The impact of weather variability and climate change on pesticides application in the US - An empirical investigation

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Abstract

Weather variability and climate change affect the application of pesticides in agriculture, in turn impacting the environment. Using panel data regression for the US, we find that weather and climate differences significantly influence the application rates of most pesticides. Subsequently, the regression results are linked to downscaled climate change scenario the Canadian and Hadley climate change models. We find that the application of most pesticides increase under both scenarios. The projection results vary by crop, region, and pesticide.

KEY WORDS: Climate change, weather variability, pesticide, regression, panel data, North America, US

1 INTRODUCTION

Pesticides are chemical products designed to prevent, destroy, repel, or reduce pests such as insects, mice and other animals, weeds, fungi, bacteria and viruses. They are widely employed and generally considered essential to modern cropping systems. They contribute to a stable supply of affordable agricultural products of uniform quality. In the US, agriculture accounts for over two thirds of domestic pesticide sales and three quarters of the total 1.1 billion pounds of active ingredients applied annually in recent years, at a cost of $10 billions (USDA, 2004). Several studies have empirically estimated the marginal productivity of pesticides for US agriculture. Most of them indicate that the average revenue increase exceeds the pesticides price. Particularly, Fernandez- Cornejo et al. (1998) find an average return for corn of above $2 per dollar of pesticides expenditure. Pimentel (1997) reports that each dollar spent on pesticide control returns about $4 in increased crop revenue.

In contrast to the economic benefits, the use of pesticides causes adverse externalities on human health and environment. Many studies evaluate the possible association between pesticides and risk of cancer (Teitelbaum et al. 2007,, Cockburn 2007, Lee et al. 2007, Alavanja et al. 2006) and other disease such as Parkinson's disease (Hancock et al.2008) heart disease (Watkinson et al. 1986) and sterility (Wheater 1978). Adverse environmental externalities of pesticide use include the loss of biodiversity. There are some known instances of significant non-target species population declines due to pesticide use. For example, the insecticide carbofuran is very efficient at killing a large number of songbirds breeding on the edge of treated fields (McLaughlin et al. 1995). Kellogg et al. (2000) estimate losses via leaching and runoff for pesticides applied on 12 major crops over a 17 year period. They report losses between 4.0 and 5.5 percent of the amount applied pesticides. Pimentel (2005) finds that pesticides applied at recommended dose rates indirectly cost the U.S. at least $10 billion a year in public health expenditures (12 percent), biodiversity losses (33 percent), cost of pesticides resistance (16 percent), crop damages (14 percent), groundwater contamination (20 percent), and governmental regulation to prevent damages (5 percent) or about 1 percent of the US GDP in 2007 of

$13.8 trillion (BEA, 2008). This figure includes losses from increased pest resistance; decline of natural pollinators (including bees and butterflies) and pest predators; reduced viability of crop, fish, and bird populations; groundwater contamination; harm to pets and livestock - and an estimated $787 million loss from human health treatments. From the conventional view, pesticides have been considered to be risk reducing, leading to higher optimal use.

During the last decade many countries have made extensive efforts to control and reduce pesticide applications. However, pesticides are still applied at large amounts. Currently, world pesticide consumption exceeds 2.2 billion kilograms of active ingredients per year (EPA, 2002).

Weather and climate affect many agricultural decisions including crop choices, water management, and crop protection. Several studies investigate agricultural consequences of climate change (Kaiser et al. (1995), Lewandrowski et al. (1999), Adams et al. (1990)). A relatively comprehensive analysis of likely effects of climate change and climate variability to the US agriculture has been carried out by the US Global Change Program (USDA, 2008). Across their and other studies, there is broad agreement that climate changes will have substantial ramifications for US agriculture. A major concern involves the impact of climate change on pest populations. Using historical data about pest infestations and migration, Patterson et al. (1999) deduced that temperature and precipitation constitute important determinants of pest incidence. Chen et al. (2001) study the relationship between pesticide and climate with a statistical model. Their results suggest that climate change will increase pesticide expenditures in US agriculture. However, their study is limited to a few products (mainly cereals) and distinguishes only broad pesticide categories, i.e. herbicides, fungicides, and insecticides.

This study uses a similar approach as in Chen et al. (2001) but considers more crop types (including all major food products) and a more detailed classification of pesticides. The pesticides are aggregated to the chemical class they belong to. Each chemical class includes a group of active ingredients (pesticides) with similar properties. To estimate the potential effects of climate change on the use of pesticides, we link panel data regression coefficients to climate change scenario results from two general circulation models. The paper proceeds as follows. Section 2 describes the data, functional form, and estimation method. Section 3 gives the basic results of the regression model. The sensitivity of pesticides application to climate change is analyzed in section 4. Finally, section 5 concludes.

2 DATA

Data on pesticide applications for 339 active ingredient compounds, 32 US states, 49 crops and 14 years between 1990 and 2004 are obtained from the Agricultural Chemical Usage survey (NASS 2005). As can be seen in Figure1, there is a relatively large variation across years, but relatively little variation across states. The biggest pesticide use occurs in California and Florida followed by Iowa, Illinois, Indiana, Nebraska, Michigan, and Minnesota. After 1996, total pesticide applications decreased in the US. Likely reasons are modifications of the two federal laws governing pesticides – the Federal Insecticide Fungicide and Rodenticide Act and the Federal Food Drugs and Cosmetics Act – in 1996 to keep risks low while allowing continued use of many important products. At the time, the pesticide standards were leading the Environmental Protection Agency (EPA) to cancel many widely used pesticide uses (CEI, 2008).

< Figure 1, here>

Data on production, yield, planted and harvested area are taken from USDA (http://www.usda.gov, USDA, 2005). Figure 2, shows the average share of treated areas over all crops for 2004. In most of states, the treated area exceeds 50 percent (USDA NASS, 2005).

< Figure 2, here>

The quantities of pesticide applications by crops between 1965 and 2004, for the entire US states, are given in

Figure 3. Corn receives most pesticides followed by soybeans and vegetables.

<
Figure 3, here >

More than 300 active ingredients were grouped into 48 chemical families based on the classification system of the Pesticide Action Network North America (for details see http://www.pesticideinfo.org). The presence of data by states and chemical family is reported in Appendix 1.

Treated area share and frequency of application differ widely across pesticides

Figure 4, shows the most widely applied pesticides across chemical classes with organophosphates, phosphinic acids, carabamates, and pyretroids covering more than 50 percent of all pesticide treated areas across the US states. Other widely used chemical classes such as urea and azole, izohexadione, and phenoxy reach treatment shares between 30 to 40 percent (USDA NASS, 2005).

<
Figure 4, here>

State-level weather and climate data (temperature and precipitation) were taken from NOAA (2006) and includes monthly averages for thousands of weather stations.

Functional form and estimation method

Our objective is to investigate how climate affects pesticide application. To do so, we regress pesticide application per hectare (kilogram of active ingredients applied) on marginal revenue, total planted area in hectares and climate and weather variables (temperature, precipitation).

A statistical summary of the regression variables is shown in Table 1. Marginal revenue is computed as the product of crop prices ($ per kilogram), and yields (kilogram per hectare). Temperature data are averaged over the entire growing season for each crop. In addition, we include one additional temperature variable for the average temperature over the period 1990-2004. The precipitation variables are annual totals for each state reflecting both rainfall and inter-seasonal water accumulation.

The functional form of the regression is given in equation (1). A set of reduced form variable input demand functions was postulated using a standard simultaneous equations framework. For this study we considered the log-linear functional form. Through the power Box-Cox parameters transformation (Box and Cox, 1982) associated with the dependent and independent variables via the using a likelihood ratio test, the preferred regression model was log-linear.

$$\begin{aligned} \ln PA_{tis} &= \alpha_{tis} \cdot \ln MR_{tis} + \beta_{tis} \cdot \ln TA_{tis} + \gamma_{ts} \cdot \ln T_{ts} + \eta_{ts} \cdot \ln PR_{ts} \\ &+ \lambda_{ts} \cdot \ln AT_{ts} + \nu_{ts} \cdot APR_{ts} \end{aligned} \tag{1}$$

where *PA* denotes pesticide application in kilograms, *MR* marginal revenue in $ US, *TA* total planted area in hectares, *T* growing season temperature in degree Celsius (°C), *PR* annual precipitation in millimeters, *AT* average temperature over the period 1990-2004 in degrees Celsius and *APR* the average precipitation over the period 1990-2004 in millimeters. Indexes *i*, *t* and *s,* correspond to pesticides, time and states, respectively. Parameters: *α, β, γ, η, ν,* and *λ,* represent the regression coefficients. The dataset yields 17,783 observations and covers 32 states and 49 crops over a period of 14 years. Initially, we also tested pesticide prices as independent variable in the regression model. However, due to the low variation in pesticide compound prices between 1990 and 2004, the estimated coefficients turned out insignificant and price ware omitted from the final model.

Regression coefficients for individual crops and pesticides are estimated jointly within the predefined crop types and chemical classes. Table 2, shows the crop types included in the analysis. The data have a panel structure. Statistical investigations of panel data have led to estimation processes which control for common factors influencing a member (state) over any repeated observation or all members in a repeated observation (i.e. events broadly occurring during a year such as a drought). The number of periods is the same across crops and states but taking into consideration that not all of the chemical classes are observed in all states and crops, the panel is unbalanced.

The appropriate specification of panel data regression models requires a series of structural tests before the final estimation. The first test determines the presence of fixed or random effects in the panel. In other words, are there state specific factors omitted from the model that significantly impact pesticide applications and need to be controlled for (fixed effects)? Or are those effects random in nature? There are several ways to test for fixed or random effects. The generally accepted way of choosing between fixed and random effects is running a Hausman test. We found with 95 percent confidence that a random state effect exist for all chemical classes, that is, the errors are panel member specific. However, using the test of Baltagi and Li (1995), we reject the possibility of systematic time effects in pesticide application for any chemical classes.

There are various estimation methods for panel data, including pooled OLS (Wooldridge (2002) and Green, (2003) and generalized least squares Baltagi and Li (1995). Some textbooks on advanced econometrics (Wooldridge (2002) and Green (2003)) recommend maximum likelihood as the best model estimation, and that is used here.

3 REGRESSION RESULTS

The estimated impacts of marginal revenue, planted area, temperature, and precipitation on pesticide applications are displayed in Table 3 to 10, where each table corresponds to a particular crop type.

For all crop types and chemical classes, pesticide applications increase with planted area and marginal revenue as one would expect. The regression coefficients for these two variables are significant for almost all chemical classes and crop types. In some cases, pesticide application increases more than linearly with area, which indicates that nearby fields with the same crop pose a risk. In other cases, pesticide application increases less than linearly with area, which indicates that spraying provides protection to nearby fields as well.
Heterogeneous coefficient signs are found for the two weather variables. Precipitation coefficients are mostly positive and significant at 5 percent level. Higher significance at 1

percent level of precipitation coefficients are obtained for most of chemical classes applied to root crops (Table 7). Negative impacts of precipitation are most frequently found for pesticides applied to berries citrus fruits and leafs and salads. Particularly, negative coefficients are estimated for carbazate (-1.02), petroleum derivative (-2.66), guanidine (-1.75) applied to berries, neonicotinoids (-1.42), priridazinon (-1.01) triazines (-0.24), applied to citrus fruits (Table 6) and triazine (-1.09), botanical pesticide (-2.00), bipyridilium (-0.72) and benzoic acid (-0.27) applied to leaves and salads crop group(Table 10).

The temperature shows mixed effects on pesticide applications in all crop type categories. However, in most cases, regression coefficients are positive and significant at the 5 percent level. For most chemical classes, the regression coefficients are higher compared to those of precipitation. Particularly, high coefficients are estimated for sulfonyl urea applied to leaves and salads (6.81 Table 10), and to stone fruits (6.59 Table 4)
For the average temperature, results are similar. In most of the regression models, the coefficients are significant at 5 or at 1 percent level. Across crop types classes, mixed effects on pesticides application are estimated. However, the regression coefficients for average temperature are lower compared to those for the temperature of the current growing season. The same characteristics can be observed between the coefficients for current precipitation and 14-year average precipitation. The fact that climate as well as weather affects pesticide application suggests that either farmers habituate to pesticide use, or that different crop varieties (with different sensitivities to pests) are planted in different climates. The fact that the climate and weather variables tend to have the same sign suggests that habituation is the more likely explanation.

The results indicate that pesticide applications are highly impacted by weather and climate variables but that these impacts substantially differ across crops. For some of common used chemical classes, we find opposite signs. Particularly, for triazine and pyretroid we find negative regression coefficients for cereals and positive for stone and pome fruits and fruiting vegetables. A possible reason for these differences could be the different growing seasons for the different crops which imply different pest problems. As discussed by Pattersson et al. (1998), different pest have different temperature optima.

4 CLIMATE CHANGE SCENARIO IMPACTS ON US PESTICIDE APPLICATIONS

The regression results are applied to investigate the potential change of pesticide use in response to climate change. We consider climate change scenarios from two models developed at the Canadian Centre for Climate and the Hadley Centre in the United Kingdom, following IPCC scenario "SRES A2". While the Canadian model projects a greater temperature increase, the Hadley model projects a wetter climate. The two models capture a plausible range of future climate conditions with one model being near the lower and the other near the upper end of projected temperature and precipitation changes over the US.

The projection of pesticide application includes the combined effects from precipitation and temperature variables. We compute impacts of Canadian and Hadley climate change scenarios for the years 2030, 2070 and 2100. For each projected time period, we use the 30-year average of the corresponding weather variables to determine the future values of the climate variables. For the base period, we use observed weather variables.

The results presented below give the changes in pesticide application by state, by crop type, and chemical class relative to the year 2000. We assume constant cropping patterns and crop areas.

The difference between the Canadian and Hadley scenarios is fairly small and ranges between one and three percent. Thus, the results are averaged over both scenarios.

Figure 5 displays the changes in pesticide applications in each US state relative to the base period. Results show increases in all US states between 14 and 33 percent by 2100.

The highest increases are found in Florida, California, Georgia and Texas with values up to 29 percent. The lowest changes are estimated in North Dakota and Minnesota with 14 and 16 percent in 2100, respectively.

Changes in pesticide applications to specific crop types are shown in Figure 6. All values represent aggregates over chemical classes and US states for all considered periods. Results show that the changes in pesticide application differ across crop types. We find the highest increase for leafs and salads with almost a factor of four and berries with a factor of five compared to the base period application. Cereals and beans will increase much less in relative terms however they continue to require the highest amount of pesticides (Figure 6)**.**

The impacts of climate change differ considerably across chemical classes. Figure 7 displays the changes in pesticide applications by chemical class aggregated over US states and crops. The values represent changes to the base period. Results indicate that climate projections will not only increase but also decrease the application of some pesticides (Figure 7). We find substantial changes for sulfonyl urea with a 41 percent increase by 2100. Other chemical classes with substantial changes in applications include organotin, organophosphorous, chloro-nicoitinide, anilide, and carbamate and phosphonoglycine (Figure 7). We also find considerable decreases in pesticides use. Particularly, botanical pesticides, cyclohexanedione, and inorganic pesticides decrease by 2100 between 8 and 23 percent (Figure 7).

5 CONCLUDING COMMENTS

This study quantifies the impacts of climate and weather on pesticide applications in the US agriculture. Pesticide application data for 14 years, 32 US states, 49 crops, and 339 active ingredients are regressed on agricultural, weather, and climate variables. Temperature and precipitation variables are found to have significant –mostly positive- impacts on pesticide applications. While more rainfall increases the plant protection needs for cereals and root crops, higher temperatures are likely to increase pesticide doses to fruits, vegetables, and beans. Crop type and chemical class specific regression coefficients are used to project the impact of climate change scenarios on changes in pesticide application. For current crop area allocations, our results suggest that in most cases the pesticide application rates increase. Fruit and vegetable treatments increase the most, but cereals and beans remain the most pesticide intensive crops. Note, however, that climate change also decreases the application for some chemical classes of pesticides. The change in pesticides application rates will affect the environment and human health. Such positive or negative impacts should be accounted for in environmental policy planning to achieve the socially optimal balance between mitigation and adaptation to global change.

Several important limitations and uncertainties to this research should be noted. First, climate change data (temperature and precipitation) are based on models. Thus, the certainty of the estimates presented here depends on the quality of these models. Second, the representation of agricultural products is limited to major food crops. Third, we do not consider land use change but keep crop area allocations constant. Fourth, due to lack of data, we ignore the variation of pesticide applications within US states. Fifth, other pest control methods like tillage change and genetically modified organisms are not considered. Finally, note this work does not cover the effects of altered CO_2 concentrations since meaningful variations in atmospheric CO_2 level are not observable in the data set. These issues should be addressed in future research.

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Table 1 Summary statistics for regression variables

Variable	Unit	Mean	Std. Dev.	Min	Max
Pesticide applications	ha	1.30	0.38	0.51	4.52
Planted area	ha	10993.87	33863.24	0.03	347200.00
Marginal revenue	$/ kg	3.02	2.82	0.23	15.49
Temperature	C^o	31.19	3.21	-3.89	39.94
Precipitation	mm	542.59	272.1	39.11	1300.26
Average Temperature	C^o	23.49	2.27	8.17	35.92
Average Precipitation	mm	707.51	291.91	156.43	1238.61

Table 2 Crop scope and aggregation

Cereals	Stone & Pome fruits	Berries	Citrus fruits	Fruiting vegetables	Leaves & salads	Beans	Root crops
Corn	Apricots	Blackberries	Grapefruit	Cucumbers	Asparagus	Beans	
Rice	Avocados	Blueberries	Lemons	Eggplant	Broccoli	Soybeans	Potatoes
Spring wheat	Cherries	Raspberries	Limes	Melons	Cabbage	Peas	
Durum wheat	Grapes	Strawberries	Tangelos	Pecans	Cauliflower		
Winter wheat	Nectarines		Tangerines	Peppers	Collards		
Sorghum	Peaches		Temples	Pumpkins	Greens		
Barley	Plums		Oranges	Squash	Kale		
	Prunes			Tomatoes	Lettuce		
	Apples				Spinach		
	Pears						

Table 3 Regression results for cereals

Chemical class	Average temperature	Temperature	Average Precipitation	Precipitation	Marginal revenue	Total area	Constant	R-Square Adjusted
Amide	0.07 *		0.59 **	1.16 **	1.98 **	0.28 **	2.40	0.5
Anilide	0.19 **	1.35 **	0.64 **	1.68 **	0.32 **	0.75 **	3.12	0.61
Azole	0.28 *	1.43 **		0.49 **	0.10 **	0.71 **	4.29	0.69
Benzoic acid			0.39 **	1.74 **	0.50	0.41 *	3.14	0.82
Bipyridylium	0.85 **		0.39 *		1.46 *	0.39 **	7.71	0.61
Carbamate	0.07 *	0.79 **	0.33 **	-1.14 **	0.23 *			0.51
Carbazate			0.13 **	0.82 **	0.93 **	0.86 *	1.23	0.65
Dinitroanilines			0.17 *	1.71 *	1.54 **	1.35 **		0.87
Diphenyl ether	0.43 **	0.87 *			0.94 **	2.19 **		0.73
Halogenated organic	0.04 *	0.23 **	0.09 **	1.45 **	2.12 **	0.14 **		0.51
Imidazolinone	0.19 **	5.82 *	0.04 **	1.40 **	1.13 *		7.23	0.64
Neonicotinoid	-0.30 **	-1.57 **		1.38 **	1.45 **	1.41 **		0.68
Organophosphorus	0.24 **		0.35 **	1.34 **	0.90 **	0.33 **	1.74	0.52
Organotin	0.03 **	1.41 *	0.63 **	1.89 **		0.24 **	3.01	0.57
Phenoxy	0.04 **	0.15 **	0.18 **		0.22 **	0.93 *	-1.18	0.52
Phosphonoglycine	0.16 **	0.65 **	0.38 **	0.88 **	0.40 **	0.55 **	-0.83	0.75
Pyrethroid	-0.03 *	-0.57 **	0.32 **	0.88 **	0.58 **	0.68 *	3.26	0.57
Pyridazinone	0.10 **	1.43 **	0.45 **		4.67 **			0.68
Strobin	0.33 *	1.05 **		2.07 **	1.00 **	2.91 *	7.82	0.63
Sulfonyl urea			0.29 **	0.93 **			3.10	0.71
Triazine	-0.08 **	-0.58 **		1.77 **	0.33 **	0.25 *	2.06	0.88
Triazolopyrimidine	-0.06 *	-0.67 **	0.08 **	1.03 *	0.10 **		1.43	0.65
Urea	-0.31 **	-2.64 **	0.43 *		0.45 **	1.11 *		0.82

Significant at the 1 percent level, ** Significant at the 5 percent level

Table 4 Regression results for stone fruits

Chemical class	Average temperature	Temperature	Average Precipitation	Precipitation	Marginal revenue	Total area	Constant	R-Square Adjusted
Anilide	0.22 *	1.39 *	0.21 **	2.68 **	0.76 **	0.46 **	2.01	0.53
Azole	0.09 **	0.86 **	0.31 *	1.23 **		0.63 **	1.93	0.57
Benzoic acid			0.07 **	1.74 **	0.98 *	1.21 **	4.47	0.57
Bipyridylium	0.03 **	0.42 **	0.02 **		0.29 **	0.28 **	5.36	0.54
Botanical	0.09	2.84 *			0.17 **	0.32 **		0.65
Carbamate	0.06 **	-1.73 **	0.07 **	1.05 **	0.70 **		0.28	0.58
Chloro-nicotinyl	0.07 *	2.88 *	0.21 *	1.67 *	1.69 *	0.58 **		0.56
Dicarboximides	-0.04 **	-1.84 **			0.48 *	0.47 *	-0.98	0.76
Dinitroanilines	0.10 **	-3.92 **	0.05 **	0.91 **	1.47 **	1.60 **	0.90	0.73
Diphenyl ether	0.19 **	-1.08 **	0.01 **	1.03 **			3.05	0.56
Halogenated organic	0.08 *	6.05 **		0.58 **	0.72 **	0.12 **	1.65	0.69
Juvenile hormone analogue			0.19 **	2.05 **	0.83 **	2.01 **		0.65
Neonicotinoid	0.12 **		-0.35 *	-1.76 **	3.76 **	4.06 **		0.66
Organochlorine	0.09 **	0.84 **		1.07 **	0.86 **		3.57	0.56
Organophosphorus	0.17 **	1.04 **		0.69 **	0.27 **	0.39 **	2.46	0.52
Organosulfur			0.22 **	0.85 *			-0.96	0.65
Organotin	0.03 *	2.04 **	-0.05 **		0.84 **	0.89 **	1.63	0.48
Petroleumderivative	0.02 **	1.02 **				0.67 **	-1.52	0.55
Phenoxy	-0.10 **	-2.66 **	0.14 **	1.99 **	0.76 *		2.54	0.74
Phosphonoglycine	-0.24 **	-0.95 **	0.06 **	0.98 **	0.74 **	0.91 **	1.78	0.60
Phthalates			0.19 *	1.08 **	0.63 **	0.76 **		0.66
Pyrethroid	0.05 **	0.38 **		0.17 **		0.73 *	2.66	0.69
Pyridazinone	0.15 *	1.90 *			0.70 *	0.28 **		0.71
Strobin	0.07 *	1.72 *	0.02 **		0.53 *			0.57
Sulfonyl urea	0.09 **	6.59 **	0.17 *	1.10 **	0.43 *	0.98 *		0.53
Triazines	0.21 **	2.42 **	0.32 **	2.36 **	0.81 **	1.82 **	2.05	0.68
Urea	-0.11 **	-0.18 **		0.58 **		0.31 *	-1.30	0.87
Xylylalanine	-0.12 **	-1.71 **	0.01 *		0.27 **	0.81 *	0.82	0.52

* Significant at the 1 percent level, ** Significant at the 5 percent level

Table 5 Regression results for berries

Chemical class	Average temperature	Temperature	Average Precipitation	Precipitation	Marginal revenue	Total area	Constant	R-Square Adjusted
Amide	0.60 **	1.22 **	0.10 *	-1.01 **	2.02 *	0.90 **	1.54	0.53
Anilide	0.19 **	1.56 **	0.03 **		0.06 *	1.04 *	5.62	0.50
Azole	-0.08 **		0.05	2.00 **	0.50 **	0.80 **	3.25	0.56
Benzoic acid	0.07 **	2.14 *	-0.05 **	-1.07 **	4.32 **	2.96 *	2.02	0.87
Bipyridylium	0.46 **	2.66 *		1.03 **		0.05 **	7.94	0.58
Carbamate	0.52 **	1.01	0.88 **	6.17 **	1.18 **	0.41 *		0.52
Carbazate	0.06 **	2.38 **	0.04 **	-0.93 *	2.43 *	2.32 *		0.64
Dicarboximide	0.04 **	1.01 **	0.01 *		1.01 **	1.00	1.14	0.52
Dinitroaniline	0.64 **	1.40 *	0.05		0.59 *	0.39 *	2.03	0.54
Diphenyl ether	0.12 *	-1.07 *	0.92 **	3.00 **		1.00	-4.23	0.57
Guanidine			-0.07 **	-1.75 **		0.16 **	7.18	0.60
Halogenated organic	0.60 *	3.48 *	0.04 **	-2.32 *	1.06 **	2.08 *	-2.16	0.69
Inorganic				-0.11 **	0.50 **	0.27 **	2.88	0.60
Organochlorine	0.03 **	0.13 **		0.10 *	0.12 *	0.08 **		0.51
Organophosphorus	0.49	0.42 **	0.05 **		0.13 **	0.37 **	6.02	0.53
Petroleumderivative			-0.55 *	-2.66 **	2.18	4.00 **	-0.84	0.64
Phenoxy		-0.38 **	0.25 **	1.08 *	1.12 *	1.04	2.43	0.52
Phosphonoglycine	0.78	2.82 *	0.09 **	0.18 **	0.08	0.86 **		0.54
Phthalate	0.00 **		0.73 **	1.00 **	1.01 **	0.60 **	0.16	0.56
Sulfonyl urea	-0.31 *	-2.00 *			1.00 **	1.02 *		0.53
Triazine		0.39 **	0.26 **	0.11 *	2.01 **		6.05	0.51
Urea	0.23 **	1.79 *	0.15 *	3.18 **		0.27 **	5.13	0.61

* Significant at the 1 percent level, ** Significant at the 5 percent level

Table 6 Regression results for citrus fruits

Chemical class	Average temperature	Temperature	Average Precipitation	Precipitation	Marginal revenue	Total area	Constant	R-Square Adjusted
Azole	0.02 *	0.92 **	0.06 **	2.00 *		0.09 **	-2.04	0.51
Bipyridylium	0.12 **	0.42 **	0.04 **	0.97 **	1.01 *	0.92 **	5.14	0.74
Carbamate	0.25 **	1.83 **	-0.15 **		0.73 **	0.53 **	-1.76	0.66
Halogenated organic	0.06 *	-7.11 **		0.71 *		0.26 *		0.53
Organochlorine	-0.27 **	0.14 **			0.90 **	0.56 **	0.68	0.58
Organophosphorus	-0.20 **	1.05 *	-0.02 **	1.27 **	0.50 **	0.40 *	0.73	0.60
Petroleumderivative	-0.10 *	-0.73 **	0.68 **	-0.23 **	1.01 **		8.59	0.54
Phenoxy	0.06 **	-0.92 *	0.12 **	1.00 **	0.40 **		-0.52	0.73
Phosphonoglycine	-0.02 **	0.74 **	-0.04 **		0.85 **	1.01 **	1.04	0.64
Pyridazinone	0.06 **	0.15 **	-0.02 **	-1.01 *	0.16 **	0.30 **	-2.05	0.56
Triazine		0.54 **	-0.09 **	-0.24 **		0.72 **	1.20	0.64
Sulfonyl urea	0.29 **	-0.49 *	0.01 *	0.89 *	0.14 **	0.44 **	-1.21	0.87
Xylylalanine	0.10 *	2.03 **		0.30 **	0.05 *	0.10 **		0.71

* Significant at the 1 percent level, ** Significant at the 5 percent level

Table 7 Regression results for root crops

Chemical class	Average temperature	Temperature	Average Precipitation	Precipitation	Marginal revenue	Total area	Constant	R-Square Adjusted
Amide	0.02 **	0.38 **	0.04 *	0.61 *	0.55 **	0.21 **	6.41	0.52
Anilide			0.15 *	0.54 **		0.39 **	1.34	0.68
Azole	0.09 **	2.17 *	0.06 **		0.61 *	0.74 **	1.74	0.72
Bipyridylium	0.04 **	0.18 **			0.68 **		-3.17	0.58
Carbamates	0.07 **	2.25 **	0.04 **	2.72 **	0.29 **	0.59 **	1.98	0.57
Chloro-nicotinyl			0.23 **	0.77 **		0.29 **		0.59
Cyclohexanedione			0.41 **	1.67 **	0.68 **	0.34 **	-1.77	0.61
Dicarboximide	0.08 **	1.48 **	0.06 **			1.53 **	0.16	0.72
Dinitroaniline			0.17 *	0.29 **	0.04 **		1.34	0.53
Diphenylether		1.61 **		1.11 **	1.05 *	2.13 **	3.27	0.65
Halogenated organic	0.03 **	0.53 **			0.04 **	0.11 *	1.75	0.77
Inorganic	0.03 **	-1.44 **	0.03 *		0.20 **	0.06 **	1.03	0.69
Microbial	0.13 *	2.39 **	0.04	2.92 *	1.47 **	1.12 *	5.20	0.77
Neonicotinoid	0.18 **	2.24 **	0.44 *		2.24 **			0.74
Organophosphorus	0.08 **	0.86 *	0.15 **	0.06 **	0.45 **		0.71	0.55
Organosulfur	0.65 **	2.92 **		3.30	0.30 *	1.02 **	3.21	0.72
Organotin	0.06 **	2.05 **				2.89 **	4.01	0.61
Phenoxy	0.08 *	1.95 **	0.34 *	-1.02 *	1.13 **	1.23 **		0.73
Phosphonoglycine	0.12 **	1.21 **	0.09 **	0.76 **	0.34 **	0.60 *	3.12	0.65
Pyrethroid	0.06 **	1.11 **	-0.08 **	1.81 *	0.66 *	0.68 **		0.58
Strobin		2.52 **	0.24 **	0.27 *	1.83 *	0.99 *		0.75
SulfonylUreas	0.05	0.67 **		2.42 **		1.30 *		0.52
Triazine				-0.58 **		0.60 **	-3.04	0.65
Urea	-0.02 **	-1.03 **		1.15 **	0.66 *		5.12	0.63
Xylylalanine	0.02 **	0.27 **	0.25 **		0.62 *		0.78	0.75

* Significant at the 1 percent level, ** Significant at the 5 percent level

Table 8 Regression results for beans

Chemical class	Average temperature	Temperature	Average Precipitation	Precipitation	Marginal revenue	Total area	Constant	R-Square Adjusted
Anilide	0.07 **	0.32 **	0.16 **	0.42 *	0.71 **	0.73 **		0.71
Azoles	0.09 **	-0.17 *			0.61 *	0.74 **	1.74	0.5
Bipyridylium	0.13 *	1.48 *	0.13 **	0.33 *	0.75 **	1.16 **		0.53
Carbamates	0.07 **	4.25 **		-1.72 **	0.29 **	0.59 **	1.98	0.66
Cyclohexanedione	0.26 **	-2.49 **	0.23 **	1.64 *	0.56 **	0.75 **	1.52	0.85
Dicarboximides	0.08 **	1.48 **	0.06 **			1.53 **	0.16	0.62
Dinitroanilines	0.09 **	-1.38 **	0.03 **	1.08 **	0.67 *	0.83 **	3.29	0.7
Diphenylethers		1.61 **		1.11 **	1.05 *	2.13 **	3.27	0.82
Halogenated organic	0.15 **	1.76 *	0.04 **	0.63 *	1.16 **	2.36 **	1.53	0.73
Imidazolinone	0.03 **	1.44 **	0.03 *	2.01 **	0.20 **	1.01 **	1.03	0.52
Isoxazolidinone	0.13 **	2.39 **	0.04 *	0.92 *	1.47 **	1.12 *	5.20	0.76
Organochlorine		2.82 **		0.94 *	1.34 *	0.90 **		0.51
Organophosphates	0.32 **	2.62 **	0.05 **	0.53 **	0.37 **	0.39 **	1.94	0.62
Phenoxes	0.03 *	-1.06 **	0.20 **		0.91	1.24 **	2.33	0.81
Phosphonoglycine	0.05 **	-1.80 *	0.22 *	-0.83 *	0.43 **	1.42	5.50	0.9
Pyrethroids	0.06	2.21 **	0.02 **	3.01	0.42	3.26 **		0.73
Strobin	0.25 **	0.25 **	0.15 **	2.35 **		1.97 **		0.6
Substituted Benzene	0.03 *	1.17 **			0.66 **	1.81 **		0.87
SulfonylUreas	0.13 *	0.31 *	0.09 **	1.92 *	0.83 **	1.05 **	0.56	0.57
Triazines	-0.05 **	-2.63 **	0.10 *	1.27 **	0.27 *	0.68 **	2.19	0.50
Triazolopyrimidine	-0.08 **	-0.18 **	0.19 **		0.52 *	0.09 **		0.74
Ureas	0.05 **	0.91 **	0.09 *	0.08 *		1.38 **		0.94
Xylylalanine	0.31	0.64 **		0.5 *		0.82	-1.07	0.64

* Significant at the 1 percent level, ** Significant at the 5 percent level

Table 9 Regression results for fruiting vegetables

Chemical class	Average temperature	Temperature	Average Precipitation	Precipitation	Marginal revenue	Total area	Constant	R-Square Adjusted
Anilide	0.06 **	0.25 *	0.02 **	-0.24 *		1.02 **	1.90	0.64
Avermectin	0.07 *	1.89 **	-0.03 *	-1.03 **	0.56 *	0.75 **	1.03	0.55
Azole	0.03 *	-3.05 **	0.19 **	1.02 **	0.82 **	0.25 **	3.70	0.64
Bipyridylium	0.14 **	2.26 *	0.26 **	1.02 **	0.49 **	0.61 **	2.17	0.53
Carbamate	0.12 **	3.95 *	0.01 *	0.15 **	0.16 *	0.13 **	1.42	0.57
Chloro-nicotinyl		1.21 **		0.08 **	0.72 **			0.60
Dinitroanilines	0.07 **	1.31 **	0.04 **		0.23 **	1.57 **	2.73	0.50
Diphenyl ether	0.02 **	0.92 **		0.71 **	1.01 **	0.45 **		0.74
Halogenated organic	-0.84 **	-1.56 **	0.07 **	0.44 **	0.36 *	0.89 **	9.15	0.66
Inorganic		0.28 **	0.04 **	0.91 **	0.50	0.15 **		0.56
Isoxazolidinone	0.03 *	1.03 **			1.14 **	1.09 **		0.70
Organochlorine	0.03 *	0.23 *	0.01 **	0.43 **		0.70 **	2.90	0.76
Organophosphorus	-0.11 **	1.05 *		0.35 **		0.92 *		0.68
Organotin	0.03 **	0.62 **	-0.03 *	-0.24 **	0.13 **	0.07 **		0.61
Phenoxy	0.02 **	1.37 *	-0.08 **	0.89 **	0.24 *	0.52 *	1.76	0.53
Phosphonoglycine		2.12 **			3.05 **	3.05 **		0.65
Pyrethroid	0.05 **	2.03 **	-0.01 **	0.73 *	1.00 **	0.97 **	-2.08	0.51
Pyridazinone	-0.12 **	-1.21 **		1.01 **	0.11 **	1.92 **		0.60
Strobin	0.03 **			0.84 **			3.08	0.66
Sulfonyl urea			-0.05 **	3.00 **	1.01 **			0.58
Triazine	-0.38 **	-1.57 *			0.17 *	0.23 **	7.30	0.71
Xylylalanine			0.04 **	0.58 **		0.45 **		0.71

* Significant at the 1 percent level, ** Significant at the 5 percent level

Table 10 Regression results for leaves and salads

Chemical class	Average temperature	Temperature	Average Precipitation	Precipitation	Marginal revenue	Total area	Constant	R-Square Adjusted
Amide	0.19 *	-0.79 **			0.50 **	0.40 **		0.63
Anilide	0.08 **	0.43 **	0.12 **	0.78 **		0.57 **		0.65
Avermectin	0.42 **	1.24 **	0.13 **	2.13 **	9.57 **	0.75 **	0.06	0.59
Azole	0.11 **	2.04 **	-0.06 **	0.52 **	0.23 **	0.79 *	3.17	0.64
Benzoic acid	0.06	0.77 **		-0.27 **	0.84 **	0.32	0.68	0.66
Bipyridylium	0.07 **	1.05 **		-0.72 **	0.97 **	0.41 **	-0.05	0.71
Botanical			0.09 **	-2.00 *	5.00 **	3.00 *		0.69
Carbamate	-0.22 **	2.13 **	0.02 **	0.45 **		0.57 **	3.40	0.60
Chloro-nicotinyl	0.12 **	2.97 **	0.05 **	0.64 **	1.00 **	1.30 **	5.31	0.56
Cyclohexanedione	-0.03 **	-3.81 **		0.30 **	1.43 **	1.89 **	0.29	0.60
Dicarboximides	0.05 *	-1.29 **			1.19 **	1.95 **	0.13	0.52
Diphenyl ether	0.20 *	0.46 *	0.02 *		0.14 **	0.26 **		0.58
Inorganic	-0.56	0.22	0.20 *	0.05 *		0.01	0.54	0.54
Organochlorine	0.31 *	0.67 **	0.02 **	0.85 **	0.06 **	0.02 **	2.84	0.56
Organochlorine	0.01	0.24 **			0.28 **	0.30 **		0.73
Organophosphorus	0.31	1.26 *	0.08 **		0.33 **		0.72	0.58
Organotin	0.11 **	3.56 **	0.01 *	0.27 **	1.00 *	1.40 *	6.28	0.51
Phenoxy	0.37 **	2.84 **	0.05 **	0.25 **		0.91 **	2.87	0.68
Phosphonoglycine	0.12 **	1.40 *	0.44 **		1.99 **	2.23 **	6.48	0.52
Pyrethroid	0.01 **	0.60 **	0.05 **	0.32 **		0.51 **	0.02	0.65
Strobin				1.01 **	0.27 **	0.21 *	1.08	0.60
Sulfonyl urea	0.72 **	6.81 **	0.09 **		0.82 **	2.00 *		0.83
Triazine	0.25	2.08 **	0.46 **	-1.09 **	0.40 **	0.55 **	2.00	0.65
Urea	0.02 **		0.18 **	0.72	0.67 **		5.72	0.78
Xylylalanine	0.03 *	1.20 *		0.90 *		1.05 **		0.63

*Significant at the 1 percent level, ** Significant at the 5 percent level

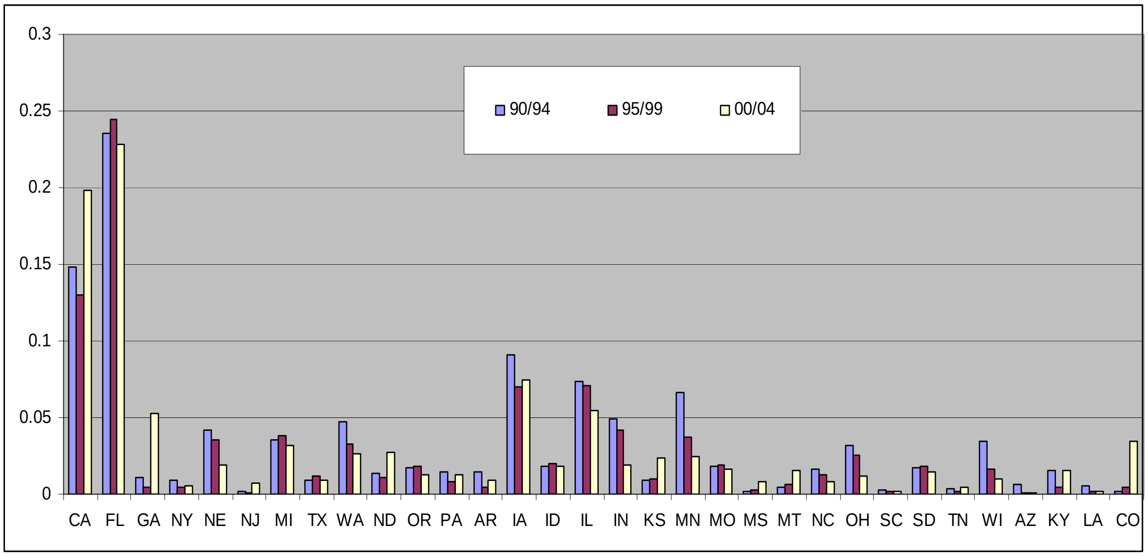

Figure 1 Data analysis: Total pesticide application by US state, 1990-2004

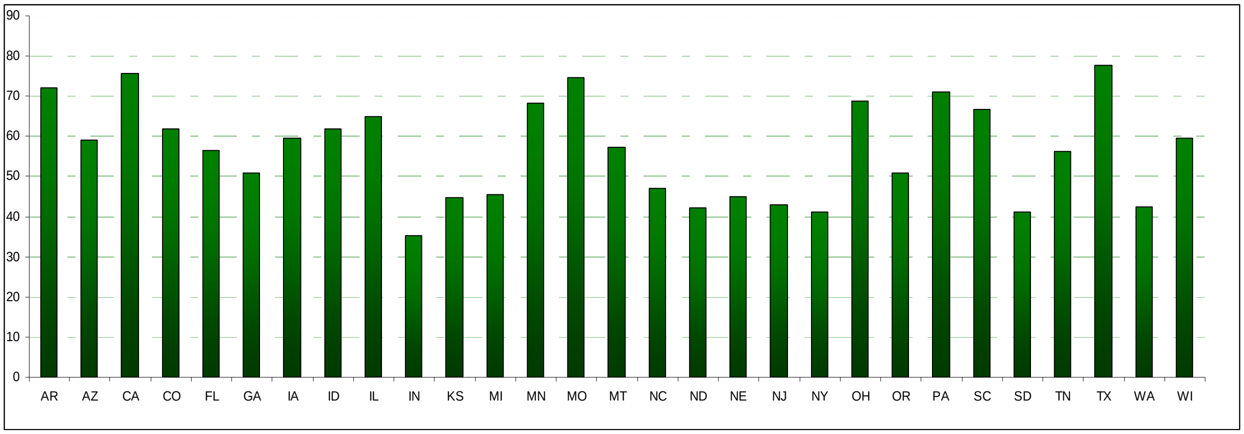

Figure 2 Data analysis: Treated to total planted area by US state, 2004 [in percent]

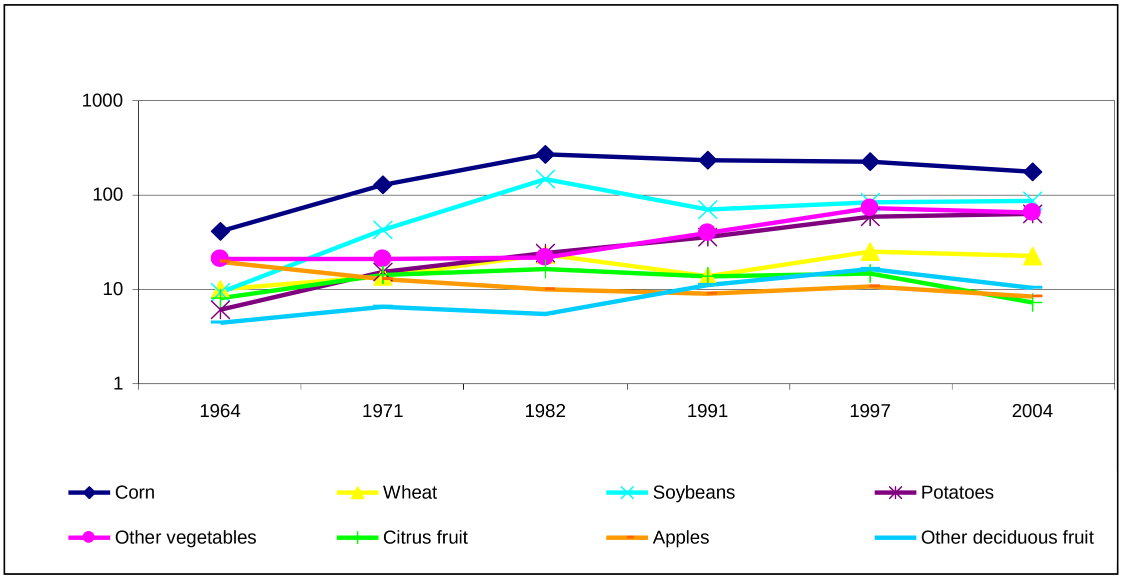

Figure 3 Data analysis: Quantity of pesticides applied to selected crops, 1964-2004 [in thousand pounds active ingredients]

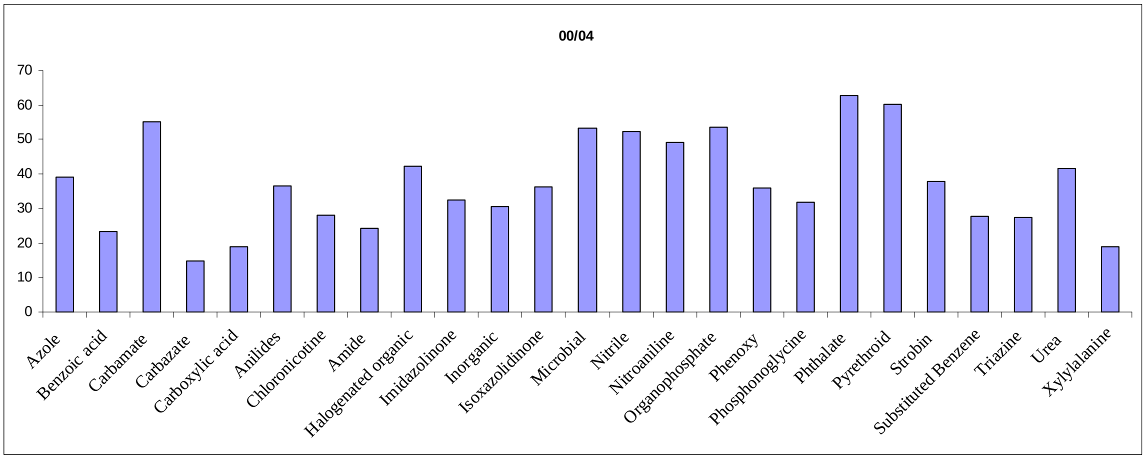

Figure 4 Data analysis: Treated to total planted area by chemical class, 2000-2004 average [in percent]

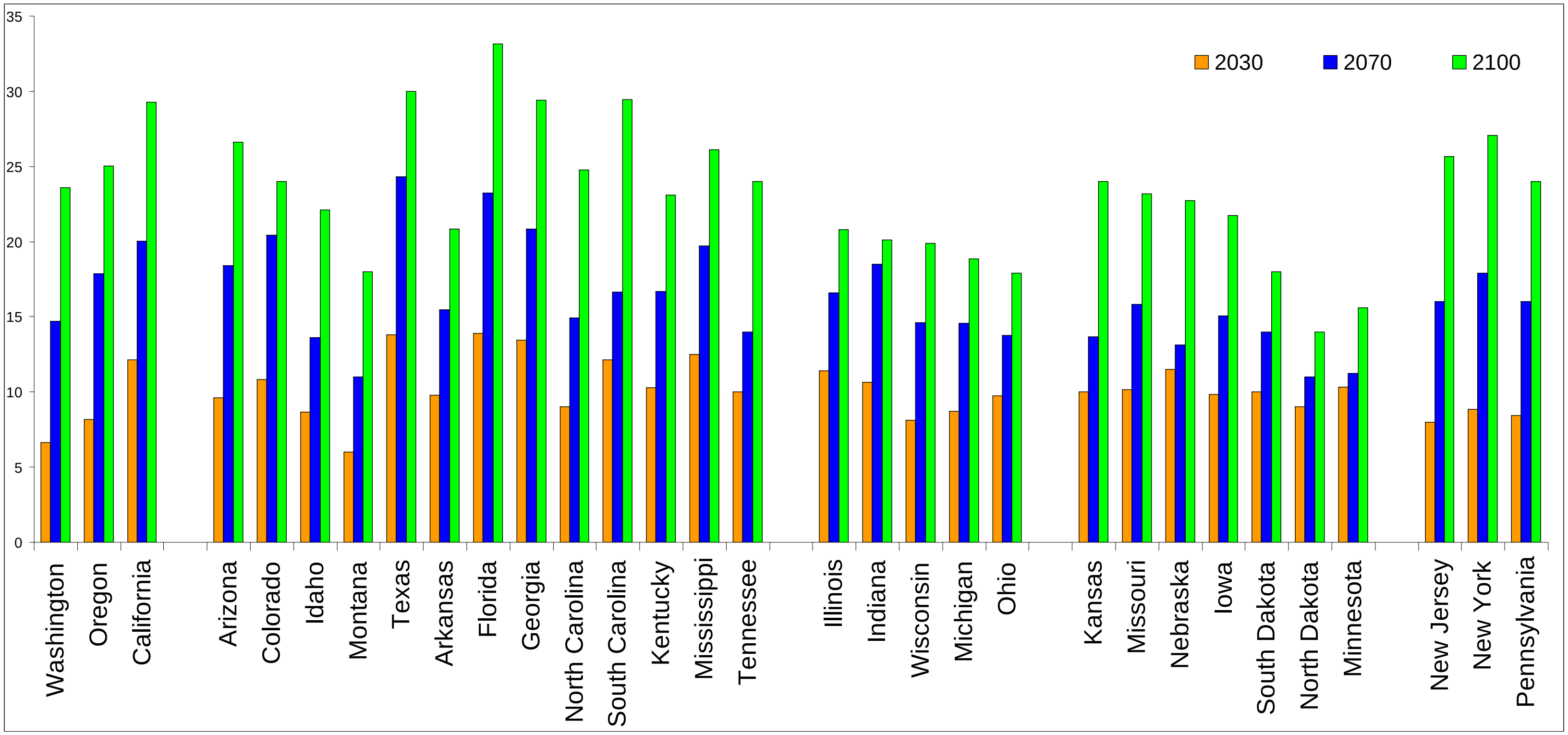

Figure 5 Climate change scenario results: Impacts on pesticide application by region [in percent]

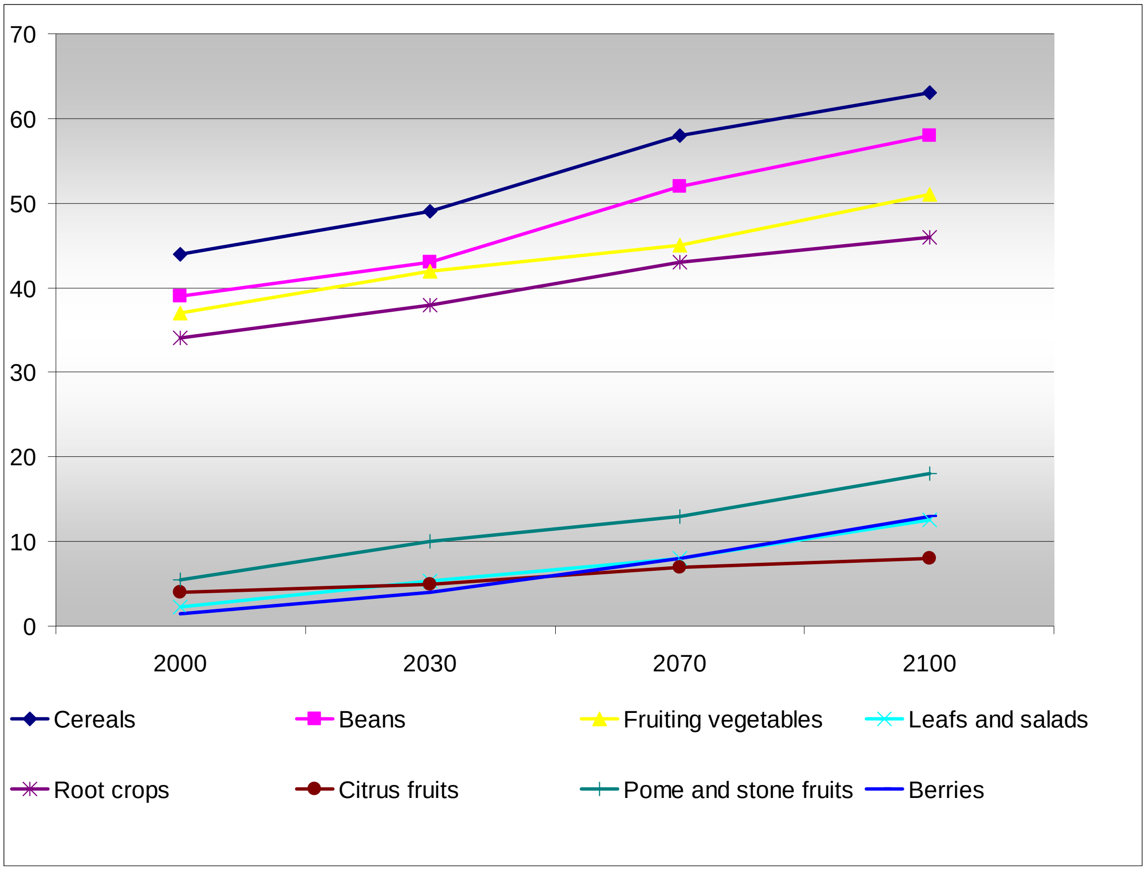

Figure 6 Climate change scenario results: Impacts on pesticide application by crop type [in thousand kilogram active ingredients]

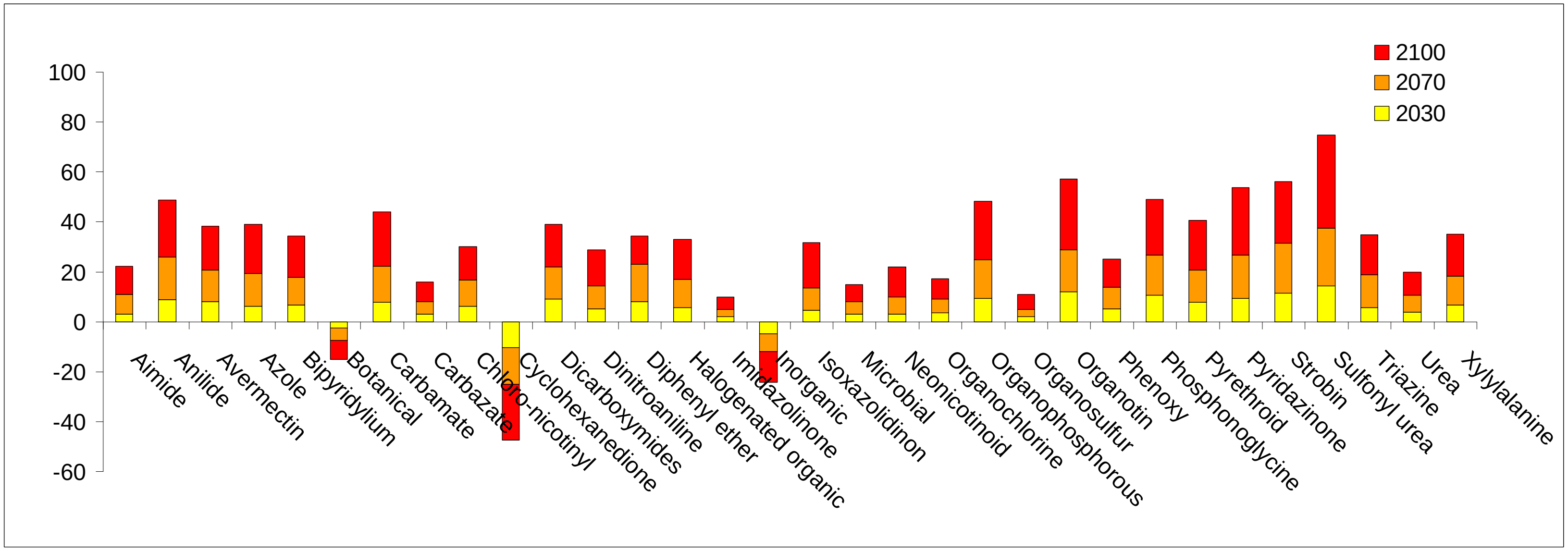

Figure 7 Climate change scenario results: Impacts on pesticide application by chemical class [in percent]

Appendix 1

Pesticide occurrence by chemical class and US state

Chemical class	STATE
Acetamiprid	CA CO ID IN MI MN NC ND NE NY OR TX WA WI
Aldehyde	CA OR
Amides	AR AZ CA CO FL GA IA ID IL IN KS LA MI MN MO MS NC ND NE NJ NY OH OR PA SC SD TN TX WA WI
Antibiotics	CA GA MI NC NJ NY OR PA SC WA
Avermectin	AZ CA FL MI NC NJ NY OR PA TX WA
Azoles	AR AZ CA CO FL GA IA IL IN KS KY LA MI MN MO MS MT NC ND NE NJ NY OH OR PA SC SD TN TX WA WI
Benzoic acids	AR AZ CA CO FL IA ID IL IN KS KY LA MI MN MO MS MT NC ND NE NJ NY OH OR PA SC SD TN TX WA WI
Bipyridylium	CA CO FL GA ID IL IN KY LA MI MN MO MS NC ND NE NJ NY OH OR PA SC TN TX WA WI
Botanical	AZ CA FL GA MI NC NJ NY OR PA TX WA WI
Carbamates	AR AZ CA CO FL GA IA ID IL IN KS KY LA MI MN MO MS MT NC ND NE NJ NY OH OR PA SC SD TN TX WA WI
Carbazate	CA CO IA IL IN KS MI MN ND NE NY OH OR PA TX WA WI
Carboxylic acids	IA ID IL IN KS MI MN MO MT ND NE OH SD WA WI
ChloroacetNitroanilines	AR AZ CA CO FL GA IA ID IL IN KS KY LA MI MN MO MS NC ND NE NJ NY OH OR PA SC SD TN TX WA WI
ChloroAmides	CO IA IL IN KS KY MI MN MO ND NE OH OR PA SD TX WA WI
Chloronicotines	AZ CA CO FL GA ID MI MN NC ND NJ NY OR PA TN TX WA WI
Cyclohexanedione	AR AZ CA FL GA IA ID IL IN KS KY LA MI MN MO MS MT NC ND NE NJ NY OH OR PA SD TN TX WA WI
Dicarboximides	AR AZ CA CO FL GA ID LA MI MN NC ND NJ NY OR PA SC WA WI
Diphenylethers	AR AZ CA FL GA IA ID IL IN KS KY LA MI MN MO MS MT NC ND NE NJ NY OH OR PA SC SD TN TX WA WI
Guanidine	CA MI NC NJ NY OR PA SC WA
Halogenated organic	AZ CA FL GA ID IN MI NC NJ OR SC TN TX WA
Imidazolinones	AR FL GA IA ID IL IN KS KY LA MI MN MO MS MT NC ND NE NJ OH OR PA SC SD TN TX WA WI
Inorganics	AR AZ CA CO FL GA IA ID IL IN KS MI MN MO NC ND NJ NY OH OR PA SC TN TX WA WI
Isoxazolidinone	AR CO FL GA IA IL IN KS KY LA MI MN MO MS NC ND NE NJ NY OH PA SC SD TN TX WA WI
Juvenile hormone analo	AZ CA FL MI NC NY OR PA TX WA
Microbials	AZ CA FL GA LA MI NC ND NE NJ NY OH OR PA SC TN TX WA WI
Nitriles	AR AZ CA CO FL GA IA ID IL IN KS KY LA MI MN MO MT NC ND NE NJ NY OH OR PA SC SD TN TX WA WI
Nitroanilines	AR AZ CA CO FL GA IA ID IL IN KS KY LA MI MN MO MS NC ND NE NJ NY OH OR PA SC SD TN TX WA WI
Organochlorines	AZ CA CO FL GA ID IN MI MN NC ND NJ NY OH OR PA SC TN TX WA WI
Organophosphates	AR AZ CA CO FL GA IA ID IL IN KS KY LA MI MN MO MS MT NC ND NE NJ NY OH OR PA SC SD TN TX WA WI
Organosulfurs	CA CO FL ID MI MN NC ND NY OR PA SC TX WA WI
Organotins	AZ CA CO FL ID MI MN NC ND NJ NY OR PA SC TX WA WI
Petroleum derivative	AZ CA FL GA MI NC NJ NY OR PA SC TX WA
Phenoxes	AR CA CO FL GA IA ID IL IN KS KY LA MI MN MO MS MT NC ND NE NJ NY OH OR PA SC SD TN TX WA WI
Pheromone	CA MI OR WA
Phosphonoglycine	AR AZ CA CO FL GA IA ID IL IN KS KY LA MI MN MO MS MT NC ND NE NJ NY OH OR PA SC SD TN TX WA WI
Phthalates	CA FL GA MI NC NJ NY OR PA SC TX WA WI
Piperazine	GA MI NC NJ OR
Pyrethroids	AR AZ CA CO FL GA IA ID IL IN KS KY LA MI MN MO MS MT NC ND NE NJ NY OH OR PA SC SD TN TX WA WI
Pyridazinone	AR CA FL GA KS MI MN MT NC NJ NY OR PA SD TX WA WI
Quinoxalines	AR FL LA MI MS NY OR PA TX WA
Strobin	AR AZ CA CO FL GA ID IL LA MI MN MS NC ND NJ NY OH OR PA SC SD TN TX WA WI
Substituted Benzene	AZ CA FL GA ID MS NC TX WA
SulfonylUreas	AR CA CO FL GA IA ID IL IN KS KY LA MI MN MO MS MT NC ND NE NJ NY OH OR PA SC SD TN TX WA WI
Triazines	AR AZ CA CO FL GA IA ID IL IN KS KY LA MI MN MO MS NC ND NE NJ NY OH OR PA SC SD TN TX WA WI
Triazolopyrimidine	AR IA IL IN KS LA MI MN MO MS NC ND NE NY OH PA SD TN WI
Uracils	AZ CA FL MI NC NJ NY OR PA SC TX WA WI
Ureas	AR AZ CA CO FL GA ID IL IN KS KY LA MI MN MO MS NC ND NE NJ NY OH OR PA SC SD TN TX WA WI
Xylylalanine	AZ CA CO FL GA ID IN MI MN NC ND NJ NY OH OR PA TX WA WI