Don't Farm So Close to Me: Testing Whether Spatial Externalities Contributed to the Emergence of Glyphosate-Resistant Weed Populations

Dallas Wood

North Carolina State University

dwwood@ncsu.edu

Selected Paper prepared for presentation at the Agricultural & Applied Economics Association's 2014 AAEA Annual Meeting, Minneapolis, MN, July 27-29, 2014.

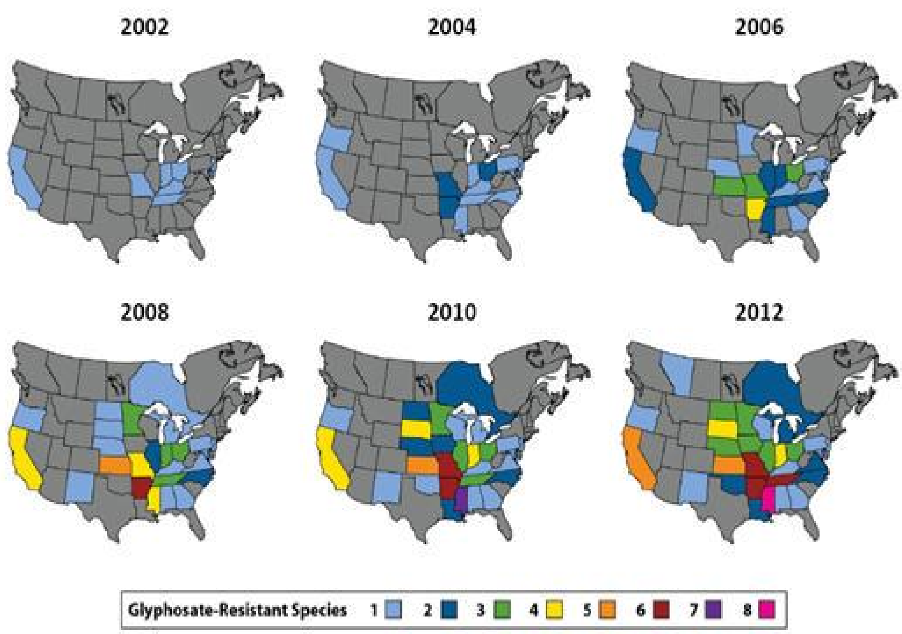
 WORKING PAPER. DO NOT CITE.

1.0 GR-Weed Populations Threaten the Value of GR-Crops.

According to recent studies, glyphosate-resistant (GR) crops (marketed by Monsanto as "Roundup Ready") represent more than 80% of the 120 million ha of transgenic crops grown annually worldwide (Duke and Powles, 2009). GR varieties of crops such as soybeans and maize (corn) have gained such wide acceptance around the world in large part because glyphosate delivers superior weed control combined with low toxicity (Duke and Powles, 2009). However, recent research suggests that the effectiveness of GR crop technology may be diminishing as the population of GR weeds spreads.

Data collected by Heap (2012) reveal that glyphosate resistance has been identified in 24 weed species worldwide. Further, GR weed populations have been confirmed in 29 states across the U.S. The spread of these GR weed populations over the past 10 years is illustrated in Figure 1.

Figure 1. Confirmed glyphosate-resistant weed populations in North America, 2002-2012



Source: Pioneer Hi-Bred (2012)

If this trend continues, this will not only threaten the economic viability of GR crops, but may threaten environmental quality as farmers turn to more toxic herbicides as glyphosate becomes less effective.

2.0 Research Goal: Explaining the Emergence of GR-Weed Populations.

The scientific explanation for why GR-Weed populations have emerged is well understood. Glyphosate is a broad-spectrum herbicide that is designed to kill a large variety of weeds. However, some individual weeds possess genetic traits that enable them to survive glyphosate treatment. As a result, these weeds have a better chance to reproduce than weeds without the trait. This leads to weeds exhibiting glyphosate resistance becoming an increasingly large fraction of the weed population. In other words, the appearance of GR weeds this season is positively related to glyphosate application last season.

While the evolutionary mechanisms describing how over-application of glyphosate can lead to GR-weeds is well understood, it is not so clear why farmers would not moderate their glyphosate application in the first place. Some agricultural economists have argued that the over-application of glyphosate is the result of a classic externalities problem. Specifically, Marsh et al. (2006) argue that some weed species that can become resistant to glyphosate are highly mobile and can travel relatively long distances. For example, wind alone can disperse the seeds of the *Conyza canadensis* up to 500 meters or farther (Dauer et al, 2007). Similarly, pollen movement of herbicide resistant genes has been shown to be at least 2.6 km (Rieger et al., 2004). This means that whether a GR-weed population emerges in a farmer's field will not only depend on his weed management practices, but those of his neighbors. As a result, any individual farmer has less incentive to moderate his use of glyphosate.

Although it seems plausible that externalities could lead to over application of glyphosate, there are still some open questions. Specifically, why has a Coasean bargain to regulate glyphosate use not been reached by farmers living in the same community? Five hundred meters is a large distance for a seed to travel, but not a farmer. Even 2.6 km could be considered a short distance to individuals living in a relatively rural community. So why are transaction costs so large? If they are not, can we be sure glyphosate use is being driven by resistance externalities at all?

An alternative explanation for why farmers have not moderated their glyphosate use is that farmers are typically myopic or misinformed in some way. For example, Doohan et al. (2010) interviewed 44 U.S. farmers and found that they are unlikely to perceive any risks associated with glyphosate use (including the development of resistance). They argue that this is due to farmers being averse to complicated weed management practices and focused on maximizing financial returns in the short term. Based on their results, Doohan et al. claim that education could be used to make farmers appreciate the risks of over using glyphosate and the practicality of preventing weed resistance. However, since their research is based on series of qualitative interviews with 44 farmers, one cannot generalize Doohan's conclusion to the entire population of U.S. farmers.

The fact that no one can fully explain why farmers do not moderate their glyphosate use makes it difficult for policy makers to choose a course of action. If farmers are truly myopic or misinformed, this would suggest that an educational campaign could be used reduce glyphosate application. However, if over-application is being driven by externalities associated with mobile weed populations, then an educational campaign would be ineffective and less popular, incentive-based policies (such as a tax on glyphosate application) would need to be considered.

Although it is critical for policymakers to understand these issues, no previous study has attempted to empirically test whether externalities are a driving factor in glyphosate application decisions. In this proposal, I will explore how such a test could be performed. First, I will develop a conceptual model that allows me to formalize the hypotheses I intend to test. Second, I will outline an empirical strategy to test these hypotheses. Lastly, I test this hypothesis using state-level data.

3.0 Conceptual Model

The amount of glyphosate a farmer applies to his field depends on the amount of glyphosate other farmers apply to their fields. This opens the opportunity for each farmer to exhibit strategic behavior that can best be captured through a game theoretic model. Specifically, I model this as a simultaneous (static) game between n players. My choice to model this as a s game rests on my assumption that farmer is only maximizing profit over 2 periods. In the second and final period, the farmer has no strategic concerns because he is not considering the payoff of glyphosate over subsequent periods. Therefore, he will simply apply glyphosate until the marginal benefit in the second period is equal to the marginal cost in the second period. All functional forms are chosen for computational simplicity.

3.1 Define Payoff Function for Farmer i

Consider a representative farmer (i) that produces a single agricultural commodity (such as GR-corn). I assume for analytical convenience that the farmer seeks to maximize profits over two cropping cycles, where profit in each season is defined as the difference between total revenue and total costs (the cost of glyphosate and all other inputs). More formally I can express the expected profits of farmer I:

$$\Pi = \left\{\mathrm{p}Q_1^i - \mathrm{w}X_1^i - \mathrm{q}g_1^i\right\} + \beta\left\{\mathrm{p}Q_2^i - \mathrm{w}X_2^i - \mathrm{q}g_2^i\right\} \qquad \textbf{(Eq.1)}$$

where p is the price of the output, Q is actual crop yield, g is the pounds of glyphosate applied by the individual farmer (i), q is the price of each pound of glyphosate, X is all production inputs not related to weed management (e.g. labor, fertilizer, etc), w is the price of these inputs, and βis the discount rate. Note, for the rest of Step 1, we drop the “i” superscript for expositional convenience. Everything written in this section refers to the representative farmer (i).

At the beginning of each cropping cycle, we assume the farmer’s crop can yield a maximum harvest of Y_t units. However, by the end of this cycle, only a fraction of this maximum yield is harvested and sold on the open market at price p. This is because some percentage of the crop is destroyed by weeds present in the field. This percentage is determined by $D(W_t)$, which is a function of the number of weeds present in the field at the end of cropping cycle.[1] Therefore, we can rewrite the total output produced by the farmer as follows:

$$Q_t = Y_t\big(1 - D(W_t)\big) \qquad \textbf{(Eq.2)}$$

Substituting this expression into the original profit function yields:

$$\Pi = \big[pY_1\big(1 - D(W_1)\big) - wX_1 - qg_1\big] + \beta\big[pY_2\big(1 - D(W_2)\big) - wX_2 - qg_2\big] \qquad \textbf{(Eq.3)}$$

To carry this analysis further, I must make some assumptions about the relationship between the percentage of crops damaged and number of weeds present at the end of the cropping cycle. Specifically, I assume that the damages done to potential crop yield are proportional to the number of weeds present in the field at the time of harvest:

$$D(W_t) = \phi W_t \qquad \textbf{(Eq.4)}$$

where ϕ is a parameter.

The number of weeds present in the field at the end of the cropping cycle will depend on the fraction of weeds that are eliminated by the farmer through the use of glyphosate (g_t). However, as previously discussed, not all weeds are equally vulnerable to glyphosate. Some portion of the weed population present in the field can be more resistant to glyphosate than others. In this simplified conceptual model, I divide weeds into two categories—those that are completely vulnerable to glyphosate (W_v) and those that are entirely resistant to glyphosate (W_r). Therefore, the number of weeds present in the field at the end of a harvest period will be determined by the following:

[1] To introduce the damage that weeds cause to GR-corn yield, I use an approach similar to the damage control model presented by Lichtenberg & Zilberman (1986).

$$W_t = W_v\left(1 - \ln\left(\frac{g_t}{g^{max}}e\right)\right) + W_r;\ \ \frac{g^{max}}{e} \leq g_t \leq g^{max} \quad \textbf{(Eq.5)}$$

where g^{max} is the amount of glyphosate that will eradicate all vulnerable weeds in the farmer's field. Note that I multiply g_t by $\frac{e}{g^{max}}$ and restrict its values to fall between $\frac{g^{max}}{e} \leq g_t \leq g^{max}$ to ensure that the product of $\ln\left(\frac{g_t}{g^{max}}e\right)$ falls between 0 and 1. I chose this functional form to obtain a weed control function that exhibits decreasing returns to scale (a decreasing percentage of weeds is destroyed as more glyphosate is applied to the field).

In order to incorporate increasing resistance with glyphosate use, I must specify the resistance function. I do this by assuming that a fixed number of weeds appear in the farmer's field each period (W_0) and that some percentage of these weeds will be resistant to glyphosate and some will be vulnerable. As a described above, we assume the percentage of GR-weeds appearing in a field is increasing in total amount of glyphosate applied by all farmers in the community in the previous period (G_{t-1}) but that it is increasing at a decreasing rate. Specifically, I assume:

$$W_r = W_0\left(\ln\left(\frac{G_{t-1}}{G^{max}}e\right)\right);\ \frac{G^{max}}{e} \leq G_{t-1} \leq G^{max} \quad \textbf{(Eq.6)}$$

where G^{max} is the amount of glyphosate that will eradicate all vulnerable weeds in the farmer's field. Note that I multiply g_t by $\frac{e}{G^{max}}$ and restrict its values to fall between $\frac{G^{max}}{e} \leq G_{t-1} \leq G^{max}$ to ensure that the product of $\ln\left(\frac{G_{t-1}}{G^{max}}e\right)$ falls between 0 and 1.

Since, by definition, the sum of W_r and W_v must equal W_0, this implied the number of weeds that are vulnerable to glyphosate each period will (W_0-W_r) or more specifically:

$$W_v = W_0\left(1 - \ln\left(\frac{G_{t-1}}{G^{max}}e\right)\right) \qquad \textbf{(Eq.7)}$$

Substituting these expressions for Wv and Wr into Eq.5 yields

$$W_t = \left[W_0\left(1 - \ln\left(\frac{G_1}{G^{max}}e\right)\right)\left(1 - \ln\left(\frac{g_2}{g^{max}}e\right)\right)\right] + \left[W_0\left(\ln\left(\frac{G_1}{G^{max}}e\right)\right)\right] \qquad \textbf{(Eq.8)}$$

Substituting this expression for Wt into the damage function and substituting the damage function back into the two period profit function yields the following payoff function for farmer 1.

$$\Pi = \left[pY_1\left(1 - \phi\left(W_0\left(1 - \ln\left(\frac{g_1}{g^{max}}e\right)\right)\right)\right) - qg_1\right] +$$

$$\beta\left[pY_2\left(1 - \phi\left(\left[W_0\left(1 - \ln\left(\frac{G_1}{G^{max}}e\right)\right)\left(1 - \ln\left(\frac{g_2}{g^{max}}e\right)\right)\right] + \left[W_0\left(\ln\left(\frac{G_1}{G^{max}}e\right)\right)\right]\right)\right) - qg_2\right] \qquad \textbf{(Eq.9)}$$

3.2 Derive Best Response Function for Farmer i

Using this modified profit equation, we can find the best response function for farmer i by taking the first derivative with respect to g_1 and g_2 and setting these derivatives equal to zero ($\frac{\partial \Pi}{\partial g_1} = 0$, $\frac{\partial \Pi}{\partial g_2} = 0$). These first order conditions are:

$$\frac{\partial \Pi}{\partial g_1} = 0 \Rightarrow \frac{pY_1\phi W_0}{\frac{g_1}{g^{max}}e} - q - \frac{\beta pY_2\phi W_0 \ln\left(\frac{g_2}{g^{max}}e\right)}{G_1} = 0 \qquad \textbf{(Eq.10)}$$

$$\frac{\partial \Pi}{\partial g_2} = 0 \Rightarrow \frac{\beta pY_2\phi W_0}{\frac{g_2}{g^{max}}e} - \frac{\beta\phi W_0 \ln\left(\frac{G_1}{G^{max}}e\right)}{\frac{g_2}{g^{max}}e} - \beta q = 0 \qquad \textbf{(Eq.11)}$$

Solving Eq.11 for g_2 yields

$$g_2 = \frac{g^{max}\phi W_0 \left(pY_2 - \ln\left(\frac{G_1}{G^{max}} e\right)\right)}{qe}$$

Substituting this back into Eq.10 yields the following profit maximization condition for applying glyphosate in period.

$$\frac{pY_1\phi W_0}{\frac{g_1^i}{g^{max}}e} = q + \frac{\beta pY_2\phi W_0 \ln\left(\frac{\phi W_0\left(pY_2 - \ln\left(\frac{G_1}{G^{max}}e\right)\right)}{q}\right)}{G_1} \qquad \textbf{(Eq.12)}$$

3.3 Equilibrium

At this point we assume the equilibrium glyphosate application rate across all farmers is symmetric and that each of the other n farmers in the community will apply the same amount of glyphosate to his field.

$$\frac{pY_1\phi W_0}{\frac{g_1}{g^{max}}e} = q + \frac{\beta pY_2\phi W_0 \ln\left(\frac{\phi W_0\left(pY_2 - \ln\left(\frac{ng_1}{G^{max}}e\right)\right)}{q}\right)}{ng_1} \qquad \textbf{(Eq.13)}$$

Taking the limit of this expression as n goes to infinity yields the following result

$$\lim_{n\to\infty}\left(\frac{pY_1\phi W_0}{\frac{g_1}{g^{max}}e}\right) = \lim_{n\to\infty}(q) + \lim_{n\to\infty}\left(\frac{\beta pY_2 bW_0 \ln\left(\frac{\beta\phi W_0\left(pY_2 - \ln\left(\frac{ng_1}{G^{max}}e\right)\right)}{q}\right)}{ng_1}\right) \qquad \textbf{(Eq.14)}$$

This yields the following result:

$$\frac{pY_1\phi W_0}{\frac{g_1}{g^{max}}e} = q \qquad \textbf{(Eq.15)}$$

As n approaches infinity, the marginal cost of applying glyphosate decreases. In fact, as n becomes very large, the marginal cost of applying glyphosate today tends to the level we would observe if the farmer did not consider the future damages from applying glyphosate (i.e. where $\beta=0$).

3.4 Testable Implications of the Conceptual Model

Based on the discussion above, we can see that if a farmer's glyphosate application rates vary with the level of agricultural activity surrounding them, this can be evidence that externalities are significant contributors to glyphosate application decisions. Therefore the hypothesis I wish to test can be stated as follows:

$$H_{null}: \frac{\partial g_{it}}{\partial n} = 0$$

$$H_{alt}: \frac{\partial g_{it}}{\partial n} > 0$$

If the null hypothesis is rejected, I would take this as evidence that resistance externalities are significant contributors to glyphosate application decisions. However, if we do not reject the null hypothesis, we cannot distinguish between the two hypotheses that 1) farmers are myopic and only focus on short-term provided or 2) the resistance externalities associated with glyphosate have been internalized through private negotiations. In the next section, I outline two empirical strategies that could be used to test this hypothesis.

4.0 Empirical Strategy

To estimate the impact that the level of farming activity surrounding a farmer will have on the amount of glyphosate that he applies to his fields, one could simply estimate the unconditional factor demand equation--$g = f(n, P, q, Z)$. A log-linear approximation of this factor demand can be expressed as:

$$\ln(g_{it}) = \beta_0 + \beta_1 \ln(n_{it}) + \beta_2 \ln(P_t) + \beta_3 \ln(q_t) + \beta_4 \ln(Z_{it}) + \varepsilon_{it} \qquad \textbf{(Eq.16)}$$

where g is glyphosate application per acre for farmer i at time t, n is the number of corn growing operations surrounding farmer i at time t, P is the world price of farmer i's output at time t, q is the world price of glyphosate at time t, Z is a vector of geographic characteristics that may influence the amount of glyphosate a farmer applies (soil quality, access to irrigation, etc.), and is ε the error term.

In Eq.16, the parameter of interest is β_1. If glyphosate application is increasing with the level of agricultural activity surrounding a farmer, this would be evidence that externalities are a driving factor in glyphosate application decisions. Therefore we would seek to test the following hypotheses:

$$H_{null}: \beta_1 = 0$$

$$H_{alt}: \beta_1 > 0$$

5.0 Data

Data on the mean glyphosate application rates of corn growers in 18 states from 1997 to 2007 using NASS QuickStat database. Specifically, state-level averages were obtained for farmers in Colorado, Georgia, Illinois, Indiana, Iowa, Kansas, Kentucky, Michigan, Minnesota, Missouri, Nebraska, New York, North Carolina, North Dakota, Ohio, Pennsylvania, South Dakota, Texas, Wisconsin. This data was collected as part of the Agricultural Resource Management Survey. As discussed in the theoretical model above, glyphosate application rates are determined by the number of operations surrounding a farmer, the price of corn, the price of glyphosate, and geographic characteristics. Data for the number of operations and the price of corn were obtained for each state listed above from 1997 to 2007. Unfortunately, data on glyphosate prices could not be obtained for years prior to 2001. Therefore, fluctuations in glyphosate prices overtime are captured using annual dummies. Similarly, to account for time-invariant geographic characteristics, we also included dummies for the USDA production region each state was located in.

6.0 Results

Results for estimating the unconditional factor demand for glyphosate represented by Eq.16 using OLS are reported in columns four and five of Table 2. The partial effect of increasing the number of corn growing operations in the state of glyphosate applications rates is positive and statistically significant. This is true even after controlling for time-invariant differences across USDA production regions. Specifically, a 1% increase the number of operations in each state increases glyphosate application rates by 0.1%.

Table 1. OLS Regressions of ln(Glyphosate Application Rates) on Number of Operations (n=114)

	Parameter Estimate	**Standard Error**	**Parameter Estimate**	**Standard Error**
	Exclude Regional and Year Dummies		Include Regional and Year Dummies	
Constant	-1.27**	0.28	-2.66**	0.51
ln(Operations)	0.06**	0.03	0.10**	0.04
ln(Corn Price)	0.37**	0.09	0.96**	0.33

Note: ** denotes p-value < 0.05, *p-value < 0.10.

7.0 Conclusions

In this paper, I have investigated the impact of spatial externalities on gylphoate use among corn farmers across the United States. I found that the impact that an increase in the number of operations surrounding a corn farmer will lead him to increase his glyphosate application rates. Based on the conceptual model described above, this suggests that spatial externalities may have led farmers to use more glyphosate on their fields than they would if such externalities had not existed, hastening the emergence of glyphosate resistant weeds.

6.0 References

Brown, Zachary S., Katherine L. Dickinson, and Randall A. Kramer. "Insecticide Resistance and Malaria Vector Control: The Importance of Fitness Cost Mechanisms in Determining Economically Optimal Control Trajectories." *Journal of Economic Entomology* 106, no. 1 (2013): 366-374.

Clark, Stephen, and Gerald A. Carlson. "Testing for common versus private property: The case of pesticide resistance." *Journal of Environmental Economics and Management* 19, no. 1 (1990): 45-60.

Dauer ,Joseph, David Mortensen, and Mark Vangessel. "Temporal and spatial dynamics of long-distance Conyza canadensis seed dispersal." *Journal of Applied Ecology* 44, no. 1 (2007): 105-114.

Doohan, Doug, Robyn Wilson, Elizabeth Canales, and Jason Parker. "Investigating the human dimension of weed management: new tools of the trade." *Weed Science* 58, no. 4 (2010): 503-510.

Duke, S. and Powles, S. (2009). “Glyphosate-Resistant Crops and Weeds: Now and in the Future”. Agbioforum. vol12(3&4). Available at <http://www.agbioforum.org/v12n34/v12n34a10-duke.htm>.

Heap, I. (2013). *The International Survey of Herbicide Resistant Weeds.* Last Accessed March 1, 2013. Available at <www.weedscience.org>.

Hueth, D., and Uri Regev. "Optimal agricultural pest management with increasing pest resistance." *American Journal of Agricultural Economics* 56, no. 3 (1974): 543-552.

Lichtenberg, Erik, and David Zilberman. "The econometrics of damage control: why specification matters." *American Journal of Agricultural Economics* 68, no. 2 (1986): 261-273.

Marsh, Sally, and Rick S. Llewellyn and Stephen B. Powles. “Social Costs of Herbicide Resistance: The Case of Resistance to Glyphosate.” Available at <http://ageconsearch.umn.edu/bitstream/25413/1/pp060795.pdf>

Regev, Uri, Haim Shalit, and A. P. Gutierrez. "On the optimal allocation of pesticides with increasing resistance: the case of alfalfa weevil." *Journal of Environmental Economics and Management* 10, no. 1 (1983): 86-100.

USDA (2010). ARMS Questionnaires and Documentation. Available at <http://www.ers.usda.gov/data-products/arms-farm-financial-and-crop-production-practices/questionnaires-manuals.aspx#27871>.