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Justification for site-specific weed management based on ecology and economics

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One of the primary benefits of site-specific agricultural technologies is the potential to reduce the use of polluting inputs, thereby minimizing ecological damage. Weeds are often found in patches, so site-specific (field scale) management offers a straightforward opportunity to minimize ecological effects related to wasteful broadcast use of herbicides. Beyond possible efficiencies related to accurate targeting, site-specific technologies, through a process of parameterizing management decision models for each field, may improve ecological understanding of weed populations and thus encourage ecologically based management. This hypothesis was assessed with a simple model that combined economic injury–level prediction with a single parameter (growing season precipitation) to represent environmental variability. Model simulations of crop yield in response to weed density at a virtual farm and six surrounding regional experiment stations suggested that localized (on-farm field) parameter estimation may help to circumvent the variability associated with damage function extrapolation from small-plot experiments at experiment stations and thereby improve predictive accuracy for site-specific weed management (SSWM) strategies. Thus, remote sensing and SSWM technologies may allow producers to reduce the risk associated with the reduced use of purchased inputs and greater reliance on natural weed population–regulating mechanisms. Effective ecologically based weed management may be dependent on local parameterization of models.

Key words: Ecologically based weed management, field-scale experimentation, integrated weed management, model parameterization, precision farming, weed ecology.

Site-specific weed management (SSWM) can be justified based on the irrefutable and tautological premise that there is no need to attempt to control weeds where they are not present in crop production fields. From a practical standpoint, however, the input cost savings associated with SSWM has been found to be rather small (Oriade et al. 1996) in relation to the costs associated with determining the location of the weeds and selectively applying the control measures. Site-specific management may include additional costs associated with rental or ownership of geographic positioning system (GPS) technology, the use of geographic information systems to create weed maps, and the cost of differential application of management across a field (Van Wychen et al. 2002). Luschei et al. (2001) found that after including technological implementation costs in a Montana spring wheat (*Triticum aestivum* L.) production system, site-specific weed control could increase net returns relative to broadcast herbicide application if the field was less than 50 to 60% infested with wild oat (*Avena fatua* L.). The maximum economic benefit that could be realized was therefore approximately half the cost of the herbicide. A wild oat control program aspiring to stop all seed production would, on average, realize a relatively small net benefit in Montana spring wheat fields. Restricting application to 30 to 40% of the field would produce a net gain of 10 to 20% of the input costs. However, in higher value corn (*Zea mays* L.) production systems of Wisconsin, roughly half the field corn producers are willing to pay more than this amount to mitigate all risks by contracting management with other consultants and application specialists (Boerboom et al. 2003), despite the incentive for those firms to overapply inputs.

Given the limited economic benefits of site-specific weed control and the apparent value placed by producers on not having to concern themselves with weed control problems, it would be difficult to justify the use of SSWM on economic grounds alone. A far stronger case exists for the linkage between SSWM and the minimization of off-target environmental effects caused by agrochemical application. Most ecological perturbations caused by agrochemicals, whether they are on- or off-farm, would be classified as external to the economic forces driving decision making.

The first ecological justification for the use of SSWM that comes to mind stems from the overwhelmingly probable notion that a lack of herbicide application perturbs local (within field or adjacent fields) ecological processes less than application of a herbicide. This is not to say that herbicides have an intrinsically negative effect on ecosystem processes or that natural systems are not robust to perturbations of food webs. We merely claim that for situations in which there are real risks that undesirable effects do occur, SSWM offers an opportunity to lower the risk of external impact of these effects. It is therefore possible that producers using SSWM will have, in comparison with non-SSWM, a net benefit that is difficult to quantify.

Although an ecological justification for SSWM may be convincing from a broad social perspective, decisions are made by land managers who will likely be focused on short-run economics. It is therefore pivotally important to investigate possible motivations causing lack of adoption and to determine which of these motivations can be tempered by improvements in research or engineering.

A second ecological justification for the use of SSWM and the focus of this article is based on the idea that use of GPS technology to georeference crop and weed response to management and the environment can produce a local body of knowledge that may allow an otherwise severely constrained management based on ecological knowledge of the weeds. Ecologically based weed management (EBWM) includes the use of density thresholds and augmentation of natural weed population–regulating mechanisms (NRC 1996). Implementation of EBWM is plagued by difficulties of extrapolation and interpolation from small-plot experiments (Jasieniuk et al. 1999; Lindquist et al. 1996, 1999). Ecological information derived from small-plot experiments about weeds has rarely been applied directly to weed management. In most cases, such information is indirectly synthesized and incorporated into decision support systems to predict weed population dynamics, weed impacts, or both on crops (Mortensen et al. 2000). We propose that site-specific parameterization of crop–weed response models offers a method to increase the predictive accuracy and thereby address a producer's concern that impedes adoption of EBWM methods. Ecologically based crop production management is inherently risky because of the uncertainty in net returns caused by the complexity of interactions that determine crop response and weed population dynamics in more naturally regulating systems (Maxwell 1999). The uncertainty is compounded by attempting to create a knowledge base of weed biological responses to management derived from small plots on experiment stations that may be at great distances from where the knowledge is applied on a farm and thus are likely to represent different climates, edaphic features, and other factors of ecological importance.

We set out to assess the question, would use of the site-specific agriculture technology data stream (crop yield and weed abundance information for a field) improve our ability to make management decisions over the use of the same type of information from small-plot competition experiments (SPCE) at different sites? We selected the economic injury level (EIL) (threshold density) for wild oat on spring wheat as the simplest ecological relationship to base our assessment. The EIL is based on the competitive relationship between the weed and the crop; thus, one can assume that it is fundamentally an ecological metric. We took this approach because we thought that if we failed to show an advantage of local (on-farm) parameterization of the yield loss function with this simplest of ecological relationships, then adding the complexity of more ecological factors (e.g., weed population demographic model parameters) would only serve to make the assessment more complex and less likely to be a productive illustration of the application of EBWM. If we were to find that site-specific parameterization of the yield loss function increased net returns to the farmer over the use of SPCE parameterization of the same function, then we could conclude some level of ecological justification for the use of site-specific technology.

Unfortunately, there were no data sets that we knew of that could be used to empirically assess this question. Thus, we chose to investigate the feasibility of the local-parameterization scheme using a method common in ecological sciences (e.g., Paice et al. 1998). We used our knowledge of weed–crop dynamics and precipitation frequencies, much of which were empirically determined, to explore the inferential consequences of several forecasting methodologies. This analytical procedure involves using our current understanding of the ecological dynamics to construct a process model (Hilborn and Mangel 1997) to which a random amount of process error (variation due to environmental stochasticity not related to the specific process) is added. We then explored how different forecasting strategies performed under several different scenarios using the data sets simulated by the stochastic process described above. In this article we therefore explored how local-parameterization schemes performed relative to SPCE extrapolation, contingent on the process model representing the true data–generating process that we will term reality.

Our general objective was to investigate how the accuracy and precision of decision-making forecasts based on wild oat EIL were degraded when a production function (yield model) was strongly driven by a stochastic variable. We speculated that extrapolation of regionally derived crop–weed relationships from SPCEs and subsequent calculation of the EIL from these experiments (EIL_e) would be particularly difficult and that local parameterization of the production function and estimation of EIL at the farm field (EIL_f) using site-specific technologies might be a means to mitigate the uncertainty involved in the decision-making process if these ecologically based models were used. Luschei et al. (2001) provided a detailed example of how site-specific technologies can be applied for local parameterization of a weed damage function at the field scale.

Materials and Methods

Process Model

The process model form was selected based on the commonly used saturation function of chemical kinetics promoted by Cousens (1985):

$$y(x) = y_0 \cdot \left(1 - \frac{i \cdot x}{1 + i \cdot x / a}\right) \qquad [1]$$

The variable x represents weed density, parameter y_0 represents the weed-free yield, i represents the per-weed yield effect for low weed densities, and a represents the maximum proportional yield loss at high weed densities. We considered the process model to included resource dependency (growing season precipitation, z) by expanding y_0 as a second-order polynomial in z and fitting the relationship to experiment station data (Table 1). The relationship between precipitation and spring wheat yield in north-central Montana is based on a 3-yr nitrogen fertilization study (R. Engel, unpublished data).

$$y(x, z) = (c_0 + c_1 z + c_2 z^2) \cdot \left[1 - \frac{(b_0 + b_1 z)x}{1 + (b_0 + b_1 z)x/a}\right] \qquad [2]$$

Because it was unclear whether i also might be a function of moisture (Mortensen and Coble 1989), we examined three separate cases: i a constant ($b_1 = 0$), i a negatively

TABLE 1. Process model and candidate prediction model structures. Parameters with "hats" are estimated from the SPCE data generated by the process model. Although the form of the 6-parameter prediction model is identical to the process generating the data, the randomness involved in the SPCE realizations cause the parameter estimates to deviate from their "true" values.

Parameters	Model structure
Process model	
6 known	$y(x, z; a, b, c) = (c_0 + c_1 z + c_2 z^2) \times \left[1 - \frac{(b_0 + b_1 z)x}{1 + (b_0 + b_1 z)x/a}\right]$
3 estimated	$y(x; \hat{a}, \hat{b}, \hat{c}) = \hat{c}\left(1 - \frac{\hat{b}x}{1 + \hat{b}x/\hat{a}}\right)$
6 estimated	$y(x, z; \hat{a}, \hat{\underline{b}}, \hat{\underline{c}}) = (\hat{c}_0 + \hat{c}_1 z + \hat{c}_2 z^2) \times \left[1 - \frac{(\hat{b}_0 + \hat{b}_1 z)x}{1 + (\hat{b}_0 + \hat{b}_1 z)x/\hat{a}}\right]$

sloped linear function of growing season precipitation ($b_1 < 0$), and *i* a positively sloped linear function ($b_1 > 0$).

The parameter *a* in Equations 1 and 2 is the maximum proportional yield loss at high weed density and was assumed to be constant in order to simplify the interpretation of results. The parameter *a* was set at 0.8 because it is at the high end of a spectrum of values found for wheat and wild oat (B. Maxwell, unpublished data) and ensures identification of an EIL. If *a* is low, there would be cases where net return would be highest with no management regardless of weed density; thus, no EIL would be identified. Variation in *a* is likely to have an effect on results (Cousens 1986), but with our attempt to simplify interactions among sources of variability, we chose to hold *a* constant. The parameter values used in the process model are included in Table 2.

Although it would have been possible to include variables like relative time of emergence in Equation 2, it would have required that additional assumptions be made about population emergence curves and their dependence on moisture. We assume that we can capture the effect of any average value in the estimates of the competitive coefficients and that the variation in yield due to precipitation can be used to cover the predictive consequences of moisture-driven biological response variability.

Distribution of Growing Season Precipitation

The March through May precipitation (pre–weed management decision precipitation or pre-GSP) and the March through August precipitation (total growing season precipitation or GSP) were calculated from historical records of many north-central Montana weather stations (Figure 1). Data were edited to remove years with incomplete records. The set of all (spatial and temporal) weather records was randomly sampled in simulations. The prediction based on the March through May precipitation was made by predicting GSP from pre-GSP. This prediction was based on the historical correlation between the two quantities. We regressed GSP on pre-GSP, resulting in the following equation ($r^2 = 0.51$):

TABLE 2. Parameter values used in the process model. The three values listed for *b* correspond to cases where the "*i*" parameter is a constant, positive, and negative linear function of growing-season precipitation, respectively. Values were determined by the analysis of independent experiments and were intended to represent typical and reasonable values for a Montana wild oat–spring wheat system.

Parameter	Value
c_0	− 1.0557
c_1	0.4415
c_2	− 0.0070
b_0	(0.010, + 0.0150, − 0.0050)
b_1	(0.000, + 0.0005, − 0.0015)
a	0.8

$$P_{\mathrm{GSP}} = 11.426 + 1.188 P_{\mathrm{March–May}}. \quad [3]$$

The within-site (across years) and within-year (across sites) variations are shown in Figure 2. Some of the weather records began in 1893, so the portion shown in the graph is a subset of all the data collected. The average within-year variation (for those years with more than four sites) was approximately three times smaller than the within-site variation. This indicates that there was both a temporal and spatial component to precipitation variability, and the temporal component was largest.

Simulated Small-Plot Data

The predictions were made using an "estimated" process model. The estimation was made after using the "true" process model to simulate the results of an additive design experiment for sets of eight SPCEs. The weed densities used were 0, 10, 25, 50, 100, and 200 plants m^{-2} replicated four times (24 observations) within a year at each site. Process noise (Hilborn and Mangel 1997) was added to data, with $\varepsilon \sim N(1, 0.2)$:

$$y_i(x, z) = y(x, z) \cdot \varepsilon_i \quad [4]$$

The noise was added in such a way as to produce a constant proportional variation rather than a constant absolute (additive) variation. This was in direct contrast to the assumptions of the regression model used to fit these data. If

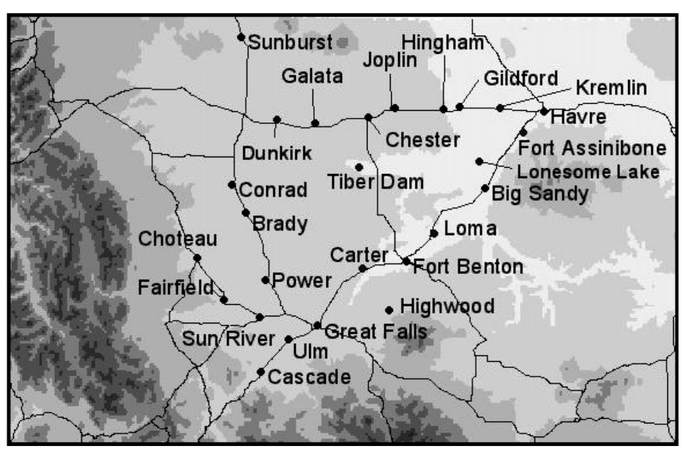

FIGURE 1. North-central Montana cities used for precipitation data records. Any eight cities became the site for a virtual small-plot competition experiments, and an additional city was selected as the site of the virtual farm field in any given replication of the simulation experiments.

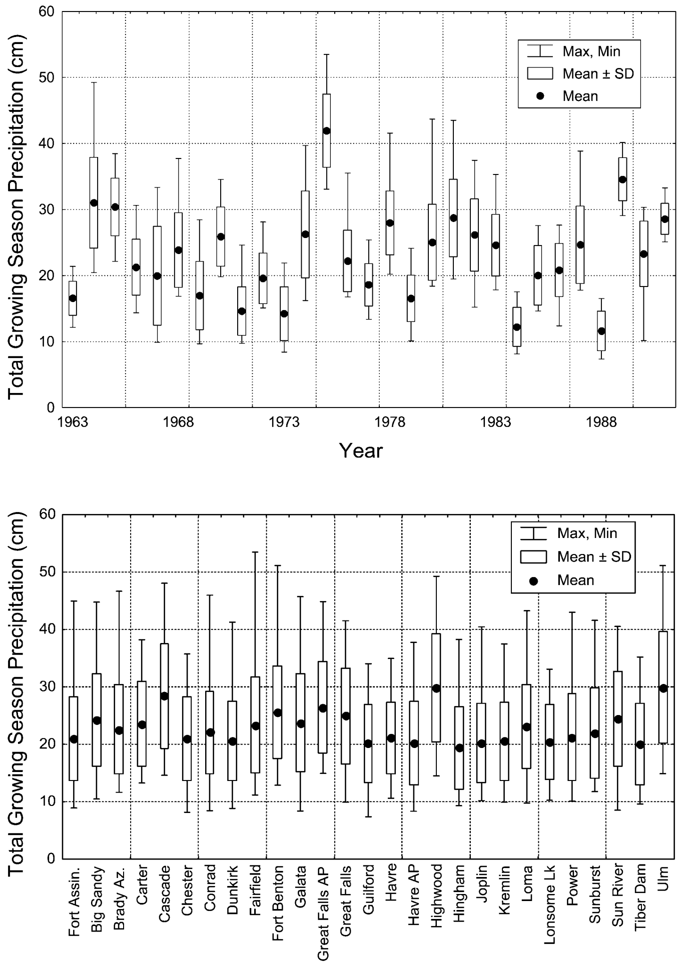

FIGURE 2. Mean, standard deviation, and maximum and minimum growing season precipitation for spring wheat growing areas in north-central Montana.

the factors responsible for process noise were connected with plant growth factors, then this assumption was reasonable.

The standard deviation of the proportion represented by the noise was 0.2 (or 20%). This value was a reasonable and conservative estimate of the level of process noise found in most wild oat SPCE (Carlson and Hill 1985; Cousens et al. 1987; O'Donovan et al. 1985).

Fixed Site Factor

To determine the loss of predictive accuracy that might accompany the variation of a site factor that differs from location to location but not year to year, each maximum yield was multiplied by $\gamma \sim N(1, 0.2)$:

$$y_0(z; \gamma) = (c_0 + c_1 z + c_2 z^2)\cdot\gamma \qquad [5]$$

All the data from any SPCE (i.e., all the plots in an additive design experiment) were multiplied by the same factor. This factor was called a fixed site factor because it was designed to represent a temporally constant local influence on the crop yield other than precipitation (e.g., depth to hardpan and background fertility). When extrapolating results, a different random number draw (for the fixed site factor) influenced the yield for the site where prediction was taking place (i.e., virtual farm field) unless prediction was occurring in the same location as the experiment station.

Evaluation of Prediction Accuracy

The simulated validation procedure began with the process model and process error. This model was used to simulate data from eight independent SPCEs between a weed and a crop. A level of growing season precipitation was assigned to each SPCE based on a random draw from a distribution of precipitation records assembled for 985 (post-editing) site-years of data from 27 sites within the wheat-producing area of north-central Montana (Figure 2). Eight experiment stations in a region surrounding a farm represents a higher density than the two experiment stations that actually exist in this region of Montana, but we entered into the analysis with the utmost optimism in maximizing the SPCE data available for making predictions.

Nonlinear least squares regression (Wolfram Research Inc. 1999) was used to fit the data combined from the eight SPCE sites. We considered three scenarios for fitting the SPCE data. The first was to fit the data without including the influence of precipitation (three-parameter model), that is, we assumed that we had no knowledge of the influence of precipitation on weed-free yield when, in fact, it was the process generating variation in weed-free yield in the simulated SPCE data. The second scenario included growing season precipitation in the regression model (six-parameter model), that is, we assumed that the specific relationship between growing season precipitation and weed-free yield was known (i.e., perfect knowledge of the cause of variation in weed-free yield). The six-parameter model was identical in form to the process model that generated the SPCE data. Thus, the only sources of variation, other than weed density, when using the six-parameter model to fit data, were the process noise (ε_i) and the fixed site factor (γ). The third scenario included pre–weed management decision precipitation (i.e., March through May accumulated precipitation) rather than full growing season precipitation in the regression model (six-parameter model). This scenario represents a more realistic partial knowledge of the precipitation amount that will occur in a given growing season when the EIL_f would be applied. One hundred trials were conducted where we drew a random sample from the weather station records and compared the calculated EIL_e with EIL_f (computed from the six-parameter full process model). We also calculated the mean and standard deviation of the prediction error of the value of control at the EIL_f. Thus, the actual value was equal to the weed control cost by definition. To examine the accuracy of using our set of SPCEs to predict the value of weed control, we repeated the whole process 100 times and reported an average mean and an average standard deviation of the prediction accuracy.

The difference between the SPCEs predicted and the actual (virtual farm field) value of weed control (when assuming 90% of the weeds were killed by the herbicide for the calculation of EIL_f) was recorded. The actual value was the difference between the true value of the lost yield and the cost of the herbicide on the virtual farm field using the EIL_f, where the true value of the lost yield is known because the parameter values are known for the virtual farm field.

$$\varepsilon_{i,j} = [\Delta\hat{y}_i(\mathrm{EIL_e}, z_j) - \Delta y(\mathrm{EIL_f}, z_j)]\cdot p \qquad [6]$$

where the subscripts i and j refer to a particular set of eight SPCEs and to a particular draw from the precipitation distribution, respectively. The quantities $\Delta\hat{y}$ and Δy are the pre-

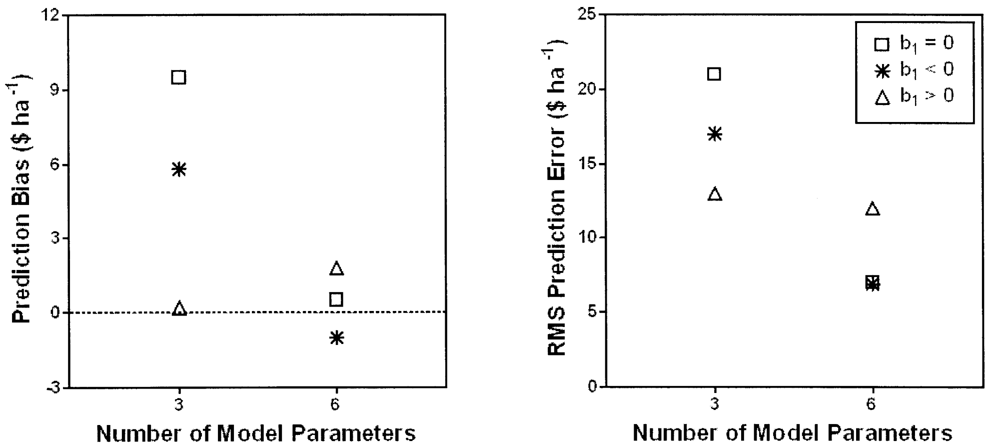

FIGURE 3. Mean bias (inaccuracy) and imprecision (RMSE) of prediction error for the six-parameter model under three competitive scenarios: (1) constant competitive strength or $b_1 = 0$, (2) $b_1 < 0$, and (3) $b_1 > 0$. Prediction accuracy was assessed using a model parameterized based on eight small-plot competition experiments and extrapolated to a hypothetical validation plot. The validation procedure was repeated to form a distribution of accuracy assessments; bias and imprecision were reported because they are the two most informative statistics describing the distribution of prediction error.

dicted (from SPCEs) and true (from virtual farm field) differences in yield that occurred when using the control treatment. The difference was defined to be:

$$\Delta y(\text{EIL}, z) = y(0.1 \cdot \text{EIL}, z) - y(\text{EIL}, z) \qquad [7]$$

The weed density EIL is the economic threshold or the density for which the value of yield recouped by application was equal to the weed control cost (c_{wc}). This is called EIL_f when calculated from the virtual farm field data and EIL_e when calculated from the SPCEs. It was found by solving the following equation for EIL:

$$\Delta y(\text{EIL}, z) \cdot p = c_{\text{wc}} \qquad [8]$$

The crop price used was \$114 t^{-1}. The herbicide cost was \$44.48 ha^{-1}. Because the threshold depends on the value of the yield lost, it also depends on all factors that modify the yield, as well as the crop price and the herbicide cost as discussed by O'Donovan (1996). For each set of eight SPCE results, we performed $n = 100$ validation trials and reported the mean error and the standard deviation of the error:

$$\varepsilon_i = \frac{1}{n} \sum_{j=1}^{n} \varepsilon_{i,j}$$

$$\sigma_{\varepsilon_i} = \left[\frac{1}{n} \sum_{j=1}^{n} (\varepsilon_{i,j} - \varepsilon_i)^2 \right]^{1/2} \qquad [9]$$

The subscripts i and j index the sets of eight SPCE and validation trials, respectively. To know, on average, how accurate the predictions were, we iterated the whole procedure $m = 100$ times and reported the mean bias and the mean standard deviation. All calculations were performed in Mathematica (Wolfram Research Inc. 1999).

$$\overline{\varepsilon} = \frac{1}{m} \sum_{i=1}^{m} \varepsilon_i \qquad \overline{\sigma_{\overline{\varepsilon}}} = \frac{1}{m} \sum_{i=1}^{m} \sigma_{\varepsilon_i} \qquad [10]$$

Results and Discussion

Using the statistics defined in Equation 10, the value of control at EIL_e was compared with the value of control at EIL_f. The logic behind an EIL-based containment strategy relies on an estimate of the value of yield recouped by pest control relative to control cost. Thus, bias and imprecision or lack of information from predictions (Clark et al. 2001) provide a solid indication of the potential usefulness of a predictive strategy. Our investigation compared the relative values of fitting SPCE data with models of increasing complexity and varied assumptions of knowledge about the process causing variation (Table 1). For two of the competitive scenarios, where competition intensity (i) was uncorrelated with moisture or negatively correlated with moisture, the prediction bias was substantially improved by including moisture in the model. The bias changed from \$10 and 6 ha^{-1} to approximately \$0 ha^{-1} (Figure 3). Likewise, the imprecision residual mean square error was decreased to 25 to 40% of three-parameter predictions using the six-parameter model. Interestingly, when competitive strength was positively correlated with precipitation (and therefore higher total yields), there was little change in the bias or precision with the inclusion of moisture into the process model used for forecasting the economic benefit of controlling weeds (Figure 3).

The scatterplots in Figure 4 show predicted EIL_e (x-axis) vs. EIL_f (y-axis). A relationship that could predict without error would thus produce points on the line with Slope 1 that passes through the origin. Each point within the plots represents a single validation trial for a relationship parameterized from a set of eight SPCEs. Because there were 100 iterations of 100 predictions, there are 10^4 points on each plot. If the points accumulated above the 1:1 line, it indicated a systematic underprediction of the EIL_f, and if they accumulated below the line, it indicated overprediction.

In all the scatterplots, the predicted and actual thresholds were higher than the 8 to 10 plants m^{-2} reported in the literature (Cousens et al. 1986). This was a direct reflection of the low value (assumed price received) for the wheat crop. Furthermore, the three-parameter model (Figure 4) was incapable of predicting the EIL_f for any of the scenarios. This was not surprising because moisture was included in the process model as a primary determinant of yield used to calculate the EIL_f, and the three-parameter model used to fit the SPCE yields and calculate the EIL_e did not include

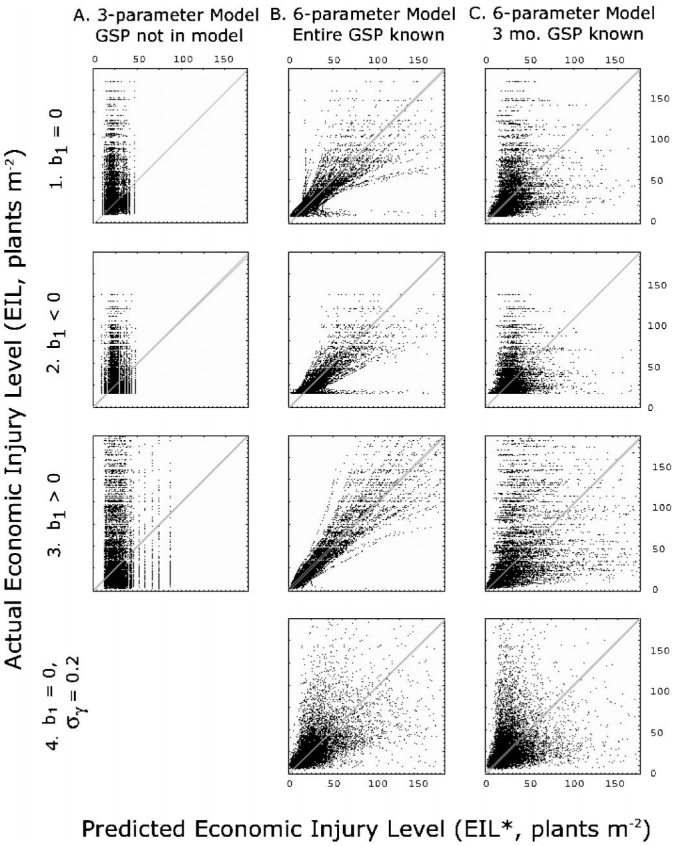

FIGURE 4. Predicted vs. actual economic injury levels for three different models under four different competitive scenarios. The three models used were (A) three-parameter model lacking any explicit dependence on GSP, (B) six-parameter model with full knowledge of GSP, and (C) six-parameter model with knowledge of only the first 3 mo of GSP. The scenarios considered include (1) constant competitive strength or $b_1 = 0$, (2) $b_1 < 0$, (3) $b_1 > 0$, and (4) $b_1 = 0$ and $\gamma = 0.2$. The last scenario examines the influence of a spatially variable but temporally constant yield perturbation, termed a fixed site factor.

the influence of precipitation on yield. If decisions were made using the EIL_e based on the three-parameter model, weed control would be applied in many cases where it was not justified on 1-yr economic grounds. This reflects the large bias present for both $b_1 = 0$ and $b_1 < 0$ cases (competitive effect a constant or negative function of growing season precipitation).

The first objective of this study was to examine the effect of excluding a variable in a predictive schema that was strongly driving yield response. The large responses shown in Figure 3, for the first two competitive scenarios, and poor performance illustrated in Figure 4A (1 to 3) reinforce the intuitive notion that leaving out major drivers of variation can cause a major loss of information that is valuable in forecasting (Clark et al. 2001). Although the performance using the actual process model itself (Figure 4B, 1 to 3) shows on average much improved predictive accuracy, the variance in prediction error remains large. In the case where the bias was low, six-parameter model for $b_1 < 0$ or $b_1 = 0$, the corresponding standard deviation was \$10 to 15 ha^{-1}, which represents 20 to 30% of the value of the weed control cost. When the decision maker is not privy to full growing season precipitation information at decision time (Column C in Figure 4), almost all predictive ability is lost and the accuracy plots resemble those in column A of Figure 4. Of particular interest was the addition of a fixed site factor that degraded the ability for SPCE predictions to be extrapolated (Figure 4B, 1 to 3, compared with Figure 4B, 4) almost as much as not having full-season precipitation records (Figures 4B compared with Figures 4C), although the process model form was entirely correct.

The inclusion of the fixed site factor (e.g., depth to hardpan) described in Equation 4 resulted in predictions that were markedly degraded when compared with the case where such site factors were not known. After adding the site factor, the standard deviation of the predicted value of control increased from \$3 to 15 ha^{-1} in the three-parameter model. When the threshold (EIL_f) was predicted based on March to May precipitation, the standard deviation increased from \$15 to 21 ha^{-1} with the inclusion of the site factor in the three-parameter model.

One of the advantages of exploring prediction accuracy using simulation was that we could explore the effects that different types of errors had on prediction. The primary source of error was process noise in the SPCE plot data. The secondary source of error arose from real-world (sampling) variation of precipitation frequencies. In combination, these two sources of error alone were sufficient to produce a prediction error in the EIL_f for management corresponding to approximately 25% of the value of control (\$10 ha^{-1}) for the case where knowledge of precipitation influence on crop yield was limited to the 3 mo before the growing season that was being predicted. The magnitude of the SPCE process error (20% variation added to the response model) was a very conservative estimate of what occurs in practice and there were many potential sources of variation that were not included. Thus, 25% error in the value of weed control may serve as a bound on the potential of precipitation inclusion in the model to improve accuracy for the wild oat–wheat system in north-central Montana, that is, if one had eight experiment station small-plot experiments (a rare scenario), precipitation data from each experiment station, and undertook to improve prediction by adding moisture to the model, then it is very unlikely that the prediction error could be reduced below 25% of the value of weed control.

The addition of an unknown site factor was seen to significantly degrade prediction, both with and without full knowledge of the GSP. There are certainly yield-influencing properties of locations that are relatively constant on the field scale but vary for a larger geographic region, depth to hardpan being an important one. In this study, we assumed that the standard deviation of such an effect was 20%. Provided that this magnitude is reasonable, there would seem to be significant improvements in prediction accuracy to be made by gaining knowledge of such factors. On-farm experimentation would be one method that could improve our knowledge of driving factors and subsequent yield prediction.

Adding more SPCEs by conducting more studies over years or sites could greatly decrease both the bias and the standard deviation when there is full knowledge of the GSP (e.g., using 32 SPCE stations and the six-parameter model decreases the mean bias to 0.08 and the mean standard deviation to 1.05) but does little to improve the accuracy of the EIL_f when pre–weed management decision precipitation rather than full growing season precipitation was used in the model.

It is easy to add SPCEs in a simulation, but competition study data are very expensive to collect. One value of this study lies in demonstrating the potential importance of adding additional studies. Because there is a correlation within years for weather data (Figure 2), within-year replication across space does not provide as much independent information as replication across time. This finding, in itself, lends the greatest support for site-specific technology–based parameterization of decision support models and thus the greatest ecological justification for this technology.

The number of independent replicate experiments will vastly increase if site-specific on-farm experimentation ever reaches the point where producers can conduct it with ease (i.e., weed abundance is easily and site specifically estimated and corresponds to yield monitor information). A mechanism to accumulate publicly available site-specific field-scale data may provide the best information for validation of weed management strategies based on ecological principles. The results of our numerical experiments emphasize, in an extremely general way, that the value of small-plot experiment station information is not likely to be found in forecasting prescriptive EBWM. Instead, these results suggest that small-plot weed ecology experiments may be used best in the development of first-principle models that can then be applied to management with on-site parameterization (Maxwell 1999).

There are clearly major barriers preventing precise prediction of effects, demographics, and other ecological phenomena that could improve the ability to manage weeds. However, as the value of production decreases and the costs of inputs such as herbicides become a large fraction of gross returns, economizing by lowering rates or occasionally forgoing the use of weed control may become more of an economic necessity than an option. Thus, studies like this that seek to improve our ability to appropriately apply ecological knowledge gained through different venues (small plots vs. farm fields) and suggest how to capitalize on technology may serve as a guide for future research into the application of EBWM.

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