distribution whose functional form depends on $S_{WI,t}$ and $F(S_{WI,t})$. MVE is a distribution comprised of the deviates from the trend as a percentage of predicted from the regression of the Equation 7, $\frac{u_{WI}}{\widehat{Weather\ Botrytis}}$.

The number of fungicide applications is estimated using simple OLS regression with Weather as an independent variable:

$$Application = \xi_1 Weather Anthracnose + \xi_2 Weather Botrytis^2 + u_A \quad (8)$$

where u_A is the error term. Following the methodology of Richardson et al. (2000) we generate stochastic predicted values from the OLS regression (Equation 7). The procedures are similar to the ones described when obtaining stochastically predicted *Weather Intensity* measure. The deviates from the trend are generated by dividing the error term by the predicted value of *Application* measure as follows: $\frac{u_A}{\widehat{Application}}$. The deviates are then sorted and arranged from minimum to maximum in a vector, $S_{A,t}$. Next, a probability is assigned to each of the sorted deviates as having an equal chance of being observed ($1/T$) in history, where T is the number of historical observations, which are used in the regression. The distribution of these deviates based on each deviate's assigned probability is represented by $F(S_{A,t})$. We define stochastically predicted *Application* as follows:

$$Application^n = Mean\ Application * [1 + MVE(S_{A,t}, F(S_{A,t}))] \quad (9)$$

where $t = 1, 2, 3, \dots, T$ historical years, and $n = 1, 2, 3, \dots, N$ simulated years, $S_{A,t}$ is a sorted vector of deviates from trend as obtained from the regression (Equation 7), $F(S_{A,t})$ represents distribution of deviates in the $S_{A,t}$ vector of sorted deviates, and MVE stands for Multivariate Empirical distribution whose functional form depends on $S_{A,t}$ and $F(S_{A,t})$. MVE is a distribution comprised of the deviates from the trend as a percentage of predicted from the regression of the Equation 9, $\frac{u_A}{\widehat{Application}}$. Since the regression in Equation 9 is dependent on the Weather variable, which happens to be from the normal distribution, $F(\cdot)$'s functional form also follows a normal distribution.

Two different types of cultivars were used in production experiments: a more disease-resistant

cultivar and a less disease-resistant cultivar – denoted M and L , respectively. In addition, in those trials three different methods of fungicide application were used: Control, Calendar-, and SAS-based.

Therefore, to distinguish among yields in each different case, let's denote yield as $Yield_{Method}^{Cultivar}$, where $Cultivar \in [1: M, 2: L]$, and $Method \in [1: Calendar, 2: SAS]$.

Thus, the regression expression for the yield in general terms is as follows:

$$Yield_{Method}^{Cultivar} = f(State\ Yield, Weather\ Anthracnose, Weather\ Botrytis, Applications) + u_{Method}^{Cultivar} \quad (10)$$

where $Cultivar \in [1: M, 2: L]$, $Method \in [1: Calendar, 2: SAS]$, and $u_{Method}^{D,Cultivar}$ is an error term.

Based on data collected during the three year experiment, a functional form for strawberry yield in anthracnose trials $Yield_{Method}^{Cultivar}$ was obtained using OLS regression:

$$\begin{aligned} Yield_{Method}^{Cultivar} = & \alpha_0 + \alpha_1 State\ Yield + \alpha_2 Weather\ Anthracnose + \alpha_3 Weather\ Botrytis \\ & + \alpha_4 Weather\ Anthracnose^2 + \alpha_5 Weather\ Botrytis^2 + \alpha_6 Applications \\ & + \alpha_7 SAS + \alpha_8 SAS * Applications + \alpha_9 SAS * Weather\ Anthracnose \\ & + \alpha_{10} SAS * Weather\ Botrytis + \alpha_{11} More\ Resistant\ Cultivar + \alpha_{12} SAS \\ & * Less\ Resistant\ Cultivar + u_{Method}^{Cultivar} \quad (11) \end{aligned}$$

where $u_{Method}^{Cultivar}$ is the error term specific to $Cultivar$ and $Method$ of fungicide application.

The dependent variable Yield is strawberry weight (in pounds/acre). The descriptive summary of independent variables including *State Yield*, *Weather Anthracnose*, *Weather Botrytis*, *Applications*, and *SASbased*, and *Cultivar*, as well as various interactions of these terms is provided in Table 2. The yield for the Calendar-based application method is chosen to be a base case scenario, while the effect of SAS-based method is modeled using dummy variables. This choice was made because the Calendar-based method of fungicide application has persisted historically among the Florida growers; therefore, historical State-average Yield data generally reflect the practices of the Calendar-based fungicide application.

Table 2. Independent variables used in regression analysis for Strawberry Yield

Variable	Description	Expected Effect on Marketable Yield	Mean	Standard Deviation
<i>State Yield</i>	State Yield during the production seasons from 2006 to 2012 as obtained from NASS in pounds per acre.	Positive	26364	3124.08
<i>Weather Anthracnose</i>	Cumulated number of days that are conducive for the development of the disease according to the Wilson-Madden weather index for the entire season ($%Inf \geq 0.15$).	Negative	22.1	6.86
<i>Weather Botrytis</i>	Cumulated number of days that are conducive for the development of the disease according to the Wilson-Madden weather index for the entire season ($%Inf \geq 0.50$).	Negative	15.8	4.85
<i>Weather Anthracnose^2</i>	Cumulated number of days that are conducive for the development of the disease according to the Wilson-Madden weather index for the entire season ($%Inf \geq 0.15$).	Negative	534.3	350.20
<i>Weather Botrytis^2</i>	Cumulated number of days that are conducive for the development of the disease according to the Wilson-Madden weather index for the entire season ($%Inf \geq 0.50$).	Negative	274.3	160.96
<i>Applications</i>	Cumulated number of fungicide applications for one production season.	Positive	9.5	4.11
<i>SAS-based</i>	Dummy variable, indicating the experimental plots treated with the model-based method (i.e., precision disease management).	Positive	0.50	0.50
<i>Cultivar</i>	Dummy Variable, indicating less disease resistant cultivar	Negative	0.6	0.497
<i>SAS-based*Application</i>	The effect of SAS-based applications	Positive	3.1	3.49
<i>WeatherAnthracnose*SAS-based</i>	An interaction of Weather Anthracnose variable and SAS-based group. Weather's effect on SAS-based group.	Na	11	8.09
<i>WeatherBotrytis*SAS-based</i>	An interaction of Weather Anthracnose variable and SAS-based group. Weather's effect on SAS-based group.	Na	7.9	8.65
<i>SAS-based*Less-Resistant Cultivar</i>	The effect of SAS-based		0.2	0.41

In conclusion, based on method of generating stochastic predicted values from the OLS regression (Richardson et al. 2000), we obtain stochastically predicted:

$$Yield_{Method}^{Cultivar^n} = Mean Yield_{Method}^{Cultivar} * [1 + MVE (S_{Method,t}^{Cultivar} F(S_{Method,t}^{Cultivar}))] \quad (11)$$

where $Cultivar \in [1: M, 2: L]$, and $Method \in [1: Control, 2: Calendar, 3: SAS]$, $t = 1, 2, 3, \dots, T$ historical years, and $n = 1, 2, 3, \dots, N$ simulated years, $S_{Method,t}^{D,Cultivar}$ is a vector of sorted deviates respectively to each method given a more- or less-resistant cultivar for each disease, and $F(S_{Method,t}^{Cultivar})$ is a vector of assigned probabilities to a specific deviate in $S_{Method,t}^{Cultivar}$ determined by the OLS regressions. It is important to mention that $S_{Method,t}^{Cultivar}$ is unique for each case (2 diseases, 3 methods, 2 cultivars) precisely because in each of those 12 cases a regression has own specific error term, $u_{Method}^{Cultivar}$.

7.0 RESULTS

The results of the regression analysis for anthracnose disease are presented in Table 3. As defined in the Section 7.4, the intercept contains the effects on the Calendar treatment method.

Tables 3. Coefficients from the Anthracnose regression for the Marketable Weight of Strawberries

Anthracnose			
Variable	Estimates		Standard Error
Weather Anthracnose	0.35188085	***	0.113785
Weather Botrytis	0.40958837	***	0.121357
Weather Anthracnose^2	-0.0062001	***	0.001665
Weather Botrytis^2	-0.0131907	***	0.003608
Method	2.2215572	***	0.718954
Application	0.13308196	*	0.069404
Method*Application	-0.4008236	***	0.089444
Method*WeatherA	0.14792395	**	0.06574
Method*WeatherB	-0.0551831	***	0.078799
M	0.76386345	**	0.202253
Method*L	-0.4293453	*	0.290485

*** signifies 0.01 significance level

** - 0.05 significance level

* - 0.10 significance level

The results of stochastic simulation for Yield in case of anthracnose disease for a more- and a less-resistant cultivars based on Equation 11 are displayed in the form of the probability density functions in Figure 6. It can be seen that SAS-based yield distribution is shifted to the right in comparison with the Calendar-based yield and Control yield, implying that at any given set of weather conditions the SAS based fungicide application method produces the highest yield as compared to the Calendar application method and Control. Table 4 presents summary statistics for the averages of the distributions that confirm visual results of the Figure 6.

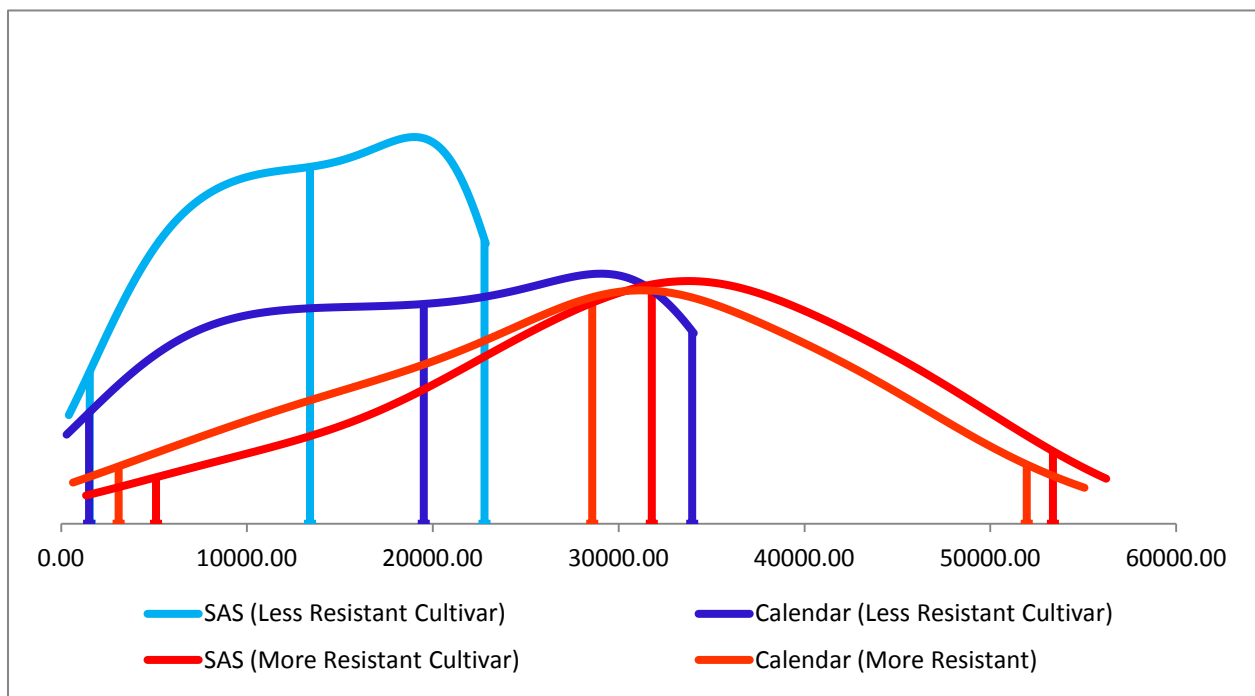


Figure 6. Probability Density Functions of Yields.

The result is interesting because the difference between SAS and Calendar-based performances seems to be different for more- and less-resistant cultivars. Specifically, SAS performs better for the more resistant cultivar while Calendar based method performs better for the less resistant cultivar. Comparing Calendar Less Resistant outcome and Calendar More Resistant cultivar, we can see the second one yields better than the first. Table 4 lists the statistics after Monte Carlo simulation.

Table 4. Yield Summary Statistics after Monte Carlo Simulation

Summary Statistics for Yield for both Cultivars in Case of Anthracnose Disease					
Name	Mean (lbs/acre)	Std Dev	Coef Var	Minimum	Maximum
More-Resistant Cultivar					
1 Calendar	28588.51	12754.7	44.61476	643.1702	55059.27
2 SAS based	31793.06	12380.82	38.94191	1344.861	56230.35
Less-Resistant Cultivar					
1 Calendar	19523.63	10238.59	52.44202	299.6293	34048.81
2 SAS based	13401.4	6511.862	48.59092	407.8245	22847.02

The coefficient of variance of the simulated yield given the SAS-based method for a more-resistant and less resistant cultivars is the lower than that of Calendar based (38.94 for a more-resistant cultivar and 48.59 for a less-resistant cultivar). Overall, by coefficient of variance, the methods given cultivar rank as follow: SAS-based (more-resistant cultivar), Calendar (more-resistant cultivar), SAS-based (less-resistant cultivar), and Calendar (less-resistant cultivar). This shows that the Calendar model runs the most risks. However, in case of less-resistant cultivar its average yield is also higher than that of SAS-based. Interestingly, the difference between the coefficients of SAS-based and Calendar variances is less in the less-resistant cultivar than that of more-resistant cultivar. This indicates that SAS-based method is significantly more effective for a more-resistant cultivar than for the less-resistant one.

Inevitably, the question rises whether a slight risk increase of the SAS-based application method is worth taking given that the method provides an increase the yields. Therefore, stochastic dominance analysis is performed. The next step is, assuming negative exponential utility function, methods we will rank ranked by choosing most efficient set based on stochastic dominance with respect to a function.

Acknowledgements

We would like to thank United States Department of Agriculture for providing full funding support in a form of a grant, “Precision Disease Management for Sustainable Strawberry Production in the Eastern U.S.” (2010–2014; PD: Dr. Natalia Peres)

We are enormously grateful to the University of Florida plant pathologists, Teresa Seijo and Dr. Natalia Peres at the Gulf Coast Research and Education Center (GCREC) in Wimauma, FL for conducting field trials (2006 - present) and providing data from the experiments.

We are thankful to Dr. Clyde Fraisse for providing insights about how the Strawberry Advisory System (SAS) works as well as his recent work on weather modeling.

REFERENCES

- Batte, M.T. 1999. Books Reviews. Precision Agriculture in the 21st Century: Geospatial and Information Technologies in Crop Management. Washington DC: National Academy Press, 1997. *American Journal of Agricultural Economics* Volume 81 Number 3: 755-756.
- Batte, M.T. and Arnholt, M.W. 2003. Precision farming adoption and use in Ohio: case studies of six leading-edge adopters. *Comput. Electron. Agric.*, Volume 38: 125–139
- Boriss, H., Brunke, H., Kreith, M., and Geisler, M. 2010. Commodity Strawberry Profile, Agricultural Marketing Resource Center. Available at http://www.agmrc.org/commodities/products/fruits/strawberries/commodity_strawberry_profile.cfm Accessed on 10/12/2011
- Bramley, R. G. V. 2009. Lessons from nearly 20 years of Precision Agriculture research, development, and adoption as a guide to its appropriate application. *Crop & Pasture Science*, 60, 197–217.
- Brophy, L.S. and Mundt, C.C. 1991 Influence of plant spatial patterns on disease dynamics, plant competition and grain yield in genetically diverse wheat populations. *Agriculture, Ecosystems, and Environment*, Vol. 35, Issue 1: 1-12.
- Bulger M.A., Ellis, M.A., and Madden, L.V. 1987. Influence of Temperature and Wetness Duration on Infection of Strawberry Flowers by *Botrytis cinerea* and Disease Incidence of Fruit Originating from Infected Flowers. *Phytopathology*, 77:1225-1230.
- Ellis M.A. and Grove, G.G., 1982. Fruit rots cause losses in Ohio strawberries, *Ohio Re. Res. Dev.*, 67: 3-4.
- Fraisse, C.W., Breuer, N.E., Zierden, D., Bellow, J.G., Paz, J., Cabrera, V.E., Garcia y Garcia, A., Ingram, K.T., Hatch, U., Hoogenboom, G., Jones, J.W., and O'Brien, J.J. 2006. AgClimate: A climate forecast information system for agricultural risk management in the southeastern USA. *Computers and Electronics in Agriculture* 53 (1): 13-27. (ISSN 0168-1699, DOI: 10.1016/j.compag.2006.03.002).

- Gebbers R. and Adamchuck, V.I. 2010. Precision Agriculture and Food Security. *Science*, 327 (February), 828 – 831.
- Godwin, R.J., T.E. Richards, G.A. Wood, J.P. Welsh and S.M. Knight. 2003 An Economic analysis of the potential for precision farming in UK cereal production.
- Griffin, T.W. and Lowenberg-DeBoer, J., 2005. Worldwide adoption and profitability of precision agriculture. *Revista de Politica Agricola* 14, 20–38,
Available at http://www.embrapa.br/publicacoes/tecnico/revistaAgricola/rpa-de-2005/pol_agr_04-2005-p-pgembrapa.Pdf
- Mackenzie, S.J. and Peres, N.A. 2012. Use of leaf wetness and temperature to time fungicide applications to control anthracnose fruit rot of strawberry in Florida. *Plant Disease* 96:522-528.
- McBratney et al. 2005. Future Directions of Precision Agriculture. *Precision Agriculture*, 6, 7 – 23.
- Mertely, J.C., Peres, N.A., and Chandler, C.K. 2009a. Anthracnose fruit rot of strawberry. PP207. Gainesville: University of Florida, Institute of Food and Agricultural Sciences. (<http://edis.ifas.ufl.edu/PP130>).
- Mertely, J.C., Seijo, T.E., and Peres, N.A. 2009b. Effect of Pre- and Post-Plant Fungicide and Fertilizer Treatments on Infection by *Colletotrichum acutatum*, Plant Survival, and Yield of Annual Strawberry in Florida. *Plant Health Progress*.
- Mitchell, C. E., Tilman, D., and Groth, J.V. 2002. Effects of Grassland Plant Species Diversity, Abundance, and Composition on Foliar Fungal Disease. *Ecology* 83:1713–1726.
- Mundt, C.C., Leonard, K.J., Thal, W.M., and Fulton J.H. 1985. Computerized Simulation of Crown Rust Epidemics in Mixtures of Immune and Susceptible Oat Plants with Different Genotype Unit Areas and Spatial Distributions of Initial Disease. *Phytopathology* 76: 590-598.
- NASS, 1995 United States Department of Agriculture, Economic Research Service, Bulletin Number 914 <http://www.nal.usda.gov/pgdic/Strawberry/ers/ers.htm>
- Oliver YM and Robertson MJ, 2009. Quantifying the benefits of accounting for yield potential in spatially and seasonally responsive nutrient management in a Mediterranean climate. *Soil Research* 47, 114–126. Available at <http://dx.doi.org/10.1071/SR08099>. Accessed on 03/08/2013.
- Pavan, W., Fernandes, J. M. C., Sanhueza, R. M. V., Ponte, E. D., Cervi, C. R., and Dalbosco, J. 2006. Web-based system to true-forecast disease epidemics- sisalert. In: Proceedings of Computers in Agriculture and Natural Resources, 4th World Congress Conference. [S.l.]: American Society of Agricultural and Biological Engineers. ISBN 701P0606.
- Pavan, W., Fraisse, C.W., and Peres, N.A. 2011. Development of a web-based disease forecasting system for strawberries. *Comput. and Electron. Agric.* 75:169-175.
- Peres N. A., Fraisse C.W., Van Sickle J., Borisova T., Gleason M., Schnabel G., Ellis M., Louws F., and G. Wilkerson, 2010a. Precision Decision Management for Sustainable Strawberry Production in the Eastern U.S., USDA. Available at <http://www.reeis.usda.gov/web/crisprojectpages/222314.html>

Peres N.A., Seijo T. E. and W.W. Turechek, 2010b. Pre- and Post-Inoculation Activity of a Protectant and a Systemic Fungicide for Control of Anthracnose Fruit Rot of Strawberry under Different Wetness Durations. *Crop Protection*, 29: 1105-1110.

Richardson J.W., Klose, S.L., Cray, A.W. 2000. An applied procedure for estimating and simulating multivariate empirical (MVE) probability distributions in farm level risk assessment and policy analysis. *Journal of Agricultural and Applied Economics*. Volume 32 Number 2: 299-315

Swinton, S.M., Lowenberg-DeBoer, J., 1998. Evaluating the profitability of site-specific farming. *Journal of Production Agriculture* 11 (4): 439, 446.

Turechek, W.W., Peres, N.A., and Werner, N.A. 2006. Pre- and post-infection activity of pyraclostrobin for control of anthracnose fruit rot caused by *Colletotrichum acutatum*. *Plant Disease* 90:862-868.

University of Florida Institute of Food and Agricultural Sciences. 2010. Cost of Production for Florida Vegetables, 2001-2002. Available from <http://www.agbuscenter.ifas.ufl.edu/cost/cop01-02/tableofcontents.htm> (accessed August 6, 2011).

VanSickle J.J., Smith, S., and Weldon, R. 2009. Impacts of EPA Proposed Buffer–Zone Restrictions on Profitability of Florida Strawberry Growers. Electronic Data Information Source. The Institute of Food and Agricultural Sciences. Publication #FE795. Accessed at <https://edis.ifas.ufl.edu/fe795> on 3/26/2011.

Waller, L.A., Carlin B. P., Xia, H., and Gelf A. E. 1997. Hierarchical Spatio-Temporal Mapping of Disease Rates. *Journal of the American Statistical Association*, Vol. 92, No. 438: 607-617.

Wilson L.L., Madden L.V. and M.A. Ellis, 1990. Influence of Temperature and Wetness Duration on Infection of Immature and Mature Strawberry Fruit by *Colletotrichum acutatum*, *Phytopathology*, 80: 111-116.