Impact of Atrazine on the Sustainability of Weed Management in Wisconsin Corn Production

Fengxia Dong
Department of Agricultural and Applied Economics
University of Wisconsin-Madison
Fdong6@wisc.edu

Paul D. Mitchell
Department of Agricultural and Applied Economics
University of Wisconsin-Madison
pdmitchell@wisc.edu

Vince M. Davis
Department of Agronomy
University of Wisconsin-Madison
vmdavis@wisc.edu

Ross Recker
Department of Agronomy
University of Wisconsin-Madison
Recker12@gmail.com

Selected Paper prepared for presentation at the Agricultural & Applied Economics Association's 2013 AAEA & CAES Joint Annual Meeting, Washington, DC, August 4-6, 2013.

Impact of Atrazine on the Sustainability of Weed Management in Wisconsin Corn Production

Introduction

The sustainability of crop production depends heavily on the ability to effectively control pests in order to protect yields. Heavy weed infestations can completely devastate crop yields. Corn growers rely primarily on a combination of practices including crop rotation, tillage, and herbicides to control weeds. Introduced more than 50 years ago, atrazine is still the second most commonly used herbicide in U.S. agriculture (Mitchell 2011). It is especially important in corn as 57% of US corn acres received atrazine in some form in 2009 (Mitchell 2011). Atrazine is effective, inexpensive, flexible in application, compatible with other pesticides, and insensitive to weather (Bridges 2011; U.S. Environmental Protection Agency 2003). However, atrazine's chemical properties make it susceptible to leaching and runoff (Ribaudo and Bouzaher 1994). It can migrate to ground and surface water and is frequently found in groundwater (Kolpin et al. 2002) and surface water (Ribaudo and Bouzaher 1994; Scribner et al. 2000) in the U.S. Atrazine in drinking water may possibly increase the risk of cancer in humans and is toxic to freshwater invertebrates (Ribaudo and Bouzaher 1994; USEPA 1991). Concerns regarding water contamination and health hazards have led to some calling for a ban on the use of atrazine, similar to that existing in Europe. For example, due to detection of well contamination in many locations, in 1990 the state of Wisconsin established atrazine prohibition areas (PAs) in which the use of atrazine is prohibited. PAs range in size from as small as 500 acres to more than 500,000 acres, and in 2011, there were 1.2 million acres in Wisconsin in an atrazine PA (DATCP 2011). The size and number of these PAs is unprecedented in the US as no other state has comparable restrictions on the use of atrazine over such a vast area.

As a soil-applied herbicide, atrazine [2-chloro-4-9ethylamino-6-(isopropylamino)-s-triazine] is used for controlling broadleaf weeds such as pigweed, cocklebur, and velvetleaf in corn (*Zea mays* L.), grain sorghum (*Sorghum bicolor* L.), and sugarcane (*Saccharum officinarum* L.) (Shaner et al. 2011). Atrazine is highly effective for weed control and has been extensively used in corn production. According to the EPA (2003), the application timing for atrazine-treated acres for field corn is apportioned as: 61% at pre-emergence, 27% at post-emergence, and 12% at both pre- and post-emergence. In addition, various cultivation methods are used on atrazine-treated corn acres: 7% acres are treated with banded applications; 12% receiving atrazine treatments are incorporated into the soil; 42% practice conventional tillage; 34% practice conservation tillage; and 24% practices no-till (USEPA 2003).

No-till is a practice of directly planting into undisturbed soil. Crop residues and vegetative cover is left on the soil surface to help keep soil from eroding and to preserve soil moisture. In contrast to conventionally tilled corn, in which tillage and herbicides are combined to control weeds, weed control is accomplished in no-till corn only by applying herbicide without tilling the soil (USEPA 2003). Because weeds are a major issue in conservation tillage and no-till, farmers depend heavily on herbicides for weed control in these production systems (Buhler 1991, 1992; Gebhardt et al. 1985; Kroskinen and Mcwhorter 1986; Fuglie 1999). Unlike glyphosate, atrazine if used alone has residual weed control so that weeds emerging after application can still be controlled.

Studies examining benefits of using atrazine and the costs of a ban initially focus on economic assessments. Several economic impact studies find that a ban on atrazine can increase farmers' herbicide costs and cause yield loss (Ribaudo and Bouzaher 1994; U.S. EPA 2003; Fawcett 2006), which consequently decreases corn acreage and increases corn price (Ribaudo and Bouzaher 1994). The occurrence of glyphosate-resistant weeds as well as the emerging focus on soil conservation as a part of agricultural sustainability has made the research on effects of atrazine on agricultural sustainability more important. Soil erosion is among the most costly environmental impacts of agriculture in the U.S. Pimentel et al. (1992, 1995) estimate that soil erosion costs U.S. society $44 billion annually. Soil erosion is one of the greatest threats facing the agricultural sustainability. Conservation compliance required by the 1985 Farm Bill and the increased understanding of the benefits of reduced tillage have been driving the increase in farmer adoption of conservation tillage or no-till (Esseks and Kraft 1991; Claassen et al. 2004; Knowler and Bradshaw 2007).

Some recent studies have argued that using atrazine can help the environment by facilitating farmer adoption of conservation tillage, which reduces soil erosion and energy use, improves soil and water quality and further enhances the sustainability of U.S. crop production (Bridges 2011; Mitchell 2011). They use figures showing the annual percentage of corn acres grown in conventional tillage, conservation tillage and no-till systems treated with atrazine over several years to illustrate the connection between reduced tillage and atrazine use (e.g., Mitchell 2011). Such illustrations to a certain degree suggest the linkage between the growth of the use of conservation and no-till system and atrazine, but can miss other factors that may contribute more to the changes in the tilling system and do not quantitatively evaluate the importance of atrazine use in the choices of no-till system. The connection between atrazine use and no-till corn remains largely unexplored in the context of current production systems that rely more on glyphosate and herbicide tolerant crops (Mitchell 2011). Therefore, examining the relation between no-till corn and atrazine use with a more rigid and systematic research is warranted.

Variation in farmer crop management practices inside and outside atrazine PAs in Wisconsin offers a unique opportunity to identify how farmers respond to restrictions on the use of atrazine, as no other state has such atrazine use restrictions over such a large area. This paper aims to investigate the impact of the availability of atrazine on farmer tillage practices using a data set on farmer crop management practices inside and outside atrazine PAs in Wisconsin. This paper focuses on the impacts of such a ban on a sustainable farming practice, namely tillage. The results will provide useful information for policy makers and other stakeholders and help them understand the impact of policy decisions regarding atrazine restrictions.

The rest of the paper is organized as follows. In the next section, background information about atrazine prohibition in Wisconsin is presented. Then methodology and the data set are presented in the section 3 and 4. Estimation and results analysis are provided in the section 5. In section 6, the paper is concluded and implications are discussed.

Wisconsin Atrazine Prohibition

Atrazine was first detected in groundwater in Wisconsin in mid-1980s. It was suspected that it occurred as of a result of the normal use of atrazine, which was confirmed by the DATCP Groundwater Monitoring Project in 1985 (Wisconsin Department of Agriculture, Trade, and Consumer Protection (DATCP) 1997). A farm well survey conducted in 1988 by Wisconsin DATCP (LeMasters and Doyle, 1989) found that 10% to 16% of these wells were contaminated with detectable levels of atrazine and the wells were located in most areas of the state where atrazine had been used. In 1988, the Wisconsin Department of Natural Resources established the groundwater enforcement standard for atrazine at 3.5 parts per billion (ppb), much lower than the 215 ppb used as the unofficial health advisory level (DATCP 1997) and further reduced it to 3.0 ppb in 1992, which is the current federal standard.

The first version of the Atrazine Rule developed by the Wisconsin DATCP became effective on April 1, 1991. The rule imposed limits on the amount of atrazine that can be used per acre, prohibited use of atrazine in some areas, and other changes in the way atrazine was used to diminish groundwater contamination (DATCP 1997). For example, the application rate of atrazine was reduced from the federally allowed maximum of 2.5 lbs per acre to between 0.75 and 1.5 lbs per acre based on soil type and previous atrazine use on the field; use is restricted to April 15 through July 31 each year; use with irrigation requires an irrigation management plan to prevent over-irrigation; and use is limited to field corn, sweet corn, and seed corn.

Other than statewide limits on atrazine application, the Atrazine Rule created atrazine prohibition areas (PAs). Use of atrazine is prohibited in each PA where concentrations in private wells exceed 3 ppb groundwater enforcement standard. By April 1, 1996, Wisconsin had created 91 Atrazine PAs, ranging from small areas with 2,500 acre around a single contaminated well to larger, multi-well regional PAs covering portions of several counties. The number of PAs increased to 102 and the total PAs were over 1.2 million acres by 2008. Figure 1 shows a map for the atrazine PAs in Wisconsin.

Because of the controversy about atrazine use and insufficient proof of atrazine's environmental impacts, the Atrazine Rule also requires that the Wisconsin DATCP evaluate the success of the rule at the end of five years using groundwater sampling programs to determine if atrazine levels were declining (DATCP 1997). Consequently, an evaluation of the rule was done in 1996 which showed a significant decline in the level of atrazine contamination in Wisconsin groundwater between 1994 and 1996. The average atrazine plus metabolite concentration in wells with detections declined from 0.96 to 0.54 ppb in the two year period (DATCP 1997). Total corn acres treated with atrazine decreases from 77% in 1985 to 46% in 1996 and the state average application rate decreased to 0.78 lb/acre from 1.6 lb/acre over the same period (DATCP 1997).

DATCP conducted another evaluation of the impact of atrazine use in PAs between 1998 and 2005 to determine if PAs can be repealed where atrazine levels in groundwater have improved (DATCP 2008). DATCP concluded that renewed atrazine use in PAs would likely lead to exceeding the enforcement standard and so no atrazine PAs have been delisted.

While DATCP's rule focus on water quality, some other studies put more emphasis on other consequences of atrazine ban, such as economic returns, benefits and costs. Although there are some studies pointing out the possible impacts of atrazine ban on tillage, no formal study has provided reliable proof. As agricultural sustainability has been garnering more attention and soil protection is one of the most important elements, it is necessary to examine impacts of atrazine ban on tillage practices. The tillage practices taken by corn producers in PAs and non-PAs in Wisconsin provide good information that can be used to conduct such analysis.

Methodology

This paper uses classification and regression tree (CART) analysis to examine the variation of weed management practice of tillage in response to a set of explanatory variables, including atrazine prohibition. CART, developed by Breiman et al. (1984), is a statistical method based on a recursive binary splitting of data into mutually exclusive subgroups containing objects with similar properties (Put et al. 2003). CART is a robust method of analysis that can deal with large numbers of both categorical and numerical variables and missing values, yet still identify significant variables that predict the response variable, even in the presence of nonlinear relationships and higher order interactions. As a non-parametric method, CART makes no assumptions about the underlying distribution of the explanatory variables (De'ath and

Fabricius 2000). In addition, CART provides a graphical representation (an inverted tree-shaped diagram) that makes interpretation of the results generally intuitive (Put et al. 2003). Empirical comparisons of methods find that CART performs well – for example, Vayssieres et al. (2000) found that CART performed better than multiple logistic regression when modeling tree species in California. For comparison, we also use a multiple logistic regression model.

Generally, the tree is built in three steps: maximal tree building, tree pruning, and optimal-tree selection. In the first step, a single variable is found to best split the data (parent node) into two groups which minimizes the impurity of the two child nodes. Then the process is applied separately to each sub-group, and so on until the subgroups either reach a user-defined minimum size or until no improvement can be made (Therneau and Atkinson 2013). The measures of impurity of a node include Gini index, information or entropy index, and misclassification rate where the third one is not used in practice. The impurity of node A is defined as

$$I(A) = \sum_{i=1}^{N} f(p_{iA}) \qquad (1)$$

where p_{iA} is the proportion of those in A that belong to class i; N is the total number of classes in the sample; and $f(\cdot)$ is impurity function (Therneau and Atkinson 2013). The information index uses the impurity function $f(p_i) = -p_i \log(p_i)$ and the impurity function with the Gini index takes the form $f(p_i) = p_i(1-p_i)$. Therefore the impurity of a node using information index is $-\sum_i p_i \ln(p_i)$ and the Gini index is $1-\sum_i p_i^2$. CART looks for the best possible variable (called the "best splitter") to maximize impurity reduction:

$$\Delta I = p(A)I(A) - p(A_L)I(A_L) - p(A_R)I(A_R) \qquad (2)$$

where A_L and A_R are child nodes of A, respectively; and $p(A)$ is the probability of A (Put et al. 2003; Therneau and Atkinson 2013).

The maximal tree obtained from the first step is generally oversized and incorporates noise in the data. The maximal tree is hard to interpret and has low predictive power (Put et al. 2003). Therefore, in the second step, the maximal tree is pruned to have the smallest predictive error. The pruning procedure generates a sequence of smaller trees, which are obtained by trimming successively branches of the maximal tree. Breiman et al. (1984) show that for any number α, there is a unique smallest tree that minimizes $R(T) + \alpha |T|$, where $R(T)$ is the risk of T (like the residual sum of square) and $|T|$ is the number of terminal nodes. Here, α is a positive number that measures the cost of adding another node to the tree. With α increasing from 0 to an arbitrary large number, a sequence of trees of decreasing size is obtained.

In the third step, Breiman et al. (1984) suggest using cross-validation to choose a best value for α. In cross-validation, the data set is divided into a number of mutually exclusive subsets of equal size (10 subsets has been found to be sufficient (Therneau and Atkinson 2013)). The process proceeds as follows: drop each subset in turn and build a tree using the remaining subsets to predict the responses for the omitted subset. Then calculate the estimated error for each subset. The optimal tree is the one having the minimal cross-validation error. Breiman et al. (1984) suggest the 1-se rule in which the optimal tree is chosen as the simplest tree with a predictive error estimate within one standard error of the minimum (De'ath and Fabricius 2000; Put et al. 2003).

Data

Data used in this study are based on a Wisconsin supplement to the USDA's 2010 Agricultural Resource Management Survey Corn Production Practices and Costs Report, which is administered jointly by the Economic Research Service and National Agricultural Statistics Service (NASS). The survey collects information on corn farm field characteristics (such as acres, ownership, seed type, yield, rotation, and land-use practices), fertilizer applications, pest management practices including both biocontrol and pesticide applications, irrigation, field operations, and farm management. The Wisconsin office of NASS collected surveys from substantially more farms than required for national ARMS data. In total, the data for this analysis contain survey responses from 805 Wisconsin farms, with 468 in an atrazine PA and 337 not in an atrazine PA.

The focus of the study is on how being inside or outside an atrazine PA affects farmer management practices, with other variables are included as CART regressors to help us understand what factors make difference in tillage practice. The dummy variable from the survey question "Did you use no-till or minimum till for the specific purpose of managing or reducing the spread of pests in this field?' is used as the response variable. Splits are based on the proportions of "yes" or "no" to this question. Explanatory variables analyzed using CART are explained and listed in Table 1. The explanatory variables include those on field characteristics such as the acres of the corn field (*acres*), the ownership of the field (*ownland*), if any part of the field was classified as highly erodible by the Natural Resource Conservation Service (*erodible*), if the field has ever been infested with weeds resistant to glyphosate, and if the corn field was covered by federal crop insurance (*CropInsurance*). The variable we are especially interested in, if the field in an Atrazine Prohibition Area (*PA*), is also included for examination. In addition, variables on the field practices, such as the crop rotation used for the previous three years (*rotation*), if products containing atrazine were applied to the field (*atrazine*), if herbicides were applied to field before weeds emerged (*Bherb*), are included to help understand if other farm practices affected no-till practice. Other variables on farm management such as if there is a written conservation plan (*Cplan*) and nutrient management plan (*Nplan*), if the operator had attended any training session on pest identification and management except pesticide applicator training (*training*) and variables on the use of the harvested corn (*cornuse*) and the seed type (*seed*) are also examined.

Estimation Results

The package “rpart” in R was used to conduct CART analysis. The variable importance whose values are scaled to sum to 100 are listed in table 2. Variables whose proportion is less than 1% are omitted. The variable importance shows that *Acres* is the most important variable in classifying no-till/minimum till practice, followed by *seed*, *cornuse*, *atrazine*, and the rest. The variable *PA*, indicating if the field in an atrazine prohibition area, only has 4% importance. The variables actually used in tree construction are *Acres*, *atrazine*, *Bherb*, *Cplan*, *Nplan*, *ownland*, *PA*, *rotation*, *training*, and *weedres*. A single usage of CART can identify the most significant variables and eliminate non-significant ones. The details of the classification showing how those variables affect the no-till/minimum till practice are presented in the maximal tree in figure 2, using the Gini rule for splitting.

The maximal tree has 32 terminal nodes. The variables on upper levels of the tree are more important than those at the bottom. The group is first separated into two subgroups according to if the field is less than 3.5 acres. In the tree, the answer of yes goes left, while the answer of no goes to the right. 19.6% (158/805) goes to the left node, meaning that those fields have less than 3.5 acres, showing that 97% (154/158) of fields with less than 3.5 acres did not use no-till/minimum till for the purpose of managing or reducing the spread of pests in the field.

For the 647 field with over 3.5 acres, they are first regrouped by *Cplan*. Among those without a written conservation plan (428 out of 647), they are then separated into two subgroups: a group with operators having attended training session on pest identification and management (67) and a group without (361). For those 361 fields, 12 fields that have been infested with weeds resistant to glyphosate are all not adopting no-till/minimum till. The rest of the tree reads similarly.

Note that the partitions in the tree include multiple splits on the same variable *Acres*. The main difference between classification trees and linear regression models is that in linear regression the information from different explanatory variables is combined linearly, while in classification trees the possible combinations include nonlinear and even non-monotone association rules, that do not need to be specified in advance, but are determined in a data driven way (Strobl, Malley, and Tutz 2010).

We focus on the variable *PA*, which appears in the classification tree under fields without written conservation plan, without operators attending training session on pest identification and management, without weeds resistant to glyphosate, and with acres between 46 and 81.5 (65 fields). All 42 (100%) such fields in the atrazine prohibition areas did not use no-till/minimum till. This terminal node is the second dominating class as it has the second largest amount of observations in the current node. The number is in contrast to the 17 of the 23 (74%) fields not in the atrazine prohibition areas did not take no-till.

PA variable also occurs under fields with less than 46 acres, but more than 3.5 acres and the fields did not apply pesticides containing atrazine. Among the 65 fields not in a PA, depending on acres, 15 fields adopted no-till/minimum-till practices and among the 106 in a PA, only 12 fields adopted no-till/minimum-till practices.

Again, the *PA* variable appears at the terminal nodes for fields with conservation plan and medium size (larger than 9.5 acres but smaller than 139.5 acres). Among the 11 fields not in a PA, 4 adopted the no-till/minimum-till practices; and among the 9 fields in a PA, 3 adopted the no-till/minimum-till practices. The maximal tree shows that whether or not a field was located in a PA did affect the adoption of no-till/minimum-till practice and fields in PAs are less likely to use no-till/minimum-till practice.

We use cross-validation and 1-se method to prune the tree and decide the optimal tree size. We also plot the complexity parameter and relative errors to examine the optimal size which is shown in figure 3. Both the cross-validation and 1-se method and the plot of complexity parameter suggest the optimal size of 13 splits. The pruned tree is displayed in figure 4. Again, *Acres* is the most important variable classifying the no-till/minimum-till practice. The variable *PA* only occurs at a terminal node, showing 23 out of 106 (22%) fields in a PA adopted no-till/minimum-till practice. Compared to the 18 out of 65 (28%) fields not located in a PA adopting no-till/minimum-till practices, we find that fields located in a PA are more likely to adopt no-till/minimum-till practice.

Logistic model

We also ran a logistic model with the dummy variable that if the field adopts no-till/minimum-till as the dependent variable. All explanatory variables are same as in CART, but take value of 1 if the answer to the question is 1 and 0 otherwise. In addition, the rotation is categorized into 3 dummy variables, instead of one categorical variable *rotation* in CART. The estimation results from the logistic regression model are listed in Table 3. The results also show that variable *PA* is not statistically significant, although we should be aware that the estimation would be biased because of endogeneity of several variables, such as seed type (*seed*), rotation (*rotation*), and application of pesticide containing atrazine (*atrazine*).

Conclusions and Discussions

In this study, we used CART model to analyze if atrazine PAs made more farmers adopt more tillage. The results did support such claims as the classification tree showed that fields located in PAs are more unlikely to adopt no-till/minimum-till. As the second dominating class, the terminal node determined by PA shows that all 42 fields in PA did not use no-till/minimum-till. Field acreage is the most important factor that affects field's tillage decision. Small fields are more likely to use tillage. The CART analysis of tillage practice in our study provides useful information for policymakers.

The CART has several advantages compared to linear regression. As a nonparametric method, CART does not require variables to be specified in advance as it can identify itself the most significant variables (Timofeev 2004). CART is also not affected by the outliers and collinearities that generally affect parametric procedures. In addition, the possible combinations in the classification trees include nonlinear and even non-monotone association rules (Strobl, Malley, and Tutz 2010). CART does however have its disadvantages. For example, it does not allow statistical inference in the analysis and so statistical tests cannot be conducted.

References

Breiman, L., J. Freidman, R. Olshen, C. Stone. 1984. Classification and Regression Trees. Wadsworth.

Bridges, D. 2011. A biological analysis of the use and benefits of chloro-*s*-triazine herbicides in U.S. corn and sorghum production. http://www.weeds.iastate.edu/mgmt/2011/atrazine/Bridges__9Nov2011.pdf.

Buhler, D.. 1991. Early Preplant Atrazine and Metolachlor in Conservation Tillage Corn (Zea mays). Weed Technol 5:66-71.

-1992. Population Dynamics and Control of Annual Weeds in Corn (Zeamays) as Influenced by Tillage Systems. Weed Sci 40:241-248.

DATCP. 1997. Groundwater Protection-An Evaluation of Wisconsin's Atrazine Rule.

DATCP, 2011. The Economic Impact of the Organic Sector in Wisconsin and Beyond. Available at http://www.organic.wisc.edu/wp-content/uploads/2011/11/Economic-Impact-of-Organics-report-June-2011.pdf. Accessed on June 3, 2013.

De'ath, G., and K. Fabricius. 2000. Classification and regression trees: a powerful yet simple technique for ecological data analysis. Ecology 81:3178-3192.

Esseks, J. and S. Kraft. 1991. Land user attitudes toward implementation of conservation compliance farm plans. *J Soil Water Conserv* 46:365-370.

Fawcett RS. 2007. Triazine Herbicide Benefits in Reducing Erosion and Fuel Use in U.S. Corn Production. *Proceedings, Southern Weed Science Society* 60:205-208.

Fuglie KO. 1999. Conservation Tillage and Pesticide Use in the Cornbelt. *Journal of Agricultural and Applied Economics* 31:133-147.

Gebhardt MR, Daniel TC, Schweizer EE and Allmaras RR. 1985. Conservation Tillage. *Science* 230:625-630.

Knowler D and Bradshaw B. 2007. Farmers' adoption of conservation agriculture: A review and synthesis of recent research. *Food Policy* 32:25-48.

Kolpin, D.W., J.E. Barbash, and R.J. Gilliom. 2002. Atrazine and metolachlor occurrence in shallow ground water of the United States, 1993 to 1995: Relations to explanatory factors. J. Amer. Water Resources Assoc. 38:301-311.

Kroskinen, W. and C. McWhorter. 1986. Weed Control in Conservation Tillage. J Soil Water Conserv 41:365-370.

LeMasters, G., and D. Doyle, 1989. Grade A Dairy Farm Well Water Survey. Wisconsin Department of Agriculture, Trade, and Consumer Protection and Wisconsin Agricultural Statistics Service: Madison, WI.

Mitchell, P. 2011. Economic assessment of the benefits of chloro-s-triazine herbicides to U.S. corn, sorghum, and sugarcane growers. University of Wisconsin Agricultural and Applied Economics Staff Paper No. 564. http://www.aae.wisc.edu/pubs/sps/pdf/stpap564.pdf.

Pimentel, D., H. Acquay, M. Biltonen, P. Rice, M. Silva, J. Nelson, V. Lipner, S. Giordano, A. Horowitz, and M. D'Amore. 1992. Environmental and economic costs of Pesticide use. Bioscience 4 2: 750-760.

Pimentel, D., C. Harvey, P. Resosudarmo, K. Sinclair, D. Kurz, M. McNair, S. Crist, L. Shpritz, L. Fitton, R. Saffouri and R. Blair. 1995. Environmental and Economic Costs of Soil Erosion and Conservation Benefits. Science 276:1117-1123.

Put, R., et al. 2003. Classification and regression tree analysis for molecular descriptor selection and retention prediction in chromatographic quantitative structure-retention relationship studies. Journal of Chromatography A (988):261-276.

Scribner, E.A., W.A. Battaglin, D.A. Goolsby, and E.M. Thurman. 2000. Changes in herbicide concentrations in Midwestern streams in relation to changes in use, 1989-1998. The Science of the Total Environment 248:255-263.

Shaner, D.L., R. A. Boydston, L. J. Krutz, H. P. Collins. 2011. Effect of Biochar on Bioavailability of Atrazine and Metribuzin in Two Soils. Weed Science Society of America Meeting Abstracts. Portland, Oregon.

Strobl, Malley, and Tutz. 2010. An Introduction to Recursive Partitioning: Rationale, Application and Characteristics of Classification and Regression Trees, Bagging and Random Forests. Psychol Methods 14(4): 323–348.

Therneau, T., and E. Atkinson. 2013. An Introduction to Recursive Partitioning Using the RPART Routines. Mayo Foundation. Available at http://cran.r-project.org/web/packages/rpart/vignettes/longintro.pdf. Accessed on June 3, 2013.

Timofeev, R. 2004. Classification and Regression Trees (CART) Theory and Application. Master Thesis, Center of Applied Statistics and Economics, Humboldt University, Berlin.

Ribaudo, M., and A. Bouzaher. 1994. Atrazine: Environmental Characteristics and Economics of Management. Agricultural Economic Report No. (AER-699), USDA.

U.S. Environmental Protection Agency (USEPA). 1991. IRIS Atrazine CASRN 1912-24-9 (01/01/91). Integrated Risk Information System. Washington D.C.

-2003. Interim Reregistration Eligibility Decision For Atrazine. Case No. 0062.

Vayssieres, M.P., R.E. Plant, and B.H. Allen-Diaz. 2000. Classification trees: an alternative non-parametric approach for predicting species distributions. J. Veg. Sci. 11:679-694.

Figure 1. Map of Atrazine Prohibition Areas in Wisconsin.

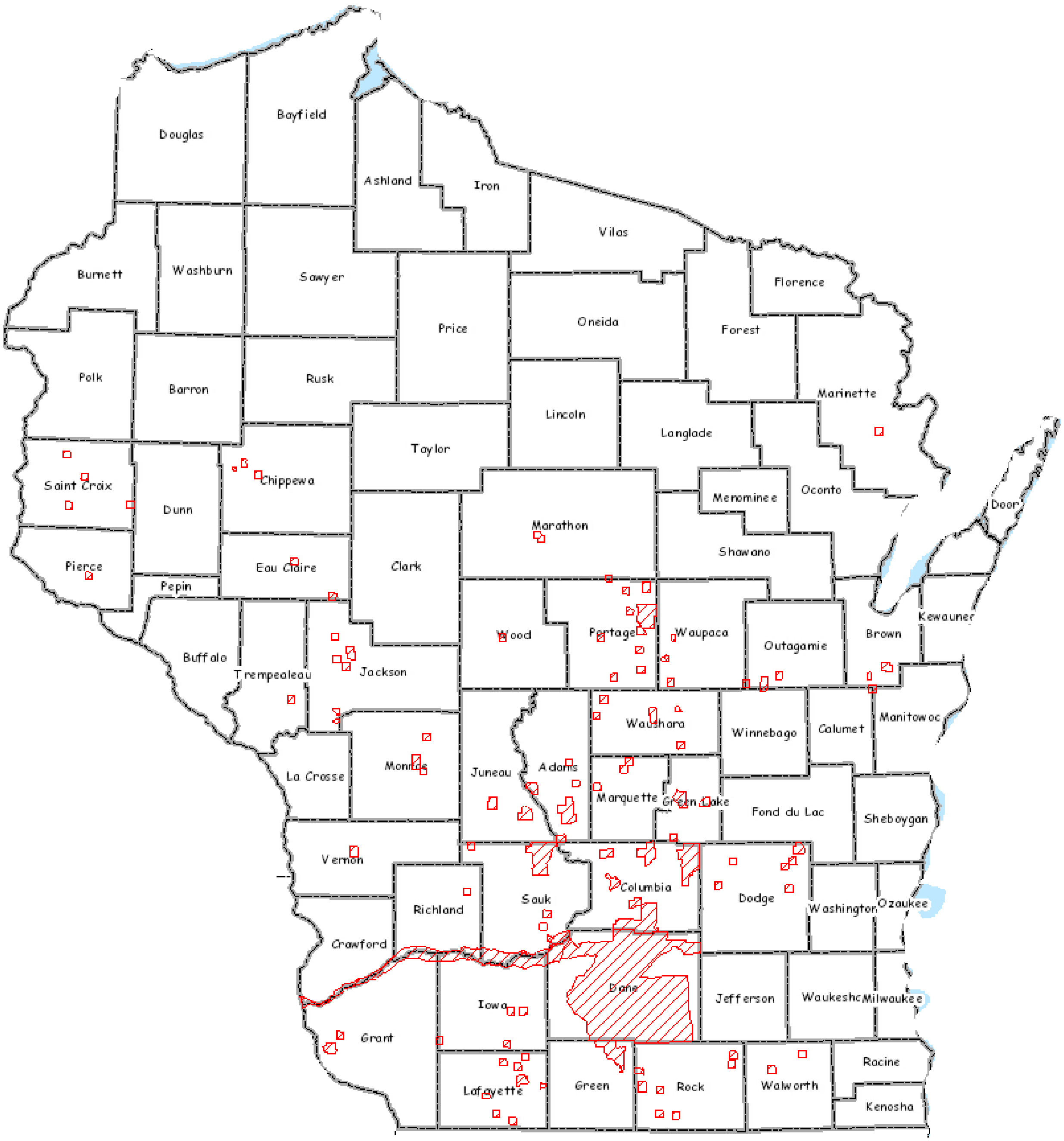

Figure 2. Maximal classification tree.

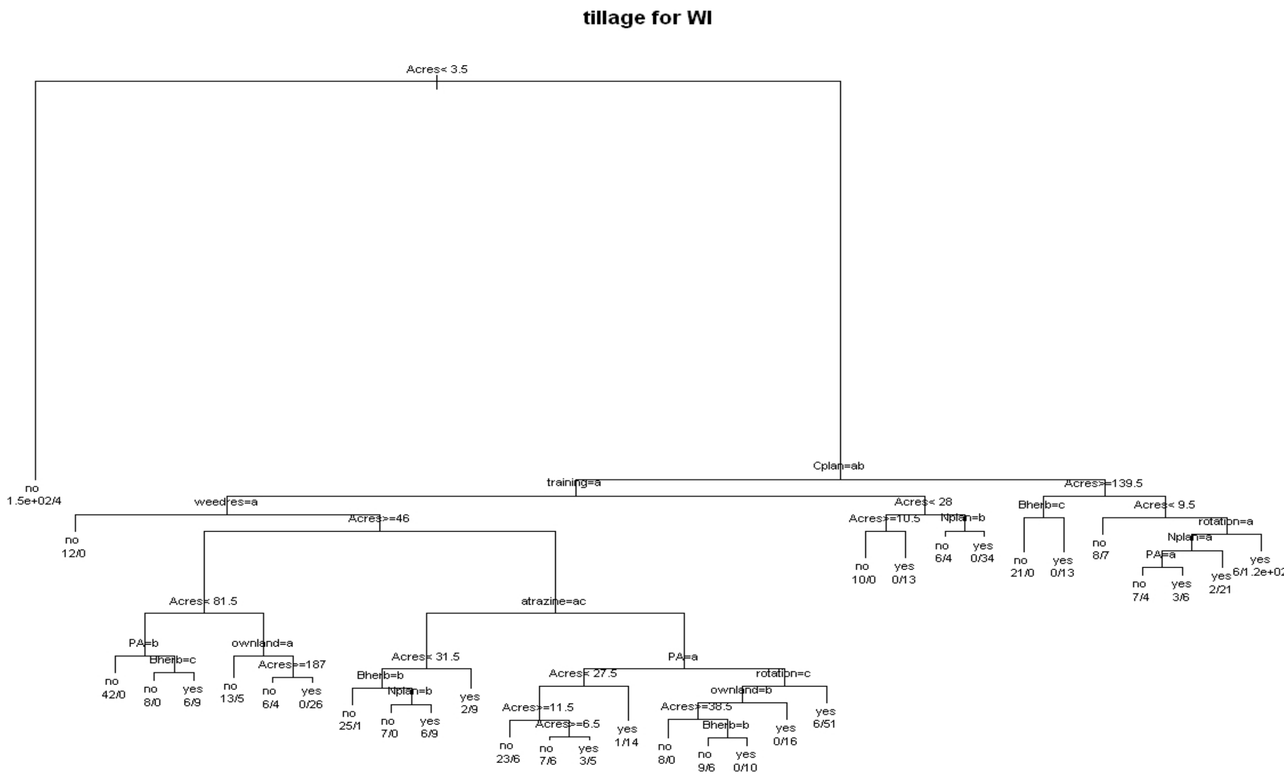

Figure 3. Size of the tree

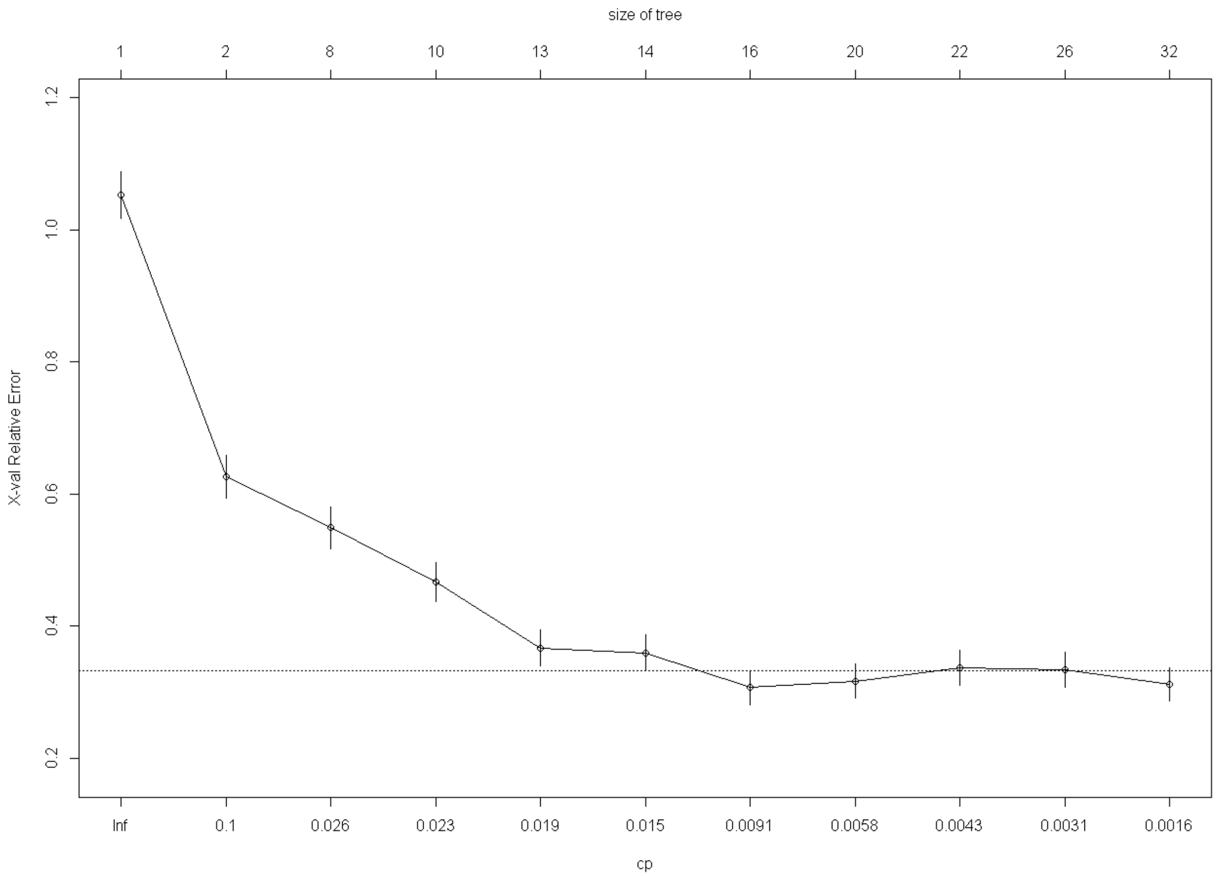

Figure 4. Pruned tree.

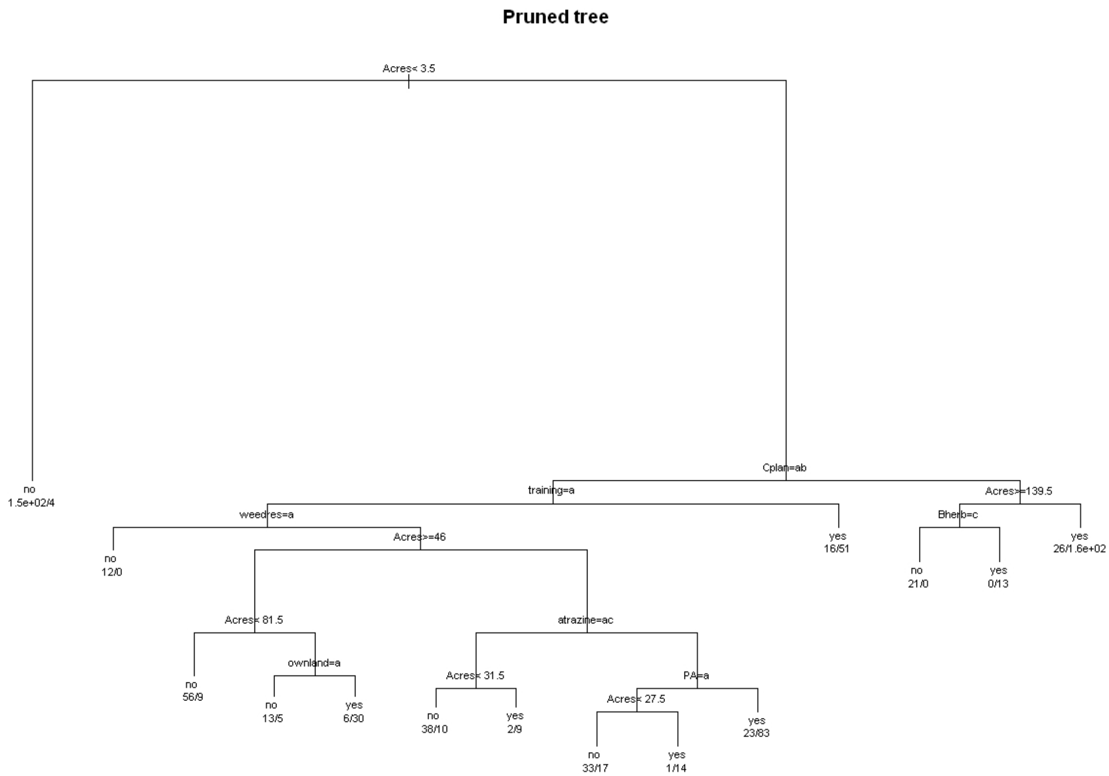

Table 1. Explanatory Variables In CART.

Variable	Description
notill	If use no-till or minimum till for the specific purpose of managing or reducing the spread of pests in this field.
Acres	Acres of corn planted in the field
ownland	= 1 if this field is owned by the operation
cornuse	The corn on the field planted with the intention of being harvested as: grain=1, silage=2, seed=3, and other=4
seed	Corn seed type, categorized into 3 types: Roundup Ready Corn (RR), Genetically-modified (GM), and other (Other)
rotation	Takes value of CCC if corn was in 2010, 2009, and 2008; takes value of CCO if corn was planted in 2010 and 2009 but not in 2008; takes value of COS is corn was planted in 2010, but not in 2009;
Cropinsurance	= 1 if the corn field was covered by federal crop insurance in 2010
Bherb	= 1 if herbicides applied to this corn field before weeds emerged
Plearly	= 1 if planted earlier or later to avoid weeds
PA	=1 if the field in an atrazine Prohibition Area
atrazine	= 1 if products containing atrazine were applied to this field
weedres	= 1 if the field has been infested with weeds resistant to glyphosate
training	= 1 if the operator attended any training session on pest identification and management after October 1, 2009, other than pesticide applicator training
Assist	= 1 if the operator receive technical assistance for planning, installing, maintaining, or using conservation practices or systems on this field in 2010
Erodible	= 1 if the Natural Resource Conservation Service has classified any part of this field as “highly erodible”
Cplan	= 1 if during 2010 there was a written conservation plan specifying practices to reduce soil erosion covering this field
Nplan	= 1 if during 2010 there was a written nutrient management plan specifying practices for applying both fertilizer and manure covering this field

Table 2. Variable importance in CART.

variable	importance	variable	importance
Acres	31	PA	4
seed	13	Cplan	3
Cornuse	12	Erodible	2
atrazine	10	Fedins	1
Nplan	5	training	1
rotation	5	weedres	1
ownland	5	Plearly	1
Bherb	5		

Table 3. Estimation from Logistic Model

parameter	Estimation	Error	Pr > ChiSq
Intercept	-1.5844***	0.5715	0.0056
PA	-0.073	0.1175	0.5341
Acres	0.0161***	0.00433	0.0002
ownland	0.8498***	0.2168	<.0001
Cornuse	-0.5842**	0.2653	0.0277
Fedins	1.1635***	0.219	<.0001
Bherb	0.3936	0.2149	0.0671
weedres	0.1638	0.5766	0.7763
Plearly	0.0742	0.4036	0.8541
training	0.7539**	0.3384	0.0259
assist	-0.277	0.645	0.6676
Erobidle	1.1129***	0.4037	0.0058
Cplan	0.8985***	0.265	0.0007
Nplan	0.2532	0.2696	0.3476
atrazine	-0.4683	0.3064	0.1264
seedRR	0.7152*	0.3828	0.0617
seedGM	0.5683	0.4977	0.2535
rotccc	0.1008	0.2544	0.692
rotcoc	1.0409***	0.2874	0.0003

Note: * indicates statistical significance at 10%; ** indicates statistical significance at 5%; and *** indicates statistical significance at 1%.