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The value of site-specific information and the environment: Technology adoption and pesticide use under uncertainty

Murat Isik[a,*], Darren Hudson[b], Keith H. Coble[b]

[a]Department of Agricultural Economics and Rural Sociology, University of Idaho, 28B Ag Science Building, Moscow ID 83844, USA
[b]Department of Agricultural Economics, Mississippi State University, Mississippi, MS, USA

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Abstract

Remote sensing technology offers an opportunity to significantly increase the amount of site-specific information about field characteristics such as pest populations. Coupled with variable rate application technologies, this added information has the potential to provide environmental benefits through reduced pesticide applications. However, producers face a complicated adoption decision because output prices and crop yields are uncertain. A model is developed to examine the potential value of remote sensing information to pesticide applications in an option-value framework under uncertainty. Simulations suggest that remote sensing information could decrease pesticide use, but uncertainty and irreversibility are likely to limit technological adoption by farmers. Potential cost-share subsidies are discussed.

Keywords: Environmental policy; Green payments; Option value; Uncertainty; Pesticide regulation; Remote sensing

1. Introduction

Agricultural nonpoint source pollution is the leading source of water quality impacts to rivers and lakes, and a major contributor to groundwater contamination and wetlands degradation (US Environmental Protection Agency (EPA) and US Department of Agriculture (USDA), 1990). Increasing public concerns about water quality and food safety are drawing attention towards alternative strategies and policies to reduce agricultural runoff of nutrients and pesticides. Pesticide regulations such as banning the pesticide use or regulating the timing of pesticide applications are a possible means of reducing pesticide use, but this approach often forces a trade-off between pesticide reductions and farm profitability (Lichtenberg et al., 1993). Information technology developments may offer a means of reducing pesticide use in a manner that minimizes adverse effects or even enhances farm profitability.

Recent technological advances in remote sensing and variable rate technologies (RSVT) make it possible for farmers to obtain detailed site-specific information about soil characteristics and pest population to predict problems with fertilizers, water, and pests within a field, and apply fertilizers and pesticides at a varying rate within the field. Variable rate technologies have the potential to improve yields, reduce fertilizer costs and reduce residuals of the applied inputs in the soil (Isik and Khanna, 2003; Isik et al., 2001). These technologies have been referred to as complementary technologies because they have the potential to provide both economic and environmental benefits. However, recent surveys show that adoption rates of these technologies are low. For example, only 15% of the surveyed farmers in Mississippi in 2000 adopted variable rate technologies for pesticides and for fertilizers (Hudson and Hite, 2003).

RSVT may improve pesticide application efficiency by disaggregating economic threshold decisions of pesticide use into site-specific levels.[1] The concept of economic

* Corresponding author. Address: Department of Agricultural Economics and Rural Sociology, University of Idaho, 28B Ag Science Building, Moscow ID 83844, USA. Tel.: +1 208 885 7214.
E-mail address: misik@uidaho.edu (M. Isik).

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[1] Economic threshold level of pest population is the level at which the pesticide application should be considered in order to prevent economic loss (Headley, 1972).

thresholds for pesticide applications has been developed to simplify pesticide application decisions by determining the level of pest population that creates meaningful economic damage to the crop (Headley, 1972; Lichtenberg et al., 1993). A primary limitation of the economic threshold concept is that it is based on the presumption that the pest population is spatially homogeneous within the field. The confluence of variable rate technology and remotely sensed (spatially referenced) data may provide an opportunity to refine the economic threshold of pesticide applications by applying the economic threshold to smaller subunits of a field. This process could lead to improved input efficiency and reduced pesticide use. However, there has been no study examining the economic and environmental benefits of RSVT in pesticide use decisions.

Recent studies of pesticide use have emphasized the importance of the temporal randomness in pest population dynamics in determining the economic threshold of pesticide use within a growing season (Saphores, 2000; Sunding and Zivin, 2000). However, both spatial and temporal pest population randomness impact the economic threshold of pesticide use and the decision to invest in RSVT by making returns from investment in RSVT uncertain. The decision to invest in RSVT is complicated because some components of RSVT investment require a large sunk cost, which must be made in the face of the well-known revenue uncertainty of agricultural production resulting from variability in output prices and crop yields. Investment in some components of RSVT involves high sunk costs because RSVT is still undergoing rapid innovation and improvement. Additionally, farmers have the option to delay the investment decisions to learn more about market conditions and the value of RSVT. These observations are consistent with the studies on investment under uncertainty that emphasize the importance of uncertainty, irreversibility and flexibility in investment timing in investment decisions (Dixit and Pindyck, 1994).

This paper has two objectives. First, it develops an option-value model to examine the factors that affect farmers' decisions to invest in RSVT for variable rate applications of pesticides under output price and yield uncertainty due to spatial and temporal randomness in pest population dynamics. It combines the randomness of the pest population through time with the randomness of the pest population density within the field to determine the economic threshold of pesticide use and analyze the factors affecting the economic and environmental implications of RSVT. Second, the paper demonstrates the potential policy relevance of considering uncertainty and irreversibility by examining the design of cost-share subsidies to achieve reductions in pesticide use by accelerating adoption of RSVT. Investment irreversibility and uncertainty often lead to delayed investment. If adoption of RSVT leads to positive external benefits (i.e. reduced pesticide use), delayed investment in technology means delayed realization of external benefits, necessitating government intervention (National Research Council, 1997, p. 71). We examine the magnitude of cost-share subsidies needed to induce adoption of RSVT. Previous studies have emphasized the use of market-based incentives to control pesticide use but largely have ignored the application of voluntary cost-sharing arrangements to accomplish this same goal (Lichtenberg et al., 1993).

This paper contributes to the literature by applying the economic threshold to smaller subunits of a field and then combining the economic threshold of pesticide use with the technology adoption decision using an option-value model. In addition, previous studies of pesticide use have focused on the randomness of the pest population in a temporal as opposed to spatial sense. This paper combines the randomness of the pest population through time with the randomness of the pest population density within the field. It also shows the extent to which farm size and heterogeneous field characteristics can mitigate the impacts of uncertainty and irreversibility on investment decisions. The paper demonstrates the potential of RSVT to address reductions in pesticide use as opposed to regulations such as banning the use of the pesticide in question or controlling the timing of applications.

2. Theoretical model

We consider a profit-maximizing farmer operating a field of A acres. Pest population varies within the field and the spatial distribution of the pest population at time t is represented by a probability density function, $g(\theta_t)$ with mean $\bar{\theta}_t$ and variance σ_t^2. Since the pest population in this study represents multiple pests, θ_t converts all pests to the 'reference pest'. This technique is also used by Swinton and King (1994) for the case of weeds control. The pest population within the field can be reduced with pesticide applications x_t. With the applied pesticide x_t, $\theta_t(1-D_t(x_t))$ of the pest will survive within the field, where $D_t(x_t)\leq 1$ is the reduction in the pest level due to the treatments x_t at time t and $D_t' > 0$. We assume a constant returns-to-scale crop response function and represent the yield per acre (y) at any time (t) as a function of the pest level per acre θ_t and the applied pesticide per acre x_t. This function is represented by $y_t = Z - Z\gamma\theta_t(1-D_t(x_t))$, where Z is the potential maximum cotton yield and γ is a constant representing percentage yield loss per individual pest.

We model the farmer's choice between two technologies: conventional practices and RSVT, denoted by superscripts C and V, respectively. Output price P_t is assumed to be changing over time and the farmer has expectations of these prices in the future. Input price w is assumed to be constant. The total cost of adoption of RSVT is K, the lifetime of the RSVT equipment is $\bar{T}$ years, and the discount rate is ρ.

2.1. Value of RSVT

We first derive the value of RSVT and determine conditions under which the farmer invests in RSVT. The profit-maximizing adoption decision under the net present value (NPV) rule requires that the farmer adopt a technology if the difference in the present value of the quasi-rents (revenue minus pesticides costs) with and without adoption is greater than the costs of adoption. This decision involves forecasting the profit-maximizing stream of expected returns with conventional practices and with RSVT, and comparing them to the total costs of adoption.

Under conventional practices, the farmer lacks information about the distribution of pest population in the field but uses a small sample of pest population to estimate the average pest population, $\bar{\theta}_t$, in the field. This approach to determining the input application rate of conventional practices is also referred to as the averaging approach (Isik and Khanna, 2002). The farmer then assumes that $\bar{\theta}_t$ is the pest level in the entire field (that is, $\sigma_t^2 = 0$) and chooses a single pesticide application per acre for the whole field by maximizing the discounted value of expected quasi-rents, π_0^C, subject to (1) as follows

$$\pi_0^C = \max_{x_t} \int_0^{\bar{T}} \mathrm{e}^{-\rho t} A E_{P\theta}[P_t(Z - Z\gamma\bar{\theta}_t(1 - D_t(x_t^C))) - w x_t^C]\mathrm{d}t \tag{1}$$

where $E_{P\theta}$ denotes the expectations operator based on the subjective probability distribution of future prices and pest population distribution given the information available at time $t=0$ and A is the farm size.[2] The economic threshold of pesticide use can be obtained from the first-order conditions of (1) to determine the optimal pesticide use in the field. The profit-maximizing single rate of pesticide use x_t^C is determined from the first-order condition, $E[P_t(Z\gamma\bar{\theta}_t D_t'(x_t^C))] = w$, as: $x_t^C = D_t'{-}1(w/(E_P[P_t Z\gamma\bar{\theta}_t]))$ which takes into account the population dynamics. Implicit in this first-order condition is the economic threshold above which the farmer will apply the pesticide ($\bar{\theta}_t^*$). The economic threshold ($\bar{\theta}_t^*$) is endogenous in the model. The optimization model determines the minimum pest density that must be present in a field before it is worthwhile to undertake pesticide application. Thus, x_t^C could be zero when $\bar{\theta}_t$ is relatively low, meaning that $\bar{\theta}_t^* > \bar{\theta}_t$. Note that $x_t^C > 0$ when $\bar{\theta}_t^* < \bar{\theta}_t$. Thus, our model determines whether any pesticide should be applied, and then obtains how much pesticides (x_t^C) should be applied if $\bar{\theta}_t^* < \bar{\theta}_t$.

Remote sensing technologies provide information about the distribution of pest population within the field, $g(\theta_t)$, making it possible for the farmer to apply the pesticide at a spatially varying rate using variable rate technologies. The input application rate x_t^V is chosen given the pest level θ_t at each point in the field to maximize the discounted quasi-rents:

$$\pi_0^V = \max_{x_t} \int_0^{\bar{T}} \mathrm{e}^{-\rho t} \int_0^{\infty} A E_P[P_t(Z - Z\gamma\theta_t(1 - D_t(x_t^V))) - w x_t^V] g(\theta_t)\mathrm{d}\theta\, \mathrm{d}t. \tag{2}$$

The pesticides level at any point in the field x_t^V is determined for each θ at time t from the first-order condition $E_P[P_t(Z\gamma\theta_t D_t'(x_t^V))] = w$, depending on the pest level at that point in the field, input price, and output price as: $x_t^V = D_t'{-}1(w/(E_{P\theta}[P_t Z\gamma\theta_t]))$. This first-order condition takes into account the population dynamics. The pesticide level x_t^V as well as the threshold level of pest population above which the farmer will apply the pesticide would vary continuously across the field as θ_t varies. Therefore, RSVT can provide opportunities to extend the concept of economic thresholds for pesticide applications by determining the level of pest population that creates meaningful economic damage to the crop at the sub-field level. The model first determines the minimum pest level (θ_t^*) that must be present in a field before it is worthwhile to undertake pesticide application for each θ_t. Thus, x_t^V could be zero for some θ_t that is relatively low. In this case, the threshold pest level would be higher than the existing pest level ($\theta_t^* > \theta_t$) so that no pesticide application would be made (i.e. $x_t^V = 0$). The first-order condition determines whether any pesticide should be applied for each θ_t by obtaining θ_t^*, and then calculates how much pesticide should be applied for each θ_t that is higher than θ_t^*.

The input levels for each technology are obtained from the first-order conditions of (1) and (2) to find the discounted quasi-rents, π_0^{C*} and π_0^{V*}. The present value of the quasi-rent differential from adopting RSVT at $t=0$ is denoted by $V_0(P, w, g(\theta), \bar{T}, A) = \pi_0^{V*} - \pi_0^{C*}$, which depends on the distribution of pest population within the field (mean, variability, and skewness of the distribution), farm size, lifetime of the RSVT equipment, and economic variables such as input and output prices. The quasi-rent differential (value of RSVT), V_0, is always nonnegative as long as there is any variability in the pest population distribution within the field.[3] This result is because input choice with RSVT is based on more information and fewer constraints on the application rate as compared to conventional practices. The value of RSVT increases as the variability in the pest population distribution increases. However, it may not always be larger than the total costs of adoption of RSVT. Under the NPV rule, which ignores uncertainty and irreversibility, it would be optimal to adopt RSVT at $t=0$ if $V_0 > K$.

[2] The dynamics of pest population (θ_t) and the output price ($\mathrm{P_t}$) are described in the empirical application.

[3] If there is no variability in pest population within the field, $x_t^C = x_t^V$ for each θt, and therefore $\pi_0^{C*} = \pi_0^{V*}$.

2.2. Investment under uncertainty

We now incorporate uncertainty in the value of RSVT into the investment decision. The value of RSVT is stochastic due to uncertainty about output prices and pest population. In order to keep our analysis tractable, we assume that the quasi-rent differential evolves as a geometric Brownian motion

$$dV = \alpha_V V\,dt + \sigma_V V\,dz \tag{3}$$

where α_V is the drift parameter; σ_V is the volatility in the drift parameter; and dz is the increment of a Wiener process with mean zero and unit variance. Eq. (3) implies that changes in the quasi-rent differentials are lognormally distributed.

The farmer's decision problem is to determine the optimal time T at which to adopt RSVT. Assuming risk neutrality, the optimal time T to invest in RSVT is obtained by maximizing the net returns of RSVT subject to (3)

$$F(V) = \max_T E[(V_T - K)e^{-\rho T}]. \tag{4}$$

Use of dynamic programming reveals that it is optimal to invest in RSVT at time T when the critical value of the quasi-rent differential is (Dixit and Pindyck, 1994):

$$V_T^* = \left(\frac{\beta}{\beta-1}\right)K \quad \text{where} \qquad \beta = \frac{1}{2} - \frac{\alpha_V}{\sigma_V^2} + \sqrt{\left(\frac{\alpha_V}{\sigma_V^2} - \frac{1}{2}\right)^2 + \frac{2\rho}{\sigma_V^2}} > 1. \tag{5}$$

The investment rule under uncertainty requires V_T to be greater than K by a factor of $\beta/(\beta-1)>1$. We refer to this as the option-value multiple for RSVT. This multiple is a positive function of the growth rate, α_V, and the volatility of the growth rate in V_T, σ_V, and a negative function of the discount rate. It varies with the variation in heterogeneous field characteristics.

A cost-share subsidy may be used to induce adoption for environmental reasons when it is not otherwise optimal to invest immediately. Under the NPV rule, the required cost-share subsidy for immediate investment is the difference between the present value of quasi-rent differential and the cost of investment when the latter is greater than the former. Under the option-value approach, the required subsidy S for RSVT is: $S = \mathrm{Max}\{0, K - ((\beta-1)/\beta)V_0\}$. The subsidy required under the option-value approach is always higher than that under the NPV rule because of the need to compensate for option values. These subsidy estimates vary with the heterogeneous farm characteristics such as farm size and pest population distributions that influence the value of the option-value multiple. In the following section we develop an empirical model to examine the value of RSVT in cotton production.

3. Empirical application

The empirical analysis considers variable rate application of pesticides to cotton production. Cotton production makes a good subject of analysis because of its relative intensive use of pesticides. Remote sensing technologies take multi-spectral photographs of farm fields to assess variation in plant growth and growing conditions within the field.[4] Several studies have shown that this information can be useful for spatially variable rate pesticide applications in cotton (Dupont et al., 2000; Plant et al., 2000; Willers et al., 1999; Sudbrink et al., 2003). For example, Willers et al. (1999) have found that insect population is directly related to the vitality of the plants growing in the field. Insect population is higher in areas of the field where plant growth is more vigorous. The photography can be used to identify portions of the field where plant growth is more vigorous and use the photographs to predict insect population distribution within the field. Thus, the remote sensing information is actually identifying areas of plant vigor, which has been shown to have a direct, predictable relationship with pest population.

The farmer obtains information about the pest population distributions to determine the shed rate distribution within the field. Square shed is evidence of injury to the cotton plant from any variety of insects (Mi et al., 1998). Square is a term used to refer to the early, immature fruit of the cotton plant. Square shed refers to the premature dropping of fruit as result of insect damage and other factors such as drought. In this study we assume that square shed is caused due to only insect damage. Given that drought is not present, pest pressure would be the primary factor affecting shed rate, and it is thus assumed that the pest population in the field is perfectly positively correlated with the square shed rate of cotton. Knowing the pest population distribution within the field makes it possible for farmers to obtain the square shed rate distribution, which is used to make spatially varying pesticide applications within the field.

The levels of square shed rate vary between 0 and 100%. The distribution of the square shed rate on a 1000-acre field is characterized by alternative Beta distributions. These 1000 acres are first divided into 400 plots with an area of 2.5 acres each. Each 2.5-acre plot is assumed to have homogenous pest population. Several studies support the use of the beta distribution in modeling yields, nutrients, and pest population distributions in the field (Caswell et al., 1993; Goodwin and Ker, 2002). Alternative square shed rate (pest population) distributions within the field are simulated by changing the means and variances of the Beta distributions, using the same random number seed. Two alternative distributions of square shed rate (negatively

[4] Manual sampling is another way to acquire information about pest population. However, it is not only less accurate in obtaining pest population distribution, but also very expensive compared to remote sensing technologies.

skewed and positively skewed) are considered with each having two alternative coefficients of variation (CV) (30 and 60%).[5] The mean level of the shed rate is 33.34% with the positively skewed distribution, and 66.67% with the negatively skewed distribution. The results from the experiments of Sudbrink et al. (2003) imply that these distributions represent the range of possible distributions that are reasonable to observe in fields.

The value of γ in the production function was obtained from the study of Mi et al., which assumes that one unit increase in the shed rate above 19% causes the cotton yield to decrease by 0.97% and there is no yield loss if the shed rate is less than 19%. This parameter reflects the pest damage occurring in the Mississippi Delta. For example, during the past 10 years, estimated annual yield losses attributed to plant bugs in Mississippi cotton have ranged from 0.2 to 3.6%, with losses as high as 4.7% being reported for the Mississippi Delta (Layton, 2004). The yield response function is used in (2) to determine the threshold level of pest population above which the farmer will apply the pesticide at each plot within the field.

We generated an aggregate pesticides index consisting of seven major commonly used insecticides (Temik 15G, Vydate C-LV, Orthene 90S, Tracer, Bidrin 8L, Karate Z, and Curacron 8E) in the Delta of Mississippi.[6] Total recommended dosage of this insecticide index is 6.38 pounds/acre and their costs are $12.04 per acre (Mississippi Agricultural and Forestry Experiment Station (MAFES), 2000). We postulate the relationship between the applied pesticide and pesticide efficacy (usefulness) as: $(1-D_{itj})=\mathrm{e}^{-0.361x_{itj}}$ (as in Saphores, 2000). Note that when x is equal to 6.38 pounds (a recommended rate of pesticide), D is equal to 0.90. It is assumed that the farmer makes at most four pesticide applications during a growing season to control the pest populations within the field, which is common in this region.[7]

The simulation model also examines the impact of potential cotton yields (Z) and farm size (A) on adoption decisions. Two alternative potential cotton yields (low with 500 pounds/acre and high with 1000 pounds/acre) are considered. These potential yields represent relatively low and relatively high productive fields in the Delta of Mississippi (MAFES, 2000). The per-acre returns of these fields reflect those of the fields covered in the MAFES (2000) extension budgets. Three alternative farm sizes, 1000 acres (1 field with 1000 acres), 3000 acres (3 fields with 1000 acres each), and 6000 acres (6 fields with 1000 acres each), are considered.

The farmer is assumed to purchase a variable rate controller along with a global positioning receiver, a yield monitor and a computer to perform spatially variable rate pesticide applications. The per-acre annual cost of remotely sensed data collection is $4.7 per acre, which includes four flyovers during a growing season. The variable rate controller along with global positioning systems, a computer, a yield monitor, maintenance and repair of equipment, and training in the use of equipment cost about $17,000. The costs of data collection and equipment were provided by GPS, Inc., Inverness, Mississippi for the typical package of RSVT in the Mississippi Delta. It is assumed that the discount rate is 10% and the lifetime of the equipment is 5 years. The present value of the total cost (the annualized per-acre cost) of adopting RSVT for a 1000-, 3000-, and 6000-acre farm is $36,598 ($7.30), $75,795 ($5.05), and $134,590 ($4.49), respectively.

The stochastic nature of the quasi-rent differentials in (3) is assumed to arise from uncertainty in the output prices and uncertainty in crop yields due to the randomness in pest population dynamics. We model the output price process as a geometric Brownian motion represented by the following discrete approximation (Dixit and Pindyck, 1994)

$$P_t=(1+\phi)P_{t-1}+\lambda P_{t-1}\nu_t \tag{6}$$

where ϕ is the expected growth rate; λ is the standard deviation in the growth rate; and ν_t is a normally distributed random variable with mean zero and unit variance at year t. Using the maximum likelihood estimation, the drift parameter is estimated as $\phi=m+(0.5)\lambda^2$, where m is the mean of the series, $\ln(P_{t+1}/P_t)$, and λ is the standard deviation of the series (Forsyth, 2000). Using the historical data on real cotton prices over the period 1920–2000 (USDA, 2002), the values of ϕ and λ are found to be -0.0029 and 0.1904, respectively. This process is used to forecast output prices for a 25-year period.

The pest population is stochastic due in part to the influence of random factors such as weather on reproduction rates. The pest population growth rate is modeled as an increasing function of the current pest population and time. The pest population dynamic at year t and growing period j is assumed to follow a geometric Brownian motion represented by (as in Saphores, 2000; Sunding and Zivin, 2000)[8]

$$\theta_{tj}=(1+\alpha_\theta)\theta_{tj-1}+\theta_{tj-1}\sigma_\theta\nu_{tj} \tag{7}$$

[5] The pest population distribution is positively skewed when it has a longer tail to the right of the mean. On the other hand, it is negatively skewed when it has a longer tail to the left of the mean. This means that most parts of the field will have lower (higher) pests than other parts of the field with the positively (negatively) skewed distribution. If the mean level of the shed rate is 50%, the pest population has a symmetric distribution.

[6] It is assumed for simplicity that the aggregate pest population can be controlled by the aggregate pesticides. In reality, farmers apply different insecticides for different insects and do not necessarily apply all these insecticides at the same time. To make empirical application transparent while focusing on the impacts of RSVT on pesticide use and farm profits, it is assumed that the pest populations can be controlled by the aggregate pesticides, rather than, each pest can be controlled by a different insecticide. However, the model developed here can be easily adapted to examine the impacts of variable rate application of a single insecticide on the value of RSVT.

[7] It is important to note that the farmer will make discrete decisions to apply pesticides. That is, at a given point in time, the farmer will examine the pest data on the 400 plots and decide if the threshold has been reached, and, if so, to apply the pesticide.

[8] Distribution of the pest population at time t is determined by applying Ito's lemma to (7) as: $\theta_t\sim\mathrm{Lognormal}[\theta_0\mathrm{e}^{\alpha_\theta t},\theta_0^2\mathrm{e}^{2\alpha_\theta t}(\mathrm{e}^{\sigma_\theta^2 t}-1)]$, where θ_0 is the initial pest population, $\theta_0\mathrm{e}^{\alpha_\theta t}$ is the mean and $\theta_0^2\mathrm{e}^{2\alpha_\theta t}(\mathrm{e}^{\sigma_\theta^2 t}-1)$ is the variance of the lognormal distribution.

where α_θ is the growth rate of pest population; σ_θ is the standard deviation in the growth rate; and dz is the increment of a Wiener process. Note that the pest dynamics also depend on whether pesticides were previously applied. Although pesticide use is not explicitly written as part of the pest dynamics in (7), it implicitly impacts pest dynamics through reduction in a given time period's pest level if pesticides are applied. Experimental evidence relating insect growth rates to environmental conditions suggest that the geometric Brownian motion is appropriate in modeling stochasticity in pest population dynamics (Sunding and Zivin, 2000). Hurley et al. (2004) also find empirical support for a lognormal pest population, which confirms the geometric Brownian motion assumption for the pest population. In the simulation model, every year a different initial pest population distribution (θ_{tj}) is drawn, depending on the pest population level at the end of the previous year (θ_{tj-1}) and the random variable (v_{tj}), then the pest population dynamics are modeled with Eq. (7) for that year. The initial pest population level in a year (θ_{tj}) would not be completely random and independent of the previous year's pest level (θ_{tj-1}) because the extent of the pesticide applications and the pest level at the end of the year would influence the following year's initial pest population level. Temperature, initial population size, and host plant availability may be important factors to overwintering of pest population. Although some of the pest populations, depending on the winter severity as reflected by low temperatures and rainfall, would die during winter, the empirical analysis considers cotton production in the Mississippi Delta where weather conditions during winter are relatively mild compared to other parts of the country. Most of the damaging pests to cotton production overwinter successfully in this region.[9] Although the overwintering effect would not likely be significant in this region, the stochastic process used here could take into account this effect.

The simulation model developed in this paper is consistent with that of Hurley et al. (2001) who model pest population dynamics as a deterministic logistic growth function. Our modeling framework extends their model by introducing the stochasticity in pest population dynamics. Because adequate time series and inter-seasonal data on the distribution of pest densities are not available, we use arbitrary but plausible values for the parameters of (7). The parameters, α_θ and σ_θ, are assumed to be 0.05 and 0.2887 per month. These values are consistent with those used by Saphores (2000) and Sunding and Zivin (2000). We also perform sensitivity analysis of the impacts of these variables on investment decisions.

The forecasted prices and the pest population dynamics are used in the numerical simulations to forecast the discounted quasi-rent differential $V_T(P,w,g(\theta),\bar{T},A)=\pi_T^{V*}-\pi_T^{C*}$, if RSVT is adopted at time $T=1,\ldots,25$. A series of V_T is estimated for the 25 years under each of the alternative assumptions about the pest population distributions and potential cotton yields. For each of these series we then estimate the parameters of the geometric Brownian motion given in Eq. (3) (α_V and σ_V) in order to determine the option values and the critical value of the quasi-rent differential in Eq. (5).

4. Results

4.1. Implications of adoption of RSVT for quasi-rent

The impacts of alternative distributions of pest population and the average crop yields on the average per-acre discounted quasi-rent over the 5-year lifetime of the equipment with conventional practices are summarized in Table 1. The quasi-rent of conventional practices increases as the average potential yields within the field increase because that increases the final crop yields. An increase in the variability of the pest population distribution within the field leads to a decrease in the quasi-rent of conventional practices. As the variability of the pest population increases, parts of the field that receive less pesticide than the optimal amount increase, leading to more yield losses on those parts of the fields. It is also found that the fields with the positively skewed distribution have higher quasi-rents than the fields with the negatively skewed distribution. Because the mean of

Table 1
Impact of RSVT on quasi-rent differentials

Potential yield[a]	Distribution of pest population		Discounted average annual quasi-rent under conventional ($/acre)	Quasi-rent differential over conventional with RSVT ($/acre)[b]
	Shape	CV (%)		
Low	Positively skewed	30	226.06	2.95
		60	221.05	11.48
	Negatively skewed	30	206.99	2.32
		60	205.22	8.39
High	Positively skewed	30	479.50	0.67
		60	476.35	7.42
	Negatively skewed	30	450.18	2.83
		60	450.15	9.42

[a] Low potential yield indicates an average potential cotton yield of 500 pounds/acre. High potential yield indicates an average potential cotton yield of 1000 pounds/acre.

[b] Note that the annualized per-acre cost of adopting RSVT for a 1000-, 3000-, and 6000-acre farm is $7.30, $5.05, and $4.49, respectively.

[9] In the Mississippi Delta, the tobacco budworm, the tarnished plant bug, and the boll weevil have historically ranked among the three most damaging pests to cotton. In recent years the boll weevil has not ranked among the most damaging pests due to a statewide eradication program. Wilson et al. (1995) found that the boll weevil overwintering emergence patterns can be predicted with considerable accuracy, depending on timing of weevil entry into overwintering habitat, winter severity, and insulating capacity of the overwintering habitat. Adult weevils commonly enter a state known as diapause, which allows them to survive the winter in a non-feeding and often dormant state. The tarnished plant bug overwinters under bark and leaves and adults become active in the spring (Polk et al., 1995). The tobacco budworm generally overwinters successfully only in southern states (Capinera, 2001).

Table 2
Adoption decision with the NPV rule and the option value

Potential yield[a]	Distribution of pest population		NPV rule			Option value			
	Shape	CV (%)	Farm size (acre)			Option-value multiple	Farm size (acre)		
			1000	3000	6000		1000	3000	6000
Low	Positively	30	N	N	N	2.654	N	N	N
	skewed	60	Y	Y	Y	1.873	N	Y	Y
	Negatively	30	N	N	N	1.456	N	N	N
	skewed	60	Y	Y	Y	2.312	N	N	Y
High	Positively	30	N	N	N	3.798	N	N	N
	skewed	60	Y	Y	Y	2.800	N	N	N
	Negatively	30	N	N	N	1.304	N	N	N
	skewed	60	Y	Y	Y	1.530	N	Y	Y

N indicates adoption of RSVT is not optimal. Y indicates adoption of RSVT is optimal.
[a] Low potential yield indicates an average potential cotton yield of 500 pounds/acre. High potential yield indicates an average potential cotton yield of 1000 pounds/acre.

the pest distribution with the positively skewed distribution is lower than that with the negatively skewed distribution, there is less need to apply pesticides to reduce yield losses as compared to the positively skewed distribution.[10]

The adoption of RSVT leads to an increase in quasi-rents relative to those with conventional practices for all the pest population distributions considered here as indicated by the quasi-rent differentials in Table 1. As the variability in the pest population distribution increases, the quasi-rent differentials with adoption of RSVT increase, as expected. The quasi-rent differential with the positively skewed distribution is higher than that with the negatively skewed distribution due to less pesticide required to reduce yield losses with the positively skewed distribution. As the potential crop yield increases, the quasi-rent differential decreases in the case of the positively skewed distribution, while it increases in the case of the negatively skewed distribution. This is because the fields with the negatively skewed distribution and/or high potential yield have more pesticides applied than the fields with the positively skewed distribution and/or low potential yields. These results are consistent with the findings of other simulation studies that examine the impacts of adoption of variable rate technologies for fertilizers (Isik and Khanna, 2003; Isik and Khanna, 2002). While these studies focus on the impacts of spatial variability in soil conditions, our findings suggest the importance of considering higher moments of the distribution as well to accurately assess the economic impact of variable rate technologies.

4.2. Investment in RSVT under uncertainty

The total discounted quasi-rent differentials of RSVT over the 5 year period the total fixed costs of adoption of RSVT on most of the pest population distributions, average potential yields, and farm sizes considered here under the NPV rule. As shown in Table 2, adoption of RSVT is preferred to conventional practices under conditions where the variability of the pest population distribution within the field is high. On the other hand, adoption of RSVT is not optimal when the variability of the pest population distribution is relatively low (i.e. CV is 30%). The farm size under the NPV rule does not have an impact on adoption of RSVT for the pest population distributions and average potential yields considered here. The reason is because both the total discounted quasi-rent differentials of RSVT and the total fixed costs of adoption increases as farm size increases.

With the uncertain prices and crop yields (option-value approach), there may be a value to waiting and observing prices in the future before incurring sunk costs in order to avoid a loss if prices were to fall.[11] The investment decision depends on the realizations of random prices and crop yields. Realization of high prices and crop yields signal a higher expected quasi-rent differential, which reduces the chance that an investment will be lost, thus, increasing the expected returns from the investment. Realization of low prices and crop yields signal the need to wait longer. The ex ante adoption decision of RSVT is obtained by calculating the critical value of the quasi-rent differential required for investment and comparing it to the expected quasi-rent differentials in each of the 25 years for all the pest population distributions and the average potential yields.

We estimated the critical value of the quasi-rent differential required for investment using the option-value multiple $\beta/(\beta-1)$ in Eq. (5) for all the pest population distributions and the average potential yields. The estimates

[10] In most of the simulations, we found that it is optimal to make two or three pesticide applications during a growing season. The number of pesticide applications and the rates of applications vary across the field conditions.

[11] Custom-hire of equipment would reduce the fixed costs of adoption. However, the farmer still needs to invest in some of the technologies such as a yield monitor, computer, and information gathering. Although custom-hire would reduce the impact of uncertainty on adoption, uncertainty still significantly impacts the adoption of RSVT.

of the option-value multiple, which determines the degree to which the quasi-rent differentials must exceed the investment costs before investment will occur given uncertainty in returns and sunk costs of investment, are reported in Table 2. The estimates of the option-value multiple vary with the distributions of pest population within the field and the average potential crop yields, highlighting the role that pest population and potential yields play in mitigating the effects of uncertainty and irreversibility on the adoption decision. The values of the option-value multiple vary between 1.3 on the fields with the negatively skewed distribution and 3.8 on the fields with the positively skewed distributions.

Immediate adoption of RSVT is only worthwhile on highly variable pest population distributions and on larger farms. On most of the other pest population distributions and farm sizes, it is optimal to delay the adoption of RSVT. This result is because high option values to RSVT create critical threshold values of net returns that are much higher than the quasi-rent differentials. This result highlights the impacts of irreversibility and uncertainty on potential adoption, and provides a reasonable explanation of why adoption rates of RSVT have been low to this point.

Unlike the NPV rule, the option-value approach suggests delay of investment decisions for most of the farm sizes considered here. As farm size increases, the per-acre fixed costs of adoption decrease and it becomes more likely to be profitable to invest in RSVT. For example, the farm with 1000 acres, 60% CV in the pest population with the negatively skewed distribution, and high potential yield would prefer to delay adoption of RSVT. An increase in the farm size from 1000 to 3000 acres reduces the fixed cost of adoption and makes it optimal for the farmer to adopt RSVT. This illustrates the role of farm size in mitigating the impacts of uncertainty and irreversibility on investment decisions.

We also examine the impacts of discount rate and the parameters of the stochastic process of the pest population on adoption decisions. A decrease in the discount rate from 10 to 5% not only marginally increases the present value of the expected returns from the investment but also marginally increases the value of the option to invest in the future. Thus, the net impact of discount rate on the adoption decisions is not found to be large. An increase in the variability of the stochastic process of the pest population σ_θ, from 0.288 to 0.308 leads to an increase in the option-value multiple, and, therefore, an increase in the critical value at which it is optimal to invest in RSVT. Therefore, an increase in the variability of the pest population within a growing season due to an increase in the variation in weather and growing conditions would reduce the incentives to invest in RSVT. This result is because ex ante increases in pest population variability within a growing season increases uncertainty about investment profitability, thereby increasing the option-value multiple.

4.3. Implications of RSVT for pesticide use

The impacts of adoption of RSVT on pesticide use are summarized in Table 3. Adoption of RSVT reduces the per-acre pesticide application relative to the levels under conventional practices on all the pest population distributions considered here. RSVT reduces the total pesticide use. It reduces the total pesticide use by 5.3–14.5% with the high potential yield and by 5.4–11.9% with the low potential yield depending on the variability of pest population distribution within the field. The reduction in pesticide use with RSVT is relatively high on the fields with negatively skewed distributions because the pesticide application is higher under negatively skewed distributions than under positively skewed distributions. As the variability in the pest population increases, pesticide-use savings with RSVT increase.

4.4. Cost-share subsidies for immediate adoption

Two results are of potential relevance to policy makers. First, RSVT has the potential to reduce pesticide use. Second, output price and yield uncertainty defer potential adoption of RSVT, delaying the realization of potential pesticide use reductions. Thus, we explore the magnitude of cost-share subsidies to induce RSVT adoption. This is important because political difficulties in imposing the ‘polluter pays principle’ on farmers have prevented the use of mandatory instruments that penalize farmers through taxes or standards. Instead, water quality protection policy in the US has been based on the provision of financial incentives to farmers for voluntarily changing their input use or technology choice so that they are more environmentally friendly (Ribaudo et al., 2000; Ribaudo and Caswell, 1999). Agricultural producers have few financial incentives to mitigate adverse environmental impacts of agricultural production and therefore green payments could provide these incentives if properly designed (Batie and Horan, 2001; Isik, 2004). An example of such a green payment

Table 3
Impact of RSVT on pesticide use

Potential yield[a]	Distribution of pest population		Pesticide use with conventional (pounds/acre)	Percentage reductions in total pesticide use with RSVT
	Shape	CV (%)		
Low	Positively	30	1.84	5.43
	skewed	60	1.84	8.15
	Negatively	30	4.47	4.92
	skewed	60	4.47	11.86
High	Positively	30	3.02	5.30
	skewed	60	3.02	9.27
	Negatively	30	6.18	5.34
	skewed	60	6.18	14.53

[a] Low potential yield indicates an average potential cotton yield of 500 pounds/acre. High potential yield indicates an average potential cotton yield of 1000 pounds/acre.

Table 4
Cost-share subsidy required for immediate adoption under the NPV rule and the option value (% of the total costs of adoption)

Potential yield[a]	Distribution of pest population		Farm size (acre)					
	Shape	CV (%)	NPV rule			Option value		
			1000	3000	6000	1000	3000	6000
Low	Positively	30	53.8	28.3	16.8	82.6	73.0	68.7
	skewed	60	0.0	0.0	0.0	3.9	0.0	0.0
	Negatively	30	63.6	43.6	34.6	75.0	61.3	55.1
	skewed	60	0.0	0.0	0.0	43.1	11.8	0.0
High	Positively	30	89.5	83.7	81.1	97.2	95.7	95.0
	skewed	60	0.0	0.0	0.0	64.1	44.3	35.3
	Negatively	30	55.6	31.2	20.2	66.0	47.2	38.8
	skewed	60	0.0	0.0	0.0	3.5	0.0	0.0

[a] Low potential yield indicates an average potential cotton yield of 500 pounds/acre. High potential yield indicates an average potential cotton yield of 1000 pounds/acre.

program is the Environmental Quality Incentives Program. The new Conservation Security Program of the 2002 Farm Bill also provides incentive payments to producers who adopt and maintain conservation practices on working lands. The 2002 Farm Bill has provisions that are likely to subsidize the use of remote sensing technologies.[12]

We estimate the cost-share subsidies required for immediate adoption of RSVT as a percentage of the total costs of adoption under both the NPV rule and the option-value approach (Table 4). The cost-share subsidy required for immediate adoption under the option value is higher than that under the NPV rule due to the need to compensate high option values. Ignoring uncertainty and irreversibility, the NPV rule underestimates the required cost-share subsides for immediate adoption of RSVT. The required subsidy for RSVT varies depending on the farm size and heterogeneous field characteristics represented by pest population distribution and potential crop yields. As farm size and/or variability in the pest population increases, the required cost-share subsidy decreases. No subsidy is needed to induce the adoption of RSVT on relatively large farms with high variability in the pest population distribution.

5. Conclusions

This paper develops an option-value model to examine the value of spatially referenced data and the decision to invest in RSVT under stochastic output prices and pest population. It incorporates the decision about RSVT adoption using the option-value approach into the economic threshold model by combining the randomness of the pest population through time with the randomness of the pest population density within the field. Unlike previous studies that examine the impact of policies such as banning pesticide use or regulating the timing of pesticide applications, this paper examines the potential of RSVT to reduce pesticide use and the potential policy relevance of uncertainty and irreversibility to achieve reductions in pesticide use by accelerating adoption.

The results indicate that the economic and environmental impacts of RSVT vary across heterogeneous farm characteristics such as pest population distribution (variance and skewness), potential crop yields, and farm size. Further, the impacts of uncertainty and irreversibility also vary across pest population distribution, potential crop yields and farm size, and the extent to which recognition of option values can influence forecasts about adoption of RSVT. The model that accounts for uncertainty about output prices and pest population using the option-value approach provides a better explanation for the low observed rates of adoption of RSVT than models based on the NPV rule. Adoption of RSVT reduces the total pesticide use. However, delayed adoption due to irreversibility and uncertainty means delayed realization of environmental benefits. A cost-share subsidy may be needed to encourage farmers to adopt RSVT to reduce the side effects of pesticides. The cost-share subsidies required vary across heterogeneous farm characteristics such as pest population distributions, average crop yields, and farm size.

This paper focused only on the decisions to switch from conventional practices to RSVT under uncertainty about output prices and crop yields due to randomness in pest populations. The possibility of other technological developments such as new crop varieties that reduce the reliance on pesticide use in the future would change the dynamics of adoption of RSVT. In addition, the possibility of a decline in the costs of adoption in the future would increase the impacts of uncertainty and would further delay the adoption of RSVT. Thus, the results presented here may underestimate the incentives to delay adoption of RSVT and the cost-share subsidies required to induce immediate adoption. Future research also includes how cost-share subsidies should be designed to achieve a given level of reduction in total pesticide use in a region with

[12] Additionally, public support for subsidies to induce adoption of remote sensing and variable rate technologies has been documented (Hite et al., 2002).

heterogeneous farms and how their cost effectiveness would be improved with increased information about farmer characteristics through remote sensing.

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