Causal Factors for Pesticide Trends in Streams of the United States—

Atrazine and Deethylatrazine

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BFI, base-flow index; CFI, comparative fit index; DEA, deethylatrazine; GCMS, gas chromatography/mass spectrometry; LVMs, latent variable models; ML, maximum likelihood; MSM, moisture supply and management; MWHs, multiple working hypotheses; PCA, principal components analysis; PHDI, Palmer hydrologic drought index; RMSEA, root mean square error of approximation; SEAWAVE-Q, a trend analysis method with seasonal wave and adjustment for streamflow; SEM, structural equation modeling, SRMR, standardized root mean square residual; USGS, U.S. Geological Survey
CORE IDEAS

- Atrazine trends are mostly downward across the conterminous United States.

- The major driver of atrazine trends is the concomitant trend in corn acreage.

- Deethylatrazine trends are mostly upward across the conterminous United States.

- Deethylatrazine trends are driven by moisture supply and management and corn acreage.
ABSTRACT

Pesticides are important for agriculture in the United States, and atrazine is one of the most widely used and widely detected pesticides in surface water. A better understanding of the mechanisms by which atrazine and its degradation product, deethylatrazine, increase and decrease in surface waters can help inform future decisions for water-quality improvement. This study considers causal factors for trends in pesticide concentration in streams in the United States and models the causal factors, other than use, in structural equation models. The structural equation models use a concomitant trend in corn and a latent variable model, indicating moisture supply and management. The moisture supply and management latent variable model incorporates long-term moisture conditions in the individual watersheds by using the Palmer Hydrologic Drought Index; human influence on the hydrologic cycle through the percent of the watershed drained by tile drains in 2012; and the base-flow contribution to streamflow, using the base-flow index. The structural equation models explain 77% and 38% of the variability in atrazine and deethylatrazine trends, respectively, across the conterminous United States. The models highlight future water-quality challenges, particularly in tile-drained settings where fall precipitation and heavy precipitation are increasing.

INTRODUCTION

The attribution of trends in pesticide concentration in surface water is challenging because of the quality and quantity of data needed to support attribution and because pesticide chemical properties vary greatly and govern how pesticides move through the environment. However, better understanding these mechanisms is important because of water-quality concerns and the importance of pesticides to society. United States expenditures for conventional pesticides
(active ingredients other than biological pesticides and antimicrobial pesticides) were approximately $13 billion in 2009 and $14 billion in 2012 (Atwood and Paisley-Jones, 2017). Approximately two-thirds of total expenditures were for agricultural purposes in 2009 and 2012 and most of those agricultural expenditures were for herbicides (Atwood and Paisley-Jones, 2017). The most commonly used herbicides in 2005, 2007, 2009, and 2012 were glyphosate and atrazine (ranked 1 and 2 respectively in table 3.4 of Atwood and Paisley-Jones, 2017), both of which are used extensively on corn (U.S. Geological Survey, 2018a).

Atrazine is a selective pre- or post-emergent herbicide that is used to control broadleaf weeds and some grassy weeds by inhibiting photosynthesis in susceptible plants (Fishel, 2006; U.S. Environmental Protection Agency, 2006). Although urban use of atrazine is less than agricultural use, atrazine was one of the most widely detected herbicides for the urban streams analyzed for trends in a 1992–2008 period (Ryberg et al., 2010). Atrazine has moderate sorption to soil, while its primary degradation product, deethylatrazine (DEA), has low sorption; both compounds are moderately persistent in soil and atrazine is moderately persistent in water (U.S. Environmental Protection Agency, 2012; Lewis et al., 2016). The primary conversion of atrazine to DEA is through metabolic activity of soil fungi and bacteria. Hence, atrazine is likely to degrade to DEA when atrazine has more contact with soil microorganisms, such as in non-point source contamination. Atrazine is less likely to degrade to DEA when there is less contact with soil microorganisms, such as in point source contamination (Scribner et al., 2005).

Atrazine use varies across the conterminous United States, but the major crop beneficiary is corn (figure 1). On a national-scale, use declined from 2002–2012, in part because of regulatory actions by the U.S. Environmental Protection Agency and an increase in the use of glyphosate on corn with a glyphosate-resistant trait (Coupe and Capel, 2015). However, changes in use and
corn acreage vary among watersheds, with reported atrazine use increasing in areas that
previously had little or no reported use (U.S. Geological Survey, 2018b) as corn acreage

From past studies, we know that most pesticide surface-water concentration trends are
similar to pesticide use-intensity trends, including atrazine trends (Sullivan et al., 2009; Ryberg
and Gilliom, 2015). For DEA though, past studies have shown that uptrends in DEA can happen
during periods with significant downtrends in both the use and concentrations of atrazine
(Ryberg et al., 2014; Ryberg and Gilliom, 2015). Ryberg and Gilliom (2015) hypothesized that
atrazine use and DEA concentration trends differ because of some factor, such as a management
practice, that has over time increased the proportion of applied atrazine that runs off to streams
as DEA, or by a transport pathway for DEA, such as groundwater, that has lags between use and
arrival at a stream. Decreases in atrazine use would eventually lead to decreases in DEA, but
there is a lag time during which the trends may be in opposing directions. Gilliom and others
(2006) reported that DEA-to-atrazine ratios were generally higher in groundwater than streams,
reflecting the longer periods of time spent in contact with soil for the atrazine compounds
detected in the groundwater system, relative to streams, because degradation takes place with the
assistance of soil microorganisms. Once atrazine is degraded to deethylatrazine, it is much more
soluble (Mackay et al., 1997), meaning it is more likely to move with water through the soil.
Hence, the setting and environmental conditions that influence degradation can be important in
determining the drivers of trends in pesticide concentration other than use.

Past studies concluded that reductions in concentrations because of improved management
practices (those unrelated to use reduction) might be difficult to discern (Sullivan et al., 2009;
Ryberg and Gilliom, 2015) and that more precise estimates of uses and ancillary data on specific
management practices would likely be needed to assess the large-scale effects. The National Water-Quality Assessment Project of the U.S. Geological Survey (USGS) National Water-Quality Program has been developing such datasets and methods for modeling the effects of factors that influence water quality. In a desire to move beyond speculation about the causes of trends, bi-variate correlation (such as that between use and concentration), or citation of such work by others, structural equation modeling (SEM) has been used to test causal hypotheses about the drivers of changes in water quality (Ryberg, 2017; Ryberg et al., 2018). This is a continuation of that effort to better understand the factors, other than use, that influence trends in pesticide concentration in streams.

Oelsner et al. (2017) completed a water-quality trends assessment for the Nation’s rivers and streams that included pesticide trends for the periods 1992–2012 and 2002–2012. The pesticide concentration and streamflow datasets used to evaluate the pesticide trends, as well as the trend results, were published in a data release (Ryberg et al., 2017). A subset of those results was used in this study to examine atrazine and deethylatrazine, the compounds with the most calculable trends across the United States.

We developed multiple working hypotheses (MWHs) for the causal factors, or drivers, of pesticide trends in general and atrazine and DEA in particular. We then acquired available data related to these hypotheses and used SEM to test these causal hypotheses. This allows us to better understand drivers of concentration trends beyond pesticide use.
MATERIALS AND METHODS

Site and Chemical Selection and Trend Analysis

A subset of the trend results presented in the national water-quality trends assessment by Oelsner et al. (2017) was used for this study. The sites were all USGS water-quality monitoring sites, and the chemical compounds were analyzed at the USGS National Water Quality Laboratory using gas chromatography/mass spectrometry (GCMS; Zaugg et al., 1995; Lindley et al., 1996; Madsen et al., 2003). The pesticide concentration data were prepared for trend analysis by adjusting concentrations to compensate for bias resulting from temporal changes in recovery of the GCMS analytical method (Martin and Eberle, 2011) and by recensoring routine nondetections by site and pesticide. The screening process to determine the sites with sampling representative of the trend period and chemicals with sufficient detections for trend analysis, as well as the data processing steps, was that described in Oelsner et al. (2017, p. 22). The trend analysis method was the seasonal wave model with adjustment for streamflow, SEAWAVE-Q (Vecchia et al., 2008; Sullivan et al., 2009; Ryberg and Vecchia, 2013). The SEAWAVE–Q model was specifically developed to address the challenges of pesticide trend analysis, including strong seasonality driven by use, a large percentage of concentrations below laboratory reporting levels, complex streamflow and concentration relations, and changing sampling frequencies (Vecchia et al., 2008). The model is a parametric regression model that incorporates flow-related variability in the form of streamflow anomalies (Vecchia, 2003; Ryberg and Vecchia, 2012), seasonality in concentration data, application season of pesticides, timing of maximum concentrations, and a decay rate representing the decline in concentration after the application season (Vecchia et al., 2008; Ryberg and Vecchia, 2013).
Selected trend results were used for this study based on which chemicals had trend results for at least 60 sites across the country. Sixty sites were deemed necessary to have a sufficient sample size for making inferences about the drivers of pesticide concentrations using SEM. This limited us to the period 2002–2012 and the two chemicals, atrazine and its degradation product DEA. Sixty-seven sites have trend results for atrazine, and 62 sites have trend results for DEA. The pesticide concentration and streamflow datasets used for this study were published in a USGS data release (Ryberg et al., 2017). Oelsner et al. (2017) also present results for 1992–2012, but few sites had a complete record for the longer period.

Multiple working hypotheses framework and causal factor data

Developing MWHs was an integral part of the SEM process, distinguishing this confirmatory process from more exploratory forms of multivariate analysis. We developed MWHs potentially describing the causes of changes in pesticide concentrations in surface water to systematically consider causal mechanisms and available data. Supplementary material 1 of Ryberg et al. (2018) provides background on the MWHs framework, which was suggested more than 100 years ago (Chamberlin, 1890) and has recently resurfaced in hydrology (Clark et al., 2011; Harrigan et al., 2014).

After developing the MWHs, in Supplement 1, for pesticide concentration trends in surface water in general, we hypothesized that the most important factors driving trends in atrazine concentration, other than use, would be corn acreage [expressed as a concomitant trend in proportion of watershed harvest corn (Falcone, 2017)]; weather and climatic conditions [represented by the Palmer Hydrologic Drought Index and available in (Falcone, 2017)] that might influence cropping and runoff patterns over the trend period; and tillage or conservation practices. We hypothesized that DEA trends might also be influenced by the same factors but
might differ from atrazine in that groundwater contribution to surface water might transport DEA and that this could be represented by the base-flow index (BFI). Base flow is the sustained, slowly varying component of streamflow, usually attributed to groundwater discharge to a stream and the BFI is a ratio of base flow to total streamflow, expressed as a percentage and ranging from 0 to 100 (Falcone, 2017).

We examined the potential for the working hypotheses using bi-variate correlation analysis. While correlation is not causal and bi-variate correlations are not necessarily indicative of variable behavior in a multivariate model (for example, once a series is adjusted for one variable, another relation may become apparent), the bi-variate correlations alerted us to non-normalities in the data, outliers, and potentially useful relations. The climate, agricultural, and other watershed characteristic data used have all been published by Falcone (2017) and the code and correlation plots are available in Supplement 2.

**Testing Causal Hypotheses with Structural Equation Modeling**

To test causal hypotheses, we used SEMs. This type of modeling has some similarities with multiple regression models (Grace, 2006). Both SEM and multiple regression models allow one to specify relations prior to statistical analysis based on known or hypothesized causal mechanisms and allow one to compare models. However, SEM offers more flexibility in how these models may be specified and allows for more complexity, given a sufficient sample size. For example, the response variable in one regression equation in an SEM may be a predictor in another regression equation within the same SEM. Additionally, variables in an SEM may influence one another directly or through other variables as intermediaries, or mediating variables. These structural equations are meant to represent causal relations among the variables.
Another advantage of SEM is that covariances between variables, which might cause multicollinearity problems in multiple regression, can be explicitly modeled in SEMs. SEMs can have one or more latent variables that are modeled themselves as latent variable models (LVMs). A reflective LVM is indicated (measured) by observed (manifest) variables (indicators) that in some cases may not be significant on their own but contribute to the latent influence. One could construct an LVM representing agricultural practices, for example, in which all agricultural practices are not measured, but multiple factors (indicators of practices), such as percent of land in agricultural production, proportion of watershed in harvested corn, and percent of agricultural land in the Conservation Reserve Program, are observed and join in an overall agricultural effect on water quality. LVMs represent the underlying structure (covariance) that produced relations among the indicator variables and need enough non-redundant information to generate unique parameter estimates (Beaujean, 2015). An LVM is similar to a common factor in factor analysis. An LVM is also similar to principal components analysis (PCA; Hotelling, 1933) in that PCA can use many variables reduced to principal components. These principal components are ascribed a meaning in terms of processes or inputs and are used in an analogous manner to SEM LVMs to describe broad mechanisms. PCA does not, however, allow users to specify relations among the variables and many find the dimension reduction difficult to understand. SEM has the advantage that it is based on causal pathways that can be visualized in a causal graph.

The number of possible variables for an SEM was constrained in this study. SEM is a large sample method [sample size considerations and “rules of thumb” are described further in Supplement 1 of Ryberg (2017)] and that meant that we needed to investigate the chemicals with the most trend results in Oelsner et al. (2017) and model causal hypotheses using relatively
simple national models, rather than complex models for a specific state or region. Given the sample sizes of 67 and 62 for atrazine and DEA, respectively, the SEM models had to be constrained to less than 10 parameter estimates to maintain stability of the estimates.

Maximum likelihood methods require multivariate normality of endogenous variables, which are internal or dependent variables in an SEM model, while no distributional assumptions are required for exogenous (or entirely explanatory) variables (Eliason, 1993; Kline 2012). The chi-squared test statistic, used as a first test of overall model fit, can be biased and indicate rejections of satisfactory models when there are distributional violations (Rosseel, 2012). A non-significant result ($p$-value > 0.01) indicates the model fits relatively well because the null hypotheses is that the hypothesized model fits the data, while a significant result would indicate that the hypothesized model is not adequate (Hoyle, 2012). The models used in this study passed the chi-squared test and, therefore, we did not transform variables.

We used the software package lavaan, latent variable analysis (Rosseel, 2012), for the statistical software R (R Core Team, 2018), to fit the SEM with maximum likelihood methods (the argument “estimator” set equal to “ML” in the sem function of lavaan). Additionally, in the sem function, the fixed.x argument was set to TRUE, fixing the means, variances, and covariances of the exogenous variables (those with no arrows pointing towards them in the causal graph, independent variables) to their sample statistics (Rosseel, 2012, 2016).

We assessed model fit using four measures. The first was the aforementioned chi-squared test from the output of sem function in lavaan (Rosseel, 2012). The second measure of model fit used was the standardized root mean square residual (SRMR), which does not compare models or account for model complexity, but simply measures absolute fit and ranges from 0 to 1, with values closer to 0 indicative of a better fit (Rosseel, 2012). The third measure was the
comparative fit index (CFI; Bentler, 1990; Beaujean, 2015), which ranges from 0 to 1, with
values closer 1 indicative of a better fit (Bagozzi and Yi, 2012; Rosseel, 2012). The fourth
measure was the root mean square error of approximation (RMSEA), which considers model
complexity and penalizes models with more parameters and ranges from 0 to 1, with values
closer to 0 being better (Beaujean, 2015). These measures of model quality and their ideal ranges
are summarized in Supplement 1, table S4 of Ryberg (2017).

RESULTS AND DISCUSSION

Trend Overview

Although the trends have been previously reported (Oelsner et al., 2017; U.S. Geological
Survey, 2017), the trend directions and geographic patterns are important for understanding the
SEM models. Numerical trend results are available in a USGS data release (Ryberg et al., 2017).
Maps showing the sites assessed and the geographic distribution of trends are shown in figures 2
and 3 and are available in an interactive USGS map application of water-quality changes at
https://nawqatrends.wim.usgs.gov/swtrends/, along with changes in many other water-quality
constituents (U.S. Geological Survey, 2017). The trends are presented as “likely” down/up,
“somewhat” likely down/up, or “about as likely as not” to have a trend based on a likelihood
approach as an alternative to a significance testing approach.

The likelihood approach is an effort to provide more intuitive information when summarizing
trend results. Trend likelihood values for pesticides were determined using the \( p \)-value reported
from the SEAWAVE-Q trend model, using the equation \( 1 - (p - \text{value}/2) \). This approach is
explained in detail in the user guide of the USGS map application (U.S. Geological Survey,
2017) and that explanation is modified here to specifically refer to pesticides. Consider an
example where the chance of an upward trend in atrazine concentrations at a site is 80 out of 100 (a trend likelihood value of 0.80). Using the significance testing approach and a traditional significance level of 0.05 or 0.01, the trend would be reported as nonsignificant. Using the likelihood approach, the trend would be reported instead as "somewhat likely up." The likelihood approach indicates that it is somewhat likely that conditions in the stream are not improving, giving resource managers more information to use when making decisions about watersheds. For example, in figure 2, there are numerous “likely down” trends in atrazine concentration in Nebraska, Iowa, and Illinois. There are also several “somewhat likely down” trends in these states. In many past trend studies using traditional trend significance, the “somewhat likely” trends would not be reported or might be reported as no trend. However, in figure 2, we see that the trend direction for the “somewhat likely” trends in the three states match the pattern of “likely” trends and contribute to the overall picture of the decline in atrazine concentration in this part of the United States over the period 2002–2012.

In contrast to the atrazine trends, most likely or somewhat likely DEA trends are upward, with downward trends predominantly in the Midwest. This pattern has been noted in trend periods starting in the late 1990s or early 2000s in other studies based on field observations (Ryberg et al., 2010, 2014; Ryberg and Gilliom, 2015). The opposing trends in atrazine and DEA are a result of the differing paths the two compounds take to streams and the many changes to atrazine regulation that began in the early 1990s. To address concerns about surface-water contamination, risk reduction measures were instituted, including a decrease in application rates for corn and sorghum, a decrease in maximum application rates for non-crop land use, discontinuation of uses for total vegetation control, well-head protection requiring 15-meter setbacks around wells when workers mix and load atrazine-containing products, a 61-meter
application setback around lakes and reservoirs, and classification of all atrazine-containing products (except those for lawn and turf care and conifers) as restricted-use pesticides (U.S. Environmental Protection Agency, 2006). In 2003, the U.S. Environmental Protection Agency found that registered uses for atrazine were eligible for interim reregistration, with several label changes and risk management measures, further explained in the Interim Reregistration Eligibility Decision for Atrazine (U.S. Environmental Protection Agency, 2006).

Well-head protection measures and setbacks from water bodies that began in the 1990s (U.S. Environmental Protection Agency, 2006), as well as agricultural management practices, such as no-till agriculture, may have resulted in longer residence time of atrazine in soil and a greater amount of transformation to DEA before runoff to a stream or transport to groundwater. Upward trends in DEA have happened in areas where both atrazine concentration trends and atrazine use trends are downward, with a possible explanation that the increased DEA in streams is from groundwater contributions reflective of higher past atrazine use (Ryberg and Gilliom, 2015).

Multiple Working Hypotheses

Table S1 of Supplement 1 lists the MWHs and associated datasets for this study. In some cases, data were not sufficient to test potential hypotheses and those cases are documented in Table S1. Based on the MWH exercise and available data, we hypothesized that, in addition to use, atrazine concentrations would be driven by corn acreage in the watershed; weather and climate, with wetter conditions increasing the likelihood that atrazine would reach the stream as atrazine, rather than its degradation product, DEA; and potentially by conservation or tillage practices. We hypothesized that DEA trends would be driven by the same factors and base-flow contribution, expressed as BFI.
Given the need to constrain the model to a small number of parameters, the correlation analysis allowed us to select the mean Palmer Hydrologic Drought Index (PHDI) from among several measures of PHDI (annual maximum, annual minimum, annual mean, annual median, and annual standard deviation). We also examined correlation between the trends in atrazine and DEA and several variables related to agricultural conservation and management, including the concomitant trend in percent of agricultural land enrolled in the Conservation Reserve Program; the percent of the watershed in 2012 drained by tile drains; percent of the watershed in 2012 drained by ditches; the percent of the watershed in 2012 on which conventional, conservation, or no-till tillage practices were used; the percent of watershed land planted to a cover crop; and the percent of watershed land under a conservation easement. After examining correlations (some of which are shown in Supplement 2) of the concentration trends with conservation practices in Falcone (2017), we determined that the best candidate for including in the SEMs was percentage of watershed drained by tile drains in 2012.

**Structural Equation Modeling to Test Causal Hypotheses**

To test our causal hypotheses about drivers of atrazine and DEA trends other than use, we created a grouped SEM in which there were two groups, one the atrazine trends, and the other the DEA trends. This allowed us to model the pesticide and its degradate with the same variables, but the parameter estimates may vary between the two compounds. Figure 4 shows the resulting model for atrazine, and figure 5 shows the DEA model. Standardized parameter estimates for the SEMs, as well as the measures of model quality, which all showed that these are excellent models, are provided in Supplement 2.

Both models have a latent variable derived from the LVM labeled “Moisture supply and management” (MSM). This is a conceptual variable representing moisture supply and
management that is measured by the mean PHDI, which is descriptive of the precipitation variation across the sites; conservation practices indicative of the percent of the watershed drained by tile drains in 2012 (tile drains); and the average BFI for the watershed. This LVM directly influences the concentration trend in percent over the period of record (concentration trend). Both models also have a variable, corn trend, that represents the change in the proportion of the watershed in harvested corn (hereafter referred to as corn) over the trend period.

Figure 4 shows that the change in corn is the major driver of the atrazine concentration trend for the period 2002–2012. The standardized coefficient for this variable is 0.873 and represents a “large” effect (Cohen, 1977). The MSM latent variable was not statistically significant for the atrazine model. The model explains 77% of the variability in the atrazine trend, with corn explaining most of the concentration trend. Because corn is the main crop on which atrazine is used (fig. 1), changes in corn over time act as a surrogate for atrazine use trends.

Figure 5 shows that the trend in corn is less important for the trend in DEA concentration than is the MSM latent variable (the absolute value of the standardized coefficient for corn is less than the absolute value of the standardized coefficient for the MSM LVM), although both variables have a “medium” effect on the concentration trend for DEA (standardized path coefficient > 0.30 and < 0.50; Cohen, 1977). The LVM, which represents the underlying correlation structure of the mean PHDI, tile drainage, and BFI, has a negative sign, while the PHDI and tile drain indicator variables have a positive sign and the BFI has a negative sign. This shows that the BFI has a positive correlation with the concentration trend, while the mean PHDI and tile drains have a negative correlation. Therefore, as BFI increases, the concentration of DEA increases. This supports our hypothesis that, because of the mechanism of degradation, the solubility of DEA, and the movement of DEA through the soil to groundwater, DEA would be
influenced by BFI, whereas atrazine would not. This also supports the past, untested hypothesis of Ryberg et al. (2014) that the sign of atrazine and DEA concentration trends differ in some cases because of a groundwater transport pathway for DEA that lags between use and arrival at a stream. The mean PHDI has a negative correlation with the DEA concentration trends. This supports the hypothesis that wetter conditions would be preferential for atrazine runoff, rather than atrazine degradation to DEA in soils and subsequent transport via groundwater. Atrazine readily dissolves in water and infiltration through soils to tile drains is a major pathway (Baker et al., 2007). The percent of the watershed drained by tile drains in 2012 (the end of the trend period) has a negative correlation with the concentration trend, supporting that tile drains may transport atrazine to streams before it degrades to DEA. This SEM explains 38% of the variability in the DEA concentration trend.

**Conclusions**

The overall trend patterns and past investigation of use trends (Ryberg et al., 2014) indicate that regulatory changes may have been successful in encouraging atrazine degradation to DEA. The acute and chronic toxicity of DEA is less than that of atrazine for aquatic organisms (Ralston-Hooper et al., 2009); therefore, increasing DEA concentration trends would be preferential to increasing atrazine concentration trends and in some cases, declines in DEA may follow declines in atrazine, with lag times depending on groundwater movement.

The complexity of the SEMs was limited because of the number of observations available for model development. Even with this limitation, SEMs were able to be developed that explained 77 and 38 percent of the variability in atrazine and DEA concentration trends, respectively. The SEMs quantitatively supported our hypotheses and past hypotheses about drivers of concentration trends for atrazine and DEA. More of the variability in atrazine trends across the
conterminous United States was explained by SEM than was variability in DEA trends; however, mechanisms behind the DEA concentration trends are more complex because of lag time with groundwater, and, importantly, we have related the trends to a management practice—tile drains. To better understand the lag time, more site-specific investigation would need to be done that is outside the scope of the national perspective presented here.

Atrazine use patterns on corn have changed over time with the adoption of genetically modified corn and the use of glyphosate. Overall the atrazine stream concentrations trends were mainly downward between 2002 and 2012, with some sites showing upward trends. Nationally, the amount of harvested corn acres increased from 2002 to 2012 by more than 15 million acres (U.S. Department of Agriculture National Agricultural Statistics Service, 2018). The growth in corn acres was likely in areas not historically dominated by corn acres and is reflected in the scattered streams that showed upward trends in atrazine stream concentrations (figure 2). These areas, like southern Idaho, western Missouri, and northern Alabama, experienced an increase in the amount of corn grown in the period 2007–2012 (Supplement 3; U.S. Department of Agriculture National Agricultural Statistics Service, 2012). Therefore, the relation between corn acres and atrazine use over time is not constant, should not be extrapolated beyond the 2002–2012 period, and varies with watershed. In addition, regulatory changes (such as setbacks) may influence both the relation between corn acres and atrazine use, as well as the relation between atrazine use and stream concentration trends. It is possible that with a larger sample size and the resulting ability to develop a more complex model, additional factors might be able to be identified as important for atrazine trends.

The SEMs show that preferential degradation to DEA might happen in drier areas without tile drains. This highlights dual challenges for keeping atrazine from the stream because of
human influence and climate change. Tile drains are negatively correlated with DEA trends and provide a pathway for atrazine to move more quickly to streams. Atrazine is sometimes applied to fields in the fall to control volunteer weeds and prepare for no-tillage planting in the spring (Comfort and Roeth, 1993). Fall has been considered a good application time because it tends to be dry in many areas; however, fall in the conterminous United States has experienced the most widespread increase in precipitation, exceeding 15% over the period 1901–2015 in much of the northern Great Plains (U.S. Global Change Research Program, 2017) where corn cultivation has been expanding (Supplement 3). In addition, the frequency and intensity of heavy precipitation events have increased across much of the United States over the period 1901–2016 and are projected to continue to increase (U.S. Global Change Research Program, 2017), and such increases could exacerbate atrazine runoff to streams. While changes in regulation and use have benefited water quality with decreases in atrazine concentrations in surface water, climate changes and human-altered landscapes need to be considered in future water-quality improvement efforts and in monitoring and analysis.

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SUPPLEMENTAL MATERIAL

Supplement 1—Table S1 of the supplemental material provides the multiple working hypotheses for drivers of pesticide trends and provides many references for mechanisms, data, and other studies.

Supplement 2—Provides the R (R Core Team, 2018) code to ingest the data, to determine the change in proportion of watershed in harvested corn over the period 2002–2012, to explore correlations, and to perform the SEM modeling.

Supplement 3—Provides a map of the change in corn harvested for grain in the contiguous United States, 2007 to 2012.

REFERENCES


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National Synthesis Project.


**FIGURE CAPTIONS**

Figure 1. Atrazine use, in million kilograms, in the conterminous United States, 2002–2012 (U.S. Geological Survey, 2018a).
Figure 2. Atrazine concentration trends for the conterminous United States, 2002–2012 (Oelsner et al., 2017; Ryberg et al., 2017).

Figure 3. Deethylatrazine concentration trends for the conterminous United States, 2002–2012 (Oelsner et al., 2017; Ryberg et al., 2017).

Figure 4. Structural equation model explaining the factors that affect trends in atrazine concentration in streams across the conterminous United States, 2002–2012. Squares are observed variables, and circles are unobserved latent variables. Green arrows are positive coefficients, and red arrows are negative coefficients. The darker the color, the larger the coefficient. The numeric values are the standardized path coefficients (placed on the path lines) and error variances (placed on the lines with both arrows pointing to a single variable). Moisture supply and management is a latent variable derived from the latent variable model indicated by PHDI, mean Palmer Hydrologic Drought Index for the watershed, 2002–2012; tile drains, conservation practices in the form of proportion of watershed drained by tile drains in 2012; and the average base-flow index for the watershed. Corn trend is the change in proportion of watershed in harvested corn from 2002–2012. Concentration trend is the atrazine concentration trend expressed as a percent over the period of record, 2002–2012. Concentration trend data from Ryberg et al. (2017) other data from Falcone (2017).

Figure 5. Structural equation model explaining the factors that affect trends in deethylatrazine concentration in streams across the conterminous United States, 2002–2012. Squares are observed variables, and circles are unobserved latent variables. Green arrows are positive coefficients, and red arrows are negative coefficients. The darker the color, the larger the coefficient. The numeric values are the standardized path coefficients (placed on the path lines)
and error variances (placed on the lines with both arrows pointing to a single variable). Moisture supply and management is a latent variable derived from the latent variable model indicated by PHDI, mean Palmer Hydrologic Drought Index for the watershed, 2002–2012; tile drains, conservation practices in the form of proportion of watershed drained by tile drains in 2012; and the average base-flow index for the watershed. Corn trend is the change in proportion of watershed in harvested corn from 2002–2012. Concentration trend is the atrazine concentration trend expressed as a percent over the period of record, 2002–2012. Concentration trend data from Ryberg et al. (2017) other data from Falcone (2017).
Other crops
Pasture and hay
Alfalfa
Orchards and grapes
Rice
Vegetables and fruit
Cotton
Wheat
Soybeans
Corn

Estimated use in million kilograms


J. Environ. Qual. Accepted Paper, posted 10/05/2019. doi:10.2134/jeq2019.03.0111
PHDI Tile drains Base-flow index

Moisture supply and management

Concentration trend

0.642

0.598 0.589 −0.350

0.372

0.878

0.553
Table S1. Multiple working hypotheses for causes of trends in pesticide concentration in surface water.

<table>
<thead>
<tr>
<th>Hypothesized causal factors</th>
<th>Potential Influence</th>
<th>Comments (additional information/mechanisms)</th>
<th>Data</th>
<th>Ability to use on a structural equation model</th>
<th>Reference from other studies that use data, qualitatively or quantitatively</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Agriculture</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pesticide-use intensity</td>
<td>Use intensity patterns result in similar occurrence patterns in streams (increasing use = increasing occurrence).</td>
<td>Stone (2013); Theilin and Stone (2013); Baker and Stone (2013)</td>
<td>Use for pesticides with agricultural use.</td>
<td>Reference from other studies that use data, qualitatively or quantitatively</td>
<td></td>
</tr>
<tr>
<td>Crop Acres</td>
<td>Increase in crop types and acres = increase in occurrence.</td>
<td>Proportion of watershed harvested corn is available in Falcone (2017).</td>
<td>Use for pesticides largely influenced by one or two crops.</td>
<td>Reference from other studies that use data, qualitatively or quantitatively</td>
<td></td>
</tr>
<tr>
<td>Soil erosion on cropland</td>
<td>Increase in soil erosion = increase in occurrence of compounds that bind to soils.</td>
<td>There may not be enough years of consistent data collection methods through time.</td>
<td>Data on soil erosion available in Falcone (2017).</td>
<td>Reference from other studies that use data, qualitatively or quantitatively</td>
<td></td>
</tr>
<tr>
<td>Conservation efforts</td>
<td>Increased conservation could decrease amounts getting to streams.</td>
<td>Annual proportion of watersheds enrolled in the Conservation Reserve Program is available in Falcone (2017). Estimate of percent of watershed drained by ditches, drained by tile drains, with conservation tillage, with conventional tillage, with no-tillage practice, with cover crops, and with conservation easements in 2012 is available in Falcone (2017).</td>
<td>Data on conservation efforts available in Falcone (2017).</td>
<td>Reference from other studies that use data, qualitatively or quantitatively</td>
<td></td>
</tr>
<tr>
<td>Changes in tillage</td>
<td>Pesticides that readily dissolve in water and infiltrate through the soils; atrazine is one such pesticide (Baker et al., 2006; Baker et al., 2007).</td>
<td>Atrazine concentrations in tile flow were higher in peak flow conditions than during normal conditions in a study in Indiana (Baker et al., 2006).</td>
<td>Data on tile drains available for 2012 only in Falcone (2017).</td>
<td>Reference from other studies that use data, qualitatively or quantitatively</td>
<td></td>
</tr>
<tr>
<td>Tile drainage</td>
<td>Pesticides that readily dissolve in water and infiltrate through the soils; atrazine is one such pesticide (Baker et al., 2006; Baker et al., 2007).</td>
<td>Atrazine concentrations in tile flow were higher in peak flow conditions than during normal conditions in a study in Indiana (Baker et al., 2006).</td>
<td>Data on tile drains available for 2012 only in Falcone (2017).</td>
<td>Reference from other studies that use data, qualitatively or quantitatively</td>
<td></td>
</tr>
<tr>
<td>Non-Agricultural Land Use</td>
<td>Pesticide-use intensity (increasing use = increasing occurrence).</td>
<td>Few data are available at the watershed level.</td>
<td>Insufficient data available.</td>
<td>Reference from other studies that use data, qualitatively or quantitatively</td>
<td></td>
</tr>
<tr>
<td>Development or population density</td>
<td>Changes in development density result in changes in occurrence of particular pesticides.</td>
<td>Estimates of proportion of land that is developed, semi-developed, or industrial are available in Falcone (2015). Population density in the watershed for 1990, 2000, and 2010 is available in Falcone (2017).</td>
<td>Use for sites without agricultural use.</td>
<td>Reference from other studies that use data, qualitatively or quantitatively</td>
<td></td>
</tr>
<tr>
<td>Hydrology &amp; Climatology</td>
<td>Precipitation intensity or erosivity index</td>
<td>Increase in number and severity of intensity events (perhaps above a particular threshold) = more occurrence.</td>
<td>Might need to examine at 15-minute precipitation data.</td>
<td>Term streamflow anomalies in SEAWAVE-Q trend model (Vecchia et al., 2008; Ryberg and Vecchia, 2013); therefore, not a candidate, given limitations on model complexity.</td>
<td>Reference from other studies that use data, qualitatively or quantitatively</td>
</tr>
<tr>
<td>Wet/dry duration</td>
<td>Changes in longer-term wet or dry conditions may affect crop and pesticide choices and may affect runoff.</td>
<td>Palmer Hydrologic Drought Index available in Falcone (2017).</td>
<td>Use Palmer Hydrologic Drought Index when sample size is sufficient.</td>
<td>Reference from other studies that use data, qualitatively or quantitatively</td>
<td></td>
</tr>
<tr>
<td>Max, Min, Mean, Precipitation</td>
<td>Daily precipitation</td>
<td>Monthly precipitation available in Falcone (2017)</td>
<td>Given small sample sizes, models cannot support this variable, which would be correlated with the short-term flow anomaly in the SEAWAVE-Q model (Vecchia et al., 2008; Ryberg and Vecchia, 2013).</td>
<td>Stone et al. (2013)</td>
<td></td>
</tr>
<tr>
<td>Max, Min, Mean, Temperature</td>
<td>Daily temperature</td>
<td>Monthly temperature available in Falcone (2017)</td>
<td>Given small sample sizes, models cannot support this variable, which would be correlated with the short-term flow anomaly in the SEAWAVE-Q model. (Vecchia et al., 2008; Ryberg and Vecchia, 2013).</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Streamflow trends</td>
<td>Increase (decreases) in streamflow may have a dilution (concentration) effect; however, increases (decreases) in streamflow may also be indicative of runoff events, which may have the opposite signal. Trends in minimum and maximum and trends in percentiles.</td>
<td>Streamflow anomalies, which incorporate streamflow variability on varying timescales, are incorporated into the SEAWAVE-Q model (Vecchia et al., 2008; Ryberg and Vecchia, 2013).</td>
<td>Streamflow information is incorporated into pesticide trend model.</td>
<td>Sullivan et al. (2009); Ryberg et al. (2010); Ryberg et al. (2014); Ryberg and Gilliom (2015); Oelsner et al. (2017)</td>
<td></td>
</tr>
<tr>
<td>Overland flow types</td>
<td>Overland flow, areas with one type of flow may be more likely to transport pesticides to streams than the other. Also, Dunne overland flow areas may also exhibit more wet areas.</td>
<td>These variables are available in Falcone (2017).</td>
<td>Could be used as a grouping variable, given adequate sample size, but not used here because of small sample size.</td>
<td>Larson et al. (2004); Stone et al. (2013)</td>
<td></td>
</tr>
<tr>
<td>Watershed Physical Characteristics</td>
<td>Presence of a soil restrictive layer impedes transport of chemicals to shallow groundwater and may increase surface transport.</td>
<td></td>
<td>Could be used as a grouping variable, given adequate sample size, but not used here because of small sample size.</td>
<td>Stone et al. (2013)</td>
<td></td>
</tr>
<tr>
<td>Soil restrictive layer</td>
<td>Presence of a soil restrictive layer impedes transport of chemicals to shallow groundwater and may increase surface transport.</td>
<td><a href="https://water.usgs.gov/GIS/metadata/usgswrd/XML/ssurgo_srlag.xml">https://water.usgs.gov/GIS/metadata/usgswrd/XML/ssurgo_srlag.xml</a></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Physical/Chemical Characteristics</td>
<td>Persistent (soil half-life)</td>
<td>Persistent pesticides may occur in streams longer than use is occurring.</td>
<td>Incorporated in the sense that each pesticide will have a separate model that is then influenced by that pesticide's chemical properties.</td>
<td>Ryberg et al. (2010); Ryberg et al. (2014); Stone et al. (2013); Mudhoo and Garg (2011)</td>
<td></td>
</tr>
<tr>
<td>Solubility</td>
<td>Insoluble pesticides may be less likely transported to streams than highly soluble pesticides.</td>
<td>Incorporated in the sense that each pesticide will have a separate model that is then influenced by that pesticide's chemical properties.</td>
<td>Ryberg et al. (2010); Ryberg et al. (2014); Mudhoo and Garg (2011)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Koc</td>
<td>Soil organic carbon-water partitioning coefficient (Koc)</td>
<td>Incorporated in the sense that each pesticide will have a separate model that is then influenced by that pesticide's chemical properties.</td>
<td>Ryberg et al. (2010); Ryberg et al. (2014); Stone et al. (2013); Mudhoo and Garg (2011)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Kow or logKow</td>
<td>Octanol/water partition coefficient</td>
<td>Incorporated in the sense that each pesticide will have a separate model that is then influenced by that pesticide's chemical properties.</td>
<td>Ryberg et al. (2010); Ryberg et al. (2014); Mudhoo and Garg (2011)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Vapor pressure</td>
<td>Indication of volatilization potential</td>
<td>Incorporated in the sense that each pesticide will have a separate model that is then influenced by that pesticide's chemical properties.</td>
<td>Ryberg et al. (2010); Ryberg et al. (2014)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Surface-water mobility index</td>
<td>Represents potential for pesticides to move from application site to streams.</td>
<td>Available for some pesticides in Chen et al. (2002),</td>
<td>Incorporated in the sense that each pesticide will have a separate model that is then influenced by that pesticide's chemical properties.</td>
<td>Chen et al. (2002); Stone et al. (2013)</td>
<td></td>
</tr>
<tr>
<td>Accumulate in depositional material and biota</td>
<td>May dampen effects of use intensity or prolong occurrence after use has discontinued.</td>
<td>Adsorbed sediments are filtered out of samples. There are limited data and studies on pesticides in sediments. This is one of the reasons use intensity is not perfectly correlated with concentration trends in filtered surface water.</td>
<td>Insufficient long-term data.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Societal changes</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Demographic changes</td>
<td>Insufficient long-term data.</td>
<td>Socioeconomic changes: A shift to a less affluent level may decrease the overall ability of people in an area to purchase and use pesticides. In the rural settings, a growth in affluence may also mark the conversion of cropland to rural estates where pesticides are applied for aesthetics.</td>
<td>Urban and agricultural settings</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Regulatory changes</td>
<td>Insufficient long-term data.</td>
<td>Not all regulatory changes are outright bans on use. Some are changes to label rates or restrictions on some crops. These changes should impact what we see in the trends.</td>
<td>Urban and agricultural settings</td>
<td>Each pesticide will have its own structural equation model, thereby indirectly representing the different regulatory changes for each pesticide.</td>
<td></td>
</tr>
<tr>
<td>Market changes</td>
<td>Insufficient long-term data.</td>
<td>Multiple influences: A new pesticide on the market may get more pressure from sales representatives to use. A pesticide that comes off patent may be picked up by other companies and marketed to be cheaper and have same effect. Some pesticides are marketed in tandem with each other. Not sure how changes in the market (company purchases, new companies, etc) may affect things.</td>
<td>Urban and agricultural settings</td>
<td>Each pesticide will have its own structural equation model, thereby indirectly representing the different market changes for each pesticide.</td>
<td></td>
</tr>
<tr>
<td>Education efforts</td>
<td>Insufficient long-term data.</td>
<td>Since the 1970's, there has been significant spending on education regarding pesticide use and alternatives. Programs such as integrative pest management have come into being during that time period. This is for both ag and non-ag settings or ag and urban. There has also been efforts to subsidize and encourage alternatives to standard pesticides, including the use of naturally occurring pesticides.</td>
<td>Farmer certification</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pest changes</td>
<td>Insufficient long-term data.</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Changes in pest pressure will influence pesticide use. For example, weeds are becoming glyphosate tolerant and there is an increasing pressure from these pests that may not have been seen for awhile, leading to changes in pesticide use. Another example would be the move of soybean rust up the Mississippi River over the last few decades. Are there any examples of new, introduced species that have changed pest pressure? In the non-ag area, we may see changes related to changes in termite, fire ant, bed bugs, kudzo, etc. Urban and agricultural settings.

Weed resistance influences the choice of pesticides—some older pesticides that had experienced a decline in use may now be experiencing an increase in use.
R Markdown

This document provides the R code (R Core Team, 2018) used to produce the results presented in the paper for which this is part of the supporting material. Before running this code, some R packages used may need to be installed by using the R function install.packages(). The plots presented in this document are not intended to be publication quality.

Data Download from ScienceBase

The datasets used for this study are from the U.S. Geological Survey data releases published by Falcone (2017) and by Ryberg et al. (2017) and can be downloaded programmatically using R and ScienceBase.

```r
library(sbtools)
library(reshape2)
library(ggplot2)
library(plyr)
library(lavaan)
## This is lavaan 0.6-2
## lavaan is BETA software! Please report any bugs.
library(semPlot)

# Use package sbtools to get all data from ScienceBase

# if necessary
# install.packages("sbtools")
library("sbtools")

# Pesticide trends results for Oelsner et al. (2017),
# published in Ryberg et al. (2017)
# Before you start working with a SB file, check to see if it exists.
identifier_exists("57c441afe4b0f2f0cebc8a37")

## [1] TRUE

# getting list of child file names
# command commented out here because it produces text that
# gets cutoff on the right, but this provides some information about
# the data
# item_list_children("57c441afe4b0f2f0cebc8a37")

# assigning each child file name
all_children <- item_list_children("57c441afe4b0f2f0cebc8a37")
children_id <- unlist(lapply(all_children, function(item) item$id))
output <- children_id[2]
```
# assigning and getting list of attached file names.
ex_id_files <- item_list_files(output)
ex_id_files$fname

## [5] "Pesticide_metadata_output.xml"

# in the [], choose which file to load
trendsCSV <- ex_id_files$url[4]

# read in the .csv file
trends <- read.csv(trendsCSV, stringsAsFactors = FALSE,
colClasses = c("NULL", rep("character", 4), rep("numeric", 21)))

pestTrends <- subset(trends, Pesticide == "Deethylatrazine" | Pesticide == "Atrazine")
sites <- unique(pestTrends$pstaid)
sites <- sort(sites)

# Convert trends to percent over period of record, this matches presentation in
# https://nawqatrends.wim.usgs.gov/swtrends/
TrendCalcs <- function(ctnd, pval, por) {
cndPpor <- formatC(100 * ((10 ^ ctnd) ^ por) - 100, digits = 4, flag = ",
        format = "f")
cndlklhd <- round(1 - pval/2, digits = 4)
trends <- c(cndPpor, cndlklhd)
return(as.numeric(trends))
}
dim(pestTrends)

## [1] 129 25

mycolNams <- c("ctndPpor", "ctndlklhd")
pestTrends[mycolNams] <- NA
dim(pestTrends)

## [1] 129 27

for (i in 1:dim(pestTrends)[[1]]) {
    pestTrends[i, 26:27] <- TrendCalcs(pestTrends$ctnd[i], pestTrends$pvaltnd[i],
                                          2012 - 2002)
}

# Before you start working with a SB file, check to see if it exists.
identifier_exists("58a5b804e4b057081a24f20c")

## [1] TRUE

# watershed characteristics data release item in ScienceBase
wcdat <- item_get("58a5b804e4b057081a24f20c")

# specific pieces of data to download
dataElements <- c(5, 6, 18, 24)

# function to download and unzip data
downloadScienceBaseData <- function(datitem, itemnum) {
    fileName <- datitem$files[[itemnum]]$name
datURL <- datitem$files[[itemnum]]$downloadUri
download.file(datURL, destfile = paste0("./data/", fileName), method = "auto")
unzip(paste0("./data/", fileName), exdir = ".".data"

# download and unzip data
for (i in 1:length(dataElements)) {
  downloadScienceBaseData(wcdat, dataElements[i])
}

# if the above download and zip does not work because of computer limitations or security
# constraints, the datasets 4, 5, 17, and 24 should be downloaded manually from ScienceBase
# at https://doi.org/10.5066/F7TX3CKP. The files should then be unzipped and placed in a folder
# called data within the current working directory of R.

# read in data
# corn
corn <- read.csv("./data/Dataset4_COA_proportion_of_county/swt_CoA_proportion_of_county_corn.txt",
                   header = TRUE, stringsAsFactors = FALSE,
                   colClasses = c("character", rep("numeric", 10)))

corn$year <- as.numeric(substr(corn$year, 5, 8))
corn <- subset(corn, year > 1991)

dimnames(corn)[[2]][[1]] <- "pstaid"
corn <- melt(corn, id = "pstaid")

corm$year <- c("pstaid", "year", "cornpct")
corn <- subset(corn, pstaid %in% sites)

dimnames(corn)[[2]][[1]] <- "pstaid"
corn <- melt(corn, id = "pstaid")

corn$year <- c("pstaid", "year", "cornpct")
corn <- subset(corn, year > 1991)

# conservation practices
                   header = TRUE, stringsAsFactors = FALSE,
                   colClasses = c("character", rep("numeric", 7)))

dimnames(cprac)[[2]][1] <- "pstaid"
cprac <- subset(cprac, pstaid %in% sites)

# base-flow index
static <- read.csv("./data/Dataset24_Static/swt_Static_Hydrology.txt", header = TRUE,
                   stringsAsFactors = FALSE,
                   colClasses = c("character", rep("numeric", 6)))

PHDI1 <- read.csv("./data/Dataset17_PHDI/swt_PHDI_1972-1992.txt", header = TRUE,
                   stringsAsFactors = FALSE,
                   colClasses = c("character", rep("numeric", 252)))

PHDI2 <- read.csv("./data/Dataset17_PHDI/swt_PHDI_1993-2013.txt", stringsAsFactors = FALSE,
                   colClasses = c("character", rep("numeric", 249)))

# plot corn data, if desired
# p <- ggplot(corn, aes(year, cornpct)) + geom_point() + facet_wrap(~pstaid, scales = "free")
# p
static <- subset(static, pstaid %in% sites)
static <- static[, c(1, 2)]
cornChange <- data.frame(pstaid = character(0), cornX = numeric(),
                        stringsAsFactors = FALSE)

# pdf("./output/cornChange.pdf")
for (i in 1:length(sites)) {
    sitedat <- subset(corn, pstaid == sites[i])
    if (dim(sitedat)[[1]] > 0 ) {
        par(las = 1, tck = 0.02, mar = c(5, 4, 3, 1) + 0.1, cex = 0.8)
        plot(sitedat$year, sitedat$cornpct, ylab = "Percent", xlab = "", cex.axis = 0.9)
        title(main = paste(sites[i], " Proportion of watershed in harvested corn ", sep = ""),
              line = 1)
        corn.lo <- loess(cornpct ~ year, sitedat, span = 1)
        corn.lo.pred <- predict((corn.lo), data.frame(year = seq(1992, 2012, 1)))
        subval <- as.numeric(min(sitedat$cornpct))
        pck <- corn.lo.pred < 0
        corn.lo.pred[pck] <- subval
        lines(seq(1992, 2012, 1), corn.lo.pred)
        if ( corn.lo.pred[1] > 0 ) {
            change <- (corn.lo.pred[21] - corn.lo.pred[1]) / abs(corn.lo.pred[1]) * 100
        } else {
            corn.lo.pred[1] <- min(corn.lo.pred[corn.lo.pred > 0])
            change <- (corn.lo.pred[21] - corn.lo.pred[1]) / abs(corn.lo.pred[1]) * 100
        }
        if (corn.lo.pred[11] > 0 ) {
        } else {
            corn.lo.pred[11] <- min(corn.lo.pred[corn.lo.pred > 0])
        }
        cornChange[i, ] <- c(sites[i], changeTP)
        title(sub = paste("Percent change is ", round(change, digits = 2),
                        " from 1992 to 2012, and ", round(changeTP, digits = 2),
                        " from 2002 to 2012", sep = ""), cex.sub = 0.8, line = 2)
    } else {
        cornChange[i, ] <- c(sites[i], NA, NA)
        print("No corn data \n")
    }
}
Percent change is −53.64 from 1992 to 2012, and −38.23 from 2002 to 2012

Percent change is −24.5 from 1992 to 2012, and −14.96 from 2002 to 2012
Percent change is −18.69 from 1992 to 2012, and −6.68 from 2002 to 2012.

Percent change is 3.48 from 1992 to 2012, and 15.24 from 2002 to 2012.
Percent change is −38.53 from 1992 to 2012, and 18.71 from 2002 to 2012.

Percent change is −27.34 from 1992 to 2012, and −6.59 from 2002 to 2012.
Percent change is 1.35 from 1992 to 2012, and 8.3 from 2002 to 2012.

Percent change is −6.27 from 1992 to 2012, and 3.88 from 2002 to 2012.
Percent change is −35.72 from 1992 to 2012, and 17.11 from 2002 to 2012.

Percent change is −60 from 1992 to 2012, and 3.27 from 2002 to 2012.
02174250 Proportion of watershed in harvested corn

Percent change is −18.32 from 1992 to 2012, and 1.24 from 2002 to 2012

02175000 Proportion of watershed in harvested corn

Percent change is −24.26 from 1992 to 2012, and 4.69 from 2002 to 2012
02318500 Proportion of watershed in harvested corn

Percent change is −67.87 from 1992 to 2012, and 48.72 from 2002 to 2012

02335870 Proportion of watershed in harvested corn

Percent change is −100 from 1992 to 2012, and −100 from 2002 to 2012
Percent change is 30.5 from 1992 to 2012, and 78.93 from 2002 to 2012.

Percent change is 2.1 from 1992 to 2012, and −8.26 from 2002 to 2012.
02469762 Proportion of watershed in harvested corn

Percent change is −6.16 from 1992 to 2012, and 19.95 from 2002 to 2012

03303280 Proportion of watershed in harvested corn

Percent change is 0.12 from 1992 to 2012, and 27.49 from 2002 to 2012
03374100 Proportion of watershed in harvested corn

Percent change is 5.4 from 1992 to 2012, and 26.08 from 2002 to 2012

03378500 Proportion of watershed in harvested corn

Percent change is 5.84 from 1992 to 2012, and 17.31 from 2002 to 2012
Percent change is −42.57 from 1992 to 2012, and −31.48 from 2002 to 2012

Percent change is 54.92 from 1992 to 2012, and 117.43 from 2002 to 2012
Percent change is 21.66 from 1992 to 2012, and 55.47 from 2002 to 2012.

Percent change is 8.43 from 1992 to 2012, and 25.05 from 2002 to 2012.
04072050 Proportion of watershed in harvested corn

Percent change is –8.92 from 1992 to 2012, and 12.29 from 2002 to 2012.

04186500 Proportion of watershed in harvested corn

Percent change is 11.96 from 1992 to 2012, and 13.78 from 2002 to 2012.
Percent change is 5.41 from 1992 to 2012, and 13.55 from 2002 to 2012

Percent change is 22.55 from 1992 to 2012, and 23.74 from 2002 to 2012
05451210 Proportion of watershed in harvested corn

Percent change is 20.45 from 1992 to 2012, and 26.39 from 2002 to 2012

05465500 Proportion of watershed in harvested corn

Percent change is 13.51 from 1992 to 2012, and 23.4 from 2002 to 2012
05531500 Proportion of watershed in harvested corn

Percent change is $-67.13$ from 1992 to 2012, and $-5.12$ from 2002 to 2012

05572000 Proportion of watershed in harvested corn

Percent change is $12.32$ from 1992 to 2012, and $12.19$ from 2002 to 2012
Proportion of watershed in harvested corn

Percent change is 9.41 from 1992 to 2012, and 13.76 from 2002 to 2012

Proportion of watershed in harvested corn

Percent change is 15.55 from 1992 to 2012, and 19.77 from 2002 to 2012
06329500 Proportion of watershed in harvested corn

Percent change is 47.57 from 1992 to 2012, and 37.71 from 2002 to 2012

06610000 Proportion of watershed in harvested corn

Percent change is 56.19 from 1992 to 2012, and 50.82 from 2002 to 2012
06713500 Proportion of watershed in harvested corn

Percent change is 80.35 from 1992 to 2012, and 28.51 from 2002 to 2012

06800000 Proportion of watershed in harvested corn

Percent change is 16.41 from 1992 to 2012, and 14.23 from 2002 to 2012
06800500 Proportion of watershed in harvested corn

Percent change is 11.08 from 1992 to 2012, and 16.06 from 2002 to 2012

06805500 Proportion of watershed in harvested corn

Percent change is 14.15 from 1992 to 2012, and 22.23 from 2002 to 2012
Percent change is 161.46 from 1992 to 2012, and 73.7 from 2002 to 2012.

Percent change is 43.39 from 1992 to 2012, and 36.79 from 2002 to 2012.
07022000 Proportion of watershed in harvested corn

Percent change is 27.01 from 1992 to 2012, and 26.95 from 2002 to 2012

07053250 Proportion of watershed in harvested corn

Percent change is 1400.33 from 1992 to 2012, and 1400.33 from 2002 to 2012
07263620 Proportion of watershed in harvested corn

Percent change is 92.24 from 1992 to 2012, and 33.91 from 2002 to 2012

07381495 Proportion of watershed in harvested corn

Percent change is 34.1 from 1992 to 2012, and 29.14 from 2002 to 2012
Percent change is 73.17 from 1992 to 2012, and −46.86 from 2002 to 2012

Percent change is −49.96 from 1992 to 2012, and −53.2 from 2002 to 2012
08364000 Proportion of watershed in harvested corn

Percent change is 101.26 from 1992 to 2012, and −17.71 from 2002 to 2012

08475000 Proportion of watershed in harvested corn

Percent change is 78.31 from 1992 to 2012, and 44.82 from 2002 to 2012
09163500 Proportion of watershed in harvested corn

Percent change is −15.02 from 1992 to 2012, and 43.09 from 2002 to 2012

# Warning in min(corn.lo.pred[corn.lo.pred > 0]): no non-missing arguments to min; returning Inf

094196783 Proportion of watershed in harvested corn

Percent change is NaN from 1992 to 2012, and NaN from 2002 to 2012
Percent change is 23.52 from 1992 to 2012, and 68.95 from 2002 to 2012.

Percent change is 71.2 from 1992 to 2012, and 16.1 from 2002 to 2012.
10168000 Proportion of watershed in harvested corn

Percent change is −56.61 from 1992 to 2012, and 23.62 from 2002 to 2012.

11074000 Proportion of watershed in harvested corn

Percent change is 64.86 from 1992 to 2012, and −29.91 from 2002 to 2012.
11303500 Proportion of watershed in harvested corn

Percent change is 104.23 from 1992 to 2012, and 41.22 from 2002 to 2012

11447650 Proportion of watershed in harvested corn

Percent change is 30.67 from 1992 to 2012, and −0.88 from 2002 to 2012
12510500 Proportion of watershed in harvested corn

Percent change is 117.05 from 1992 to 2012, and 45.84 from 2002 to 2012

13092747 Proportion of watershed in harvested corn

Percent change is 302.18 from 1992 to 2012, and 153.21 from 2002 to 2012
13154500 Proportion of watershed in harvested corn

Percent change is 305.79 from 1992 to 2012, and 109.3 from 2002 to 2012

14206950 Proportion of watershed in harvested corn

Percent change is 11.37 from 1992 to 2012, and −46.65 from 2002 to 2012
14211720 Proportion of watershed in harvested corn

Percent change is 31.43 from 1992 to 2012, and 3.28 from 2002 to 2012

14246900 Proportion of watershed in harvested corn

Percent change is 161 from 1992 to 2012, and 98.78 from 2002 to 2012
394340085524601 Proportion of watershed in harvested corn

Percent change is 8.68 from 1992 to 2012, and 17.48 from 2002 to 2012

```r
# dev.off()
cornChange$cornX <- as.numeric(cornChange$cornX)
pck <- cornChange$ps1aid == "094196783"
cornChange[pck, 2] <- c(0)
dimnames(PHDI1)[[2]][1] <- "ps1aid"
varnames <- dimnames(PHDI1)[[2]][grep("phdi", dimnames(PHDI1)[[2]])]
varnames <- sub("phdi_", ",", varnames)
dimnames(PHDI1)[[2]][grep("phdi", dimnames(PHDI1)[[2]])] <- varnames
dimnames(PHDI2)[[2]][1] <- "ps1aid"
varnames <- dimnames(PHDI2)[[2]][grep("phdi", dimnames(PHDI2)[[2]])]
varnames <- sub("phdi_", ",", varnames)
dimnames(PHDI2)[[2]][grep("phdi", dimnames(PHDI2)[[2]])] <- varnames
dfs <- list(PHDI1, PHDI2)
PHDI <- join_all(dfs, by = "ps1aid")
PHDI <- subset(PHDI, ps1aid %in% sites)
PHDI <- melt(PHDI, id = "ps1aid")
dimnames(PHDI)[[2]] <- c("ps1aid", "date", "phdi")
PHDI$year <- as.numeric(substr(PHDI$date, 4, 5))
PHDI$monthC <- as.character(substr(PHDI$date, 1, 3))
PHDI <- PHDI[, c(1, 4, 5, 3)]
pck <- PHDI$year > 70
PHDI$year[pck] <- PHDI$year[pck] + 1900
PHDI$year[!pck] <- PHDI$year[!pck] + 2000
PHDI <- subset(PHDI, year > 2001 & year < 2013)
PHDI$monthC <- 0
```
for (i in 1:length(PHDI$pstaid)) {
  if (PHDI$monthC[i] == "jan") {
    PHDI$month[i] <- 1
  } else if (PHDI$monthC[i] == "feb") {
    PHDI$month[i] <- 2
  } else if (PHDI$monthC[i] == "mar") {
    PHDI$month[i] <- 3
  } else if (PHDI$monthC[i] == "apr") {
    PHDI$month[i] <- 4
  } else if (PHDI$monthC[i] == "may") {
    PHDI$month[i] <- 5
  } else if (PHDI$monthC[i] == "jun") {
    PHDI$month[i] <- 6
  } else if (PHDI$monthC[i] == "jul") {
    PHDI$month[i] <- 7
  } else if (PHDI$monthC[i] == "aug") {
    PHDI$month[i] <- 8
  } else if (PHDI$monthC[i] == "sep") {
    PHDI$month[i] <- 9
  } else if (PHDI$monthC[i] == "oct") {
    PHDI$month[i] <- 10
  } else if (PHDI$monthC[i] == "nov") {
    PHDI$month[i] <- 11
  } else if (PHDI$monthC[i] == "dec") {
    PHDI$month[i] <- 12
  } else {
    PHDI$month[i] <- 13
  }
}

PHDI <- PHDI[, c(1, 2, 5, 4)]

PHDImean <- aggregate(phdi ~ pstaid, data = PHDI, mean)
dimnames(PHDImean)[[2]][2] <- "phdiMean"

PHDImax <- aggregate(phdi ~ pstaid, data = PHDI, max)
dimnames(PHDImax)[[2]][2] <- "phdiMax"

PHDImin <- aggregate(phdi ~ pstaid, data = PHDI, min)
dimnames(PHDImin)[[2]][2] <- "phdiMin"

PHDImed <- aggregate(phdi ~ pstaid, data = PHDI, median)
dimnames(PHDImed)[[2]][2] <- "phdiMed"

PHDIstd <- aggregate(phdi ~ pstaid, data = PHDI, sd)
dimnames(PHDIstd)[[2]][2] <- "phdiSd"

dfs <- list(PHDImean, PHDImax, PHDImin, PHDImed, PHDIstd)
PHDI <- join_all(dfs, by = "pstaid")
sites <- sites[order(sites)]

deaTrends <- subset(pestTrends, Pesticide == "Diethylatrazine")
attrTrends <- subset(pestTrends, Pesticide == "Atrazine")
Bi-variate Correlations

The following plots show a histogram for each variable on the diagonal and a x-y scatterplot of each pair of variables below the diagonal. Above the diagonal, each box has Kendall’s tau correlation [a measure of monotonic correlation, Kendall (1976)] and an indicator of its statistical significance. The larger the absolute value of the correlation, the larger the text reporting the correlation value. A red square indicates statistical significance at the 0.10 significance level. One red asterisk indicates statistical significance at the 0.05 significance level. Two red asterisks indicate statistical significance at the 0.01 significance level. Three red asterisks indicate statistical significance at the 0.001 significance level.

```r
def <- list(deaTrends, static, cprac, cornChange, PHDI)
deaTrends <- join_all(def, by = "pstaid")
def <- list(atrTrends, static, cprac, cornChange, PHDI)
atrTrends <- join_all(def, by = "pstaid")
```

```r
mtitl <- "Deethylatrazine, 2002-2012"

# pdf("./output/DEACorrelation.pdf", width = 15, height = 15)
pairs(deaTrends[, c(26, 28:36)], lower.panel = panel.smooth, upper.panel = panel.cor, main = mtitl, diag.panel = panel.hist)
```

```r
Bi-variate Correlations

panel.cor <- function(x, y, digits = 2, prefix = "", cex.cor) {
  usr <- par("usr"); on.exit(par(usr))
  par(usr = c(0, 1, 0, 1))
  r <- cor(x, y, use = "complete.obs", method = "kendall")
  txt <- format(c(r, 0.123456789), digits = digits)[1]
  txt <- paste(prefix, txt, sep = "")
  if (missing(cex.cor)) cex <- 0.75 / strwidth(txt)
  test <- cor.test(x, y, na.action = "na.omit", method = "kendall")
  Signif <- symnum(test$p.value, corr = FALSE, na = FALSE,
                   cutpoints = c(0, 0.001, 0.01, 0.05, 0.1, 1),
                   symbols = c("***", "**", "*", ".", " "))
  text(0.5, 0.5, txt, cex = max(cex * abs(r),.9))
  text(0.8, 0.8, Signif, cex = cex, col = 2)
}

panel.hist <- function(x, ...) {
  usr <- par("usr"); on.exit(par(usr))
  par(usr = c(usr[1:2], 0, 1.5))
  if (min(x, na.rm = TRUE) < max(x, na.rm = TRUE)) {
    h <- hist(x, plot = FALSE)
    breaks <- h$breaks; nB <- length(breaks)
    y <- h$counts; y <- y/max(y)
    rect(breaks[-nB], 0, breaks[-1], y, col = "cyan", ...)
  }
}
```

```r
mtitl <- "Deethylatrazine, 2002-2012"

# pdf("./output/DEACorrelation.pdf", width = 15, height = 15)
pairs(deaTrends[, c(26, 28:36)], lower.panel = panel.smooth, upper.panel = panel.cor, main = mtitl, diag.panel = panel.hist)
```
Deethylatrazine, 2002–2012

pairs(deaTrends[, c(26, 37:41)], lower.panel = panel.smooth, upper.panel = panel.cor, main = mtitl, diag.panel = panel.hist)

# dev.off()

mtitl <- "Atrazine, 2002–2012"
pairs(atrTrends[, c(26, 28:36)], lower.panel = panel.smooth,
     upper.panel = panel.cor, main = mtitl, diag.panel = panel.hist)

Atrazine, 2002–2012

pairs(atrTrends[, c(26, 37:41)], lower.panel = panel.smooth,
     upper.panel = panel.cor, main = mtitl, diag.panel = panel.hist)

Atrazine, 2002–2012
Structural Equation Model

The structural equation model presented in the journal article for which this is supplemental material is generated by the code below, which also provides measures of model quality. The p-value for the goodness of fit test is 0.828 and this is not statistically significant at the 0.05 significance level. The null hypothesis is that there is no significant difference between the observations and the expected values from the model. The null hypothesis is not rejected; therefore, this is an acceptable model and other measures of model quality are examined. The standardized root mean square residual, srmr in the output of the fitMeasures() function, is 0.039 and is indicative of a model that fits the data well (srmr should be less than or equal to 0.08). The comparative fit index, cfi in the output of the fitMeasures() function, is 1 indicating that the model fits the data well (cfi should be greater than or equal to 0.95, with an upper limit of 1). The the root mean square error of approximation, rmsea, is 0.000, also indicating good model fit (rmsea should be less than or 0.06).

```r
allTrends <- rbind.data.frame(atrTrends, deaTrends)
pestChange <- ctndPpor ~ MSM + cornX
MSM =~ phdiMean + CPRAC_tiledrains + BFI_AVE
pestChangeM <- sem(pestChange, data = allTrends, group = "Pesticide",
estimator = "ML", verbose = FALSE, std.lv = TRUE,
std.ov = TRUE, fixed.x = TRUE, warn = TRUE)
summary(pestChangeM, stand = TRUE, rsq = TRUE, fit.measures = FALSE)
```

```
# lavaan 0.6-2 ended normally after 34 iterations
##
## Optimization method           NLMINB
## Number of free parameters    26
##
## Number of observations per group
## Atrazine          67
## Deethylatrazine   62
##
## Estimator          ML
## Model Fit Test Statistic 5.841
## Degrees of freedom  10
## P-value (Chi-square) 0.828
##
## Chi-square for each group:
##
## Atrazine          3.365
## Deethylatrazine   2.476
##
## Parameter Estimates:
##
## Information          Expected
## Information saturated (h1) model Structure
## Standard Errors      Standard
##
## Group 1 [Atrazine]:
```
## Latent Variables:

| Estimate | Std.Err | z-value | P(>|z|) | Std.lv | Std.all |
|----------|---------|---------|---------|--------|---------|
| MSM =~   |         |         |         |        |         |
| phdiMean | 0.458   | 0.208   | 2.208   | 0.027  | 0.458   | 0.462   |
| CPRAC_tiledrns | 0.878 | 0.343 | 2.557 | 0.011 | 0.878 | 0.884 |
| BFI_AVE | -0.235  | 0.153   | -1.535  | 0.125  | -0.235  | -0.237  |

## Regressions:

| Estimate | Std.Err | z-value | P(>|z|) | Std.lv | Std.all |
|----------|---------|---------|---------|--------|---------|
| ctndPpor ~ |         |         |         |        |         |
| MSM | -0.095  | 0.072   | -1.330  | 0.184  | -0.095  | -0.097  |
| cornX | 0.868   | 0.058   | 14.894  | 0.000  | 0.868   | 0.873   |

## Intercepts:

| Estimate | Std.Err | z-value | P(>|z|) | Std.lv | Std.all |
|----------|---------|---------|---------|--------|---------|
| .phdiMean | -0.000  | 0.121   | -0.000  | 1.000  | -0.000  | -0.000  |
| .CPRAC_tiledrns | 0.000 | 0.121 | 0.000 | 1.000 | 0.000 | 0.000 |
| .BFI_AVE | 0.000   | 0.059   | 0.000   | 1.000  | 0.000   | 0.000   |
| .ctndPpor | 0.000   | 0.059   | 0.000   | 1.000  | 0.000   | 0.000   |
| MSM | 0.000   |         |         |        |         |

## Variances:

| Estimate | Std.Err | z-value | P(>|z|) | Std.lv | Std.all |
|----------|---------|---------|---------|--------|---------|
| .phdiMean | 0.775   | 0.208   | 3.732   | 0.000  | 0.775   | 0.787   |
| .CPRAC_tiledrns | 0.215 | 0.580 | 0.370 | 0.711 | 0.215 | 0.218 |
| .BFI_AVE | 0.930   | 0.167   | 5.574   | 0.000  | 0.930   | 0.944   |
| .ctndPpor | 0.223   | 0.039   | 5.667   | 0.000  | 0.223   | 0.228   |
| MSM | 1.000   |         |         |        | 1.000   |

## R-Square:

<table>
<thead>
<tr>
<th>Estimate</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
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</tr>
<tr>
<td>ctndPpor</td>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

## Group 2 [Deethylatrazine]:

## Latent Variables:

| Estimate | Std.Err | z-value | P(>|z|) | Std.lv | Std.all |
|----------|---------|---------|---------|--------|---------|
| MSM =~   |         |         |         |        |         |
| phdiMean | 0.593   | 0.165   | 3.606   | 0.000  | 0.593   | 0.598   |
| CPRAC_tiledrns | 0.584 | 0.164 | 3.566 | 0.000 | 0.584 | 0.589 |
| BFI_AVE | -0.347  | 0.158   | -2.194  | 0.028  | -0.347  | -0.350  |

## Regressions:

| Estimate | Std.Err | z-value | P(>|z|) | Std.lv | Std.all |
|----------|---------|---------|---------|--------|---------|
| ctndPpor ~ |         |         |         |        |         |
| MSM | -0.483  | 0.146   | -3.296  | 0.001  | -0.483  | -0.493  |
| cornX | 0.367   | 0.107   | 3.433   | 0.001  | 0.367   | 0.372   |

## Intercepts:

| Estimate | Std.Err | z-value | P(>|z|) | Std.lv | Std.all |
|----------|---------|---------|---------|--------|---------|
| .phdiMean | -0.000  | 0.126   | -0.000  | 1.000  | -0.000  | -0.000  |
## CPRAC_tiledrns  -0.000  0.126 -0.000  1.000 -0.000 -0.000
## BFI_AVE  -0.000  0.126 -0.000  1.000 -0.000 -0.000
## ctndPpor  0.000  0.115  0.000  1.000  0.000  0.000
## MSM  0.000  0.000  0.000  0.000  0.000  0.000

## Variances:

| Parameter       | Estimate | Std.Err | z-value | P(>|z|) | Std.lv | Std.all |
|-----------------|----------|---------|---------|---------|--------|---------|
| phdiMean        | 0.632    | 0.181   | 3.497   | 0.000   | 0.632  | 0.642   |
| CPRAC_tiledrns  | 0.643    | 0.179   | 3.591   | 0.000   | 0.643  | 0.653   |
| BFI_AVE         | 0.864    | 0.170   | 5.079   | 0.000   | 0.864  | 0.878   |
| ctndPpor        | 0.594    | 0.144   | 4.129   | 0.000   | 0.594  | 0.619   |
| MSM             | 1.000    | 1.000   | 1.000   | 1.000   |

## R-Square:

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<th>Estimate</th>
</tr>
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<tr>
<td>ctndPpor</td>
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</tr>
</tbody>
</table>

`fitMeasures(pestChangeM, c("chisq", "df", "pvalue", "srmr", "cfi", "rmsea"))`

```
# chisq   df   pvalue  srmr   cfi   rmsea
# 5.841  10.000  0.828  0.039  1.000  0.000
```

mi <- `modindices(pestChangeM, power = TRUE)`

mi[mi$mi > 14,]

```
# [1] lhs op rhs block group level mi
# [8] epc sepc.all delta ncp power decision
# <0 rows> (or 0-length row.names)
```

`parameterEstimates(pestChangeM, standardized = TRUE)`

```
# lhs op rhs block group est   se    z
# 1  ctndPpor  - MSM    1  1  -0.095  0.072  -1.330
# 2  ctndPpor  - cornX  1  1  0.868  0.058  14.894
# 3   MSM  -- phdiMean 1 1  0.458  0.208  2.208
# 4  BFI_AVE  -- CPRAC_tiledrns 1 1  0.878  0.343  2.557
# 5   BFI_AVE  -- BFI_AVE  1 1  0.235  0.153  1.535
# 6  phdiMean  -- phdiMean 1 1  0.775  0.208  3.732
# 7 CPRAC_tiledrns  -- CPRAC_tiledrns 1 1  0.215  0.580  0.370
# 8  BFI_AVE  -- BFI_AVE  1 1  0.930  0.167  5.574
# 9  ctndPpor  -- ctndPpor 1 1  0.223  0.039  5.667
#10   MSM  -- MSM    1 1  1.000  0.000  NA
#11  cornX  -- cornX  1 1  0.985  0.000  NA
#12  phdiMean  -1  1  1  0.000  0.121  0.000
#13 CPRAC_tiledrns  -1  1  1  0.000  0.121  0.000
#14  BFI_AVE  -1  1  1  0.000  0.121  0.000
#15  ctndPpor  -1  1  1  0.000  0.059  0.000
#16   cornX  -1  1  1  0.000  0.000  NA
#17   MSM  -1  1  1  0.000  0.000  NA
#18  ctndPpor  - MSM  2 2  -0.483  0.146  -3.296
#19  ctndPpor  - cornX 2 2  0.367  0.107  3.433
#20   MSM  -- phdiMean 2 2  0.593  0.165  3.606
#21  BFI_AVE  -- CPRAC_tiledrns 2 2  0.584  0.164  3.566
#22   MSM  -- BFI_AVE  2 2  0.347  0.158  2.194
```
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<th>variable2</th>
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<th>ci.upper</th>
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<td>phdiMean</td>
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<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
</tbody>
</table>
The first plot is the model for atrazine. The second plot is the model for deethlyatrazine.

```
semPaths(pestChangeM, what = "stand", edge.label.cex = 0.6, sizeMan = 8, sizeLat = 8,
        nCharNodes = 0, nCharEdges = 0, exoVar = FALSE, exoCov = FALSE,
        nDigits = 3, intercepts = FALSE, label.scale = FALSE, label.cex = 0.75,
        layout = "tree2", ask = FALSE)
```
Hardware, Software, Additional Packages, and Versions Used to Generate Results

In support of making this research reproducible, the versions of hardware, software, and additional software packages are provided below.

```r
print(sessionInfo(), locale = TRUE)
```

##
## Tue 11 Jun 2019 10:22:35

##
## R version 3.5.1 (2018-07-02)
## Platform: x86_64-apple-darwin15.6.0 (64-bit)
## Running under: macOS High Sierra 10.13.6
##
## Matrix products: default
## BLAS: /Library/Frameworks/R.framework/Versions/3.5/Resources/lib/libRblas.0.dylib
## LAPACK: /Library/Frameworks/R.framework/Versions/3.5/Resources/lib/libRlapack.dylib
##
## locale:
##
## attached base packages:
## [1] stats graphics grDevices utils datasets methods base
##
## other attached packages:
## [1] semPlot_1.1 lavaan_0.6-2 plyr_1.8.4 ggplot2_3.0.0
## [5] reshape2_1.4.3 sbtools_1.1.6
##
## loaded via a namespace (and not attached):
## [1] nlme_3.1-137 RColorBrewer_1.1-2 htr_1.3.1
## [4] rprojroot_1.3-2 mi_1.0 tools_3.5.1
## [7] backports_1.1.2 R6_2.2.2 d3Network_0.5.2.1
## [10] rpart_4.1-13 Hmisc_4.1-1 lazyeval_0.2.1
## [13] colorspace_1.3-2 nnet_7.3-12 withr_2.1.2
## [16] tidyselect_0.2.4 gridExtra_2.3 mnormt_1.5-5
## [19] curl_3.2 compiler_3.5.1 fdrtool_1.2.15
## [22] qgraph_1.5 htmlTable_1.12 network_1.13.0.1
## [25] scales_0.5.0 checkmate_1.8.5 psych_1.8.4
## [28] pbapply_1.3-4 sem_3.1-9 stringr_1.3.1
## [31] digest_0.6.15 pbivnorm_0.6.0 foreign_0.8-70
## [34] minqa_1.2.4 markdown_1.10 rio_0.5.10
## [37] base64enc_0.1-3 jpeg_0.1-8 pkgconfig_2.0.1
## [40] htmltools_0.3.6 lme4_1.1-17 lirisR_0.1.4
## [43] htmlwidgets_1.2 rlang_0.2.1 readxl_1.1.0
## [46] huge_1.2.7 rstudioapi_0.7 bindr_0.1.1
## [49] jsonlite_1.5 gtools_3.8.1 statnet.common_4.1.4
## [52] acepack_1.4.1 dplyr_0.7.6 zip_1.0.0
## [55] car_3.0-2 magrittr_1.5 OpenMx_2.9.6
## [58] Formula_1.2-3 Matrix_1.2-14 Rcpp_0.12.17
## [61] munsell_0.5.0 abind_1.4-5 rockchalk_1.8.111
## [64] whisker_0.3-2 stringi_1.2.3 yaml_2.1.19
## [67] carData_3.0-1 MASS_7.3-50 matrixcalc_1.0-3
## [70] grid_3.5.1 parallel_3.5.1 forcats_0.3.0
## [73] lattice_0.20-35 haven_1.1.2 splines_3.5.1
## [76] hms_0.4.2 snas_2.4 knitr_1.20
```
## References


Corn Harvested for Grain -
Change in Acreage: 2007 to 2012

1 Dot = 2,000 Acres Increase
1 Dot = 2,000 Acres Decrease

2012 Census of Agriculture
12-M162
U.S. Department of Agriculture, National Agricultural Statistics Service