Yield Loss in Sweet Corn Caused by *Puccinia sorghi*: A Meta-Analysis

Denis A. Shah and Helene R. Dillard, Department of Plant Pathology, New York State Agricultural Experiment Station, 630 W. North St., Geneva 14456

ABSTRACT

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Data sets meeting established criteria were included in a meta-analysis of the relationship between percent common rust severity and percent relative yield loss in sweet corn (processing: 20 data sets; fresh market: 14 data sets). The slope of the linear, zero intercept relationship was estimated from each data set. Overall slopes and their respective 95% confidence intervals for the processing and fresh market situations were estimated by a random effects meta-analysis. Results indicated that for processing sweet corn, every 10% increase in rust severity reduced yield by 2.4 to 7.0%; the corresponding reduction for fresh market sweet corn was between 3.0 and 6.2%. A meta-regression analysis did not identify any factors that could account for the observed variability between data sets. An expression was then obtained for Δ_s , the reduction in rust severity a single strobilurin fungicide spray ought to cause for the cost of the treatment to be offset by the value of the resulting yield improvement. The empirical distribution of Δ_s was derived by stochastic simulation, which showed that fungicide usage could be cost effective 90% of the time when rust severity is reduced by 12% in processing sweet corn and by 5% in fresh market sweet corn.

Additional keywords: common maize rust, loss estimation

Common rust of sweet corn, caused by the fungus *Puccinia sorghi* Schwein., was aptly described as a troublesome, endemic disease (25). Host resistance is the most cost-effective means of managing common rust (25). Until about 6 years ago, the *Rp1d* allele successfully controlled common rust in the continental United States. In 1999, U.S. sweet corn producers experienced the extensive appearance of a new strain of *P. sorghi* capable of causing widespread and high disease severities on sweet corn carrying the *Rp1d* allele (27,28). Although newer hybrids with novel and more effective resistance gene combinations are becoming available, they may provide only a temporary respite from common rust; preliminary research showed that *P. sorghi* populations present in the United States in 2004 were capable of infecting sweet corn with other *Rp* alleles, not only those with *Rp1d* (17). Another relevant factor to consider is the fact that resistant hybrids are not always preferred by producers, or in some market segments. Many rust-susceptible or partially resistant hybrids will continue to be grown (25).

When common rust resistance is not effective, or not present in a hybrid of

choice, fungicides become the primary means of disease management if the risk of disease warrants concern (26). Over time, fungicide preferences for common rust control have shifted from dithiocarbamates (7,10,16), chlorothalonil (3,13), and triazoles (18,31) to strobilurins (1,2,5,6). Strobilurin fungicides are very effective in preventing further sporulation from existing common rust pustules, and they also suppress new infections. Moreover, resistance to strobilurins, although present in populations of other plant-pathogenic fungi, has not been observed in *P. sorghi* (11). Because of cost considerations, producers are unwilling to apply strobilurin products to a sweet corn crop more than once during the season.

Given that multiple applications of a strobilurin fungicide against common rust are cost-prohibitive, several questions naturally arise, including (i) whether a single spray is capable of providing cost-effective control of common rust, and (ii) at what rust severity threshold should that application be made. In this paper, we addressed the first question by asking how much a single strobilurin application should reduce common rust severity in order to be cost-effective. One may define cost-effectiveness in terms of an equivalency (at the minimum) between the value of a yield increase associated with a given disease control measure and the cost of the control measure. Our approach required the quantification of the relationship between yield loss and rust severity, and also the derivation of an equation linking rust

severity reduction to the factors determining the cost-effectiveness of the fungicide application. The specific objectives of this research were therefore to (i) use meta-analytic techniques to estimate the relationship between yield loss and common rust severity in sweet corn, and (ii) estimate the severity reduction required for the cost-effective use of a single strobilurin fungicide application against common rust.

MATERIALS AND METHODS

Data collection. Searches of electronic databases (Agricola, CAB Abstracts, Science Citation Index) and of published reports (*Fungicide and Nematicide Tests, Tests of Agrochemicals and Cultivars*) identified 69 data sets from 1977 to 2004 reporting some measure of common rust severity in sweet corn. Two additional data sets were obtained from a conference report (23). The criteria established for inclusion in the meta-analysis were: (i) no confounding diseases (such as northern corn leaf blight, gray leaf spot, or viral diseases), or if present, sufficient data were recorded to model their effects on yield; (ii) adequate weed and insect control; (iii) common rust severity was assessed over whole plants; (iv) yield data (weight, number of marketable ears, or both) were reported on a per unit (plot, acre, hectare, for example) basis; and (v) disease ratings were done no more than 20 days before harvest and yield determination. Of the 71 data sets, 20 met the above criteria for inclusion in a meta-analysis of yield recorded as weight (representative of the processing situation) in response to common rust severity. Fourteen data sets met the inclusion criteria for a meta-analysis of the effects of common rust severity on marketable ears (representing the fresh market situation). A marketable sweet corn ear has to meet the following requirements: husked ears must be at least 15.24 cm (6 in.) long; no more than one-fourth of the husked ear can remain unfilled at the tip; no more than 25% of the area of the leaf blades attached to the husk may be discolored; and kernel rows must show uniform kernel development. Rust pustules on the leaf blades attached to the husk are a significant cosmetic concern in some fresh markets. It was assumed that marketable ear data in the reports adhered to the above criteria, although it was not explicitly stated as such. Sources of the data sets included in the meta-analysis are listed in Table 1.

Corresponding author: D. A. Shah
E-mail: das28@cornell.edu

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For data set 31, rust severity had been recorded on a 1 to 10 ordinal scale where, for instance, the ordinal rating of 4 represented severities in the range of 6 to 12% (14). Ordinal values were converted to percentages by assuming a linear approximation over the severity range ascribed to the ordinal value. For example, an ordinal rating of 4.1 = 6 + [(12 – 6) × 0.1] = 6.6%. For data sets 59 – 67, data were presented graphically. Individual data points were extracted from pdf copies of the published graphs using DigitizeIt (Ver. 1.5.7, I. Bormann, Germany). Maximum disease severity was less than 10% in data sets 1 (5) and 22b (4).

Meta-analytic procedures. The common metric subjected to meta-analysis was the slope ($z_{p(j)}$ and $z_{f(j)}$) relating percent relative yield loss (for processing and fresh market yield measures within data set j , respectively) to percent rust severity. The metrics were derived from each data set as described by Rosenberg et al. (33). The first step was to estimate, for each data set j , the yield potential in the absence of rust ($\beta_{0(j)}$). The estimate ($\hat{\beta}_{0(j)}$) was given by the intercept term of a linear regression of yield (y) against percent rust severity (s), as previous studies have suggested that sweet corn yield decreases linearly with rust severity (24):

$$y = \beta_{0(j)} + \beta_{1(j)}s + \varepsilon \quad (1)$$

Then, within each data set, data were expressed in terms of percent relative yield loss (l_i ; yield loss relative to $\beta_{0(j)}$):

$$l_i = 100 \times \frac{\hat{\beta}_{0(j)} - y_i}{\hat{\beta}_{0(j)}}, i = 1, \dots, n_j \quad (2)$$

where n_j is the number of data points in

data set j . With data sets 59 – 67, the data presented graphically were the percent maximum yield (max) as a function of rust severity. For these particular data sets, $l_i = 1 - (\text{max}_i/100)$. A second regression of l against s , with the intercept term restricted to zero (i.e., $l = \zeta s + \delta$), was used to obtain the estimate $\hat{\zeta}_j = z_j$ (i.e., $z_{p(j)}$ or $z_{f(j)}$) and its variance in each data set j .

We used a maximum likelihood-based approach to meta-analysis (35). Weight and marketable ear data were analyzed separately. For illustration, we shall consider just one of the yield metrics, and therefore drop the subscripts p and f for simplicity. One may consider the unknown slope for each data set, ζ_j , to be some random sample from a population that is normally distributed, i.e., $\zeta_j \sim N(\zeta, \sigma^2)$, in which σ^2 is the between-data set variance and ζ is the expected slope across all data sets. This model therefore assumes heterogeneity in the true slopes, and is considered a random-effects meta-analysis model. The fixed effects model, on the other hand, assumes $\zeta_1 = \zeta_2 = \dots = \zeta_n = \zeta$, that is, the true slopes are the same across all data sets. We have estimated ζ_j (i.e., $z_j = \hat{\zeta}_j$), $j = 1 \dots n$, independently from each of n data sets. The resulting model for the estimated slopes is $z_j \sim N(\zeta, \sigma^2 + s_j^2)$, where s_j^2 is the within-data set variance of the estimated slope. The test for heterogeneity is equivalent to testing whether $\sigma^2 = 0$ (35). The likelihood ratio test for $H_0: \sigma^2 = 0$ versus $H_1: \sigma^2 > 0$ was significant ($P < 0.0001$) for both processing and fresh market data sets, indicating a random (rather than fixed) effects meta-analysis was appropriate. The estimate of ζ from the random-effects meta-analysis (mean effect

size) is given by z (i.e., z without the j subscript). Standard errors and confidence intervals of the mean effect sizes were determined as described by van Houwelingen et al. (35).

Meta-regression. The between-data set variability was further examined by meta-regression (35). Meta-regression examined state, year in which the data were collected, hybrid, endosperm type, kernel color, minimum and maximum rust severity, severity range, and time between the final rust severity assessment and harvest as individual covariates which could possibly account for the between-data set variability (29). Meta-regression was done for both yield metrics.

Simulations. Percent relative yield loss (l) is linked to percent rust severity (s) via one parameter, say, α :

$$l = \alpha \times s \quad (3)$$

Let the simultaneous equations

$$l_n = \alpha \times s_n \quad (4a)$$

$$l_f = \alpha \times s_f \quad (4b)$$

represent percent relative yield loss in the absence of (l_n) and with the use of fungicide (l_f). s_n and s_f are the percent rust severities without and after a fungicide application, respectively, measured prior to harvest. The implicit assumption is that a fungicide does not completely eradicate rust for the remainder of the season after its application. Equations 4a and 4b can be expressed as

$$100 \times \frac{\text{yield}_{\text{max}} - \text{yield}_n}{\text{yield}_{\text{max}}} = \alpha \times s_n \quad (5a)$$

Table 1. Studies included in a meta-analysis of the effects of common rust on sweet corn yield

Data set ^b	Year	Hybrid	Type ^c	KC ^d	State	Rust severity (%)		Yield measure ^a		Ref.
						Minimum	Maximum	Weight (n)	Marketable ears (n)	
1	1999	Zenith	sh2	y	NY	0.00	1.46	8	8	(5)
2	1998	Zenith	sh2	y	NY	0.01	19.04	8	8	(6)
8	2000	Silver Queen	su	w	NY	1.50	24.30	8		(9)
10	2001	Ice Queen	sh2	w	VA	2.50	28.80		5	(1)
11	2001	Bold	su	y	NY	20.49	77.31	10		(8)
22a	1997	Zenith	sh2	y	NY	1.40	19.40	4	4	(4)
22b	1997	Rival	su	y	NY	1.50	6.30	4		(4)
31	1993	HMX 83865	sh2	y	MI	5.40	57.50	4	4	(14)
35	1992	Yankee Belle	sh2	y	MI	2.60	85.80	7		(13)
50	1984	Jubilee	su	y	NY	8.08	15.50	4		(7)
59	1984	Florida Stay Sweet	sh2	y	IL	5.59	62.83	32	29	(24)
60	1985	Florida Stay Sweet	sh2	y	IL	10.45	55.20	15	25	(24)
61	1986	Florida Stay Sweet	sh2	y	IL	1.55	17.65	12	13	(24)
62	1984	Gold Cup	su	y	IL	15.45	59.91	24	33	(24)
63	1985	Gold Cup	su	y	IL	7.60	50.08	28	27	(24)
64	1986	Gold Cup	su	y	IL	1.67	20.57	17	24	(24)
65	1984	Stylepak	su	y	IL	23.63	67.68	32	25	(24)
66	1985	Stylepak	su	y	IL	7.50	49.84	20	30	(24)
67	1986	Stylepak	su	y	IL	1.42	17.40	18	16	(24)
70	2001	Snow White	sh2	w	IL	23.00	65.00	21		(23)
71	2001	Sterling	su	w	IL	18.00	59.00	21		(23)

^a Yield recorded per some specified unit (plot, section, etc). The number of data points (n) for each data set is shown.

^b A number assigned to the data set for labeling purposes only.

^c Endosperm type. su = sugary, sh2 = shrunken-2.

^d Kernel color. y = yellow, w = white.

$$100 \times \frac{\text{yield}_{\max} - \text{yield}_f}{\text{yield}_{\max}} = \alpha \times s_f \quad (5b)$$

where yield_n and yield_f are the yields ($\text{kg} \cdot \text{ha}^{-1}$, number of marketable ears per hectare, for example) obtained with and without fungicide, and $\text{yield}_{\max}$ is the yield potential in the absence of common rust. For a spray program to be economical, it must lead to a yield increase ($\text{yield}_f - \text{yield}_n$) satisfying

$$\text{yield}_f - \text{yield}_n \geq \frac{\text{cost}}{\text{price}} \quad (6)$$

where cost is the cost of the fungicide treatment (chemical plus application; \$ per ha) and price is the farm gate value for sweet corn (\$ per kg). From equations 5a, 5b, and 6, one can calculate the rust severity reduction a fungicide spray ought to bring about so as to pay for itself:

$$\Delta_s = s_n - s_f \geq \frac{100 \times \text{cost}}{\alpha \times \text{yield}_{\max} \times \text{price}} \quad (7)$$

The parameters α , price, $\text{yield}_{\max}$, and cost are all variable. We derived, by simulation, empirical distributions for Δ_s for both processing and fresh market sweet corn. In the simulations, pseudo-random values for α , price, $\text{yield}_{\max}$, and cost were generated from underlying probability distributions, which are listed in Table 2. The distributions for cost and α were simple. Cost was assumed to vary uniformly between \$37 and \$50 per ha, representing a single application of a strobilurin fungicide (R. Wildman, Agricultural Consulting Services, Inc., Rochester, NY, *personal communication*). A normal distribution was assumed for α , that is, $\alpha \sim \text{Normal}(\zeta, \sigma^2)$ with ζ and σ^2 being replaced by z and its variance.

Processing and fresh market sweet corn yield and price data for the period 1995 to 2004 were downloaded from the National Agricultural Statistics Service website. Nonparametric kernel density estimation was used as a preliminary exploration of the price and yield distributions, following the procedures outlined by Rose and Smith (32). This preliminary analysis revealed that fresh market and processing yield distributions were bimodal. Price distributions were skewed (longer right tails), in addition to a possible secondary mode to the right of the main mode in the fresh market price distribution. Yield data were assumed to represent the distribution of $\text{yield}_{\max}$ within a domain specified by a lower limit of 0.9 times the minimum reported yield value, and an upper limit of 1.1 times the maximum yield value. The $\text{yield}_{\max}$ and price data distributions were described by relatively more complex component-mix probability density functions fitted to the data by maximum likelihood. Separate probability distributions were fit to $\text{yield}_{\max}$ and price because these variables were not positively correlated in

either the processing ($r = -0.04$) or fresh market ($r = -0.53$) situations. Fits of the distributions to the data were checked by frequency plots of observed and expected values, and by χ^2 goodness of fit tests.

Pseudo-random number generation for cost and α was straightforward using built-in functions in the software (see below) for the normal and uniform probability distributions. For the component-mix distributions, pseudo-random numbers were generated by the rejection method (30). The empirical distribution of the minimum values of Δ_s satisfying equation 7 was derived from 20,000 simulations.

Software. Regressions were done using the SAS Reg procedure (SAS Institute, Cary, NC). Meta-analysis and meta-regressions were done with SAS Proc Mixed as described by previous authors (35). Simulations were done with Mathematica (Ver. 4.1, Wolfram Research Inc., Champaign, IL).

RESULTS

Meta-analysis. Figure 1 shows the point estimates $z_{p(j)}$ and $z_{f(j)}$ and associated 95% confidence intervals. The mean (overall) effect sizes (z_p and z_f) are also shown. The within-data set variability is shown by the individual confidence interval widths around each point estimate. To illustrate, there was much higher within-data set variability in data set 1 compared with any other data set, in both the fresh market and processing situations. The between-data set variability is shown by the variation in the point estimates across data sets. All but two point estimates (of $z_{p(j)}$) were to the right of zero, indicating a relative yield loss in response to common rust severity. Confidence intervals which include zero indicate that there was no statistical evidence for a common rust-relative yield loss

relationship in those individual data sets. However, the 95% confidence intervals (CI) for the mean effect sizes z_p and z_f did indicate that processing and fresh market sweet corn yields are significantly reduced by common rust ($z_p = 0.470$, s.e. = 0.112, 95% CI_p = [0.236, 0.704]; $z_f = 0.455$, s.e. = 0.074, CI_f = [0.296, 0.615]). Put another way, for processing sweet corn, every 10% increase in rust severity results in a 2.4 to 7.0% reduction in processing yield, whereas for fresh market sweet corn the reduction in marketable ears is between 3.0 and 6.2%.

Meta-regression. The range of rust severities reported was markedly varied among the data sets (Table 1), reflecting how conducive conditions were for disease development at the time of experimentation. Minimum, maximum, and range of rust severity within data sets did not account for the observed between-data set variability either for processing or for fresh market yield (Table 3). This result indicated a consistent yield-reducing effect of common rust across a wide range of severities. Hybrid was the only factor explaining a relatively large portion of the between-data set variability for both processing and fresh market situations. However, this result is likely due to overfitting (35), as there were 12 levels for hybrid over 20 processing sweet corn data sets; for the fresh market analysis, there were 6 hybrids over the 14 data sets.

Simulation. Histograms of $\text{yield}_{\max}$ and price data, as well as the fitted probability density functions, are depicted in Figure 2. The plots convey the skewness in the price distributions (Fig. 2A and B) and the bimodal nature of the yield distributions (Fig. 2C and D). Fresh market prices were on average five times higher than processing prices per kilogram (Fig. 2A and B).

Table 2. Probability distributions used in the stochastic simulation of common rust severity reduction leading to a sweet corn yield increase value equivalent to the costs associated with a single fungicide application against the disease

Variable	Distribution	Parameter values	Constraints
Processing			
α	Normal(ζ, σ^2)	$\zeta = 0.470, \sigma = 0.112$	$\alpha > 0$
cost (\$/ha)	Uniform(a, b)	$a = 37, b = 50$	
$\text{yield}_{\max}$ (kg/ha)	$\omega \text{Beta}(a_1, b_1) + (1 - \omega) \text{Beta}(a_2, b_2)$	$a_1 = 4.269, b_1 = 10.720$ $a_2 = 30.405, b_2 = 13.551$ $\omega = 0.685$	$\text{yield}_{\max} \in [9475, 24541]^a$
price (\$/kg)	$\phi \text{Normal}(\mu, \lambda^2) + (1 - \phi) \text{Beta}(a_3, b_3)$	$\mu = 0.117$ $\lambda = 0.015$ $a_3 = 4.493, b_3 = 9.813$ $\phi = 0.054$	price $\in [0.0521, 0.1528]$
Fresh market			
α	Normal(ζ, σ^2)	$\zeta = 0.455, \sigma = 0.074$	$\alpha > 0$
cost (\$/ha)	Uniform(a, b)	$a = 37, b = 50$	
$\text{yield}_{\max}$ (kg/ha)	$\omega_1 \text{Beta}(a_1, b_1) + (1 - \omega_1) \text{Beta}(a_2, b_2)$	$a_1 = 13.881, b_1 = 6.616$ $a_2 = 4.213, b_2 = 11.133$ $\omega_1 = 0.229$	$\text{yield}_{\max} \in [2318, 23408]^a$
price (\$/kg)	$\omega_2 \text{Beta}(a_3, b_3) + (1 - \omega_2) \text{Beta}(a_4, b_4)$	$a_3 = 10.951, b_3 = 17.929$ $a_4 = 4.740, b_4 = 3.171$ $\omega_2 = 0.594$	price $\in [0, 1]$

^a Beta distributions were rescaled to the given intervals. $X \sim \text{Beta}(\alpha, \beta)$ lies within the range [0, 1]. The transformation $Y = t_1 + (t_2 - t_1)X$ rescales X so that Y is within the range $[t_1, t_2]$, but has the same distributional shape as X .

Yields of both fresh market and processing sweet corn exhibited a wide range (Fig. 2C and D). Formal χ^2 goodness-of-fit tests indicated that the fitted probability density functions were adequate descriptors of the empirical data (processing price: $P = 0.54$, 5 df; processing yield_{max}: $P = 0.29$, 6 df; fresh market price: $P = 0.81$, df = 7; fresh market yield_{max}: $P = 0.02$, 9 df). The empirical distribution of Δ_s for processing sweet corn had a mean of 7.9% and median of 7.3%; for the fresh market situation, the mean of the empirical distribution of Δ_s was 2.8% and the median was 2.4% (Fig. 3). Quantile plots of the empirical distributions are shown in the inset graph

of Figure 3. The inset plots indicate (on the x-axis) what proportion of simulated values lie below the value of Δ_s specified on the y-axis.

DISCUSSION

In this paper, we quantified the yield loss-rust severity relationship in sweet corn by a meta-analysis of available data instead of engaging in traditional yield loss field experimentation. Meta-analysis does not substitute for experimentation, but rather provides a quantitative assessment of evidence to date, which in turn can be used to guide further practical research efforts. Meta-analysis can be broadly de-

fined as a statistical technique for synthesizing the results obtained from several individual experiments (22,29). When data from previous studies are accessible in sufficient detail to allow it, a meta-analysis is capable of providing a more insightful perspective than that given by any one study alone. Qualitative interpretation of the results of individual studies can be problematic, especially if sample sizes are quite variable between studies and if the results are contradictory (20). The quantitative nature of meta-analysis overcomes the shortfalls of qualitative syntheses. General introductions to meta-analysis within an ecological framework are available elsewhere (12,21), and other authors have illustrated how the technique could be applied to questions of an agricultural nature (20,33). Meta-analysis has already found utility in some crop production situations (15,29,34).

One of the first steps in a meta-analysis is the choice of an appropriate metric which is estimated from each study (or data set). The metric depends on the question being addressed. In this paper, we chose the slope coefficient (ζ) relating percent relative yield loss to percent common rust severity, as we were eventually interested in estimating rust severity reductions (Δ_s) associated with the cost-effective application of a strobilurin fungicide. The relative yield loss-rust severity relationships for fresh market and processing sweet corn were similar, as evidenced by the similar values of the mean slope estimates ζ_p and ζ_f and of the confidence intervals for ζ_p and ζ_f . The strictly positive confidence intervals for ζ_p and ζ_f showed there was a significant, consistent reduction in yield by common rust in both fresh market and processing sweet corn. As the original studies had been done in different regions, years, and with various hybrids, there was no rationale for doing a fixed effects meta-analysis which assumes homogeneity of the metrics across studies. The more formal likelihood ratio test for the between-data set variance attested to this fact. The extension of the analysis by meta-regression failed to conclusively identify any factors which could account for the observed variability in ζ across data sets.

Publication bias refers to the tendency for studies reporting statistically significant results to have a higher likelihood of being published than those in which trends or effects were not significant, and can be an obstacle in meta-analysis (12). With the exception of data sets 59 – 71, all other data sets used for the meta-analyses in this paper were derived from the results of trials comparing the efficacy of different fungicides and were not specifically concerned with determining the relationship between rust severity and yield loss. As Rosenberg et al. (33) point out, publications such as *Fungicide and Nematicide*

Fig. 1. Estimates (z) of the linear regression slope (ζ) relating percent relative yield loss to percent rust severity in **A**, processing and **B**, fresh market sweet corn for independent data sets. The overall metric was calculated from a random effects meta-analysis. Confidence intervals (95%) are shown.

Tests are more likely to include results that are not statistically significant. Therefore, publication bias may not be as much of an issue as in other meta-analyses.

Equation 7 was used to estimate Δ_s , the reduction in common rust severity required of a single strobilurin fungicide application so that the resulting yield increase value is

at least equivalent to the cost of spraying; that is, the treatment pays for itself. The magnitude of Δ_s could vary depending on the maximum attainable yield and on the value of the crop. That is, one could regard Δ_s as a variable itself. We obtained an empirical distribution for Δ_s by simulation, under specific assumptions quantified by

probability distributions for the variables listed on the right hand side of the inequality in equation 7. The empirical distribution of Δ_s was re-expressed in terms of a quantile plot, which showed the proportion of simulated $\Delta_s \leq x$, where x is between 0 and 100. The quantiles can be interpreted as a measure of risk. For example, if one wanted to achieve cost-effective rust control 90% of the time in processing sweet corn (i.e., 0.9 on the x -axis), then a fungicide treatment (in the present context, a single strobilurin spray) ought to reduce rust severity (in comparison to the untreated situation) by at least 12%. The corresponding value for fresh market sweet corn is 5%. The quantile plots showed that, for an equivalent risk value, larger rust severity reductions are needed in processing versus fresh market sweet corn for a fungicide treatment to be cost-effective. This result is related to the comparatively higher value of fresh market sweet corn as reflected in the price distributions shown in Figure 2A and B. The simulations do imply that a single strobilurin fungicide spray can be economical when common rust disease pressure is a production risk factor. Determining the timing of that intervention relative to crop phenology and the rate of increase of common rust epidemics is a subject worthy of further investigation.

The relationships between common rust severity and yield loss that we developed are applicable in the broad sense, that is, they were derived from data collected over different regions and years. Further re-

Table 3. Covariate analysis in a meta-regression of relative yield loss in sweet corn (processing and fresh market) due to common rust

Covariate ^a	Residual between-data set variance	Variance explained (%) ^b
Processing		
State (categorical)	0.213	0.05
Year (categorical)	0.282	0.00
Minimum rust severity	0.227	0.00
Maximum rust severity	0.223	0.00
Rust severity range	0.222	0.00
Hybrid (categorical)	0.064	70.21
Time between last disease assessment and harvest	0.147	31.15
Endosperm type (categorical)	0.212	10.88
Kernel color (categorical)	0.212	11.09
Fresh market		
State (categorical)	0.058	0.00
Year (categorical)	0.058	0.00
Minimum rust severity	0.059	0.00
Maximum rust severity	0.060	0.00
Rust severity range	0.061	0.00
Hybrid (categorical)	0.036	34.75
Time between last disease assessment and harvest	0.054	2.48
Endosperm type (categorical)	0.061	0.00
Kernel color (categorical)	0.060	0.00

^a Because of the relatively small number of data sets available, covariates were modeled individually, either as continuous or categorical variables.

^b The percentage of the between-data set variability explained by a covariate is calculated as $100 \cdot (v - r)/v$, where v is the between-data set variance in the absence of the covariate, and r is the residual between-data set variance (given in the second column) when the covariate is specified. For the processing sweet corn data, $v = 0.214$; for the fresh market data, $v = 0.056$.

Fig. 2. Data histogram and fitted probability density functions for sweet corn commodity value (price) and assumed yield potential in the absence of common rust ($y_{\max}$), where f (frequency; y -axis) is given in absolute units (number of values in a class, or predicted number based on the probability functions). **A**, processing price. **B**, fresh market price. **C**, processing $y_{\max}$. **D**, fresh market $y_{\max}$. Price is in U.S. dollars.

Fig. 3. Empirical distribution, derived from stochastic simulation, of the required reduction in percent common rust severity (Δ_s) in response to a single application of a strobilurin fungicide for that application to be cost-effective. Simulated distributions are shown for processing (p) and fresh market (f) situations. Input values for the simulations were drawn from the probability distributions specified in Table 2. The inset shows the proportion (quantile) of simulated values below the value of Δ_s specified on the y-axis.

gional or hybrid-specific relationships can be derived, following the general methodology we have presented. Together, the quantification of ζ and the empirical distribution of Δ_s can guide additional studies determining the severity threshold at which a fungicide should be applied for cost-effective control of common rust. On a final note, the quantitative estimates obtained and reported in this paper represent the type of information useful for estimating yield losses from disease survey data, or for justifying the importance of a plant disease to interested groups or agencies (19).

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