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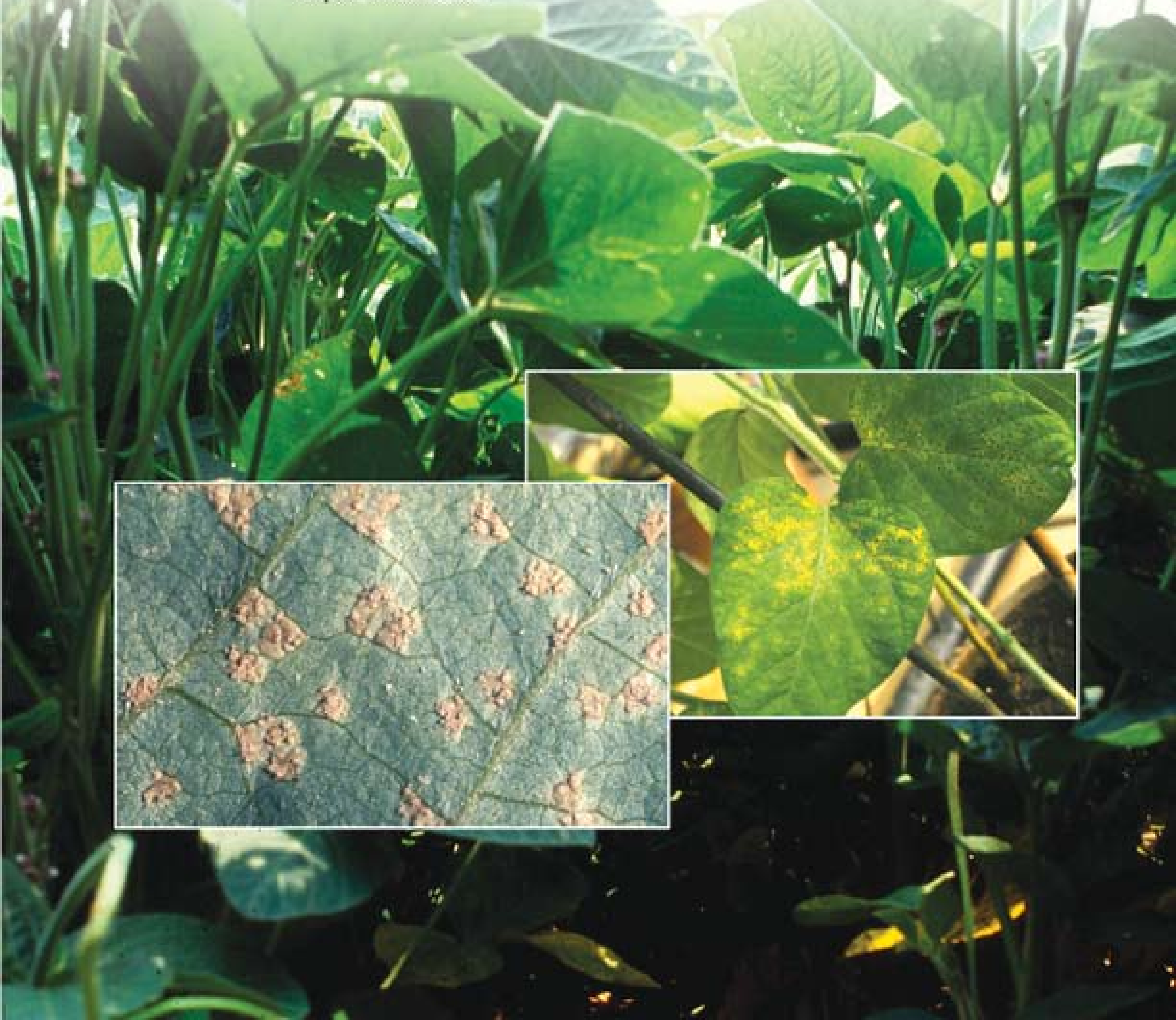
The Value of Plant Disease Early-Warning Systems

A Case Study of USDA's Soybean Rust Coordinated Framework

Michael J. Roberts, David Schimmelpfennig, Elizabeth Ashley,
Michael Livingston, with contributions by Mark Ash and
Utpal Vasavada



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Abstract

Early-warning systems for plant diseases are valuable when the systems provide timely forecasts that farmers can use to inform their pest management decisions. To evaluate the value of the systems, this study examines, as a case study, USDA's coordinated framework for soybean rust surveillance, reporting, prediction, and management, which was developed before the 2005 growing season. The framework's linchpin is a website that provides real-time, county-level information on the spread of the disease. The study assesses the value of the information tool to farmers and factors that influence that value. The information's value depends most heavily on farmers' perceptions of the forecast's accuracy. The study finds that the framework's information is valuable to farmers even in a year with a low rust infection like that of 2005. We estimate that the information provided by the framework increased U.S. soybean producers' profits by a total of \$11-\$299 million in 2005, or between 16 cents and \$4.12 per acre, depending on the quality of information and other factors. The reported cost of the framework was between \$2.6 million and almost \$5 million in 2005.

Keywords: Soybean rust, farmers' perceptions, forecast accuracy, updating beliefs, value of information, real-time disease location, plant disease management, pest management, risk management

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Contents

Summary

Early-warning systems for plant diseases are valuable when the systems provide timely forecasts that farmers can use to mitigate potentially damaging events through preventative management. For example, soybean rust (SBR), a soybean fungus, which entered the United States in late 2004, posed a new, uncertain, and potentially large threat at the beginning of the 2005 U.S. soybean season. Farmers anticipated markedly reduced soybean yields on fields infected with SBR, but with sufficient notice, they could treat the fields in advance with preventative fungicides, a costly, but prudent, measure.

What Is the Issue?

In 2005, USDA developed an early-warning system that provides real-time, county-level forecasts of soybean rust. This system provides farmers, crop consultants, and others with interests in the U.S. soybean crop timely forecasts of SBR infections that could sharply reduce soybean yields. Forecasts and recommended management activities are provided via a publicly accessible website, the first time a web-based system has been used for this purpose. The information on the website is developed through a large coordinated framework that involves many government and nongovernment organizations that regularly collect samples from fields, test them, and incorporate them into forecasting models. But how valuable is the information provided by the framework? This question has become particularly salient in light of modest outbreaks of SBR in 2005. This study uses the SBR system as a case study to determine the effectiveness of such early-warning systems.

What Did the Study Find?

The value of the framework's information depends on many factors, particularly farmers' perceived risk at the beginning of the season of SBR infection and the accuracy of the system's forecast. These factors cannot be precisely quantified, but our analysis shows that, although the value of information from the system varies somewhat geographically, overall the system's value exceeded its costs in 2005. Even if forecasts are imprecise, resolving only 20 percent of SBR infection uncertainty for all fields planted with soybeans, the system's value is an estimated $11 million in farmer profits in the first year. If forecasts resolve 80 percent of infection uncertainty, the estimated value is $299 million. Our analysis suggests that the value of the information in 2005 likely exceeds reported costs of developing the information of between $2.6 million and almost $5 million.

The study also analyzes two more subtle features that affect estimated information values: anticipated price shocks in the event of large rust outbreaks and soybean farmers' aversion to risk. We found that both of these factors reduce the largest estimated values and increase the smallest ones, but the magnitude of the effects are modest relative to the perceived forecast quality. The potential benefits of the framework suggest that similar programs for other crop pests can be cost effective if, as in the case of soybean rust, preventative action can strongly mitigate damages in the event of an outbreak.

How Was the Study Conducted?

The study applies conceptual methods from decision science to evaluate how much expected profits increase if farmers are able to fine-tune their rust management decisions in response to SBR forecasts. These methods are combined with USDA data on historical soybean yields, data from USDA's Agricultural Resource Management Survey, estimated soybean rust damages from Brazil and Paraguay, and spore dispersion estimates based on an aerobiology analysis and historical experience with wheat stem rust. Information values were calculated over a broad range of assumptions because some of the parameters were not estimable and some parameter estimates were uncertain.

Introduction

Information is valuable because it allows individuals to adjust their actions to suit the situation at hand. Quantifying the value of information involves determining the expected value of actions with and without the benefit of information and subtracting the second from the first.

Information is an economic good, but it is not the same as other economic goods like oranges, airplanes, or computers. Markets do not always create and disseminate information as efficiently as they handle other kinds of goods and services, mainly because it is hard for businesses to control access and charge all users. The government can step in to provide information, like hurricane or crop forecasts, that private markets may not provide when that information is needed by individuals to make better personal decisions. The U.S. Department of Agriculture (USDA) and other agencies also implement regulations that create incentives for individuals and businesses to provide information they otherwise may not. For example, the Food and Drug Administration (FDA) requires “Nutrition Facts” labels on food products. FDA also regulates food additives and drugs, requiring extensive testing via clinical trials, which provides information about their safety and efficacy. These examples are only a few of many ways government influences the creation and dispersal of information.

Because information is not normally traded in competitive markets like oranges are, quantifying its value is difficult, mainly because it involves quantifying what decisions would have been made without the information, and what the consequences of those decisions would have been. Information usually has some value because it matters to most decisions. Housing price forecasts influence demand and supply of homes. Information on the prices of everyday consumer goods at various retailers affects where people shop, how much they spend, and how much they can afford to buy. The magnitude of this information may or may not be as great as that stemming from forecasts of natural disasters, but the basic concept of value is much the same: Information simply allows individuals to make better decisions. The explosion of Internet use and the growing wealth of information it provides surely generate great value, despite the difficulty of quantifying it.

Type and timing of information are probably preeminent influences on value. Old information is hardly ever worth very much, nor is information of poor quality, even if it arrives on time. In determining the quality of information, the integrity of the source and its reputation are crucial because information, unlike many other kinds of goods and services, have many public goods attributes (see box, “Public Goods: Why Information Is More Like a Sunset and Less Like an Apple”). Characteristics of consumers of information, such as risk tolerance, and the structure of the market in which they operate also affect the information’s value.

Agriculture is an area in which various kinds of timely information can profoundly affect market and individual actions. Katz and Murphy conducted a relatively detailed analysis of the value of advance weather information, but little is known about factors influencing the value of early-warning systems for plant disease. This report begins to fill this gap.

To illustrate the value of early-warning systems for plant disease, this report considers as a case study the value of real-time, county-level information provided to farmers via the publicly accessible website http://www.sbrusa.net. USDA developed the website and its underlying coordinated framework to help soybean farmers cope with a new pest, *Phakopsora pachyrhizi*, a fungus commonly known as soybean rust (SBR). SBR, a recurrent problem for soybean producers in much of the southern hemisphere, was first detected in the U.S. in fall 2004, late enough in the season that it posed no threat to that year's soybean crop. After overwintering in the South, SBR posed a new, uncertain, and potentially large threat at the beginning of the 2005 U.S. soybean season. Farmers anticipated that fields infected with SBR would see markedly reduced soybean yields, but with sufficient notice, the fields could be treated in advance with preventative fungicides. An alternative response to an SBR threat is to monitor and treat with curative fungicides, but this requires even more timely information on the spread of SBR. The website and infrastructure were built and tested before SBR had caused any significant U.S. crop losses. They were developed to provide real-time forecasts of

Public Goods: Why Information Is More Like a Sunset and Less Like an Apple

Economists distinguish public goods from private goods, not by whether government or private markets physically provide them, but according to two characteristics of the goods themselves: rivalry and excludability. An apple is a rival good because, if one person consumes it, there is nothing left for someone else to consume. In contrast, one person watching a sunset probably does little to diminish the value of another person watching the same sunset—sunsets are nonrival goods. Like a sunset, information, such as a good SBR infection forecast, is nearly as valuable to the second person as it is to the first. An apple is also excludable: It is relatively easy for a person who owns it to keep others from consuming it. In contrast, it is more difficult to exclude others from consuming information and sunsets—they are nonexcludable. So, a private good is both rival and excludable, and a public good is both nonrival and nonexcludable.

The private-good label comes from the natural incentive of private markets to efficiently create and allocate rival and excludable goods and services. Private markets have less of an incentive to provide efficient amounts of nonrival and nonexcludable goods, which is why governments are more likely to provide public goods. Some argue, however, that few if any goods are purely public or private; most are somewhere in between. As a result, it is often debatable whether or not the Government should be involved with provision of goods that have public-good characteristics but are not pure public goods. Even sunsets, or at least some of the best places to watch them, reside on private property, so property owners can exclude others from watching them. And if a good viewing point becomes congested with too many sunset watchers, it may become congested, diminishing the value of the view to others. So a sunset can be partially rival, too. Similarly, information can sometimes be partially excludable and partially rival. But the public-good nature of SBR forecasts suggests that private markets may have not held an incentive to develop and distribute information as detailed and comprehensive as that provided by the SBR coordinated framework.

the local impending SBR threat and therefore to aid efficient monitoring of crops and application of preventative and curative fungicides—the first time a web-based system was used for this purpose.

Now, a full year after its first detection in the U.S., SBR has posed thus far little threat to the 2005 U.S soybean crop. Given the expense of developing the website and its underlying infrastructure, some have questioned whether the infrastructure was a worthwhile endeavor. After all, if some farmers had simply managed their crops as if there were no SBR threat, it is possible that they would have fared as well or better than they actually did in 2005.

This view overlooks a key point: Although weather conditions did not facilitate dispersion of SBR spores to key soybean-producing regions in 2005, this factor could not have been known in advance. A potential SBR threat existed at the beginning of the season, but how farmers might have prepared for that threat in the absence of the coordinated framework is not clear. Indeed, without the framework, individual farmers may have incurred even greater expenses by monitoring their own fields, perhaps spraying fungicides for a threat that did not exist in their area, or forgoing planting entirely.[1] Even if you build it and rust does not come, the information from the coordinated framework could have significant benefits.

[1]In this case study, we do not consider farmers' planting decisions, only their fungicide application decisions, provided they do plant. By ignoring this decision, we underestimate the value of information provided by the framework.

This study shows how various factors influence the benefits to farmers from the framework. It explains how farmers' prior beliefs about the likelihood of infection (based on location and perhaps other factors), the perceived accuracy of the framework's SBR forecasts, and the costs and benefits of different rust management strategies collectively influence the value of information provided. The value may also depend on farmers' risk preferences and how soybean prices would be affected by SBR-induced production shocks.

Our analysis indicates that the value of the coordinated framework depends on how much it enables farmers to fine-tune their management practices rather than the presence of rust itself. Information is most valuable to farmers when ambiguity is greatest about whether or not to apply chemicals. Regional factors, including the likelihood of rust, farm size, profitability, and yields in the absence of rust, create information values that vary across the country. This report estimates the value of the framework only for soybean producers. The framework, however, could also benefit other groups: fungicide companies, which might use the information to shift stocks of chemicals between outlets to meet evolving needs; livestock producers, who might be able to fine-tune their management decisions; and consumers (e.g., livestock producers), who might benefit from accurately anticipating supply shifts and their implied effects on soybean prices.

Valuing the Information Provided by the Coordinated Framework

USDA's coordinated framework provides a range of services that farmers may use, directly or indirectly, to manage SBR risks. Elements of the program include surveillance and monitoring of potential infections, predictive modeling, developing fungicide management strategies, and communication and outreach. The framework involves collaboration of many government and nongovernment agencies and universities, with the culmination of their efforts reported on the publicly accessible website.[2]

Our analysis of the information provided by the framework need not presume that all farmers access the website. The framework provided fungicide companies, crop consultants, extension specialists, and perhaps other intermediaries with an accessible repository of information that could have been channeled to farmers. A picture of the website is given in figure 1. More detail about the framework is described in the box, "The Coordinated Framework and www.sbrusa.net."

The value of information is closely tied to whether the framework provides farmers with useful information to fine-tune their SBR management decisions. Without the information, farmers may be more likely to monitor their fields and apply costly fungicides when it is inappropriate to do so (when SBR risk is low) or not monitor and apply costly fungicides when they are likely to be most effective (when SBR risk is high).

During the growing season, after the soybean crop is planted, the main SBR management decisions a farmer must make are whether or not to apply a preventative fungicide, to monitor fields and apply a curative fungicide if SBR occurs, or to do nothing (fig. 2 and app. fig. 1).[3] The optimal strategy depends on farmers' perceived risk of SBR. Thus, the better information farmers have about the threat, the more likely they will choose the optimal management strategy and the greater their expected profits will be. We calculate the value of information as the increase in expected profits, as viewed from the beginning of the growing season, stemming from improved SBR forecasts that arrive between first plant emergence and flowering.

Although the information is public and freely available, one might also view its value as the most farmers would have been willing to pay for the information service at the beginning of the season. It is important to consider the expected value of information before the season, not after, because that is when decisions about investments in information technologies are necessarily made.

Strategies for Managing Soybean Rust

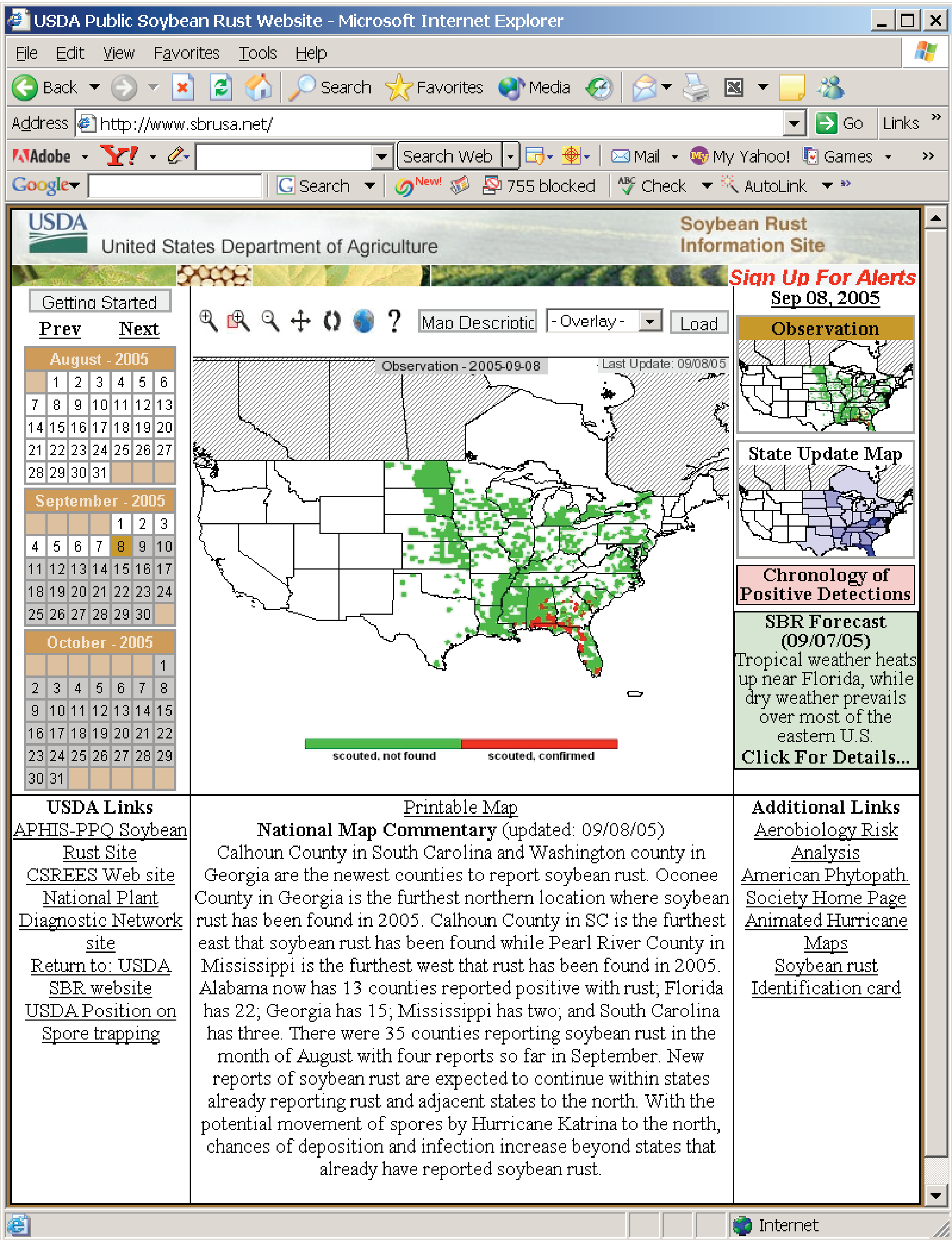
Developing estimates of this value requires estimates of the costs and benefits of each of the three management strategies: (1) applying a preventative fungicide, (2) monitoring fields and then applying a curative fungicide in the event SBR occurs, or (3) doing nothing and bearing SBR losses should they occur.[4] The website provides information that might be used to forecast an impending SBR threat, and farmers may use the information in choosing a management strategy. Here we describe the costs and benefits of each strategy.

[2]These agencies include Animal and Plant Health Inspection Service (APHIS), USDA; Cooperative State Research, Education and Extension Service (CSREES), USDA; Agricultural Research Service (ARS), USDA; National Plant Board (NPB); American Soybean Association (ASA); United Soybean Board (USB); American Seed Trade Association (ASTA); and North Central Soybean Research Program (NCSRP) (see "Abbreviations" at the end of the report for all acronym definitions). The framework also drew on the collaboration of the Cooperative State Extension Services based mainly at land-grant universities.

[3]To simplify our analysis, we focus on farmer management decisions that occur after planting. In reality, farmers may react to the possibility of soybean rust infection by switching to other crops or taking some of their acreage out of production. Calculating the pre-planting value of information would lead to different results than what we present in this report. The framework may also allow farmers to improve the timing of the application of preventative sprays that improve their efficacy. Poorly timed sprays could lead to the need for second applications. We do not attempt to quantify the value of improved timing, which would likely increase the presented estimates of the value of information. See Dorrance, Draper, and Hershman for current fungicide use guidelines.

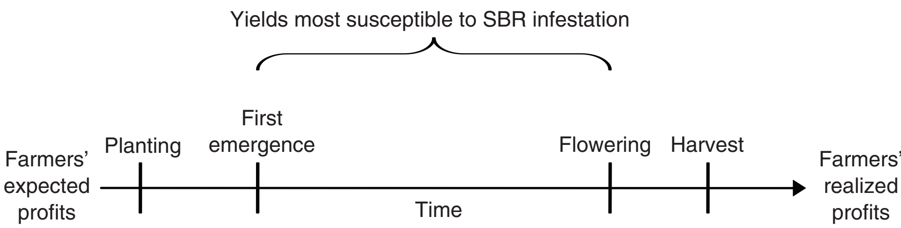
[4]We have chosen two strategies for the analysis that might be combined under some field conditions. One spraying regimen for the monitor-and-cure strategy that has been used is to apply both curative and preventative fungicides at the same time.

Figure 1
The SBR website on September 8, 2005, www.sbrusa.net



The first strategy is to apply a preventative fungicide, which must be done before infection to be effective. Using estimates developed in previous ERS research and discussed in the appendix, at $25.63 per acre, the estimated cost of preventative fungicide is high, but if applied before an impending SBR threat, estimated yield losses due to SBR are estimated to be 1 percent.

Figure 2
Timeline for SBR management decisions



The Coordinated Framework and www.sbrusa.net

Two SBR websites are maintained under the framework: One is public, and one is not. The nonpublic website is designed to integrate information from the large network of disease-management professionals who gather data and analyze it. The nonpublic website has different screens for the different user groups. The layouts of these screens include a calendar of archived products, a map display, Geographic Information System (GIS) tools for navigating the maps, map reference overlays, support materials to identify SBR in the field, an entry tool for commentary, an edit tool for links, a researcher observation map (which displays suspected as well as confirmed infections), and a list of model simulation maps. The simulation maps, which are selectively displayed for each user group, include daily spore transport, daily wet deposition of spores over land, accumulated wet deposition of spores over land, and other forecast model variables.

The public website (http://www.sbrusa.net), a snapshot of which is displayed in figure 1, is linked to USDA's homepage (http://www.usda.gov/) and is the central reference tool for farmers, researchers, and others who want to know about the advent and management of the SBR fungus. The national map shows where SBR was either found and confirmed by standard laboratory operating procedures (red) or not found (green) in a given county. A calendared archive allows viewers of the map to track the movement of SBR across the United States and Canada. The website provides a user with GIS tools for zooming from the national to the subcounty scale and offers interstate highways, soybean-growing areas, county boundaries, and major cities as reference overlay options. A State Update map provides periodic commentary by State specialists, including a history of observations, current growth stages, management, forecast outlook, scouting recommendations, and scouting techniques. A Chronology of Positive Detections provides the public with a pop-up text box listing positive finds by date, State, and county. The SBR Forecast is a pop-up text box that informs the public about daily forecasts of transport and deposition of SBR spores made from prevailing and forecasted weather conditions and soybean rust model predictions.

Visitors can also view pictures and descriptions to identify soybean rust, read up on the disease, and find links to other SBR sources. These sources include the National Plant Diagnostic Network (NPDN), the Plant Management Network, the American Phytopathological Society, Extension Disaster Education Network, regional Integrated Pest Management centers, and the USDA National Agricultural Library. The site's fungicide section includes best practices guidance and product approval updates from the Environmental Protection Agency. The crop insurance link offers an agent locator, along with policy information and news from USDA's Risk Management Agency.

The first component of the detection program is a sentinel plot system. Funded by USDA and the United Soybean Board (USB), these plots are located in over 30 States and are examined regularly for signs of soybean rust. In addition to providing real-time warnings of new disease discoveries via the SBR map, testing allows for quantification of the timing of spore production and the collection of data for epidemiological research. Sentinel plots are usually planted to early-maturing soybean varieties and are located in areas with heavy soybean production and in possible overwintering havens (i.e., areas south of the 28° F line, which is the latitude limit of SBR overwintering). The plots can be made up of alternative hosts of the disease, including pigeon pea, yam, beans, kudzu, and leguminous winter cover crops, in addition to soybeans. The plots are inspected for disease at least every 3 days in high-risk areas and at least once a week elsewhere.

Once the crop is infected with SBR, a different, curative fungicide may be applied at a lower cost of $13.81 per acre. The curative option is somewhat precarious, however, as it must be applied within the first few days after soybean plants are infected. Curative fungicides also tend to be less effective, resulting in an estimated yield loss of 7 percent. This option, therefore, requires regular monitoring of fields between emergence and full podset, at an estimated cost of $6.71 per acre, so that farmers can apply the curative fungicide in a timely manner. If farmers choose this strategy, they must pay monitoring costs regardless of whether or not an SBR infection actually occurs.

The third option is simply to do nothing. This option clearly has the lowest cost but results in estimated yield losses of 25 percent in the event the field is infected with SBR.[5]

[5]Yield loss estimates are based on analysis of yield data from Brazil and Paraguay, where farmers have some experience with actual rust infections. More details about our estimates of fungicide costs, monitoring costs, and yield losses are in the appendix.

In order to extend the capacity of the monitoring program beyond the scope of sentinel plots, the coordinated framework dispatches mobile teams to observe disease incidence in assigned regions. Cooperative Extension Services urge county extension agents, growers, and private crop consultants to scout for SBR and to bring samples to the closest land-grant university diagnostic laboratory. Samples from these sources, as well as sentinel testers and mobile teams, are submitted to NPDN, a network that links plant disease and pest diagnostic clinics from around the country.

After initial screenings for SBR are performed by State laboratories or the NPDN, positive findings are sent to USDA's Animal and Plant Health Inspection Service (APHIS) for confirmation. APHIS's Plant Protection and Quarantine (PPQ)-National Identification Service morphologically examines samples for physical damage from SBR, and the PPQ-Center for Plant Health Science and Technology performs real-time polymerase chain reaction procedures. Diagnostic authorities enter all results in one of several SBR databases, either the Plant Diagnostic System (PDIS), the Southern Plant Diagnostic Network (SPDN), the National Pest Information System (NAPIS), or APHIS records. NAPIS, located at Purdue University, serves as the archive for data from regional networks. Information from APHIS, PDIS, and SPDN is transferred to NAPIS and, from there, is uploaded to the SBR map.

Besides results gleaned from its own diagnostic activities, the coordinated framework incorporates pertinent information from a variety of other sources. Industry surveys provide rust location information for areas outside the reach of sentinel plots, international networking allows for the monitoring of offshore SBR source areas, and rain is sampled for spore presence.

All the data are used to develop SBR early-warning systems and to calibrate spore deposition models. APHIS joined with North Carolina State University (NCSU) and ZedX, Inc., to develop the NCSU/APHIS Plant Pest Forecast System. Concurrently, Penn State University and ZedX, Inc., developed the Integrated Aerobiological Modeling System (IAMS) in collaboration with APHIS. IAMS combines biological and meteorological science to predict movement patterns for windborne species, such as soybean rust. IAMS was modified to address the specifics of SBR, and the resulting model is known as the Soybean Rust Aerobiology Prediction System. The forecasts describe risk levels for sensitive plants in potential rust-harboring regions throughout the United States. Predictive forecasting, although in its first year of testing, may provide useful data well before SBR is observed in the field. For example, it could be used to time fungicide applications, thereby delaying first applications and eliminating second applications. As an additional benefit, these models inform decisions as to which sentinel plots merit increased frequency of monitoring.

Agencies affiliated with the coordinated framework have engaged in communication and outreach activities to disseminate surveillance and modeling results to growers beyond making information available on the website. These activities include workshops, symposia, telephone hotlines, and e-mail alert lists. Land-grant university extension personnel have also made special efforts to communicate with soybean producers on such topics as fungicide selection and timing, decision criteria and risk management, and correct interpretation of the SBR map.

Table 1 presents the outcomes from the three management strategies cross-tabulated with the two possible SBR events: an SBR infection (the first column) and no SBR infection (the second column). Costs and benefits vary somewhat across regions, depending mainly on regional differences in typical yields in the absence of SBR. For example, because yields in the Corn Belt are about 65 percent greater than those in the Southeast, so are the potential losses from an SBR infection.

An important caveat is that the estimated returns in table 1 exclude possible yield-enhancing effects from fungicide application even when SBR does not occur. After the fall 2005 harvest, fields sprayed with fungicides but not infected with SBR nevertheless had higher yields than fields not sprayed, suggesting that the fungicides mitigated losses from pests other than SBR and thus enhanced yields despite SBR's absence. Table 1 does not account for this possible auxiliary benefit to spraying, mainly because it would seem unlikely that the benefit would have been anticipated in advance but also because the magnitude of this yield-enhancing effect remains uncertain. If one wished to incorporate this effect into the analysis, one could do so by adjusting the payoffs associated with the preventative treatment.

The Uncertainty of SBR Infection

We assume farmers would like to fine-tune their decisions to the SBR event, but which event will arise is uncertain. If SBR does occur, scenario 1, applying preventative treatment, has the highest profit (table 1). If SBR does not occur, scenario 6, no SBR management (or doing nothing), has the highest profit. In other words, given the values in table 1, applying the preventative fungicide if an SBR infection is sure to occur is most profitable and doing nothing is most profitable if SBR is sure not to occur.

Because the SBR event is uncertain, farmers may find at harvesting that their strategy was not optimal. On the one hand, farmers who believe an infection is very likely and, thus, apply the preventative fungicide could needlessly apply the costly fungicide if SBR does not occur. On the other

Table 1
Possible farm outcomes from the possibility of SBR infection

Management strategy	SBR infection	No SBR infection
Apply preventative treatment	Payoff 1: 1% yield loss, cost of $25.63/acre	Payoff 2: Cost of $25.63/acre
Monitor fields and apply curative treatment if SBR	Payoff 3: 7% yield loss, cost of $2.52/acre	Payoff 4: Cost of $6.71/acre
No SBR management	Payoff 5: 25% yield loss	Payoff 6: Base return (as if no SBR threat)

Source: M. Livingston, R. Johansson, S. Daberkow, M. Roberts, M. Ash, and V. Breneman, *Economic and Policy Implications of Wind-Borne Entry of Asian Soybean Rust into the United States*, Outlook Report No. OCS-04D-02, Economic Research Service, U.S. Department of Agriculture, April 2004, Available at http://www.ers.usda.gov/Publications/ocs/apr04/ocs04d02/.

hand, farmers who believe an infection is unlikely may choose to do nothing and will find that the decision is not optimal if their fields are infected. If farmers choose the monitoring-curative option, they will always find that their decision is suboptimal at harvesting, but the loss is less than if they choose the worst of the other two strategies. The optimal decision thus depends not just on the costs and benefits of each strategy under certainty, but also on the probability that an SBR infection will occur.

The Role of Information

Information does not affect the possible outcomes, only farmers' beliefs about whether SBR will occur and the management actions taken in response to those beliefs. An accurate forecast of an impending SBR threat will cause farmers to increase their perceived probability that rust will occur and may cause them to choose the preventative strategy. Alternatively, an accurate forecast that SBR poses little or no threat may cause them to do nothing. For the forecast to have economic value, it needs to be timely enough and reliable enough to influence farmers' management strategies. If the information influences farmers' decisions in this way, it reduces the chance of after-the-fact errors, described earlier. In other words, the better the SBR forecast, the more likely that farmers will end up in scenarios 1 or 6 and the less likely that they will end up in one of the other scenarios and regret their decision later. The reduced error rate translates into higher expected profits at the beginning of the season, creating value to the producer.

Two key features needed to value information in this way are farmers' beliefs about the probability of SBR occurring in the first place (their prior beliefs) and the perceived quality of the SBR forecast, which may cause farmers to change their beliefs. Prior beliefs matter because if farmers are already confident that an infection will or will not occur, new information is unlikely to affect their management strategy, and therefore creates little value. Conversely, information will have the greatest value to farmers with prior beliefs near the critical probabilities of SBR that mark changes in the optimal management strategies. For these farmers, the website information may cause them to change their management strategy and reduce their after-the-fact errors.

In this report, information quality refers to the accuracy of the framework's SBR forecast. The greater the quality, the more weight farmers will give to the forecast relative to their prior beliefs and the more likely they will be to alter their management strategies in light of information received. Because it is difficult to quantify the framework's quality of information in its first season, we consider a range of information qualities. The appendix provides a more precise explanation of the broader framework, including how the range of information qualities was derived.

Results

The Corn Belt Region

We begin by focusing on basic results for a single region in order to clarify the concepts just discussed. We chose the Corn Belt because it produces more soybeans than any other region. In subsequent sections of the report, we examine other regions and the U.S. as a whole. We assume base production costs (irrespective of rust), a per bushel soybean price equal to the early season (May 2, 2005) futures price, and other average farm characteristics.[6] These assumptions can be combined with the data in table 1 to estimate profits for a representative farmer in the Corn Belt, which are reported in table 2.

From the possible outcomes in table 2, we evaluate the profit-maximizing management strategy and expected profits for a representative farm in the Corn Belt, depending on farmers' prior beliefs. Farmers' prior beliefs are given by the probability of being in the first column (an SBR infection) or the second column (no SBR infection). Because we cannot know farmers' prior beliefs, we evaluate their optimal (expected profit-maximizing) management strategies over a range of prior beliefs.

We find that, for that farmer, if the prior belief is a less than 19-percent chance of SBR, the optimal management strategy is to do nothing. If the prior belief is between a 19- and 63-percent chance of SBR, the optimal management strategy is to monitor fields and apply a curative fungicide if SBR occurs. If the prior belief is a greater than 63-percent chance, the optimal strategy is to apply the preventative treatment.

For each of many prior beliefs over the full range of 0-100 percent, we then evaluate the value of information associated with each of three information qualities. The information qualities are ranked on a scale from 0 to 1, with 0 indicating a forecast with no predictive power and 1 corresponding to an ideal in which the coordinated framework perfectly predicts SBR infections in advance. We consider three information qualities: low, with a value of 0.2; medium, with a value of 0.5; and high, with value of 0.8. One may think about these information qualities as the proportion of uncertainty

[6]Base production costs do not affect the value of information because they are subtracted from revenues under all SBR management strategies and SBR outcomes. The representative acreage size affects only the value of information per farm, not value per acre. The purpose of these numbers is to provide a tangible perspective for the profit values.

Table 2
Possible profit outcomes for a representative Corn Belt farm[1]

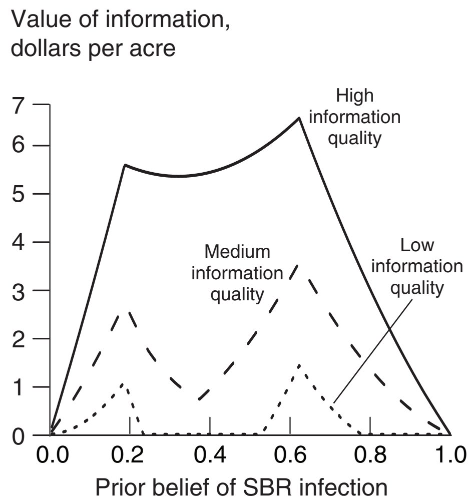
Management strategy	SBR infection	No SBR infection
	Dollars	
Apply preventative treatment	Payoff 1: 91,031	Payoff 2: 93,079
Monitor fields and apply curative treatment if SBR	Payoff 3: 82,532	Payoff 4: 107,118
No SBR management	Payoff 5: 60,885	Payoff 6: 112,097

[1]For this farm, production costs are $125 per acre, base yield is 44.6 bushels per acre (calculated from the regional soybean yield trend evaluated for 2004), and the farm has 742 acres of soybeans. The representative farm is defined as the farm associated with the average acre of soybean in the region. See the appendix for details.

resolved by information provided by the framework.

Per acre information values for these three information qualities are plotted in figure 3 over the whole range of possible prior beliefs. For each information quality, the value peaks at 2 points, at prior infection beliefs of 19 percent and 63 percent. These points correspond to critical prior beliefs that mark switching points between the optimal strategies and the points with greatest ambiguity for farmers. Values are highest near these switching points because information has the greatest scope for altering farmers' decisions.

Figure 3
Possible information values for the Corn Belt



Depending on farmers' prior beliefs and information quality, the value of the framework's information ranges from $0 to $6.38 per acre, or from $0 to $4,732 for the representative farm. The appendix reports a more detailed description of these values for a range of prior beliefs.

Base Case Result for All Regions

One cannot objectively quantify prior beliefs and the information provided by the coordinated framework. These values are ultimately subjective and will vary across regions and individual farmers. Although beliefs are subjective, one can reasonably expect them to be grounded roughly according to objective knowledge. For example, southern regions are thought to be more susceptible to SBR, so farmers in the South will reasonably believe that the probability of infection is high compared with that further north. To develop proxies for farmers' beliefs, we estimated the probability of infection for each region and assumed that the estimated probability represented farmers' prior beliefs of infection. Details about this estimation procedure are given in the appendix.

The estimates suggest that a reasonable average prior infection probability for the Corn Belt is 0.55. This probability corresponds to information values in the middle to higher range of those plotted in figure 3 and reported in appendix table 3, depending on the quality of information.

Scenarios similar to those presented for the Corn Belt were developed for other U.S. regions by using representative soybean production values for each region, but rather than consider a range of prior beliefs, we set assumed prior beliefs equal to our estimated probability of infection. Like the analysis of the Corn Belt region previously discussed, we consider each of three information qualities: low (0.2), medium (0.5), and high (0.8).

Regional information values per acre (app. table 2) vary due to differences in the probability of infection (column (a)) and differences in soybean yields in the absence of SBR (column (c)) across the Nation. Value per farm also varies due to regional differences in representative soybean acreage. For the lowest information quality, values range from $0 (Delta, Lake States, Northern Plains, and Southeast) to $0.64 per acre (Appalachia). For the medium information quality, values range from $0.82 (Northern Plains) to $2.48 per acre (Corn Belt). For the highest information quality, values range from $3.48 (Southeast) to $6.01 per acre (Corn Belt).

Besides the probability of infection, information quality, and base yields, the per acre value of information also depends on assumptions about farmers' risk preferences, how SBR-induced yield losses affect soybean prices, and how beliefs about the probability of infection vary within regions. In the following sections, we examine how the value of information changes as these assumptions are altered.

Risk Aversion

For the base case scenarios (app. table 2), farmers are assumed to maximize expected profits—what they would earn on average if they faced the same chances of SBR infections repeatedly over many seasons. If, however, farmers are risk averse, they also care about profit variability. For example, everything else being equal, a risk-averse farmer will be more inclined to choose the preventative treatment because the worst and best outcomes are more similar under this management decision than they are under the others. We, therefore, examine how the information values change if farmers are strongly risk averse.

We formalize the notion of risk aversion by assuming that farmers have *diminishing marginal utility of wealth*, which means that each additional dollar in wealth (or profits) is valued somewhat less than dollars already possessed. We consider the reported net worth for the representative farm in each region as a base level of wealth. We then examine how wealth and utility of wealth change for different management decisions and SBR outcomes. Additional discussion of our application of risk aversion to the problem of modeling the value of SBR information is in the appendix.

Incorporating risk aversion into the analysis increases the value of information for some regions and scenarios and reduces it for others. Overall, the difference between the risk-averse scenarios and the base case scenarios are modest relative to the influence of information quality and prior infection beliefs (app. table 3). For example, in the Corn Belt, a strongly risk-averse farmer values low-quality information at $0.37 per acre versus the base case value of $0.22. Alternatively, the same risk-averse farmer values high-quality information at $4.89 per acre, somewhat less than the base case value of $6.01.

In general, risk aversion tends to increase the lowest information values and reduce the highest values compared with base case values. The reason for this pattern is rather subtle: High-quality information has a stronger influence on management decisions, which ultimately causes profits to be more variable. Because risk-averse farmers dislike profit variability, high-quality information is valued somewhat less by risk-averse farmers compared with risk-neutral farmers. Low-quality information tends to affect decisions less, which tends to reduce profit variability, making the information more valuable to risk-averse farmers compared with risk-neutral farmers.

Commodity Price Effects

In the base case scenario, we assume that soybean prices were fixed at the early-season, May 2 futures price of $6.19. In reality, commodity prices vary markedly over time, depending on various events that affect supply and demand, including pest infections. This point is discussed more fully in the appendix. If SBR were to cause marked yield losses for a significant share of U.S. soybean acreage, one might expect soybean prices to increase as a result of the reduced supply. We, therefore, examine how the base case values change when accounting for these price effects.

We approximate the price effect of SBR yield losses by examining how historical yield shocks are associated with price changes. A region's "yield shock" refers to deviations from the regional trend in yields. Positive yield shocks tend to be associated with lower prices, and negative yield shocks tend to be associated with higher prices. These associations are stronger in regions with higher levels of soybean production (such as the Corn Belt)—because the yield shocks have a greater effect on the overall market—and less strong in regions with less soybean production. We estimated these associations by using regression analysis. Details of the analysis are available in the appendix.

For most regions, accounting for price effects has a small effect on information values relative to information quality and prior infection beliefs. The effect is somewhat greater in the Corn Belt and Northern Plains because yield shocks in these soybean-intensive regions have larger estimated price effects (app. table 4). In the Corn Belt, for example, the value of low-quality information increases from the base case amount of $0.22 per acre to $0.70 per acre and declines from $6.01 to $5.75 for high-quality information. In the Southeast, where the estimated price effects are far smaller, the values of both low-quality and high-quality information are unchanged at $0 and $3.48 per acre, respectively.

Heterogeneous Infection Beliefs

In appendix table 1, we illustrate how the framework's information value critically depends on farmers' beliefs about the probability of SBR infection (for the Corn Belt). In the base case scenarios, we assume that all farmers within a region hold similar infection beliefs and that those beliefs vary from one region to another. In appendix table 5, we consider information values when farmers within each region have widely varying beliefs about the likelihood of SBR infection. In other words, we assume that, within each region, before receiving any information from the framework, some farmers believe an SBR event would almost surely occur, some believe SBR almost surely would not occur, and others hold beliefs at all points between these extremes. On average, however, we assume that farmers within a given region have similar beliefs about the probability of infection, as presented in column (a) of the base case scenario (app. table 2).

This subtle difference in our assumption about farmers' infection beliefs can have a strong influence on the estimated information values. The difference stems from the lower value that farmers with especially high or low prior beliefs of SBR infection place on information. Thus, the more widely varying or heterogeneous farmers' beliefs are, the more we encounter farmers with extreme beliefs that generate both low and high information values (app. table 5). Compared with the base case scenario, average information values for the Corn Belt decline from $6.01 to $4.04 for high-quality information and increase from $0.22 to $0.25 for low-quality information. Similar differences are observed for other regions. In general, heterogeneous infection beliefs tend to reduce the highest information values and increase the lowest ones. The highest values decline because they are associated with the highest value prior beliefs—those near the critical probabilities that mark the switching points between strategies. With heterogeneous beliefs, these high-value prior beliefs are averaged with lower value prior beliefs, bringing down the overall average. Conversely, the lowest value prior beliefs are averaged with higher value prior beliefs, which bring those values up.

Aggregate Costs and Benefits of USDA's Coordinated Rust Framework

A portion of the effort in developing and running the framework involves redirecting existing resources into activities that support the framework. Some of the salaries and overhead expenses are difficult to attribute to the framework, although without the framework, these funds would likely have been allocated to other activities. In 2005, USDA expected to spend $180,000 on six mobile survey teams to be deployed after the first confirmations of soybean rust in specific regions. USDA estimated that soybean rust diagnostic services would come to $45,000 for each of 26 States. The U.S. Government Accountability Office (GAO) (2005) surveyed 31 States, and the respondents reported a total estimated diagnostic cost of $703,180, or $22,683 per State in 2005. Finally, a spore deposition sampling program is expected to cost $300,000 in 2005 (USDA, 2005a). These data and estimates suggest a range of total costs for the coordinated framework of between $2,357,303 (GAO, 2005) and $4,355,000 (GAO, 2005; USDA, 2005a) for 2005. Measured against reported planting intentions, this cost comes to $0.03-$0.06 per planted soybean acre (USDA, 2005b).

Additional data provided by the National Program Office of USDA's Cooperative State Research, Education, and Extension Service (CSREES) included estimates of what USDA ($800,000) and the North Central Soybean Research Program (NCSRP) or United Soybean Board (USB) ($287,000) had actually spent on the sentinel plot program and an estimate of diagnostic lab spending ($600,000) in 2005. These updated estimates include updated allowances for labor costs. The total number of sentinel plots for 2005 is 906, 720 of which are funded by USDA and USB and an estimated 186 are funded by growers, agribusinesses, and State departments of agriculture. USDA (2005a) estimated that maintenance would take 1.6-2.4 hours per week per sentinel plot during the 3-4 months that the plots were to be maintained, which translates into roughly 17,000-34,000 extension specialist hours. These figures provide an estimate of the total cost of the coordinated framework for 2005 of between $2,632,000 and almost $5 million. These rough estimates of framework costs could be refined by identifying one-time fixed costs to build the framework separately from variable (annual and recurring) costs. Appropriate discounting could then be applied to the separate costs.

To approximate the coordinated framework's value of information in 2005, we aggregate estimated per acre values for individual regions. Table 3 provides these figures for each information quality level and scenario (base case, risk aversion, price feedback, and heterogeneous beliefs). We aggregate the values by multiplying each region's acreage by the per acre information value associated with the particular quality level and then sum across regions.

Aggregate values range from $11.2 million (base case) to $28.8 million (price feedback) for low-quality information, $81.2 million (heterogeneous beliefs) to $124 million (price feedback) for medium-quality information, and $210.1 million (heterogeneous beliefs) to $298.5 million (base case) for high-quality information. Although the information quality may in fact be higher in some regions than in others, these aggregate values should provide approximate values, depending on the framework's quality of information.

Risk aversion, price feedback, and heterogeneous beliefs all increase the lowest information values and reduce the highest information values compared with the base case but each for a different reason. This variation causes the ranking of values across scenarios to be different for different information qualities. For example, the base case scenario has the lowest aggregate value for low-quality information and the highest value for high-quality information.

Table 3
Aggregate information values for the U.S.

Scenario	Information quality		
	Low (0.2)	Medium (0.5)	High (0.8)
		Dollars	
Base case:			
U.S. total	11,247,380	113,715,650	298,521,730
Average per acre	.16	1.57	4.12
Risk aversion:			
U.S. total	16,870,790	119,851,600	233,582,010
Average per acre	.23	1.66	3.23
Price feedback:			
U.S. total	28,773,280	124,143.000	285,412,460
Average per acre	.40	1.72	3.94
Heterogeneous beliefs:			
U.S. total	16,777,090	81,237.100	210,149,490
Average per acre	.23	1.12	2.90

Conclusions and Cautions

This report provides a comprehensive case study that examines the value of a plant disease early-warning system. The analysis shows how the value of the system can be traced to the costs and benefits of different management strategies and to the precision and timeliness of the system's forecasts. To our knowledge, this study is the first to examine the value of a disease-warning system. The study is also unique in its scope, examining how risk aversion, price feedback effects, and heterogeneous beliefs affect the value of information.

Our aggregate regional estimates of the value of information provided by USDA's coordinated framework to soybean producers in 2005 range from $11 million to $299 million over the many scenarios considered. Although the range is broad and the estimation requires us to make assumptions that are not verifiable, the results suggest that the framework's benefits exceed its budgetary cost, which was between $2.6 million and almost $5 million. The value, whatever it may be, does not depend on whether SBR outbreaks occur or not. Rather, the value depends on prior beliefs—subjective beliefs at the beginning of the season about the probability that SBR will occur. It also depends on the framework's quality of infection forecasts. Information about farmers' prior beliefs may be more difficult to ascertain, especially because the beliefs are likely to change over time. Complicating factors, like risk aversion and market price impacts stemming from infection-related yield losses, have been shown to be of lesser importance.

Given the potential benefits of improved SBR forecasts in this case study, exploring the broader applicability of web-based information systems also might be useful to management of other crop pests. Our analysis of the SBR framework suggests that the potential benefits would be greatest for pest problems that can be mitigated through preventative management activities.

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Abbreviations

APHIS	Animal and Plant Health Inspection Service, USDA
APS	American Phytopathological Society
ARL	Air Resources Laboratory
ARS	Agricultural Research Service, USDA
ASA	American Soybean Association
ASTA	American Seed Trade Association
CPHST	Center for Plant Health Science and Technology
CSREES	Cooperative State Research, Education, and Extension Service, USDA
EDEN	Extension Disaster Education Network
EPA	Environmental Protection Agency
HYSPLIT	Hybrid Single Particle Lagrangian Integrated Trajectory
IAMS	Integrated Aerobiological Modeling System
IPM	Integrated Pest Management
NAPDFC	North American Plant Disease Forecast Center
NAPIS	National Agricultural Pest Information System
NAPPFAST	NSCU/APHIS Plant Pest Forecast System
NCSRP	North Central Soybean Research Program
NCSU	North Carolina State University
NIS	National Identification Service
NOAA	National Oceanic and Atmospheric Administration
NPB	National Plant Board
NPDN	National Plant Diagnostic Network
NPGBL	National Plant Germplasm and Biotechnology Lab
PCR	Polymerase Chain Reaction
PDIS	Plant Diagnostic System
PDMP	Pest Detection and Management Programs
PPQ	Plant Protection and Quarantine
RMA	Risk Management Agency, USDA
SBR	Soybean rust
SPDN	Southern Plant Diagnostic Network
SRPS	Soybean Rust Prediction System
USB	United Soybean Board

Appendix: Modeling the Value of Information

Information has value to the extent that it helps individuals and firms make better decisions. Currently, an improved SBR forecast allows farmers to make SBR management decisions more suited to the actual SBR situation. The more accurate the forecast, the more decisions can be fine-tuned to the situation and the less likely farmers will be to make management decisions that turn out to be suboptimal—that is, the less likely they will be to spray fungicides when SBR is not a threat and not spray fungicides when SBR does occur. This appendix provides a detailed description of how we formalized a concept of the value of SBR information and arrived at the estimates described in the body of the report.

Our approach to valuing information has broad theoretical underpinnings in the literature on Bayesian decisionmaking. Our updating mechanism is necessarily more rudimentary than commonly applied because of the rough data available on farmer's prior and posterior probabilities of infection. For more background, Lindley reviews the basic concepts underlying the value of information in decision science. Lawrence provides a number of applications of the basic theory. The edited volume by Katz and Murphy examines the value of weather forecasts and includes analyses that use methods similar to the one presented here.

The most crucial assumption in assessing the value of information concerns the quality of the information provided. In this context, information quality pertains to the accuracy of the SBR forecast implicit in information provided by the framework. The more accurate the forecast affecting farmers' prior belief about the probability of infection, the more it affects farmers' SBR management decisions and the less likely farmers will be to regret their management decisions at harvest time. Unfortunately, information quality is also the most difficult feature to objectively quantify. Our solution to this quandary is to estimate information values for a range of information qualities.

The Conceptual Framework

To estimate the value of information, we evaluate farmers' profit-maximizing management decisions with and without information from the framework and estimate the difference in expected profits. In our base case, this difference in expected profits is the economic value of information. In the other cases, the concept is similar but with some additional features.

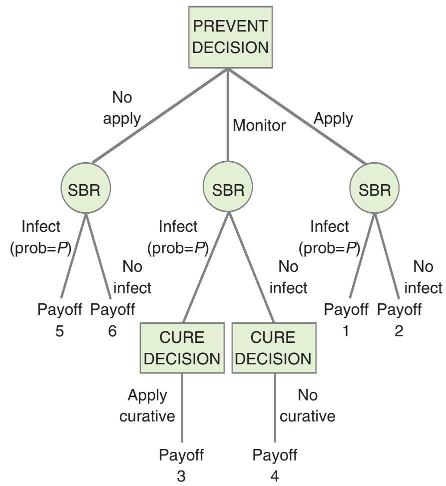
SBR Management and Expected Profit Without the Framework

We first consider farmers' optimal management strategies and expected profits without the benefit of information from the framework. Our analysis assumes that farmers have three possible management strategies: (1) apply a preventative fungicide before SBR occurs; (2) intensively monitor fields and then apply a curative fungicide if SBR occurs; or (3) do nothing—that is, manage soybean fields as if SBR were not a potential threat. Any given farmer's profit-maximizing decision depends on the costs of preventative and curative fungicides, monitoring costs, yield losses in the event of an SBR infection for each management strategy, soybean prices, and farmers' perceived likelihood that an SBR infection will occur. These assumptions were described in the body of the report and a more detailed description of how we arrived at these assumptions is given below.

Appendix figure 1 shows how the three strategies lead to six possible outcomes, depending on farmers' strategies and whether or not an SBR infection actually arises on their farm. These six possible outcomes were given in table 2 and are labeled in the figure as Payoffs 1-6.

Appendix figure 1

Decision tree without information about SBR infection



The six payoffs embody the costs and benefits of each strategy. The first strategy (preventative fungicide) has the benefit of minimizing yield losses in the event of an SBR infection but at a high per acre cost of fungicides. The second strategy (monitor fields and apply a curative fungicide if SBR is detected) costs less per acre than the preventative treatment but results in larger yield losses in the event of SBR. It also saves fungicide costs in the event SBR does not occur. The third strategy (do nothing) is the least costly alternative but results in the largest yield losses in the event of an SBR infection.

We assume farmers choose the strategy that maximizes their expected profits. For each strategy, expected profits equal the sum of the probabilities of each possible outcome multiplied by the associated payoffs. Each strategy has just two possible outcomes, one occurring with probability P (in the event SBR occurs) and one occurring with probability $1-P$ (in the event SBR does not occur). Thus, the expected profits for the three strategies are as follows:

Strategy	***Expected profits***
Preventative treatment:	$P \times$ Payoff 1 + $(1-P) \times$ Payoff 2
Monitor-curative if SBR:	$P \times$ Payoff 3 + $(1-P) \times$ Payoff 4
Nothing:	$P \times$ Payoff 5 + $(1-P) \times$ Payoff 6

Decisions may differ among farmers, depending on differences in the payoffs and farmers' beliefs about P. Parameter P represents farmers' *prior beliefs*, as described in the body of the report. The prior belief is a subjective probability—what a farmer believes the probability of infection to be given his or her prior knowledge and information. This subjective view of probability is also called the Bayesian view of probability. The Bayesian view of probability contrasts with the Frequentist view of probability, which holds that probabilities are objective, fixed values that are unknowable to human observers. Under the Frequentist view, expected values and information values cannot be calculated because the true probabilities that enter these calculations are not knowable. In this analysis, we assume farmers are rational economic actors with prior beliefs that are correct—that is, prior beliefs are the true probabilities.

For the base case scenario, we consider a representative farmer in each region and assume (implicitly) that all farmers within each region choose the same strategy—that is, they have the same prior beliefs. The six payoffs are constructed using the assumptions presented in table 1 and described later in more detail.

Given our assumptions about the six payoffs, farmers' optimal strategies and resulting expected profits crucially depend on P. In general, farmers will tend to apply a more costly management strategy the greater the probability of infection. If P is low (e.g., below 0.19 in the Corn Belt), the optimal strategy is to do nothing. In a broad intermediate range (e.g., for P, 0.19-0.62 in the Corn Belt), the optimal strategy is to monitor fields intensively and spray a curative fungicide if SBR arises. If P is sufficiently high (e.g., above 0.62 in the Corn Belt), the optimal strategy is to apply the preventative fungicide. Assumptions about farmers' prior beliefs in the base case, illustrated in figure 3, are based on an aerobiology analysis of SBR and wheat stem rust. Derivation of these probabilities is described later in more detail.

Note that if farmers knew *for certain* whether or not SBR would occur (P=0 or P=1), the optimal strategy in all regions would be to apply the preventative treatment if SBR were going to occur and do nothing if SBR were not going to occur. With known SBR occurrence, a monitor and cure strategy would never be optimal. In contrast, given our estimated values for P, the optimal strategy in all regions in the absence of any information is to monitor fields and apply the curative fungicide in the event SBR occurs. This difference in optimal strategies with and without information allows us to value the information.

SBR Management and Expected Profit With the Framework

We just considered farmers' SBR management strategies and expected profits in the hypothetical context where the coordinated framework did not exist. Now, we consider farmers' optimal strategies and expected profits in the observed situation where farmers can obtain information about the incidence of SBR via the framework. In this context, farmers choose their management strategies after learning about the incidence of SBR in their area.

We illustrate this environment by using the decision tree in appendix figure 2. This figure differs from appendix figure 1 in that farmers receive a "high-risk" or "low-risk" signal before choosing their management strategy. The two segments of the tree that follow each of these signals are much like the no-information tree in appendix figure 1, except the probability of infection is now β if the farmer receives a "high-risk" signal and γ if the farmer receives a "low-risk" signal. If the information signal provides a useful forecast, then $\beta > P$ and $\gamma < P$; that is, the "high-risk" signal increases the farmer's perceived risk of SBR and the "low-risk" signal reduces the farmer's perceived risk of SBR. Thus, unlike the no-information environment, here farmers may fine-tune their management strategies to the risk signal they receive and maximize expected profits *conditional* on the risk signal.

Thus, conditional on the risk signal, expected profits for the three strategies are as follows:

If "high-risk" signal,

Strategy	*Expected profits*
Preventative treatment:	$\beta \times$ Payoff 1 + $(1-\beta) \times$ Payoff 2
Monitor-curative if SBR:	$\beta \times$ Payoff 3 + $(1-\beta) \times$ Payoff 4
Nothing:	$\beta \times$ Payoff 5 + $(1-\beta) \times$ Payoff 6

If "low-risk" signal,

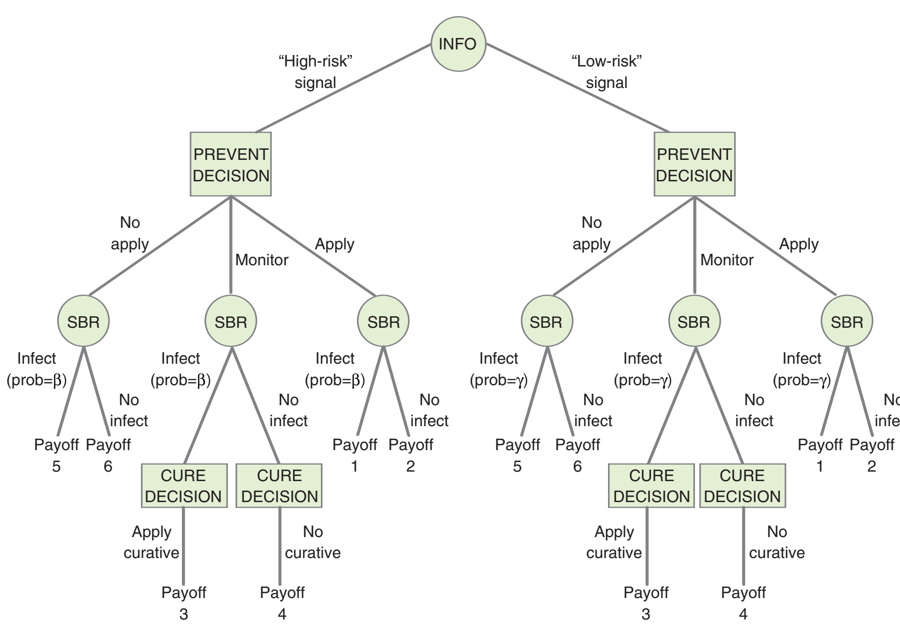
Strategy	*Expected profits*
Preventative treatment:	$\gamma \times$ Payoff 1 + $(1-\gamma) \times$ Payoff 2
Monitor-curative if SBR:	$\gamma \times$ Payoff 3 + $(1-\gamma) \times$ Payoff 4
Nothing:	$\gamma \times$ Payoff 5 + $(1-\gamma) \times$ Payoff 6

To calculate overall expected profits, we sum the expected profits from the optimal strategy conditional on each signal multiplied by the probability of receiving each signal. The probability of a "high-risk" signal is denoted by α, and the probability of a "low-risk" signal is given by $(1-\alpha)$. Thus, with information, expected profits are as follows:

$\alpha \times$ "high-risk" expected profit + $(1-\alpha) \times$ "low-risk" expected profit

Probabilities in this environment are logically connected to the prior belief P in the no-information environment. This connection comes from the fact that the information provided by the framework does not change the overall chance that an SBR infection will occur, only farmers' knowledge about whether it will occur. Mathematically, this connection requires that $P = \alpha \times \beta + (1-\alpha) \times \gamma$.

Appendix figure 2
Decision tree with partial information about SBR infection



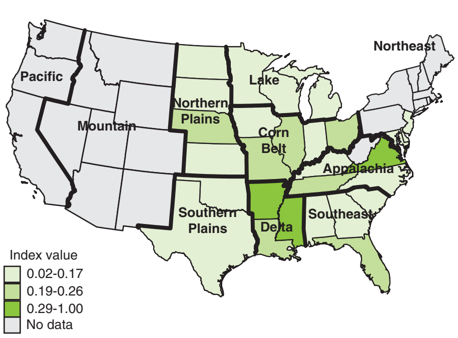
Information Quality

In general, one might quantify information quality in many ways. We have simplified matters considerably by assuming that the framework will provide just two possible information signals, "high-risk" and "low-risk." In reality, the framework may provide a continuum of possible signals. If information quality were perfect, however, we would expect only two signals, one perfectly forecasting an impending arrival of SBR and one perfectly forecasting the nonarrival of SBR—that is, β would equal 1 and γ would equal zero. To approximate a continuum of information qualities, we, therefore, suppose just two signals remain but that the signal itself may have different levels of accuracy. Thus, if neither of the two signals contain informational content, they would not affect farmer's prior beliefs ($P=\beta=\gamma$), and farmers would choose the same management strategy in the information environment as they would in the no-information environment.

To develop an index of information quality, we calculate a regional index of support from the coordinated framework from survey results provided to us by the Government Accountability Office (app. fig. 3). The survey also helped us develop the previous discussion of the framework's operation. An index of support is calculated from the number of sentinel plots and rust extension agents in each State. When we consider this map along with the prior beliefs probability map, we find that farmers in some States clearly have high prior beliefs and low support (Alabama, Georgia, North and South Carolina, and Texas) and vice versa (Arkansas).

In making these calculations, we find that, while the index of support might represent regional differences in data collection for the framework, it did not reliably portray regional differences in how accurate producers would find the information to be. The quality of the information to soybean producers would depend on access, timeliness, and interpretation at the local level. To develop an operational index of information quality, we assume both information signals affect prior beliefs (P) by the same proportion. Mathematically, we suppose $\beta = \phi(1-P) + P$ and $\gamma = P(1-\phi)$, where ϕ is the information quality index that may take on any value between 0 and 1. This parameterization implies that, when $\phi = 0$, $P = \beta = \gamma$, and as ϕ increases, β increases and γ declines until $\phi = 1$, when $\beta = 1$ and $\gamma = 0$. This parameterization also implies $\alpha = P$: The probability of a "high-risk" signal always equals the probability that an infection will occur. Note, however, that a "high-risk" signal does *not* imply that an infection will occur for certain, unless $\phi = 1$.

Appendix figure 3
Coordinated framework index of support in USDA production regions



Because we do not have objective estimates for information quality, we evaluate farmers' optimal conditional strategies and expected profits over a range of information qualities: $\phi = 0.2$ (low), $\phi = 0.5$ (medium), and $\phi = 0.8$ (high). One may think of these information qualities as the proportion of uncertainty resolved by the coordinated framework. We then calculate farmers' overall expected profits by multiplying the conditional expected profits by the probabilities of each signal and summing them.

The Value of Information

In the base case scenarios, the value of information simply equals the difference in expected profits between the no-information and partial-information environments, calculated as we just described. These values, calculated for each region and each information quality, are reported in appendix table 2. In appendix table 1 and figure 3, we report information values for the Corn Belt over the full range of possible values for *P*, rather than our estimated *P* (described later) to show how sensitive our results might be to a range of values of *P*.

Assumptions

This section describes how we arrived at the assumptions used to develop estimates of the six payoffs and prior beliefs (*P*) for each region.

Soybean Yield Impacts

Yield data, before and after the arrival of *P. pachyrhizi*, are not available for the United States, nor are efficacy trial data for U.S. fungicides. Efficacy data also were not available at the time of this study for climatic regions similar to the United States. Thus, to estimate treated and untreated yield impacts of SBR epidemics relative to rust-free yields, we evaluate the impacts of rust on soybean yields in South America.

Livingston et al. analyzed fungicide efficacy trials in Brazil and Paraguay during 2001-03, aggregate yield data for 10 states in Brazil during 1993-2002, and data on the introduction of *P. pachyrhizi* into those same states. Rust-free yields averaged 2.604 (±0.422) metric tons per hectare, and treated and untreated yields averaged 2.578 (±0.201) and 2.025 (±0.363) metric tons per hectare. Treated and untreated yields, therefore, were lower by an average of 4.3 percent (±5.2 percent) and 25.0 percent (±11.9 percent), respectively, than the estimated rust-free yields.

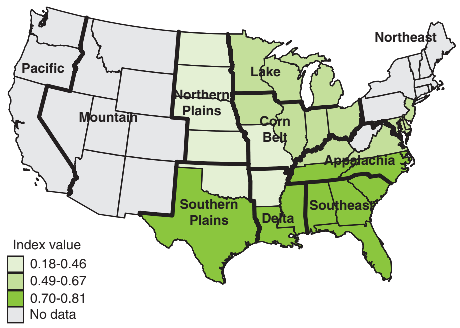
We use the Livingston et al. estimate of untreated yield impacts to estimate payoffs when rust occurs but no fungicide is applied. Because the treated yield impacts from the Livingston et al. study were estimated with yield data reported from soybean plots sprayed with curative, protectant, or curative plus protectant fungicides, we need to separate the impacts of the different treatments. Replicating the Livingston et al. methods, we find that the average yield impact for the protectant class of fungicides is -0.97 percent with a mean of 1.00 applications evaluated. Fourteen protectant fungicide efficacy trials were conducted, each of which evaluated the impact of one application. Also, the average yield impact for the curative class of fungicides is -6.95 percent with a mean of 1.39 applications evaluated. Seven curative fungicide efficacy trials evaluated the impact of 2 applications, and 11 curative fungicide efficacy trials evaluated the impact of 1 application (app. table 7).

Prior Probabilities of Soybean Rust Occurring

Soybean producers in different regions are likely to assign different probabilities to the chance of rust occurring in their area (earlier denoted as *P*) (app. fig. 4). We call these probabilities “prior probabilities” and assume that they depend on regional differences in climate, soybean planting dates, and distance from *P. pachyrhizi* overwintering sites.

Appendix figure 4

Prior probability of soybean rust in USDA production regions



Wheat is the only other crop for which we have U.S. rust infection data. We, therefore, use data on the occurrence of stem rust epidemics of durum, winter, and other spring wheat for 1921-62 (Hamilton and Stakman) to estimate how often *P. pachyrhizi* spores may be present in most States where soybeans are produced (USDA, 2005a). We also use data on daily temperature extremes, rainfall, and humidity for 1992-2001 to estimate the proportion of years conditions may favor the development of soybean rust in each State (Livingston et al.). Because *P. pachyrhizi* may be able to overwinter along the coastlines of Alabama, Florida, Georgia, Louisiana, Mississippi, and Texas (Pivonia and Yang), we set the proportion of years that climatic conditions may favor the development of soybean rust to 1 for these States. *P. pachyrhizi* cannot survive without a plant host. We, thus, use data on the most likely soybean planting and harvest dates for each State (USDA, 1997) to adjust the proportion of years climatic conditions may favor rust epidemics.

We use the product of the proportion of years that stem rust epidemics occurred and the adjusted proportion of years climates may favor the development of rust epidemics to estimate State-level prior probabilities that rust epidemics may occur. To obtain regional prior probabilities, we weighted the State-level prior probabilities by mean soybean production for 1995-2004 (USDA, 1998-2005). Our estimate of the prior probability that the average U.S. soybean acre experiences rust is 0.53; and our estimates of the regional prior probabilities for Appalachia, Corn Belt, Delta, Lake States, Northeast, Northern Plains, Southeast, and the Southern Plains are 0.67, 0.55, 0.55, 0.49, 0.62, 0.43, 0.76, and 0.51, respectively. These are the estimates we used to calculate information value in the base case and other scenarios.

Summary Statistics About Representative Soybean Farms

We calculate estimates of the value of information per farm for farms having 443-1,956 acres of soybeans, depending on the region (app. table 6). We determine the acreage by estimating the weighted average of farms by soybean acre in each region. We weight farms by soybean acreage in order to represent the average soybean acre rather than the average farm. Weighting farms in this way is important because farms are extremely heterogeneous, with most producing little or no soybeans and smaller numbers producing vast soybean acreages. We estimate the base wealth used in the analysis of risk-averse farmers (see next section) by weighting farm households' net worth by soybean acre.

Note that the acreages of the representative farms affect only information values for the representative farm, not the estimated values per acre. The base wealth estimates affect only information values in the analysis of risk-averse farmers.

The data used to construct these averages come from the 2003 Agricultural Resource Management Survey. The sample design of the survey is complex; it samples farms of different sizes with different frequencies (see http://www.ers.usda.gov/briefing/ARMS/). The regional averages also incorporate sample weights implied by the survey design.

Modeling Information Values of Risk-Averse Farmers

Estimated information values for risk-averse farmers assume that farmers have diminishing marginal utility of wealth, which means that farmers value each additional dollar less than dollars already possessed (app. table 3). Diminishing marginal utility of wealth is characterized as risk aversion because it implies a constant level of wealth is preferred to variable levels of wealth with the same average value.

More specifically, our estimates of information values in the case of risk aversion assume that farmers' preferences are characterized by constant relative risk aversion (CRRA), with a coefficient of relative risk aversion equal to 4. This may be expressed with the utility function: $u(W) = -AW^{-3}/3$, where W indicates wealth and A is an arbitrary constant.

The utility function implies that farmers are strongly risk averse. We made this assumption to throw into stark relief the potential impact of risk aversion. More realistic assumptions about the level of risk aversion would imply even smaller differences from the base case. The extremity of our assumption may be observed by noting that a farmer with this utility function and a wealth of \$200,000 values an additional dollar 16 times as much as the same farmer with a wealth of \$400,000 and 625 times as much as the farmer with a wealth of \$1 million. Farmers with less risk aversion would have information values closer to the base case, holding all else the same.

Calculating information values for risk-averse farmers' proceeds similarly to the base case described earlier, except that farmers are assumed to maximize *expected utility* rather than *expected profits*. In only a few cases does the extreme level of risk aversion cause farmers' decisions to be different than those in the base case. It changes information values, however, mainly because different information environments may lead to marked differences in profit variability. For example, consider a farmer who would have applied the preventative strategy without information. Suppose that if armed with a high-quality SBR forecast, the farmer splits his or her decision between prevention and "do nothing" across the "high-risk" and "low-risk" signals. The information would cause his or her average profits to increase but would also cause his or her profit variability to increase, so the information would be valued less by risk-averse farmers than by profit-maximizing farmers. This example illustrates the main reason that the largest information values decline in the risk-averse scenarios compared with the base case.

Modeling the Effect of Price Feedback on Information Values

In the base case scenarios, we assume that soybean prices are constant. However, both economic theory and our historical evidence indicate that soybean prices will vary with yield, implying that, because each decision (prevent, monitor/cure, or no management) and each outcome (rust infection, no rust infection) lead to a different yield, each must also lead to a different post-harvest price. Appendix table 4 reports information values that result from taking these soybean price effects into account, rather than assuming that prices are constant. This section explains how these values are calculated.

Equilibrium in the Soybean Market

The soybean futures price must reflect a possible variety of post-harvest prices. Specifically, the futures price must equal the average of these potential end-of-season prices, weighted by the probabilities that they will occur, which in the case where no information is available, means the following:

Prob (*SBR infection*) × (*Post-harvest price w/SBR infection*) +
Prob (*no infection*) × (*Post-harvest price w/o infection*) = *Futures price*.

With partial information, this condition becomes the following:

Prob (*infection and "high risk" signal*) × (*Post-harvest price w/infection and "high risk" signal*) + Prob (*infection and "low risk" signal*) × (*Post-harvest price w/infection and "low risk" signal*) +
Prob (*no infection*) × (*Post-harvest price w/o infection*) = *Futures price*.

Many factors can influence futures prices, but the following is how we assume that rust might affect futures prices. Underlying the equations are two concepts: Prices affect farmer treatment decisions, and farmer treatment decisions simultaneously affect prices. These circular effects must be taken into account when looking for equilibrium in the soybean market. Specifically, equilibrium should be characterized as follows: Individual farmers, taking post-harvest prices as given, maximize their own profits, while the industry as a whole, comprised of these individual profit-maximizing farmers, satisfies the equations, thus determining post-harvest prices.

In computing the equilibria seen in appendix table 4, we look wherever possible for symmetric, pure-strategy equilibria—pure strategy meaning that each farmer pursues a single best option, and symmetric meaning that, for all farmers, the best option is the same. In two cases, however, such equilibria do not exist. For the Northern Plains receiving information quality of 0.5 and for the Southern Plains receiving information quality of 0.2, we are forced to consider the potential for farmers to mix strategies. (An example of a mixed strategy would be tossing a coin and applying preventive fungicide if it came up heads and doing nothing if it came up tails.) Mixing strategies will occur only when individuals are indifferent to the two options; in these two cases, farmers are indifferent between monitoring and no management when they receive a low-risk signal. An equilibrium will result in the Northern Plains scenario when, in response to a low-risk signal, about 35 percent of acreage is monitored; the remainder is unmanaged; and the post-harvest price, when the signal indicates low risk but infection occurs anyway, is $6.91. Similarly, the Southern Plains will reach equilibrium when, in the face of low risk, about 27 percent of acreage is monitored; 73 percent is unmanaged; and the post-harvest price, when the signal indicates a low risk signal but infection occurs anyway, is $6.45.

Estimating the Effect of Yield Losses on Soybean Prices

In order to determine how soybean prices might respond to yield shocks, we use yearly (1950-2004) yield and price data published by the National Agricultural Statistics Service (NASS). Our first step was to aggregate, using production-weighted averages, the State-level data from NASS to the regional level presented in this report. Next, in order to abstract from yearly variations in output while still accounting for productivity increases over time, we fitted a smooth trend curve for yields in all nine soybean production regions.[7] Example results for the Corn Belt and Southeast can be seen in appendix figure 5, with the open dots representing actual observations and solid lines forming the trend curves.

[7]Trend curves were created with the "lowess" function in the program R, version 2.1.1.

This fitting process allows us to calculate, for each region in each year, a percentage residual yield (i.e., the difference between actual yield and yield predicted by the trend, divided by the yield predicted by the trend).

Having isolated deviations from the trend for yields, we turn to estimating variations in regional soybean prices. We approximate the percentage change in the latter by calculating the year-to-year difference in the natural logarithm of the price, deflated to 1983 dollars. By regressing this value on the percentage residual yield,[8] we obtained an estimate of the percentage change in price that would result from a percentage deviation from the yield trend.[9]

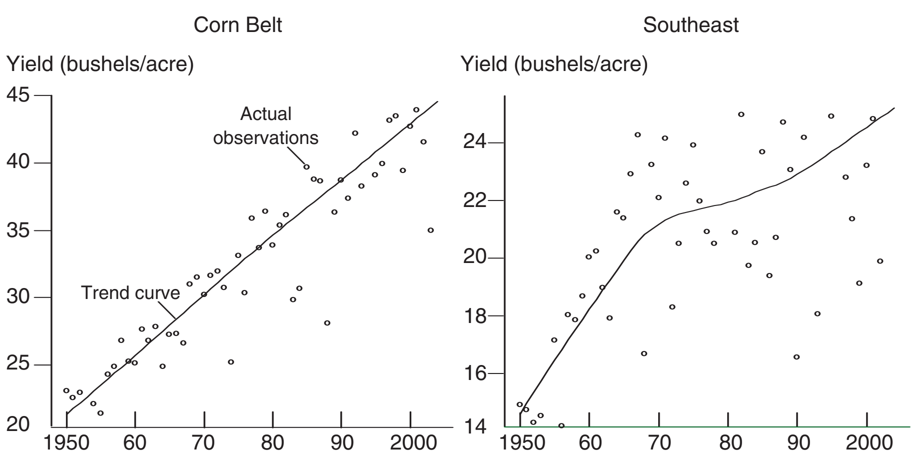
[8]Only the 20 most recent observations (1984-2004) were included in this regression.

[9]Percentage change in price from year to year will depend not only on this year's yield shocks but also on yield shocks that may have affected the previous year's price. However, including previous year yield residuals as an explanatory regression variable did not lead to significant changes in estimates of the coefficients on current-year price-shock effects.

Note that, while these estimates provide some insight into how regional soybean prices and yields have been correlated historically, there is no

Appendix figure 5

Yield trends and shocks in the Corn Belt and Southeast, 1950-2004



guarantee that soybean rust will exhibit similar effects as the weather and other production shocks of the past two decades. Especially note the spatial nature of the impacts. If, for example, soybean rust were to spread over the entire soybean-producing part of North America (but drought tends to affect only a few regions at a time), a rust-induced regional price increase would likely be greater than the increase resulting from yield loss caused by drought. Other patterns could cause the reverse to be true.

Consumer Versus Producer Welfare

We calculate the value of information by comparing expected profits with information to expected profits without information. When we account for price-feedback effects, small changes in expected yield lead to small changes in expected price (i.e., the futures price). Thus, if information causes a small increase in expected yield, expected prices tend to decline. If the expected price decline is large enough, farmers' expected profits may decline as a result of the information, even though individual farmers find the information valuable (because, individually, farmers take prices as given). For soybean consumers, however, this price decline is a gain—it simply represents a transfer from producers to consumers. Of course, the opposite is true if the information causes a small decline in expected yield: Prices increase, producers gain more, and consumers lose as a result of the information.

Estimating Average Information Values for Farms with Heterogeneous Prior Beliefs

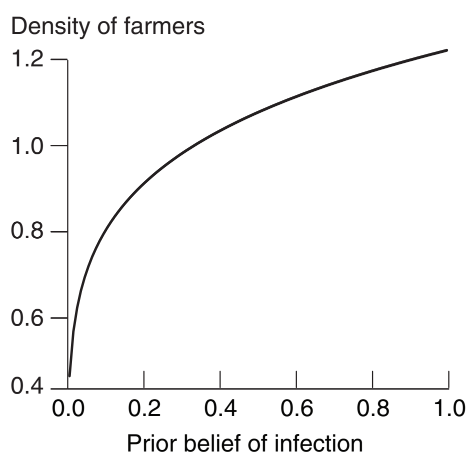
We estimate the average value of information for farmers with heterogeneous prior beliefs of an SBR infection by assuming that these beliefs are distributed according to a beta distribution (see http://mathworld.wolfram.com/BetaDistribution.html). For each region, the beta parameter of the distribution is assumed to equal 1 and the alpha parameter is set so that the average value equals the prior belief in the base case. This distribution assumption implies that farmers' beliefs within each region are widely varying.

The assumed distribution for the Corn Belt is plotted in appendix figure 6. The height of the density curve (labeled "Density of farmers") shows the relative proportion of farmers in the region assumed to have the prior belief of infection plotted along the horizontal axis.

We estimate average information values for each region and information quality by taking 1,000 random draws from the assumed beta distribution, plugging in each draw as the value for P, calculating the associated information values from each draw, and then taking the average of the values resulting from the 1,000 draws.

Appendix figure 6

Assumed density function for farmers' beliefs in the Corn Belt



Appendix table 1

Information values for a representative Corn Belt farm

(a) Prior belief of infection	(b) No information decision	(c) EV, with no information	(d) Quality of information on a scale from 0 to 1	(e) Post-information ("high-risk") probability of infection β	(f) Post-information ("low-risk") probability of infection γ	(g) High-risk decision	(h) Low-risk decision	(i) EV, with information	(j) Value of information per farm	(j) Value of information per acre
		Dollars						------------*Dollars*------------		
0.10	N	106,976	0.2	0.280	0.080	M	N	107,223	248	0.33
.10	N	106,976	.5	.550	.050	M	N	107,942	967	1.30
.10	N	106,976	.8	.820	.020	P	N	109,105	2,130	2.87
.20	M	102,201	.2	.360	.160	M	N	102,776	575	.77
.20	M	102,201	.5	.600	.100	M	N	104,054	1,853	2.50
.20	M	102,201	.8	.840	.040	P	N	106,310	4,110	5.54
.30	M	99,742	.2	.440	.240	M	M	99,742	0	0
.30	M	99,742	.5	.650	.150	P	N	100,615	873	1.18
.30	M	99,742	.8	.860	.060	P	N	103,712	3,970	5.35
.40	M	97,284	.2	.520	.320	M	M	97,284	0	0
.40	M	97,284	.5	.700	.200	P	M	97,979	695	.94
.40	M	97,284	.8	.880	.080	P	N	101,311	4,027	5.43
.50	M	94,825	.2	.600	.400	M	M	94,825	0	0
.50	M	94,825	.5	.750	.250	P	M	96,257	1,432	1.93
.50	M	94,825	.8	.900	.100	P	N	99,106	4,281	5.77
.60	M	92,366	.2	.680	.480	P	M	93,139	772	1.04
.60	M	92,366	.5	.800	.300	P	M	94,761	2,395	3.23
.60	M	92,366	.8	.920	.120	P	N	97,098	4,731	6.38
.70	P	91,646	.2	.760	.560	P	M	92,071	425	.57
.70	P	91,646	.5	.850	.350	P	M	93,491	1,845	2.49
.70	P	91,646	.8	.940	.140	P	N	95,286	3,640	4.91
.80	P	91,441	.2	.840	.640	P	P	91,441	0	0
.80	P	91,441	.5	.900	.400	P	M	92,445	1,005	1.35
.80	P	91,441	.8	.960	.160	P	N	93,671	2,230	3.01
.90	P	91,236	.2	.920	.720	P	P	91,236	0	0
.90	P	91,236	.5	.950	.450	P	M	91,625	390	.53
.90	P	91,236	.8	.980	.180	P	N	92,253	1,017	1.37

Notes: In decision columns (b), (g), and (h), M is monitor/cure, P is prevent, and N is do nothing. In (c) and (j), EV is expected value.

Appendix table 2

Information values for representative farms in all regions

Region	(a) Prior belief of infection	(b) No information decision	(c) Expected yield without SBR	(d) Quality of information on a scale from 0 to 1	(e) High-risk decision	(f) High-risk EV	(g) Low-risk decision	(h) Low-risk EV	(i) EV with information	(j) Value of information per farm	(j) Value of information per acre
			Acres				*Dollars*	------------------------*Dollars*	------------------------		
Appalachia	0.67	M	35.80	0.2	P	77,530	M	83,015	79,358	714	0.64
	.67	M	35.80	.5	P	77,282	M	89,572	81,379	2,734	2.45
	.67	M	35.80	.8	P	77,034	N	99,743	84,604	5,959	5.33
Corn Belt	.55	M	44.60	.2	P	91,776	M	96,390	93,873	166	.22
	.55	M	44.60	.5	P	91,497	M	100,413	95,549	1,842	2.48
	.55	M	44.60	.8	P	91,217	N	106,510	98,169	4,461	6.01
Delta	.55	M	31.80	.2	M	93,057	M	103,850	97,963	0	0
	.55	M	31.80	.5	P	87,415	N	114,271	99,623	1,659	.85
	.55	M	31.80	.8	P	86,890	N	130,022	106,496	8,533	4.36
Lake States	.49	M	41.50	.2	M	56,831	M	60,227	58,573	0	0
	.49	M	41.50	.5	P	55,720	M	62,708	59,304	731	1.37
	.49	M	41.50	.8	P	55,509	N	67,085	61,446	2,873	5.38
Northeast	.62	M	38.70	.2	P	41,276	M	43,889	42,281	172	.36
	.62	M	38.70	.5	P	41,145	M	46,559	43,228	1,119	2.37
	.62	M	38.70	.8	P	41,015	N	50,697	44,739	2,630	5.56
Northern Plains	.43	M	36.30	.2	M	67,717	M	72,916	70,688	0	0
	.43	M	36.30	.5	P	63,767	N	77,141	71,409	721	.82
	.43	M	36.30	.8	P	63,428	N	83,496	74,895	4,207	4.78
Southeast	.76	M	25.20	.2	M	1,887	M	4,078	2,408	0	0
	.76	M	25.20	.5	P	1,765	N	7,146	3,046	638	1.44
	.76	M	25.20	.8	P	1,715	N	11,095	3,949	1,540	3.48
Southern Plains	.51	M	26.00	.2	M	21,244	N	29,647	25,343	371	.24
	.51	M	26.00	.5	M	15,652	N	39,069	27,075	2,102	1.38
	.51	M	26.00	.8	P	13,499	N	48,491	30,568	5,596	3.67
Other	.53	M	33.90	.2	M	66,216	M	72,469	69,159	0	0
	.53	M	33.90	.5	P	63,194	N	77,837	70,085	926	.84
	.53	M	33.90	.8	P	62,869	N	86,977	74,214	5,056	4.61

Notes: In decision columns (b), (e), and (g), M is monitor/cure, P is prevent, and N is do nothing. In (f), (h) and (j), EV is expected value. Zero values of information are due to rounding of discrete data.

Appendix table 3

Information values with risk aversion

Region	Prior belief of infection	Base wealth	No information decision	EU, no information	CE of EU, no information	Quality of information on a scale from 0 to 1	High-risk decision	Low-risk decision	CE of EU with information	Value of information per farm	Value of information per acre
		Dollars			*Dollars*				---------------*Dollars*---------------		
Appalachia	0.67	1,649,807	M	1.354	78,371	0.2	P	M	79,248	877	0.78
	.67	1,649,807	M	1.354	78,371	.5	P	M	81,249	2,878	2.57
	.67	1,649,807	M	1.354	78,371	.8	P	N	83,259	4,888	4.37
Corn Belt	.55	1,348,667	M	.889	93,500	.2	P	M	93,772	272	.37
	.55	1,348,667	M	.889	93,500	.5	P	M	95,446	1,946	2.62
	.55	1,348,667	M	.889	93,500	.8	P	N	97,129	3,629	4.89
Delta	.55	918,870	M	(1.184)	96,556	.2	M	M	96,556	0	0
	.55	918,870	M	(1.184)	96,556	.5	P	M	98,085	1,529	.78
	.55	918,870	M	(1.184)	96,556	.8	P	N	101,801	5,245	2.68
Lake States	.49	1,430,615	M	.990	58,476	.2	M	M	58,476	0	0
	.49	1,430,615	M	.990	58,476	.5	P	M	59,251	775	1.45
	.49	1,430,615	M	.990	58,476	.8	P	N	60,424	1,948	3.65
Northeast	.62	1,030,815	M	(.700)	42,017	.2	P	M	42,241	223	.47
	.62	1,030,815	M	(.700)	42,017	.5	P	M	43,183	1,166	2.46
	.62	1,030,815	M	(.700)	42,017	.8	P	N	44,128	2,111	4.46
Northern	.43	1,389,427	M	.929	70,461	.2	M	M	70,461	0	0
Plains	.43	1,389,427	M	.929	70,461	.5	P	N	70,763	302	.34
	.43	1,389,427	M	.929	70,461	.8	P	N	72,540	2,079	2.36
Southeast	.76	1,300,438	M	.493	2,375	.2	M	M	2,375	0	0
	.76	1,300,438	M	.493	2,375	.5	P	N	2,895	520	1.17
	.76	1,300,438	M	.493	2,375	.8	P	N	3,450	1,074	2.43
Southern	.51	1,572,391	M	1.181	24,516	.2	M	N	24,516	0	0
Plains	.51	1,572,391	M	1.181	24,516	.5	M	N	24,516	0	0
	.51	1,572,391	M	1.181	24,516	.8	P	N	26,423	1,907	1.25
Other	.53	915,964	M	(1.492)	68,666	.2	M	M	68,666	0	0
	.53	915,964	M	(1.492)	68,666	.5	P	M	69,613	947	.86
	.53	915,964	M	(1.492)	68,666	.8	P	N	71,780	3,114	2.84

Numbers in parentheses are negative values.

Notes: In the decision columns, M is monitor/cure, P is prevent, and N is do nothing. In other column headings, EU is expected utility and CE is certainty equivalence, which is an expected value calculated under uncertainty.

Appendix table 4

Information values with price effects

Region	Prior belief of infection	No information decision	EV, no information	Quality of information	High-risk decision	Low-risk decision	Low-risk EV	EV, with information	Value of information per farm	Value of information per acre
			Dollars				-----------	-------------*Dollars*	-------------	-----------
Appalachia	0.67	M	78,519	.2	P	M	84,533	79,442	923	0.83
	.67	M	78,519	.5	P	M	90,070	81,174	2,655	2.37
	.67	M	78,519	.8	P	N	100,507	84,540	6,021	5.39
Corn Belt	.55	M	93,302	.2	P	M	99,471	93,819	517	.70
	.55	M	93,302	.5	P	M	101,722	95,424	2,121	2.86
	.55	M	93,302	.8	P	N	107,547	97,568	4,265	5.75
Delta	.55	M	98,203	.2	M	M	104,540	98,203	0	0
	.55	M	98,203	.5	P	N	112,914	99,763	1,560	.80
	.55	M	98,203	.8	P	N	129,996	106,859	8,657	4.43
Lake States	.49	M	58,608	.2	M	M	59,945	58,608	0	0
	.49	M	58,608	.5	P	M	62,826	59,217	610	1.14
	.49	M	58,608	.8	P	N	67,108	61,239	2,632	4.93
Northeast	.62	M	41,936	.2	P	M	45,307	42,216	279	.59
	.62	M	41,936	.5	P	M	47,192	43,152	1,216	2.57
	.62	M	41,936	.8	P	N	51,267	44,481	2,545	5.38
Northern Plains	.43	M	70,621	.2	M	M	72,032	70,621	0	0
	.43	M	70,621	.5	P	M/N	77,804	70,588	(33)	(.04)
	.43	M	70,621	.8	P	N	83,612	74,551	3,930	4.47
Southeast	.76	M	2,419	.2	M	M	3,997	2,419	0	0
	.76	M	2,419	.5	P	N	7,570	3,037	618	1.39
	.76	M	2,419	.8	P	N	11,239	3,962	1,543	3.48
Southern Plains	.51	M	24,807	.2	M	M/N	30,006	24,703	(103)	(.07)
	.51	M	24,807	.5	M	N	38,578	26,605	1,798	1.18
	.51	M	24,807	.8	P	N	48,787	30,456	5,649	3.71
Other	.53	M	69,085	.2	M	M	72,481	69,267	0	0
	.53	M	69,085	.5	P	N	78,162	70,097	830	.76
	.53	M	69,085	.8	P	N	86,884	74,039	4,772	4.35

Numbers in parentheses are negative values.

Notes: In the decision columns, M is monitor/cure, P is prevent, and N is do nothing. In other column headings, EV is expected value.

Appendix table 5

Information values with heterogeneous prior beliefs of an infection

Region	Average prior belief of infection	"alpha" parameter for Beta prior	"beta" parameter for Beta prior	No information decision	EV, no information	Quality of information on a scale from 0 to 1	Average value of information per farm	Average value of information per acre
					Dollars		----------*Dollars*	----------
Appalachia	0.67	2.00	1.00	M	78,644	0.2	239	0.21
	.67	2.00	1.00	M	78,644	.5	1,465	1.31
	.67	2.00	1.00	M	78,644	.8	3,957	3.54
Corn Belt	.55	1.20	1.00	M	93,707	.2	182	.25
	.55	1.20	1.00	M	93,707	.5	1,132	1.53
	.55	1.20	1.00	M	93,707	.8	3,001	4.04
Delta	.55	1.20	1.00	M	97,963	.2	391	.20
	.55	1.20	1.00	M	97,963	.5	2,360	1.21
	.55	1.20	1.00	M	97,963	.8	6,504	3.33
Lake States	.49	.95	1.00	M	58,573	.2	137	.26
	.49	.95	1.00	M	58,573	.5	801	1.50
	.49	.95	1.00	M	58,573	.8	2,185	4.09
Northeast	.62	1.60	1.00	M	42,109	.2	107	.23
	.62	1.60	1.00	M	42,109	.5	660	1.39
	.62	1.60	1.00	M	42,109	.8	1,793	3.79
Northern Plains	.43	.75	1.00	M	70,688	.2	179	.20
	.43	.75	1.00	M	70,688	.5	1,077	1.22
	.43	.75	1.00	M	70,688	.8	3,009	3.42
Southeast	.76	3.20	1.00	M	2,408	.2	81	.18
	.76	3.20	1.00	M	2,408	.5	450	1.01
	.76	3.20	1.00	M	2,408	.8	1,111	2.51
Southern Plains	.51	1.05	1.00	M	24,973	.2	243	.16
	.51	1.05	1.00	M	24,973	.5	1,465	.96
	.51	1.05	1.00	M	24,973	.8	3,734	2.45
Other	.53	1.13	1.00	M	69,159	.2	234	.21
	.53	1.13	1.00	M	69,159	.5	1,396	1.27
	.53	1.13	1.00	M	69,159	.8	3,846	3.51

Notes: In the decision column, M is monitor/cure. In other column headings, EV is expected value and "alpha" and "beta" parameters are defined in the appendix.

Appendix table 6

Summary statistics used for representative farms

Region	Soybean acreage	Net household worth
	Acres	*Dollars*
Appalachia	1,118	1,649,807
Corn Belt	742	1,348,667
Delta	1,956	918,870
Lake States	534	1,430,615
Northeast	473	1,030,815
Northern Plains	880	1,389,427
Southeast	443	1,300,438
Southern Plains	1,524	1,572,391
Other	1,097	915,964

Appendix table 7

Protectant and curative fungicide yield impacts relative to stimates of rust-free yields[1]

Rust-free yield estimate	Efficacy trial yield	Protectant yield impact	Treatments	Curative yield impact	Treatments	Source
Acres	*Acres*	*Percent*	*Number*	*Percent*	*Number*	
2.223	1.914			-14	2	2
2.223	1.765			-21	2	2
2.223	1.776			-20	2	2
2.549	2.149			-16	2	3
2.549	2.190			-14	2	3
2.549	2.090			-18	2	3
2.549	1.832			-28	2	3
2.549	2.767			9	1	4
2.549	2.946			16	1	4
2.549	2.548	0	1			4
2.549	2.712	6	1			4
2.549	2.926			15	1	5
3.359	3.969	18	1			6
3.359	3.641	8	1			6
3.359	3.813	14	1			6
3.359	3.531			5	1	6
3.359	3.656			9	1	6
3.359	3.313	-1	1			6
3.359	3.375	0	1			6
3.359	2.938	-13	1			6
3.359	2.984	-11	1			6
3.359	2.703			-20	1	6
3.359	3.313			-1	1	6
3.359	3.250	-3	1			6
3.359	3.328	-1	1			6
3.359	2.984			-11	1	6
3.359	3.203			-5	1	6
2.750	2.469	-10	1			7
2.750	2.516	-9	1			7
2.750	2.406	-13	1			7
2.750	2.578			-6	1	7
2.750	2.625			-5	1	7
2.686	2.568	-0.97	1.00	-6.95	1.39	Mean

Blank fields indicate no data: Each study considers efficacy of either protectant or curative fungicide treatments.

[1]Soybean yield is reported in metric tons per hectare.

[2]Bayer (2003a) (Trials 1 and 2). The lower bound of the rust-free yield estimate for Mato Grasso do Sul [2.678 (±0.455)] during 2001-02 is used.

[3]Bayer (2003b) (Trial 14). The estimate for rust-free yield in Minas Gerais [2.549 (±0.488)] during 2002-03 is used.

[4]Bayer (2003b) (Trial 15). The estimate for rust-free yield in Minas Gerais [2.549 (±0.488)] during 2002-03 is used.

[5]Bayer (2003b) (Trial 16). The estimate for rust-free yield in Minas Gerais [2.549 (±0.488)] during 2002-03 is used.

[6]BASF (2003) (Jesus, Paraguay). The upper bound of the rust-free yield estimate for Parana [2.862 (±0.497)] during 2002-03 is used.

[7]BASF (2003) (Pirapo, Paraguay). The estimate for rust-free yield in Mato Grasso do Sul [2.750 (±0.476)] during 2002-03 is used.