Economic Thresholds of Wheat Streak Mosaic in the Texas High Plains

Brian P. Mulenga,* B. Wade Brorsen, Francis M. Epplin, Fekede Workneh, and Charles M. Rush

Core Ideas
• Expected wheat yield declines exponentially with increasing wheat streak mosaic severity.
• For reflectance readings taken on 27 April, 4 May, and 10 May, economic threshold reflectance values are 8.3, 9.5, and 9.4, respectively.
• At the threshold infection severity expected grain yield is approximately 1910 kg ha\(^{-1}\).
• Wheat growers could potentially save resources by discontinuing input applications and introduce cattle for grazing.

ABSTRACT
Wheat streak mosaic (WSM), caused by *Wheat streak mosaic virus*, is the most widespread and economically important virus disease affecting winter wheat (*Triticum aestivum* L.) in the Great Plains of the United States. Using reflectance data from a hand-held hyperspectral radiometer and yields from a field experiment, this study estimated economic thresholds of WSM beyond which it is uneconomical to continue with mid-season input applications. Disease severity assessments based on reflectance measurements were taken from 99 plots across the field at three time points, namely 27 April, 4 May, and 10 May in the 2015–2016 wheat season. A log-linear regression model of yield on reflectance indicates potential yield losses of up to 35% for every unit increase in infection severity (as measured by reflectance readings). Using regression and partial budget analysis, results show varying thresholds of WSM depending on the date of disease severity assessments. The 27 April assessment had the lowest threshold when compared with the other assessment dates. Threshold analysis indicates potential to save resources by discontinuing mid-season input applications and introducing cattle for grazing, in about 14% of the sampled plots, but only 1% if grazing was not possible.

Abbreviations: BM, biomass; BYDV, *Barley yellow dwarf virus*; HPWMoV, *High Plains wheat mosaic virus*; TriMV, *Triticum mosaic virus*; TVC, total variable cost; VBM, value of biomass; WSM, wheat streak mosaic; WSMV, *wheat streak mosaic virus*.

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grasses, and even corn (*Zea mays* L.), infested with the virus-carrying wheat curl mites are nearby when wheat seedlings emerge. Volunteer wheat provides a convenient green bridge (plants growing between the harvest of last year's wheat crop and emergence of the new wheat crop) for the mites, and thus WSMV disease outbreaks (e.g., Christian and William, 1993; McMullen and Waldstein, 2010; Price, 2015). Eliminating green bridges destroys the mites' food source and thus the mites do not live to infest subsequent crops.

When volunteer wheat is left growing late in the summer, after harvest, mites move from volunteer wheat to newly planted fields of winter wheat, completing the green bridge, with newly emerged wheat plants now hosting viruliferous mites. When conditions for disease development are conducive (i.e., warm temperatures coupled with wind) during the fall, wheat curl mites transmit the virus from infected plants (Christian and William, 1993; Price, 2015) to other parts of the field and to other fields in the vicinity. The disease has been found to spread from an infested field to a healthy field, a distance of 2.3 km (1.4 miles) (McMullen and Waldstein, 2010). Although infections can occur both in the fall, soon after plant emergence, and in the spring, after the crop comes out of dormancy, the disease may not be noticed until temperatures begin to warm in late spring.

Previous research found that the severity of WSM can be quantified by remote sensing, based on tissue reflectance, when the crop is at Feekes growth stage of 5 to 9 (usually about mid-April in the Southern Plains) (Mirik et al., 2013; Workneh et al., 2009, 2017). Common symptoms of the disease include chlorosis, streaking, and mosaic, and also stunting when plants are infected at an early stage. Infection may occur at any stage of development, but if infection occurs during the early stages of crop development, the effects on crop growth and yield are more severe (Workneh et al., 2009). As there is no curative treatment, there is little a farmer can do once the crop is infected. Therefore, eradication of green bridge hosts, planting resistant or tolerant varieties, and avoiding early planting dates are the only means of reducing risk of loss from this disease (Byamukama et al., 2014).

Given the economic significance of WSM to wheat production and profitability, it should be beneficial to model and quantify wheat yield response to varying levels of WSM infection. In addition, it is also important to estimate the level of WSM severity that would reduce yield enough so that discontinuing application of inputs to the crop and grazing it out as pasture would be a more economical option. Determining this level of infection is important, because it would equip farmers with information to make informed decisions soon enough in the season to enable reductions in input applications and associated expenses.

Literature on the relationship between WSM and yield is mainly based on descriptive analysis. A few exceptions are Workneh et al. (2017), Almas et al. (2016), Pradhan et al. (2015), and Byamukama et al. (2014), who used regression analysis to model this relationship. Byamukama et al. (2014) focused on the effect of the disease on yield determinants such as tillering, shoot weight, and plant height, which they found to be significantly reduced by WSMV infection. Workneh et al. (2017) and Almas et al. (2016) estimated regressions and found an exponential relationship between WSM and wheat yield. Almas et al. (2016) treated WSM reflectance readings (sensing variable) as a discrete variable, rather than continuous, which could potentially lose information.

These studies provided important insights into the potential effect of WSM on yield. The current study builds on these analyses and presents a more nuanced yield response estimate, which is used to estimate an economic infection threshold. Most existing literature on disease thresholds focuses on optimal timing of treatment for crop disease control (Kuosmanen, 2006; Mbah et al., 2010). However, since there is no curative treatment for WSM, determining an economic threshold for WSM early in the growing season so farmers could discontinue input applications, has potential to save resources and reduce costs.

With this goal in mind, the objectives of the current study were twofold: (i) determine wheat grain yield response to WSM severity as estimated by remote sensing; and (ii) determine the disease severity threshold, beyond which it is uneconomical to continue with crop inputs.

**THEORY**

Previous research has found that reflectance measurements at 555 nm are positively correlated with severity of WSM symptoms, which are negatively correlated with final grain yields (e.g., Workneh et al., 2009; Almas et al., 2016). At Feekes growth stage of 5 to 6, reflectance readings, measured as reflectance values as in other studies (e.g., Workneh et al., 2009; Almas et al., 2016), from healthy plants generally are around 5 at maximum depending on the cultivar: light-colored healthy cultivars may give higher readings than dark-green ones. Almas et al. (2016) used 4 as a maximum value for healthy, WSM-free plants. A field with a high incidence of WSM may go undetected by a grower until late in the growing season, at which point the yield potential of severely infected plants will be significantly reduced relative to uninfected plants. However, because incidence and severity of WSM in a field is progressive over time (Workneh et al., 2009), parts of a field may be severely infected whereas other parts of the field may be healthy. Such a scenario makes it extremely difficult for a grower to know whether additional crop inputs for the entire field are worth the expense. However, with the advent of precision agriculture and site-specific management options, growers can now apply different management strategies to different parts of a field and focus on those parts of the field with the highest yield potential.

Wheat streak mosaic severity estimates between late March and early May can be made using remote sensing technologies to determine the relationship between disease severity, at a given time, and yield potential of the infected part of the field. Based on this information, a farmer could determine whether to continue to invest inputs in the crop or to abandon the entire crop, or at least the part of the crop with low yield potential. To salvage some value from the abandoned crop or part of the field, a farmer could harvest the wheat for hay or bring in cattle and graze it out. The current study seeks to determine optimal post remote sensing strategies, based on the sensor reading level, i.e., disease severity. After scanning the crop with remote sensing, the expected optimal strategy may be to: (i) continue with input applications and harvest; (ii) abandon the field, or at least the portion with the lowest yield potential, discontinue input applications, and graze-out or harvest for hay; and (iii) discontinue input applications, let the crop mature and harvest (expected yield is greater than harvest cost).1

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1 The third strategy would require knowledge of yield from an abandoned crop, which was not captured in our data. However, the third strategy was included only for conceptual completeness. Our empirical analysis focuses only on the first and second strategies.
Farmers are faced with deciding whether to continue applying mid-season management inputs—such as fertilizer, pest 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:

\[
\max_{\text{b}i} E\Pi = \left[ P^w E(y) \times (1 - D) + (P^b \times BM_i) \times (D) - TVC_{(D)} \right] \\
\text{s.t} \\
E(y) = \beta_0 + \beta_1 S_i \\
D = I(3 \geq \theta) \tag{1} \\
BM_i = E(y_i) \times 2.5 \\
TVC_{(D)} = f(D)
\]

where \(E\Pi\) is expected profit; \(P^w\) is the average seasonal wheat price (assumed constant); \(\theta\) is the WSM infection threshold; \(E(y)\) is expected wheat grain yield, which is dependent on WSM infection severity of the \(r\)th plot at a particular remote sensing time \(t\), represented by \(S_i\); \(P^b\) is the price of wheat biomass (pasture); and \(BM\) is the amount of biomass available to graze-out, and is a function of expected grain yield. The value 2.5 is a conversion factor from grain yield to biomass as suggested by Xue et al. (2006). The variable \(D\) is the decision whether to abandon and graze-out an infected section, which takes a value of 1 if a farmer abandons and 0 otherwise; TVC denotes total variable input costs such as fertilizer, pest control, irrigation, and labor for producing wheat (US$ ha\(^{-1}\)), which varies depending on \(D_i\); and \(\beta_0\) and \(\beta_1\) are parameters to be estimated.

One important assumption regarding the decision to abandon is that a farmer would only cease input applications if expected return from harvesting is lower than additional input costs and the grazing value. Thus, in the above formulation, it is assumed a farmer would graze-out the wheat if a section is abandoned, to salvage some value from the wheat biomass and offset the cost of inputs applied before ceasing additional input applications. Based on estimated timing of input applications, a farmer can save costs on fungicide, supplemental N application, some level of irrigation, and harvest, since these activities would not be necessary if, after remote sensing, the farmer decides to discontinue further input applications and graze-out the wheat.

To link disease severity and wheat profitability, the effect on potential yield of a given level of WSM severity at a particular point in time was estimated and the estimates were used to calculate expected profits. Estimate of a WSM severity threshold for that time point that would render continuation of input application unprofitable can then be estimated.

Economic threshold is then defined as the level of expected yield \((y)\) at which net revenue from grain equals net revenue from grazing out wheat biomass. Mathematically, this can be represented by the equation:

\[
P^w \times E(y) - TVC_1 = VBM_1 - TVC_2 \tag{2}
\]

where \(P^w\), \(P^b\) and \(y\) are as previously defined; \(VBM_1\) is the variable cost of all inputs applied including grain harvest; \(VBM_2\) is value of biomass \((BM \times P^b)\), which is represented by the value of weight gain of cattle grazed on wheat biomass; and \(TVC_2\) is total variable cost of inputs applied only up to the time of remote sensing.

**DATA**

Data for this study were obtained from a field experiment conducted in the 2015–2016 wheat season in the Dalhart area of Texas. To control for location and time effect, a second experiment was set up at the Bushland Experiment Station, Texas, in the 2013–2014 season. Unfortunately, the second experiment was hailed out and so no yield was recorded. Thus, only data from the first experiment was used in this study. The experiment was conducted on a 47.75-ha field, which was planted to the cultivar TAM 304 on 6 Nov. 2015, and was under center-pivot irrigation. The following inputs were applied: 16.8 kg N, 32.1.6 kg P, and 16.8 kg S ha\(^{-1}\), and each were applied as dry fertilizers with seeds. Additionally, 112.4 kg of N ha\(^{-1}\) was applied through the center-pivot irrigation system in three applications. For herbicides, 1.0 L ha\(^{-1}\) of huskie (pyrasulfotole, bromoxynil octanoate, and bromoxynil heptanoate, Bayer CropScience, Research Triangle, NC) and 0.29 ha\(^{-1}\) of Starane Ultra (fluoroxypr 1-methylheptyl ester, Dow AgroScience, Indianapolis, IN) were applied. Fungicide Prosaro (prothioconazole and tebuconazole) was applied at 0.3 L ha\(^{-1}\) (Bayer CropScience, Research Triangle, NC). Wheat streak mosaic virus severity assessment was conducted in this field by first establishing a transect, running from one side of the field to the other. The field contained a total of 113 sampling plots (measuring 1 m\(^2\)), established across a transect, with distances between sampling locations ranging approximately from 4 to 10 m. However, only 99 plots had usable data, as the first 14 plots, which were located along the edge of the field, already had extremely high infection severity at the time of the first remote sensing (27 April).\(^2\) The length of the transect and distances between locations were determined based on the disease severity gradient from the edges of the field.

When wheat reached growth stage 5–6 on the Feekes scale (Large 1954), the severity of WSM in each 1-m\(^2\) area (5 rows) was measured by taking reflectance readings (scanning) with a handheld hyperspectral radiometer (SD 2000, Ocean Optics, Dunedin, FL) held at 2 m above the canopy. All reflectance measurements were taken between 1130 and 1330 h on non-cloudy days. Previous studies (Workneh et al., 2009) demonstrated high correlation between severity of WSM and leaf reflectance at 555 nm, so this reflectance wavelength was used as a quantitative measure of disease severity. Remote sensing of WSM was done on three dates; 27 April, 4 May, and 10 May. Symptomatic leaves from 62 randomly selected plots were collected and tested for WSMV, Triticum mosaic virus (TriMV), High Plains wheat mosaic virus (HPWMoV), and Barley yellow dwarf virus (BYDV). This was done to ensure that the observed symptoms were due to WSMV since the wheat curl mite also transmits other viruses. All the 62 symptomatic samples tested positive for WSMV, with only 6.5% of the samples testing positive for TriMV (in association with WSM). None of the samples tested positive for HPWMoV or BYDV, indicating WSM was by far the main disease in the field and the cause of observed symptoms.

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\(^{2}\) Excluding these data from the analysis resulted in a lower mean reflectance reading for April, and thus increased the responsiveness of grain yield to WSM infection level for April readings. This is because for a given yield level, the mean April reading for the 99 plots was lower than the reading with all the 114 data points. Overall, exclusion of these data points resulted in a lower April threshold relative to May readings.
Regression analysis was used to estimate the effect of WSM infection severity on yield. The general formulation of the model is:

$$\ln y_t = \beta_0 + \beta_1 s + \nu_t$$  \[3\]

where $y_t$ is the wheat yield (kg ha$^{-1}$) in the $t$th plot, $s_t$ is reflectance value measured from each plot at time $t$ ($t = 1$ for 27 April, $t = 2$ for 4 May, and $t = 3$ for 10 May), $\beta_0$ and $\beta_1$ are coefficients, and $\nu_t \sim N(0, \sigma^2_\nu)$ is the stochastic error term.

Accurate prediction of final yield based on reflectance reading is critical to determining disease severity threshold. Model selection and misspecification tests were conducted to help select a model with the best fit. To evaluate the correlation between yield and reflectance values, a scatter plot of yield against each of the reflectance values was graphed (Fig. 1). The fitted line and goodness of fit test for all three reflectance readings suggest a log-linear relationship, implying an exponential decline in yield as WSM severity increased, consistent with other studies (Workneh et al., 2009; Byamukama et al., 2014; Almas et al., 2016).

### EMPIRICAL MODEL AND ESTIMATION

Based on the graphed yield and reflectance values, a log-linear regression model was estimated for all three reflectance reading dates, using the specification in Eq. [3]. Because the natural logarithm is a nonlinear transformation, expected yield cannot be calculated by simply setting the error term to zero, as this will lead to biased expected yield estimates. Yield follows a lognormal distribution, so expected yield is obtained by taking exponents on both sides of the Eq. [3] and $(\sigma^2_\nu / 2)$ is included to get the expected value of a lognormal distribution as shown in Eq. [4]:

$$\hat{y}_t = e^{\hat{\beta}_0 + \hat{\beta}_1 s + (\sigma^2_\nu / 2)}$$  \[4\]

where $\sigma^2_\nu$ is the sample variance of the error term, and all other variables and parameters are as previously defined, with the hat on parameters indicating that the parameters are estimated.

### PROCEDURE

Information on input costs and timing of applications were obtained from the farmer where the experiment was conducted, and supplemented with Oklahoma State University Department of Agricultural Economics Extension wheat enterprise budgets data for the wheat season 2016–2017 (Department of Agricultural Economics, Oklahoma State University, 2017). At the time of the first remote sensing, all inputs except fungicide and irrigation were fully applied. Fungicide was applied in mid-May, and irrigation continued until early June. In each of the 5-row plots, the three center rows (0.6 m$^2$) were harvested for yield. Grain from each plot was hand-harvested on 29 June 2016, threshed, and weighed to determine yield per plot. Grain yield per plot was used to determine yield in bushels per acre. Table 1 presents a summary of descriptive statistics of the reflectance values at different remote sensing dates and corresponding final yield.

The radiometer used in this experiment is about 15 yr old, the purchase price is unknown, and the model is no longer produced. A new radiometer would cost around US$7000 and models with more features would cost substantially more. It would take about 5 h to collect the spectral data. There would be additional time to analyze the data, travel time, and time to pick up the sensor if it were rented, which we assume to be two additional hours. A producer is unlikely to be able to justify purchasing a sensor. If this were adopted, it might be provided by a service provider much like grid soil sampling. Grid soil sampling is provided locally for $25 ha^{-1}. The $25 ha^{-1}$ provides an upper bound for likely cost of sensing. It is also possible that producers would need to pay very little for this technology, as they might arrange with their consultants to have drones fly over their fields and get similar multispectral data that would include reflectance from the diseased and healthy areas of the fields.

### Table 1. Descriptive statistics for three reflectance values taken at 555 nm and yield.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>SD</th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>First reflectance (27 Apr)</td>
<td>6.11</td>
<td>1.73</td>
<td>3.83</td>
<td>11.63</td>
</tr>
<tr>
<td>Second reflectance (4 May)</td>
<td>7.19</td>
<td>1.66</td>
<td>4.78</td>
<td>11.96</td>
</tr>
<tr>
<td>Third reflectance (10 May)</td>
<td>6.74</td>
<td>1.57</td>
<td>4.13</td>
<td>11.45</td>
</tr>
<tr>
<td>Overall reflectance</td>
<td>6.96</td>
<td>2.13</td>
<td>3.83</td>
<td>11.96</td>
</tr>
<tr>
<td>Yield, kg ha$^{-1}$</td>
<td>4392.61</td>
<td>1824.77</td>
<td>457.33</td>
<td>7363.33</td>
</tr>
</tbody>
</table>

![Graph](image-url)
Substituting Eq. [4] in Eq. [2] and solving for the threshold, $S$, at time $t$, yields:

$$S_t = \ln \left[ \frac{\text{VBM} - \text{TVC}_2 + \text{TVC}_1}{P^\alpha} \right] - \left( \frac{\sigma_t^2}{2} \right) - \beta_{0t} \left( \frac{\sigma_t^2}{2} \right)$$

where all variables and coefficients are as defined before.

Analysis proceeded in two stages. The first stage involved regression analysis to estimate yield response function to WSM, and the second stage used the coefficients from the estimated yield function in the partial budget analysis to calculate the threshold values. A nonparametric bootstrap, with 1000 replications, was used to obtain the sampling distributions of the threshold estimates (mean, standard deviation, and confidence interval).

**Misspecification Tests**

Model misspecification tests were performed because misspecification can lead to biased and inconsistent estimators, resulting in inappropriate inferences (McGuirk et al., 1993). A scatter plot of reflectance readings against wheat yield suggested an exponential yield-reflectance reading relationship (Fig. 1), and thus a log-linear model was fitted. Following (D’Agostino et al., 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 for the 4 May and 10 May sensor readings. Although the 27 April readings were not normally distributed, the errors from the regression were. Other tests conducted include the Lagrange multiplier test for heteroskedasticity (Breusch and Pagan, 1980) and the joint conditional mean and conditional variance tests, using the comprehensive specification tests as suggested (McGuirk et al., 1993). None of the tests detected statistically significant misspecification.

**RESULTS AND DISCUSSION**

Table 2 presents regression estimates of effect of WSMV infection severity (reflectance readings) on wheat yield for all three reflectance reading dates. All three fitted regressions predicted final yield relatively well, as indicated by relatively narrow confidence intervals, small standard errors, and high $R^2$ values. Of the three reflectance data collection dates, the 10 May readings predicted yields more accurately, with an $R^2$ value of 0.78, followed by the 27 April readings at 0.71, and lastly the 4 May readings with $R^2$ of 0.70. The coefficients on reflectance readings representing WSMV infection severity are negative and statistically significant in all three regression models, confirming the negative relationship between WSMV severity and final yield. In terms of magnitude, holding all else equal, a one unit increase in the 27 April reflectance value corresponded to a 30% reduction in expected final yield, whereas a similar increase in the second and third reflectance values corresponded to yield reductions of 31 and 35%, respectively.

The difference in magnitude across time (i.e., across the three sets of reflectance values) can be attributed to increased infection severity over-time, since the same plots had reflectance readings taken at three different time points. Therefore, at lower levels of infection severity (early in the season), an increase in infection severity has a lower effect on the expected final yield, compared with a similar increase later in the season, when infection severity is high, such that a marginal increase in infection would result in relatively higher yield loss. This finding is consistent with previous reports (Workneh et al., 2017; Almas et al., 2016; Byamukama et al., 2012). However, this may not be the case if the same level of infection was observed at different times. For example, Pradhan et al. (2015) inoculated wheat with the same level of WSM at different developmental stages and found higher yield impacts for earlier infection than later.

After estimating the WSM–yield potential relation (yield predictor), a partial budget analysis was performed to evaluate economic threshold yield potential. Next, the economic WSM infection threshold was estimated as the level of infection corresponding to the threshold yield potential for each remote sensing date. A comparison was conducted of returns from two production decisions, namely: (i) continue input applications and harvest grain at the end of the season; and (ii) cease input applications mid-season and graze-out. Estimates of graze-out revenue were obtained by converting expected grain yield to biomass using a conversion factor of 2.5, suggested by Xue et al. (2006). As mentioned earlier, the value of biomass is represented by the value of beef cattle gain (value of gain), determined as the difference in the weight of beef cattle before and after placement on wheat pasture.

The value of gain estimate draws from previous analyses, such as Belasco et al. (2009) and Tumusiime et al. (2011), who estimated dry matter feed conversion into beef gain. Tumusiime et al. (2011) assume that for every 10 pounds of wheat forage biomass consumed, a steer gains 1 pound, and each pound of gain is valued at $0.45 (i.e., a 1:10 ratio). In terms of kg, this translates in 1 kg weight gain of biomass is represented by the value of beef cattle gain ($0.45 × 2.2$ pounds $\text{kg}^{-1}$). Their analysis was based on WSM-free wheat forage during the winter months. However, forage quality from a WSM-infected crop is expected to be low and the crop is approaching senescence; thus, cattle would have to consume relatively higher quantities of the “poor quality” forage per kg of gain. Further, during April and May (period of interest for the analysis), the price of wheat forage would adjust downward to reflect abundance of grass forage at that time of the year. To account for quality decline, the quantities (kg) of forage required for 1 kg of gain were adjusted from 10 to 20.

To account for availability of substitute forage during that time of the year as well as potential costs of moving cattle or electric fencing to fence off part of a field, price of forage was adjusted downward by 23% from $0.99 to $0.77 kg$^{-1}$. Although arbitrary, to some extent, these adjustments partially help account for changes in forage quality, as well as capturing seasonal fluctuations in forage price. Using these assumptions, revenue from graze-out was calculated as $(\text{BM}/20) \times 0.77$, which gives a per-kg biomass price of $0.039$.

One important estimate from partial budget analysis is the total variable costs a producer could potentially save in inputs by the time of remote sensing, which is the same time that a decision whether to cease input application and graze-out is to be made. Based on

<table>
<thead>
<tr>
<th>Estimate</th>
<th>27 April</th>
<th>4 May</th>
<th>10 May</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>10.099**</td>
<td>10.502**</td>
<td>10.487**</td>
</tr>
<tr>
<td></td>
<td>(0.125)</td>
<td>(0.154)</td>
<td>(0.124)</td>
</tr>
<tr>
<td>Coefficient</td>
<td>-0.303**</td>
<td>-0.313**</td>
<td>-0.351**</td>
</tr>
<tr>
<td></td>
<td>(0.020)</td>
<td>(0.021)</td>
<td>(0.019)</td>
</tr>
</tbody>
</table>

**p < 0.01.
† Standard errors are in parenthesis. The number of observations is 99.
information on timing of input application, at the time of remote sensing (27 April–10 May), producers could save $148.97 ha\(^{-1}\) in inputs and irrigation, if they decide to abandon the crop and graze it out due to low yield potential. This amount also represents cost savings as a result of the decision to stop input application and graze-out the biomass mid-season, when potential grain yield is low.

Using the above-mentioned assumptions, the economic threshold yield was estimated by setting net returns from grain harvest equal to returns from graze-out. This gave a threshold grain yield of about 1910 kg ha\(^{-1}\). At this yield level, net returns from grain harvest and graze-out are equal (Fig. 2). The WSM infection threshold was then calculated as the level of severity that corresponds to a grain yield potential of approximately 1910 kg ha\(^{-1}\).

Following estimation of economic threshold yield, the economic infection severity threshold for each remote sensing date was calculated using the estimated yield predictor and partial budget estimates (Table 3). Specifically, Eq. \([5]\) was used to estimate threshold values for all three remote sensing dates from 1000 bootstrapped samples. Table 4 presents a summary of threshold estimates and their sampling distributions. It should be noted that the threshold estimates presented in Table 4 are a function of input and output prices. Therefore, the threshold will vary not only depending on remote sensing dates, but also contingent on input and output prices used to construct the partial budget. Results indicate varying WSM severity threshold levels for all the three remote sensing dates. The 4 May readings had the highest threshold value at about 9.5, followed by 10 May with a threshold value of 8.4, and in the third place was the 27 April readings at 8.3. This result is expected, except for 4 May having a higher threshold than the 10 May readings. It is important to point out here that thresholds estimates are likely to vary across wheat cultivars, as disease progression may not be uniform across cultivars.

As the severity thresholds correspond to a point where net returns from graze-out and grain sales are equal (Fig. 2), the

![Fig. 2. Economic threshold yield and returns for wheat streak mosaic infected crop.](image)

Table 3. Partial budget—decision to graze-out from a Wheat streak mosaic virus–infected crop.

<table>
<thead>
<tr>
<th>Item</th>
<th>Item $ ha(^{-1})</th>
</tr>
</thead>
<tbody>
<tr>
<td>Added income due to graze-out:</td>
<td></td>
</tr>
<tr>
<td>Grazing revenue (251.50 kg of gain at $0.77 kg(^{-1}) of gain)</td>
<td>193.65</td>
</tr>
<tr>
<td>Reduced costs due to graze-out:</td>
<td></td>
</tr>
<tr>
<td>Fungicide</td>
<td>46.43</td>
</tr>
<tr>
<td>Irrigation (25% of total irrigation cost)</td>
<td>47.61</td>
</tr>
<tr>
<td>Harvest (Machine + Labor)</td>
<td>55.43</td>
</tr>
<tr>
<td>Subtotal</td>
<td>343.12</td>
</tr>
<tr>
<td>Net change: 343.12 – 343.11 = 0</td>
<td>0.00</td>
</tr>
</tbody>
</table>

Table 4. Wheat streak mosaic virus infection threshold by remote sensing date under graze-out and complete abandonment scenarios.†

<table>
<thead>
<tr>
<th>Remote sensing date</th>
<th>Threshold estimate</th>
<th>SE</th>
<th>95% Confidence interval</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>Lower limit</td>
</tr>
<tr>
<td>Graze-out</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>27 April</td>
<td>8.31</td>
<td>0.26</td>
<td>8.26</td>
</tr>
<tr>
<td>4 May</td>
<td>9.52</td>
<td>0.30</td>
<td>9.47</td>
</tr>
<tr>
<td>10 May</td>
<td>8.39</td>
<td>0.17</td>
<td>8.36</td>
</tr>
<tr>
<td>Complete abandonment</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>27 April</td>
<td>11.04</td>
<td>0.49</td>
<td>10.94</td>
</tr>
<tr>
<td>4 May</td>
<td>11.99</td>
<td>0.52</td>
<td>11.89</td>
</tr>
<tr>
<td>10 May</td>
<td>10.63</td>
<td>0.30</td>
<td>10.58</td>
</tr>
</tbody>
</table>

† Results are based on 1000 nonparametric bootstrapped samples from 99 sampled plots.
The difference in thresholds values between the 4 May and 10 May is inconsistent with most studies on crop disease infection and final yield (e.g., Hunger et al., 1992; Price, 2015) that suggest lower threshold for earlier infection than later. A plausible explanation for this finding is that high disease severity early in the season (4 May in our case) could have resulted in senescent tissue, which was not yellow but brown, and thus a lower reading at 555nm for the latest (10 May) readings. It could also be the case that there was background contamination from bare soil due to loss of canopy as infection severity increased further by the time of the 10 May remote sensing.

Detecting the disease early enough in the season is critical for making mid-season management decisions. The farmer would have had more opportunity to adjust inputs if the disease had been detected earlier than it was in this study. Ideally, farmers should determine disease incidence and severity between late-March to mid-April, and if reflectance readings (disease severity) exceed the threshold, then farmers should consider ceasing input applications and graze-out the wheat biomass. However, the best strategy is for farmers to prioritize good management practices that eliminate the green bridges. Although wind may carry mites from one field to another, elimination of the green bridges may prevent and/or reduce chances of infection.

To compare the returns to grazing and the cost of remote sensing, average yield for all the hectares of the field was estimated and converted to biomass, which was subsequently valued using weight gain from grazing it out. The total returns on the field from harvesting for grain, even if producers were to pay for remote sensing. However, our study represents the first analysis to estimate the economic threshold of the disease during the growing season. Estimates indicated the threshold reflectance to range from about 8.3 to 9.5 for readings taken around late April to early May, and are sensitive to input and output prices used in the construction of partial budgets. With well over one-tenth of the sampled plots having reflectance values greater than the threshold, results suggest farmers may potentially save resources and salvage some value by discontinuing input applications and grazing out the wheat forage from infected fields whose infection severity exceeds the estimated threshold values at a particular time.

This study quantified WSM effects on grain yield and severity threshold using data from one field experiment for a single year, and were thus unable to control for year, cultivar, and location effects. More precise estimates could be obtained from future studies that obtain data from multiple years, cultivars, and locations. In addition, future studies should consider obtaining data on yield, and input costs from grazed-out fields as a counterfactual to grain-harvested fields, with and without additional inputs. Furthermore, given that mite vectored virus disease symptoms typically begin to show up in late March, it is critical that future studies begin sensing early to avoid plant tissue senescence, which negatively impacts the correlation between reflectance values at 555 nm and disease severity.

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**REFERENCES**

