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Linkages among agronomic, environmental and weed management characteristics in North American sweet corn

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ABSTRACT

Much of our understanding of weed communities and their interactions with crops comes from studies conducted at, or below, the spatial scale of individual fields. This scale allows for tight control of experimental variables, but systematically ignores the potential for regional-scale environmental variation to affect agronomic operations and thereby influence weed management outcomes. We quantified linkages among agronomic, environmental and weed management characteristics of 174 commercial sweet corn fields throughout the north central United States and evaluated crop and weed responses to these variables using classification and regression tree (CART) analysis. Multi-model selection indicated that characteristics of weed management systems, especially total cost and herbicide rate, were important predictors of weed diversity, interference and fecundity. Adding agronomic variables, such as planting date, or environmental variables, such as latitude, explained additional variation in weed floristic measures. We tested yield predictions of the most parsimonious CART model against a verification data set comprised of over 1500 published observations from 25 experiments conducted in the major North American regions where sweet corn is grown for processing. Yield values fell within the 95% confidence interval of observed data for most branches of the tree, suggesting the experimental and analytical approaches were reasonably robust. Several characteristics favoring sweet corn productivity and weed management sustainability were identified. This work resulted in easily interpretable models, both by scientists and producers, which place crop and weed responses within the context of regional-scale variation in agricultural management and the environment.

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1. Introduction

Plant species composition and abundance at a given time reflect outcomes from a suite of dynamic forces including environmental characteristics, management practices and species interactions (Harper, 1977). In agroecosystems, knowledge of weed community structure is considered critical in the planning of sustainable weed management systems and directing future research (Dewey and Andersen, 2004; Thomas and Dale, 1991). This knowledge is routinely used in a descriptive way, as when inventories of weed species composition are used to characterize weed diversity of specific agroecosystems, compare effectiveness of management practices, and document changes in weed community structure over time (Frick and Thomas, 1992; Van Acker et al., 2000; Webster and Coble, 1997). Less frequent is the use of weed community data to retrospectively understand the agronomic and environmental forces shaping an agroecosystem.

The majority of North American sweet corn (*Zea mays* L.) is grown for processing, with the Pacific Northwest and north central region (NCR) accounting for most of the production. Illinois, Minnesota, and Wisconsin account for 98% of the processing production capacity in the NCR (U.S. Government Printing Office, 2006) and a majority of Canada's sweet corn is produced in southern Ontario (Statistics Canada, 2008). Environmental conditions vary greatly within a growing season because sweet corn is planted and harvested over a wide range of dates to optimize processing plant capacity and extend market availability. Moreover, numerous crop production issues and niche produce markets have resulted in some 600 commercial hybrids which vary considerably in agronomic traits relevant to crop-weed interactions (So et al., 2009; Williams et al., 2006).

Efficacy of weed management systems in sweet corn has improved during the last five decades; however, weed interference continues to compromise crop yield in a majority of fields despite extensive use of herbicides (Williams et al., 2008b). Contradictory experimental results among sites and years, particularly with non-chemical tactics, call into question the extent that general weed management recommendations can be broadly applied. We

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believe one reason for the lack of correspondence between weed management research and performance in production fields may be the small spatial scale at which most of our understanding of weed–crop relations is constructed. Experimental data generated and analyzed at, or below, the field scale may systematically ignore salient variation in management and environmental factors that are homogeneous within fields, but heterogeneous at a regional scale. For instance, work by McDonald et al. (2004) identified climatic drivers of competition between maize and velvetleaf (*Abutilon theophrasti* Medik), namely, temperature following maize establishment and water stress during exponential crop growth. This knowledge improves not only the understanding of an agroecosystem–environment interface, but will improve performance of weed management decision support systems.

The purpose of our work was to identify primary linkages among agronomic, environmental and weed management characteristics in commercial sweet corn production systems across the NCR. We were particularly interested in how these linkages relate to crop production issues such as weed interference and crop yield.

2. Methods

One-hundred seventy-four fields grown under contract for sweet corn were identified throughout the NCR in Illinois, Minnesota and Wisconsin from 2005 to 2007 (Fig. 1). To help us locate sweet corn fields over a range of harvest times (i.e. July through early October), collaborators in the processing industry

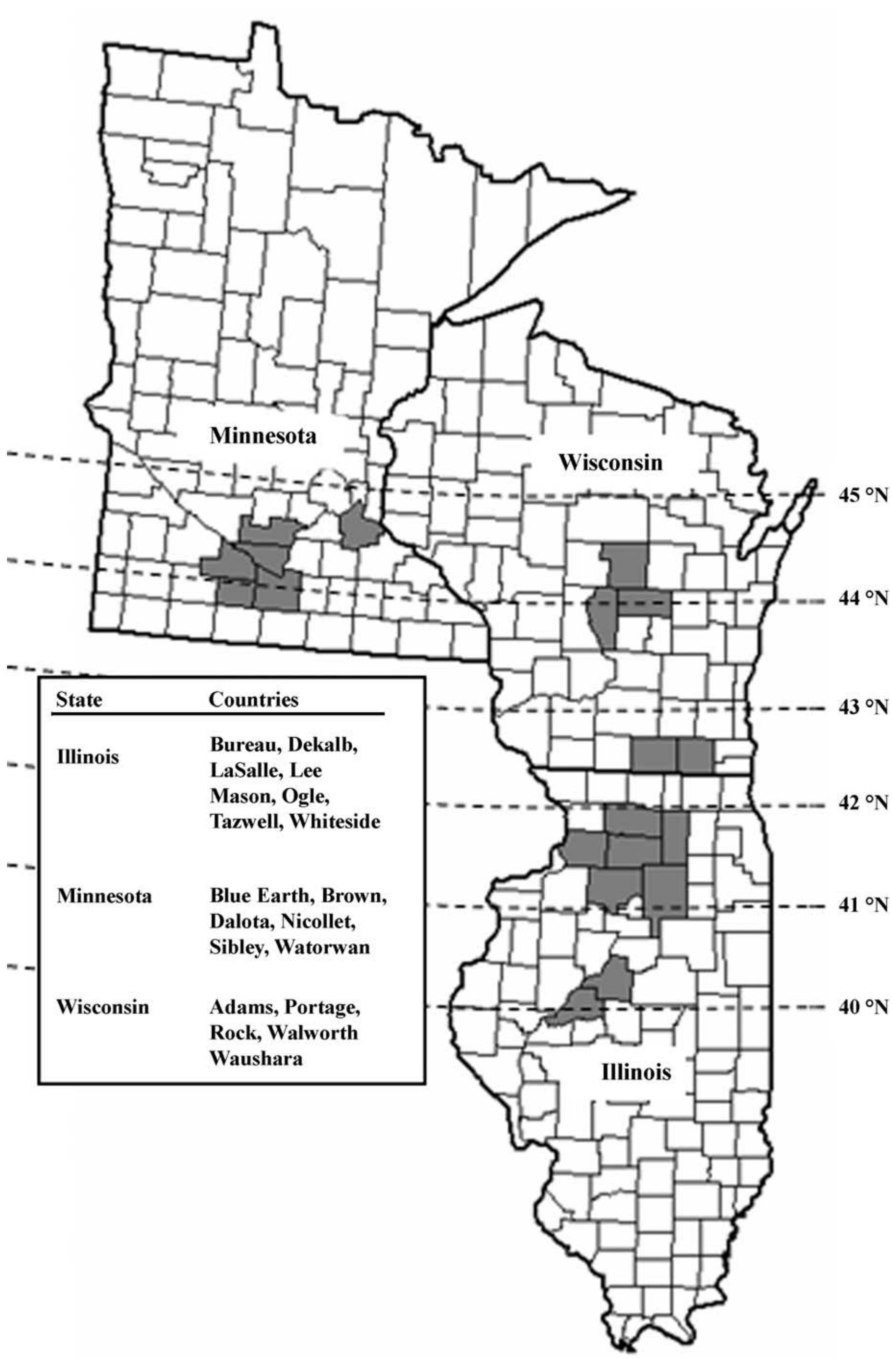

Fig. 1. Sampling locations (shaded counties) of sweet corn fields from 2005 to 2007.

provided weekly lists of fields scheduled for harvest from which random samples were drawn.

2.1. Data collection

The weed community at harvest (hereafter called 'residual' weed community) of each field was characterized using the methodology of Thomas (1985) with some modification. Weed species and density were enumerated in 30 1-m^2 quadrats placed randomly along a 300- to 500-m loop through the field, leaving a 20 m buffer area near field margins. Species that produced mature (i.e. filled and hard) seed by the time of sweet corn harvest were recorded. Based on weed community structure, crop and weed size distributions, perceived loss of ear mass relative to weed-free conditions, and expert opinion, fields were scored visually for overall level of weed interference. One of four outcomes was used, including 1 = no interference and yield loss unlikely; 2 = low interference and yield loss of $\leq$5%; 3 = moderate interference and yield loss $>$5 to $\leq$20%; and 4 = severe interference and yield loss $>$20%. Complete details on weed sampling are provided by Williams et al. (2008b).

After crop harvest, collaborators in the processing industry provided copies of management records of sampled fields, from which the following agronomic and environmental data were extracted: previous crop, timing and type of tillage, crop row spacing, irrigation practices, sweet corn hybrid, planting date, herbicide usage (including preemergence herbicide (PRE) and/or postemergence herbicide (POST) application dates and usage rates of active ingredients), crop harvest date and yield. Based on tillage and herbicide use in each field, weed management expenditures were calculated using costs of herbicides (Boerboom et al., 2008) and machinery costs for herbicide applications and tillage practices (University of Minnesota Extension, 2008).

Daily rainfall and minimum and maximum air temperatures were estimated for the period from planting to harvest from the closest weather station to each field (Midwestern Regional Climate Center, 2009). Growing degree days (GDD) were determined using daily minimum and maximum air temperatures, where a base temperature of 10 °C was used as the minimum temperature for sweet corn growth. Cumulative GDD and cumulative precipitation (PPT) were calculated for the periods of time including: planting to application of POST herbicides (GDD_{PA}, PPT_{PA}), POST herbicide application to harvest (GDD_{AH}, PPT_{AH}), and planting to harvest (GDD_{PH}, PPT_{PH}).

2.2. Statistical analyses

The compiled data set for this study was large, encompassing more than 20 environmental variables, more than 30 agronomic variables, and floristic measures for 56 species. We used classification and regression trees (CART; Breiman et al., 1984) to highlight the primary associations between environmental, agronomic and weed management variables to crop and weed dependent variables, including crop yield, weed alpha diversity based on the Shannon's index, weed fecundity (number of species producing viable seed) and level of weed interference. The number of fields used for analyzing crop yield was 172; all other response variables were analyzed with data from 174 fields.

The use of CART in analyzing complex ecological data sets has become increasingly common due to the ability of this method to describe patterns and processes for a wide range of data types, including numerical and categorical data, with output that is simple to understand (De'ath and Fabricius, 2000). The basic algorithm underlying CART is to repeatedly partition a data set into more and more homogeneous groups, evaluating the relative "impurity" of the data before and after a split to determine the most parsimonious tree (Breiman et al., 1984). The output is represented graphically as a dichotomous tree, with criteria for the various splits (i.e. nodes) represented by values of classification or numeric variables, dividing homogeneous groups onto terminal branches (i.e. leaves). We implemented CART in the "rpart" package of R statistical computing software version 2.7.1 (R Development Core Team, 2006). For each of the four dependent variables, we found the most parsimonious model by examining trees for the seven factorial combinations of environmental (GDD_{PH}, PPT_{PH}, latitude and state), agronomic (interrow cultivation, irrigation practice, hybrid maturity and planting date), and weed management variables (herbicide application timing [i.e. PRE, POST, or both], total herbicide application rate, atrazine use and total weed management costs) that maximized the proportion of variance explained (Table 1). We evaluated the predictive power of each candidate tree for each combination of dependent and independent variables through 50 runs of 10-fold cross-validation, in which nine-tenths of the data set was used to predict values in the remaining tenth in each iteration (De'ath and Fabricius, 2000).

Following the reduction of data with CART models for each of the four dependent variables of interest (crop yield and weed diversity, interference and fecundity), we built multiple regression models (Neter et al., 1996) for the same data types. Model selection was accomplished in two phases. First, fitted CART models were

Table 1

Comparison of classification and regression tree (CART) models of sweet corn yield and associated weed floristic measures in relation to agronomic, environmental and weed management variables of commercial sweet corn fields in Illinois, Minnesota, and Wisconsin in 2005 to 2007.

Dependent variable	Predictors[a]	Size of tree[b]	Variance explained (%)[c]
Crop yield	E	0	0
	A	4	24
	W	1	27
	E + A	8	**41**
	E + W	1	5
	A + W	9	38
	E + A + W	3	21
Weed diversity	E	2	38
	A	6	37
	W	7	40
	E + A	1	35
	E + W	1	35
	A + W	8	**51**
	E + A + W	1	35
Weed interference	E	7	38
	A	1	37
	W	1	28
	E + A	2	40
	E + W	4	33
	A + W	2	39
	E + A + W	8	**43**
Weed fecundity	E	2	33
	A	1	12
	W	2	12
	E + A	1	19
	E + W	8	**46**
	A + W	1	21
	E + A + W	1	43

[a] Abbreviations for classes of predictor variables: E = environmental (including total precipitation from planting to harvest, growing degree days from planting to harvest, latitude and state), A = agronomic (including planting date, hybrid maturity and interrow cultivation), W = weed management (including herbicide application timing (e.g. PRE, POST, both, or none), total herbicide application rate, atrazine use and total weed management cost).

[b] Size of tree = the number of nodes in each CART.

[c] CART models for each dependent variable were built from factorial combinations of the listed predictor variables, and the models explaining the greatest proportion of observed variation in the data (shown in bold) were selected for graphic presentation in Figs. 2–5.

used to help select independent variables to be included in the full regression model for each dependent variable as follows: (a) crop yield {cultivation (C), latitude (L), hybrid maturity (M), GDD, planting date (P), C × M, C × L, GDD × M, M × L}; (b) weed diversity {herbicide application rate (R), M, herbicide application timing (H), P, management cost (Co), R × M, R × H, R × P}; (c) weed interference {L, P, GDD, Co, PPT, L × P}; and (d) weed fecundity {L, PPT, GDD, R, Co, state (S)}. Second, an automated maximum likelihood model simplification routine ("*step*") was used within the *lme4* library of R 2.7.1 (R Development Core Team, 2006) to identify the most parsimonious model for each dependent variable (i.e. the model that minimized the penalized log-likelihood function, AIC, Akaike's Information Criterion) out of the set of all possible combinations of variables in the full model. Akaike weights (w_i), representing the weight of evidence in favor of the selected model having the best fit to the data within the given set of models, were calculated as

$$w_i = \frac{e^{(-1/2\Delta_i)}}{\sum_{r=1}^{R} e^{(-1/2\Delta_r)}} \tag{1}$$

where Δ_i represents the difference in AIC between the ith model in the set (for which w_i is being calculated) and the best model in the set, R represents the total number of models within the set being considered, and r represents individual models within the set (Burnham and Anderson, 2002). Regression diagnostics were used to determine whether the selected models met assumptions of normality and homoscedasticity (Crawley, 2007). All models performed well according to these criteria, therefore no transformations were applied. Finally, linear associations between variables were quantified using Pearson correlation coefficients.

2.3. Yield model verification

A total of 25 experiments were conducted in recent years to quantify crop-weed interactions in sweet corn under a range of environmental conditions and agronomic practices, including locations in Illinois, Oregon, Washington, and Ontario, Canada (So et al., 2009; Williams, 2006, 2008; Williams and Masiunas, 2006; Williams et al., 2006, 2008a, 2009). Yield of 30 sweet corn hybrids was quantified in the research under varying weed management treatments (e.g. season-long weedy, partial weed control, and season-long weed-free) that resulted in a range of interference from weed species common to North America. Data from this research were compiled into two verification sets; one that included crop yields in all treatments regardless of weed management level (ALL trts) and another that only included experimental yield in weed-free treatments (WF trts), for a total of 1595 and 415 observations, respectively. Using the final CART model for crop yield, each experimental observation was classified to the appropriate leaf according to environmental and agronomic variables specific to the observation. Experimental yield means were compared to CART model yields using 95% confidence intervals.

3. Results

3.1. Crop yield

The regression tree model explaining the largest amount of variation in crop yield (41%) had eight nodes using only two environmental variables (latitude and GDD_{PH}) and three agronomic variables (interrow cultivation, hybrid maturity and

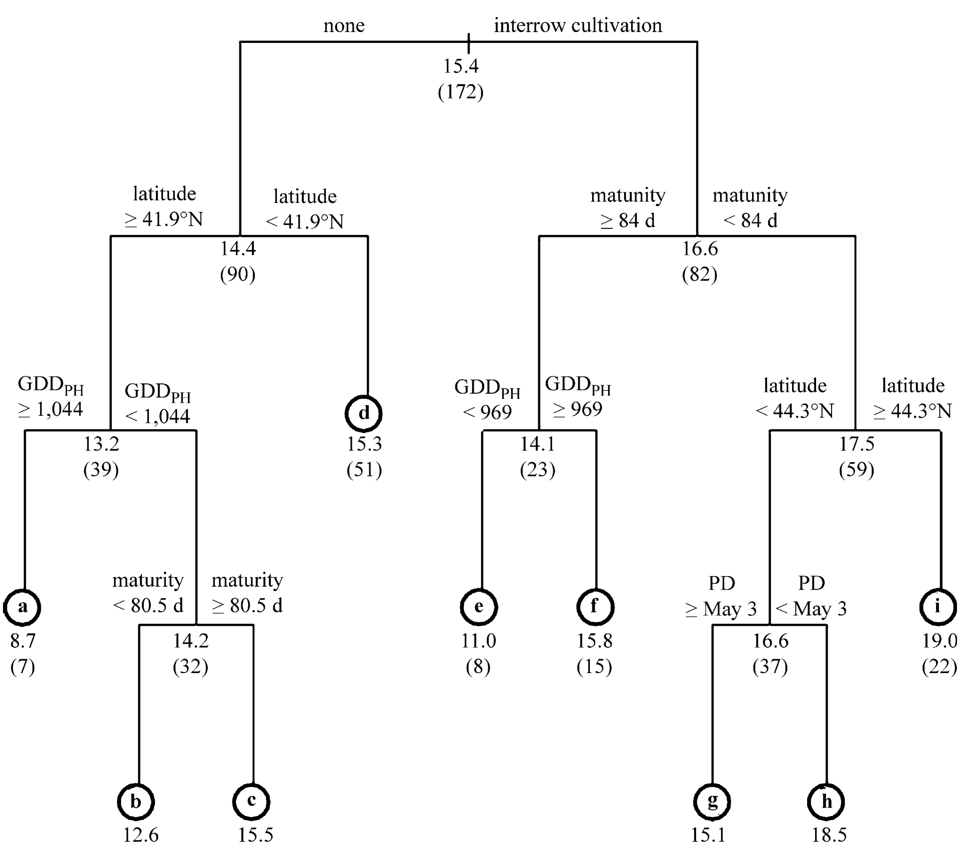

Fig. 2. Final classification and regression tree for crop yield. Mean sweet corn yield (Mt/ha) is reported below each node and leaf, with the number of fields in parentheses. Explanation of variables: GDD_{PH}, cumulative growing degree days from planting to harvest; maturity, maturity of sweet corn hybrid; PD, crop planting date.

planting date) (Table 1). The combination of interrow cultivation, use of hybrids that matured in less than 84 days, and fields located above 44.3°N had the highest sweet corn yields (mean = 19.0 Mt/ha) (Fig. 2). In contrast, fields requiring more than 1044 GDD_{PH} located above 41.9°N without interrow cultivation had the lowest yields (mean = 8.7 Mt/ha). The effect of planting earlier in the season (before May 3) was associated with higher yields of most hybrids (<84 days maturity) for interrow cultivated fields located below 44.3°N.

3.2. Weed diversity

The CART model with eight nodes using two agronomic variables (hybrid maturity and planting date) and three weed management variables (total herbicide rate, herbicide timing, and weed management cost) was the most parsimonious model for weed diversity (Table 1). Fields that received the highest herbicide rates (≥4.52 kg/ha) had the most diversity (Shannon's index = 1.59) (Fig. 3). In contrast, several fields receiving less than 1.42 kg/ha of herbicide had the lowest weed diversity (Shannon's index = 0.30). In some cases, fields planted on or after May 6 had lower weed diversity indices than in fields planted before May 6. See Williams et al. (2008b) for a detailed characterization of weed species communities in these fields.

3.3. Weed interference

A combination of environmental, agronomic and weed management variables resulted in a CART model accounting for most of the variation in weed interference (43%) observed in growers' fields (Table 1). Specific variables included planting date, weed management cost, latitude, GDD_{PH} and PPT_{PH}. The highest weed interference (mean = 2.9) was observed in fields below 42.2°N, planted before June 15, and when weed management costs exceeded $142/ha (Fig. 4). In contrast, fields located above 42.2°N and planted after May 31 had among the lowest weed interference (mean = 1.2). Low precipitation from planting to harvest (<210 mm) and longer periods of crop growth were associated with fields with greater weed interference.

3.4. Weed fecundity

The CART model explaining the largest amount of variation in weed fecundity (46%) had eight nodes using four environmental variables (latitude, state, and GDD_{PH} and PPT_{PH}) and two weed management variables (total herbicide rate and weed management cost) (Table 1). Fields with the lowest fecundity (mean = 0.5 species/field) were in Illinois and Minnesota above 41.9°N when PPT_{PH} was ≥186 mm (Fig. 5). The combined effect of weed management costs less than $148/ha, PPT_{PH} < 209 mm, and fields below 41.9°N had the highest weed fecundity (mean = 5.2 species/field). In fields below 41.9°N, greater PPT_{PH} (≥209 mm), longer crop growth periods (≥991 GDD_{PH}), and lower herbicide use (<4.25 kg/ha) were associated with reductions in weed fecundity.

3.5. Comparison of CART and multiple regression

The most parsimonious multiple regression models for each of the four dependent variables of interest provided strong support for the effects of agronomic, environment, and weed management

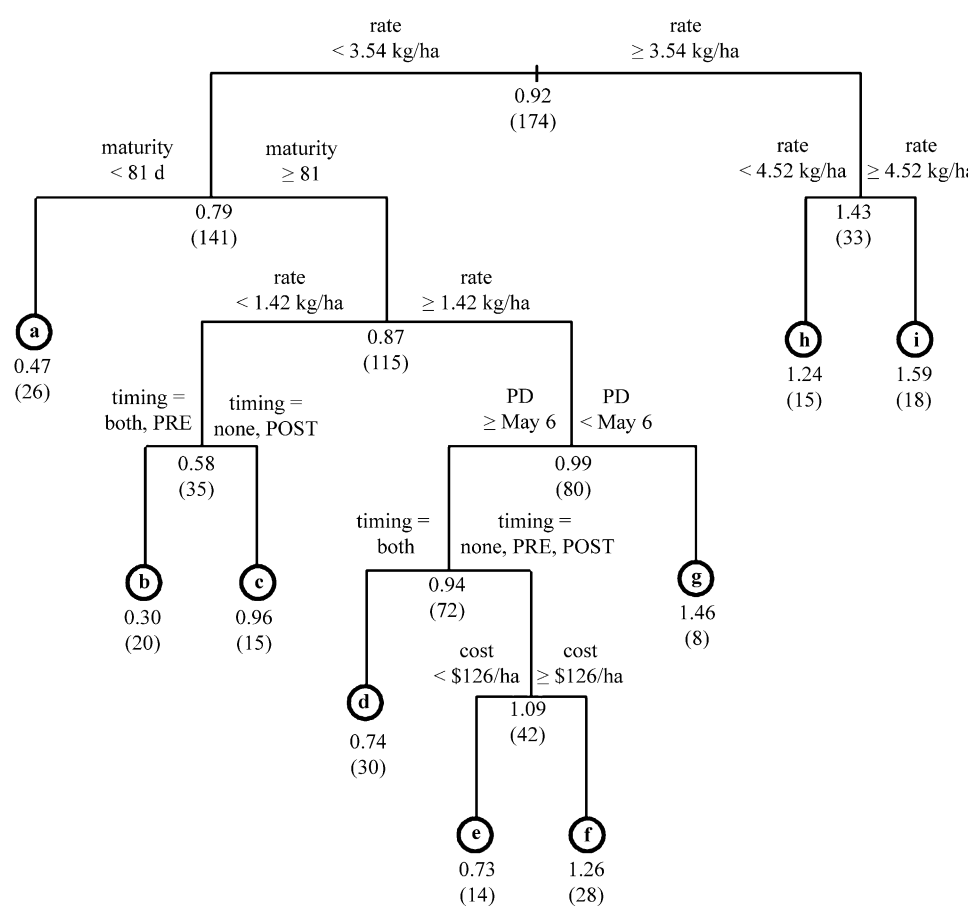

Fig. 3. Final classification and regression tree for weed diversity. Mean weed diversity (Shannon's index) is reported below each node and leaf, with the number of fields in parentheses. Explanation of variables: cost, total weed management costs; maturity, maturity of sweet corn hybrid; PD, crop planting date; rate, total herbicide application rate; timing, herbicide application timing (e.g. PRE, POST, both, or none).

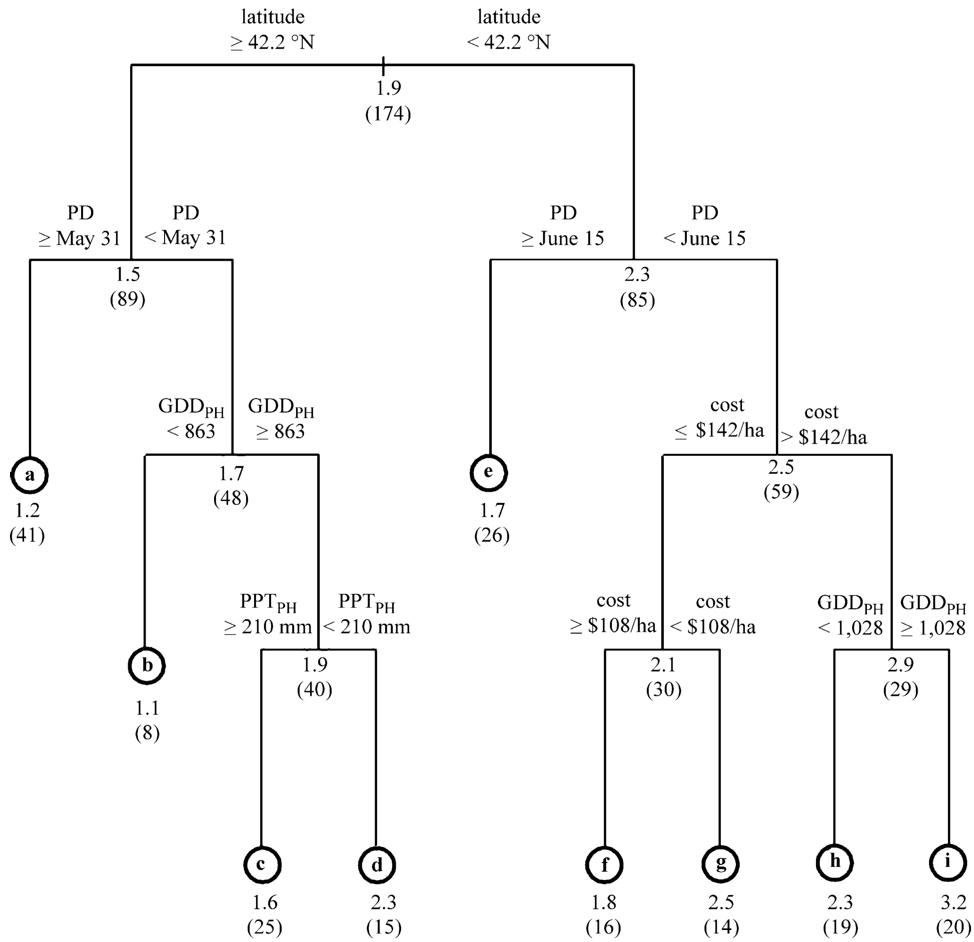

Fig. 4. Final classification and regression tree for weed interference. Mean weed interference (scale from 1 = none to 4 = severe) is reported below each node and leaf, with the number of fields in parentheses. Explanation of variables: cost, total weed management costs; GDD_{PH}, cumulative growing degree days from planting to harvest; maturity, maturity of sweet corn hybrid; PD, crop planting date; PPT_{PH}, cumulative precipitation from planting to harvest.

effects on sweet corn yield and weed floristic measures described by the CART models (Table 2). For instance, the multiple regression model for crop yield showed a cultivation by latitude interaction ($p < 0.001$). This interaction is evident in the CART yield model (Fig. 2), whereby in the absence of interrow cultivation, crop yield is superior at lower latitudes (i.e. <41.9°N). However when cultivation is practiced, crop yield is superior in northern latitudes (i.e. >44.3°N). While the multiple regression models also provide a quantitative description of response variables, the benefit of the CART approach is that the models are readily interpretable and could be used for educational purposes.

3.6. CART yield model verification

Greater parsimony was observed between yields in the CART model and field experiments when the verification data set contained data only from weed-free plots. The CART yields at leaves *b*, *c*, *d*, *e*, and *i* were within the 95% confidence intervals of the weed-free experimental yields (Fig. 6). The CART yields were less than weed-free experimental yields for leaves *f* and *g*. In contrast, experimental yields of the complete verification data set (all treatments) were in agreement with CART yields only at leaves *d*, *e*, and *i*.

4. Discussion

By using CART analysis on agricultural and environmental data from ≥172 fields, we identified the combination of best predictors of crop yield and residual weed diversity, interference and fecundity. The most parsimonious models explained between 41% and 51% of the variation observed in several crop and weed floristic measures. Including additional explanatory variables (e.g. fertility practices, soil moisture and disease severity) might explain small amounts of additional variation; however, our analysis resulted in models that explained the most variation possible with the fewest variables for which reliable information could be obtained (Breiman et al., 1984). This work is practical, in that easily interpretable models were developed, reflecting crop and weed responses relevant to the current agriculture–environment interface.

Use of the longest maturing hybrids in the northern latitudes of the NCR is currently avoided, likely because of concern of insufficient thermal time to maturity. This was supported by the relationship between latitude and maximum hybrid maturity, where a strong negative correlation (−0.982; $p = < 0.001$) was observed at latitudes above 41°N. However, as long as a particular hybrid maturity group was appropriate to a shorter season, these northern latitudes provided more favorable growing conditions than to the south, as evidenced by the highest crop yields (Fig. 2). High temperatures and drought are two major abiotic stresses continuing to limit yield improvement in maize (Duvick, 2005). Higher yields in the model in the most northern latitudes (e.g. >44°N) are likely due to decline in the frequency of heat stress with increasing latitudes in the NCR (Midwestern Regional Climate Center, 2009). In the rest of the production region (e.g. <44°N), planting earlier in the season (e.g. <May 3) resulted in higher

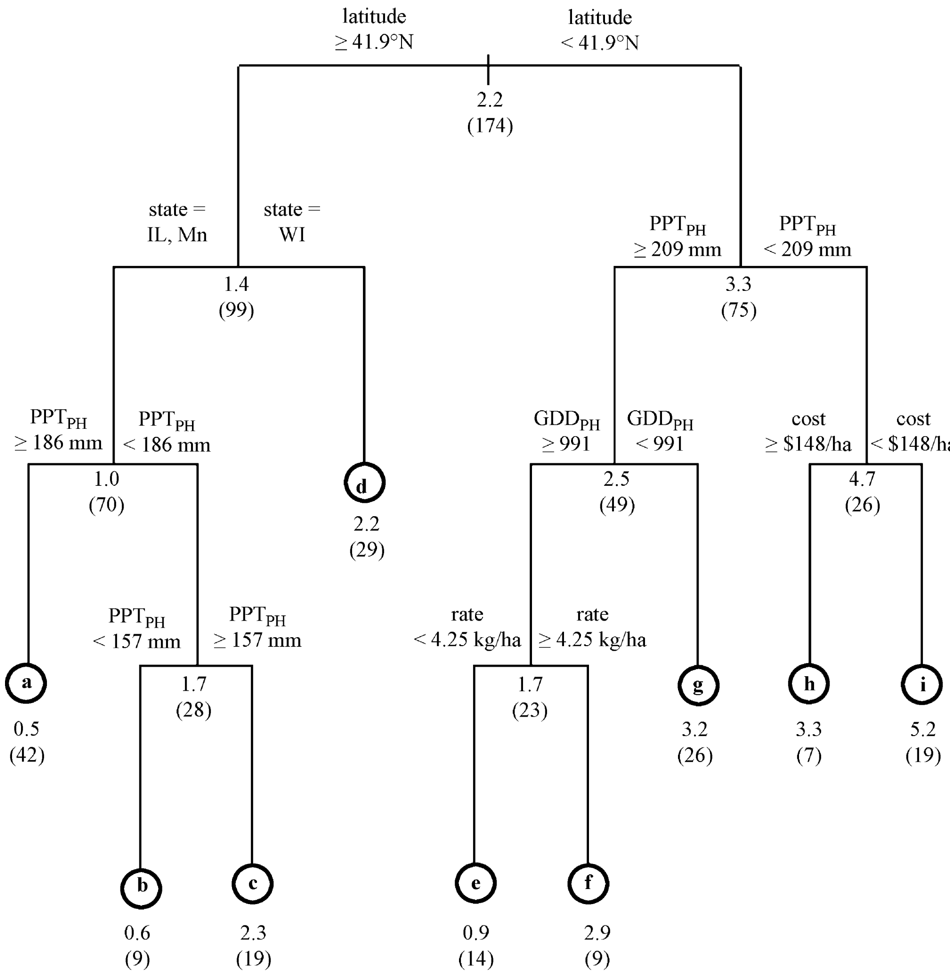

Fig. 5. Final classification and regression tree for weed fecundity. Mean weed fecundity (no. species producing viable seed/field) is reported below each node and leaf, with the number of fields in parentheses. Explanation of variables: cost, total weed management costs; GDD_{PH}, cumulative growing degree days from planting to harvest; maturity, maturity of sweet corn hybrid; PPT_{PH}, cumulative precipitation from planting to harvest; rate, total herbicide application rate.

yields than later plantings (Fig. 2). Compared to earlier plantings, later plantings at these latitudes are subject to more biotic and abiotic stresses, and sometimes decreased yield potential (Williams, 2008). For instance, populations of several serious insect and disease pests of sweet corn are transported from the south and increase during the planting season, creating more stressful environmental conditions to later-planted sweet corn (Revilla and Tracy, 1997; Tracy, 2001).

Agreement between CART yields and weed-free experimental yields showed relatively robust linkages among agronomic and environmental variables that comprised the final CART yield model (Fig. 6). However, yield for leaves *f* and *g* was not consistent with experimental yields. The verification data set testing leaf *g* represented data entirely from central Illinois. In previous work (Williams et al., 2008b), we found yield loss due to weed interference in growers' fields in Illinois was higher than fields in Minnesota and Wisconsin. Perhaps the weed-free data in the verification failed to accurately characterize the extent of weed interference more commonly observed in growers' fields at leaf *g*. This is supported by the observation that the CART model yield exceeded experimental sweet corn yield at leaf *g* when the complete verification data set (ALL trts) was used (Fig. 6). Higher CART yield, relative to yield in the complete verification data set (ALL trts), may be explained by severe weed treatments (e.g. season-long weedy) resulting in artificially high yield losses, skewing experimental yields below that of growers' fields. Also, the CART model showed lower sweet corn yield at leaf *f*. The verification data set testing leaf *f* was represented heavily by experimental data from Washington; the warm days, cool nights, irrigation, and low humidity result in higher-yielding plants with fewer disease issues compared to the NCR (Tracy, 2001; U.S. Government Printing Office, 2006; Williams et al., 2006). By limiting the verification data set to only NCR fields, CART model yield was similar to the complete verification data set yield (data not shown).

An unexpected result was that weed diversity was highest in fields that received the highest herbicide rates (e.g. >4.52 kg/ha), and diversity was low in fields receiving some of the lowest herbicide rates (e.g. <1.42 kg/ha) (Fig. 3). Greater herbicide use is unlikely to be a cause of higher weed diversity; herbicide rates were more likely increased in response to greater severity of local weed problems. The decline in weed diversity in fields planted on or after May 6 is likely the result of several factors associated with later-season plantings, including: reduced weed seedbank densities (Buhler and Gunsolus, 1996; Gower et al., 2002), decreased emergence frequency of early emerging species, and for mid-June and July plantings, greater weed suppressive ability of sweet corn (Williams, 2006, 2009). Several researchers have discussed potential benefits of maintaining weed diversity in agroecosystems below levels resulting in crop losses (Clements et al., 1994; Dekker, 1997). In this work, a positive correlation (0.204, $p = 0.007$) was observed between weed diversity and weed interference, indicating more diverse fields were associated with greater weed interference and crop yield loss.

Table 2
Multiple regression models of agronomic, environmental, and weed management effects on sweet corn yield and weed floristic measures of commercial sweet corn fields in Illinois, Minnesota and Wisconsin in 2005–2007.

Dependent variable	Predictors[a]	Parameter estimates	Model performance[c]			
			$F_{(\mathrm{dfn,dfd})}$	$P > F$	R^2	w_i
Crop yield	Intercept	−7.22	$6.05_{(5,166)}$	<0.0001	0.13	0.50
	Cultivation	29.28				
	Maturity	0.34*[b]				
	Latitude	−0.15				
	C × M	−0.55**				
	C × L	−0.43†				
Weed diversity	Intercept	−2.76*	$10.45_{(6,166)}$	<0.0001	0.25	0.42
	Herbicide (none)	0.94†				
	Herbicide (POST)	0.33*				
	Herbicide (PRE)	0.16*				
	Maturity	0.034*				
	Herbicide a.i. kg ha^{-1}	0.22***				
	Weed control cost	0.0019†				
Weed interference	Intercept	4.43*	$5.41_{(4,168)}$	<0.001	0.10	0.39
	GDD	0.001†				
	Latitude	−0.065*				
	Planting date	−0.0089**				
	Weed control cost	0.0044*				
Weed fecundity	Intercept	12.53*	$12.57_{(4,169)}$	<0.0001	0.21	0.47
	State (MN)	−1.35*				
	State (WI)	−0.24*				
	PPT	−0.004†				
	Latitude	−0.209†				

[a] Explanation of predictor abbreviations: cultivation = interrow cultivation used in production system; maturity = hybrid maturity; herbicide a.i. kg ha^{-1} = kilograms of herbicide active ingredient applied per hectare; GDD = growing degree days (base 10) accumulated between planting and harvest; PPT = precipitation (mm) accumulated between planting and harvest.
[b] The symbols †, *, ** and *** denote significance of individual regression parameters at the 0.10, 0.05, 0.01 and 0.001 α levels, respectively.
[c] Explanation of model performance abbreviations: dfn and dfd = numerator and denominator degrees of freedom, respectively; w_i = Akaike weights.

The greatest weed interference was observed in fields located in the southern part of the production region, planted before mid-June, and when weed management costs exceeded $142/ha (Fig. 4). Greater weed interference in earlier plantings was consistent with other work (Williams, 2006, 2009; Williams and Lindquist, 2007) that also documented more competitive weed communities in April and May plantings, compared to later-season plantings. Later-planted fields generally had less weed interference in this work, too, as evidenced by a negative correlation (−0.19; p = 0.013) between weed interference and harvest date. Finally, greater weed interference in fields with low precipitation and long periods of crop growth could be explained in part by reduced uptake and efficacy of PRE and POST herbicides under dry conditions (Medd et al., 2001), as well as decline in soil herbicide bioavailability over time (Appleby, 1985).

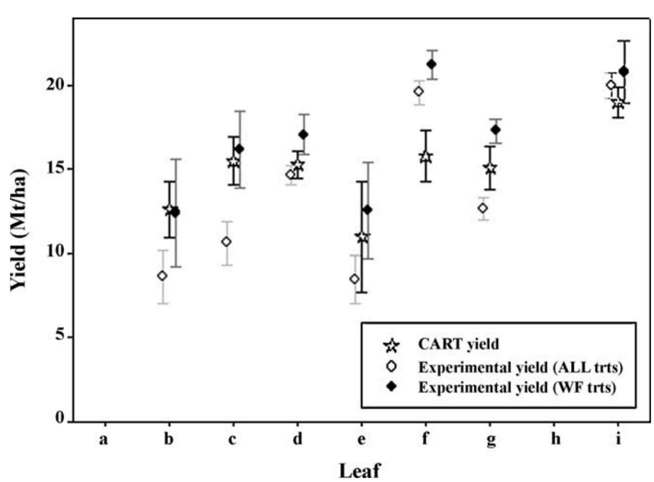

Fig. 6. Verification of final classification and regression tree (CART) for sweet corn yield. Leaves correspond to terminal nodes of the CART shown in Fig. 2. The CART yield represents observed sweet corn yield from 172 growers' fields in Illinois, Minnesota, and Wisconsin. Experimental yield is sweet corn yield from independent field experiments (25 experiments total) conducted in Illinois, Oregon, Washington (U.S.), and Ontario (Canada). Experimental yield included data sets that contained all weed management treatment levels (ALL trts) and only weed-free treatments (WF trts). Error bars represent 95% confidence intervals.

In the NCR, sweet corn is often rotated with field corn or soybean (*Glycine max* (L.) Merr.). Unlike sweet corn, which has a relatively short growth period, weeds persisting in field corn and soybean often complete their life cycle, senesce, and annual species produce abundant viable seed. Not all weed species selected under these long-season conditions produce viable seed by the time of sweet corn harvest (Williams, 2009; Williams et al., 2008b). Further evidence of the severity of weed populations in the southern part of the production region was that latitude was the strongest predictor of fecundity, with higher fecundity in most Illinois fields compared to Minnesota and Wisconsin (Fig. 5). This work shows that low precipitation is associated with increased fecundity, which could be attributed to reduced herbicide activity mentioned earlier, and reduced growth and interference from the crop. Furthermore, the highest weed fecundity was observed when weed management costs were below $148/ha. The lower weed management costs were the result of using less-expensive herbicides, which may have had a narrower spectrum or poorer level of control. For some fields, lower herbicide use was associated with reduced weed fecundity. Most newer herbicides are applied at considerably lower use rates than older herbicides such as atrazine (6-chloro-*N*-ethyl-*N*′-(1-methylethyl)-1,3,5-triazine-2,4-diamine), the most widely used herbicide in North American sweet corn. In this work, atrazine was applied to all fields where >3 kg/ha of total herbicide was applied. We saw no difference in weed management expenditures between programs that did or did not include atrazine (data not shown). Again, it appears the weediest fields (in terms of weed diversity, interference and fecundity) received the highest rates of herbicides. Because atrazine is relatively inexpensive and largely effective, the herbicide continues to be used extensively, particularly in fields with a weed community that is difficult to manage.

5. Conclusion

This research quantified linkages between the environment and agricultural practices, and their relation to crop and weed responses in North American sweet corn production. Using a CART modeling approach, characteristics of weed management systems such as total cost and herbicide rate were important predictors of all weed response variables. Adding agronomic variables (e.g. planting date) or environmental variables (e.g. latitude, GDD_{PH}, PT_{PH}) helped explain additional variation in weed diversity, interference and fecundity. Several characteristics of more sustainable weed management systems were identified, including: (1) planting weediest fields in June or July, (2) adequate precipitation or irrigation likely improved herbicide activity, (3) the northern part of the NCR (above $\sim$42°N) has lower weed interference and fecundity in sweet corn, and (4) while particularly weedy fields may be receiving greater herbicide use (in terms of multiple applications and elevated rates), these inputs are unlikely to be highly effective and protect yields compared to less-weedy fields with lower weed seedbanks. In addition, several characteristics that benefit sweet corn productivity were identified, including: (1) use of interrow cultivation, (2) planting less-weedy fields before June, and (3) choosing the latest maturing hybrid within each site-specific growing season. Results from this analysis are intuitive and supported by published literature. Clear trends emerged from data on fields dispersed in space and time, suggesting a robust approach to quantifying crop and weed responses to the agroecosystem–environment interface.

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