Economic Impacts of Soybean Rust on the US Soybean Sector

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Abstract: The spread of Asian Soybean Rust (ASR) represents a real threat to the U.S. soybean sector. We analyze potential impacts of ASR on domestic soybean production and commodity markets as well as the competitive position of the US in the soybean export market using a price endogenous mathematical programming sector model. The model takes into account the spatial dynamics of the spread of disease during the cropping season, the inherent uncertainty regarding the risk of infection, and the dichotomous decisions that farmers make (no treatment, preventive treatment, and curative treatment) facing the risk of infection. Our results indicate substantial impacts from potential ASR spread on the agricultural output, prices and exports. The simulation results suggest that losses to the US soybean industry may be avoided by establishing effective soybean rust control policies particularly in the gateway regions on the south-to-north path of the ASR spread. Due to the spatially varying risk factors resulting from climatic differences, a significant shift occurs in soybean production from lower-latitude states toward higher-latitude states where ASR threat is less.

Keywords: Asian Soybean Rust, Stochastic Models, Dynamic Models

JEL: C61, Q13

Introduction

Asian Soybean Rust (ASR) is among the most severe foliage diseases of soybeans. It spreads rapidly and can reduce yields drastically (Miles, Frederick, and Hartman 2003). In the US it was first detected in Southern Louisiana in 2004 and experts believe that its spores were brought by summer storm winds originating in South America. Since then, it has been observed in soybeans and kudzu (an important ASR host plant for its spores) in several Southern coastal states, including Alabama, Florida, Georgia, Mississippi and Texas (USDA 2009). ASR has also been a major threat to farmers in South America since 2001. It has been present in Argentina since 2002 and by 2005 it had spread to virtually all production regions in the country. In 2004 soybean output in Brazil dropped by nearly 5% due to ASR infection. The US, Argentina and Brazil are the main suppliers of soybeans in world markets, with a total share of more than 90% in international markets. Therefore, a significant change in the supply of any of these countries may have serious impacts on domestic commodity and livestock markets and on international soybean markets.

The spread of ASR represents a real threat to the U.S. soybean sector and warrants its strict surveillance. Consequently, in 2005 the U.S. Department of Agriculture initiated a sophisticated Soybean Rust Coordinated Framework to monitor and control the spread of the disease. The premise for creating this coordinated framework is that publicly provided information creates value by allowing farmers make better decisions regarding actions for the control and prevention of ASR infection (Roberts and Schimmelpfennig 2006). Information about ASR spread in the United States is communicated through various channels including an interactive website in which users can observe daily maps of ASR incidence, education on management strategies to control spread of the disease, links to recent research findings on ASR, and expert advice as to possible disease spread patterns (see Figure 1 and Figure 2). The framework contributes to coordinate communication between individuals monitoring ASR in sentinel plots and soybean production areas, government officials, academic researchers and stakeholders (Roberts and Schimmelpfennig 2006).

In spite of its importance and the current government-led efforts to control ASR spread, very few studies have been presented so far about potential economic impacts of ASR in the U.S. soybean sector. Agricultural economists started to evaluate impacts of ASR only recently as data on disease spread patterns and possible control strategies became available. Johansson et al. (2006) examined the impact of alternative scenarios for spread of ASR in the US and found increased prices and substantial reductions in soybean production and exports. Bekkerman et al. (2008) conducted a risk analysis that takes into account spatial and temporal correlations to price possible annual insurance contracts to cover soybean rust damages. This study contributes to the empirical literature on ASR's economic impact assessment and welfare implications by using a stochastic programming model in which spatial patterns of ASR dispersion are taken into account explicitly and farmers' decision making under uncertainty is simulated in a price endogenous sector modeling framework. Simulating the spatial dynamics of ASR spread delineates this study from Johansson et al. (2006).

The specific objectives of this study are two-fold: i) assess the impacts of ASR on domestic soybean production and commodity markets, ii) analyze the competitive position of the US in the soybean export market. Our hypothesis is that an effective control of the spread of ASR domestically may protect US soybean producers against production losses and may also improve the competitive position of U.S. in the export markets. The ASR influences agricultural production in several ways. It reduces soybean yields (which can be drastic unless adequate preventive measures are taken), increases production costs (due to additional fungicide applications), and may encourage farmers to switch to alternative crops (to reduce production risk). All these factors are likely to alter the equilibria in commodity markets. Moreover, changes in crop patterns are expected to vary across regions due to the spatial differences in climatic conditions, hence the effectiveness of ASR, and the comparative advantage of individual regions in producing alternative crops.

This article is organized as follows. The next section reviews earlier literature on the economic impacts of plant disease in general and ASR in particular. The third section describes the stochastic dynamic programming model developed in this study. The fourth section described the data employed to calibrate the model. The fifth section discusses the results and the last section concludes and proposes areas for future research.

Literature Review

Plant disease risks and economic approaches

Plant diseases are becoming increasingly important in the design of domestic and international policies affecting food and agriculture. Plant health issues as well as the resulting policies in response to plant disease challenges may impact food security, international trade, economic welfare and sector performance. Consequently, governments are making efforts in data collection to detect and monitor the spread of plant diseases. The increasing amount of data available together with the wide variety of economic issues related to plant diseases have attracted the attention of agricultural economists interested in assessing the economic costs of plant diseases and in identifying appropriate strategies to eliminate or contain disease spread.

Oude Lansink (2007) summarizes recent research advances in the study of economic impacts of plant disease. At the heart of these new approaches is how to respond optimally to a plant disease-related problem with inherent risk and uncertainty. A stream of research focuses on the costs and benefits of phytosanitary measures to avoid or control disease spread such as pre-emptive actions, continuous monitoring and scouting, border inspections, and curative actions to control disease. For instance, Moffit et al. (2007) combines an info-gap model and the principle of stochastic dominance to develop a robust inspection strategy when inspection budgets are limited. Surkov et al. (2007) develops a conceptual model to allocate scarce resources in the context of quarantine risks related to the international trade of agricultural products. They find that more effective risk reductions can be achieved by allocating greater resources to the inspection of riskier disease paths; and smaller resources to inspection of less risky pathways.

Spatial models have been employed to evaluate the risks and economic impacts of disease spread. Goodwin and Piggott (2007) constructs a spatiotemporal model to quantify the risk of Asiatic citrus canker disease for commercial producers of oranges in Florida. The authors employ a large database of inspections spanning the period 1998-2004 to estimate probit and Poisson regression models. Based on their parameter estimates, the authors develop a risk model that contributes to determine the value of insurance contracts for protection against the disease. In the same spirit, Acquaye et al. (2007) employs a partial equilibrium framework to evaluate the economic impact of hurricanes on the spread of Asiatic citrus canker disease and the subsequent eradication policy in Florida. The model takes into account the spatial and temporal aspects or disease spread as well as the costs and benefits of the eradication policy. The authors show that farmers' welfare increases from Asian citrus cancer and from the eradication policy at the expense of reduced economic welfare from other sectors in society. Breukers et al. (2007) focus on the spread of brown-rot potato disease in the Netherlands. Their approach combines an epidemiological stochastic model that simulates the spatial spread of brown-rot disease and an economic model of the private costs of efforts to contain the disease. They find that low monitoring efforts are more efficient if the product is offered in domestic markets. In contrast, high monitoring efforts are desirable if the product is intended for the international market.

Another stream of research focuses on the non-monetary impacts of phytosanitary policies. Researchers have developed methods to elicit stakeholder willingness to pay (WTP) for measures to control disease spread. Areal and Macleod (2007) investigate the WTP for trees at risk of infection from *Phytophthora ramorum*, a disease that cause sudden oak death. The authors use a discrete choice model and a double-bound bid likelihood function and find that the average WTP of the British taxpayer for disease control is about 55 pound per year over a five-year period. Mourits and Lansink (2007) take a broader approach to assess the impact of phytosanitary regulation. They employ a tool called Multi-Criteria Decision Making, which allow them to integrate such disease-relater aspects as epidemiology, economic and ethical. They show the value of using this tool to assess various strategies to control animal quarantine diseases in animals.

Overall, these studies emphasize the importance of modeling the stochastic nature of plant disease spread as well as the spatiotemporal patterns of disease dispersion when evaluating alternative policies and private strategies for disease control. At the same time, this literature stresses the need to quantify the costs and benefits of phytosanitary measures that affect agricultural sectors.

Soybean Rust in the United States

Five years ago, when ASR was first detected in the United States, policy makers and agricultural economists started to examine potential economic impacts of ASR, given the importance of the soybean sector in the country. Roberts and Schimmelpfennig (2006) examined the value of publicly available information about ASR versus the costs of USDA's Soybean Rust Coordinated Framework initiated in 2005. They showed that the costs accrued to the framework are much lower than the value of the information provided. For farmers who face potential ASR infection, information about the likelihood of disease occurrence can help them make better decisions about the amount and timing of fungicide applications, which will ultimately increase their profits.

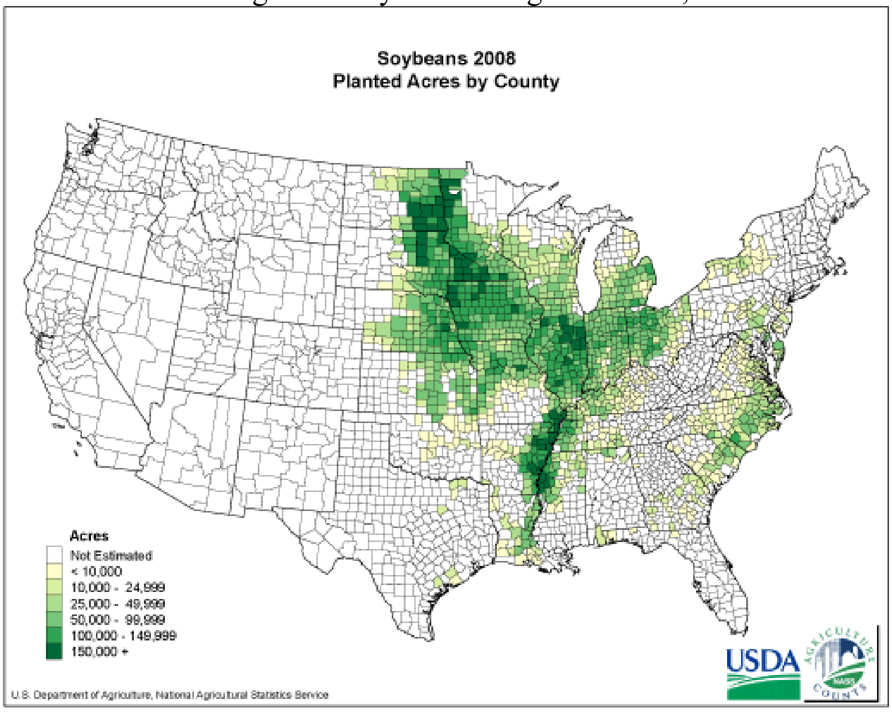
Relatively little research has been conducted on the economic impacts of ASR in the US soybean sector, in part because it was first detected in Louisiana quite recently. To our knowledge, only two studies have addressed the economic impacts of ASR spread in the US

(Johansson et al. 2006; Bekkerman et al. 2008). Johansson et al. (2006) conducted an early assessment of ex-ante ASR impacts by considering alternative scenarios for spread and control of the disease in the US. The authors examined economic consequences of three possible ASR impact scenarios on production costs and yields: do nothing, apply a preventive fungicide treatment, and apply a curative fungicide treatment. They use a partial equilibrium mathematical programming model developed by USDA's Economic Research Service to simulate the regional yield and cost impacts and subsequent changes in equilibrium prices and quantities (Livingston et al. 2004). The model assumes an adjustment period of five years so the expected impacts are calculated for a steady state in 2010. The model considers forty five geographic regions in the US and the markets for twenty three agricultural inputs including labor, land and water, among others. The model is calibrated employing data on the spatiotemporal distribution of ASR, on the spread patterns of other similar wheat and corn diseases that have occurred in the past, and on the available information regarding the costs of fungicides necessary for disease control. Their results suggest that economic impacts of ASR may be higher than expected in earlier assessments and will likely result in smaller soybean harvests, reduced exports, and increased prices by 2010. Specifically, the authors find that losses to US agriculture are lowest with a curative fungicide application strategy, followed by the no-treatment strategy. The preventive fungicide application strategy results in the highest losses for US agriculture. The authors, however, point out to that the restrictive assumptions of their model suggest that uncertainty about ASR impacts remain and more studies are necessary to evaluate, ex-ante, the potential impacts of this disease for US agriculture. While the study by Johansson et al. considers spatial variation in the incidence of rust across soybean producing states, by using an estimated fraction for rust infected acreage in each region, it does not explicitly incorporate the movement patterns of rust over space and time. Although this is a complicated issue which is not fully understood yet, the approach we use in this paper attempts to incorporate the movement patterns (to our best knowledge) in farmers' preventive fungicide application decisions. Besides the differences in price endogenous modeling methods, this issue distinguishes the present study from the Johansson et al. study.

More recently, Bekkerman et al. (2008) analyzed the economic impacts of ASR in the context of risk and severity to quantify the risk of ASR infection and to simulate possible prices of ASR-related insurance contracts or indemnification programs. The authors use data from the disease inspection and monitoring program established by the USDA and information about climatological and biological factors to develop a model of the risks of ASR infection in the US. The model results are used to calculate fair premium rates for insurance policies conditional to the severity of crop losses. The study uses over 35,000 field-level inspections spanning the period 2005-2007, and includes county-level weather statistics, planting dates and maturity groups from various sources. The econometric model of ASR risk infection is aggregated at the county level and the parameter estimates are obtained from alternative models, including simple probit, zero-inflated Poisson and negative binomial models. The authors provide a careful treatment of the endogeneity that may exist between inspections and ASR findings. The conditional probabilities of ASR infection estimated above are employed to compute expected losses and the subsequent fair premiums of insurance contracts. The results indicate a high degree of variability in ASR infection probabilities and in the corresponding insurance premiums across soybean production regions in the United States. The estimated average premium rates are lower in northern regions (1.59%) and substantially higher in southern regions (27.66%). The authors point out the need to do further research to understand the links between economic impacts and spread patterns of ASR.

Overall, the few studies summarized above indicate a high degree of uncertainty regarding the impacts of ASR infection on the US agricultural sector. Our study contributes to this literature by developing a stochastic programming sector model with explicit consideration of spatial and temporal dynamics of rust spread to assess the economic impacts of ASR on US agriculture. The model takes into account ASR spread during the cropping season, the inherent uncertainty regarding the risk of infection, and the dichotomous decisions that farmers make facing the risk of disease spread.

Figure 1. Soybean acreage in the US, 2008



Source: USDA, NASS

The Model

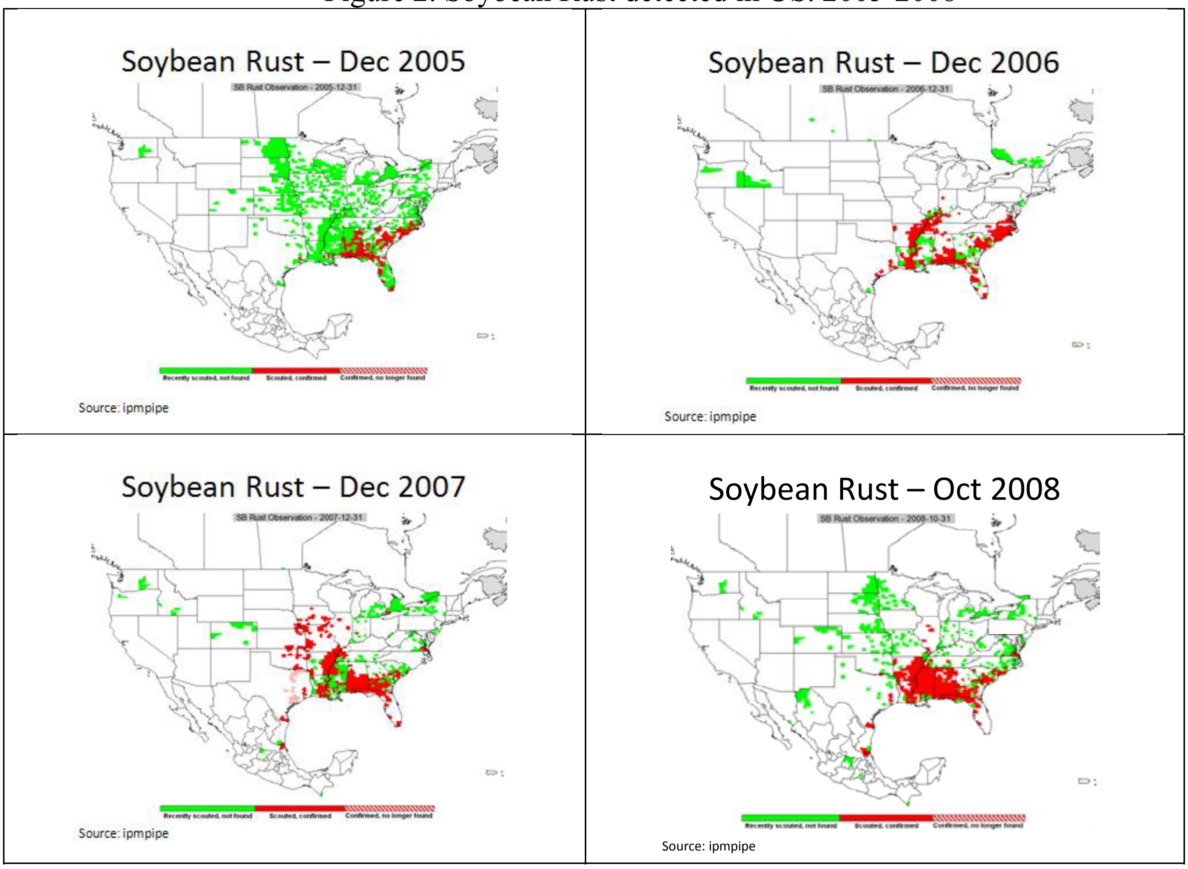
In order to address the research issues stated above, we develop a multi-market, multi-product spatial equilibrium model employing the well known social-surplus maximization approach (Takayama-Judge, 1971; McCarl and Spreen, 1980). Consumer demand is incorporated via aggregate demand functions for major commodities and a detailed supply response component simulates the allocation of agricultural land among crops, technology choices, and resource utilization at a spatially disaggregate level. We formulate the US soybeans production component of the model in a discrete stochastic programming framework considering three periods during the growing season. The appearance of ASR in any region and time period is stochastic and optimal fungicide application in each region and time period depends on what happens in the 'downstream' region on the path of ASR. To do this, we follow the surveillance system established by the USDA in 2004, which shows that the spread of ASR follows a path from the Gulf States early in the cropping season and moves towards north as far as Minnesota around September.

As production activities the model considers planting three crops, corn, soybeans and wheat. These are the three main crops competing for land in the Corn Belt region, which in turn is the major supplier of soybeans in the U.S.; together produce about two thirds of the total US soybean production). This limited coverage allows us to address the main research issues without overly complicating the model. The three cropping activities produce five products (commodities), namely corn, soybeans, soybean meal, soybean oil, and wheat, which are either sold in the domestic markets or exported. We include an explicit demand function for each of these commodities for human/industrial consumption, feed use, and exports to international markets. The model takes into account all the commodity demand functions and the competition between cropping activities producing those commodities when determining the market equilibrium. The optimal production possibilities in each region depend on the comparative advantage of each region in producing these crops. This is modeled using linear (Leontief or input/output) production functions, incorporating land as the primary input and crop yields as the output, varying across regions. Land is considered as the only input whose availability is limited, while the availability of all other inputs (fertilizers, chemicals, seed, credit, labor, machinery services, etc.) is assumed to be unlimited at constant prices. The costs of all those production factors and processing costs (soybean crushing) are summed and given as an aggregate per-acre cost (crop budget).

The model considers regional variations in crop production costs, yields, and resource (land) availability at state level. Twenty-two states are included in the model. Because of their climatic characteristics and the related ASR threat level these states are grouped into four broad regions: Region-I includes Texas, Louisiana, Mississippi, Alabama, Georgia, and South Carolina, which are most prone to rust occurrence; Region-II includes transition states Arkansas, Tennessee, North Carolina, Kentucky, which are on the pathways of rust movement from south to north; Region-III includes Nebraska, Iowa, Illinois, Indiana, Ohio, Kansas and Missouri; and finally Region-IV includes N. Dakota, S. Dakota, Minnesota, Wisconsin and Michigan, which are least susceptible to rust incidence (see Figures 2, 3 and 4). Together these 22 states supply more than 98% of the soybeans produced in the US.

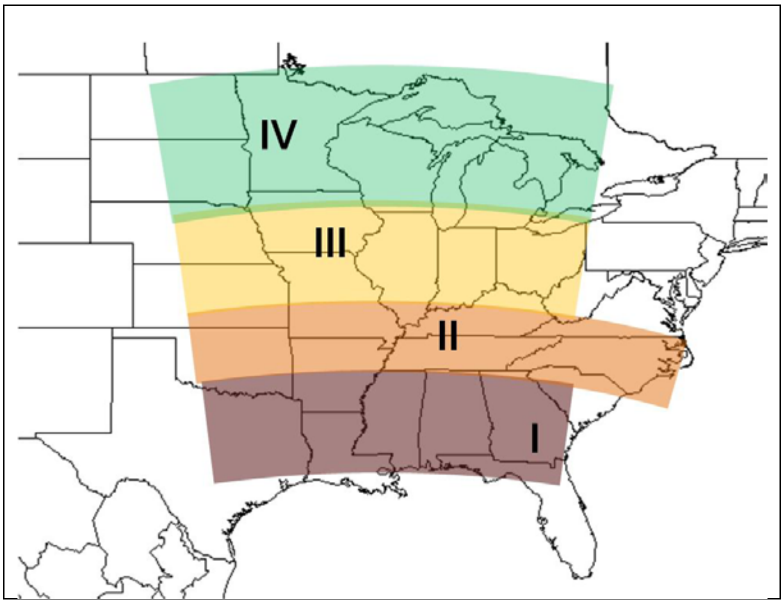
The model structure is too complex to provide all the details here. Instead we provide a sketchy description of the major constraints. The demand and supply balances for individual commodities (at national level) represent the disappearance of commodities while the availability of agricultural land determines the crop supplies (acreage) at state level. A difficulty that is often encountered when working with programming models is the extreme specialization of production activities, where each producing region is assigned a few –even a single- production activity in the optimal solution. This difficulty is lessened by considering crop rotation activities in some models or planting flexibility is limited by upper and lower bounds (the latter approach is ad hoc and typically lacks proper justification). To alleviate the extreme specialization problem, in this study we use the historical crop mix approach originally proposed by McCarl (1982) as a mathematical modeling method. In this approach the feasible solutions (land allocation among crops) are restricted to be a weighted average of the historically observed crop patterns (in mathematical terms the solution vector must be in the convex hull of the observed crop patterns -vectors). Unlike the limited planting flexibility approach (upper/lower bounds), this approach has a theoretical justification and founded on mathematical programming theory (Önal and McCarl, 1991). In addition, the model takes into account most common rotation practices employed in the agricultural production regions considered in the study.

Figure 2. Soybean Rust detected in US. 2005-2008



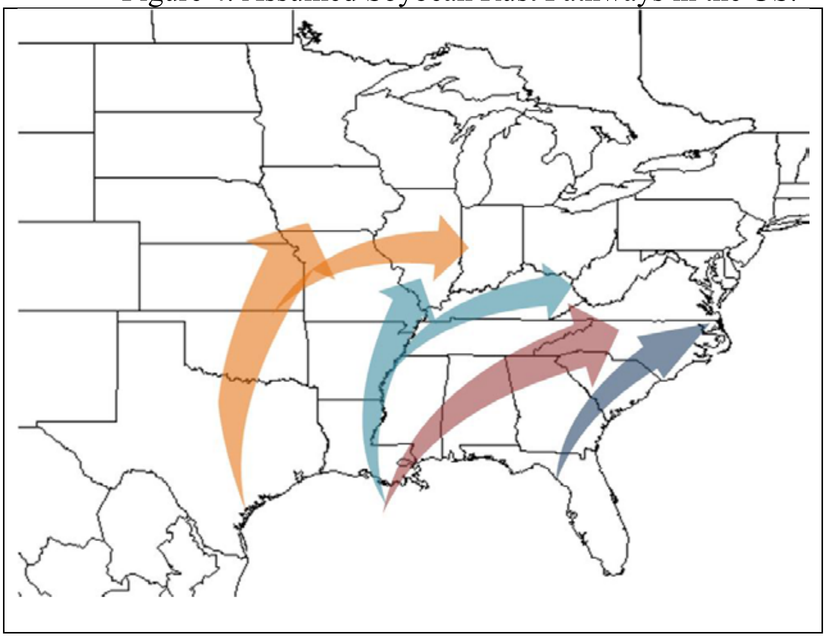
The most complicated details of the model relate to the movement of ASR and farmers' fungicide application decisions. Based on the recent literature, we employ the following assumptions in the development of our stochastic dynamic programming model of ASR spread (Roberts et al. 2006; Rossman 2008; Robinson 2005; Mueller et al. 2006; Mueller et al. 2006; Sweets et al. 2004; Livingston et al. 2004; Isard et al. 2005; Isard et al. 2007; Integrated Aerobiology Modeling System 2009):

Figure 3. Grouping of US Soybean Producing Regions based on ASR occurrence.



- ASR is permanently present in the southern region of the United States (Region-I, including Texas, Louisiana, Mississippi , Alabama, Georgia, South Carolina) because the climatic conditions in this region are conducive to ASR overwinter; subsequently, as spring progresses, the disease starts to spread toward the central (or transition) region (Region-II, including Arkansas, Tennessee, North Carolina, Kentucky); and it continues moving gradually northward to lower Great Plains and the Midwest (Region-III, including Nebraska, Kansas, Iowa, Illinois, Indiana, Ohio, Missouri). It is believed that ASR threat is minimal or nonexistent in the northern states (Region-IV, including South Dakota, North Dakota, Minnesota, Wisconsin and Michigan). It cannot overwinter in the Central and Midwest Northern regions (i.e. Regions II and III), and it moves from the southern states to the northern states during the cropping season, depending on the climatic conditions (temperature, humidity) and wind patterns (see Figure 4).

Figure 4. Assumed Soybean Rust Pathways in the US.



- In the cropping season farmers can avoid ASR infestation by applying preventive fungicide in the first two reproductive stages of the soybean crop.
- Farmers who do not apply preventive fungicide treatment have between 60% and 80% probability of ASR infestation; when ASR is observed they apply curative fungicide treatment and are not affected by ASR in the remaining of the cropping season; however, their yields are reduced by about 7% at harvest.
- Farmers in Regions II and III periodically check whether ASR infection occurs in the adjacent downstream region (i.e. to the South). More specifically, Region-II watches ASR

infections in Region-I, and Region-III watches ASR infection in Region-II. We model these considering two cases: 1) if the amount of land in the adjacent southern region infested with ASR is less than 5% of the total soybean acreage in that region, then a farmer in the upstream (northern) region has a "low risk" of infestation and does not apply preventive fungicide; and 2) if 5% or more of the soybean acreage in the downstream (southern) region is infested, farmers in the adjacent upstream region are in "high risk" of ASR infestation, in which case they have the choice to apply or not to apply preventive fungicide.

- Farmers in Region-I plant soybeans two weeks earlier than farmers in Region-II; and farmers in Region-II plant soybeans two weeks earlier than farmers in Region-III.

Based on these assumptions, we develop a stochastic model of three distinct regions (Regions I, II, and III) and three time periods during the cropping season. The producers are assumed to be profit maximizers and consider the costs of both preventive and curative fungicide applications when making their decisions to protect against ASR risk. If a proper application is not done and rust occurs, the model penalizes this by reducing the soybean yield on the land that exhibits ASR infestation (which coincides with the land on which curative fungicide treatment is applied). For readability, we provide the algebraic details of the model in Appendix.

Data

The model described above requires a considerable amount of data. Specific data requirements include base year commodity prices and demands at the farm gate, price elasticities of food, feed and export demands, historical crop mixes (areas planted to individual crops -we considered the period 1990-2006 for this), and regional crop yields and itemized crop budgets for all producing regions. We employ year 2006 as the base year to conduct our simulations.

The data are obtained from various secondary sources including USDA's National Agricultural Statistics Service, Economic Research Service and Foreign Agricultural Service; the farm decision outreach central at the University of Illinois. The costs of curative and preventive fungicides treatments are obtained from Roberts et al. (2006).

Results

Table 1 presents the results of the base run, which demonstrates the validity of the model. The first column presents the observed (actual) acreage data in 2006. The second column presents the model output with no ASR incidence. In general, the planted acres reported in the model solution column are highly close to the actual acreage, particularly for states that are major producers of the respective crops. Overall, the acreage of corn, soybeans and wheat are simulated with 1.4, 0.1 and 6.0 % deviation from the actual total acreages, respectively (see the third column values). The fifth and sixth columns present the actual and simulated production of the three crops. Again, the simulation values are highly satisfactory, showing 2.0%, 3.5%, and 10% deviation from the actual production values of corn, soybeans, and wheat, respectively, in the base year. This is a strong indication of the model's validity. Therefore, it can be used safely for ASR analysis.

Table 2 presents the simulated impacts of ASR infestation and the farmers' response to control ASR spread, in terms of percent changes in acres planted, production, exports and prices of soybeans, wheat and corn, relative to the base run (without ASR incidence). The simulation results reveal substantial economic impacts associated with the ASR spread. Although at the national level the soybean acreage declines marginally (0.6%), the production and exports decline substantially by 8.4%, 26.3%, respectively, after ASR is introduced. The decrease in production is mainly because of the adverse yield effects, rather than an acreage decline. The relatively stable soybean acreage may be puzzling, but this is not surprising because the reduced output increases the price, from $6.9 to $8.6 per bushel (23.4%), which encourages farmers to plant soybeans despite the disease risk and increased production costs due to repeated fungicide applications.

The regional breakdown of the simulated acreage figures shows interesting findings. The impacts of ASR on acres planted vary substantially across states. In particular, the scenario with ASR infection indicate that the most dramatic reductions in soybean acreage occur in states bordering the southern region (i.e. Arkansas and Tennessee) and in Missouri. These states may substitute soybeans with other crops to avoid higher production costs due to additional fungicides and lower yields resulting from ASR. In contrast, under the ASR infection scenario, Northern states such as Minnesota, the Dakotas, Wisconsin, Michigan and Iowa either increase of keep the same planting levels of soybeans. Interestingly, our results show substantial differences regarding the impact of ASR in the largest soybean-producing states: soybean acreage increases by 5.4% in Iowa, keep constant in Illinois, increases 6.9% in Michigan, and decreases by 19,6% in Missouri.

Other results no presented suggest that ASR infection may influence the structure of agriculture across regions and across states. At the national level, the results show that corn acreage, production and exports may experience modest reductions with ASR, -0.58%, -0.78% and -3.54%, respectively; and corn prices could increase by 6.38%. Similarly, our simulations suggest that the wheat sector exhibits changes in the presence of ASR infection. Specifically, in the scenario with ASR, national wheat production increases by 0.1%, exports and prices hold constant. The simulation results also indicate large changes in the structure of field crops agriculture at the state level, with general gains in acreage and production in Northern states and loses of acreage and production in Southern states.

Table 3 presents the simulation results corresponding to the soybean acreage on which preventive and curative fungicide treatments are applied to control ASR spread and reduce yield risk. The results indicate that the profit driven disease control strategy emphasizes curative fungicide treatments in most of the southern states, in particular Mississippi, Louisiana, and S. Carolina. This result makes sense because ASR tends to overwinter in those states. As expected, the results suggest that region II and region III prefer to share the risk applying both preventive and curative treatment due to relatively less risk of ASR incidence in those states. Also, the Dakotas, Michigan and Minnesota would not apply preventive fungicide treatments since they are immune to the disease because of their cold winter and cool summer conditions and relatively drier weather. In the main soybean-producing states such as Iowa, Illinois, Ohio and Indiana, the average number of preventive fungicide applications is 0.27, which means that preventive fungicide application would be chosen by less than half of the soybean producers in those states. While this may look like a good sign, the assumed probability of rust incidence is high in those states if a preventive application has not been done. Therefore, on those acres (75% of the total soybean acreage) a curative fungicide application may become necessary. All of these results are intuitive.

Finally, Table 4 displays the welfare implications of ASR, namely consumers' surplus, producers' surplus (net returns) and social surplus (sum of producers' and consumers' surplus) considering the three crops and five commodities. The income effect of ASR on soybean and corn producers is particularly noteworthy, 22.8% increase, which results from the price increase following the reduced production. These gains are offset by the welfare losses of consumers, particularly the losses of the consumers (buyers) of soybean products (soy oil and soy meal, 7.1% and 9.6%, respectively). The net effect on social welfare is a minor loss, about 0.1%. Therefore, while assessing the economic and welfare impacts of ASR the distributional impacts must be taken into account in addition to the total economic impact.

Table 1. Model Validation

State	Acreage (1000 Ac)		%	Production (1000 bu)		%
	Observed 2006	Model	Change	Observed 2006	Model	Change
Corn						
IL	11,295.2	11,750.0	4.0%	1,817,450.0	1,889,826.3	4.0%
IN	5,497.7	5,682.3	3.4%	844,660.0	872,654.4	3.3%
IA	12,594.6	12,827.1	1.8%	2,050,100.0	2,087,057.6	1.8%
KS	3,348.6	3,350.0	0.0%	345,000.0	345,000.0	0.0%
MN	7,296.9	7,449.6	2.1%	1,102,850.0	1,125,451.8	2.0%
MO	2,698.8	2,650.0	1.8%	362,940.0	356,218.9	1.9%
NE	8,096.5	8,100.0	0.0%	1,178,000.0	1,178,000.0	0.0%
ND	1,689.3	1,690.0	0.0%	155,400.0	155,400.0	0.0%
OH	3,148.7	3,441.0	9.3%	470,640.0	514,119.2	9.2%
SD	4,498.1	3,800.0	15.5%	312,340.0	263,753.8	15.6%
Total	**71,849.3**	**72,885.8**	**1.4%**	**9,986,980.0**	**10,190,257.1**	**2.0%**
Soybean						
IL	10,095.7	9,950.0	1.4%	482,400.0	490,086.8	1.6%
IN	5,697.6	5,482.3	3.8%	284,000.0	281,960.8	0.7%
IA	10,145.7	9,924.5	2.2%	510,050.0	498,716.6	2.2%
KS	3,148.7	3,150.0	0.0%	98,560.0	105,336.0	6.9%
MN	7,346.9	7,199.2	2.0%	319,000.0	312,455.6	2.1%
MO	5,147.8	5,100.0	0.9%	194,180.0	207,918.7	7.1%
NE	5,047.8	5,050.0	0.0%	250,500.0	250,500.0	0.0%
ND	3,898.3	3,900.0	0.0%	119,970.0	119,970.0	0.0%
OH	4,648.0	4,518.0	2.8%	217,140.0	212,293.9	2.2%
SD	3,948.3	4,500.0	14.0%	130,900.0	149,126.6	13.9%
Total	**73,268.7**	**73,341.1**	**0.1%**	**3,117,560.0**	**3,226,716.7**	**3.5%**
Wheat						
IL	929.6	920.0	1.0%	60,970.0	60,314.4	1.1%
IN	469.8	788.3	67.8%	31,740.0	53,234.4	67.7%
IA	25.0	23.4	6.4%	1,188.0	1,111.6	6.4%
KS	9,795.8	9,800.0	0.0%	291,200.0	291,200.0	0.0%
MN	1,749.3	1,751.2	0.1%	80,340.0	80,397.2	0.1%
MO	999.6	1,350.0	35.1%	49,140.0	66,339.0	35.0%
NE	1,799.2	1,800.0	0.0%	61,200.0	61,200.0	0.0%
ND	8,796.2	8,800.0	0.0%	251,770.0	252,016.0	0.1%
OH	989.6	876.2	11.5%	65,280.0	57,775.2	11.5%
SD	3,308.6	3,025.0	8.6%	84,090.0	76,746.9	8.7%
Total	**37,624.9**	**39,888.6**	**6.0%**	**1,179,035.0**	**1,297,042.1**	**10.0%**

Table 2. Soybean Rust Effects on Soybean Planted Acres and Production

Region	State	Acreage (1000 Ac)		%	Production (1000 bu)		%
		Base Run	Soybean Rust	Change	Base Run	Soybean Rust	Change
Region 1	TX	260.0	225.1	-13.4%	4,325.5	3,476.0	-19.6%
	LA	902.4	921.9	2.2%	33,055.5	31,811.4	-3.8%
	MS	1,516.8	1,516.8	0.0%	42,129.2	39,423.5	-6.4%
	Al	172.2	172.2	0.0%	3,477.1	3,252.9	-6.4%
	GA	212.5	212.5	0.0%	6,787.6	6,454.4	-4.9%
	SC	538.4	538.4	0.0%	20,315.9	19,258.8	-5.2%
Region 2	AR	3,466.0	3,114.2	-10.2%	142,447.5	102,452.0	-28.1%
	TN	1,154.0	1,110.2	-3.8%	54,085.4	43,193.0	-20.1%
	NC	1,475.0	1,475.0	0.0%	59,740.7	56,549.4	-5.3%
	KY	1,220.0	1,220.0	0.0%	70,277.5	64,865.3	-7.7%
Region 3	IA	9,924.5	10,464.5	5.4%	498,716.6	495,928.5	-0.6%
	IL	9,950.0	9,950.0	0.0%	490,086.8	398,186.3	-18.8%
	IN	5,482.3	5,482.3	0.0%	281,960.8	266,415.6	-5.5%
	NE	5,050.0	5,050.0	0.0%	250,500.0	236,244.0	-5.7%
	OH	4,518.0	4,518.0	0.0%	212,293.9	200,287.3	-5.7%
	MO	5,100.0	4,100.0	-19.6%	207,918.7	129,696.3	-37.6%
	KS	3,150.0	3,150.0	0.0%	105,336.0	99,844.4	-5.2%
Region 4	MI	2,000.0	2,138.9	6.9%	89,550.0	95,768.8	6.9%
	MN	7,199.2	7,350.0	2.1%	312,455.6	319,000.0	2.1%
	ND	3,900.0	3,900.0	0.0%	119,970.0	119,970.0	0.0%
	SD	4,500.0	4,500.0	0.0%	149,126.6	149,126.6	0.0%
	WI	1,650.0	1,691.2	2.5%	72,160.0	73,961.4	2.5%
	Total	**73,341.1**	**72,801.1**	**-0.7%**	**3,226,716.7**	**2,955,166.1**	**-8.4%**
Exports and price effect							
Exports (1000 bu)		1,128,368.2	831,429.2	-26.3%			
Price $/Bu		6.9	8.6	23.4%			

Table 3. Fungicide Applications and Related Costs

Region	State	Planted Area (1000 Ac)	Area with Fungicide aplication (1000 Ac)				Total Cost of fungicide applications (1000 US $)
			Preventive	%	Curative	%	
Region 1	TX	225.1	0.0	0%	223.3	99%	1,563.4
	LA	921.9	184.4	20%	741.2	80%	9,798.3
	MS	1,516.8	0.0	0%	1,504.6	99%	10,532.4
	Al	172.2	0.0	0%	170.8	99%	1,195.4
	GA	212.5	0.0	0%	210.8	99%	1,475.3
	SC	538.4	0.0	0%	534.1	99%	3,738.6
Region 2	AR	3,114.2	2,123.0	68%	1,610.1	52%	64,345.9
	TN	1,110.2	756.9	68%	574.0	52%	22,940.1
	NC	1,475.0	0.0	0%	1,435.2	97%	10,046.2
	KY	1,220.0	183.0	15%	985.8	81%	11,475.3
Region 3	IA	10,464.5	1,569.7	15%	8,507.7	81%	98,795.5
	IL	9,950.0	4,895.3	49%	6,346.8	64%	166,810.0
	IN	5,482.3	822.3	15%	4,457.1	81%	51,758.3
	NE	5,050.0	757.5	15%	4,105.7	81%	47,677.1
	OH	4,518.0	677.7	15%	3,673.1	81%	42,654.3
	MO	4,100.0	2,050.0	50%	2,476.4	60%	68,584.8
	KS	3,150.0	694.9	22%	2,507.3	80%	34,923.6
Total		**53,221.0**	**14,714.7**	**28%**	**40,063.9**	**75%**	**648,314.4**

Table 4. Welfare effects

	Good	Base Run model ($)	Scenario with SR ($)	Change
Consumer Surplus*				
Non Feed Consumption	CORN	51,008,108.0	50,422,296.9	-1.1%
	WHEAT	7,313,752.9	7,313,882.9	0.0%
	SOY OIL	26,230,922.7	24,358,536.1	-7.1%
Feed consumption	CORN	41,563,852.7	40,614,155.1	-2.3%
	WHEAT	679,327.3	679,327.3	0.0%
	SOY MEAL	9,204,163.6	8,324,640.8	-9.6%
Total	**(a)**	**136,000,127.2**	**131,712,839.0**	**-3.2%**
Producer surplus**				
	CORN	7,571,641.3	9,299,399.3	22.8%
	SOYBEAN	9,985,208.1	12,264,655.1	22.8%
	WHEAT	262,025.5	250,434.3	-4.4%
Total	**(b)**	**17,818,875.0**	**21,814,488.7**	**22.4%**
Crush Cost	**(c)**	**1,976,645.6**	**1,883,258.4**	**-4.7%**
Social Surplus	**(a) + (b) - (c)**	**151,842,356.5**	**151,644,069.4**	**-0.1%**

Conclusions and Future Research

In this study we evaluate the impacts of ASR on domestic soybean production and commodity markets as well as the competitive position of the US in the soybean export market. The study contributes to the empirical literature by developing a stochastic programming model in which prices are determined endogenously and the spatial and temporal dynamics of ASR dispersion are considered explicitly. Our simulation results suggest that the total soybean acreage may be relatively stable, but substantial differences may occur in the regional distribution of acreage and production. Specifically, the simulation results show that more land may be allocated to soybean production particularly in the northern regions where soy rust effect is minimal or virtually nonexistent. The results further indicate a gradual shift in soybean production from lower-latitude states toward higher-latitude states, particularly towards the traditional soybean-producing states such as Iowa, Illinois, Missouri and Nebraska. The southern states bear the highest costs on preventive and curative fungicide treatments, in particular in the

Gulf States. Despite the total acreage maintain almost constant, total production of soybeans in the US may decline substantially, as much as 8.4%, which would go hand in hand with a dramatic price increase (23.4%). As a result, US exports would decline by 26%, and consumers suffer a welfare loss (3.2%).

The next step of this study is to extend the model to assess the impacts of ASR on domestic soybean production and commodity markets as well as the competitive position of US versus Argentina and Brazil in the soybean export market. Our hypothesis is that an effective control of the spread of ASR domestically may protect US soybean producers against production losses and may also improve the competitive position of US in the export markets. Conversely, adverse effects of ASR overseas may encourage U.S. producers to plant more soybeans in the short or medium-run given higher price expectations.

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Appendix. Algebraic Description of the model.

Objective Function: Maximize the value of total domestic demand for food and feed goods, and world demand for goods; minus production and harvesting costs; minus export costs; minus crush costs (for soybeans only); minus fungicide costs (for soybeans only):

$$
\begin{aligned}
(1) \quad & \max \quad \sum_{fo}\left[H_{fo}(\alpha_{fo}-0.5\beta_{fo}H_{fo})\right] \\
& +\sum_{fe}\left[F_{fe}(\alpha_{fe}-0.5\beta_{fe}F_{fe})\right] \quad +\sum_{g}\left[E_{g}(\alpha_{g}^{\exp}-0.5\beta_{g}^{\exp}E_{g})\right] \\
& -\sum_{s}\sum_{Cr}\mathrm{c}_{Cr,s}^{production} * Planted_{Cr,s} - \sum_{g}\mathrm{c}_{g}^{export} * E_{g} - \quad \mathrm{c}_{soy}^{crush} * Crush \\
& -\sum_{s}\sum_{t}\mathrm{c}^{CF} * (X_{s,t}^{SR} - X_{s,t-1}^{SR}) \text{-} \sum_{s}\sum_{t}\mathrm{c}^{F} * X_{s,t}^{F}
\end{aligned}
$$

Restrictions:

i) Market clearing conditions: Domestic demand for food and feed plus export demand must equal production of commodities.

(2) For corn and wheat: $H_{fo} + F_{fe} + E_{g} \leq \text{Production}_{c}$

(3) For soybean: $Crush \leq \text{Production}_{Soybean}$

(4) For soybean meal: $F_{Soybean\ meal} + E_{Soybean\ meal} \leq 0.8 * Crush$

(5) For soybean oil: $H_{Soybean\ oil} + E_{soybean\ oil} \leq 0.19 * Crush$

ii) Supply and demand balance restrictions:

(6) For corn and wheat: $\text{Production}_{c} = \sum_{s} y_{c,s} * Survival\_rate_{c,s} * Planted_{c,s}$

(7) For soybeans:

$$
\begin{aligned}
& \text{Production}_{soybean} = \sum_{s} rust\_y_{soybean,s} * Survival\_rate_{soybean,s} * X_{s,T}^{SR} \\
& + \sum_{s} y_{soybean,s} * Survival\_rate_{soybean,s} * X_{s,T}^{NSR}
\end{aligned}
$$

iii) Land available restriction: Total planted equals total land available (by State)

$$\sum_{Cr} Planted_{Cr,s} \leq land\_av_s \qquad \forall s \tag{8}$$

iv) ASR treatment decision: A critical component of the model relates to the farmer's decision of applying or not applying preventive fungicide treatment, which depends on ASR infection in the adjacent downstream (southern) region. This is achieved by using a binary variable that reflects whether the severity of rust occurrence (rust infested area / soybean acreage) in the downstream region exceeds a specified threshold level[1] . For each period (t), we define slack and surplus variables, *S* and *U*. If S>0, the threshold level is not reached, therefore the rust incidence is not considered as severe. If U>0, the threshold value is exceed (by the amount U). In each situation, only one of these two cases can occur. We reflect this by a binary variable Z, where Z = 1 if the threshold level is exceeded, otherwise Z = 0. The following equations depict these possibilities:

$$\begin{aligned} &X^{SR}_{s-1,t} + S_{s,t} = Treshold * X_{s-1} + U_{s,t} \qquad s>1 \quad \wedge \quad \forall t \\ &S_{s,t} \leq m(1-Z_{s,t}) \qquad s>1 \quad \wedge \quad \forall t \\ &U_{s,t} \leq mZ_{s,t} \qquad s>1 \quad \wedge \quad \forall t \\ &Z_{s,t} \geq Z_{s,t-1} \qquad s>1 \quad \wedge \quad t>1 \end{aligned} \tag{9}$$

(where *m* is an arbitrarily specified large number)

v) Land to allocate either to apply preventive fungicide or do anything:

$$\begin{aligned} &X^{F}_{s,t} + X^{NF}_{s,t} = X_s \qquad \forall s \quad \wedge \quad t=1 \\ &X^{F}_{s,t} + X^{NF}_{s,t} = X^{NSR,NF}_{s,t-1} \qquad \forall s \quad \wedge \quad t>1 \\ &X^{F}_{s,t} \leq mZ_{s,t} \qquad s>1 \quad \wedge \quad t>1 \end{aligned} \tag{10}$$

vi) Land with ASR

[1] This threshold is region-specific. This means that each region has a unique probability of ASR infection, depending on such climatic conditions as temperature, humidity and wind speed.

$$X_{s,t}^{SR} = P(SR_{s,t} \mid NF_{s,t}) X_{s,t}^{NF} \qquad \forall s \quad \wedge \quad t = 1$$

$$(11) \qquad X_{s,t}^{SR} = P(SR_{s,t} \mid F_{t-1}) X_{s,t-1}^{F} + X_{s,t-1}^{SR} + P(SR_{s,t} \mid NF_{s,t}) X_{s,t}^{NF} \qquad s > 1 \quad \wedge \quad t > 1$$

$$X_{s,t}^{SR} \leq m Z_{s,t} \qquad s > 1 \quad \wedge \quad \forall t$$

vii) Land without SR and without fungicide application

$$X_{s,t}^{NSR,NF} = (1 - P(SR_{s,t} \mid NF_{s,t})) X_{s,t}^{NF} \qquad \forall s \quad \wedge \quad t = 1$$

$$X_{s,t}^{NSR,NF} = (1 - P(SR_{s,t} \mid F_{s,t-1})) X_{s,t-1}^{F} + (1 - P(SR_{s,t} \mid NF_{s,t})) X_{s,t}^{NF} \qquad \forall s \quad \wedge \quad t > 1$$

$$(12) \; X_{s,t}^{NSR,NF} \leq (1 - P(SR_{s,t} \mid NF_{s,t})) X_{s,t}^{NF} + m(1 - Z_{s,t}) \qquad s > 1 \quad \wedge \quad t = 1$$

$$X_{s,t}^{NSR,NF} \leq (1 - P(SR_{s,t} \mid F_{s,t-1})) X_{s,t-1}^{F} + (1 - P(SR_{s,t} \mid NF_{s,t})) X_{s,t}^{NF} + m(1 - Z_{s,t}) \qquad s > 1 \quad \wedge \quad t > 1$$

$$X_{s,t}^{NSR,NF} \leq X_{s,t}^{NF} \qquad s > 1 \quad \wedge \quad \forall t$$

ix) Land without SR

$$(13) \qquad X_{s,t}^{NSR} = X_{s,t}^{F} + X_{s,t}^{NSR,NF} \qquad \forall s \quad \wedge \quad \forall t \, .$$

The first three equations in system (9) indicate that if ASR is greater than 5% in a given region, then S must be 0 and U must be greater than 0; otherwise S should be greater than 0 and U equal to 0 and farmers in the region do not apply fungicide treatment and wait for the following period. The fourth equation indicates that farmers decide whether or not to apply preventive fungicide because ASR was found in the previous period in the downstream region in excess of the region-specific threshold. In this case the risk of infection is high.

We employ separable programming procedures to linearly approximate the nonlinear functions involved in the objective function (representing the producers' and consumers' surplus). This is needed because the nonlinear solver GAMS/MINOS cannot handle binary decision variables. After linear approximation of the nonlinear functions the optimization problem is solved using GAMS/CPLEX.