Economic Threshold of Wheat Streak Mosaic Virus in the Texas High Plains

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Abstract

Wheat streak mosaic virus is among the most economically important viruses affecting winter wheat in the Great Plains region. Depending on infection severity, the virus can lead to significant yield loss, rendering continuation of mid-season input application uneconomical. Determining an economic threshold infection severity soon enough in the season so that farmers could discontinue input application, could increase farmer net returns and save resources. Using data from a field experiment involving 114 sample plots, which were sensed for the presence of the virus using reflectance readings, we conducted econometric and partial budget analysis to estimate the effect of the virus on yields, and determine the economic threshold level of infection. Results indicate varying threshold infection severity depending on the date of sensing, with earlier sensing having a higher threshold than sensing at a later date. Further, estimates show that the virus can reduce yields by as much as 35 percent for every unit increase in reflectance readings, between growth stages Feekes 5 and 6. Without a better predictor of yield losses, however, it is rarely going to be the case that it would pay to discontinue input application.

Key words: Wheat streak mosaic, yield, economic threshold, profit

JEL Codes: D24, Q12,

Introduction

Wheat streak mosaic is a wheat viral disease caused by the wheat streak mosaic virus (WSMV), which is transmitted by the wheat curl mite. WSMV is becoming the most prevalent and economically important virus infecting winter wheat in the Great Plains region of the United States (Workneh et al. 2017; Velandia et al. 2010; Burrows et al. 2009). The disease infection may be confined to a specific part of the field, or can spread to the entire field, even across fields. Infection generally occurs in the fall if green vegetative plants such as volunteer wheat, pasture wheat grasses, and even corn, infested with the virus-carrying wheat curl mites are present when wheat seedlings emerge. However, studies (e.g., Price 2015; McMullen and Waldstein 2010; Christian and Wallis 1993) show that volunteer wheat is the major contributor to WSMV disease outbreaks.

When volunteer wheat is left growing late in the summer, after harvest, wheat curl mites move from volunteer wheat to newly planted emerged winter wheat, completing what is dubbed the "green bridge", with newly emerged wheat plants now hosting the virus-carrying wheat curl mites. When conditions for disease development are conducive, usually warm temperature coupled with wind, during the fall, wheat curl mites, act as vectors blown by wind, carrying the virus from infected volunteer wheat (Price 2015; Christian and Wallis 1993) to other parts of the field as well as across fields, particularly where there is no fence to separate the fields. Although much of the infection occurs in the fall, the disease may not be noticed until spring. Common symptoms of the disease include yellowing of leaves, which later turn brown as the disease progresses, and eventually the leaves die (McMullen and Waldstein 2010). Infection may occur at any stage of development. However, if infection occurs during the early stages of the crop's development, the effects on crop growth and yield may be more severe (Hunger et al. 2004).

The disease affects both spring and winter wheat, with effects ranging from minimal to complete crop loss. Once the crop is infected, there is little a farmer can do to address the problem, making prevention the best management. Byamukama et al. (2014) suggest controlling volunteer wheat and using the few available disease resistant cultivars, as some of the management practices to help in controlling the disease. However, since the disease can spread from an infested field to a healthy field, with relative ease, within a distance of 1.4 miles (McMullen and Waldstein 2010), prevention is not a guarantee that a field will not be infected.

Although the disease is of economic significance to wheat production and profitability, few studies have attempted to model and quantify wheat yield response to varying levels of WSMV infection. In addition to measuring the yield response to disease severity, it is also important to estimate a level of WSMV infection which would substantially reduce yield such that discontinuing application of inputs to the crop would result in a smaller loss than continuing with application. Determining this level of infection is important as it would equip farmers with information to make informed decisions soon enough in the season and save resources.

The copious literature on the relationship between WSMV and yield is mainly based on descriptive analysis. A few exceptions here are Workneh et al. (2017), Almas et al. (2016), and Byamukama et al. (2014) who use regression analysis to model this relationship. Byamukama et al. (2014) focus on the disease's effect on yield determinants such as tillering, shoot weight, and plant height, which they find to be significantly reduced by WSMV infection. Workneh et al. (2017) and Almas et al. (2016) apply regression analysis to estimate wheat yield response to WSMV, and find an exponential relationship between WSMV and yield. Almas et al. (2016) treat WSMV reflectance readings (sensing variable) as a categorical variable, rather than continuous, hence most likely losing variability between categories. These studies provide important insights, both economic and agronomic, into the potential effect of WSMV on yield. The current study builds on these analyses and provide a more nuanced yield response estimate, which is used to estimate an economic infection threshold. Most existing literature on disease threshold focus on optimal timing of treatment for crop disease control (e.g., Mbah et al. 2010; Kuosmanen 2006). However, with WSMV, once a field is infected there is little a decision maker can do to control it. Thus, determining an economic threshold infection severity soon enough in the season so that farmers could discontinue input application, could aid increase farmer net returns and save resources.

Against this backdrop, the objectives of the current study are twofold; 1) to determine wheat grain yield response to WSMV severity; and 2) to determine the disease severity threshold, beyond which it is uneconomical for a farmer to continue with input application.

Theory

Farmers are faced with management decision questions of whether it will be profitable to continue applying midseason management inputs, such as fertilizer, insect control and irrigation, to wheat fields infected with WSMV. This question is unanswered, largely, due to lack of information on profitability thresholds for varying levels of disease incidence and severity (Almas et al. 2016). The farmer's profit maximization problem, taking into account the level of WSM infection, can be represented by the equation

(1)
$$\max_{\theta \in \mathbb{R}^+} E\pi = [PE[y(D)] - TVC(D)]$$
s.t.
$$\mathrm{E}(y) = \begin{cases} 0, & \text{if } D = 1 \\ \beta_0 + \beta_1 S_{it}, & \text{if } D = 0 \end{cases}$$
$$D = I(S \geq \theta)$$

$$TVC = f(D)$$

where $E\pi$ is expected profit, P is the average seasonal wheat price (assumed constant), θ is the WSMV infection threshold, E(y) is expected wheat yield, which is dependent on WSMV infection severity of the i^{th} plot at a particular sensing time t, represented by S_{it} and the decision whether to abandon an infected section (D) which takes a value of 1 if a farmer abandons and 0 otherwise, TVC denotes total variable input costs such as fertilizer, insect control, irrigation, and labor for producing wheat ($/acre), which varies depending on D, while β_0 and $\beta_1$are parameters to be estimated. One important assumption regarding the decision to abandon is that a farmer would only abandon a section if expected yield from the section is zero. Thus in the above formulation, we assume zero yield if a section is abandoned, and hence a farmer would suffer a loss equivalent to the value of inputs they would have applied before abandoning, which is based on the budget. Based on estimated timing of input application, a farmer can save costs on fungicide, some level of irrigation, and harvest, since these activities would not be necessary if the farmer decides to discontinue input application after sensing.

In order to link disease severity and wheat profitability, we need to determine the effect of varying levels of disease severity on yield, and use these estimates to calculate profits, using equation (1) at different WSMV severity. We can then estimate a disease severity threshold that would render continuation of input application unprofitable (i.e., a farmer would incur more losses by continuing with input application than discontinuing). Making this decision requires the farmer to know, a priori, what level of infection is severe enough to cause higher revenue loss compared to abandoning a section. Provided with this information, it is expected that a farmer would decide to abandon a section of the field with WSMV severity level equal to or greater than the threshold, in order to minimize total variable costs. However, abandoning a section will result in zero yield.

Thus, the decision to abandon the field saves a farmer resources but since expected yield is zero, the farmer still incurs a loss.

To estimate the threshold infection level, we need to calculate the expected level of infection at which the difference in expected profits between the abandoned and non-abandoned fields is zero. This can be calculated from the following indirect profit functions;

(2) $$\mathrm{E}(\pi_1) = P * \mathrm{E}(y_1) - TVC_1$$

(3) $$\mathrm{E}(\pi_2) = P * \mathrm{E}(y_2) - TVC_2.$$

where $\mathrm{E}(\pi)$is expected profit, *P* is wheat price, *TVC* is total variable costs, *y* is yield, the subscripts 1 and 2 represent non-abandoned and abandoned field, respectively. Equating (2) and (3) and replacing E(y_1) with $(\beta_{0t} + \beta_{t1}S_{it})$, and assuming E($y_2$) = 0 (since expected yield from an abandoned field is zero), we obtain

P*$(\beta_{0t} + \beta_{1t}S_{it}) - TVC_1 = -TVC_2$. Rearranging and solving for S_{it} (threshold reflectance reading) yields

(4) $$S_{it} = \frac{\frac{TVC_1 - TVC_2}{P} - \beta_{0t}}{\beta_{1t}}$$

Data

Data for this study was mainly drawn from field experiments conducted in the 2015-2016 wheat season in Dalhart, Dallam County, Texas[1]. The experiment was conducted on a farmer field measuring 121 acres. The field was planted to the cultivar TAM 304 on November 6th, 2015, and was under center-pivot irrigation. The following inputs were applied, fertilizer (urea) 150lb N8 -13 -12, 30.16 inches of irrigation, herbicide 2-4 D at a rate of 1 pint per acre, pesticide (Loresban) also at 1 pint per acre, and fungicide (Prosaro). WSMV severity assessment was conducted in this field by first establishing two transects, running from the outside edge to the center of the field. The field contained a total of 114 sampling plots (measuring $1m^2$), established across the two transects, with sampling intervals ranging from 2 – 4 m. The length of the transect and sampling intervals were determined based on disease severity gradient from the edges of the field.

When wheat reached growth stage measuring between 5 – 6 on the Feekes scale, presence and severity of WSMV infection in a $1m^2$ area (5 rows) was measured by taking reflectance readings (sensing) at 555nm, using a hand-held hyper-spectral radiometer. Sensing of WSMV was done at 3 different times, that is, April 27th, May 4th, and May 10th. Symptomatic leaves from 62 randomly selected plots were collected and tested for WSMV, TriMV, HPWMoV, and *Barley yellow dwarf virus* (BYDV) using ELISA. This was done to ensure that the observed symptoms were due to WSMV. All the 62 symptomatic samples tested positive for WSMV, with only 6.5% of the samples testing positive for TriMV (in association with WSMV),

[1] Originally, two experiments were set up in Dalhart 2015-16 season and Bushland 2013-14 season. However, the field in Bushland experienced a severe hailstorm, which significantly affected crop growth and yield. Thus we were unable to use the Bushland data.

while none were positive for HPWMoV or BYDV, indicating that WSMV was by far the main cause of observed symptoms.

At the time of sensing, all inputs except fungicide and irrigation were fully applied. Fungicide was applied in mid-May, and irrigation continued until early June. Each sampling plot had 5 rows and only 3 center rows ($0.6m^2$) were harvested per plot. Grain from each plot was hand-harvested on June 29, 2016, threshed and weighed to determine yield per plot. Table 1 presents a summary of descriptive statistics of the reflectance values at different sensing dates and final yield.

[Table 1 about here]

In addition to experimental data, the study also utilized wheat enterprise budgets prepared by Oklahoma State University, Department of Agricultural Economics Extension, for information on variable costs. These budgets are available at http://agecon.okstate.edu/budgets/sample_pdf_files.asp. Wheat price data (average for the year 2016) was obtained from USDA - National Agricultural Statistics Services available at https://www.nass.usda.gov/Publications/.

Procedure

Estimating a model that accurately predicts final yield based off of WSMV severity early in the season is crucial for estimating the economic threshold of WSMV. This entails estimating wheat yield response to WSMV, whose effect may vary from minimal to complete yield loss, depending on infection severity. The availability of disease severity levels (reflectance values) and yield data obtained from the experiment makes it possible to analyze wheat yield response to different levels of WSMV severity.

To estimate the yield effect of WSMV we use ordinary least squares (OLS). The model is specified by the equation

(5) $$y_i = \beta_{0t} + \beta_{1t} S_{it} + \varepsilon_i$$

where y_i is the wheat yield (bu/acre) in the i^{th} plot, S_{it} is reflectance values measured from each plot at time t (t= 1 for April 27th , t=2 for May 4th, and t=3 for May 10th), β_0 and β_1 are coefficients, and $\varepsilon_i \sim N(0, \sigma^2)$ is the stochastic error term.

Considering the cost of sensing, it is more economical to sense only once. Hence, there is a need to assess which of the three sensing times (April 27th, May 4th, or May 10th) predicts final yield best. Model selection and misspecification tests were conducted to help select a good fitting model, one that predicts final yield more accurately. Our estimation, though based on a single year and location, and thus unable to control for year and location effects, has potential to provide information on the varying effects of WSMV on yield, and provide a cue regarding the timing of sensing. To evaluate the correlation between yield and reflectance values, yield was graphed against each of the reflectance values, on a scatter plot (Figure 1). The fitted line equations and respective goodness of fit statistic (R-squared) suggest a log-linear relationship, implying an exponential decline in yield as WSMV severity increased. Of the three reflectance values, the third reading (May 10th reading) seem to explain much of the variation in the final yield, with coefficient of determination of 0.81, followed by the first reflectance reading at 0.76 and lastly the second at 0.69.

[Figure 1 about here]

Empirical Model and Estimation

Based on the graphed correlations between yield and WSMV, we estimated a simple log-linear regression model for the first and third reflectance readings (since these explain more of the variation in final yield than the second) as shown below;

$$(6) \qquad \ln y_i = \beta_0 + \beta_1 S_{it} + \nu_i$$

where all variables and parameters are as defined before, and ν_i is the random error term.

We then obtain expected yield as E(y) = $e^{(\beta_0 t + \beta_1 t S_{it})}$ and replace it in equation (4) to obtain the threshold *S* as

$$(7) \qquad S_{it} = \frac{\ln\left[\frac{TVC_1 - TVC_2}{P}\right] - \beta_{0t}}{\beta_{1t}}$$

Data were analyzed using SAS software (version 9.2) PROC MIXED, and PROC NLMIXED to obtain regression estimates and numerical solution for the threshold, respectively. To address the second objective, of estimating a WSMV infection threshold, we used partial budget estimates of differences between TVC of the abandoned and non-abandoned fields (reduced costs due to abandonment [Table 4]), and regression coefficient estimates, in equation (7) to obtain a numerical solution.

Misspecification Tests

Model misspecification can potentially lead to biased and inconsistent estimators, resulting in inappropriate inferences and policy recommendations (McGuirk et al. 1993). Before estimating our final model, misspecification tests were conducted. A scatter of reflectance readings against wheat yield seems to suggest an exponential yield-WSMV relationship (Figure 1), thus a log-linear model was fitted. Following D'Agostino (1990), the K^2 omnibus test of normality was conducted, and the test did not detect deviations from normality due to either skewness or kurtosis. Other tests conducted are Lagrange multiplier test for heteroskedasticity (Breusch and Pegan 1980); and a joint conditional mean and conditional variance tests, using the comprehensive specification tests as suggested by McGuirk et al. (1993). None of the tests detected significant misspecification.

Results and Discussion

Tables 2 and 3 present OLS estimates of effect of WSMV infection severity on wheat yield, for the first and third reflectance readings, (measured on April 27th, and May 10th), respectively. The reflectance readings are negative and significant in both regression models, as expected. The effect of WSMV varies depending on time of sensing, with earlier sensing showing relatively smaller effect compared with the third. In terms of magnitude, holding all else equal, an increase in the first reflectance value by one reduces yield by 22 percent, while a similar increase in the third reflectance value reduces yield by almost 35 percent. The difference in magnitude of the two reflectance values can be attributed to increased infection severity overtimes. Thus, as infection levels progressed, the effect on yield also increased, exponentially. This finding is consistent with others, notably Workneh et al. (2017), Almas et al. (2016), and Byamukama et al. (2012). The use of multiple reflectance values, collected under farmer field conditions, in the current study provides an indication of the rate of disease progression and how this affects yield under the conditions in a farmer managed field.

[Table 2 about here]

[Table 3 about here]

Further analysis was conducted to determine the threshold reflectance value (WSMV severity) beyond which it is uneconomical for a farmer to continue with input application. Predicted yield used for threshold analysis are based on estimates obtained by running a regression with only one sensing measure each for the first and third sensing. Information on input costs and timing of application were obtained from the farmer where the experiment was conducted, and supplemented with Oklahoma State University Department of Agricultural Economics Extension wheat budgets data, available at http://agecon.okstate.edu/budgets/sample_pdf_files.asp, were used to construct a partial budget (Table 4).

[Table 4 about here]

Using cost estimates from partial budget, and predicted yield from regression estimates, we apply equation (7) to estimate the threshold for the two reflectance readings. This yielded different results depending on the reflectance values used with the April 27th reading giving a higher threshold at 12.9 than the May 10th reading at 10.4 (Table 5), with expected yields of 13.2 bu/acre and 13.9 bu/acre, respectively. This difference in threshold estimates is expected since higher infection severity at an earlier date would most likely lead to higher yield loss by the end of the season, compared to a similar severity later in the season, a finding consistent with most studies on crop disease infection (e.g., Hunger et al. 1992; Price 2015). However, it is important to point out that only a few observations (3% each from the first and third readings) in our data had reflectance readings equal to or greater than the estimated threshold, perhaps an indication that it is rarely going to be the case that abandoning a field or section would pay off. Given this possibility, it would be more helpful for farmers to prioritize good management practices to prevent and/or reduce chance of infection.

[Table 5 about here].

Conclusion

This study used field experiment data under farmer managed field, mainly, to estimate WSMV infection threshold beyond which continued application of inputs is uneconomical. Results of the analysis indicate exponential yield decline with increasing severity. For example, our estimates show that by April 27th, an increase in reflectance readings by one would reduce yield by 22 percent, while a similar increase by May 10th may reduce yield by as much as 35percent. This result indicates how quickly WSMV severity progresses, and how much yield can potentially be lost for a given level of infection during the season. Since the third reading predicted final yield more accurately than the first, it would be more economical for a farmer to sense around May 10th for a crop seeded around November 6th.

Our results are consistent with those of others who have attempted to estimate this effect. In regards to threshold analysis, our estimated values differ depending on time of sensing. Our estimates indicate the threshold reflectance to range from about 10.4 to 12.9, for readings taken around May 10th and April 27th, respectively. These results somewhat suggest farmers may potentially save resources by abandoning infected fields or sections with reflectance readings exceeding the threshold. However, only 3% from each set of sensing values in our data had infection levels equal to or greater than the threshold estimates. It would therefore be more helpful for farmers to prioritize good management practices such as clearing the field of volunteer wheat and weeds early enough before planting, to destroy the "green-bridge", and reduce chances of infection. Farmer may also consider other alternatives such as bringing in cattle to graze out the infected crop, or harvest the crop for hay.

The results presented in this study are an initial stage towards determining economic WSMV infection threshold, under farmer managed fields. In this study, we have attempted to quantify WSMV effects on yield, and infection threshold using data from one field experiment for a single year, thus unable to control for year and location effects. To the extent possible, future studies should incorporate more realism in the analysis by using multiple year data from different locations, and collect actual yield and input costs data from abandoned fields as a counterfactual to non-abandoned fields.

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Table 1. Descriptive Statistics for Three Assessment Dates and Yield

Variable	Mean	Std. Dev.	Minimum	Maximum
First reflectance (April 27th)	6.920	2.679	3.825	15.469
Second reflectance (May 4th)	7.510	1.777	4.776	11.956
Third reflectance (May 10th)	6.741	1.747	4.125	11.450
Yield (bu/acre)	59.019	29.819	6.786	109.271

Table 2. Ordinary Least Squares Estimates of the Effect of WSMV on Wheat Yield (log Bu/acre) at the First Sensing

Variable	Estimate
Intercept	5.446**
	(0.088)
First reflectance reading	-0.222**
	(0.014)

Note: Standard errors in parenthesis; *p < 0.05, and **p < 0.01. Number of observations =113

Table 3. Ordinary Least Squares Estimates of the Effect of WSMV on Wheat Yield (log Bu/acre) at the Third Sensing

Variable	Estimate
Intercept	6.15**
	(0.111)
Third reflectance reading	-0.336**
	(0.018)

Note: Standard errors in parenthesis; *p < 0.05, and **p < 0.01. Number of observations =113

Table 4. Partial Budget - Decision to Abandon a WSMV Infected Field

Item	$/Acre	Item	$/Acre
Added income due to abandonment:		**Added costs due to abandonment:**	
None	0	None	0
Reduced costs due to abandonment:		**Reduced income due to abandonment:**	
Fungicide	19	Revenue loss: 62 bushels at $3.45/bu	219.903
Irrigation (20% of total irrigation cost)	4.936		
Harvest (Machine + Labor)	20.54		
Subtotal	44.476	Subtotal	219.903
Net change: 44.476 -219.903 =	**-175.427**		

Table 5. WSMV Infection Threshold and Yield Estimates

Variable	Threshold Estimate	Lower Bound	Upper Bound	Expected Yield at Threshold (Bu/acre)
April 27th Reflectance Threshold	12.914** (0.383)	12.155	13.672	13.185
May 10th Reflectance Threshold	10.472** (0.181)	10.113	10.831	13.893

Note: Standard errors in parenthesis; *p < 0.05, and **p < 0.01. Number of observations =113

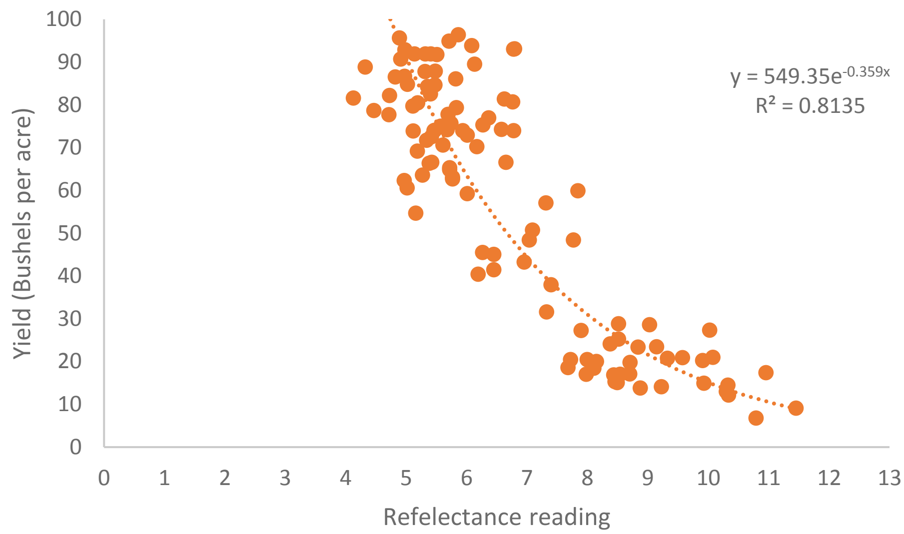

Figure 1. Relationship between Third Reflectance Reading and Wheat Grain Yield (Kg/hectare) for Dalhart[2]

[2] Similar graphs for the first and second reflectance reading were generated, although not presented here.