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Modeling Joint Dependence of Managed Ecosystems Pests: The Case of the Wheat Stem Sawfly

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Many invasive and opportunistic pests cause multiple, interdependent adverse outcomes on agricultural production. Often, however, these impacts are modeled independently, which can bias empirical inferences and contribute to inaccurate recommendations. We use a copula function to more accurately model the joint behavior and provide an empirical example of its application to assess the impacts of the wheat stem sawfly (WSS). We use a unique farm-level dataset to estimate the expected losses associated with WSS and then evaluate two popular WSS management strategies. We find that strategies minimizing long-run infestation levels are preferred to those that seek to maximize yield potential in exchange for higher risk of intertemporal infestation.

Key words: biological control, copula, harvest decisions, host plant resistance

Introduction

Invasive or opportunistic pests can have economically significant impacts on agricultural and natural resource industries. In many cases, however, these impacts are characterized and measured as a single aggregate consequence, even though there is likely a portfolio of interrelated effects that compose the estimated total loss. For example, timber-stand infestations by mountain pine beetles—insects that bore into and can eventually kill pine trees—can result in a range of outcomes, from trees being uninfested, to infested trees that recover, to infested trees that can only be marketed at a discount, to dead trees with almost no market value. Other examples include field bindweed—an aggressive species whose vines climb and constrict crop plants—which can have no effect, shade plants but not impair primary metabolism, shade plants and impair assimilate accumulation, or prevent plant maturation, as well as tree fruit fire blight—a bacterial disease that requires excision of damaged tissue—which can fail to infect an orchard, infect an orchard but trees recover, or infect and kill infected trees.

When the research objective is to simply estimate the overall economic impact of invasive or opportunistic pests, it is less critical to accurately model and assess the interdependencies of individual perils due to the pest. However, when the objective is to assess optimal intervention and management decisions, accounting for interactions of perilous outcomes becomes more important because of the potential trade-offs associated with correlated biological dynamics and human intervention. Most research on natural hazards accounts for biological correlations within a regression framework but then uses the estimated *ceteris paribus* marginal effects to develop management recommendations. This can significantly limit assessments of interventions. We

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develop a model for combining existing regression analyses of biological perils with methods for empirically characterizing the joint distributional properties of peril outcomes in order to improve management strategy assessments.

Our research focuses on the wheat stem sawfly (WSS), an insect that challenges agricultural production across numerous interrelated dimensions. The WSS is an opportunistic, adaptive species endemic to native North American prairie (Lesieur et al., 2016). It has perennially affected North American wheat production since shortly after cultivation began (Weiss and Morrill, 1992). The area traditionally impacted by WSS has been the spring wheat production regions of the northern Great Plains and southern Canadian prairies, but the pest's adaptation to changing environmental and production conditions during the past several decades has made it a significant threat to winter wheat producers. In the past decade, WSS infestation and damage has been reported in Colorado, Kansas, and Nebraska, with increasing pressure in Montana and North Dakota. These Wheat Belt states accounted for approximately 48% of U.S. wheat production in the last 10 years (averaging 1.01 billion bushels of annual production) and thus represent a major economic vulnerability if WSS continues to increase its role as an annual, systematic production risk.

This research is the first to develop and estimate an economic model of the pest and to explicitly account for interdependencies across multiple pest-related perils. We first describe an expected yield loss function faced by farmers who are at risk of WSS infestations. The loss function depends on a number of factors that are both external and endogenous to wheat producers. We show that agricultural producers who seek to minimize yield losses from pest infestations must consider not only the extent to which a specific peril affects production outcomes but also the interrelation of biological and management decision. We then use a unique farm-level dataset that describes infestation and yield losses for numerous WSS perils in locations across the northern Great Plains during 1998–2011 to estimate the two components of the expected loss function: a peril's conditional probability and resulting yield damage.

Specifically, we first use copula functions to empirically model the joint distribution of WSS infestation and wheat damage outcomes. Copula functions are designed to provide a flexible method for modeling joint probabilistic relationships among random variables and have been used in financial and economics research of risk assessment and management, portfolio analysis, and for investigating and developing financial derivatives contracts (see Patton, 2012, for a survey of copula model applications in the financial and economics literature). This methodology is particularly well-suited for characterizing multifaceted pest behaviors and impacts. The temporal length, granular detail, and number of observations in our data allow us to use semi-parametric estimation and fit assessments to identify the best-fitting copula function to represent the joint distribution of WSS outcomes. Second, we use the data to estimate a model of conditional wheat yield losses related to WSS. The regression model controls for variation in wheat classes and cultivars, field-level characteristics, area of impact, climatic differences across production years, and unobservable geographic and year-level impacts that can affect yields. The estimation results help quantify the average losses associated with three types of WSS perils to wheat yields. The model and results represent the first geographically and temporally diverse quantification of WSS impacts.

The estimations of the joint WSS outcome distributions and the conditional yield losses are then used to evaluate the trade-offs of two most-used WSS management strategies in the northern Great Plains: planting solid-stem wheat varieties and swathing prior to harvest. The solid-stem management strategy impacts the insect during its development cycle, but at the cost of lower yield potential. The swathing strategy continually uses the highest-yielding varieties but has additional operations costs and can lead to the propagation of a WSS population. We extend the portfolio model to demonstrate how producers' management decisions can have intertemporal impacts on the probability of observing a WSS peril and the extent of potential damage from that peril. Using the estimated joint dependency structure of WSS perils and yield loss regression results, we simulate returns to the two strategies across a multi-year implementation periods in order to assess which of the strategies is economically optimal.

The results of the simulation analysis show that during the first 4–5 years after an initial WSS infestation, the two strategies lead to relatively similar economic returns. However, in the longer run, the swathing approach—which trades off higher yield potential with decreased ability to suppress insect population—leads to over 10% lower returns relative to using the solid-stem strategy. As climate changes lead to more favorable conditions for WSS populations to develop in more productive central and southern regions of the U.S. Wheat Belt, our results can provide critical insights about empirical methods for quantifying WSS impacts as well as a baseline for farm-level management recommendations. More broadly, this study demonstrates the importance of accounting for the joint distributional properties of pests and the use of appropriate models to capture those interdependencies and serves as an example of how these models can be used to evaluate returns to alternative interventions.

Overview of the Wheat Stem Sawfly

Wheat stem sawflies have been perennial pests of North American grain crops for more than 100 years. The first record of *Cephus cinctus*, the species prominent in the Great Plains, is from a specimen collected in 1872 from a native grass in Colorado (Norton, 1872). Hollow-stemmed prairie grasses are the primary plant hosts of WSS, and these grasses can be native or introduced (Ainslie, 1920), with the latter being either cultivated or noncultivated (Ainslie, 1929). The cultivated hosts that currently suffer the greatest injury include hard red spring and winter and durum wheat classes (Beres et al., 2011b).[1] Commercial crop damage due to this insect was first observed during 1895 in central Saskatchewan and western Manitoba (Ainslie, 1920) and in the United States in 1900 (Wallace and McNeal, 1966). These discoveries alerted entomologists of the potential economic risks associated with the pest, and subsequent research began to identify WSS in many locations in the northern Great Plains and southern Canadian Prairie Provinces in both wheat and grasses (Wallace and McNeal, 1966).

Since this initial discovery, WSS presence has been recorded in all but one continental state west of the Mississippi River and seven wheat-producing states as far east as Georgia and Pennsylvania (Ivie, 2001). However, the pest's presence and adverse effects on commercially produced wheat have been concentrated in the northern Great Plains, largely in the hard red spring and durum wheat production areas of northern and eastern Montana, northern and central North Dakota, and the southern Canadian Prairie Provinces. In the past 3 decades, this relatively concentrated impact area has expanded, primarily due to the insect's synchronization of its emergence patterns to the winter wheat growth stage (Irell and Peairs, 2011; Lestina et al., 2016). As a result, WSS-related losses have been regularly reported to the west, south, and southeast of the traditional WSS high-damage areas. Figure 1 illustrates areas of reported grain crops damaged by WSS, with darker areas representing locations with the most severe losses due to WSS and lighter areas indicating regions that are increasingly subject to higher infestation and damage risks. Major U.S. wheat production areas are now at elevated risk for WSS infestation and losses.

Wheat Stem Sawfly Life Cycle

In the late spring or early summer, WSS adults emerge after overwintering (Ainslie, 1920). The timing of emergence is associated with ambient temperature and relative humidity (Perez-Mendoza, Weaver, and Morrill, 2006). Despite being relatively weak fliers, WSS can readily move far enough to locate suitable plant hosts for oviposition; movement is often more pronounced during warm, dry

[1] Other cereals—such as barley, oats, and rye—may receive eggs from the pest but are less or not at all (as in the case of oats) suitable for pest development and are therefore relatively unaffected by WSS (Platt and Farstad, 1946). Wildland grasses such as orchardgrass, smooth brome, and a number of wheatgrasses can host WSS populations. However, in some locales the emergence of WSS from wildland hosts is not synchronized with the emergence of cultivated crops, making these hosts (at least currently) not a major threat for harboring and initiating a continually renewing pest population (Painter, 1953).

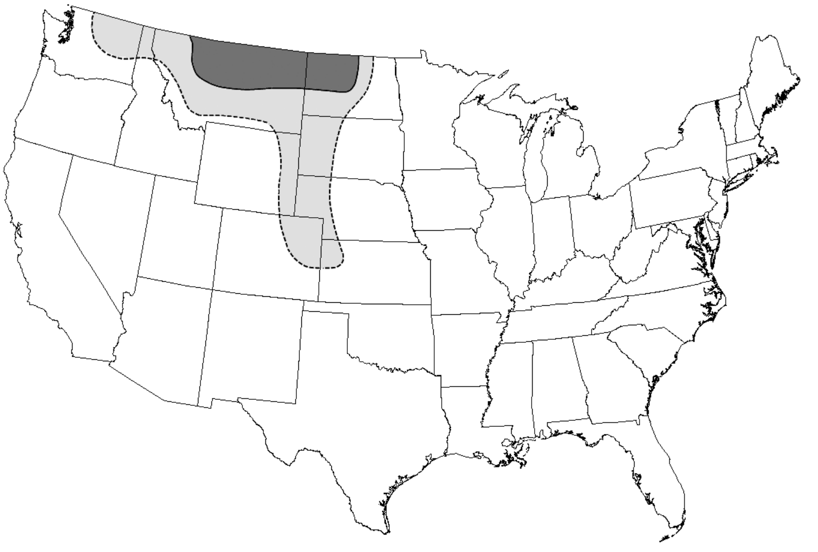


Figure 1. Map of Identified and Potential WSS Wheat Impact Areas

Notes: The darker area indicates regions with acute, perennial WSS infestation and damage. The lighter area indicates regions that have reported WSS infestation and damage and where more severe WSS presence is likely.
Source: The figure is constructed by the authors and corresponds closely to previous estimates (Weaver, 2009) as well as pest reporting and information about historical wheat production capacity as of 2016.

weather without excessive winds (Ainslie, 1920). Mating occurs immediately after emergence and oviposition takes place within the next several days. A female WSS, which can produce up to 50 eggs, saws open the stem of a wheat plant and deposits an egg into the hollow portion of the stem interior (Ainslie, 1929; Seamans, 1945).

On the sixth or seventh day after oviposition, the larvae exit the egg and emerge on the surface of a stem's interior lumen (Ainslie, 1920). Upon hatching, larvae begin stem-boring activity (Ainslie, 1920). While adult WSS trivially impact a wheat plant during oviposition, a larva's stem-boring can lead to excessive losses, which are manifest in two ways: First, larvae boring through the wheat plant's soft tissues is closely linked to significant reductions in the plant's photosynthetic capabilities, reducing the crop's ability to produce kernels and lowering the weight of each kernel (Seamans, Manson, and Farstad, 1945; Macedo, Weaver, and Peterson, 2007). Because the larvae typically feed within the stem until the wheat plant is nearly mature (Beres et al., 2011b), potential production losses are positively correlated with the length of time that a viable larva feeds.

The second risk occurs as a wheat plant matures and dries. At this time, a larva prepares to overwinter by moving down the stem cavity and then encasing itself in a silken cocoon (Ainslie, 1920; Wallace and McNeal, 1966). The insect's preparation for overwintering in the lower part of a wheat plant weakens the stem and can lead to the plant falling to the ground as it continues to dry. Toppled stems can be especially evident near field edges and after particularly windy weather events; these stems contribute to additional production losses because they are more difficult to harvest and may lose kernels (Beres et al., 2011b). This is known as stem cutting or lodging.

Larval WSS can overwinter successfully because they are well protected within the sealed environment of the cocoon and located near the root crowns of the plant host (Holmes, 1979; Buteler et al., 2015). Therefore, WSS is relatively impervious during its dormant stage, largely unaffected by low ambient air temperatures, high moisture environments, and farmers' actions such as reducing stubble height or performing a controlled burn (Weaver et al., 2004). The overwintering period ends after at least 40 days of temperatures above 50°F, typically beginning in late March in major wheat production regions. Unless extremely high temperatures (95°F and above) or exceedingly dry

Table 1. Overview of Alternative WSS Management Strategies

Chemical controls:	Using insecticides to control adult WSS populations. Effectiveness depends on whether the insecticide comes in direct contact with WSS adults, making this management approach largely ineffective.
Burning:	Relatively ineffective because overwintering larvae are protected and burning can reduce parasitoid populations.
Nutritional control:	Altering the application of nitrogen and phosphorous in the production process. This strategy has been found either to have no effect on or increase WSS populations.
Biological control:	Introducing parasitoids into areas with high WSS populations. Potentially effective, but requires time to build up parasitoid populations.
Tillage:	Effectiveness is uncertain; tillage may reduce parasitoid populations.
Strip cropping:	Alternating thin strips of cropped and fallow land. This historical erosion-control strategy has been found to exacerbate the problem because WSS can more easily move between the strips, resulting in more field margins with greater damage.
Solid-stem cultivars:	Wheat varieties with solid stems, which help reduce stem-cutting rates and may lower feeding damages. Solid-stem cultivars typically have lower yields and may incur additional capital costs.
Trap cropping:	Planting a border of attractive solid-stem cultivars around a less attractive, higher-yielding primary crop of hollow-stem varieties. Economic returns to trap cropping are still being researched.
Swathing:	Preemptively cutting stems into windrows prior to harvesting, helping reduce losses due to unrecovered heads. Swathing is associated with additional variable costs and can lower parasitoid populations.

Sources: Luginbill and McNeal (1954); Wallace and McNeal (1966); DePauw and Read (1982); Lafond et al. (1996); Morrill et al. (2001); Runyon et al. (2002); Weaver et al. (2004); Delaney, Weaver, and Peterson (2010); Knodel and Beauzay (2010); Knodel, Shanower, and Beauzay (2010); Beres et al. (2011b).

conditions occur (Holmes, 1979), the insect enters the pupation stage and transforms into an adult sawfly, beginning its life cycle anew.

Among the natural enemies of WSS are two specialist braconid wasps, which are the only WSS parasitoids that commonly occur in wheat (Runyon et al., 2002). These parasitoids move among host plants until they locate a WSS larva feeding inside a stem. Once a host is identified, females paralyze the sawfly larva with their ovipositor and deposit eggs into the wheat stem (Holmes et al., 1963). After emergence, the parasitoid larvae feed on and eventually consume the WSS larvae. Mortality due to parasitoids (or "parasitism") significantly reduces the physiological damages caused by WSS and prevents lodging by infested stems (Buteler, Weaver, and Miller, 2008).[2]

WSS Management Strategies

Throughout more than a century of WSS surveys and bionomics research, a variety management methods have been proposed, adopted, and abandoned (Wallace and McNeal, 1966; Beres et al., 2011b). While a comprehensive review of these methods is outside the scope of this study, Table 1 provides a summary of the more researched management strategies. Planting solid-stem wheat cultivars and swathing wheat prior to harvest are currently the two most widely adopted risk management approaches in the perennially affected northern Great Plains.

Solid-stem wheat varieties are bred to have an increased amount of pith within the stem (Kemp, 1934). These cultivars decrease the survival rates of WSS larvae and help reduce cutting rates and losses from boring activity (Holmes and Peterson, 1961; Talbert et al., 2014). For example, Figure 2 shows that cutting risk is higher in hollow-stem varieties of both the hard red winter and hard red (dark northern) spring wheat classes. Moreover, solid-stem cultivars were not observed to have any

[2] The success of parasitoids in reducing WSS damage depends in part on the population density of the pest. Developing parasitoids may not survive in stems containing more than one WSS larva (Nansen et al., 2005), which occurs frequently at higher population densities (Buteler, Weaver, and Peterson, 2009).

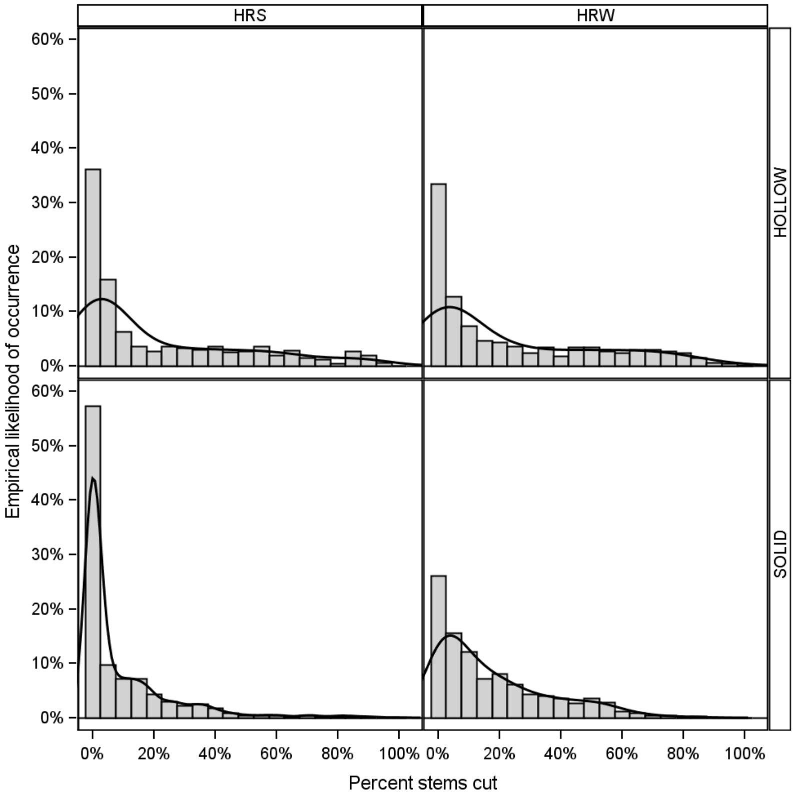


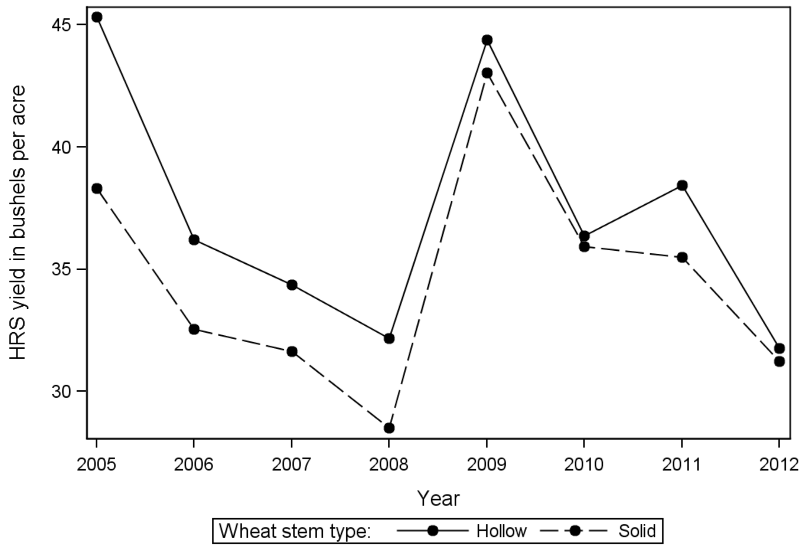
Figure 2. Empirical Distribution of Cutting Risk by Wheat Class and Stem Type

Notes: Cutting refers to the proportion of total sampled stems that were determined to have been cut by WSS activity.
Source: The figure is constructed by the authors using data collected by the Montana State University Wheat Stem Sawfly Research Lab. Data range from 1998 to 2011 and across numerous locations in Montana and the Canadian Prairie Provinces.

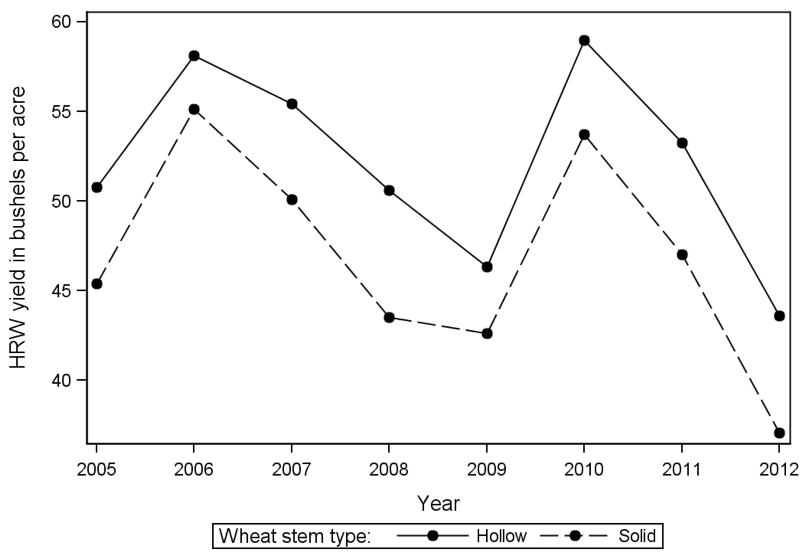
cutting above 40% for spring wheat or above 60% for winter wheat. Despite the beneficial aspects of solid-stem varieties, they have historically had lower maximum-yield potential than their hollow-stem counterparts because the plant uses a portion of its energy to produce stem pith rather than increase the number or size of seeds. Figure 3 shows the average observed yields across numerous Montana locations for the top five hard red spring wheat and winter wheat hollow- and solid-stem cultivars between 2005 and 2012.[3] In both classes, hollow-stem varieties have consistently resulted in higher yields, with substantially larger differences in hard red winter wheat. These data imply that there are economic trade-offs associated with planting solid-stem wheat varieties: These varieties can help decrease losses associated with WSS (especially when infestation levels are high) but have lower maximum yields when WSS infestation levels are low.

Swathing is the second popular management approach (Beres et al., 2011a). Swathing involves cutting wheat into windrows, allowing the stems to dry on the ground before harvesting, and using a combine with a pickup header to collect the grain. While this helps reduce losses associated with not recovering cut wheat stems, the strategy only prevents losses from stem cutting and is ineffective in managing population growth because swathing must occur late in the wheat-growing process (after most WSS-related physiological damages have already occurred) and the WSS larvae have migrated close to the wheat root (Holmes and Peterson, 1965; Beres et al., 2011b). Despite the relatively limited utility of this management strategy, producers rapidly adopted the tactic, perhaps in an

[3] In 2012, for example, these five cultivars accounted for approximately 67% of all planted spring wheat and 65% of all planted winter wheat cultivars in Montana.



(a) Hard red spring wheat yield trends



(b) Hard red winter wheat yield trends

Figure 3. Reported Wheat Yield Trends, by Stem Type

Notes: Yields represent averages for the top five planted cultivars, which accounted for approximately 67% of all planted spring wheat and 65% of all planted winter wheat cultivars in Montana during 2012.
Source: The figure is constructed by the authors using historical yield potential data provided by the Montana Southern Agricultural Research Center across numerous locations in Montana.

attempt to plant higher-yielding wheat varieties and chase high wheat prices in the mid-2000s or by adopting recommendations that may not be widely generalizable (for example, Knodel, Shanower, and Beauzay, 2010, recommend that all producers swath when infestation level exceed 15%). Prior to the late 1990s, approximately 50% of Montana hard red spring wheat acres were planted with solid-stem varieties, but these represented only 22% of planted acres in 2012 (Montana Agricultural Statistics Service, 2002–2012), even though WSS risks increased. Furthermore, while swathing can reduce yield losses due to cutting, the practice increases both capital and labor costs without reducing the overall WSS population. In fact, WSS populations may increase because swathing eliminates natural enemies (parasitoids) that may overwinter in wheat stems (Beres et al., 2011a,b), exacerbating intertemporal infestation risks and increasing the potential for physiological losses over time.

Modeling Pest Impact Dependencies and Losses

We model the expected yield losses associated with WSS. This model consists of two components: the risk of observing yields below an expected maximum yield due to a WSS peril and the expected loss associated with the peril, conditional on the loss actually occurring. That is, if an infestation could result in only one peril, *i*, a farmer's expected yield loss from that peril *i* could be modeled as

$$E[\text{Loss}_i] = \int_0^1 \int_0^1 [\mu - f(X; D_i, W)] g(D_i) h(W) \mathrm{d}D_i \mathrm{d}W, \tag{1}$$

where μ represents the maximum potential yield from a wheat plant and $f(X;D_i,W)$ is the observed yield, composed of a deterministic component, X, which represents production inputs and management decisions made by a farmer, as well as two random components: D_i and W. The term D_i is the proportion of damage resulting from peril i due to WSS infestation, and W is the proportion of the field infested by WSS. Finally, $g(D_i)$ and $h(W)$ are the probability density functions of the stochastic variables D_i and W.

There are four quantifiable outcomes of interest. One outcome is simply the level of WSS infestation. On its own, the outcome is benign; however, equation (1) shows that infestation is associated with perils that can result in yield losses. There are three such yield loss outcomes: i) the number of stems that are infested and cut, representing major physiological yield losses and potential for full yield loss if those stems are not recovered by a combine; ii) the number of stems that are infested, not cut, but subject to partial adverse effects associated with the level of physiological yield loss due to WSS boring before the larvae died; and iii) stems that are infested but in which a WSS larva was subsequently parasitized, representing the least yield loss.

If there were only one yield-reducing peril or the three perils were independent of one another, then equation (1) would accurately describe the conditionality between a particular peril *i* and the level of infestation W. However, for WSS (as for numerous pests and invasive species), there also exist interdependences among yield-reducing outcomes across perils. That is, the expected loss function is more accurately modeled as

$$E[\text{Loss}_i] = \int_0^1 \int_0^1 \int_0^1 [\mu - f(X; D_i, D_j, W)] g(D_i) k(D_j) h(W) \mathrm{d}D_i \mathrm{d}D_j \mathrm{d}W, \tag{2}$$

where D_j represents the proportion of damage resulting from peril j. As such, modeling the probability of a loss event and expected losses from particular perils now depends on appropriately identifying the joint distribution of infestation and multiple yield-reducing outcomes. Doing so is critical for accurately estimating total expected losses from WSS and the potential trade-offs for choosing particular management strategies.

Probability of Loss Events

Generally, the probability of observing a yield loss outcome for each of the three perils can be determined from the underlying distribution of the loss outcomes. However, as shown in equation (2), the loss outcome distribution is conditional on the distribution of infestation outcomes. This implies that in modeling and empirically estimating loss outcome distributions, not accounting for the relationship between infestation levels and the probability of a particular loss outcome (i.e., estimating unconditional probability distribution functions for loss outcomes) could bias the probability estimates.

In addition to the dependency between WSS infestation levels and loss outcomes for any one of the three perils, there are also linkages among these three factors. For example, at the field level, the probability of observing high rates of cut wheat stems is likely to be lower when there are relatively low rates of stem boring. Similarly, boring rates are expected to be lower in fields where parasitism rates are high. Such multiple dependencies are observed in many other pests and invasive species from which multiple adverse impacts are possible.

As such, to correctly characterize and quantify the underlying interdependent risk distributions for the four WSS outcomes of interest—infestation, boring, cutting, and parasitism—it is necessary to consider the joint relationship among these outcomes. We model the distribution interdependence using copula functions. Copulas provide a relatively simple and flexible approach to accommodate high-dimensional correlation structures among stochastic variables (Joe, 1997; Nelsen, 1999).

The copula approach is flexible in that the marginal distributions (i.e., the unconditional distributions of the four outcomes of interest) can be modeled and estimated separately from the structure of the joint dependence among these distributions. That is, consider a random vector $\mathbf{Y} = (y_1, y_2, \ldots, y_k)'$ composed of realizations of random variables $y_1, \ldots, y_k$. The objective is to estimate the distribution of $\mathbf{Y}$. If $F_1, \ldots, F_k$ represent univariate continuous cumulative probability densities, then the marginal probability density function for each random variable can be characterized as $f(y_k) = F_k^{-1}(U_k)$, where U_k is a uniform distribution on the interval $[0,1]$.

Using this representation of the marginal density functions, the probability density function of the joint dependence can be expressed as

$$f(\mathbf{Y}) = f(y_1, \ldots, y_k) = C(f(y_1), \ldots, f(y_k)|\boldsymbol{\theta}), \tag{3}$$

where $C(\cdot)$ represents the copula function that combines each of the marginal probability density functions and $\boldsymbol{\theta}$ is a vector of dependence parameters that characterize the dependence structure among the marginal densities. In the context of this study, the joint distribution of the random variables infestation (W), cutting (T), boring (B), and parasitism (P) is characterized by the function

$$f(W,T,B,P) = C(f(W), f(T), f(B), f(P)|\boldsymbol{\theta}), \tag{4}$$

which implies that two components need to be estimated: the marginal probability density functions for each of the WSS outcomes and the dependence parameter, $\boldsymbol{\theta}$. For each of these components, we implement data-driven, semi-parametric approaches.

First, we estimate the empirical cumulative density function for each of the four WSS outcome variables using the observed data across differentially infested fields rather than assuming an underlying distribution and using the data to fit its parameters. That is,

$$\hat{F}(y_k) = \frac{1}{n}\sum_{i=1}^{n} 1(y_i \leq y), \tag{5}$$

where $1(\cdot)$ is an indicator function that equals 1 when the condition is true and 0 otherwise. With a sufficient number of observations, the empirical density function can be effectively estimated and provide a more representative characterization of the underlying marginal probability function because no assumptions about the distribution's shape are required.

Second, we estimate the long-run relationships among the four WSS outcomes using Spearman's rank-based correlation structure. We use this structure to estimate the copula function parameters,

$\boldsymbol{\theta}$, under several parametric assumptions about the shape of the copula function. These assumptions include the most common copula functional forms—the multivariate Gaussian and the Archimedean Clayton, Gumbel, and Frank copulas. To determine the copula function that provides the best fit to the data, we compare each estimated parametric copula to an empirical copula. Deheuvels (1981) shows that the empirical copula uniformly converges to the underlying parametric copula specification.

This data-driven, semi-parametric approach helps model the interdependencies among the four WSS outcomes and is used as a foundation for simulating risk distributions that are more representative of those that have been observed at the field level. That is, the modeling method helps preserve the numerous intricacies associated with the interdependent biological relationships of WSS infestation and related damage outcomes. This increases the accuracy of estimating the probabilities of yield loss outcomes and assessing management decisions.

Modeling Yield Losses

In addition to modeling the probability of WSS perils that can result in yield losses, we model the expected yield losses associated with those perils (i.e., equation 2). Similar to other types of pests, the effects of WSS cannot be simplified to a binary outcome that either a complete loss occurred or that no loss occurred. Rather, physiological damages to a wheat plant can lead to partial yield losses.

Estimating these physiological losses is therefore critical, but losses from WSS may be confounded by other factors that may not be related to the pest's presence. For example, wheat yields are affected by the class of wheat, the cultivar, the location where the wheat is grown, the temperature and precipitation during the growing season, and farmers' production choices (e.g., fertilizer levels, chemical levels, experience).

As such, we model yields as

$$\begin{aligned}(6)\qquad \ln(Yld)_{ijt} &= \beta_0 + \textstyle\sum_k \beta_k \left(\frac{\text{Stems}_{kijt}}{\text{Stems}_{\text{inf},ijt}}\right) + \mathbf{HS}_{ijt}\boldsymbol{\beta}_{hs} + \beta_{sd}\text{SD}_{ijt} + \beta_m \text{M}_{ijt} + \beta_{m2}\text{M}^2_{ijt} \\ &\quad + \mathbf{TmpPrcp}_{jt}\boldsymbol{\beta}_{tmp} + \delta_j + \delta_t + \varepsilon_{ijt},\end{aligned}$$

where Yld_{ijt} represents a wheat head's seed weight for sample i in a field on a farm at location j in year t; Stems_{kijt} is the number of stems experiencing a WSS outcome $k \in \{\text{uninfested, cut, parasitized}\}$; $\text{Stems}_{\text{inf},ijt}$ is the number of stems that experienced physiological losses due to boring activity but were neither cut nor parasitized; $\mathbf{HS}_{ijt}$ is a vector of the indicator variables that specify whether a seed weight outcome is from a hollow-stem hard red spring wheat, solid-stem spring wheat, hollow-stem hard red winter wheat, or solid-stem winter wheat (with hollow-stem spring wheat used as the comparison group); SD_{ijt} represents a stem-density measure that is normalized to unity, with observations whose values are greater than 1 characterizing a sample in which wheat plants are expected to have higher-than-average yield potential and observations with values less than 1 characterizing lower-than-average yield potential; M_{ijt} is the distance in meters of a sample from the edge of a field; $\mathbf{TmpPrcp}_{ijt}$ is a vector of total precipitation (in inches) and average temperatures observed during the growing season in year t; δ_j and δ_t are field location and time fixed effects, which control for unobservable heterogeneity that can affect wheat yields across time (i.e., affecting all locations in the sample) and across locations (e.g., differences in farmer abilities, land productivity, and other directly unmeasurable factors); and ε_{ijt} is an idiosyncratic error term.

In the above log-linear model, β_k, represents the three main parameters of interest. The estimated values are marginal effects on wheat yields from an additional stem being infested and cut, infested but parasitized, or uninfested, relative to a stem that was infested but neither cut nor parasitized (i.e., the control group). The log-linear specification of the model implies that the β_k parameters can be interpreted as semi-elasticities, which provides for a straightforward interpretation and scalability of the estimation results to more aggregated spatial levels (e.g., farm, region).

Data and Empirical Results

We empirically estimate two components of the expected loss model presented in equation (2). We use a unique, large database of field-level infestation and loss records. The data were collected by Montana State University's Wheat Stem Sawfly Laboratory and represent infestation and loss information from 31 locations across Montana and southern Canada over the period 1998–2011. The data are a pooled cross section describing field-level wheat samples analyzed to determine the level of infestation within a sample of wheat stems, the number of stems that were cut as a result of WSS, the number of stems with parasitoids (i.e., parasitized stems), and the stems that had boring activity but that were neither cut nor parasitized.

The database also contains information about the class and variety of wheat, whether the stem type was hollow or solid, density of wheat stems, and the distance into a field at which a sample was obtained. Additionally, we collected data about the average temperature and total precipitation during the March–September growing period from the North American Regional Reanalysis (NARR) database, which uses a northern Lambert conformal conic grid spatial model to triangulate weather conditions to a 7.7-square-mile block, allowing us to more accurately associate meteorological conditions with specific fields. In total, 4,274 sample-level observations describe WSS infestation, cutting, and parasitism outcomes, with a subset of 676 observations characterizing yields in the cut, parasitized, partially damaged (i.e., stems with boring activity), and uninfested wheat stems.

Table 2 shows the descriptive statistics of the relevant variables.[4] The data show that, on average, 36% of sampled stems were infested with WSS. Conditional on being infested, 63% of stems were observed to have some damage from boring activity, 30% of stems had severe damage and were cut, and 7% of infested stems were found to be parasitized. In the data subsample with yield information, average yield of sampled units was approximately 30.5 bu/acre. The average yield for nonirrigated hard red spring and winter wheat across Montana during 1998–2011 was approximately 31.2 bu/acre (U.S. Department of Agriculture, National Agricultural Statistical Service, 2017), suggesting that our sample is representative of typical production conditions in the state.[5]

Copula Estimation

We estimate alternative copula functions and evaluate their fit to determine the best specification for characterizing the interdependent relationships among WSS outcomes. Figure 4 provides visual and statistical summaries of the empirical marginal distributions. The figure shows scatter plots for the proportion of wheat stems in a sampled location that are infested with WSS, the proportion that were cut, the proportion that were parasitized, and the proportion in which boring activity was evident but the stems were neither cut nor parasitized. The data show that there are relatively distinct positive relationships across each outcome pair. This relationship is also made evident by the Spearman rank correlation statistics, which show that the strongest relationships are among the proportion of infested stems and the other three outcomes and that statistically significant (albeit somewhat weaker in magnitude) relationships exist among these three damage outcomes.

The Spearman rank correlation matrix is used as the estimate of the underlying interdependence structure for identifying the copula function. Empirical cumulative density functions are used to estimate the marginal distributions shown in Figure 4 and we estimate the Gaussian, Clayton, Gumbel, and Frank copula functions. To determine the best fit of these four alternative copula

[4] The presented descriptive statistics are the mean, median, and 25th and 75th percentiles of the empirical distribution. Standard deviation is not presented because of substantial skewness for many of the variables.

[5] Figure A1 also shows the geographic distribution of locations from which wheat samples were collected and county-level production during the sampling period. The figure makes clear that samples were collected from locations that specialize in commercial wheat production, adding further evidence that our data are representive of a typical commercial wheat farmer.

Table 2. Descriptive Statistics of Relevant Variables

	Sampled Units	Mean	Median	25th Percentile	75th Percentile
Proportion infested stems	4,274	0.36	0.26	0.04	0.67
Unconditional					
Proportion stems cut	4,274	0.15	0.04	0.00	0.23
Proportion stems parasitized	4,274	0.02	0.00	0.00	0.01
Proportion stems with boring	4,274	0.18	0.11	0.00	0.29
Conditional on Sample Being Infested					
Proportion stems cut	4,274	0.30	0.20	0.00	0.53
Proportion stems parasitized	4,274	0.07	0.00	0.00	0.02
Proportion stems with boring	4,274	0.63	0.56	0.27	0.88
Subsample with Yield Information					
Seed weight (bu/acre)	676	30.51	30.46	21.59	38.25
Proportion HRS, hollow stem	676	0.63	1.00	0.00	1.00
Proportion HRS, solid stem	676	0.18	0.00	0.00	0.00
Proportion HRW, hollow stem	676	0.09	0.00	0.00	0.00
Proportion HRW, solid stem	676	0.09	0.00	0.00	0.00
Stem-density index	676	1.00	1.00	1.12	0.86
Distance into field (meters)	676	50.69	40.00	20.00	80.00
Average temperature (°F)	676	55.99	55.89	55.59	57.80
Total precipitation (inches)	676	4.21	3.26	3.14	4.57

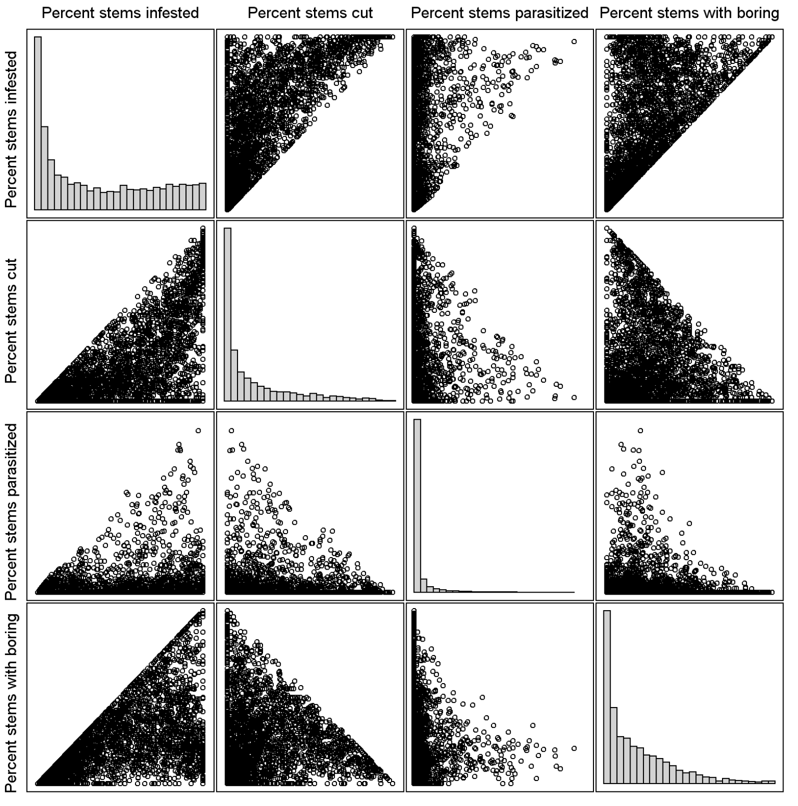
Notes: Seed weight is originally measured in grams per kernel, but has been converted to bushels per acre for easier interpretation. The initialisms HRS and HRW signify hard red spring wheat and hard red winter wheat, respectively. Average temperature and total precipitation represent data collected during April through September, which characterizes the typical growing season for wheat in the northern Great Plains.

functions, we compare predicted outcomes from each estimated copula function to the outcomes of the empirical copula function (Deheuvels, 1981).

Table 3 presents these comparisons at numerous percentiles of the joint outcome distribution. The table also shows the sum of squared differences between the predicted outcomes of each parametric copula function and the empirical copula. The results clearly indicate that the Clayton copula provides the best fit to the joint distribution. This is not surprising, because the Clayton copula allows for asymmetric dependence in the joint distribution tails, with stronger correlation in the lower tail. That is, when the likelihood of observing one of the WSS outcomes is relatively low, there is greater certainty in observing low likelihoods of other outcomes. For example, when the WSS population is small, there is a higher likelihood of observing relatively sparse instances of WSS perils; however, when WSS populations are high, the dependence (and thus predictability) across the three other outcomes is weaker because numerous additional factors could influence event realizations.

Yield Loss Estimation

Table 4 presents the estimation results for the yield loss model in equation (6). The estimated parameters of interest are those indicating the marginal effects on wheat seed weight when a stem that has been infested and incurred physiological damage due to boring activity becomes (hypothetically) uninfested due to mortality, incurring additional damage such that the stem is cut, or in which a WSS becomes parasitized. The estimation results indicate that, relative to stems with boring activity, a 1-percentage-point increase in stems that are cut (3% increase relative to the sample



Spearman Correlation Table, n=4,274

	% Infested	% Cut	% Parasitized	% Boring
% Infested	1	0.79	0.33	0.83
% Cut	0.79	1	0.29	0.47
% Parasitized	0.33	0.29	1	0.15
% Boring	0.83	0.47	0.15	1

Figure 4. Dependence Relationships among WSS Outcomes

Notes: All Spearman correlation statistics are statistically significant at the 1% level. Graphs on the diagonal represent empirical histograms for each variable.

mean), on average, is associated with an additional 8% loss in seed weight (i.e., yield). But a 1-percentage-point increase in stems in which WSS is parasitized (14% increase relative to the sample mean) is associated with seed weights that are, on average, 11% higher.

A 1-percentage-point increase in uninfested stems is associated with, on average, only a 2% higher seed weight than stems with physiological damage. While this last result may appear, at first glance, too small, it characterizes the WSS adult female's ability to discriminate host quality before ovipositing (Buteler, Weaver, and Peterson, 2009; Buteler et al., 2010). Stems that are not selected to receive eggs (i.e., remain uninfested) may innately have lower yield potential (Wallace and McNeal, 1966). Thus, infested stems in which the WSS larva is killed by parasitoids (or otherwise dies) can have the greatest yields (Buteler, Weaver, and Peterson, 2009). Our estimation results are consistent with these past findings: An initially high-quality wheat plant that is infested and becomes subject to moderate physiological damage would, on average, produce yields approximately equivalent to a naturally low-yielding plant.

Therefore, a better representation of expected losses due to boring activity is not to compare yield outcomes from an uninfested plant with one that was infested and for which boring activity led

Table 3. Empirical Comparison of Alternative Copula Functions

Percentile	Empirical	Normal	Gumbel	Clayton	Frank
5th	0.017	0.016	0.021	0.014	0.014
10th	0.031	0.034	0.040	0.028	0.030
15th	0.048	0.054	0.059	0.044	0.048
20th	0.067	0.074	0.082	0.062	0.067
25th	0.086	0.096	0.106	0.085	0.089
30th	0.109	0.118	0.129	0.109	0.116
35th	0.132	0.143	0.156	0.134	0.144
40th	0.160	0.172	0.181	0.164	0.172
45th	0.192	0.201	0.210	0.197	0.206
50th	0.230	0.231	0.240	0.234	0.245
55th	0.288	0.265	0.281	0.289	0.286
60th	0.368	0.320	0.325	0.352	0.343
65th	0.448	0.377	0.368	0.414	0.396
70th	0.528	0.432	0.414	0.482	0.447
75th	0.594	0.497	0.462	0.558	0.504
80th	0.708	0.565	0.518	0.655	0.564
85th	1.000	0.659	0.580	0.790	0.622
90th	1.000	0.792	0.676	1.000	0.725
95th	1.000	1.000	1.000	1.000	1.000
100th	1.000	1.000	1.000	1.000	1.000
Sum of squared differences	–	0.207	0.358	0.052	0.258

Notes: For an *i.i.d.* sequence $X_t = (X_{1t}, \ldots, X_{nt})$ that is represented by a continuous CDF F and marginal distributions F_j, the empirical copula is defined by Deheuvels (1981) as $\hat{C}\left(\frac{t_1}{T}, \ldots, \frac{t_n}{T}\right) = \frac{1}{T}\sum_{t=1}^{T}\prod_{j=1}^{n} 1(r_j^t \geq t_j)$, where $1(\cdot)$ is a 0/1 indicator function and r_j^t is a rank statistic of X_t. The sum of squared differences represents the aggregation across percentiles of differences between the empirical copula and each of the parametric copulas.

to physiological damage. A more realistic scenario—in which we assume that producers attempt to maximize yields and thus the majority of wheat stems are of high quality—is to compare an infested stem to one that had been infested but in which the WSS was parasitized. That is, boring activity is associated with, on average, an 11% decrease in wheat yields.

The control variable parameter estimates are all statistically significant at least at the 10% level and exhibit expected relationships with the dependent variable. Solid-stem spring wheat varieties help mitigate some yield losses, but both the hollow- and solid-stem winter wheat plants have lower yields than the infested hollow-stem spring wheat control group. *Ceteris paribus*, yields are higher in samples with a higher stem-density index (i.e., better growing environment) and in samples located further from field edges, where WSS populations are less concentrated. Lastly, higher yields are associated with warmer and wetter locations.

Risk Management Strategies

Estimating the copula function and yield losses provides an opportunity to assess and compare the two most widely adopted strategies in the northern Great Plains—swathing wheat prior to harvest or planting solid-stem wheat cultivars—and provides insights about optimal management strategies. In the first management strategy, farmers plant a hollow-stem wheat variety, swath wheat into windrows shortly before harvest, allow the wheat to dry, and then harvest the grain using a pickup combine header. The underlying intuition behind this strategy is that windrowing and combining with a specialized header will minimize the amount of grain lost from plants that are cut by WSS. A second strategy is to alternate planting solid-stem wheat varieties. Solid-stem cultivars are bred to have a

Table 4. Yield Loss Model Estimation Results

	Parameter Estimate	t-Statistic
Uninfested stem	0.02***	9.06
Cut stem	−0.08***	−7.29
Parasitized stem	0.11**	2.33
HRS solid-stem variety, binary indicator	0.67***	9.94
HRW hollow-stem variety, binary indicator	−1.46***	−12.13
HRW solid-stem variety, binary indicator	−1.78***	−14.33
Stem-density index	0.11*	1.69
Distance into field, meters	0.50***	4.06
Distance into field, meters squared	−0.33***	−3.26
Average growing season temperature (°F)	0.11***	13.24
Total growing season precipitation, inches	0.33***	15.51
Intercept	−7.89***	−15.58
Location fixed effects	Yes	
Year fixed effects	Yes	
Adjusted R^2	0.65	

Notes: Dependent variable: ln(Wheat seed weight). Single, double, and triple asterisks (*, **, ***) indicate statistical significance at the 10%, 5%, and 1% level. Uninfested, cut, and parasitized stems are proportional measures relative to the number of infested (but not cut) stems in a sample. The initialisms HRS and HRW signify hard red spring wheat and hard red winter wheat, respectively.

large amount of pith in the wheat stem, which decreases the survival capabilities of WSS larvae and helps reduce cutting rates and losses from boring activity.[6]

Naturally, there are trade-offs between the two management practices. While the planting of solid-stem varieties helps limit the WSS life cycle, the plant's creation of pith in the stem implies that fewer resources are available to produce and grow grain kernels. Historically, this has resulted in solid-stem varieties having a lower maximum potential yield than hollow-stem cultivars. For example, among the most-used wheat varieties in Montana, solid-stem spring wheat yields approximately 2 bu/acre less than the hollow-stem variety; for winter wheat, this difference is approximately 5 bu/acre.[7] The swathing management strategy does not suffer from the lower yield potential, because it involves always planting hollow-stem varieties and thus has a higher ceiling for market revenues. However, because swathing must occur late in wheat's growing cycle, this strategy can only help reduce losses related to stem cutting (Beres et al., 2011b). It does not help reduce infestation levels or physiological losses (i.e., lower yields) due to WSS boring (Holmes and Peterson, 1965). Moreover, swathing incurs additional variables costs (both capital and labor) or hiring custom swathers, and windrowing wheat can decrease the number of parasitoids available in future years to compete with WSS.

The two strategies therefore require producers to evaluate the trade-offs of using a higher-yielding wheat variety but incurring swathing costs and increasing intertemporal loss risks, or using a lower-yielding cultivar that does not have additional operational costs but can reduce intertemporal

[6] As Table 1 shows, other management strategies exist, but these are not frequently used by farmers. Thus, there is insufficient data to empirically assess their cost-effectiveness. Because this work analyzes the most economically relevant pest-management strategies, we leave the investigation of other approaches to future research.

[7] Historical and ongoing plant breeding efforts have focused on reducing the difference between solid- and hollow-stem varieties. Because WSS infestation of spring wheat has had a longer history, a longer period of plant breeding research has led to the smaller yield difference for this wheat class. Recent advancements have also been made for winter wheat, but we use data only for those varieties that have had sufficient historical presence in the northern Great Plains to provide a reliable estimate of maximum yield potential.

WSS impacts.[8] We represent the intertemporal relationship by amending equation (1) as follows:

$$E[\text{Loss}_{it}] = \int_0^1\int_0^1 [\mu - f(X_t, X_{t-1}; D_{it}, W_t)]g(D_{it})h(W_t)\mathrm{d}D_{it}\mathrm{d}W_t. \tag{7}$$

The expected loss from peril i in time t is now a function of a management decision made in in the preceding period, X_{t-1}, because this management decision affects the WSS population that overwinters and emerges in the subsequent year. This would, in turn, affect the probability of observing a particular peril and the expected yield loss from that peril.

Simulation Setup

Unfortunately, there are no multi-year, longitudinal farm-level data that can be used to directly estimate intertermporal returns to alternative management decisions. Therefore, we use empirical results described in the previous section and experts' assessments about intertemporal WSS dynamics under alternative production conditions to simulate farm-level outcomes. Specifically, we simulate a representative risk-neutral farmer who operates a nonirrigated wheat farm on which half of the acres are rotated between production and summer fallow.[9] Farmers are assumed to grow either spring or winter wheat, and simulations are performed separately for each wheat class. After observing the presence of WSS during the initial period, the farmer chooses one of two management strategies: i) always plant a hollow-stem variety and swath or ii) plant a hollow-stem variety when the expected WSS damage level is sufficiently low and a solid-stem variety when the expected infestation level is high. The farmer is assumed to maintain the same management strategy throughout the entire simulation time window.[10]

Damage levels are measured using cutting outcomes, which are the easiest WSS outcomes for a typical wheat farmer to observe and thus the most widely used signal for making the decision to plant a solid- or hollow-stem cultivar. Regardless of the management choice, the initial cutting level is assumed to be 5%. The initial damage levels are the same regardless of the strategy choice.[11] For each wheat class and each management strategy, the simulation algorithm is as follows:

1. Conditional on the cutting level, make a cultivar decision. For the swathing strategy, the hollow-stem cultivar is always chosen. For the solid-stem strategy, the cultivar choice depends on the cutting level observed in the previous period. If the cutting level in $t-1$ is less than 10%, then a hollow-stem variety is chosen. If the cutting rate is equal to or greater than 10%, then the farmer plants a solid-stem variety.

2. The cutting level in the previous period, $t-1$, is assumed to be the expected level in the current period, t. Using this cutting level and the estimated Clayton copula function

[8] Swathing operations are completed approximately 5–14 days prior to harvesting (Schneiter and French, 1969). Therefore, farmers are unlikely to face labor or equipment constraints due to overlapping farming operations.

[9] Fallowing farmland to accumulate moisture has been a common practice for most operations in the low-precipitation regions of the northern Great Plains (Cochran et al., 2006). While this practice is being replaced with more intensive cropping systems, it is still the dominant management approach for many northern Great Plains operations. We assume a no- or low-tillage fallow practice, which is the dominant production management approach in the region.

[10] To our knowledge, no research has examined farmers' strategic decisions to switch management strategies within or between production seasons. However, anecdotal evidence from personal communications with producers suggests that farmers' WSS management strategies are relatively sticky. Additionally, there is a general consensus in the agricultural economics literature about the lengthy time-to-adoption of new and alternative technologies by farmers (for an overview, see Sunding and Zilberman, 2001).

[11] The simulation also assumes that the infestation and damage rates are uniform across a field and across a farm. This may not be the case, because the edges of a field are more likely to have greater infestation levels. However, because the spatial dynamics of these infestation pressures have not been well studied or quantified across alternative management strategies and making additional complex assumptions would make the interpretation of the simulation results less clear, we make the simplifying assumption of uniform insect dispersion. Future research is necessary to address this issue more rigorously.

described above, simulate the other WSS outcomes—infestation, boring, and parasitism—that are jointly conditional on the cutting level.

3. Using the jointly estimated WSS outcomes and the estimation results of the model in equation (6), determine the expected yield loss, $E[\text{Loss}]$. Calculate the expected yield, $E[\text{Yld}] = (\text{Yld}_{\text{max}} - E[\text{Loss}])$, where Yld_{max} represents the maximum yield potential for a hollow- or solid-stem cultivar.

4. Simulate a market price for the wheat and calculate the expected post-management per acre net revenue, $E[\text{Rev}] = (P \times E[\text{Yld}] - \text{TC}_{\text{swath}})$. Total costs for swathing, TC_{swath}, are nonzero only for the swathing management strategy. All other variable and fixed costs are assumed to be the same and, for clarity, are excluded from the revenue calculation.

5. Conditional on the management strategy and the number of periods that the management strategy has been implemented, simulate the cutting rate in the next period, $t + 1$. This new cutting rate is a probabilistic function of the expected WSS cutting rate in the current period, t, a random shock term, $\nu \sim N(0,1)$, and an assumed time-dependent outcome threshold.

   Specifically, for the solid-stem strategy, the likelihood of having a cutting level below 10% after using a solid-stem variety for one period is 60%; after using a solid-stem variety for 2 consecutive periods, the probability of falling below the 10% cutting threshold is 90%; and after using a solid-stem variety for 3 consecutive periods, the probability is 100%. The inverse is assumed for exceeding the 10% cutting level threshold when using hollow-stem cultivars. For the swathing management strategy, reaching a 90% cutting asymptote is assumed to occur within 3 years of implementing the strategy.[12]

6. Repeat steps (1)–(5) for T periods.

7. Repeat steps (1)–(6) for N farmers.

In the simulation, the maximum potential yields for both spring and winter wheat are estimated as the average of the top five planted cultivars of each stem type (hollow and solid) between 2008 and 2012. These data are maintained by the Montana Southern Agricultural Research Center, which collects yield information from experiment plots across the northern Great Plains. These yields are assumed to represent the maximum potential because the wheat is grown as part of small plot trials, which tend to represent best-case production conditions. Empirical market price distributions are estimated using daily wheat prices (adjusted for inflation) across six Montana regions between July 1988 and December 2012 U.S. Department of Agriculture, Agricultural Marketing Service, and Wyoming Department of Agriculture (1988–2012). Annual variable and fixed swathing costs are represented by a custom rate for swathing, \$9.66/acre (North Dakota State University, 2013).[13]

The simulation is performed separately for four production scenarios, which are a combination of the wheat class (spring or winter) and management choice (solid stem or swathing). For each of the four scenarios, we simulate $N = 1,000$ farmers who, after choosing a management strategy, operate the farm for $T = 10$ years. To ensure that the choice of farmers and periods does not impact the simulation results, we performed numerous robustness checks using larger values of N and T. Altering these parameters resulted in minor quantitative differences in the simulation results and no qualitative differences in the insights.

[12] Because no field-level longitudinal data exist, we are unable to empirically estimate intertemporal transition probabilities. Instead, we rely on informed hypothesized values provided by entomologists with extensive experience and expertise in WSS research. Furthermore, we assess the robustness of these assumptions by bootstrapping the simulation analysis with alternative values for both the cutting rate threshold and intertemporal transition probabilities. That is, we randomly generate deviations from the baseline percentage values (within a 5-percentage-point range) and regenerate the simulation. Average results from these permutations provide qualitatively identical insights as the baseline assumptions. Full results of the simulation bootstrapping are available upon request.

[13] North Dakota dryland wheat production systems are relatively representative of other production systems across the northern Great Plains.

Table 5. Farm-level Management Strategy Simulation Results

Management Strategy	Cut Stems (percent)	Yield Loss (bu/acre)	Annual Revenue after WSS Management (USD/acre)
Solid stem when cutting > 10%			
Spring wheat	12.27%	0.75	$207.96
Winter wheat	12.21%	1.01	$262.28
Hollow stem + annual swathing			
Spring wheat	74.34%	4.12	$185.08
Winter wheat	74.29%	5.78	$238.84

Notes: Each of the four scenarios represents a separate simulation, which simulates 1,000 farmers who observe outcomes of choosing a management strategy over a 10-year period. Results in the table represent the average outcomes across all simulated farmers and time periods. Annual revenues represent those based on prices that are simulated using an empirically estimated price distribution and accounting for swathing costs when appropriate; all other variable and fixed costs are assumed to be the same across management strategies.

Simulation Results

Table 5 presents the results from each of the four scenario simulations. The results represent the average outcomes across all simulated farmers and time periods. The simulation analysis indicates that the optimal strategy is the use of the solid-stem cultivars when cutting levels reach or exceed 10%. When this strategy is chosen, the representative farmer faces an average of 12% cutting for either spring or winter wheat over a 10-year period. This corresponds to approximately a 1 bu/acre reduction (relative to the maximum potential) in winter wheat and less than a bushel reduction in hard red spring wheat. In contrast, the continuous swathing strategy results in an average 74% cutting rate and a reduction of 4–6 bu/acre.

Table 5 also helps show that choosing a management strategy that trades off some of the yield potential—by planting lower-yielding solid-stem varieties—in order to reduce long-run WSS population pressures results in higher average annual net revenues. Relative to the swathing strategy, the average net revenues under the solid-stem strategy are $23/acre higher for hard red spring wheat and $24/acre higher for hard red winter wheat. This implies that even though the average annual yield potential of the swathing strategy is larger, the expected losses associated with WSS damage and swathing costs significantly outweigh the benefits of those higher yield potentials.

Figure 5 provides a more detailed time series perspective of the simulation results. For each of the 10 simulated periods, the figure shows average yield losses and expected per acre net revenues. For both spring and winter wheat classes, yield losses are approximately similar through the first 3 periods, with a stark divergence afterward. This divergence represents the long-run difference in the two management strategies' abilities to limit WSS population levels. While the solid-stem strategy stabilizes WSS impacts at a relatively low level, the swathing approach leads to the insect reaching its biological population asymptote, which occurs at a significantly higher level. Furthermore, Figure 5 makes evident the speed with which this asymptote is reached.

The time series simulation results of expected post-management net revenues provide a similar story. In the first 4–5 periods, expected revenues are relatively similar, mostly due to the fact that higher yield potential of the continually planted hollow-stem varieties is sufficient to offset costs associated with WSS damage and swathing. However, as WSS populations stabilize at significantly different levels across the two management strategies, farmers are more likely to benefit by accepting a lower yield potential in order to maintain a more stable, lower infestation level.

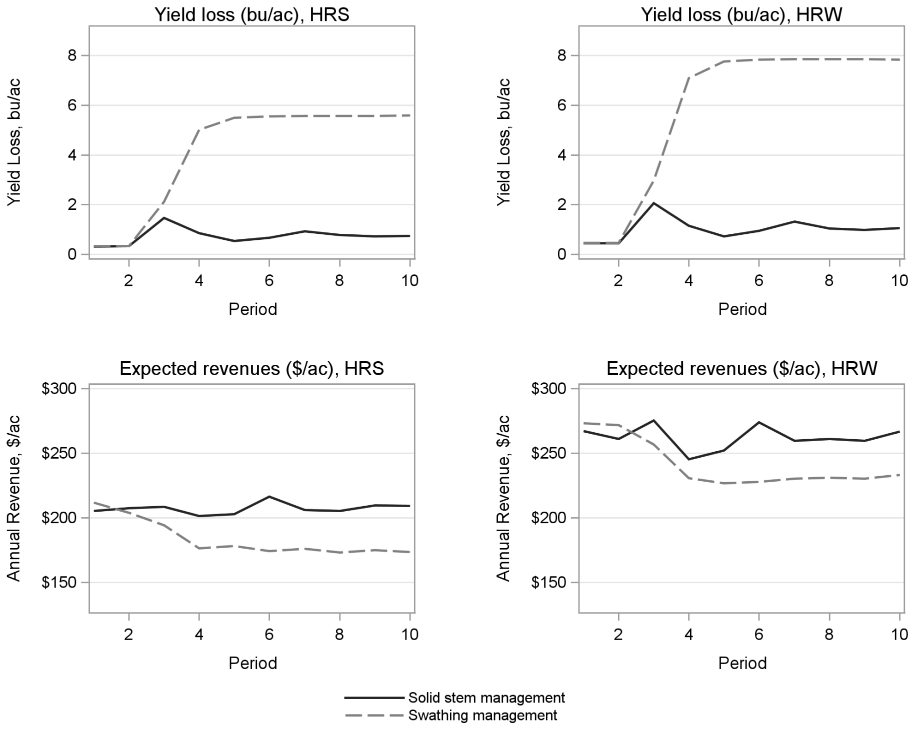


Figure 5. Average 10-Year Simulation Outcomes across Management Strategies

Notes: Each of the four scenarios represents a separate simulation, which simulates 1,000 farmers who observe outcomes of choosing a management strategy over a 10-year period. Results in the table represent the average outcomes across all simulated farmers for each time period. Annual revenues represent those based on prices that are simulated using an empirically estimated price distribution and accounting for swathing costs when appropriate; all other variable and fixed costs are assumed to be the same across management strategies.

Concluding Remarks

Many pests, invasive species, and other biological processes can cause multiple, interrelated perils that affect agricultural production, natural resource extraction, or environmental outcomes. Traditional regression analyses are useful for evaluating the specific marginal effects of each peril, but post-estimation assessments—such as evaluating management strategies—require the estimation and use of the correlation structure among the interdependent perils.

Using unique field-level data describing WSS infestation and perils, we estimate copula functions that empirically characterize the joint distribution of the pest's adverse outcomes. We then use historical WSS outcome data describing damage types and yield outcomes to estimate the degree to which each of the perils affects wheat production. We then combine these two sets of estimates to develop a simulation for assessing management strategies for the pest. The simulation structure accounts for the joint distribution of perils and can therefore be used to appropriately evaluate the trade-offs of management approaches that target an individual peril. Our research results indicate that when managing WSS, profit-maximizing strategies should focus on reducing long-run pest populations (at the cost of a lower revenue ceiling) rather than attempting to plant wheat varieties with higher yield potential but with the potential for higher yield reductions from WSS infestations.

This methodological strategy can be particularly useful for empirically modeling many other biological processes because, in many cases, the analysis requires assessment of multiple interrelated outcomes. Moreover, the copula method can provide an important avenue for investigating extreme outcomes of jointly dependent perils. While our study is one of the first (to our knowledge) to jointly model spatial pest distributions; mortality factors coupled with yield outcomes; and data from field surveys that address a continuum of infestation, losses, and management strategies over a broad area, we believe that data exist for most major pest species and can be used to similarly model and identify most parameters we present in this study. These data have likely already been independently used in publications about, for example, spatial distributions, yield losses, and impacts of natural enemies.

As such, the intuition, models, and methods described in this paper would be applicable to developing integrated bio-economic assessments of many pest species, even though the underlying data may come from different research teams and may have been obtained at different times. Moreover, we believe that by demonstrating the empirical power and relevant insights that can be gleaned from assembling such datasets and modeling the joint distributions of infestation and perils, our work can serve as a call for continued efforts to conduct unified analyses on both crop losses due to pests and associated management approaches that account for the joint, stochastic nature of pest outcomes. As climatic changes continue to exacerbate potential perils from natural events and new agricultural production technologies become available, increased interdisciplinary data assembly, modeling, and methodological efforts will be needed to accurately model the complexities of pest-related hazards and to develop effective and adaptive management strategies.

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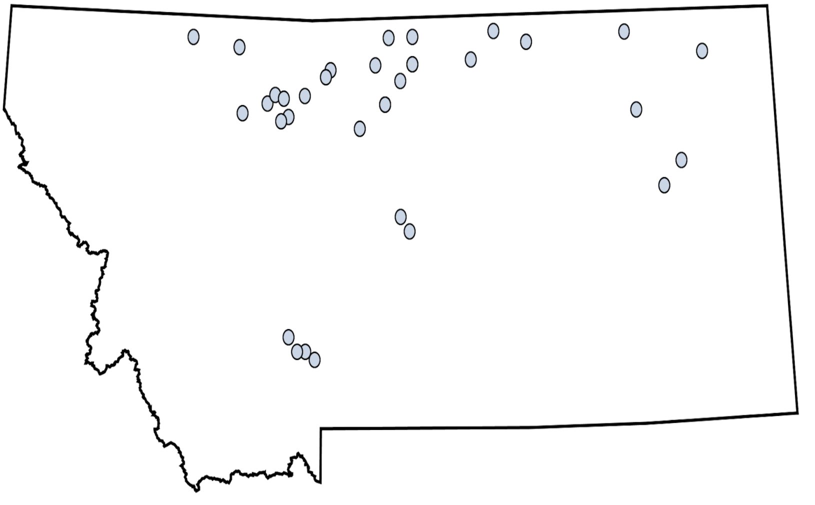
Appendix A: Supplemental Figures

(a) Locations of Collected Wheat Samples, 1998–2011



(b) Average Production of Wheat, 1998–2011

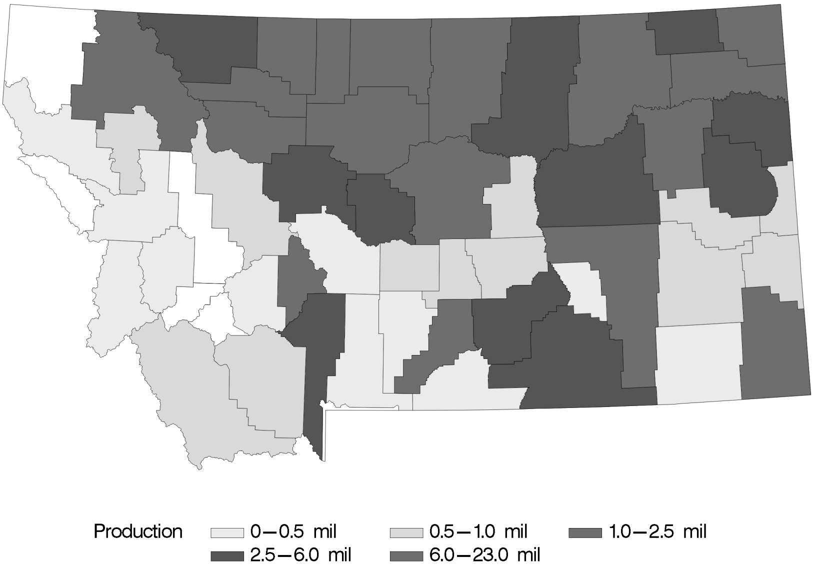


Figure A1. Locations of Wheat Samples and Average Wheat Production by County

Notes: Six locations in Canada are not shown. Production data represent average annual production in total bushels of hard red winter and hard red (dark northern) spring wheat classes for the period 1998–2011.