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Herbicides, glyphosate resistance and acute mammalian toxicity: simulating an environmental effect of glyphosate-resistant weeds in the USA

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Abstract

BACKGROUND: With the emergence of glyphosate-resistant (GR) weeds, the environmental consequences of alternatives to GR technology are of increasing importance. A well-known acute mammalian toxicity measure, the LD_{50} dose for rats, is used to assess one potential environmental impact of the loss of GR technology. A new dataset with this index is used to estimate and simulate the effects for corn, soybeans and cotton.

RESULTS: With conventional tillage it is found that the use of GR seeds reduces the number of LD_{50} doses applied per hectare by 17–98% depending on crop. With no-till, the use of GR seeds reduces LD_{50} doses only in corn. If farmers switch to conventional seeds because of GR weeds but maintain the same tillage practice, the present simulations suggest that LD_{50} doses could increase by as much as 100 LD_{50} doses per hectare in soybeans, and 500 LD_{50} doses per hectare in cotton, or 11.4 and 19.8% respectively.

CONCLUSIONS: This is the first study to use field-level data to assess GR technology with a mammalian toxicity environmental indicator. It has been found that GR crops have a positive environmental effect, and that alternatives to GR technology increase toxicity.

Keywords: genetically modified organisms; herbicide toxicity; treatment effect model; glyphosate resistance; environmental index

1 INTRODUCTION

The use of genetically modified (GM) glyphosate-resistant (GR) crops has grown dramatically in the United States since the 1990s. Currently, the GR trait is commercially available for three crops – corn, cotton and soybeans. GR soybeans are the dominant GM crop in the USA, accounting for 87% of the US soybean area in 2005.[1]

GR crops are an example of an input-substituting technological innovation. With the use of this technology, producers substitute GR seeds and glyphosate, a broad-spectrum herbicide, for other weed-controlling technologies such as cultivation and the use of non-GR seeds, other herbicides and management inputs.

The adoption of GR technology is driven by profitability considerations for the crop producer. The use of GR soybeans reduces the management costs associated with weed identification and herbicide choice. Fernandez-Cornejo and Caswell[1] report that increasing yields, reducing input cost, saving management time and making farming easier are the primary motivating factors for adopting GR seed.

Adoption of GR technology can also have environmental effects. For example, it can reduce the number of times a tractor must be driven through the field, so reducing fuel costs, pollution and soil compaction. Environmental effects do not factor into the adoption process because they do not affect profitability. Any environmental costs are 'external' to the farm. The authors focus specifically upon one environmental impact, an acute mammalian toxicity indicator developed by Nelson and Bullock[2] and based on rat LD_{50} doses. Nelson and Bullock[2] simulated profit-maximizing weed control in soybean production both with and without the use of GR seeds. They found that the use of GR technology in soybeans reduces

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LD_{50} doses. They found that the reduction depends to some degree on the latitude of the farm. The further north soybean production takes place, the smaller is the reduction in LD_{50} doses as competition from weeds becomes less serious and the profitability of the GR technology is reduced.

Glyphosate-resistant weeds might require farmers to switch to other herbicides with higher LD_{50} doses. In this paper, the authors assess this possibility, building upon the work of Nelson and Bullock[2] by using a new dataset and modeling technique to examine the effects of GR technology on soybeans and two additional crops that have GR varieties, corn and cotton. How the use of GR technology and no-till cropping affects the mammalian toxicity indicator is estimated. The impact of complete glyphosate resistance in weeds so that conventional seeds must be used everywhere is then simulated. Use is made of Agricultural Resource Management Survey (ARMS) data collected by the United States Department of Agriculture (USDA) to calculate actual farm-level LD_{50} doses, and a treatment effect regression model is employed to test the hypotheses proposed by Nelson and Bullock.[2]

2 HERBICIDE USE AND ENVIRONMENTAL INDICATORS

Some previous attempts to assess quantitatively the relative environmental consequences of GR soybeans have focused largely on the volume of herbicides applied,[3] but volume is at best an imperfect proxy for what is really of interest, the external effects of herbicides. Using active ingredient as an environmental indicator also has problems. The concept of active ingredient applies to the intended use of the pesticide, not any unintended effects. Furthermore, the other ingredients in a pesticide can have toxic effects of various kinds.

In this study, use is made of what Nelson and Miranowski[4] call a type 2 economic environmental indicator with elements of a type 3 indicator. A type 2 economic environmental indicator measures the *potential* for an environmental problem, while a type 3 indicator measures the existence and severity of an environmental problem. This indicator is used to estimate one potential environmental effect of GR soybeans, mammalian acute toxicity. The indicator might also be correlated with other environmental effects, although no attempt is made to assess that possibility in this paper. The environmental indicator is derived from a widely available measure of acute oral mammalian toxicity, the rat oral LD_{50} dose. To determine this value for a compound, a population of rats is fed increasing amounts of the active ingredient. An LD_{50} dose is the mg formulated ingredient kg^{-1} body weight that kills 50% of the population. It is important to emphasize that chemicals with a higher LD_{50} dose value are less toxic per milligram of formulated ingredient than those with low LD_{50} dose values.

The employed unit of measurement is the number of LD_{50} doses applied ha^{-1}. A single herbicide application will contain multiple doses. The widespread availability of the LD_{50} amount makes it possible to aggregate across different herbicide formulations to construct a standardized measure of acute mammalian toxicity.

3 DATA AND METHODS

In 1996 the United States Department of Agriculture (USDA), in conjunction with the National Agricultural Statistics Service (NASS), implemented the Agricultural Resource Management Survey (ARMS), which uses a stratified probability-weighted sampling design [USDA (http://www.ers.usda.gov/data/arms/GlobalDocumentation.htm)]. Probability weights are designed to give undersampled farms more influence[5] and in some cases are needed to obtain unbiased estimates.[6] Each year a different crop is chosen for intensive data collection. For the present study, use was made of field-level corn, soybeans and cotton data collected in 2001, 2002 and 2003 respectively. Survey respondents answered detailed questions regarding cultivation techniques, herbicide quantities and application practices. Over 80% of US soybean farmers report using GR seeds, and 41% practised no-till in 2002. For cotton farmers in 2003, the comparable figures are 75% GR seeds and 23% no-till. In sharp contrast, corn farmers in 2001 report only 3% use GR seeds and 19% practise no-till.

The total quantity of each herbicide product was converted to grams and divided by the LD_{50} value, which can be found on the material safety data sheets (MSDSs) provided by Crop Data Management Systems [CDMS (http://www.cdms.net)] or the Illinois Pest Management Handbook [University of Illinois Extension (http://www.extension.uiuc.edu/~vista/abstracts/aiapm2k.html)]. The total number of LD_{50} doses applied per hectare is computed by summing across all herbicides used on a field.

Table 1 reports ten herbicides commonly used in each crop and the number of milligrams of formulated material in an LD_{50} dose. For all crops, herbicides containing glyphosate are the most common (Roundup Ultra Max, Roundup Ultra, Roundup original, Glyphomax, and generic glyphosate). The most toxic of the remaining common herbicides are Touchdown Atrazine 4 L, Aatrex 4 L and Harness Extra in corn, and Direx 4 L and Cotoran 4 L used in cotton. All of these have an LD_{50} dose value of less than 2000 mg kg^{-1} body weight, whereas the LD_{50} dose value is truncated at 5000 mg for glyphosate because volume effects outweigh toxicity effects above 5000 mg. By way of comparison, the LD_{50} dose value of table salt is 3300 mg and aspirin is 750 mg. The insecticide Lorsban 4E, which is commonly used in corn and cotton and contains the active ingredient chlorpyrifos, has an LD_{50} dose value of 776.

Table 1. Ten common herbicides, by crop. LD_{50} (mg AI kg^{-1} body weight) values in parentheses[a]

Soybeans 2002	Corn 2001	Cotton 2003
Roundup Ultra Max (5000)	Atrazine 4 L (2000)	Roundup Ultra Max (5000)
Roundup Ultra (5000)	Roundup Ultra (5000)	Roundup Ultra (5000)
Roundup original (5000)	Bicep II Magnum (3271)	Roundup original (5000)
Touchdown (1298)	Clarity 4 L (3512)	Staple (4000)
Glyphomax (5000)	Hornet (5000)	Triflurian 4 EC (3738)
Extreme (5000)	Accent 75 WDG (5000)	Direx 4 L (1919)
Generic glyphosate (5000)	Aatrex 4 L (1075)	Prowl 4 EC (3956)
Canopy XL (3297)	Harness Extra (1338)	Caparol (5000)
Flexstar (3888)	Atrazine 90 DF (4346)	Cotoran 4 L (1841)
First Rate (5000)	Dual II Magnum (2675)	Glyfos X-TRA (5000)

[a] Source: authors' calculations from ARMS dataset, and material safety data sheets available at www.cdms.net. Note that the maximum LD_{50} dose value is 5000. Above that amount the volume effects of consuming the compound become significant. In that sense, the LD_{50} doses used overestimate the potential toxicity.

Table 2. Average LD_{50} herbicide doses ha^{-1} by crop, tillage practice and technology choice[a,b]

	Conventional tillage		No-till[c]	
	Non-GR	GR	Non-GR	GR
Corn (2001)	1468	748	2020	NR
Soybeans (2002)	756	591	844	847
Cotton (2003)	1910	1662	NR	1821

[a] Source: authors' calculations from ARMS dataset.
[b] Conventional tillage figures included farms that specified reduced tillage practices. Farms with LD_{50} doses per hectare greater than 25 700 and fields less than 2 hectares were removed from the dataset.
[c] NR – estimate is not reported owing to USDA/NASS confidentiality restrictions.

Table 2 reports the mean LD_{50} doses applied per hectare, by crop, cropping practice and technology choice. Since conventional tillage practices and herbicides are to some degree substitutes, the average LD_{50} doses for farms using conventional tillage are well below farms that use no-till without GR crops. Glyphosate has a low LD_{50} rate, so the use of GR crops lowers LD_{50} applications generally. In order to protect the confidential nature of the data, the authors are not permitted to present estimates that are based on less than 50 observations. Thus, the average number of LD_{50} doses for no-till GR corn or no-till conventional cotton cannot be reported. Based on a simple comparison of means, it appears that there is no substantial difference between no-till GR soybeans and conventional-till GR soybeans. However, comparing means is not a valid way to determine the impact of GR technology on LD_{50} doses. Simple means may depend upon factors not reported in Table 2, such as weed pressure.

Figures 1, 2 and 3 are maps showing the location of the NASS sample farms and the distribution of actual LD_{50} doses per hectare. There appears

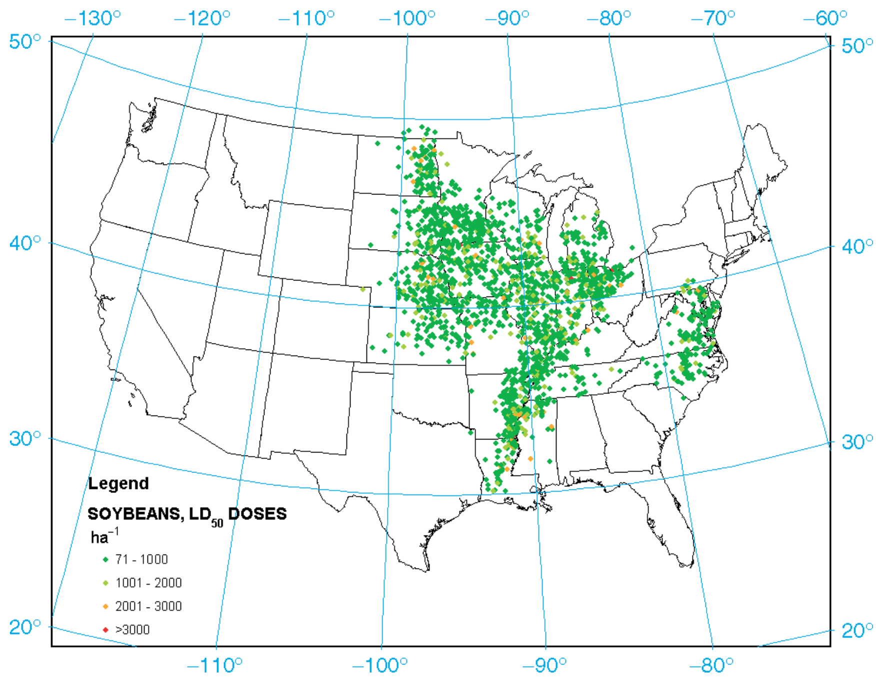

Figure 1. Soybean LD_{50} doses ha^{-1}, 2002, NASS sample farms.

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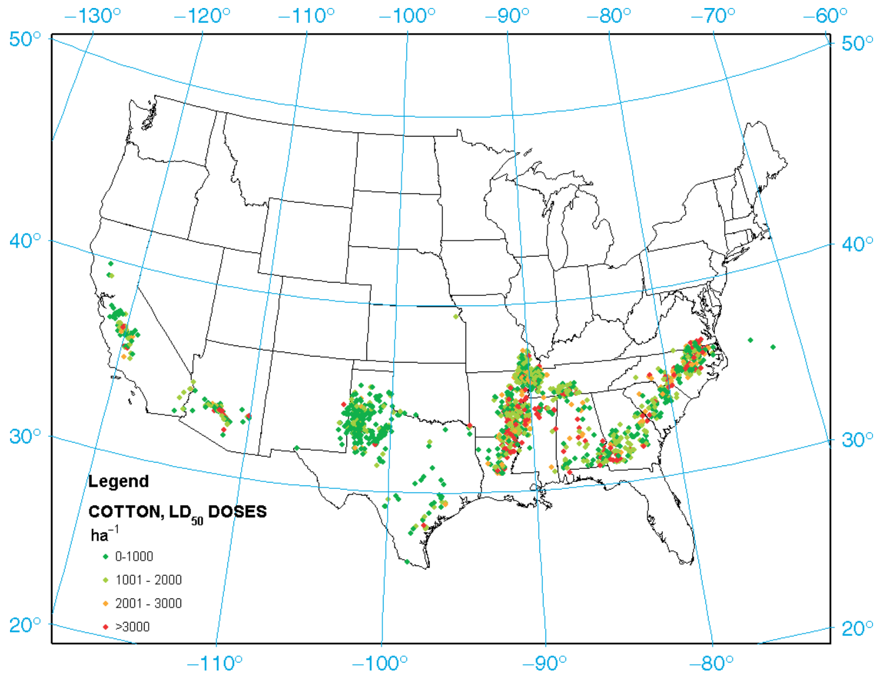

Figure 2. Corn LD_{50} doses ha^{-1}, 2001, NASS sample farms.

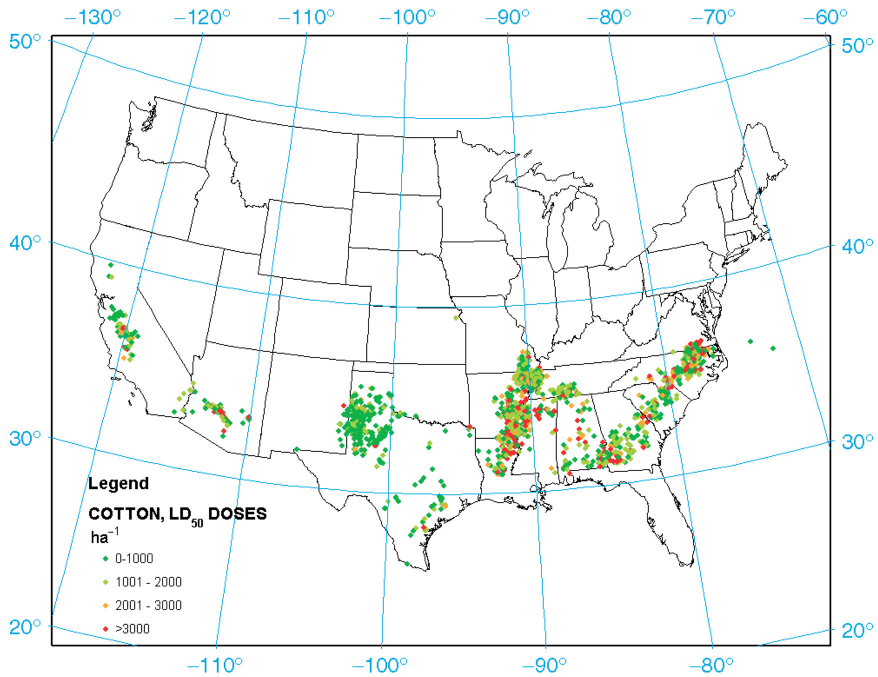

Figure 3. Cotton LD_{50} doses ha^{-1}, 2003, NASS sample farms.

to be a spatially heterogeneous distribution of LD_{50} doses in each figure, but identification of clear relationships between LD_{50} doses and various potential explanatory variables must rely on statistical analysis.

A treatment effect model is used to estimate the determinants of the differences in LD_{50} doses for GR and non-GR farmers.[7,8] The treatment effect model takes the form

$$LD_{50} = \alpha + \gamma_{NT}D_{NT} + \gamma_{GR}D_{GR} + \gamma_{GR,NT}D_{GR,NT} + \sum_{i=1}^{K} \beta_i x_i + \varepsilon$$

where LD_{50} is the number of LD_{50} doses applied for weed control, and D_{NT}, D_{GR} and $D_{NT,GR}$ are dummy variables that account for tillage and seed type combinations. If all three are zero, the field uses conventional tillage and conventional seeds. D_{NT} is 1 when no-till and conventional seeds are used. D_{GR} indicates the use of conventional tillage and GR seeds. When $D_{NT,GR}$ is 1, no-till and GR seeds are used. The term $\sum_{i=1}^{K} \beta_i x_i$ is known as the control function, and ε is a random error term. The objective is to estimate the three treatment effect parameters (γ_{NT}, γ_{GR} and γ_{GR}) conditional on the control function. The control variables x_i ($i = 1, 2, \dots, K$) are latitude, two variables related to size of operation, yield, an indicator of whether the farmer or a commercial operator applied pesticides, rainfall and a farmer assessment of the extent of weed pressure. The purpose of the control function is to provide for the unbiased estimate of the treatment parameters. Variable definitions are presented in Table 3, and descriptive statistics are presented in Table 4.

If the treatment effect is exogenous, then ordinary least-squares (OLS) estimation will provide an unbiased estimate of the treatment effect parameters.[9] In a regression context, a variable is exogenous if it is not correlated with the error term; in other words, if $Cov(x_j, \varepsilon) = 0$, OLS can be used to estimate an unbiased coefficient for the variable x_j. Otherwise x_j is endogenous and an instrumental variables method or two-stage least-squares (2SLS) is required to estimate an unbiased coefficient.

The treatment effect can be thought of as the conditional mean. Given the observable control variables, γ_{GR} is the average difference in LD_{50} doses that can be attributed to GR crop adoption on a conventional-till field. Some elements of the control function may be of importance, but their primary purpose is to allow for the unbiased estimation of the treatment parameters. This approach also allows for the inclusion of endogenous control variables.

Nelson and Bullock[2] found that pest pressure and therefore the resulting toxicity of chemical weed control methods decrease as production moves north. A latitude variable is included to control for this possibility. Nelson and Bullock[2] argue that this effect is likely to be due to precipitation or temperature differences. The present authors include a variable for annual average precipitation, which was not available to Nelson and Bullock.

Table 3. Variable descriptions

Variable	Description
Cultivation and seed choice dummies	
Till with GR	Tillage and glyphosate-resistant seed used
No-till	Tillage not used and glyphosate-resistant seed not used
No-till with GR	Tillage not used and glyphosate-resistant seed used
Latitude	Latitude in degrees
Farm size	Farm size, hectares
Field size	Hectares in the field selected for detailed data collection
Yield	kg ha^{-1}
(Farm size)^2	Farm size squared
(Field size)^2	Field size squared
(Yield)^2	Yield squared
Pesticide applicator dummies	
Employee	Dummy variable (1 = a paid employee applied pesticides)
Custom	Dummy variable (1 = a custom contractor applied pesticides)
Pressure	Pest pressure index: 0–3 for cotton and soybeans; 0–20 for corn
Precipitation	cm year^{-1} (average annual precipitation, 1961–1990, nearest-neighbor interpolation based on FAO's NewLocClim data and software)

Two variables related to size are included – total hectares planted on the farm and the size of the sampled field – as well as squared versions of these variables. The authors have no hypotheses about their impacts on acute toxicity. Farm size can also serve as a proxy for capital.

Table 4. Variable means and ranges (in parentheses)[a]

Variable	Corn (2305)[b]	Soybeans (2102)[b]	Cotton (1471)[b]
LD_{50} doses ha^{-1}	1900 (35–12 226)	729 (71–4324)	1716 (47–24 633)
Cultivation and seed choice dummies (base is till with no GR)			
Till with GR	0.019 (0–1)	0.038 (0–1)	0.569 (0–1)
No-till	0.189 (0–1)	0.525 (0–1)	0.16 (0–1)
No-till with GR	0.003 (0–1)	0.327 (0–1)	0.198 (0–1)
Yield (kg ha^{-1})	6,613 (0–16 948)	2,533.6 (53.8–4909.3)	865 (0–2242)
Farm size (100 ha)	1.661 (0.081–34.087)	2.195 (0.081–28.328)	1.143 (−2.514–4.051)
Field size (ha)	15.114 (0.405–809.4)	24.201 (0.121–392.545)	1.916 (−0.435–5.780)
Pesticide applicator dummies			
Custom	0.426 (0–1)	0.403 (0–1)	0.169 (0–1)
Employee	0.020 (0–1)	0.067 (0–1)	0.372 (0–1)
Pest pressure index	4.137 (0–20)	1.572 (0–3)	1.777 (0–3)
Precipitation	180.4 (26.2–356.9)	199.2 (51.2–341.2)	225.9 (16.5–356.9)
Latitude	34.1 (26.2–39.8)	40.2 (30.2–49.6)	34.1 (26.2–39.8)

[a] Source: authors' calculations from the ARMS dataset, except precipitation, which is derived from the FAO NewLocClim software and dataset.
[b] Number of observations used in regression.

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Yield effects on LD_{50} doses are also unclear. Low weed pressure could both increase yields and decrease acute toxicity. Alternatively, high weed pressure could cause farmers to make heavy herbicide applications, which might lead to higher yields. The dataset reports farmer perception of pest pressure relative to previous years, which is used as a measure of pest pressure.

It is hypothesized that γ_{GR} is negative. If GR technology is used with conventional tillage, it reduces the need for more toxic herbicides. The expected sign of $\gamma_{NT,GR}$ is not clear because it represents the effect of both a change from conventional tillage to no-till, which is expected to increase the use of more toxic herbicides, and the use of GR technology, which should reduce toxicity. As no-till cropping practices substitute chemical weed control for mechanical weed control, the no-till coefficient is expected to be positive. The latitude coefficient is expected to be negative because weed pressure should be less of a problem as production moves north. The precipitation variable is expected to have a positive sign. The authors have no hypotheses regarding the coefficients for the remainder of the control variables.

Prior to estimation, two specification tests were performed. The first, outlined by Ullah and Bruening,[10] was used to test the hypothesis that the survey weights are informative. It was found that the weight was only informative in the corn model, and it was estimated using a weighted regression. The second was the Durbin–Wu–Hausman endogeneity test.[11] Using the price of seed and the decision to use GR technology and no-till in the previous year as instruments, endogeneity was found in the corn models. Hence, 2SLS was used to estimate the model, while the cotton and soybean models were estimated via OLS. Studentized residuals (the regression residual divided by the standard deviation of observations) were used to detect and remove outliers in all three models. Observations with a studentized residual greater than 2.5 in absolute value were removed from the sample.

Table 5. Econometric results (the dependent variable is LD_{50} doses ha^{-1})[a,b]

	Corn		Soybeans		Cotton	
Intercept	5.77	**	7.4193	**	4.3513	**
Cultivation and seed choice dummies (base is till with no GR)						
Till with GR	−3.188	**	−0.1063	**	−0.1751	
No-till	0.113		0.1864	**	−0.2607	
No-till with GR	−1.209		0.1791	**	−0.1588	
Latitude	0.001		−0.0272	**	0.0522	**
Farm size	0.052	**	0.0183	*	0.0102	
Field size	−0.001		0.0047	**	0.0009	
Yield	0.000		0.0001		0.0001	
$(\text{Farm size})^2$	−0.001	*	−0.0009		−0.0003	
$(\text{Field size})^2$	0.000	**	0.0000	**	0.0000	
$(\text{Yield})^2$	0.000		0.0000		0.0000	
Pesticide applicator dummies						
Employee	0.002		0.0877	*	0.2692	**
Custom	0.169	**	0.0561	**	0.1804	*
Pressure	0.062	**	0.0189		−0.0102	
Precipitation	0.005	**	−0.0011	**	0.0034	**
F	17.65	**	15.19	**	5.99	**
N	2305		2102		1471	
Estimation type	Weighted		Unweighted		Unweighted	
Estimate technique	2SLS		OLS		OLS	

[a] See Table 3 for variable definitions. The farm size coefficient is based on the farm size divided by 100.
[b] Statistical significance: ** 1%; * 5%.

Table 6. Effect of change in treatment effect variable on LD_{50} doses relative to conventional till, conventional seeds (%)[a,b,c]

	Corn	Soybeans	Cotton
No-till, conventional seeds	NS[b]	20.1**	NS
Conventional till, GR seeds	−97.7*	−10.2**	−16.5*
No-till, GR seeds	−93.6**	19.5**	NS

[a] Unbiased estimated percentage change based on Kennedy's (1981) approximation method for semi-logarithmic equations.
[b] NS – does not differ significantly from zero.
[c] Statistical significance: ** 1%; * 5%.

4 RESULTS

4.1 Effect of various cropping factors on LD_{50} dose levels

As can be seen in Table 5, the present models, one for each crop, are statistically significant at the 1% level based on an overall *F*-test. All three models were estimated using a semi-log functional form. The dependent variable is the natural logarithm of the number of LD_{50} doses ha^{-1}. Care must be taken when interpreting the coefficients of dummy variables when using the semi-log form. Using Kennedy's method,[12] unbiased estimates of the percentage change attributable to the present dummy variables are given in Table 6.

In all three models the effect of shifting from tillage and conventional seeds to tillage and GR seeds is statistically significant and results in an average reduction in LD_{50} doses of 97.7% for corn, 10.2% for soybeans and 16.5% for cotton. Switching from conventional till to no-till using conventional seeds increases LD_{50} doses in soybeans by 20.1%, but has no statistically significant impact in corn and cotton. Switching from conventional tillage and conventional seeds to no-till and GR seeds results in a 93.6% decrease in LD_{50} doses in the corn, a 19.5% increase in soybeans and no significant change in cotton.

In the soybean model the null hypothesis that with no-till cultivation the choice of seed type had no effect on the number of LD_{50} doses could not be rejected at the 5% level using an *F*-test. The implication is that, from a mammalian toxicity indicator standpoint, there is no difference between GR and non-GR no-till fields. This could be due to the similarities in weed control strategies. Glyphosate can be used in a preplanting burndown phase in both cases. After the crop emerges, the canopy it creates will aid in weed control in both cases. The only difference in weed control strategy is the choice of post-emergence herbicide. In these data, that difference is not significant.

The coefficient on the latitude variable is statistically different from zero and negative only in the soybean model. Holding everything else constant, moving 1° north reduces the number of LD_{50} doses by 2.72%. Unexpectedly, the latitude coefficient is positive and significant in the cotton model. The authors suspect that this is due to the relatively small range of latitudes in which cotton is grown. The latitude effect is not statistically significant for corn. The precipitation coefficient is positive and significant in the corn and cotton models; increasing rainfall will increase weed pressure, and thus the optimal number of LD_{50} doses also increases. Interestingly, the soybean model shows a statistically significant and negative precipitation coefficient. This may be the result of collinearity between latitude and rainfall.

4.2 Simulating the effect of GR weeds

As glyphosate-resistant weeds evolve, the use of GR seeds will become less effective. Using the present econometric results, the effect of switching all farms currently using GR technology to conventional seeds is simulated. An important assumption is that the same tillage practices are used before and after the change. In fact, it is possible that some farmers would switch from no-till to conventional tillage when faced with GR-resistant weeds. However, there is no way of identifying which farmers would change tillage. Simulated changes in LD_{50} doses ha^{-1} were created by using the present estimated models to generate predicted values both with and without the use of GR seeds. Figures 4, 5 and 6 show the results of the simulation.

The simulation of the effect of GR weeds shows the smallest changes for soybeans. The average soybean farm has a 11.4% increase, which in absolute terms translates into an increase of 20–120 LD_{50} doses ha^{-1}. There appears to be a spatial pattern to the simulated changes, with the increase in LD_{50} doses decreasing as production moves north. This is consistent with Nelson and Bullock's hypothesis[2] that farms in the south have a large reduction in the number of LD_{50} doses when GR seeds are used.

For corn, the GR weed simulation shows a potential increase of over 3000 LD_{50} doses ha^{-1}. However, the number of corn fields with a simulated change is very small. This result can be attributed to the very low GR corn adoption rates in 2001, and it is unclear how reliable this result is.

The average cotton farm has a 19.8% increase, which in absolute terms translates into an increase of 1–500 LD_{50} doses ha^{-1}. The cotton simulation shows a strong east–west pattern, likely owing to rainfall and the associated weed pressure. An anonymous reviewer noted that rainfall leads to runoff and leaching of herbicides in addition to weed growth, thus pointing out another way that rainfall can increase the effects of LD_{50} doses. The present simulations show that cotton farms in the southeast would be subject to very large increases in LD_{50} doses, while farms in Texas, New Mexico and California would be subject to smaller increases if they were no longer able to plant GR cotton.

6 CONCLUSIONS

In this paper, a national farm-level dataset and a treatment effect model are used to assess an environmental impact of the use of GR technology in corn, soybeans and cotton production, and the potential consequences of its loss due to glyphosate-resistant weeds. The results for soybeans are similar to

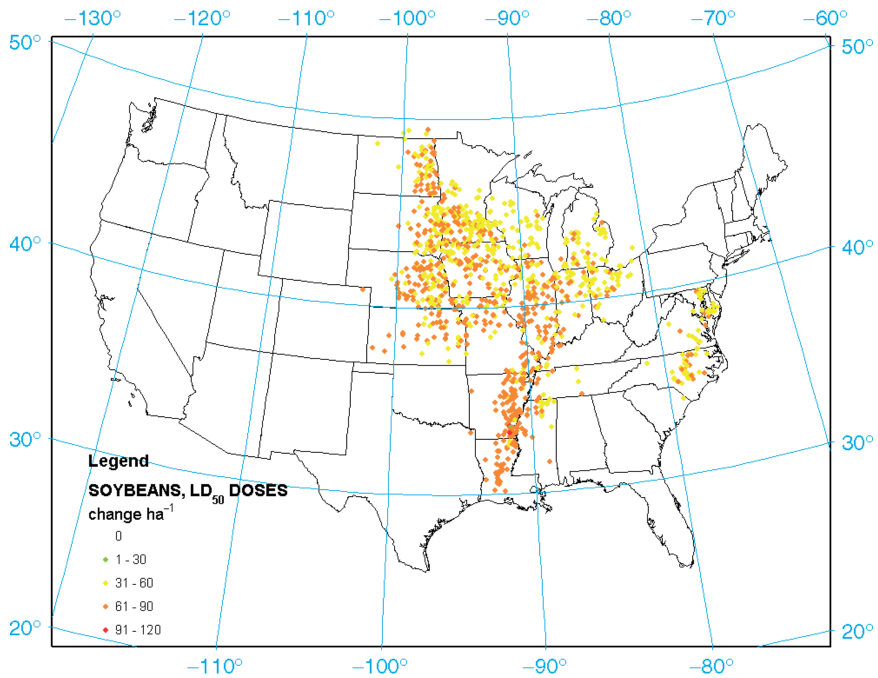

Figure 4. Change in LD_{50} doses ha^{-1} when GR technology is not available, soybeans.

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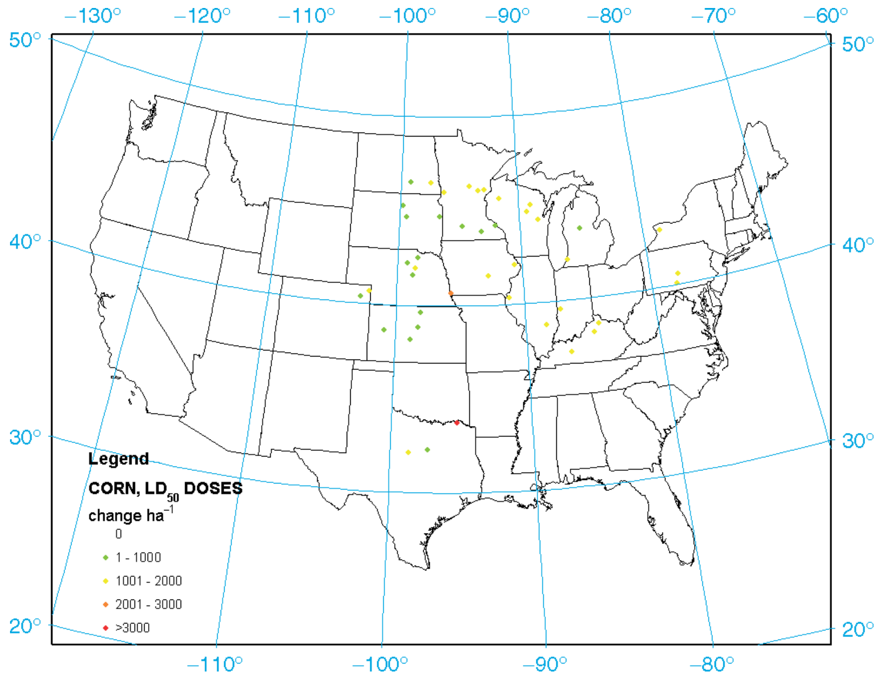

Figure 5. Change in LD_{50} doses ha^{-1} when GR technology is not available, corn.

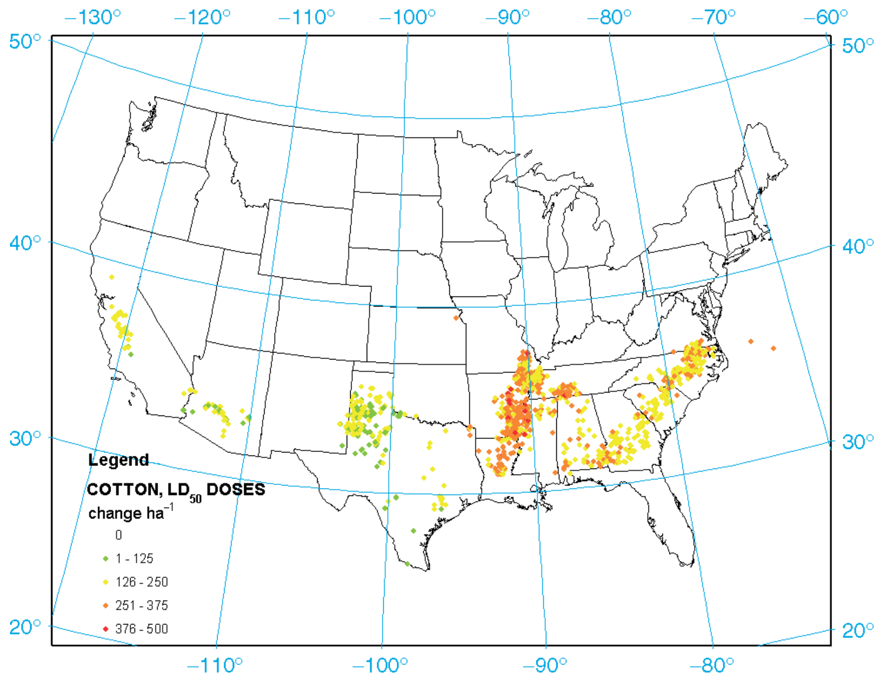

Figure 6. Change in LD_{50} doses ha^{-1} when GR technology is not available, cotton.

earlier work done by Nelson and Bullock,[2] who found that the use of GR technology decreases the number LD_{50} doses applied per hectare. More generally, it is found that the extent of the reduction depends on crop and whether the tillage system changes. With conventional tillage, a switch from conventional seeds to GR seeds resulted in reductions in LD_{50} doses ha^{-1} by 97.7% on the average corn field, 10.2% on the average soybean field and 16.5% on the average cotton field. Switching to no-till and to GR seeds results in a reduction in the number of LD_{50} doses ha^{-1} by 93.6% in corn, an increase of 19.5% in soybeans and no statistically significant change in cotton. Because no-till replaces mechanical weed control with chemical weed control, it is expected to increase the LD_{50} doses, as in fact it does for all three crops, even with the use of GR seeds.

The authors simulated the effect of glyphosate-resistant weeds by assuming the extreme case that all farmers would switch to non-GR seed technology. Thus, it is a worst-case scenario that is being examined, where farmers are not able to control GR weeds by adding additional herbicides to the tank mix. The present simulation assumed that the farmers would not change tillage practice, and the results show a wide range of potential impacts, with the smallest impacts in soybeans. Removing GR seed technology results in an increase in LD_{50} doses of up to 100 in soybeans and up to 500 in cotton, increases of 11.4 and 19.8% respectively. Given the small number of farms using GR corn in the present sample, the corn results are suspect. More conclusive corn results await newer data.

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