CLIMATE CHANGE AND PESTICIDE USE AN INTEGRATED ECONOMIC ANALYSIS

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ABSTRACT

Agricultural pesticides impact adversely on the environment and human health. These impacts are sensitive to climate change, because pest pressure and optimal pesticide application rates vary with weather and climatic conditions. This dissertation provides an integrated economic analysis on climate change and US pesticide applications. A panel data regression model, for thirty two states, is used to quantify the effect of weather variability and climate change on pesticide application. The results indicate that weather and climate differences significantly influence the application rates of most pesticides. Subsequently, the regression results are linked to a downscaled climate change scenario, the Canadian and Hadley climate change models. Results show that the application of most pesticides increases under both scenarios. The projection results vary by crop, region and pesticide.

Increases in pesticide application doses may amplify the negative impacts on the environment. One important issue is the effect on aquatic species. Aquatic risk indicator, REXTOX and climate change projection on pesticide applications from the panel data regression model, are combined to examine the impact of climate change on aquatic risk from agricultural pesticides in the US. On average, climate change is likely to increase the toxicity risk to aquatic species by 47 percent, because of increased applications of agricultural pesticides. Daphnia and fish are the most affected aquatic species categories. Across eight broad crop groups, pesticides used on pome and stone fruits and on fruiting vegetables contribute the most to aquatic risk. Within the thirty two US states examined, more than 90 percent of the climate change-induced pesticide pollution impact on the aquatic environment is caused by only thirteen states near the coast. Because projections on aquatic risk are based on uncertain regression coefficients with an error distribution and projection period covering 100 years, a Monte Carlo simulation and prediction intervals system is used to estimate the uncertainty of the risk estimates.

Simultaneously, projections on pesticide application are linked with the Pesticide Environmental Accounting (PEA) tool, to compute the impact of climate change on the external cost of pesticide applications. The current average external cost of pesticide use in US agriculture is calculated at US$42 per hectare. Under projected climate change this cost could increase to $72 per hectare by 2100.

Subsequently, pesticide external cost estimations and climate change projections on pesticide application, together with alternative pest control data, climate state specific data on agricultural crop yields, irrigation water requirements and production costs are integrated within the Agricultural Sector and Mitigation of Greenhouse Gas (ASMGHG) model, to examine alternative assumptions about regulations of external costs from pesticide applications in US agriculture under different climatic conditions. The impact of the internalization of the pesticide externality and climate change, are assessed both independently and jointly. Results indicate that without external cost regulation, climate change benefits from increased agricultural production in the US, may be more than offset by increased environmental costs. The internalization of the pesticide externalities increases farmers' production costs but also increases farmers' income, because of price adjustments and associated welfare shifts from consumers to producers. The results also show that full internalizations of external pesticide costs substantially reduce preferred pesticide application rates for corn and soybeans, as climate changes.

Additionally, a partial equilibrium model of the US agricultural sector is modified to examine the effects of alternative regulations of the pesticide and greenhouse gas emission externality. Simulation results indicate that without pesticide externality regulations and low greenhouse gas emission mitigation strategy, climate change benefits from increased agricultural production in the US are more than offset by increased environmental costs. Although the combined regulation of pesticide and greenhouse gas emission externalities increases farmers' production costs, their net income effects are positive because of price adjustments and associated welfare shifts from consumers to producers. The results also show heterogeneous impacts on preferred pest management intensities across major crops In absence of greenhouse gas emission policy, pesticide externality regulation substantially increases the total water use for irrigation.

Empirical results from this dissertation show the importance of accounting for pesticide externalities. Overall increased negative externalities from pesticide applications could provide an argument for more mitigation, i.e. for stronger greenhouse gas emission control policies. Related to this argument, the externality estimates can help to improve the scope of climate change impacts in integrated assessment and earth system models. Furthermore, the examined pesticide policy could be interpreted as a pesticide tax, where the tax level corresponds with the environmental and human health damage. Such a policy is different from most existing regulations, which only prohibit pesticides but impose no charge on admitted ones. The results further could also affect agricultural research programs because the anticipated social returns to research on alternative pest control strategies depend also on the expected external cost change.

ZUSAMMENFASSUNG

Der Gebrauch von Pestiziden in der Landwirtschaft hat nachteilige Auswirkungen auf die Umwelt und die menschliche Gesundheit. Diese Auswirkungen sind abhängig vom Klima, weil Schädlingsbelastung und optimaler Pestizideinsatz sich mit den Wetter- und Klimabedingungen verändern. Diese Dissertation liefert eine integrierte ökonomische Analyse des Einflusses der Klimaentwicklung auf den Pestizideinsatz in der US-amerikanischen Landwirtschaft und der externen Auswirkungen auf die aquatische Umwelt.

Im ersten analytischen Teil der Dissertation wird ein auf Paneldaten basierendes Regressionsmodell benutzt, um die Auswirkung von Wetter und Klima auf den Pestizideinsatz in 32 Staaten zu quantifizieren. Die Ergebnisse zeigen, dass Wetter- und Klimaunterschiede die Anwendungsraten der meisten Pestizide bedeutend beeinflussen. Anschließend werden interpolierte Klimaszenariodaten sowohl des Kanadischen Klimamodells als auch des Klimamodells vom Hadley-Zentrum in die geschätzten Regressionsgleichungen integriert. Die dadurch erhaltenen Projektionen zeigen, dass die Anwendung der meisten Pestizide zunimmt. Die Werte variieren jedoch nach Nutzpflanzenart, Region und Pestizid.

Erhöhte Ausbringungsraten von Pestiziden können die negativen Auswirkungen auf die Umwelt vergrößern. Dabei spielen die Auswirkungen auf Wasserorganismen eine wichtige Rolle. Der aquatische Risikoindikator REXTOX und aus der Paneldatenregression abgeleitete, klimaabhängige Projektionen der Pestizidanwendung werden kombiniert, um die Auswirkung des Klimawandels auf das Risiko für Wasserorganismen zu untersuchen, das von Pestiziden in der US-amerikanischen Landwirtschaft ausgeht. Die Ergebnisse zeigen, dass der Klimawandel das Toxizitätsrisiko für Wasserorganismen wegen gestiegener Anwendungen von Pestiziden in der Landwirtschaft um durchschnittlich 47 Prozent erhöht. Daphnien und Fische sind die am meisten betroffenen Wasserorganismen. Von den acht untersuchten Kulturpflanzenkategorien tragen Pestizide, die auf Kern- und Steinfrüchte sowie auf fruchtbildendem Gemüse verwendet werden, am meisten zum aquatischem Risiko bei. Innerhalb der 32 untersuchten US-Staaten werden mehr als 90

Prozent der vom Klimawandel hervorgerufenen Pestizidschäden auf die Wasserwelt von nur dreizehn Staaten in Küstennähe verursacht. Weil die 100 Jahre umspannenden Projektionen auf unsicheren Regressionskoeffizienten mit einer Fehlerverteilung beruhen, werden Monte Carlo Simulationen durchgeführt und Vorhersage-Intervalle berechnet, um die Unsicherheit der Risikowerte einzuschätzen.

Außerdem werden die Projektionen der Pestizidanwendung mit dem Pesticide Environmental Accounting (PEA)-Instrument verknüpft, um die Auswirkung des Klimawandels auf die externen Kosten der Pestizidanwendungen zu monetarisieren. Die daraus berechneten gegenwärtigen externen Kosten der Pestizidanwendung in der US-amerikanischen Landwirtschaft betragen durchschnittlich US$42 pro Hektar. Durch den Klimawandel können diese Kosten auf durchschnittlich $72 pro Hektar bis 2100 steigen.

Im weiteren Verlauf der Dissertation werden klimaabhängige Daten über Pestizidintensitäten unter alternativen Schädlingskontrollstrategien und damit verbundene Einflüsse auf Nutzpflanzenerträge, Wasserbedürfnisse, Produktionskosten und externe Pestizidkosten, in das Agricultural Sector and Mitigation of Greenhouse Gas (ASMGHG)-Modell integriert, um alternative Szenarien über mögliche Regulierungen von externen Kosten der Pestizidanwendungen in der US-amerikanischen Landwirtschaft unter verschiedenen klimatischen Bedingungen zu untersuchen. Die Auswirkungen der Internalisierung der externen Pestizidkosten und des Klimawandels werden sowohl unabhängig voneinander als auch gemeinsam beurteilt. Die Ergebnisse zeigen für die USA, dass ohne eine Pestizidregulierung die Klimawandelgewinne aus der gestiegenen landwirtschaftlichen Produktion durch die gestiegenen externen Umweltkosten mehr als kompensiert werden. Die Internalisierung der externen Pestizidwirkungen erhöht zwar die Produktionskosten der Landwirte, aber wegen der Preisanpassungen und damit verbundenen Veränderungen von Konsumenten- und Produzentenrenten auch deren Einkünfte. Die Ergebnisse offenbaren auch, dass eine vollständige Internalisierung der externen Pestizidkosten die optimalen Anwendungsraten für Pestizide im Getreide- und Sojabohnenanbau beträchtlich reduzieren würde, wenn sich das Klima verändert.

Die empirischen Ergebnisse dieser Doktorarbeit zeigen wie wichtig die Berechnung der externen Pestizidkosten ist. Eine Zunahme der negative externen Effekte durch Pestizidanwendungen liefert ein Argument für eine strengere politische Kontrolle der Treibhausgasemissionen. In diesem Zusammenhang können die durchgeführten Kostenberechnungen auch helfen, die Repräsentation der externen Effekte des Klimawandels in integrierten Bewertungs- und Erdsystemmodellen zu verbessern. Die untersuchte Pestizidregulierung kann als eine Pestizidsteuer interpretiert werden, bei der das Steuerniveau dem Schaden für Umwelt und menschliche Gesundheit entspricht. Eine solche Politik würde sich von den meisten existierenden Regelungen unterscheiden, die nur Pestizide verbieten oder genehmigen, aber keine Kosten auf die erlaubten Pestiziden auferlegen. Die Erkenntnisse dieser Dissertation können auch Landwirtschaftsforschungsprogramme beeinflussen, weil der erwartete gesellschaftliche Nutzen der Forschung zu alternativen Schädlingskontrollstrategien von der erwarteten Veränderung der externen Kosten abhängt.

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CHAPTER 1

INTRODUCTION

1. BENEFITS AND RISKS FROM THE USE OF PESTICIDES

More than 10,000 insects, 600 weeds and 1,500 fungi, commonly named pests, adversely affect daily human life. They reduce the quality and quantity of food produced, by lowering production and destroying stored produce, compete with humans for food and cause a variety of diseases to humans, animals and crops.

Humans began to control pests at the same time as they started farming. Over the years several pest management systems have been applied: manual removal of weeds and animal pests, cultivation breaks for vulnerable crops, mechanical soil treatment, biological pest control, genetic engineering and use of chemical pesticides. Across all available pest management systems, pesticides have become the most frequently selected alternative for pest control.

In the available literature, many definitions of pesticides appear. The most complete one is proposed by FAO, where a pesticide is defined as: ”any substance or mixture of substances intended for preventing, destroying or controlling any pest, including vectors of human or animal disease, unwanted species of plants or animals causing harm during or otherwise interfering with the production, processing, storage, transport or marketing of food, agricultural commodities, wood and wood products or animal feedstuffs, or substances which may be administered to animals for the control of insects, arachnids or other pests in or on their bodies. The term includes substances intended for use as a plant growth regulator, defoliant, desiccant or agent for thinning fruit or preventing the premature fall of fruit, and substances applied to crops either before or after harvest to protect the commodity from deterioration during storage and transport”.

Using pesticides to control pests is not a new idea. While the first recorded use of chemicals to control pests dates back to 2500 BC, it is only in the last 50 years that chemical control has been widely used (Hock, 1991) and become indispensable, because of a number of advantages such as:

- Cost effectiveness. Farm chemicals are often the cheapest way, with regard to private costs, to control pests. They require low labor input and allow large areas to be treated quickly and efficiently. It has been conservatively estimated that for every dollar a farmer spends on farm chemicals, he receives a $4 return (Pimentel, 1997). Production per labor unit has increased, while production costs and energy inputs have decreased.

- Timeliness and flexibility. A suitable farm chemical is available for most pest problems. Different products can be chosen for different situations. This allows more flexibility in management options and better timing of pest control.

- Quality, quantity and price of produce. Farm chemicals ensure a plentiful supply and variety of high quality, wholesome food at reasonable prices. Modern society demands nutritious food, free from harmful organisms and blemishes.

- Prevention of problems. Farm chemicals are frequently used to prevent pest problems from occurring, e.g. preventing weeds in gardens and lawns, treatment of export and import produce to prevent the spread of pests, treatment of stored products to prevent pest attacks and destruction during storage.

- Protection of humans from house insects.

- Saving land from degradation through soil erosion by reducing the need for cultivation.

Despite these benefits, pesticide use raises a number of environmental and human health concerns. Over 90 percent of applied pesticides reach a destination other than their target species, including non-target species, air, water, bottom sediments and food (Pimentel, 1993). Via spray and vapor drift, runoff and leaching, pesticides can contaminate other areas.

Once disseminated to the environment, pesticides may cause changes in the natural biological balances and may reduce biodiversity. Since pesticides are designed to be toxic to living species, they may also adversely affect human health. Worldwide, the application of 3 million metric tons of pesticide, results in more than 26 million cases of human pesticide poisonings (Richter, 2002). Of all the pesticide poisonings, about 3 million cases are hospitalized and there are approximately 220 000 fatalities and about 750 000 chronic illnesses every year (Hart and Pimentel, 2002). There is some evidence that poisoning from exposure to pesticides may cause neurological, respiratory and reproductive disorders, sensory disturbances, cognitive problems and cancer (Teitelbaum et al., 2007; Cockburn, 2007; Lee et al., 2007; Alavanja et al., 2006).

Bearing in mind these adverse impacts, in the 1960s researchers began developing a different approach to pest control called "integrated pest management" (IPM). The integrated pest management approach claims to keep pests at economically tolerable levels through a diverse set of control strategies which discourage pests, promote beneficial predators or parasites that attack pests and time pesticide applications to coincide with the most susceptible period of the pests' life cycles. However, even with integrated pest management, pesticides are frequently the only way to deal with emergency pest outbreaks (Delaplane, 2007). Therefore, agriculture may be able to reduce the inputs of chemicals, but their complete elimination is currently economically not feasible. While political leaders, citizens, and government officials try to mediate and resolve conflicts between the risks and benefits of pesticide use by producing safer chemicals, selective pesticides, better application methods and stronger pesticide admission rules, climate change is likely to expand these conflicts.

1.2 Climate change impacts on pests and pesticide use

Long-term changes of climate have already been detected and there is wide agreement that the climate will continue to warm over the 21st century (IPCC, 2001a; 2001b). Global warming might increase pest activity.

Several entomologists and biologists have investigated the potential effects of climate change on pest populations (Patterson et al., 1999; Porter, et al., 1991). They confirm that projected warming will help some pest species to survive winters and will accelerate the development of summer-active species. In any particular location, climate change may not mean more pest animals and weeds, but it could mean new pest animals and weeds. The range of pests will generally shift to higher latitudes as a result of warming trends. On the one hand, an increase in extreme events, such as cyclones, storms and associated floods, may increase the dispersal of weed species that rely on wind and water to move seeds or pollen. On the other hand, habitats disturbed by extreme events such as drought, leave empty niches which pest animals and weeds could colonize. In addition, there is evidence that pests often recover from extreme climatic events faster than other species.

Therefore, the use of pesticides may increase and subsequently the negative impacts on society and the environment may be amplified. Although the range of studies conducted in the field of climate change agriculture–environment interactions is wide, the information on climate change pesticide-use environment interactions is quite limited. Such interactions have to be addressed and taken into consideration in the formulation of climate change mitigation and adaptation policies.

1.3 Purpose, aims and scope

This dissertation will provide an integrated economic analysis on climate change pesticide-use environment interactions. The aims of the thesis are:

1. to establish the quantitative relationship between weather, climate and variable pesticide use,

2. to use these relationships to estimate the potential changes in pesticide use due to climate change,

3. to quantify the potential negative impact on the aquatic environment based on the projection on pesticide applications,

4. to compute the impacts of climate change on the external cost of pesticide applications and

5. to use the projections on pesticide application and pesticide external costs and to examine alternative assumptions about regulations of external costs from pesticide applications in agriculture.

6. to quantify the impacts of pesticide externality and GHG emission regulations and climate change on land use, management intensities, economic surplus, and externality mitigation in US agricultural sector.

The extensiveness and diversity of pesticide use has led to this thesis being focused on the US agricultural sector. The US is the biggest pesticide consumer in the world, accounting for 25 %. Furthermore, 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 billion (USDA, 2004). For these reasons, along with the relative ease of access to pesticide data, the US makes an ideal focus for this thesis.

1.4 Outline of the thesis

This thesis contains four papers, which are presented in chapters 2-5. The chapters are written in such a way that each can be read independently, although some of them are closely related.

Chapter 2 provides an empirical analysis of the relationship between pesticide use and weather and climate variables, using historical observations across regions and time periods. Pesticide application data for 14 years, 32 US states, 49 crops and 339 active ingredients are regressed on agricultural, weather and climate variables. The Regression model extends earlier research by looking at a large sample of crops and pesticides.

The regression results are linked to downscaled climate change scenarios from the Canadian and Hadley climate change models. Projections cover the time period between 2000 and 2100. Chapter 2 corresponds to the following paper:

Koleva, N.G., U.A. Schneider, and R.S.J. Tol. (2010), The impact of weather variability and climate change on pesticide applications in the US - An empirical investigation, International Journal of Ecological Economics & Statistics 18(S10):64-81.

The potential change in pesticide applications, due to climate change, may have a substantial impact on ecosystems. Chapter 3 focuses on the risk for the aquatic species in the US states, as climate and pesticide use change. The climate change projections on pesticide use, presented in chapter 2, are combined with the environmental risk indicator REXTOX developed by the OECD (OECD, 2000). The aquatic environment is represented by three species categories: daphnia, fish and algae. Since projections on aquatic risk are based on uncertain regression coefficients with an error distribution and the projected period is relatively long -100 years, Monte Carlo simulations and prediction intervals are used to estimate the uncertainty of risk estimates. Chapter 3 corresponds to the following paper:

Koleva, N.G. and U.A. Schneider (2010), The impact of climate change on aquatic risk from agricultural pesticides in the US, International Journal of Environmental Studies 67(5):677-704.

In chapter 4, previous studies on pesticide external cost estimates are extended and placed in the context of climate change. Statistical data on pesticide applications for 339 active ingredients, 32 US states and 49 crops for the period 2000-2005 (NASS, 2005) and data on the environmental impact of pesticides, developed by (Kovach, 1992), are used. The Pesticide Environmental Accounting tool (Leach and Mumford, 2007) and statistically estimated relationships between pesticide applications, weather and climate (chapter 2) are combined to compute the monetary values of pesticide externalities due to climate change. Chapter 4 corresponds to the following paper:

Koleva, N.G. and U.A. Schneider (2009). The impact of climate change on the external cost of pesticide applications in US agriculture. International Journal of Agricultural Sustainability 7(3):203-216

Chapter 5 focuses on how pesticide externalities are affected by climate change and by pesticide regulations that would hold farmers accountable for environmental damages caused by pesticides, as well as the role of alternative pest management regimes. Climate state specific data on agricultural crop yields, irrigation water requirements and production costs from Alig et al. (2002), climate specific pesticide application rates from chapter 2 and the pesticide external cost estimation from chapter 4, are incorporated in the Agricultural Sector and Mitigation of Greenhouse Gas (ASMGHG) model (Schneider et al., 2007). To analyze the role of alternative pest management regimes, three pest management options are introduced: conventional pesticide application, 50 percent reduction of pesticide use and 100 percent pesticide reduction. The data on cost reductions and corresponding yield changes are based on Knutson et al. (1999). Chapter 5 corresponds to the following paper:

Koleva, N.G., U.A. Schneider, and B.A. McCarl (2009), Pesticide externalities from the US agricultural sector - The impact of internalization, reduced pesticide application rates, and climate change, submitted to Journal of Climatic Change

Chapter 6 extends previous chapters and show how climate change impacts with greenhouse gas emission and pesticide externality mitigation options affect US agricultural sector, how these climate adaptation impacts differ under projected changes in climate under different pest management options and across the periods, and how the individual and combined impacts of pesticide externality regulations and climate change mitigation policies, influenced producers' preferences pest and crop intensities. Chapter 6 corresponds to the following paper:

Koleva, N. G. (2010), Pesticide and greenhouse gas externalities from US agriculture – The impact of their internalization and climate change on land use, management intensities, economic surplus, and externality mitigation, in preparation for submission.

In the final chapter, 7, the results of the previous chapters are summarized. The policy implications and recommendations for future research are given.

CHAPTER 2

THE IMPACT OF WEATHER VARIABILITY AND CLIMATE CHANGE ON PESTICIDES APPLICATION IN THE US – BASED ON EMPIRICAL INVESTIGATION

2.1 INTRODUCTION

Weather and climate affect many agricultural decisions including crop choice, water management, and crop protection. During the past decades, average global temperatures have increased and there is wide agreement that the climate will continue to warm over the 21st century (IPCC, 2007). Numerous studies have investigated agricultural consequences of climate change (Kaiser et al., 1993; Lewandrowski et al., 1999; Adams et al., 1990; Mendelsohn et al., 1999; Reilly et al., 2003). 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 this and other studies, there is broad agreement that climate change will have substantial ramifications for US agriculture. A major concern involves the impact of climate change on pest populations. Based on historical data about pest infestations and migration, several studies have investigated the interaction of pests and climate (Porter et al., 1991; Patterson et al., 1999) and have concluded that climate change is likely to increase pest activity, leading to greater risk of crop losses.

Chen and McCarl (2003) examine climate change effects on pesticide application using a statistical model which relates pesticide expenditure to climate. Their results suggest that climate change will increase pesticide expenditures in US agriculture. However, their study is limited to a few agricultural products (mainly cereals) and distinguishes only broad pesticide categories, i.e. herbicides, fungicides, and insecticides.

This study uses a similar approach as in Chen and McCarl (2003) but considers more crop types (including all major food products) and a more detailed classification of pesticides. Individual active ingredients for pesticides are grouped into classes with similar biochemical 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 chapter 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 and section 6 appends information about pesticide occurrence by chemical class and US state.

2.2 DATA

Data on pesticide applications, treated area share, and frequency of application for 339 active ingredient compounds, 32 US states, 49 crops between 1990 and 2004 are obtained from the Agricultural Chemical Usage survey (NASS 2005).

The 339 active ingredient compounds were grouped into 48 chemical families based on the classification system of the Pesticide Action Network North America (PAN, 2006). The chemical families reported by state are identified in section 6, Appendix.

Data on production, yield, and price, planted and harvested area between 1990 and 2004 are taken from ARS/USDA (2006).

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

2.2.1 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 Table2- 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.

Table 2- 1 Summary of statistics

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	272.10	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

The functional form of the regression is given in equation (2-1). 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 double-log.

$$\begin{aligned} \ln PA_{tis} &= \alpha_{tis} \cdot \ln MR_{tis} + \beta_{tis} \cdot \ln TA_{tis} + \gamma_{ts} \cdot \ln T_{ts} + \eta_{ts} \cdot \ln PR_{ts} \\ &+ \lambda_{ts} \cdot \ln AT_{ts} + \nu_{ts} \cdot APR_{ts} \end{aligned} \tag{2- 1}$$

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, *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 has 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 prices were omitted from the final model.

Table 2- 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						

Regression coefficients for individual crops and pesticides are estimated jointly within the predefined crop types and chemical classes. Table 2-2, 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 rejected fixed effect with 95 percent confidence or a random state effect exist for all chemical classes, that is, the errors are panel member specific. However, using the test of Baltagi (2001), we reject the possibility of systematic time effects in pesticide application for any chemical classes.

There is various estimation methods for panel data, including pooled OLS (Wooldridge, 2002; Green, 2002) and generalized least squares (Baltagi, 2001). Some textbooks on advanced econometrics (Wooldridge, 2002; Green 2002) recommend maximum likelihood as the best model estimation, and that is used here.

2.3 REGRESSION RESULTS

The estimated impacts of marginal revenue, planted area, temperature, and precipitation on pesticide applications are displayed in Tables 2- 3 to 2- 10, where each table corresponds to a particular crop type.

Table 2- 3 Regression results for cereals

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

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

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.

Table 2- 4 Regression results for stone and pome fruits

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

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

Table 2- 5 Regression results for citrus fruits

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

Table 2- 6 Regression results for berries

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

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

Table 2- 7 Regression results for root crops

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

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

Different 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 2-7). Negative impacts of precipitation are most frequently found for pesticides used on berries, citrus fruits and leaves and salads. Particularly, negative coefficients are estimated for carbazate (-1.02), petroleum derivative (-2.66), guanidine (-1.75) applied to berries, neonicotinoid (-1.42), priridazinon (-1.01) triazine (-0.24), applied to citrus fruits (Table 2-5), and triazine (-1.09), botanical pesticide (-2.00), bipyridilium (-0.72), benzoic acid (-0.27) applied to leaves and salads (Table 2-10).

Table 2- 8 Regression results for beans

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

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

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. Particularly, high coefficients are estimated for sulfonyl urea applied to leaves and salads (6.81 Table 2-10), and to stone fruits (6.59 Table 2-4)

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.

Table 2- 9 Regression results for fruiting vegetables

Chemical class	Averge temperature	Temperature	Average precipitation	Precipitation	Marginal revenue	Total area	Constant
Anilide	0.06 **	0.25 *	0.02 **	-0.24 *		1.02 **	1.90 **
Avermectin	0.07 *	1.89 **	-0.03 *	-1.03 **	0.56 *	0.75 **	1.03 **
Azole	0.03 *	-3.05 **	0.19 **	1.02 **	0.82 **	0.25 **	3.70 **
Bipyridylium	0.14 **	2.26 *	0.26 **	1.02 **	0.49 **	0.61 **	2.17 *
Carbamate	0.12 **	3.95 *	0.01 *	0.15 **	0.16 *	0.13 **	1.42 **
Chloro-nicotinyl		1.21 **		0.076 **	0.72 **		
Dinitroanilines	0.07 **	1.31 **	0.04 **		0.23 **	1.57 **	2.73 **
Diphenyl ether	0.02 **	0.92 **		0.71 **	1.01 **	0.45 **	
Halogenated organic	-0.84 **	-1.56 **	0.07 **	0.44 **	0.36 *	0.89 **	9.15 *
Inorganic		0.28 **	0.04 **	0.91 **	0.50	0.15 **	
Isoxazolidinone	0.03 *	1.03 **			1.14 **	1.09 **	
Organochlorine	0.03 *	0.23 *	0.01 **	0.43 **		0.70 **	2.90 **
Organophosphorus	-0.11 **	1.05 *		0.35 **		0.92 *	
Organotin	0.03 **	0.62 **	-0.03 *	-0.24 **	0.13 **	0.07 **	
Phenoxy	0.02 **	1.37 *	-0.08 **	0.89 **	0.24 *	0.52 *	1.76 *
Phosphonoglycine		2.12 **			3.05 **	3.05 **	
Pyrethroid	0.05 **	2.03 **	-0.01 **	0.73 *	1.00 **	0.97 **	-2.08 *
Pyridazinone	-0.12 **	-1.21 **		1.01 **	0.11 **	1.92 **	
Strobin	0.03 **			0.84 **			3.08 **
Sulfonyl urea			-0.05 **	3.00 **	1.01 **		
Triazine	-0.38 **	-1.57 *			0.17 *	0.23 **	7.30 **
Xylylalanine			0.04 **	0.58 **		0.45 **	

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

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.

Table 2- 10 Regression results for leaves and salads

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

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

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 Patterson et al. (1999), different pest have different temperature optima.

2.4 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"(IPCC, 2006). 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 33-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. 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 2-1 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.

The impacts of climate change differ considerably across chemical classes. Figure 2-2 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 2-2). We find substantial changes for sulfonyl urea with a 42 percent increase by 2100. Other chemical classes with substantial changes in applications include organotin, organophosphorous, chloro-nicoitinide, anilide, carbamate and phosphonoglycine (Figure 2-2). We also find considerable decreases in pesticides use. Particularly, botanical pesticides, cyclohexanedione, and inorganic pesticides decrease by 2100 between 8 and 25 percent (Figure2-2).

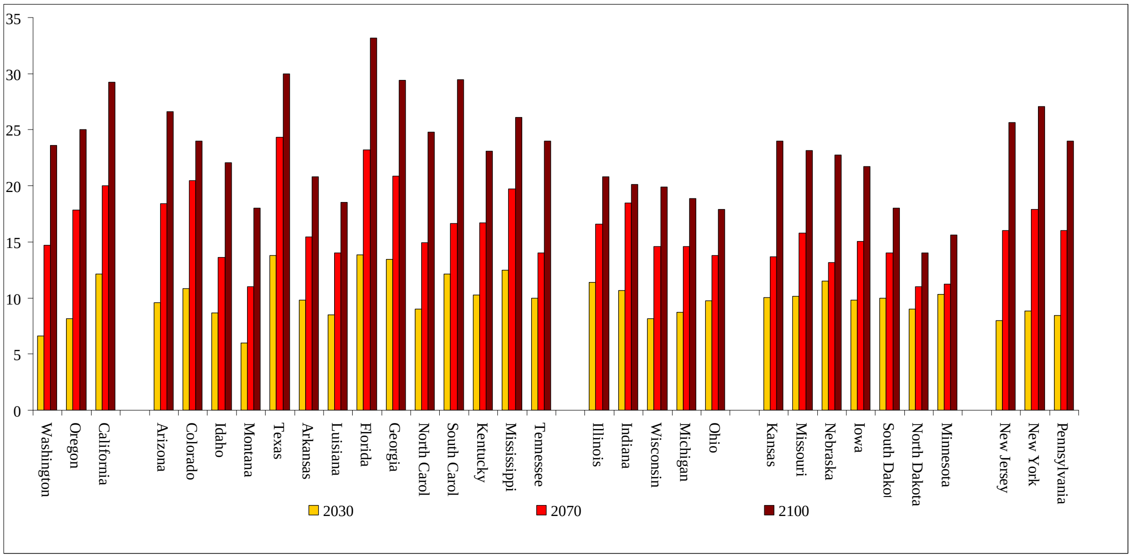

Figure 2- 1 Climate change scenario results: Impacts on pesticide application by region in geographic order [in percent]

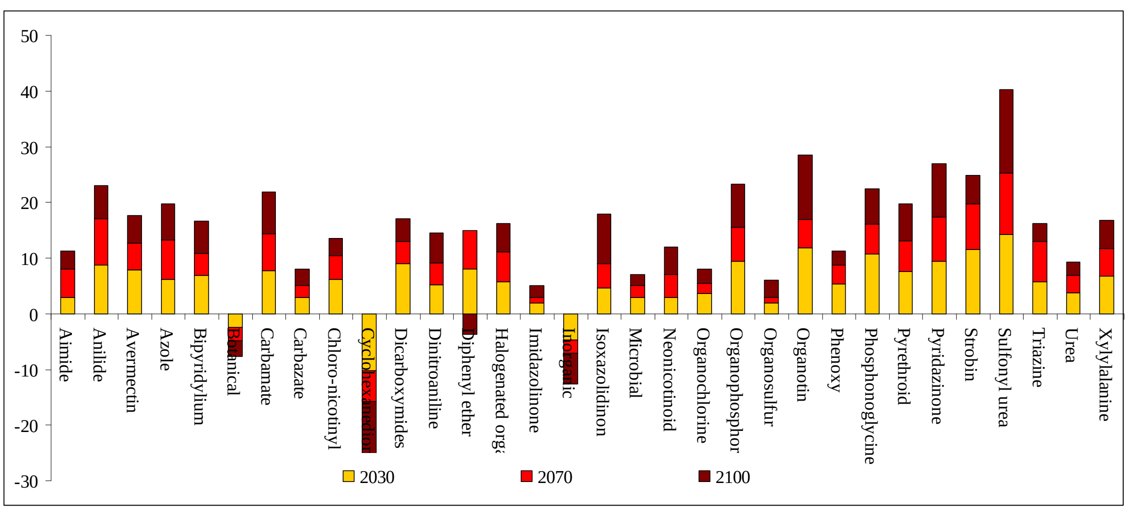

Figure 2- 2 Climate change scenario results: Impacts on pesticide application by chemical class [in percent]

Pesticide applications for the base period and due to climate change by specific crop types are shown in Figure 2-3. 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 leaves and salads with almost a factor of four and berries with a factor of five compared to the base period application. Pesticides use for cereals and beans will increase much less in relative terms however they continue to require the highest amount of pesticides (Figure 2-3).

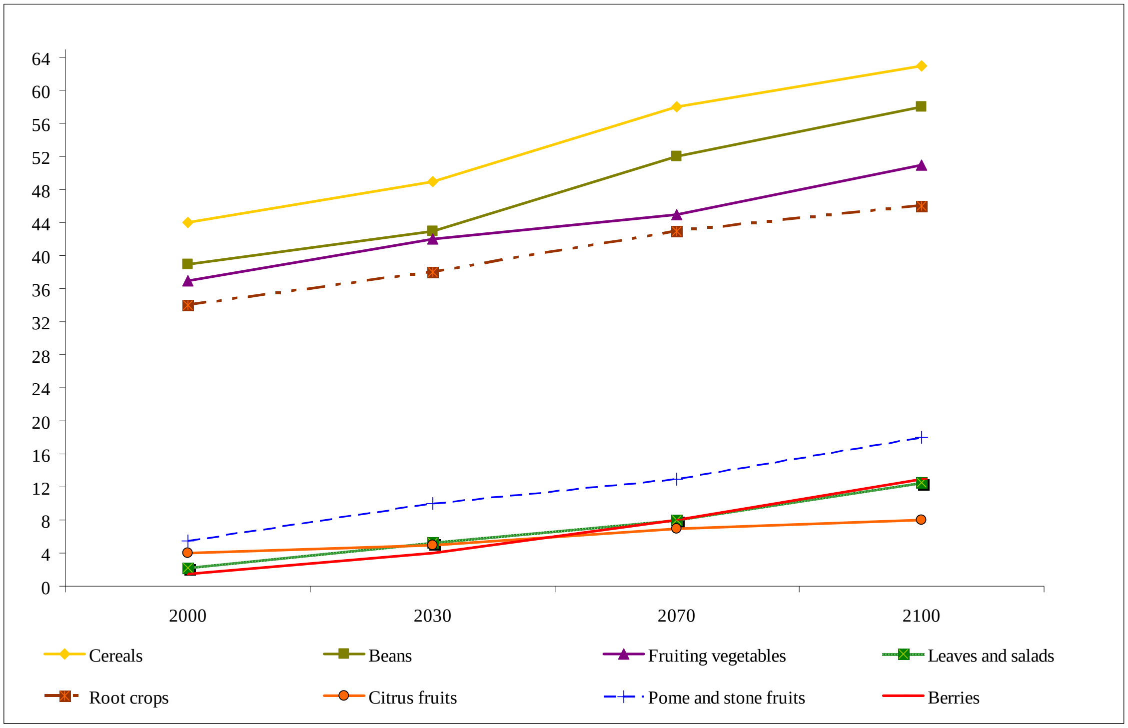

Figure 2- 3 Climate change scenario results: Impacts on pesticide application by crop type [in thousand kilogram active ingredients]

2.5 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.

2.5 Appendix

2.5.1 Pesticide occurrence by chemical class and US state

Chemical class	US States
Acetamiprid	CA CO ID IN MI MN NC ND NE NY OR TX WA WI
Aldehyde	CA OR
Amide	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
Antibiotic	CA GA MI NC NJ NY OR PA SC WA
Avermectin	AZ CA FL MI NC NJ NY OR PA TX WA
Azole	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 acid	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
Carbamate	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
Carboxylic acids	WI IA ID IL IN KS MI MN MO MT ND NE OH SD WA WI
Nitroaniline	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
ChloroAmide	CO IA IL IN KS KY MI MN MO ND NE OH OR PA SD TX WA WI
Chloronicotine	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
Dicarboximide	AR AZ CA CO FL GA ID LA MI MN NC ND NJ NY OR PA SC WA WI
Diphenyl ether	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
Imidazolinone	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
Inorganic pesticide	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 analogue	AZ CA FL MI NC NY OR PA TX WA
Microbial	AZ CA FL GA LA MI NC ND NE NJ NY OH OR PA SC TN TX WA WI

Chemical class	US States														
Nitrile	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	
Anilide	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	
Organochlorine	AZ	CA	CO	FL	GA	ID	IN	MI	MN	NC	ND	NJ	NY	OH	OR	PA
	SC	TN	TX	WA	WI											
Organophosphate	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
Organosulfur	CA	CO	FL	ID	MI	MN	NC	ND	NY	OR	PA	SC	TX	WA	WI	
Organotin	AZ	CA	CO	FL	ID	MI	MN	NC	ND	NJ	NY	OR	PA	SC	TX	WA
Petroleum derivative	AZ	CA	FL	GA	MI	NC	NJ	NY	OR	PA	SC	TX	WA	WI		
Phenoxy	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
Phthalate	CA	FL	GA	MI	NC	NJ	NY	OR	PA	SC	TX	WA	WI			
Piperazine	GA	MI	NC	NJ	OR											
Pyrethroid	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
Quinoxaline	AR	FL	LA	MI	MS	NY	OR	PA	TX	WA	WI					
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							
SulfonylUrea	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	
Triazine	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													
Uracil	AZ	CA	FL	MI	NC	NJ	NY	OR	PA	SC	TX	WA	WI			
Urea	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			
Xylylalanine	AZ	CA	CO	FL	GA	ID	IN	MI	MN	NC	ND	NJ	NY	OH	OR	PA
	TX	WA	WI													

CHAPTER 3

THE IMPACT OF CLIMATE CHANGE ON AQUATIC RISK FROM AGRICULTURAL PESTICIDES IN THE US

3.1 INTRODUCTION

There is now convincing evidence that the world's climate is changing and that the climate will continue to warm over the 21st century (IPCC, 2007). Climate influences every aspect of life on this planet from our ability to produce food and sustain future development, to the distribution of biomes and associated levels of biodiversity. Complex agriculture-climate-environment interactions are particularly important for understanding the impacts of climate change. One important component within these interactions is the influence of climate on agricultural pesticide use and its environmental consequences.

Mainly comprised of plant protection products, pesticides are designed to control harmful organisms by reducing their ability to live and multiply. Currently, pesticides are employed on a large scale and generally considered as indispensable in modern farming. They have contributed to increased crop yields, more homogeneous product quality, and reduced post harvest losses. However, their biocidal characteristics may endanger aquatic ecosystems and diminish the quality of water suppliers.

Pesticides can migrate from agricultural fields into the aquatic environment through surface, subsurface, and groundwater flows and subsequent river transport (Richards, 1987; Pereira et al., 1993; Schulz, 2001; Flury et al., 1996; Battaglin et al., 2003). Regular inflow and high persistence can result in high pesticide concentrations in surface waters over weeks and months (Groenendijk et al., 1994; Beketov and Liess et al., 2008; Dores et al., 2001). Their influences on aquatic species include direct killings (Pimentel, 2005; Erdogan, 2007; Perschbacher et al., 2008), functional disorders and reproductive abnormalities (Henny et al., 2008; Hontela et al., 2008; Moore, 2007; Boone, 2008), and adverse impacts on prey species (Kim et al., 2008; Couillard et al., 2008).

Recent studies of major rivers and streams in the US document that 96 percent of all fish samples, 100 percent of all surface water samples, and 33 percent of major aquifers contained at least one pesticide at detectable levels (EPA, 2001).]. In recognition of these adverse impacts, the US has implemented extensive legal changes over the last decades to control and regulate the use of pesticides. While political leaders, citizens, and government officials try to mediate and resolve conflicts between benefits and externalities of pesticide use, climate change is likely to intensify these conflicts.

There is a small but growing research field that focuses on the estimation of climate change impacts on pesticide applications. Chen and McCarl (2003) empirically study the relationship between pesticide and climate associated with treatment costs of pesticides use. Their results suggest that climate change will increase pesticide treatment costs for major crops. In chapter 2 we use a similar approach but consider all major food crops and a more detailed classification of pesticides. We develop a panel data regression model and investigate how weather variability and climate change affect the application of pesticides in US agriculture and link the regression results to states' downscaled climate change scenarios from the Canadian and Hadley climate models. Our results indicate that for current crop area allocations, pesticide application rates might substantially increase. This will affect the environment because an increase in the amount of active ingredients applied to agricultural fields will increase the amount of active ingredients entering water bodies both through surface runoff and sub-surface leaching (Larson et al., 1995).

An important issue is how potential changes in pesticide applications with respect to climate change will affect aquatic environment. In this study, we provide such an examination. Adverse impacts of agricultural pesticides on non-target organisms are evaluated through risk indicators. The risk assessment for pesticides in the aquatic environment relies on a comparison between estimated exposure concentrations in surface water bodies and endpoint concentrations from a series of effect tests.

Considering the negative impacts of pesticides on the aquatic environment, a variety of aquatic risk assessment models have been developed during the last two decades. These modes range from simple empirical models to comprehensive, physics-based distribution models that require complex parameterizations (Kellogg, 2000; Schuler et al., 2008; Probst, 2005; Junghans et al., 2006; Renaud et al., 2008; Ritter et al., 2004; Cheplick et al., 2004; Carsel et al., 1985; Arnold et al., 1998; Borah et al., 2004; Zhou et al., 2008). However, none of these risk assessment models can be considered universally valid.

Uncertainty about the accuracy of model results relates to the adequacy of model equations and input parameters.

In light of the above mentioned uncertainties, the OECD designed and developed risk assessment tools for national authorities to monitor progress of measures designed to reduce the environmental risk from pesticide use and to plan pesticide management regulations. Several countries including Switzerland, Germany, Sweden, The Netherlands, and Japan tested and validated the OECD methodology with their own input data. The reports of these countries suggest that the methodological tools can be adapted to different regional conditions including different weather, soil, and landscape features.

In this study, we combine the aquatic risk indicator REXTOX proposed by the OECD (2001) with statistically estimated impacts of climate change on pesticide use in US agriculture (chapter 2) to quantify the risk for aquatic species resulting from the climate - pesticide interaction. To our knowledge, no such studies have been published in the peer-reviewed literature to date.

Chapter 3 proceeds as follows. Section 2 describes the data, climate change projections on pesticide application from chapter 2, basic structure of Aquatic risk indicator REXTOX, and their incorporation. The sensitivity of aquatic species to climate change induced changes in pesticide application is analyzed in section 3. Finally, section 4 concludes. Additionally, section 5 provides detailed information about structure of Aquatic risk indicator REXTOX

3.2 Data and Methods

The availability, reliability, and completeness of input data determine the quality of the REXTOX results. For this study, we consider 150 active ingredients including the most frequently detected pesticides in water bodies in coastal region of US states.

State-level data on pesticide usage for agricultural production from 1990 to 2004 were obtained from the Agricultural Chemical Usage survey (NASS, 2005). These data include statistics on pesticide applications covering 339 active ingredients, 32 US states, 49 crops, and a 14 year history from 1990 to 2004. The survey contains information on application rates, treated area, recommended number of applications, and the actual dose rate for each pesticide. Crops are classified into eight groups (Table 2-2). Furthermore, data on the proportion between surface water area and planted area are taken from the 1997 National Resources Inventory (USDA, 1997)

Data on chemical properties and the environmental fate related to degradation pathways, half-life, and organic carbon absorption coefficients (Koc) for the studied pesticides are obtained from a USDA database (ARS, 2002).

Toxicity values are an important component for the REXTOX indicator calculation. There are two commonly distinguished types of toxicity: acute toxicity for toxic effects resulting from a short exposure to a substance, and chronic toxicity for toxic effects resulting after a long exposure (up to several years). For several active ingredients, toxicity parameters differ considerably across the referenced data sources. In addition, the median toxicity endpoint (EC50) and lethal (LC50) concentration rates differ for some chemical compounds. These differences may in part be explained by inconsistent endpoint measurements. Exact values for chronic and long-term toxicity are not available for all active ingredients. Sometimes, these values are given as lower bounds, i.e. as No Observed Effect Concentrations (NOEC). The data on pesticide toxicity values are obtained from the Pesticide Action Network Database (PAN Pesticides Database, 2007).

Any substance can be toxic at a sufficiently high dose. LC50, EC50, and NOEC are generated for many test animals and pests. For the aquatic environment the toxicity tests are made on algae, daphnia, and fish. Therefore the aquatic environment is represented by those three main groups (EPA, 2009).

In this analysis, we employ REXTOX to assess the impacts of changes in pesticide applications in response to climate change. The Ratio of EXposure to TOXicity (REXTOX) is entirely mechanistic and integrates the actual data through a series of mathematical equations that mirror scientific understanding of the environmental processes that contribute to risk.

REXTOX uses 21 variables to produce short-term risk indices and 22 to produce long-term risk indices. These variables are listed in Table 3-1.

As shown in Table 3-1, REXTOX combines pesticide properties and pesticide use data with environmental and physical parameters. Therefore, the estimation of REXTOX consists of three parts. The first part includes a calculation of pesticide losses that are expected to reach surface water bodies. Note that this calculation only accounts losses due to spray drift and runoff because they are considered to be the main pathways for surface water pollution. The second part computes exposure in surface waters. In the last part, exposure is divided by the appropriate toxicity value to obtain the REXTOX risk value. More details on individual equations appear in last section of this chapter.

The relationship between pesticide use and climate is taken from chapter 2 where we use a panel data based regression model to quantify the impact of weather and climate variables on pesticide applications in US agriculture. Details on the specification of the regression model and coefficient estimates appear in chapter 2.Furthermore, in chapter 2 we use the estimated regression coefficients to project the impact of climate change on changes in pesticide applications. We employed climate change scenarios include two regionally downscaled projections for the IPCC's "SRES A2" scenario (IPCC, 2006) from the climate models developed at the Canadian Centre for Climate and the Hadley Centre in the United Kingdom. For 2030, 2070 and 2100, a 33-year average of the corresponding weather variables is used to determine the future values of the climate variables. More details on projection results appear in chapter 2.

Table 3- 1 REXTOX Parameters from OECD report (OECD, 2000)

Variables			
Pesticide Toxicity	*Pesticide use*	*Environmental factors*	*Pesticides fate*
Fish, 96-hr LC50	Treated area (acres)	Water index (Wi) (ha) Proportion between water surface area and land area	DT 50, soil (half-life in soil)
Fish, 21-day NOEC	Recommended dose rate - RDR(kg/ha)	Water depth (m)	Koc(Organic carbon coefficient)
Daphnia, 48-hr EC50	Applied dose rate-ADR(kg/ha)	Slope of treated agricultural area	
Daphnia, 21-day NOEC	Frequency of treatment per season AFA- number of application	Season mean precipitation per state (inches)	
Algae, 96-hr ErC50	Method of application[1]	% of organic carbon in the soil	
Algae, 96-hr NOEC	Width of spry drift buffer (m)	Soil type (Loamy or sandy)	
	Width of runoff buffer (m)	Crop stage treatments (early/late)	
	Compliance width of spry drift buffer (0-100%)	Plant interception 0% when crop stage early 70% when crop stage late	
	Compliance width of runoff buffer (0-100%)	Precipitation (mm)	

[1] Ground spray, air blast, areal, granular broadcast, granular incorporated, punning paint, soil sterilant, seed treatment

The estimation of climate change impacts on pesticide concentrations in the aquatic environment involves several steps. First, observed data on pesticide applications are used to calculate the current REXTOX value for each aquatic species category. Second, assuming a linear relationship between pesticide application rates and pesticide exposure in the aquatic environment, we compute climate specific exposure concentrations. Particularly, we scale the observed exposure concentration data by scenario specific relative changes in pesticide applications for the Canadian and Hadley climate models from chapter 2. To calculate the potential exposure, we add to the proposed OECD equation (section 3.5 Table 3A-1) the change in pesticide application due to climate change. The modified exposure equation is given in equation 3-1.

$$EXP_{wscp} = ADR_{scp} \times \left[\frac{\sum L_p \%}{WD_s} \right] \times WI_s \times BTA_{csp} \times NApp_{scp} \times \Delta PA_{wscp} \qquad (3\text{-}1)$$

where EXP_{wscp} denotes the pesticide exposure concentration under a given climate change projection, ADR_{scp} the actual dose rate, L_p the losses in percent via spray drift and run-off, WD_s the water depth, WI_s the water index, BTA_s the basic treated area, $NApp_{pcs}$ the number of applications per crop year, and ΔPA_{wscp} the changes in pesticide application based on the projections from chapter 2. The indexes *s, p, c*, and *w* correspond to state, pesticide, crop, and weather, respectively.

Third, to compute the risk value, climate specific exposure concentration is divided by the corresponding median lethal concentration for each pesticide and aquatic species category.

3.3 RESULTS

The observed pesticide application data for the years between 1990 and 2004 are used to compute the REXTOX base value. Climate change is then represented through the projections from the Canadian and Hadley climate model for the years 2030, 2070 and 2100. Since the differences in REXTOX values between the two climate projections turned out fairly small, the results presented here are averaged over both projections.

Tables 3-2 to 3-4 display the computed risk values by state and aquatic species category. All estimates are given in absolute values, i.e. as ratios of exposure concentration to median lethal concentration. Within the thirty two examined US states, more than 90 percent of the climate change induced pesticide pollution impacts on the aquatic environment are caused by thirteen states which are near to the coast. For the other states, we find relatively low aquatic risk impacts of pesticide applications both for current and projected climate conditions. Therefore, in Tables 3-2 to 3-4 we present only 13 from 32 states.

For US states with relatively high risk values under current pesticide application rates, climate change is likely to increase substantially the aquatic species risk. Particularly, in South Carolina with base REXTOX values of acute risk of 6.72 for daphnia and 5.03 for fish and chronic risk values of 4.20 for daphnia(Table 3-3, column 9), and 6.00 for fish (Table 3-4, column 9), we estimate an increase of average pesticide application rates by 29.44 percent in 2100. This increase amplifies the acute and chronic risks for daphnia between 2 and 3 times and almost doubles the chronic fish risk. However, for other states such as Texas, and Georgia, considerable increases in pesticide applications due to the climate change leave the aquatic species risk at the base or moderately higher levels. In some states, we estimate considerable changes in risk, although the projected changes in pesticide applications are relatively small. In New York, for example, climate change causes a moderate 17 percent increase in pesticide applications. However, we find a 100 percent increase in chronic daphnia risk in 2100 compared to the base risk value (Table 3-3, column 12). One reason is the fact that different states have different crop management regimes with different pesticide requirements. On the other hand, the toxicity values vary substantially across pesticide and aquatic species category.

Note that the current and future risk values vary across states and aquatic species category. While Florida incurs the highest acute algae risk (Table 3-2, column 5) and substantial acute fish risk (Table 3-4, column 5), the chronic fish risk is relatively small and does not change over the entered period. South Carolina incurs the highest fish and daphnia risk. The changes in risk due to the climate are presented by aquatic species category for all US states in Figure 3-1. For all aquatic species categories, the chronic risk increases more than the acute toxicity risk. We find fish the most influenced species by the interaction between climate change pesticide use. Substantial increases both in acute and chronic daphnia risk are estimated for all periods (Figure 3-1).

Table 3- 2 Aquatic species risk from agricultural pesticides under different climate scenarios-Algae

Aquatic species	US State	Average pesticide application (million lpb)	Changes in pesticide applications from chapter 2 (percent)			Acute aquatic risk[2] $(\frac{C^{Ex}}{LC^{50}})$				Chronic aquatic risk $(\frac{C^{Ex}}{LC^{50}})$			
		2000	2030	2070	2100	2000	2030	2070	2100	2000	2030	2070	2100
Algae	Washington	1.9	8.2	13.9	18.0	0.1	0.1	0.1	0.1	0.9	1.3	1.6	1.7
	Oregon	2.7	8.2	16.9	21.0	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.2
	California	19.7	12.1	20.0	27.3	0.2	0.2	0.2	0.2	0.3	0.4	0.4	0.4
	Texas	1.5	13.8	19.3	30.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	Arizona	1.3	10.1	18.7	27.1	0.0	0.0	0.0	0.0	0.2	0.0	0.0	0.0
	Georgia	5.7	13.5	21.9	26.4	0.1	0.1	0.1	0.2	0.2	0.2	0.2	0.2
	Florida	17.0	13.9	25.2	33.2	0.6	0.7	0.9	0.9	4.1	4.3	4.9	5.0
	South Carolina	1.2	12.1	18.7	29.4	0.1	0.1	0.2	0.2	1.7	2.6	3.0	3.2
	North Carolina	2.7	10.0	16.5	23.9	0.5	0.5	0.6	0.6	0.7	0.7	0.8	0.9
	New Jersey	0.5	8.0	15.9	19.7	0.5	0.6	0.6	0.7	1.3	1.4	1.5	1.6
	New York	0.8	8.8	14.9	17.1	0.2	0.2	0.2	0.2	0.6	1.0	1.1	1.2
	Pennsylvania	1.2	8.1	16.8	24.9	0.0	0.1	0.1	0.1	2.9	4.6	5.0	5.8
	Michigan	3.2	9.3	15.4	19.1	0.1	0.1	0.1	0.1	0.4	0.4	0.6	0.6

[2] C^{Ex} =exposure concentration, LC^{50} = median lethal concentration

Table 3- 3 Aquatic species risk from agricultural pesticides under different climate scenarios–Daphnia

Aquatic species	US State	Average pesticide application (million lpb)	Changes in pesticide applications from chapter 2 (percent)			Acute aquatic risk[3] $(\frac{C^{Ex}}{LC^{50}})$				Chronic aquatic risk $(\frac{C^{Ex}}{LC^{50}})$			
		2000	2030	2070	2100	2000	2030	2070	2100	2000	2030	2070	2100
Daphnia	Washington	1.9	8.2	13.9	18.0	0.7	0.8	0.9	0.9	1.7	2.4	2.8	3.1
	Oregon	2.7	8.2	16.9	21.0	0.8	0.9	0.9	1.0	0.1	0.2	0.2	0.2
	California	19.7	12.1	20.0	27.3	1.0	1.1	1.2	1.2	0.8	1.0	1.0	1.1
	Texas	1.5	13.8	19.3	30.0	0.4	0.4	0.4	0.5	0.0	0.0	0.0	0.0
	Arizona	1.3	10.1	18.7	27.1	0.0	0.1	0.1	0.1	0.9	1.2	1.3	1.5
	Georgia	5.7	13.5	21.9	26.4	0.9	1.0	1.1	1.1	0.0	0.0	0.0	0.0
	Florida	17.0	13.9	25.2	33.2	1.5	1.6	1.8	1.8	0.7	0.7	0.8	0.8
	South Carolina	1.2	12.1	18.7	29.4	6.7	7.2	7.8	8.2	4.2	6.0	6.9	7.5
	North Carolina	2.7	10.0	16.5	23.9	0.2	0.2	0.2	0.2	0.3	0.4	0.4	0.4
	New Jersey	0.5	8.0	15.9	19.7	2.6	2.9	3.2	3.4	0.1	0.1	0.1	0.1
	New York	0.8	8.8	14.9	17.1	0.3	0.3	0.3	0.3	1.0	1.6	1.8	2.0
	Pennsylvania	1.2	8.1	16.8	24.9	0.3	0.3	0.4	0.4	4.6	5.3	6.1	7.0
	Michigan	3.2	9.3	15.4	19.1	1.0	1.5	1.6	1.7	0.5	0.8	0.9	0.9

[3] C^{Ex} =exposure concentration, LC^{50} = median lethal concentration

Table 3- 4 Aquatic species risk from agricultural pesticides under different climate scenarios–Fish

Aquatic species	US State	Average pesticide application (million lpb)	Changes in pesticide applications from chapter 2 (percent)			Acute aquatic risk[4] $(\frac{C^{Ex}}{LC^{50}})$				Chronic aquatic risk $(\frac{C^{Ex}}{LC^{50}})$			
		2000	2030	2070	2100	2000	2030	2070	2100	2000	2030	2070	2100
	Washington	1.9	8.2	13.9	18.0	0.4	0.5	0.5	0.5	2.1	3.3	3.9	4.2
	Oregon	2.7	8.2	16.9	21.0	0.6	0.6	0.7	0.7	0.2	0.2	0.3	0.3
	California	19.7	12.1	20.0	27.3	1.6	1.8	1.8	1.9	0.4	0.5	0.6	0.6
	Texas	1.5	13.8	19.3	30.0	1.2	1.3	1.4	1.4	0.0	0.0	0.0	0.0
	Arizona	1.3	10.1	18.7	27.1	0.2	0.2	0.2	0.3	0.2	0.2	0.2	0.3
	Georgia	5.7	13.5	21.9	26.4	1.1	1.2	1.3	1.4	0.0	0.0	0.0	0.0
Fish	Florida	17.0	13.9	25.2	33.2	2.6	3.0	3.4	3.4	0.1	0.1	0.1	0.1
	South Carolina	1.2	12.1	18.7	29.4	5.0	5.7	6.1	6.4	6.0	8.9	10.3	11.2
	North Carolina	2.7	10.0	16.5	23.9	0.5	0.5	0.6	0.6	0.0	0.0	0.0	0.0
	New Jersey	0.5	8.0	15.9	19.7	4.5	5.4	5.9	6.2	0.0	0.0	0.0	0.0
	New York	0.8	8.8	14.9	17.1	1.3	1.4	1.5	1.6	1.5	2.4	2.8	3.1
	Pennsylvania	1.2	8.1	16.8	24.9	1.0	1.0	1.1	1.1	5.1	5.3	6.1	8.8
	Michigan	3.2	9.3	15.4	19.1	2.2	2.3	2.4	2.5	0.6	1.0	1.1	1.2

[4] C^{Ex} =exposure concentration, LC^{50} = median lethal concentration

Aquatic risk impacts differ substantially across active ingredients of pesticides. Figure 3-2 shows the risk estimates under current application rates by pesticide and aquatic species. While some pesticides cause high risk across all aquatic species categories, others impact only one category. Some pesticides such as cyprodini, dimethoate, and diquat impact both acute and chronic risk in all aquatic species categories; others such as cinazine only affect acute daphnia and fish risk.

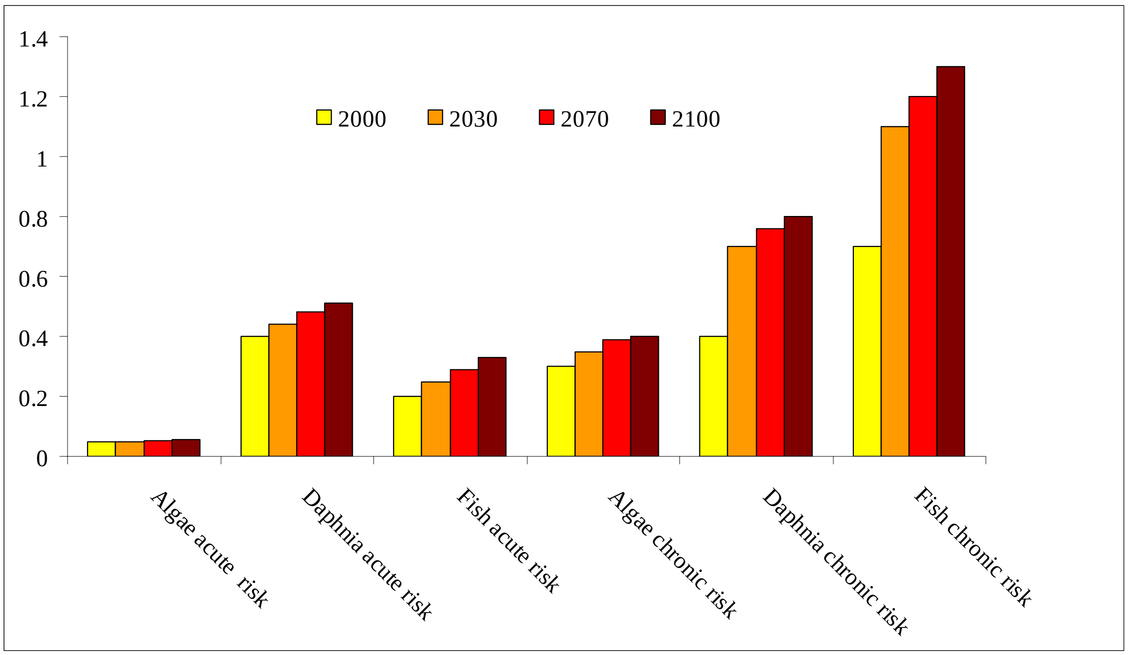

Figure 3- 1 Impact of climate change on aquatic species risk [in absolute values]

In chapter 2 we find the climate change effect on pesticide applications to vary substantially across chemical classes therefore the changes in aquatic risk due to climate change also vary. Our results indicate that the interaction between climate change and all examined pesticides increases the overall risk for all aquatic species categories. However, substantial changes in risk compared to the base risk will not cause unacceptable damages if current pesticide applications cause very low risk. The relative changes in risk due to climate change are given in Table 3-5 for some of the more hazardous pesticides.

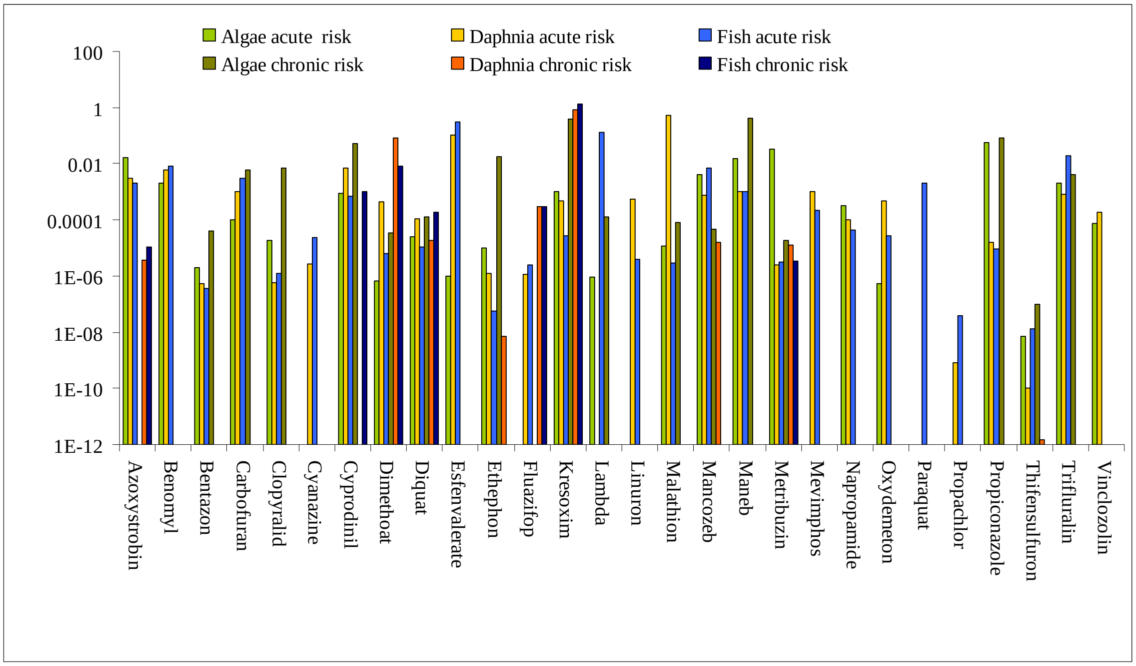

Figure 3- 2 Current aquatic species risk by pesticide ingredient [in absolute values]

Table 3-5 also provides the toxicity rank according to the Pesticide Action Network database Particularly, we find increases in chronic fish risk of 213 percent from Carbofuran, increases in acute daphnia risk of 117 percent from clopyralid, and increases in acute algae risk of 110 percent from benomyl, all comparing the 2100 estimate to the year 2000 risk value. However, most of the strongly increasing pesticides have low toxicities and low absolute risk values at present. Therefore, their consequences to the aquatic environment will be moderate. For pesticides with high basic toxicity values, we find climate change to increase risk by less than 50 percent compared to the year 2000 (Table 3-5), except for kresoxim-methyl and azoxistrobin.

Table 3- 5 Impact of individual pesticide ingredients on aquatic species risk

Pesticide	Aquatic impact category	Base risk ($\frac{C^{Ex}}{LC^{50}}$) 2000	Relative change to base risk (in percent) 2030	2070	2100	Toxicity in PAN database
Azoxystrobin	Algae acute risk	0.078	27	46	58	high
Benomyl	Algae acute risk	0.006	52	68	110	slight
Maneb	Algae acute risk	0.034	8	18	25	high
Metribuzin	Algae acute risk	0.003	22	39	43	high
Propiconazole	Algae acute risk	0.32	4	12	19	high
Metribuzin	Algae acute risk	0.155	22	38	43	high
Carbofuran	Algae chronic risk	0.057	46	65	68	high
Kresoxim-methyl	Algae chronic risk	0.971	60	68	95	high
Vinclozolin	Algae chronic risk	0.02	19	47	109	slight
Azoxystrobin	Daphnia chronic risk	1.80E-05	28	56	59	high
Fluazifop	Daphnia chronic risk	0.002	11	17	19	high
Kresoxim-methyl	Daphnia chronic risk	0.265	55	77	80	high
Azoxystrobin	Daphnia acute risk	0.015	22	44	60	high
Benomyl	Daphnia acute risk	0.022	10	18	27	high
Clopyralid	Daphnia acute risk	1.20E-06	66	94	117	slight
Cyprodinil	Daphnia acute risk	0.043	8	18	24	high
Linuron	Daphnia acute risk	0.73	34	50	59	high
Mevimphos	Daphnia acute risk	0.155	4	6	9	high
Oxydemeton	Daphnia acute risk	0.002	11	19	27	high
Trifluralin	Daphnia acute risk	0.01	12	33	47	high
Esfenvalerate	Daphnia acute risk	0.392	14	23	28	high
Azoxystrobin	Fish acute risk	0.009	26	59	87	high
Benomyl	Fish acute risk	0.03	3	9	16	high
Carbofuran	Fish acute risk	0.024	73	112	213	slight
Clopyralid	Fish acute risk	2.50E-06	67	93	113	slight
Mevimphos	Fish acute risk	0.001	3	7	8	high
Trifluralin	Fish acute risk	0.237	8	31	47	high
Esfenvalerate	Fish acute risk	0.876	14	22	27	high
Lambda-cyhalotrin	Fish acute risk	0.975	3	9	12	high
Azoxystrobin	Fish chronic risk	5.40E-05	27	45	59	high
Dimethoat	Fish chronic risk	0.126	8	16	22	high
Fluazifop	Fish chronic risk	0.004	10	13	18	high
Kresoxim-methyl	Fish chronic risk	0.823	53	79	94	high

The risk estimates in this study consider 49 crops grouped into 8 crop classes which differ in pesticide choice and pest management practices. Therefore, these pesticides have different impacts on aquatic risk. Figures 3-3 to 3-4 show the aquatic risk contributions by crop and aquatic species category under current and projected climate.

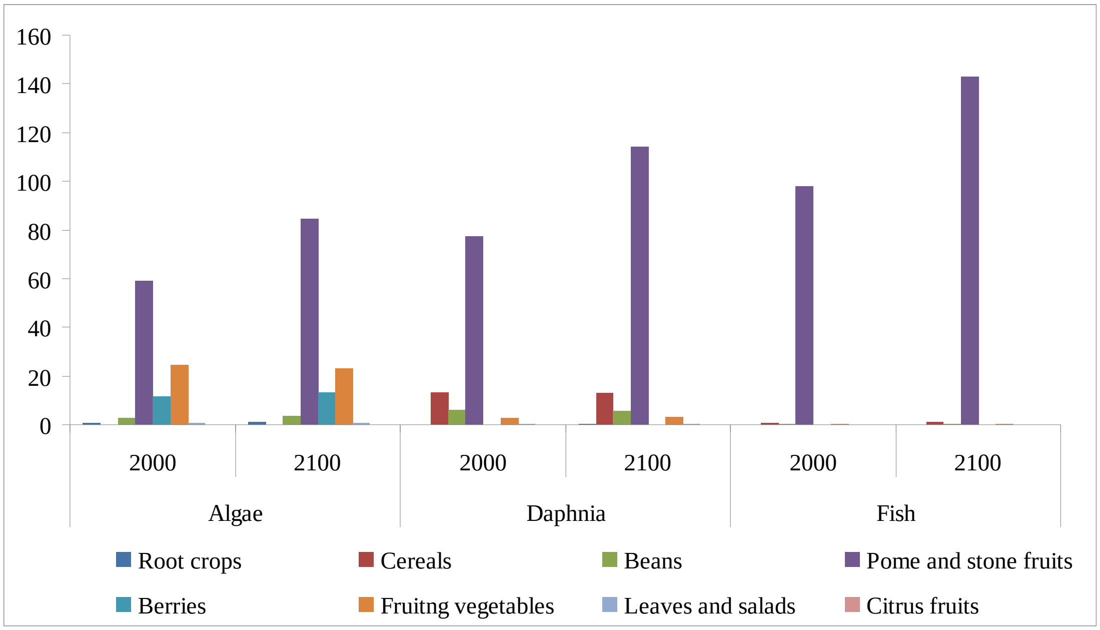

Figure 3- 3 Chronic risks contribution from individual crop type class for base and last period [in percent]

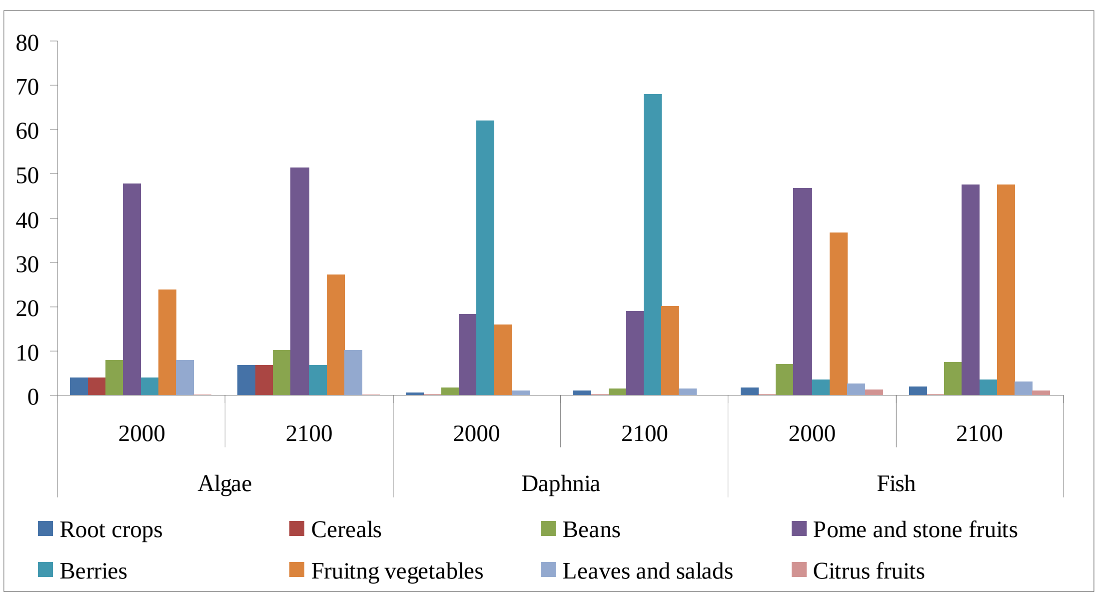

Figure 3- 4 Acute risks contribution from individual crop type class for base and last period [in percent]

Since we do not find substantial non-linear pattern across the four time periods, we only show the aquatic risk contributions for the years 2000 and 2100. Regarding chronic risk, we find pome and stone fruit pesticides to have the biggest impact on all aquatic species categories. For example, we estimate their contribution to fish risk at 98 percent (Figure 3-3). Under the projected climate for 2100, the contribution to chronic risk from pome and stone fruit management will increase for all aquatic species categories by more than 20 percent compared to the current situation (Figure 3-3). On the other hand, the contribution of pesticides applied to fruiting vegetables, leaves and salads, and citrus fruits to chronic algae risk will decrease until 2100. Pesticides used for pome and stone fruits also affect considerably the acute risk of aquatic species. Under current climate, they contribute 48 percent to acute algae and fish risk, and close to 18 percent to daphnia risk (Figure 3-4). The acute daphnia risk incurs the biggest contribution from berry pesticides both in 2000 and 2100. In contrast to their impact on chronic risk, the contribution to acute risk from pesticides for stone fruits increases only very little for all aquatic species categories (less than 2 percent compared to the current risk contribution). While the acute risk share of pome and stone fruit pesticides does not change substantially, the share of pesticides for fruiting vegetables increases.

Despite the fact that conventional cereal production systems require a large amount of pesticides, we find a relatively low contribution to both acute and chronic risks across all aquatic species. Our results indicate an increasing share of cereal pesticides to the acute algae risk (Figure 3-4) and a less than 1 percent increasing share of the chronic risk to daphnia (Figure 3-3). The risk contribution of pesticides applied to other crop classes are relatively small (less than 10 percent) and the changes in their risk shares do not exceed 3 percent.

Since projections on aquatic risk are based on uncertain regression coefficients with an error distribution, we use a Monte Carlo simulation to estimate the uncertainty of our risk estimates. We consider 50 random draws over the distribution of all regression coefficients from chapter 2 to re-calculate REXTOX. A statistical summary of the Monte Carlo simulations is shown in Table 3-6. Due to only small differences, the REXTOX values between the two climate model projections are averaged. For most categories of aquatic species risk, we find the standard deviation to exceed 20 percent of the associated mean risk. The highest variation is observed for chronic toxicity of fish with a standard deviation equal to 59 percent of the computed mean risk for 2100. Across time, the standard deviation change relatively little not exceeding 8 percent.

Table 3- 6 Summary statistics for Monte Carlo simulations

Date	Aquatic impact category	Minimum (% of mean)	Mean	Maximum (% of mean)	Standard deviation (% of mean)
2030	Algae acute risk	18	0.047	376	42
	Daphnia acute risk	19	0.454	271	37
	Fish acute risk	39	0.298	287	28
	Algae chronic risk	35	0.407	204	21
	Daphnia chronic risk	27	0.752	189	52
	Fish chronic risk	36	1.093	218	51
2070	Algae acute risk	91	0.054	262	48
	Daphnia acute risk	23	0.501	314	36
	Fish acute risk	27	0.301	421	23
	Algae chronic risk	30	0.402	245	19
	Daphnia chronic risk	20	0.804	119	49
	Fish chronic risk	42	1.300	193	58
2100	Algae acute risk	20	0.058	113	38
	Daphnia acute risk	31	0.503	166	35
	Fish acute risk	19	0.301	192	27
	Algae chronic risk	15	0.403	249	22
	Daphnia chronic risk	29	0.856	175	45
	Fish chronic risk	17	1.402	189	59

Our pesticide application projections over a 100-year horizon are based on statistically estimated relationships for the recent past. The more climate and weather variables in the future deviate from the historical mean, the higher is the uncertainty of the projection.

Using the 95% prediction intervals on pesticide applications for all projected dates and all regressions from chapter 2, we compute an uncertainty estimate for each aquatic risk category. Particularly, for each US state, projection date, and aquatic species category, we use the highest upper boundary and the highest lower boundary of all pesticide-specific prediction intervals as estimate of the overall upper and lower 95% confidence boundary on the corresponding aquatic risk prediction (Table 3-7)

Table 3- 7 95 percent confidence interval on aquatic risk projection

Date	Aquatic impact category	Lower bound (absolute value)	Lower bound (relative value to the mean)	Upper bound (absolute value)	Upper bound (relative value to the mean)
2030	Algae acute risk	0.04	0.85	0.05	1.06
	Daphnia acute risk	0.41	0.90	0.50	1.10
	Fish acute risk	0.25	0.84	0.34	1.15
	Algae chronic risk	0.37	0.91	0.44	1.09
	Daphnia chronic risk	0.55	0.73	0.95	1.27
	Fish chronic risk	0.96	0.88	1.23	1.13
2070	Algae acute risk	0.03	0.56	0.07	1.30
	Daphnia acute risk	0.35	0.70	0.65	1.30
	Fish acute risk	0.20	0.66	0.40	1.34
	Algae chronic risk	0.25	0.62	0.55	1.37
	Daphnia chronic risk	0.45	0.56	1.16	1.44
	Fish chronic risk	0.79	0.61	1.81	1.39
2100	Algae acute risk	0.02	0.34	0.10	1.66
	Daphnia acute risk	0.21	0.40	0.81	1.59
	Fish acute risk	0.10	0.33	0.52	1.66
	Algae chronic risk	0.10	0.25	0.71	1.76
	Daphnia chronic risk	0.41	0.48	1.30	1.52
	Fish chronic risk	0.68	0.49	2.12	1.51

Because we did not find substantial differences between the two climate change models, their uncertainty estimates are averaged. As shown in Table 6, the confidence intervals widen substantially over time. Furthermore, the changes in confidence are highly non-linear. For example, in 2030, the 95% confidence interval for chronic risk to algae is smaller than those for all other aquatic risk categories. However, in 2100, estimates of chronic risk to algae have the widest confidence interval and thus the highest uncertainty.

3.4 Conclusions

This study estimates the impact of climate change induced adjustments of pesticide applications on the aquatic environment. On average, increased applications of agricultural pesticides will increase the aquatic risk by 47 percent. These impacts are mainly caused by states near to the coast. Climate change impacts on agricultural pesticides vary and hence, their contribution to changes in aquatic toxicity risk differs. Because different crops require different pesticides, the contribution also differs across crops. For all major crop types, our analysis shows that the aquatic risk contribution is likely to increase under climate change. Pesticides applied to pome and stone fruits, berries and fruiting vegetables contain the most harmful substances for aquatic species and have the highest contribution to overall risk.

Our results have important research and policy implications. First, our estimates can help to improve the mathematical representation of external impacts from agricultural pesticide use in integrated assessment models. These models are increasingly used for the design and justification of climate and other environmental policies. Second, if the overall external effects of agricultural pesticides are indeed negative the socially optimal response to climate change moves away from adaptation towards mitigation. Third, our results could affect agricultural research programs because the expected social returns to research on alternative pest control strategies would depend on the expected external cost change. Particular, fruits and vegetables may cause substantial environmental damages. Furthermore, our results may have important implications for the design of future crop insurance programs.

Several important limitations and uncertainties to this research should be noted. First, the projections of pesticide applications under climate change are based on statistically estimated dependencies of pesticide applications on weather and climate variables and on model based climate simulations. Thus, the certainty of the estimates presented here depends on the quality and certainty of the underlying models. Second, meaningful variation in CO_2 levels is not observable in the data for the climate change effects on pesticides use. Third, the estimates of risk generated by the REXTOX include precise information on spray drift and runoff but ignore other routes of potential aquatic exposure such as leaching. Furthermore, there is no account of pesticides applied through seed treatment or fertilization. Thus, the values produced by REXTOX may somewhat underestimate the real risk. Fourth, the states data from NASS and toxicity data from PAN pesticides database we have used may differ in quality and scope across space and time. Therefore, these results might overestimate the impacts of climate change on pesticides application and risk to the aquatic environment.

3.5 Appendix

3.5.1 Structure of the Aquatic risk indicator REXTOX

In 2000, the OECD designed and developed several aquatic risk assessment tools for national authorities to monitor progress on measures designed to reduce the environmental risk of pesticides. The proposed indicators were ADSCOR, SYSCOR and REXTOX. They represent different combinations of mechanistic and scoring approaches and use information on pesticide application and environmental consequences at national or regional level. In all three indicators relative risk values are estimated by calculating the "exposure-toxicity ratio". While all indicators include toxicity to the same organisms (algae, daphnia, and fish), they differ in the approach of exposure estimation. Of the three alternatives, REXTOX uses a mechanistic approach and is the only indicator considering several field site properties. Thus, REXTOX resembles most closely risk assessment in its basic structure and concept.

REXTOX consists of three major equations blocks. The first block calculates losses which are defined as the amount of pesticides leaving agricultural fields via spray drift, run-off or lathing. The second block calculates exposure of pesticides in surface waters. The third part calculates the toxicity risk. More details on each of these blocks appear below.

Table 3A- 1 Model equations, sets, subsets and list of variables

I. Losses

$$\sum_{c}^{n} Lsd_{ics}\% = (a - b \times \ln(Wbz_{is}{}^{2}))$$ 3A-1

$$\sum_{c}^{m} Lsd_{ic}\% = \frac{1}{(a + (b \times Wbz_{ic}{}^{2}))}$$ 3A-2

$$\sum_{c}^{p} Lsd_{ic}\% = \left(a + \frac{b}{Wbz_{ic}{}^{2}} \right)$$ 3A-3

$$\sum_{c}^{q} Lsd_{ic}\% = EXP(a - b \times \ln(Wbz_{ic}\ )$$ 3A-4

$$Lsd_{ic}\% = (Lsdnbz_{ic}\%) \times (1 - Compliance_{SDB_{ic}}) + (Lsd_{ic}\%) \times (Compliance_{SDBic})$$ 3A-5

$$Lro_{ics}\% = (Q_s / \Pr_s) \times Cr \times f1(Slope) \times f2(Run - off\ \_BZ) \times 100$$ 3A-6

$$Lro_{ic}\% = (Lronbz_{ic}\%) \times (1 - Compliance_{RODB_{ic}}) + (Lro_{ic}\%) \times (Compliance_{ROBic})$$ 3A-7

$$Cr = \exp\left(-3 \times \frac{\ln 2}{DT_{50} soil} \right) \times \left(\frac{1}{1 + \left(\frac{Koc \times \%OC}{100} \right)} \right) \times \left(\frac{1 - Pl\,\mathrm{int}}{100} \right)$$ 3A-8

$$f1_{slope} = 0.02153 slope + 0.001423 slope^{2};$$ 3A-9

$$f2_{BZ} = 0.83^{Wbz};$$ 3A-10

II. Exposure

$$EX_{(i,c,s)} = Adr_{ics} \times \left(\frac{Lsd_{ics}\% + Lro_{ics}\%}{Wd_s} \right) \times Wi_s \times Nap_{ics} \times Bta_{ics}$$ 3A-11

Table 3A- 2 Model equations, sets, subsets and list of variables continue

III.Risk

$$\text{REXTOX Scaled\_Acute}_{(i,c,s,l)} = \frac{Ex_{(i,c,s)}}{Atox_{(i,l)}} \qquad \text{3A-12}$$

$$\text{REXTOXScaled\_Chronic}_{(i,c,s,l)} = \frac{Ex_{(i,c,s)}}{Chrtox_{(i,l)}} \times LTF_{is} \qquad \text{3A-13}$$

$$LTF_{is} = \frac{C_{is}}{Ci_{is}} = \frac{1 - e^{-\frac{\ln 2}{DT_{50}} \times 21}}{\frac{\ln 2}{DT_{50}} \times 21} \qquad \text{3A-14}$$

Sets	***Subsets***
i -pesticides	$m \in c$ *early fruits*
c – crops	$n \in c$ *late fruits*
s- region	$p \in c$ *early arable*
l- aquatic species category	$q \in c$ *late arable*

List of variables

Lsd - Losses via spray;

Lro - Losses via run-off

Lsdnz- loses via spray drift without buffer

Lronbz - losses via run off without buffer

Koc- sorbcion coefficient of organic carbon

Plint- plant interception

Ex - exposure scaled;

Napp – number of application;

REXTOX Scaled_Acute- aqute risk;

REXTOX Scaled_Chronic- chronic risk;

LTF- long-time factor;

Adr -dose rate applied by farmers;

Q- runoff volume drift;

Pr - precipitation;

DT50 soil – soil degradation;

Wbz - water buffer zone;

OC- organic carbon;

Wd- water depth;

Wi - water index

f1,f2- slop of fields;

a,b- regression coefficients;

Bta – basic treated area;

Cr - Pesticides in soil surface;

C - concentration ;

CALCULATION OF LOSSES

Spray drift losses *(Lsd),* are calculated using parameters (equations 3A-1to 3A-5) from a regression model (Ganzelmeier et al., 1997). The terms of equations are**:** *a* and *b* **-** regression coefficients obtained from Ganzelmeier's tables (OECD, 2000*)*, and Width of water buffer zone (*Wbz*). By definition *Wbz* depends on the distance between the spray and the water bodies and the size of the water body (OECD, 2000*)*. As a condition for their legal permission and registration, some pesticides require the implementation of buffer zones to ensure the adequate protection of the aquatic organisms. A stationary buffer distance (6 m from the water's edge or 5 m from the bank top) is required for most of the agricultural pesticides (EPA, USA, 2006).

The indexes *m,n,p,q* capture differences between crop cultivation types and pesticide application timing (Ganzelmeier et al., 1997). Following the original REXTOX model, management practices are linked to the stage of crop development. The equations are split between the early fruits m, and late fruits n, and between early arable crops *p* and late one *q*.

The total amount of losses via spray drift is calculated in equation 5. The spray drift buffer compliance factor is incorporated by calculating *Lsd(%)* with and without buffer and putting the value in the equation 3A-5. Losses via run-off are calculated in equation (3A-3A-6). By equation (3A-6) the relative loss via run-off (Lro_{ics}%) is proportional to application dose rate available in run-off water as dissolved substances, *Q* – runoff volume (mm). The run-off volume is obtained from tables based on models by Lutz (1984) and Maniak (1992), which cover two soil types (sandy, loamy) and three scenarios considering application time, crop and soil moisture: Scenario 1 application in autumn on bare soil with high soil moisture; Scenario 2 application in early spring on bare soil with low soil moisture; Scenario 3 application in early summer on bare soil with low soil moisture; Depending of the soil type and scenario the corresponding run-off volume is picked up from the table for each value of precipitation between 1 and 100 mm. Pr_s is the mean of daily precipitation (mm/day) during growing seasons. Rain events are assumed to occur 3 days following application of pesticides (OECD, 2000). *Cr* is the amount of pesticides relative to the dose applied available for runoff 3 days after application. The calculation of that amount of pesticides (*Cr*) is given by equation (3A-8)

Within the first tree days the compound is depredate under first order kinetics (exp -3 x *Ln2/ DTsoil50). DT 50* soil is the half-life time (days) of the active ingredient in the soil. Only the contribution to the dissolved concentration in the water is considered.

{(*Koc x %OC)/100*} is the ratio of dissolved to sorbet pesticides concentrations with *Koc* the sorption coefficient of active ingredient to organic carbon and *%OC* organic carbon content in the soil.

Finally, the proportion of pesticides reaching the soil depends on the amount that is intercept by the plant (*Plint*) when it is applied {(1- *Plint*) /100} (equation 3A-7).

Equation 8 show the correction factor for slopes of fields (*f1,f2).* Below 20 % losses via runoff increase following the formula (equation 9) and are constant for the slops larger than 20 % to 20 % *f1* is set to 1. The correction factor for the buffer zone is calculated with equation 10. The losses via runoff increase exponentially with the width of the buffer zone. If the buffer zone is not densely covered with the plants, the width is set to zero (0 m).

The total amount of losses via runoff is calculated similar to the total amount of losses via spray drift (equation 3A-10). As is done for spray drift, runoff buffer compliance factor is incorporate by calculating *Lro* % with and without buffer in the following formula (equation 3A-10).

CALCULATION OF EXPOSURE

Exposure is calculated at three levels. The levels can be used separately or as a complex which allows comparing risk in association with recommended and practice. The first level exposure is calculated based on the recommended dose rate or base on the maximum quantities of pesticides that are suggested to be applied. The others two Exposures "*Unscaled*" and "*Scaled"* are based on the actual dose rate the quantities of pesticides applied by farmers. Exposure "*Unscaled*" represents the average of typical treatment on one average hectare in agricultural practice. Calculation is called "*Unscaled*" because it is done at the unit level rather than scaled up to a regional or national level. The third level so called Exposure *"Scaled"* is calculated to the national or regional level. Scaled Exposure calculation is given by equation 3A-11. The terms of equation 3A-11 are as follows: Actual dose rate (*Adr)* of applied pesticides multiplied by sum of losses (from spry drift and runoff in percent) divided by water depth, Water index which stands for the proportion of agricultural area bordered by surface water bodies, number of application, and basic treated area which is the proportion between treated with pesticides area and total planted area.

CALCULATION OF TOXICITY RISK

The risk index is calculated as a proportion between exposures to toxicity ratio Equation (3A-12, 3A-13).The terms of equation 13 are as follows: REXTOX_Acute is the acute risk index; Ex is the exposure and *Atox* is the laboratory value of *LC 50* or lethal concentration or concentration that have lethal effect on 50 % of the tested species; *i* is pesticide, *c* is crop group, s is state, *l* is aquatic species group.

Long-term risk is calculated on the same principle (equation 3A-14) but exposure is multiplying with a so-called long term factor (equation 3A-15). This factor indicates the ratio of the weighted average pesticide concentration (calculated on the basis of first-order degradation kinetics requiring *DT50*, water values) over a certain period (default value of 21 days was considered in correspondence to regular time period of long-term toxicity tests) and the initial concentration (OECD, 2000).

CHAPTER 4

THE IMPACT OF CLIMATE CHANGE ON THE EXTERNAL COST OF PESTICIDE APPLICATIONS IN US AGRICULTURE

4.1 INTRODUCTION

Long-term changes of climate have already been detected and there is wide agreement that the climate will continue to warm over the 21st century (IPCC, 2001). Climate and agriculture are locally and globally interrelated. Climate change is likely to have both detrimental and beneficial impacts on the agricultural sector (Adams et al., 1990; Lewandrowski and Schimmelpfennig, 1999). One concern of agriculturalists involves the effects of climate change on pest populations. Several studies investigate the interaction of pests and climate (Patterson et al., 1999; Porter, et al., 1991). The results from these studies indicate that pest activity is likely to increase under climate change, leading to greater risk of crop losses (Gutierrez et al. 2008, Patterson et al. 1999). There is a small but growing research field that focuses on how climate change will affect pesticide applications. Chen and McCarl (2003) empirically study the relationship between pesticide and climate associated with treatment costs of pesticides use. Their results suggest that climate change will increase pesticide treatment costs for major crops. In chapter 2 we use a similar approach but consider all major food crops and a more detailed classification of pesticides. We develop a panel data regression model and investigate how weather variability and climate change affect the application of pesticides in US agriculture. Furthermore we link the regression results to downscaled climate change scenarios from the Canadian and Hadley climate models. Our results indicate that for current crop area allocations, pesticide application rates mainly increase.

Pesticides are widely employed and generally considered essential to modern cropping systems. They contribute to a stable supply of affordable agricultural products with uniform quality. In contrast to their beneficial economic effects, pesticides may cause damage to natural resources, wildlife and ecosystem biodiversity, and human health. Pesticides migrate from agricultural fields into atmosphere, pedosphere, and hydrosphere (Schulz et al., 2001; Flury, 1996; Battaglin et al., 2003). Regular inflow and high persistence can lead to high pesticide concentrations in environmental compartments over time and affect non-target species (Beketov and Liess, 2008; Dores and Lamonica-Freire 2001). In the United States, approximately 67 million birds and between 6 and 14 million fish are estimated to die each year immediately after exposure to agricultural pesticides (US Fish & Wildlife Service, 2000; Gilliom, 2005; Pimentel, 2005). Note, however, that these values do not include animals that perish after a period because of functional disorders and reproductive abnormalities (Henny et al., 2008), secondary poisoning from consuming poisoned insects, rodents, and other prey, reduced survival, growth, and reproductive rates from exposure to sub-lethal dosages (Elliot et al., 1998), and habitat reduction through eliminated food (D'Aneri et al., 1987).

Human health is significantly affected as well. The total number of pesticide poisonings in the US is estimated at 300,000 annually (EPA, 1992). Backer et al. (2003) investigate pesticide residues in supermarket foods and find detectable levels of pesticides in most products. The Center for Disease Control and Prevention (CDC, 2002) reports more than 250 food transmitted diseases which cause an estimated 76 million illnesses, 325,000 hospitalizations, and 5,200 deaths annually in the US. Many studies analyze a variety of chronic human health effects caused by pesticides. These studies address heart diseases, sensory disturbances, and cognitive effects such as memory loss and language problems. Furthermore, some pesticides have been found to cause testicular dysfunctions or sterility (Colborn and Carroll, 2007). Pesticide residues in food are also linked to several types of cancer (Teitelbaum et al., 2007; Cockburn, 2007; Lee et al., 2007; Alavanja et al., 2006). Currently, 18 insecticides and about 90 percent of all fungicides are considered carcinogenic (USDA, 1987).

Various attempts have been made to describe and quantify the negative impacts of pesticides on the environment and human health. While some studies concentrate only on the external cost of pesticides (Waibel & Fleischer, 1998 [Germany]; Pretty et al.,2001 [UK, US, Germany]; Pimentel, 2005 [US]), others consider the full suite of externalities from agricultural systems (Davison et al., 1996 [Netherlands]; Schou, 1996 (Denmark); Bailey et al., 1999 [UK]; Tiezzi, 1999 [Italy]; Le Goffe, 2000 [France]; Pretty et al., 2000 [UK]). In the US, most of the work addresses multiple external impacts from agriculture. For example, the studies by Hrubovcak et al. (2000), Smith (1992) and Steiner et al. (1995) investigate the combined external cost from soil erosion, pesticide application and fertilization, using data from national statistics. The research by Tegtmeier and Duffy

(2004) updates these studies and improves the assessment by involving a larger data structure, thereby also replacing several crude assumptions from Pimentel et al. (1993). According to Tegtmeier and Duffy (2004), US agricultural production negatively impacts on the environment and human health at an estimated cost of \$6–17 billion per year. Damages of \$5–16 million are due to crop production and over \$700 million are due to livestock production. The total external cost from agriculture is estimated to lie between \$30 and \$96 per hectare and year. About 75 per cent of these costs are due to pesticides applied to crops. All calculations are in 2001 US dollars.

Pretty et al. (2001) estimate the environmental cost of pesticides per hectare and kg active ingredients for three countries and provide consistent and comparable reference points. In particular, their results indicate external cost values of £8.56 per hectare and kilogram active ingredients for the UK, £2.24 for the US, and £3.25 for Germany. All numbers are expressed in 1996 pounds sterling. Pimental (2005) finds that agricultural pesticides use in the US cause external cost to the environment and society of about \$10 billion per year. This value includes damages to human health (\$1.1 billion), biodiversity losses (\$3 billion), costs from increased pesticides resistance (\$1.5 billion), crop losses (\$1.4 billion), groundwater contamination (\$2.0 billion and costs of governmental regulations to prevent damages (\$0.470 billion).

The above studies do not address individual environmental and human health impacts of individual pesticides. Leach and Mumford (2008) introduce the Pesticide Environmental Accounting (PEA) tool for the assessment of environmental and human health effects from individual pesticides by combining ecotoxicological behavior data and field application rates.

In this study, we combine the external cost estimation method by Leach and Mumford (2008) with statistically estimated consequences of climate change on pesticide use in US agriculture from chapter 2. To our knowledge, all existing studies on the external cost of pesticides use current pesticide application rates. Chapter 4 proceeds as follows. Section 2 describes the data and basic structure of the PEA model and regression model that estimated effect of weather and climate variability in US pesticide applications to climate change (chapter 2). The regression results monetary estimates of external cost associated with climate change are analyzed in section 3. Finally, section 4 concludes. Additionally section 5 provides detailed information about Environmental Impact Quotient (EIQ) and Pesticide Environmental Accounting (PEA) tool structures.

4.2 Data and Methods

Data on pesticide usages for agricultural food production from 1990 to 2004 are obtained from the Agricultural Chemical Usage survey (NASS, 2005). These data include statistics on pesticide applications covering 339 active ingredients, 32 US states, and 49 crops. The survey contains information on application rate, treated area, recommended number of applications, and actual dose rate for each active ingredient. For the purpose of this study, crops with similar botanical characteristics are aggregated into 8 classes (Table 2-2).

The cost estimation follows Leach and Mumford. (2008), who propose the PEA tool for the assessment of monetized environmental and health impacts for all pesticides with known ecotoxicological behavior and field application rates. In particular, PEA combines aggregated pesticide externality results from Pretty et al. (2001) in a region or country with the Environmental Impact Quotient (EIQ) developed by Kovach et al. (1992).

The EIQ integrates data from several sources including EXTOXNET (Hotchkiss et al. 1989) for information on acute and chronic toxicity; SELCTV (Theiling et al., 1988) for information about impacts on beneficial insects; and GLEAMS for estimates of ground water mobility of individual pesticides (Leonard et al., 1987). The computation of the EIQ (Appendix 4.5.1) follows an approach suggested by Kovach et al., (1992) and considers three principal components of agricultural production systems: farmers, consumers, and the environment. Each component consists of several subcomponents or factors (Figure 4-1). The impact potential of a specific pesticide on an individual environmental factor is equal to the toxicity of the chemical compound times the potential of exposure. Currently, the EIQ dataset covers 325 active ingredients and contain total values and values for each individual component. The EIQ data used in this study are obtained from the New York State Integrated Pest Management Program (2009).

The aggregated external costs used in the PEA model are based on Pretty et al. (2001) and distinguish six broad categories of adverse effects: 1) contamination of drinking water, 2) fish deaths, and governmental transaction costs for monitoring and regulating pesticide use, 3) biodiversity losses, 4) impacts on landscape, culture, and tourism, 5) bee colony losses, and 6) acute effects of pesticides on human health. However, Leach and Mumford (2008) adjust the average external per-hectare-costs of pesticides estimated by Pretty et al. 2001 to 2006 prices. Particularly, they find the average costs per kg active ingredient to equal €15.49 for the UK, €3.22 for the US, and €7.65 for Germany. In the PEA model, these costs are assigned to the each subcomponent used in the EIQ system. The proportional allocation of external costs to the EIQ subcomponents proposed by Leach and Mumford (2008) is presented in Appendix 4.5.2, Table 4A2-1

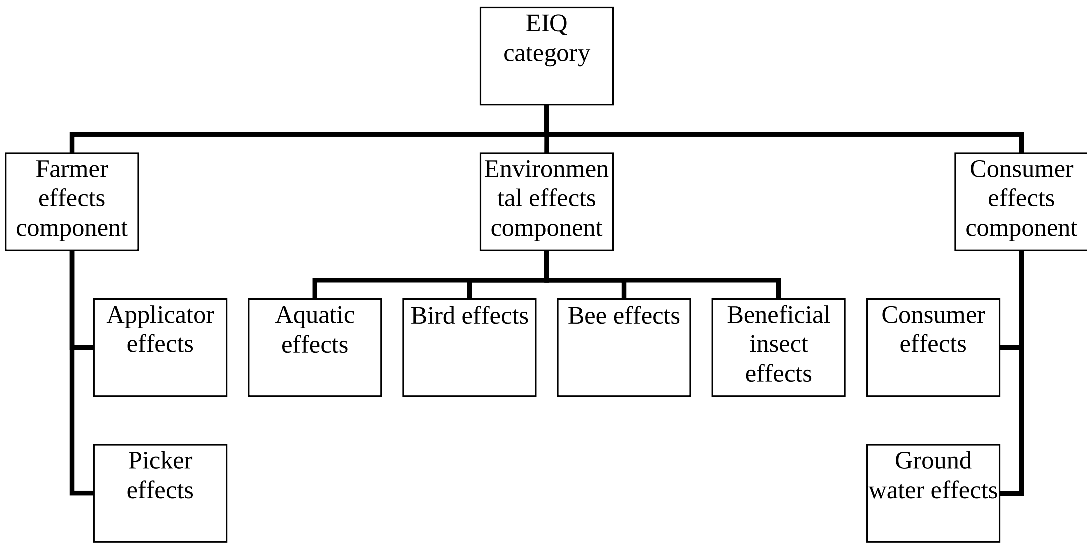

Figure 4- 1 EIQ category after Kovach et al (1992)

To incorporate the adverse effect categories proposed by Pretty et al. (2001) with EIQ environmental factors, Leach and Mumford (2008) derived for each environmental impact in the PEA model three scores identifying low, medium, and high ecotoxicological impacts. The average active ingredient costs for each EIQ category are then scaled by a factor of 0.5, 1, and 1.5 for low, medium and high impacts, respectively. In addition, the PEA model can transform these active ingredient costs into pesticide costs accounting for the active ingredient concentration and field application rates of different pesticide formulations. More details on PEA model structure are given in Appendix 4.5.2

Table 4- 1 Average external costs of pesticide application in US agriculture

Cost category (after Pretty et al., 2001)	$/kg/ha
Pesticides in sources of drinking water	6.99
Pollution incidents, fish deaths and monitoring costs	1.01
Biodiversity/wildlife losses	0.65
Cultural, landscape, tourism, etc.	1.66
Bee colony losses	0.16
Acute effects of pesticides to human health	0.49
Total	10.96

In this study, we use the PEA model to calculate the external costs of recent pesticide applications in the US. The cost data from Leach and Mumford (2008) for the US are revised and updated to reflect changes in prices. The final external cost values in this study are expressed in 2007 US dollars. Table 4-2 shows the external costs for the effect categories proposed by Pretty et al. (2001). If not indicated all values are adjusted based on the consumer price index for 2007. The cost distribution from the PEA model with the updated values is presented in Table 4-1.

Table 4- 2 PEA based mapping of external costs categories in $2007/kg/ha

EIQ category	Category after Pretty et al. (2001)						
	Pesticides in sources of drinking water	Pollution incidents, fish deaths and monitoring costs	Biodiversity / wildlife losses	Landscape / cultural / tourism value	Bee colony losses	Acute effects of pesticides to human health	Sum
Applicator effects	0.7					0.39	1.09
Picker effects	0.7					0.07	0.77
Consumer effects	4.19			0.83		0.02	5.04
Ground water	0.7	0.51					1.21
Aquatic effects	0.7	0.51	0.2				1.4
Bird effects			0.2	0.33			0.53
Bee effects			0.07	0.17	0.16		0.39
Beneficial insect effects			0.2	0.33			0.53
Sum of above	6.99	1.01	0.65	1.66	0.16	0.49	10.96

The estimation of climate change impacts on external environmental and human health costs from pesticide applications involves three steps. First, scenario projections from the Canadian and Hadley climate models are downscaled to obtain regional changes in relevant weather and climate parameters. Second, for each scenario, changes in pesticide applications are computed by updating the climate and weather parameters of an econometric model (chapter 2). Third, scenario specific changes in pesticide applications are used to compute external cost changes from pesticide use in the US.

4.3 RESULTS

This section presents the external cost estimates for the analyzed scenarios. To facilitate the internalization of external costs at different levels of decision making, all values are expressed in US dollars per kilogram active ingredient and per hectare treated. The observed pesticide application data from the year 2000 are used to compute the external cost base values. Climate change is integrated through Canadian and Hadley climate model based projections for the years 2030, 2070 and 2100. However, since the differences in external costs between the two climate projections and the four time periods turned out fairly small, the results of both climate change models are averaged. Furthermore, all external cost values are adjusted to 2007 values using the consumer price index.

The effects of climate change projections on external costs from broad pesticide classes are shown in Figure 4-2. Our results indicate that the external cost increase in all pesticide classes, however, at different rates. The highest change takes place in insecticides with external costs per kilogram active ingredient and treated hectare increasing from $31 in 2000 to $49 in 2100. External costs from fungicide and herbicide use change less and incur increases of $7 and $3 respectively. The total external costs over all pesticide classes increase from $43 in 2000 to $72 in 2100. We do not find large non-linear patterns between 2000 and 2100.

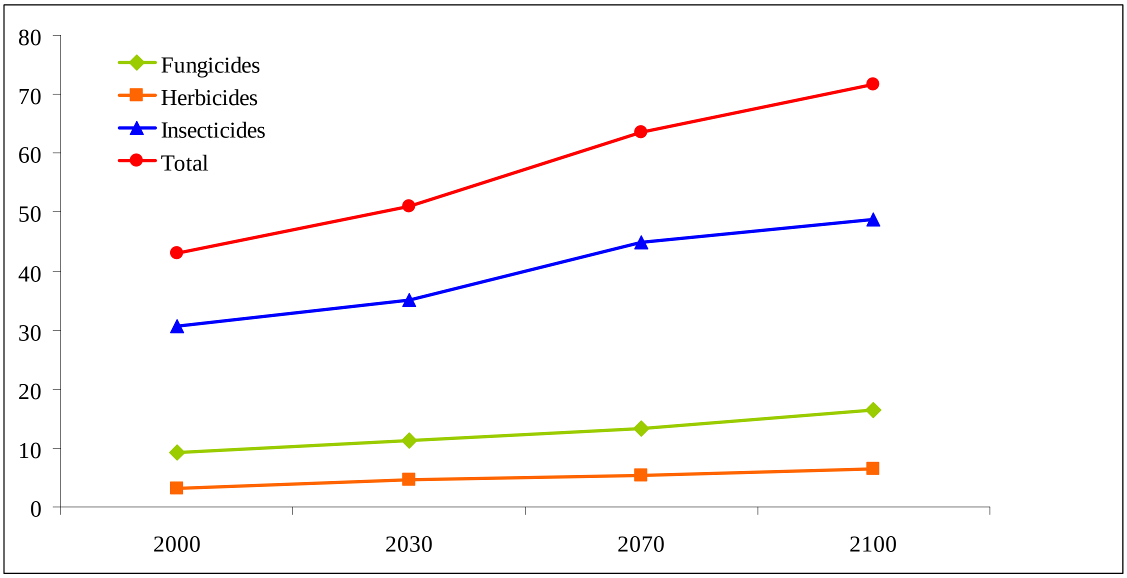

Figure 4- 2 The external cost of pesticides $2007/kg/ha by pesticide type

The contribution of different crop types to changes in external costs is summarized in Figure 4-3. Since we did not find substantial non-linear pattern across the four time periods, we show only cost estimates for 2000 and 2100. Results indicate increases in total external costs for all crop types. Pome and stone fruits ($7.76), berries ($4.07), and fruiting vegetables ($5.89) increase the most, followed by citrus ($2.68), leaves and salads ($3.20), cereals ($2.05), and beans ($1.86). The lowest total cost changes across all pesticide classes are found for root crops with increases slightly above $1 per kilogram active ingredient and treated hectare.

Figure 4-3 also reveals the combined impact of crop type and pesticide class.The highest absolute changes until 2100 are found for insecticides applied to berries, fruiting vegetables, pome and stone fruits with increases of almost $5 per kilogram active ingredient and treated hectare. In relative terms, however, fungicides applied to cereals and root crops increase the most, followed by insecticides applied to cereals and herbicides applied to root crops.

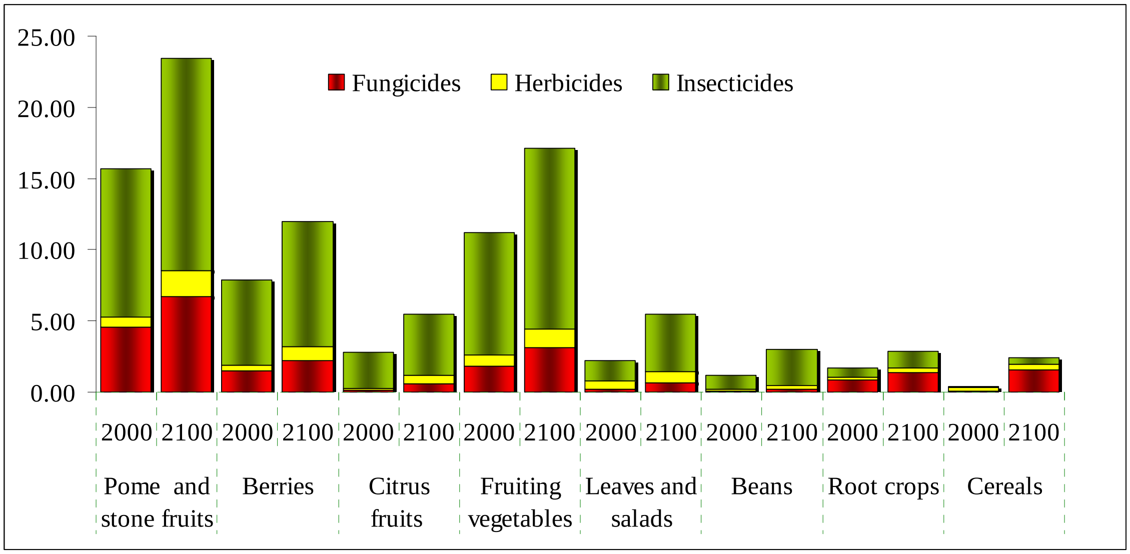

Figure 4- 3 The external cost of pesticides in \$2007/kg/ha by crop type classes for current conditions and 2100 climate projections

Figure 4-4 shows the external cost changes of pesticides by EIQ category and pesticide type. Again the values in 2100 are averages over the climate projections from both climate change models. There is a large difference in costs among the individual environmental categories. The highest costs are found for the consumer effect category above \$17 for the base period and \$24 in 2100. Within the three pesticide classes, insecticides show the highest magnitudes. The lowest costs are computed for effects on bees below \$2 in 2000 and slightly below \$4 in 2100.

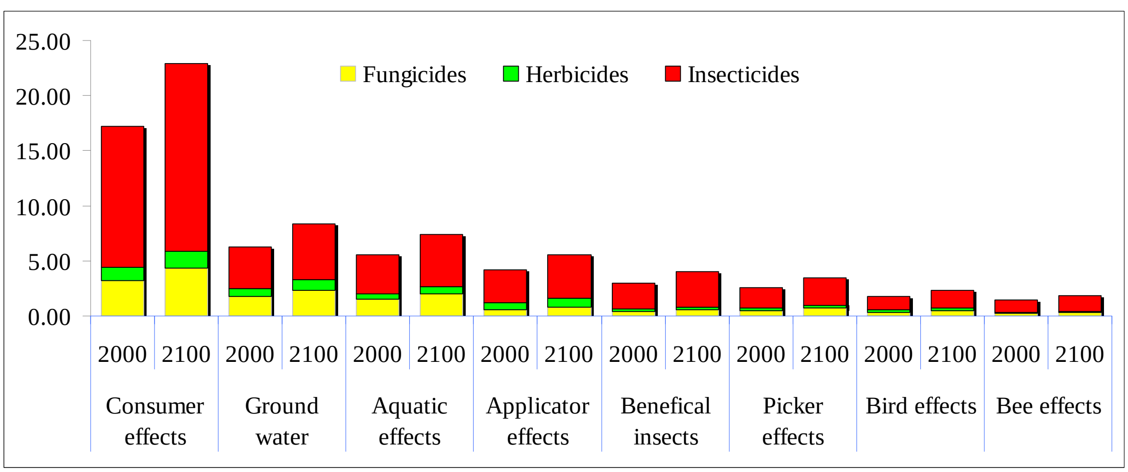

Figure 4- 4 The external cost of pesticides in \$2007/kg/ha by EIQ subcomponents classes for current conditions and 2100 climate projections

Table 4-3 shows the estimated external costs for the 35 currently most influential pesticides. We find a substantial variation of impacts with values ranging from below $1 to almost $40. For all listed pesticides, the external cost increase between 3 to 8 times by 2100. The ranking shows that the relative importance of individual pesticides may change over time.

Table 4- 3 External cost changes by crop and pesticide in $/kg/ha with ranks in ()

Crops	Pesticides	2000		2030		2070		2100	
Apples	Maneb	7.54	(1)	18.31	(1)	27.64	(1)	38.20	(1)
Pears	Simazine	5.31	(2)	8.41	(4)	10.03	(5)	13.67	(4)
Apples	Carbaryl	4.24	(3)	6.11	(5)	9.05	(4)	11.99	(3)
Apples	Dodine	3.69	(4)	9.75	(2)	15.84	(7)	21.34	(13)
Eggplants	Carbaryl	3.67	(5)	9.13	(22)	17.72	(2)	22.80	(2)
Pears	Ziram	3.34	(6)	5.17	(3)	8.05	(13)	10.95	(6)
Potatoes	Methamidophos	3.21	(7)	5.07	(26)	10.25	(8)	13.08	(11)
Tomatoes	Methomyl	2.98	(8)	4.81	(11)	9.07	(3)	12.23	(7)
Apples	Dimethoat	2.93	(9)	5.11	(13)	8.74	(14)	12.14	(8)
Nectarines	Simazine	2.70	(10)	4.56	(16)	5.81	(16)	7.96	(14)
Apricots	Diazion	2.54	(11)	5.83	(8)	8.54	(15)	13.01	(15)
Pears	Mancozeb	2.53	(12)	4.11	(6)	6.26	(11)	8.86	(16)
Cauliflowers	DCPA	2.43	(13)	5.37	(15)	9.89	(22)	14.05	(5)
Potatoes	Oxamyl	2.38	(14)	4.13	(7)	9.03	(6)	12.06	(23)
Peaches	Captan	2.28	(15)	4.93	(19)	8.71	(19)	11.95	(20)
Cabbages	Methomyl	2.25	(16)	5.27	(9)	8.94	(25)	11.27	(24)
Nectarines	Norflurazon	2.16	(17)	3.55	(23)	5.81	(10)	7.92	(12)
Nectarines	Ziram	2.13	(18)	3.28	(10)	4.75	(12)	6.97	(26)
Potatoes	Aldicarb	2.01	(19)	3.59	(14)	5.01	(23)	6.46	(30)
Apples	Metiram	1.76	(20)	4.63	(12)	7.24	(9)	9.75	(9)
Squashes	Acephate	1.74	(21)	2.93	(29)	3.68	(17)	4.71	(17)
Cucumbers	Mancozeb	1.70	(22)	2.43	(18)	4.94	(30)	6.05	(10)
Apples	Captan	1.62	(23)	6.14	(17)	8.22	(29)	9.89	(35)
Potatoes	Maneb	1.59	(24)	2.93	(34)	3.74	(18)	4.83	(18)
Squashes	Malathion	1.52	(25)	3.09	(30)	4.89	(21)	6.00	(31)
Eggplants	Maneb	1.49	(26)	5.84	(25)	6.98	(31)	8.29	(32)
Spinach	Cycloate	1.46	(27)	2.73	(20)	4.68	(24)	5.67	(19)
Potatoes	Metiram	1.39	(28)	2.93	(24)	4.07	(33)	5.28	(22)
Squashes	Carbofuran	1.22	(29)	3.77	(31)	5.03	(26)	7.96	(25)
Cabbages	Maneb	1.12	(30)	3.14	(35)	5.38	(32)	6.94	(34)
Potatoes	Carbofuran	1.11	(31)	2.93	(33)	4.91	(34)	6.58	(27)
Tangerines	Ferbam	1.07	(32)	1.98	(27)	2.49	(27)	4.09	(28)
Potatoes	Diazion	0.95	(33)	3.19	(21)	4.86	(20)	6.03	(21)
Peaches	Phosmet	0.94	(34)	2.93	(28)	4.21	(28)	7.20	(33)
Peaches	Carbaryl	0.90	(35)	1.88	(32)	2.73	(35)	2.99	(29)

4.4 CONCLUSIONS

This study employs the Pesticide Environmental Accounting tool to compute the impact of climate change induced adjustments of pesticide applications on the external environmental cost. Our results suggest that in absence of crop choice adaptation, climate change is likely to increase the plant protection need the associated external environmental cost. Particularly, we find that the current average value of $43 per hectare and kg active ingredient would increase by up to 60 percent by 2100.

The findings of this study have research and policy implications. Most importantly, they contribute to an improved understanding of climate change impacts and therefore affect the socially optimal policy response to climate change. Overall increased negative externalities from pesticide applications could provide an argument for more mitigation, i.e. for stronger greenhouse gas emission control policies. Related to this argument, the externality estimates can help to improve the scope of climate change impacts in integrated assessment and earth system models. These models are increasingly used for the design and justification of climate and other environmental policies. Furthermore, the results could affect agricultural research support programs because the expected social returns to research on various pest control strategies depend also on the expected external cost change. This may particularly be relevant for pome fruits, stone fruits, berries, and fruiting vegetables, which together contribute more than 50 percent to the total external costs. Finally, our results may affect the optimal design and premiums of crop insurance programs.

Several important limitations and uncertainties to this research should be noted. First, we do not have data and thus do not explicitly account for climate change impacts on pest populations. Second, because we use statistically estimated relationships over a relatively short time horizon of 14 years, we do not include the potential impact of increased CO_2 concentrations on pesticide applications. Third, the projection of pesticide application externalities under climate change is based on statistical, climate, and environmental accounting models. Thus, the validity of the estimates presented here depends on the quality of these models and associated data. The quality and scope of the employed NASS data on pesticide applications may differ across space and time. Fourth, crop choice and crop management adaptations are ignored in this analysis. However, this aspect is partially addressed in a follow-up chapter 5.

4.5 APPENDIXES

4.5.1 THE EIQ EQUATIONS

The formula for determining the EIQ value of individual pesticides is shown below and gives the average of the farm worker, consumer, and ecological components:

$$EIQ=\{C[(DT*5)+(DT*P)]+[(C*((S+P)/2)*SY)+(L)]+[(F*R)+(D*((S+P)/2)*F3)+(Z*P*F3)+(B*P*F5)]\}/3, \quad (4A\text{-}1)$$

Where, DT = dermal toxicity, C = chronic toxicity, SY = systemicity, F = fish toxicity, L = leaching potential, R = surface loss potential, D = bird toxicity, S = soil half-life, Z = bee toxicity, B = beneficial arthropod toxicity, P = plant surface half-life, and F3, F5 = Impact multipliers corresponding to levels of 3 and 5, respectively.

Farm worker risk is defined as the sum of applicator exposure (DT* 5) plus picker exposure (DT*P) times the long-term health effect or chronic toxicity (C). Within the farm worker component, applicator exposure is determined by multiplying the dermal toxicity (DT) rating to small laboratory mammals (rabbits or rats) times a coefficient of five to account for the increased risk associated with handling concentrated pesticides. Picker exposure is equal to dermal toxicity (DT) times the rating for plant surface residue half-life potential (the time required for one-half of the chemical to break down). This residue factor takes into account the weathering of pesticides that occurs in agricultural systems and the days to harvest restrictions that may be placed on certain pesticides.

The consumer component is the sum of consumer exposure potential (C*((S+P)/2)*SY) plus the potential groundwater effects (L). Groundwater effects are placed in the consumer component because they are more of a human health issue (drinking well contamination) than a wildlife issue. Consumer exposure is calculated as chronic toxicity (C) times the average for residue potential in soil and plant surfaces (because roots and other plant parts are eaten) times the systemic potential rating of the pesticide (the pesticide's ability to be absorbed by plants).

The ecological component of the model is composed of aquatic and terrestrial effects and is the sum of the effects of the chemicals on fish (F*R), birds (D*((S+P)/2)*3), bees (Z*P*3), and beneficial arthropods (B*P*5). The environmental impact of pesticides on aquatic systems is determined by multiplying the chemical toxicity to fish rating times the surface runoff potential of the specific pesticide (the runoff potential takes into account the half-life of the chemical in surface water).

The impact of pesticides on terrestrial systems is determined by summing the toxicities of the chemicals to birds, bees, and beneficial arthropods. Impact on birds is measured by multiplying the rating of toxicity to birds by the average half-life on plant and soil surfaces times three. Impact on bees is measured by taking the pesticide toxicity ratings to bees' times the half-life on plant surfaces times three. The effect on beneficial arthropods is determined by taking the pesticide toxicity rating to beneficial natural enemies' times the half-life on plant surfaces times five. Mammalian wildlife toxicity is not included in the terrestrial component of the equation because mammalian exposure (farm worker and consumer) is already included in the equation, and these health effects are the results of tests conducted on small mammals such as rats, mice, rabbits, and dogs.

4.5.2 THE PESTICIDE ENVIRONMENTAL ACCOUNTING (PEA) SYSTEM STRUCTURE

The Pesticide Environmental Accounting (PEA) system combines the general costs of all pesticides used for several known countries with the ecotoxicological behaviour of specific pesticides, and incorporating a calculation that extrapolates to other countries.

The external pesticide data presented in Pretty et al. (2001) are basic in the PEA model structure. The data are converted to Euros at 2005/2006 rates. The PEA uses the mean value of the three countries from each category to provide a single baseline external cost for 1 kg of active ingredient of an average pesticide. The PEA model transpose the average per kg active ingredient external cost categories and apportion these to the eight specific components used in the EIQ system: Applicator, Picker, Consumer, Ground water, Aquatic, Bird, Bee, and Beneficial insect effects. Table 4A2-1 shows how costs from Pretty et al. categories were distributed over the EIQ system categories.

Table 4A2- 1 Proportional distribution of external cost in PEA model Leach and Mumford (2008)

	Categories after Pretty et al. (2001).					
EIQ system categories	Pesticides in sources of drinking water	Pollution incidents, fish deaths and monitoring costs	Biodiversity / wildlife losses	Landscape / cultural / tourism values	Bee colony losses	Acute effects of pesticides to human health
Applicator effects	0.10					0.8
Picker effects	0.10					0.15
Consumer effects	0.60			0.50		0.05
Ground water	0.10	0.50				
Aquatic effects	0.10	0.50	0.30			
Bird effects			0.30	0.20		
Bee effects			0.10	0.10	1.00	
Beneficial insect effects			0.30	0.20		
Sum	1.00	1.00	1.00	1.00	1.00	1.00

To determine the range of possible initial EIQ scores, the EIQ model is set so that all the inputs were given the lowest possible eco-toxicological score and then for each of the eight classes listed above the score for this lowest (most environmentally benign) notional pesticide was noted. This is repeated for a hypothetical "medium" pesticide (all EIQ inputs set to medium) and "high" pesticide, representing a particularly damaging pesticide where all the EIQ inputs categories were set to high. Thus for each EIQ category a range of scores was derived that was divided into three classes as low, medium and high. Because the EIQ quotients in each category are non-linear the class boundaries were allocated at the mid-point between the value with all EIQ inputs set at low and with all set at medium (for the low—medium boundary) and similarly between the values with all inputs at medium and high (for the medium—high boundary) (Table 4A2-2). When data for a real pesticide are put into the model the average active ingredient per kg costs for each EIQ category are applied at half, unchanged or one-and-a-half times the costs for low, medium and high classifications, respectively. This gives an estimate of environmental costs for the application of 1 kg of active ingredient of any specific pesticide and, as in the EIQ system, the PEA allows for these costs to be adjusted to the active ingredients concentration and field application rates of different formulations for each chemical.

Table 4A2- 2 PEA quotient classification by EIQ category form from Leach and Mumford (2008)

EIQ categories	Low range	Medium range			High range
	Lowest possible	Low medium boundary	Middle	Medium high boundary	Highest Possible
Applicator effects	5	25	45	85	125
Picker effects	1	14	27	76	125
Consumer effects	2	16	30	55	80
Ground water	1	2	3	4	5
Aquatic effects	1	5	9	17	25
Bird effects	3	15	27	51	75
Bee effects	3	15	27	51	75
Beneficial insect effects	5	25	45	85	125

CHAPTER 5

PESTICIDE EXTERNALITIES FROM THE US AGRICULTURAL SECTOR – THE IMPACT OF INTERNALIZATION, REDUCED PESTICIDE APPLICATION RATES, AND CLIMATE CHANGE

5.1 INTRODUCTION

Climate change is already widely considered a reality (IPCC, 2007). An extensive literature has emerged on the interdependencies between climate and agriculture. Earlier studies have focused primarily on the vulnerability of the agricultural sector to changes in climate and weather variability (Rosenzweig and Hillel 2002; Reilly et al., 1996; Fischer, 1993; Strzepek and Smith, 1995; Adams et al., 1990; Mendelsohn et al., 1994; Darwin et al., 1995). There is general agreement that the degree of vulnerability depends on many local environmental and management factors (IPCC 2007). Changes in temperature, precipitation, and CO_2 will alter local land and water managements and in turn affect agricultural production and agricultural sector welfare.

A series of studies measure the economic consequences of various climate change impacts on the agricultural sector. Adams et al. (1990) combine general circulation, biologic, and agricultural economic models to analyze the economic implications of climate change on US agricultural production. They find increasing crop prices due to reduced yields and increased crop water requirements due to changes in precipitation and temperature regimes. They conclude that under relatively adverse cases of climate change, domestic and foreign consumers' surplus will moderately decrease while the US producers' surplus will increase with the roughly same amount. In a later study, Adams et al. (1993) investigate the effects of climatic conditions on farmers’ input and output choices. Accounting for carbon dioxide fertilization effects and commodity trade impacts, they estimate net gains in agricultural surplus between 9 and 10.8 billion dollars. The 2001 US National Assessment finds similar results (Reilly et al., 2001). Darwin et al. (1995) make a similar investigation on the issue and find climate change impacts on US agriculture to range between 4.8 and 5.8 billion dollars. Reilly et al. (1994, 1996) approximate global welfare changes in the agricultural sector (without adaptation) find estimates that range from losses of 61.2 billion dollars and gains of 0.1 billion dollars. This is in contrast to losses of 37 billion dollars to gains of 70 billion dollars with appropriate adaptations in place.

A few studies provide have addressed the actual vulnerability of agriculture to variability related factors such as the increased frequency of extreme events including droughts and floods, changes in precipitation and temperature variance. Using a dynamic crop model, Rosenzweig et al. (2002) simulate the effect of heavy precipitation on crop growth and plant damage from excess soil moisture. They estimate damages from changes in weather variability on US corn production to equal approximately 3 billion dollars per year. Lobel and Asner (2003) find a 17 percent decrease in corn and soybean yields in the US for each degree increase in growing season temperature, indicating a higher observed sensitivity of agriculture to temperature than studies had predicted previously.

As climate change, the outbreak of and induced plant damage from agricultural pests may increase. Studies on carbon dioxide concentration changes suggest positive yield and plant growth effects not only for agricultural crops but also for weeds due to increased water use efficiency and photosynthesis (Darwin, 2001; Hulme, 1996; Rosenzweig and Hillel, 1995). Several studies have examined the interaction between pests and climate change (Patterson et al., 1999; Porter et al., 1991; Gutierrez et al., 2008) concluding that pest activity especially of insects will increase and lead to higher crop losses. Chen and McCarl (2003) estimate the cost implications of a potential increase in pest invasion and find that climate change will increase the treatment cost for major crops. The same authors went further in their analysis to examine the US wide costs showing increased pesticide treatment costs reduced welfare by 100 million dollars. However, this estimate does not account for the external costs of pesticide use.

During the last three decades, agricultural pesticides have been increasingly recognized for their adverse effects on the environment and human health. There are numerous studies on these external costs. Pimentel (2004) estimates the external cost of pesticide applications at recommended dose rates to equal approximately 9 billion each year comprising 1.1 billion dollars of human health impacts, 2.0 billion dollars groundwater contamination, and 6.3 billion dollars of other environmental losses. In a similar study, Tegtmeier and Duffy (2004) calculate the external cost in the US agricultural sector between 5.7 and 16.9 billion dollars. Pretty et al. (2001) employ a relatively comprehensive dataset and compute annual external costs of pesticide applications in UK, Germany and the US. They find the total cost in the US at about 35 billion dollars. While most existing studies investigate current external cost, in chapter 4 we provide external cost changes from changes in US pesticide applications due to climate change. In chapter 4 we couple the pesticide environmental accounting tool (Leach and Mumford, 2008) with statistically estimated adjustments in US pesticide applications to climate change (chapter 2) and calculate external cost increases of up to 25 dollars per hectare until 2100. However, this estimate neglects possible agricultural adaptations regarding crop and management choice.

This study analyzes a hypothetical regulation of the pesticide externality in the US under current climate conditions and for different projections of climate change. Two major questions will be addressed both of which are relevant to researchers, policymakers, and the general public. First, we want to quantify the net impacts of pesticide regulations on the US agricultural sector including likely consequences for agricultural producers, consumers, and the environment. Second, we want to estimate if and how these impacts differ under projected changes in weather and climate. We hope that the answers to these questions will provide more insight into the ongoing debate about the scope, degree, and justification of environmental policies. To simultaneously portray the diverse spectrum of agricultural production options, feedback from national and international commodity markets, climate change impacts, and external effects of pesticides, we integrate the results from chapter 2, chapter 4, and Knutson et al. (1999) in the Agricultural Sector and Mitigation of Greenhouse Gas (ASMGHG) model (Schneider et al. 2007).

Chapter 5 proceeds as follows. Section 2 describes the data and basic structure of the ASMGHG model. The monetary estimates of agricultural surplus, market shifts, and land use changes associated with climate change are analyzed in section 3. Finally, section 4 concludes and section 5 appends details on mathematical structure of ASMGHG

5.2 Data and Methods

The basic methodology of this study involves five major components. First, we use the estimates from chapter 2 on the effects climate change has on pesticide use. Second, we use the estimates from Pretty et al. (2001) on how pesticide use causes external costs. Third, we use estimates of the effects of climate change on yields, and water use that are derived from Alig et al. (2002). Fourth, we use results from Knutson et al. (1999) to depict the impact of reduced pesticide application rates on crop yields and costs. Fifth, we integrate all of these into an agricultural sector model to estimate the welfare costs and influence of considering pest related differences. Each of these steps is reviewed in more detail below.

5.2.1 Pesticide intensities and climate change

To estimate the effects of weather and climate on conventional pesticide application rates, in chapter 2 we investigate crop and chemical class specific panel data across 14 years and 32 US states. In chapter 2, we regress pesticide application rates on marginal revenue, total crop area, and climate and weather variables related to temperature and precipitation and found temperature and precipitation variables have significant –mostly positive- impacts on pesticide applications. Particularly, we find more rainfall increases the plant protection needs for cereals and root crops, while higher temperatures are likely to increase pesticide doses to fruits, vegetables, and beans. Furthermore in chapter 2 we combine the regression coefficients with downscaled climate projections developed at the Canadian Centre for Climate and the Hadley Centre in the United Kingdom based on the IPCC's A2 scenario (IPCC, 2006). Our study explicitly considers three time periods: 2030, 2070 and 2100. For each time period, a 33-year average over the relevant weather and climate variables is used to estimate changes in pesticide application rates. For current crop area allocations, our results suggest that in most cases the pesticide application rates increase. Fruit and vegetable treatments increase the most, however, that climate change also decreases the application for some chemical classes of pesticides. The results are displayed in chapter 2.

5.2.2 External costs of pesticides

The external cost calculations for pesticide applications in the US are based on our estimations in chapter 4. In chapter 4 we updated the cost component estimates by Pretty et al. (2001) and integrate them with the Pesticide Environmental Accounting (PEA) tool developed by Leach and Mumford (2008). We use the year 2000 as base period and project external costs of individual pesticides to three future dates including 2030, 2070 and 2100. For the base period, our cost estimates are based on observed data on individual pesticide applications from NASS (2009). The impact of climate change on external costs is based on the above calculated projections of pesticide applications in chapter 2. Using data from 32 US states, 49 crops, and 339 pesticides, the current average external cost of pesticide use in US agriculture is calculated at $42 per hectare. Under projected climate change this value increases up to $72 per hectare by 2100.More details on the external cost estimates appears in chapter 4.

5.2.3 Crop impacts of climate change

Reilly et al. (2003) examine the impacts on US agriculture of transient climate change as simulated by 2 global general circulation models focusing on the decades of the 2030s and 2090s. They use site-specific crop models to project biophysical impacts and linked economic models to simulate commodity trade and market effects. Crop modeling studies are conducted at 45 national sites for wheat, maize, soybean, potato, citrus, tomato, sorghum, rice, and hay, both under dry land and irrigated conditions. Impacts on barley, oats, sugar cane, sugar beet, and cotton are extrapolated. The biophysical impacts on yields and water requirements are passed from the crop models to an economic model. Expert knowledge is used to project additional adjustments with respect to crop management costs, The final results of this national assessment indicate substantial regional differences. Particularly, under the Canadian scenario, the authors find agricultural production to increase between 40 and 80 percent in the Corn Belt and the Lake States but to decrease by as much as 60 percent in the Southeast. For the Hadley scenario, all regions show increased crop production with a more than 100 percent increase in the Lake States. The Canadian model based scenario leads to a much warmer and much drier climate, particularly in the 2030 period, thus projecting less positive effects on overall crop production and more negative effects in the Southern and Plains areas of the US. For this study, we use the climate, region, and crop specific data on yields, irrigation water requirements, and production costs from Reilly et al. (2003).

5.2.4 Pest management

We introduce three alternative pest management options: conventional pesticide application rates, 50 percent reduction of overall pesticide rates, and pesticide free crop management. The data on associated cost and yield changes are based on Hall et al. (1994) and Knutson et al. (1999). Both studies investigate empirically the potential effect of reduction or elimination of various pesticides in US agriculture and find that the broader the group of pesticides eliminated, the greater are the yield impacts. Their results also show that fruits and vegetables are more adversely affected by a broad-based reduction in pesticides than are field crops. Note that the 50 percent reduction scenario does not refer to a 50 percent reduction of all individual pesticides applied to a specific crop but rather an elimination of one or several individual pesticides which account for approximately 50 percent of the total application of active ingredients. Additionally, the authors observe that alternative pest control options to compensate the lack of chemicals are hardly sensible because the percentage increase in alternative treatment cost is generally larger than the percentage increase in revenue from avoided yield losses.

5.2.5 Integrating agricultural sector model

The above described impact estimates of climate on the pesticide externality did not depict possible agricultural adaptation regarding crop acreage, livestock numbers, and management intensity. To include these impacts, we use the model ASMGHG (Schneider et al. 2007). Here we briefly describe the general mathematical structure of ASMGHG model and specific modifications for the purpose of this study. A more detailed technical description is given in the section 5, Appendix 5.5.1 and is also available in Schneider et al. (2007).

ASMGHG is designed to emulate US agricultural decision making along with the impacts of agricultural decisions on agricultural production factors, international agricultural commodity markets, and the environment. The model has been used for the analysis of technological developments and policy scenarios including environmental, agricultural, and energy regulations. ASMGHG is an extended version of Agricultural Sector Model of McCarl and associates (McCarl et al. 1980; Chang et al. 1992). Schneider (2000) modified and expanded ASM to include a comprehensive GHG emission accounting module along with emission mitigation possibilities. ASMGHG portrays the following key components: natural and human resource endowments, agricultural production factor markets, agricultural technologies (Table 5-1), primary and processed commodity markets, and agricultural policies. The model depicts representative crop and livestock enterprises in 63 aggregated US production regions. International markets and trade relationships are portrayed through 27 international regions for 8 major crops and through one rest-of-the-world region for 32 other commodities including various crop, livestock and processed products. A brief summary of ASMGHG's spatial resolution is contained in Table 5-2.

The objective function of the model maximizes total agricultural economic surplus subject to a set of constraining equations, which include resource limits, supply and demand balances, trade balances, policy restrictions, and crop mix constraints. The economic surplus equals the sum of consumers' surplus, producers' surplus, and governmental net payments to the agricultural sector minus the total cost of production, transportation, and processing. Based on economic theory, the optimal variable levels can be interpreted as equilibrium levels for agricultural activities after adjustment to given economic, political, and technological conditions. The shadow prices on supply demand balance equations identify market clearing prices.

Table 5- 1 Scope of agricultural management alternatives in ASMGHG

Management parameter	Available options
Crop choice	Cotton, Corn, Soybeans, Winter wheat, Durum wheat, Hard red winter wheat, Hard red and other spring wheat, Sorghum, Rice, Barley, Oats, Silage, Hay, Sugar Cane, Sugar Beets, Potatoes, Tomatoes, Oranges, Grapefruit
	Switchgrass, Willow, Hybrid poplar
Irrigation	No irrigation
	Full irrigation
Tillage	Conventional tillage (<15% plant cover)
	Reduced tillage (15-30% plant cover)
	Zero tillage (>30% plant cover)
Fertilization	Observed nitrogen fertilizer rates
	Nitrogen fertilizer reduction corresponding to 15% stress
	Nitrogen fertilizer reduction corresponding to 30% stress
Pesticide application	Conventional (Average current rate)
	Reduced (50% of current rate)
	Minimum (No pesticide application)
Animal production	Dairy, cow-calf, feedlot beef cattle, heifer calves, steer calves, heifer yearlings, steer yearlings, feeder pigs, pig finishing, hog farrowing, sheep, turkeys, broilers, egg layers, and horses
Feed mixing	1158 specific processes based on 329 general processes differentiated by 10 US regions
Livestock production	Four different intensities (feedlot beef), two different intensities (hog operations), liquid manure treatment option (dairy and hog operations), BST treatment option (dairy)

Table 5- 2 Spatial Scope of ASMGHG

Region Set	Region Set Elements	Associated Features
Non-US world regions	Canada, East Mexico, West Mexico, Caribbean, Argentina, Brazil, Eastern South America, Western South America, Scandinavia, European Islands, Northern Central Europe, Southwest Europe, France, East Mediterranean, Eastern Europe, Adriatic, former Soviet Union, Red Sea, Persian Gulf, North Africa, West Africa, South Africa, East Africa, Sudan, West Asia, China, Pakistan, India, Bangladesh, Myanmar, Korea, South East Asia, South Korea, Japan, Taiwan, Thailand, Vietnam, Philippines, Indonesia, Australia	Excess demand and supply function parameter for 8 major crop commodities; transportation cost data; Computation of trade equilibrium
US	US	Demand function parameters for crop, livestock, and processed commodities
US macro regions	Northeast, Lake States, Corn belt, Northern Plains, Appalachia, Southeast, Delta States, Southern Plains, Mountain States, Pacific States	Feed mixing and other process data; labor endowment data;
US minor regions	Alabama, Arizona, Arkansas, N-California, S-California, Colorado, Connecticut, Delaware, Florida, Georgia, Idaho, N-Illinois, S-Illinois, N-Indiana, S-Indiana, W-Iowa, Central Iowa, NE-Iowa, S-Iowa, Kansas, Kentucky, Louisiana, Maine, Maryland, Massachusetts, Michigan, Minnesota, Mississippi, Missouri, Montana, Nebraska, Nevada, New Hampshire, New Jersey, New Mexico, New York, North Carolina, North Dakota, NW-Ohio, S-Ohio, NE-Ohio, Oklahoma, Oregon, Pennsylvania, Rhode island, South Carolina, South Dakota, Tennessee, TX-High Plains, TX-Rolling Plains, TX-Central Blackland, TX-East, TX-Edwards Plateau, TX-Coastal Belt, TX-South, TX Transpecos, Utah, Vermont, Virginia, Washington, West Virginia, Wisconsin, Wyoming	Crop and livestock production data and activities, land type and water resource data
US Land types	Agricultural Land: Land with wetness limitation, Low erodible land (Erodibility Index (EI) < 8), Medium erodible land ($8 < EI < 20$), Highly erodible land (EI < 20), Pasture, Forest	Land endowments; Cost, yield, and emission data adjustment

ASMGHG is setup as mathematical programming model and contains more than 20,000 individual variables and more than 5000 individual equations. All agricultural production activities are specified as endogenous variables. The equations are indexed and listed in in section 5, Appendix 5.5.1 Model solutions provide projection on land use and commodity production within the 63 US regions, commodity production in the rest of the world, international trade, crop and livestock commodity prices, processed commodity prices, agricultural commodity consumption, producer income effects consumer welfare effects, and various environmental impacts.

To do this study we integrate pest costs and yield changes under the SRES based A2 climate change scenario following the procedures used in the US National assessment. When we add the external costs we run the model with and without the externality internalized.

5.3 RESULTS

The objective of this study is to find out how pesticide externalities are affected by climate change and by the internalization of the pesticide externality that would hold farmers accountable for the environmental damages of pesticides. Furthermore, we want to analyze the role of alternative pest management regimes. To accomplish these objectives, we consider a total of 28 scenarios which result from combinations of four time steps (2000, 2030, 2060, 2090), two climate projections (Canadian and Hadley), and four alternative internalizations of the pesticide externalities (internalization of external environmental costs at 0, 50, 100, 200 percent of pesticide use). We use different internalization rates to address the uncertainty of the estimated external costs. For each scenario, we solve a scenario specific version of the ASMGHG model.

5.3.1 AGRICULTURAL MARKET AND WELFARE IMPACTS

Table 5-3 summarizes the individual and combined effects of climate change and the degree of internalization of the pesticide externality on agricultural market and welfare indicators. Climate and pesticide policy impacts affect agricultural markets in opposite directions.

Table 5- 3 Economic surplus and market effects in US agriculture in response to pesticide policy and climate change [5] [6]

		US Agricultural market (Fisher Index)				*Change in agricultural surplus (Billion $)*				
Internalization of External Pesticide Impacts	Climate Projection[7]	Production	Prices	Exports	Imports	US Producers	US Consumers	Foreign Producers	Foreign Consumers	Total Surplus[8]
None	2000	100	100	100	100	0	0	0	0	0
	2030 H	111	80.2	130.8	79.5	-2.42	9.4	-0.99	3.88	9.86
	2030 C	106	87.2	118	91.9	-1.48	5.52	-0.39	3.33	6.98
	2060 H	117	73.4	154.5	79.1	-4.17	12.81	-1.68	7.12	14.1
	2060 C	107	87	120.5	96.6	-0.73	4.31	-0.15	4.12	7.55
	2090 H	125	69.3	191.6	75.3	-2.09	13.82	-1.87	8.38	18.2
	2090 C	106	92	124.5	112.4	2.87	0.22	-0.08	5.14	8.15
50%	2000	84.9	131.8	53.7	132.8	-3.05	-18.64	3.23	-5.52	-24
	2030 H	90.1	119.6	70.5	104	-4.58	-12.39	2.09	-2.5	-17.4
	2030 C	90	125.5	69.7	110.3	-3.36	-15.96	2.77	-3.58	-20.1
	2060 H	93.8	116.6	85.9	114.6	-2.89	-12.38	1.6	-0.49	-14.2
	2060 C	87.8	133.3	69	114.7	-1.03	-20.82	3.01	-3.29	-22.1
	2090 H	98.3	109.9	103.4	114.3	-2.79	-9.83	0.92	1.57	-10.1
	2090 C	87.3	138.9	72	127.6	0.66	-24.57	3.13	-2.68	-23.5
100%	2000	77.1	170.2	34.6	168.3	6.51	-38.39	5.61	-8.53	-34.8
	2030 H	81.1	165.9	50.9	147.7	9.77	-37.63	4.88	-6.29	-29.3
	2030 C	80.2	172.9	47.6	141	9.57	-39.95	5.69	-7.97	-32.7
	2060 H	83.4	163.2	59.3	149.4	11.87	-37.27	4.38	-4.66	-25.7
	2060 C	78.7	193.4	48.7	163.4	17.3	-51.34	6.25	-7.95	-35.7
	2090 H	85.4	154.2	66.5	129.5	10.45	-32.1	3	-2.64	-21.3
	2090 C	78.3	211.6	51.9	167.8	23.1	-61.12	6.4	-7.29	-38.9
200%	2000	70.2	242.1	21	230.7	29.68	-74.03	9.47	-13	-47.9
	2030 H	72.8	246.5	31	177	34.28	-74.03	7.37	-10.7	-43
	2030 C	72.2	256.3	28.6	174.8	33.21	-76.82	8.33	-12.4	-47.7
	2060 H	74.6	246.4	40.5	173.8	38.92	-75.16	6.95	-9.57	-38.9
	2060 C	71	285.6	28.7	182.7	43.17	-91.51	8.83	-12.5	-52
	2090 H	76.2	240	46.5	166.4	40.94	-73.04	6	-7.53	-33.6
	2090 C	70	353.3	35.2	212.7	68.37	-124.5	10.87	-13.1	-58.3

[5] H=Hadley Climate Model, C=Canadian Climate Model,

[6] Includes internalized external environmental and human health effects

Especially under the Hadley climate change projection, we find substantial increases in US crop production. While production increases continuously under the Hadley projection until 2100, the Canadian climate projection ceases to increase production after 2030. A 50 percent internalization of external environmental costs of pesticides more than offsets the positive impacts of climate change. If stronger regulations of external costs are used, i.e. 100 or 200 percent, the negative impacts on production amplify. Agricultural crop prices and exports mirror the impacts on crop production. Climate change alone decreases prices and increases pesticide use. Note, however, that we kept the international crop supply functions constant. If crop production outside the US decreased substantially due to climate change, the downward pressure on crop prices from increases US crop production could have been mitigated. The combination of climate change and pesticide policy projections yields more complex price effects because the external costs are sensitive to climate change affects. Under the Canadian climate projection, a full (100 percent) internalization of external costs decreases US production by 20 percent and this almost doubles crop prices in the last simulation period.

Agricultural welfare impacts are displayed in the last four columns of Table 5-3. In absence of pesticide externalities internalization, total agricultural sector surplus monotonically increases for both climate projections. These changes are increasingly higher for the Hadley projection, and in the last period with a projected increase of 19 billion dollars about twice as high as the 10 billion dollar increase under the Canadian projection. With the combined impact of climate change and the assumed pesticide policies, total agricultural sector surplus decreases. The decreases are the consequence of increasing market prices and reduced supply. It is important to note that the combined impacts do not equal the sum of individual impacts. For example, the Canadian projection for 2060 increases total agricultural surplus by 9 billion US dollars. On the other hand, the 50 and 100 percent externality regulation scenarios decrease total agricultural surplus by 26 and 38 billion US dollars, respectively. However, the combined effect of climate change and the internalization of the pesticide externality decrease total surplus by 23 and 39 billion US dollars for the 50 and 100 percent internalization scenarios, respectively. The non-additionality of climate change and the internalization of the pesticide externality impacts arises for two reasons. First, downward sloped demand and upward sloped supply cause non-linear responses with non-constant rates of welfare changes. Second, climate change affects pesticide applications and thus the magnitude of external costs from agricultural pesticides. The increased benefits under climate change from positive supply shifts are partially or completely offset by the increased external costs from the additional use of pesticides.

Table 5-3 also reveals the distribution of agricultural surplus between US producers, US consumers, and foreign countries. The direction of changes in consumers' surplus reflects price changes. The more prices increase, the higher are losses to US consumers. The impact on producers is more diverse because price and supply impacts work in opposite directions. Particular, supply increases lead to higher sales at lower prices and vice versa. Our simulation results show that the supply enhancing impact of climate change projections do not benefit producers. A 50 percent internalization of pesticide externalities worsens producer surplus. However, if the external costs are fully internalized, producers gain because the beneficial producer surplus effects of increased prices outpace the negative effects of reduced supply. Under a 200 percent internalization, this effect becomes much stronger. Foreign countries' surplus aggregates foreign producer and consumer surplus changes. The net effects are moderately positive for climate change in absence of US pesticide policies and, with few exceptions, moderately negative under the combined impact of climate change and pesticide policies. Again, it is important to note that we did not have adequate data to shift the crop supply functions in foreign countries.

Details on pesticide externality impacts in US agriculture in response to the internalization of the pesticide externality and climate change are displayed in Table 5-4. In absence of internalization, climate change leads to relatively minor changes in US total agricultural revenue (TAR) but substantial increases in total environmental and human health costs (TEHH) this was not introduced above. Particularly, the latter costs increase relative to total US agricultural revenue from about one third in 2000 to about one half in 2090. While, the total environmental and human health costs increase continuously under the Hadley projection, they cease to increase after 2030 for the Canadian climate projection. An internalization of the external costs of pesticides increases moderately total US agricultural revenues but decrease substantially the total environmental and human health costs. The increase in total revenue implies that supply reductions are more than compensated for by associated price changes. At a 100 percent internalization rate, agricultural revenues change by no more than 11 percent but pesticide externalities decrease by 80 percent and more across all climate scenarios. If stronger or weaker regulations of external costs are used, the magnitude of effects changes accordingly.

Table 5- 4 Pesticide externality impacts in US agriculture in response to pesticide policy and climate change

Internalization rate of external pesticide impacts	Climate Projection	Average internalized pesticide costs ($/kg/ha)	Total Environmental and Human Health Costs in US (TEHH)	Total Internalized Costs in the US	Total Agricultural Revenues in the US (TAR)	Absolute Change in TEHH	Absolute Change in TAR	TAR Levels Relative to Base	TEHH Levels Relative to Base
			- - - - - - - - in Billion US dollars				- - - - - - - - - - -	in % - - -	
None	2000	0.00	125.2	0.00	357.1	0.0	0.0	100.0	100.0
	2030 H	0.00	150.8	0.00	351.6	25.6	-5.5	98.5	120.5
	2030 C	0.00	161.0	0.00	353.5	35.8	-3.6	99.0	128.6
	2060 H	0.00	172.0	0.00	350.8	46.9	-6.3	98.2	137.4
	2060 C	0.00	175.4	0.00	356.3	50.2	-0.8	99.8	140.1
	2090 H	0.00	186.4	0.00	349.7	61.2	-7.4	97.9	148.9
	2090 C	0.00	178.3	0.00	359.1	53.1	2.0	100.6	142.5
50%	2000	21.50	27.5	13.7	367.7	-97.7	10.6	103.0	21.9
	2030 H	25.09	31.5	15.8	364.9	-93.6	7.8	102.2	25.2
	2030 C	25.87	34.1	17.0	366.4	-91.1	9.3	102.6	27.2
	2060 H	31.19	31.5	15.8	364.7	-93.7	7.6	102.1	25.2
	2060 C	32.37	34.8	17.4	368.0	-90.3	10.9	103.1	27.8
	2090 H	33.98	31.1	15.5	364.2	-94.1	7.1	102.0	24.8
	2090 C	35.44	39.4	19.7	371.3	-85.8	14.2	104.0	31.4
100%	2000	42.99	18.1	18.1	380.3	-107.1	23.2	106.5	14.5
	2030 H	50.19	18.2	18.2	378.8	-107.0	21.7	106.1	14.5
	2030 C	51.73	19.3	19.3	378.2	-105.9	21.1	105.9	15.4
	2060 H	62.38	17.9	17.9	378.9	-107.3	21.8	106.1	14.3
	2060 C	64.74	20.1	20.1	386.7	-105.0	29.6	108.3	16.1
	2090 H	67.96	17.1	17.1	375.0	-108.0	17.9	105.0	13.7
	2090 C	70.88	24.4	24.4	397.0	-100.8	39.9	111.2	19.5
200%	2000	85.98	10.5	21.1	401.4	-114.6	44.3	112.4	8.4
	2030 H	100.37	10.8	21.6	400.1	-114.4	43.0	112.0	8.6
	2030 C	103.46	12.3	24.5	402.0	-112.9	44.9	112.6	9.8
	2060 H	124.75	10.1	20.2	402.1	-115.1	45.0	112.6	8.1
	2060 C	129.49	13.2	26.4	413.0	-112.0	55.9	115.7	10.6
	2090 H	135.92	9.4	18.9	401.5	-115.7	44.4	112.4	7.5
	2090 C	141.75	15.1	30.2	438.6	-110.1	81.5	122.8	12.1

5.3.2. Pesticide Application Intensities

Climate change and pesticide externality internalization affect agricultural decisions in multiple ways. Farmers may grow different crops, use different rotations, and change the intensity of management related to irrigation, tillage, fertilization, and pesticide use. These adjustments are represented in ASMGHG to the degree specified in Table 5-2. The simulated combined effects of climate projections and internalization on pest management strategy are provided in Table 5-5.

The first table section shows the change in total crop area summed over all pesticide application intensities. Total area decreases both in response to climate change and regulations of external costs from pesticides. Note, however, that the impacts of the two drivers do not add up. For example, a full internalization of external pesticide cost under climate 2000 conditions would reduce the cropped area by almost 14 percent. Equivalently, climate 2060 projections without internalization of external cost would reduce cropping areas by 13 to 14 percent for both climate models. The combined impact of climate change and pesticide impact internalization on cropping is only slightly stronger than the individual effects and amounts to 14 and 16 percent reduction, for the Canadian and Hadley projection, respectively.

The following table sections show the area allocated to different pesticide application intensities. In absence of pesticide externality internalization, agricultural producers fare best with conventional pesticide intensities under all climate projections. As the regulation of external costs increases, the planted area fully treated with pesticides decreases and reduced or zero pesticide application intensities become more frequent. Particularly, if 50 percent of the external environmental costs of pesticides are internalized (columns 3 and 4 of Table5- 5), the land share under conventional pesticide application intensity decreases by about 35 percent and goes to reduced and zero application intensities.

Table 5- 5 Effect of climate projections and the internalization of the pesticide externalities on pesticide application rates

Pesticide Application Rate	Climate Projection	Internalization Rate of External Environmental Costs of Agricultural Pesticides: None (Base)		50 Percent		100 Percent		200 Percent	
		in million acres (in percent relative to base)							
All Pesticide Management	2000	330	(100.0)	299	(90.5)	280	(84.7)	275	(83.5)
	Hadley	321	(97.2)	274	(83.0)	270	(81.9)	262	(79.5)
	Canada	308	(93.3)	284	(86.0)	280	(84.7)	269	(81.6)
	Hadley	318	(96.2)	284	(86.0)	273	(82.7)	263	(79.6)
	Canada	303	(91.9)	284	(85.9)	279	(84.6)	267	(80.8)
	Hadley	313	(94.9)	286	(86.7)	267	(80.8)	254	(77.1)
	Canada	296	(89.8)	275	(83.2)	273	(82.8)	265	(80.4)
		in million acres (share of total acreage)							
Conventional (100 Percent)	2000	330	(100.0)	194	(58.7)	165	(50.1)	156	(47.1)
	Hadley	321	(100.0)	172	(52.1)	154	(46.8)	145	(43.8)
	Canada	308	(100.0)	183	(55.4)	167	(50.5)	154	(46.8)
	Hadley	318	(100.0)	172	(52.0)	149	(45.1)	143	(43.2)
	Canada	303	(100.0)	180	(54.3)	162	(49.2)	152	(45.9)
	Hadley	313	(100.0)	171	(51.9)	150	(45.3)	138	(41.7)
	Canada	296	(100.0)	168	(50.8)	158	(48.0)	151	(45.8)
Reduced (50 Percent)	2000	0	(0.0)	73	(22.1)	60	(18.2)	28	(8.4)
	Hadley	0	(0.0)	64	(19.4)	56	(17.0)	29	(8.8)
	Canada	0	(0.0)	64	(19.4)	48	(14.5)	32	(9.6)
	Hadley	0	(0.0)	70	(21.3)	44	(13.4)	21	(6.4)
	Canada	0	(0.0)	56	(17.0)	45	(13.8)	26	(8.0)
	Hadley	0	(0.0)	65	(19.6)	35	(10.7)	17	(5.1)
	Canada	0	(0.0)	60	(18.2)	42	(12.8)	20	(6.1)
Minimum (0 Percent)	2000	0	(0.0)	32	(9.7)	54	(16.4)	92	(27.9)
	Hadley	0	(0.0)	38	(11.5)	60	(18.2)	89	(26.9)
	Canada	0	(0.0)	37	(11.1)	65	(19.7)	83	(25.2)
	Hadley	0	(0.0)	42	(12.7)	80	(24.2)	99	(30.0)
	Canada	0	(0.0)	48	(14.7)	71	(21.6)	89	(26.9)
	Hadley	0	(0.0)	50	(15.2)	82	(24.8)	100	(30.2)
	Canada	0	(0.0)	47	(14.2)	73	(22.0)	94	(28.5)

For stronger regulations of external costs, the land shares under conventional application rates decrease further and the area with zero pesticide application rates reaches about one third of the entire crop area.

Our simulation results indicate that climate change coupled with internalization of the externality mostly decreases conventional and reduced pesticide application intensity, but increases the share of pesticide-free crop management. The changes in area shares of different pesticide application intensities due to climate are relatively small and do not exceed 10 percent across the entire simulation period. The simulation results from Table 5-5, represent weighted averages over major crop groups. To show the influence of climate change and full external pesticide cost internalization on individual crop categories, Figures 5-1 to 5-4 display the total and pest management specific areas allocated to all major crops. To keep the graphical display manageable, the results from both climate change models are averaged.

Figure 5-1 shows for major crop categories the combined impact of climate change and full external cost internalization on total area relative to the base area in 2000 without internalization of the pesticide externality. We find changes in areas for all crop groups however, these changes differ substantially between crops. Cotton is the only crop which increases - by 9 percent - compared to the base area. The highest decrease in area occurs for citrus fruits and tomatoes with some reductions above 50 percent. In most cases, the internalization of the pesticide externality effect dominates the climate change effect, i.e. area change for the year 2000 is higher than additional, climate changed based adjustments at subsequent dates. For cereals and sugar crops, we find monotonous decreases until 2100. All other crop groups show a mixed response to climate changes involving both increases and decreases in total area relative to previous date. The area changes due to climate change remain below 5 percent except for citrus fruits and tomatoes.

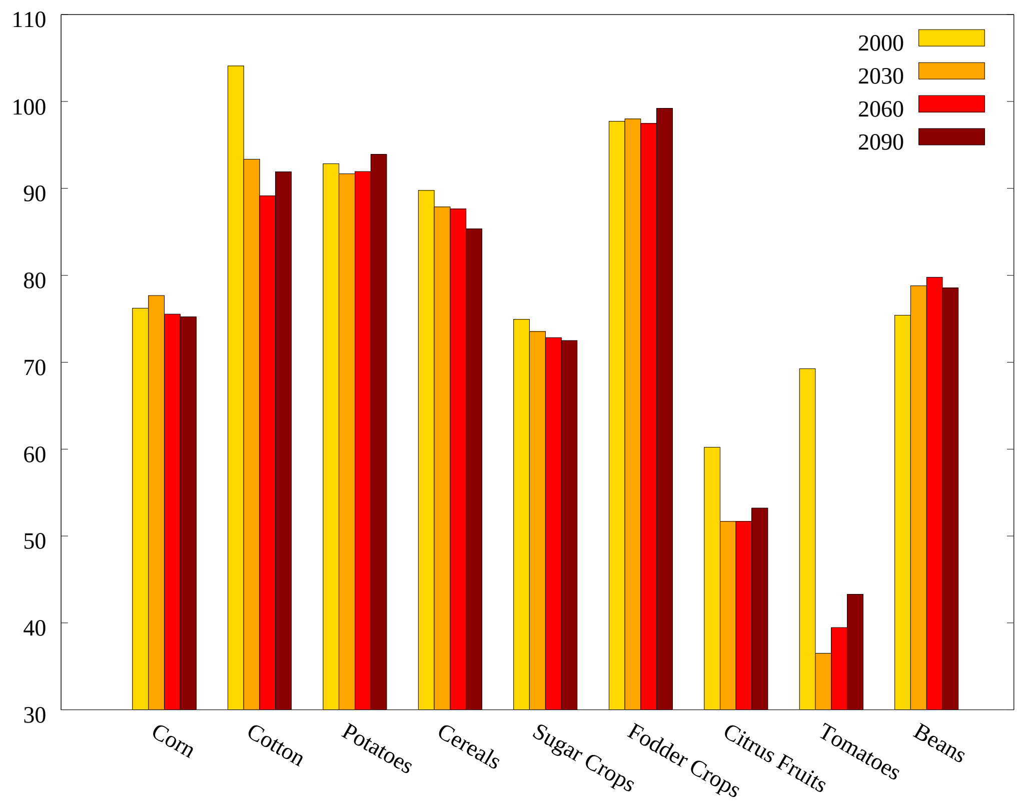

Figure 5- 1 Effect of projected climate change and 100% internalization of external environmental cost of pesticides on total crop area (in percent) relative to no internalization and year 2000

Figures 5-2 to 5-4 display the combined impact of climate change and full external cost internalization on area shares for alternative pesticide intensity options. We find that conventional pesticide rates dominate reduced rate strategies for all crops except for corn and soybeans. Almost no pesticide rate reductions are observed for cereals and potatoes, however, there is a substantial reduction in conventional pest management averaging about one third of the total area across the different climate scenarios. Sugar crops, fodder crops, and tomatoes show no or relatively little change in pesticide intensities. Climate change projections affect the preferred pesticide intensities for corn and soybeans and lead to monotonously increasing shares of pesticide free management at the expense of the area under reduced pesticide applications. Citrus fruit shows high potential importance of pesticide free management only under current climate conditions. For all other crop groups, climate change has relatively little impact on non-conventional pesticide control strategies.

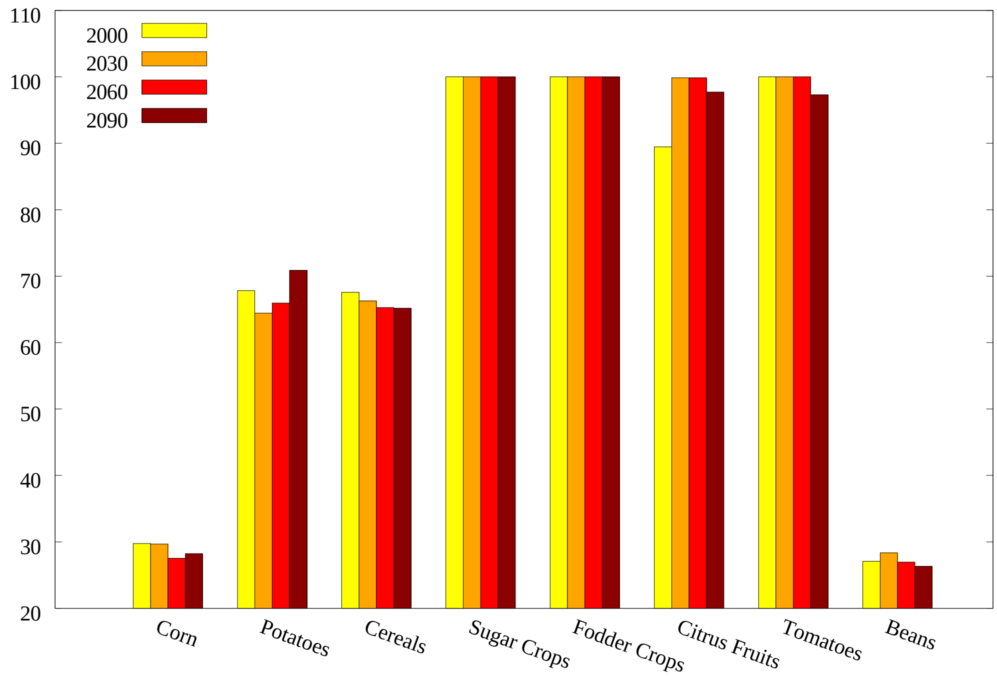

Figure 5- 2 Effect of projected climate change and 100% internalization of external environmental cost of pesticides on area share (in percent) under conventional pesticide management by crop group

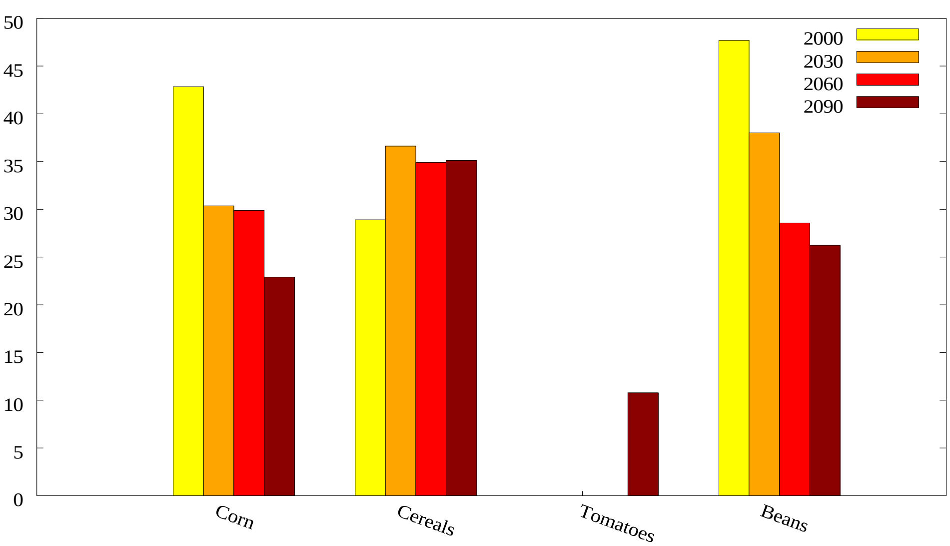

Figure 5- 3 Effect of projected climate change and 100% internalization of external environmental cost of pesticides on area share (in percent) under reduced pesticide management by crop group

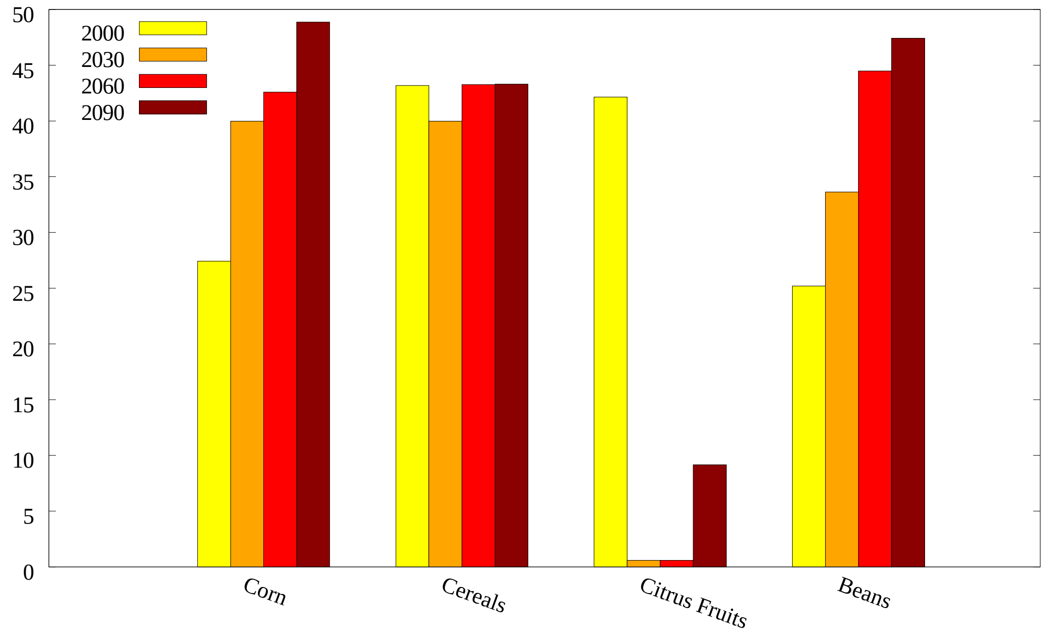

Figure 5- 4 Effect of projected climate change and 100% internalization of external environmental cost of pesticides on area share (in percent) under pesticide free management by crop group

5.4 CONCLUSIONS

This study examines alternative assumptions about regulations of external costs from pesticide applications in US agriculture under different climate conditions. The impacts of the internalization of the pesticide externality and climate change are assessed both independently and jointly. Without external cost regulation, climate change benefits from increased agricultural production in the US may be more than offset by increased environmental costs. While the internalization of the pesticide externalities may increase farmers' production costs, they are likely to increase farm income because of price adjustments and associated welfare shifts from consumers to producers. Our study also illustrates that full consideration of pesticides' external costs motivate farmers to substantially reduce pesticide applications for corn and soybeans and considerably for cereals and potatoes. While the additional impact of climate change on preferred pesticide intensities is marginal for most crops, it is substantial for corn and soybeans.

Our results have important research and policy implications. First, this analysis quantifies the tradeoff between agricultural market surplus and external pesticide costs under different climate conditions. Our estimated benefits from internalization may be contrasted with policy transaction costs, to judge whether externality regulation is desirable. The examined pesticide policy could be interpreted as a pesticide tax, where the tax level corresponds to the environmental and human health damage. Such a policy is different from most existing regulations, which only prohibit pesticides but impose no charge on admitted ones. Second, if climate change leads to higher pesticide applications, the socially optimal response to climate change moves away from adaptation towards mitigation. Third, our results could affect agricultural research programs because the expected social returns to research on alternative pest control strategies depend also on the expected external cost change. Fourth, our study can help to improve the mathematical representation of agricultural externalities in integrated assessment models. These models are increasingly used for the design and justification of climate and other environmental policies.

Several important limitations and uncertainties to this research should be noted. First, the findings presented here reflect agricultural management options for which data were available to us. Alternative pesticide management options are limited to three levels of application rates. In reality, farmers could adopt any application rate and could consider many other pest control adaptations which are not considered here. Second, the data for pesticide treatment costs, yield impacts, irrigation water requirements, and external costs involve regression analyses and mathematical simulation models. Thus, the certainty of the estimates presented here depends on the quality of these models and the certainty of all associated input data. Third, not monetized in this analysis were costs or benefits from reduced levels of other agricultural externalities, and costs or benefits of changed income distribution in the agricultural sector. Fourth, we operate with 32 crops mainly grains and not many fruits and vegetables which have higher contribution to the external cost of pesticide use. Fifth, the reductions in external costs due to regulation may be overstated because of leakage of pesticide intensive crops to other countries. Finally, all simulated results are derived from the optimal solution of the mathematical program and as such constitute point estimates without probability distribution.

5.5 APPENDIX

5.5.1 MATHEMATICAL STRUCTURE OF ASMGHG

ASMGHG is setup as mathematical programming model and contains more than 20, 000 individual variables and more than 5, 000 individual equations. These equations and variables are not entered individually but as indexed blocks. All agricultural production activities are specified as endogenous variables and denoted here by capital letters. In particular, the variable block CROP denotes crop management variables, LUTR = land use transformation, LIVE = livestock raising, PROC = processing, and INPS = production factor (input) supply variables. Additional variable blocks reflect the dissemination of agricultural products with DOMD = U.S. domestic demand, TRAD = U.S. interregional and international trade, FRXS = foreign region excess supply, FRXD = foreign region excess demand, EMIT = Emissions, and SEQU = Emission reduction or sequestration variables. WELF denotes total agricultural welfare from both U.S. and foreign agricultural markets.

Demand and supply functions are denoted in italic small letters. Equations, variables, variable coefficients, and right hand sight variables may have subscripts indicating indices with index c denoting the set of crops, f = production factors with exogenous prices (subset of index w), g = greenhouse gas accounts, h = processing alternatives, i = livestock management alternatives, j = crop management alternatives, k = animal production type, l = land transformation alternatives, m = international region (subset of index r), n = natural or human resource types (subset of index w), r = all regions, s = soil classes (subset of index n), t = years, u = U.S. region (subset of index r), w = all production factors, and y = primary and processed agricultural commodities.

Equation block (1) shows the set of commodity supply and demand balance equations employed in ASMGHG. Note that equation block (1) is indexed over U.S. regions and commodities. Thus, the total number of individual equations equals the product of 63 U.S. regions times the 54 primary agricultural commodities.

$$(1) \qquad \begin{aligned} &-\sum_{c,s,j}\left(a^{CROP}_{u,c,s,j,y}\cdot CROP_{u,c,s,j}\right)-\sum_{k,i}\left(a^{LIVE}_{u,k,i,y}\cdot LIVE_{u,k,i}\right)-\sum_{r} TRAD_{r,u,y} \\ &\qquad +DOMD_{u,y}+\sum_{h}\left(a^{PROC}_{u,h,y}\cdot PROC_{u,h}\right)+\sum_{r} TRAD_{u,r,y}\le 0 \end{aligned} \qquad \text{for all u and y}$$

The structure of equation block (1) allows for production of multiple products and for multi level processing, where outputs of the first process become inputs to the next process. All activities in (1) can vary on a regional basis.

Supply and demand relationships are also specified for agricultural production factors linking agricultural activities to production factor markets. As shown in equation block (2), total use of production factors by cropping (CROP), livestock (LIVE), land use change (LUTR), and processing (PROC) activities must be matched by total supply of these factors (INPS) in each region.

$$(2) \qquad \begin{aligned} &INPS_{u,w}-\sum_{c,s,j} a^{CROP}_{u,c,s,j,w}\cdot CROP_{u,c,s,j}-\sum_{l} a^{LUTR}_{u,l,w}\cdot LUTR_{u,l} \\ &\qquad -\sum_{k,i} a^{LIVE}_{u,k,i,w}\cdot LIVE_{u,k,i}-\sum_{h} a^{PROC}_{u,h,w}\cdot PROC_{u,h}\le 0 \end{aligned} \qquad \text{for all u and w}$$

The mathematical representation of natural resource constraints in ASMGHG is straightforward and displayed in equation block (3). These equations simply force the total use of natural or human resources to be at or below given regional resource endowments $b_{u,n}$. Note that the natural and human resource index n is a subset of the production factor index w. Thus, all $INPS_{u,n}$ resource supplies also fall into constraint set (2). The number of individual equations in (3) is given by the product of 63 U.S. regions times the number of relevant natural resources per region.

$$(3) \qquad INPS_{u,n} \le b_{u,n} \text{ for all u and n}$$

In ASMGHG, trade activities by international region of destination or origin are balanced through trade equations as shown in equation blocks (4) and (5). The equations in block (4) force a foreign region's excess demand for an agricultural commodity ($FRXD_{m,y}$) to not exceed the sum of all import activities into that particular region from other international regions ($TRAD_{\tilde{m},m,y}$) and from the U.S. ($TRAD_{u,m,y}$). Similarly, the equations in block (5) force the sum of all commodity exports from a certain international region into other international regions ($TRAD_{m,\tilde{m},y}$) and the U.S. ($TRAD_{m,u,y}$) to not exceed the region's excess supply activity ($FRXS_{m,y}$).

(4) $$-\sum_{u} TRAD_{m,u,y} - \sum_{\tilde{m}} TRAD_{m,\tilde{m},y} + FRXD_{m,y} \le 0 \quad \text{for all m and y}$$

(5) $$\sum_{u} TRAD_{u.m,y} + \sum_{\tilde{m}} TRAD_{\tilde{m},m,y} - FRXS_{m,y} \le 0 \quad \text{for all m and y}$$

The number of individual equations in blocks (4) and (5) equals the product of the number of traded commodities times the number of international regions per commodity.

Based on decomposition and economic duality theory (McCarl 1982, Onal and McCarl 1991), it is assumed that observed historical crop mixes represent rational choices subject to weekly farm resource constraints, crop rotation considerations, perceived risk, and a variety of natural conditions[equation (6)].

(6) $$-\sum_{t}\left(h_{u,c,t}^{CMIX} \cdot CMIX_{u,t}\right) + \sum_{s,j} CROP_{u,c,s,j} = 0 \quad \text{for all u and c}$$

The utilization of (6) has several important implications. First, many diverse constraints faced by agricultural producers are implicitly integrated. Second, crop choice constraints impose an implicit cost for deviating from historical crop rotations. Note that the sum of the CMIX variables over time is not forced to add to unity. Therefore, only relative crop shares are restricted, allowing the total crop acreage to expand or contract. Third, crop choice constraints prevent extreme specialization by adding a substantial number of constraints in each region and mimicking what has occurred in those regions. Fourth, crop choice constraints are a consistent way of representing a large entity of small farms by one aggregate system (Dantzig and Wolfe 1961, Onal and McCarl 1989).

Crop mix constraints are not applied to crops, which under certain policy scenarios are expected to expand far beyond the upper bound of historical relative shares. In ASMGHG, the biofuel crops of switchgrass, poplar and willow fall into this category.

The mix of livestock production is constraint in a similar way as crop production [equation (7)].

(7) $$-\sum_{t}\left(h^{LMIX}_{u,y,t}\cdot LMIX_{u,t}\right)+\sum_{k,i}\left(a^{LIVE}_{u,k,i,y}\cdot LIVE_{u,k,i}\right)=0 \quad \text{for all u and y}$$

Agricultural land owners do not only have a choice between different crops and different crop management strategies, they can also abandon traditional crop production altogether in favor of establishing pasture or forest. In ASMGHG, land use conversions are portrayed by a set of endogenous variables LUTR. As shown in (8), certain land conversion can be restricted to a maximum transfer $d_{u,l}$, whose magnitude was determined by GIS data on land suitability. If $d_{u,l}$ = 0, then constraint (8) is not enforced. In such a case, land use transformations would only be constraint through constraint set (3).

(8) $$LUTR_{u,l}\le d_{u,l}\big|_{d_{u,l}\ge 0} \quad \text{for all u and l}$$

The assessment of environmental impacts from agricultural production as well as political opportunities to mitigate negative impacts is a major application area for ASMGHG. To facilitate this task, ASMGHG includes environmental impact accounting equations as shown in (9) and (10). A detailed description of environmental impact categories and their data sources is available in Schneider (2000).

(9) $$\begin{aligned} EMIT_{u,g} = &\sum_{c,s,j}\left(a^{CROP}_{u,c,s,j,g}\cdot CROP_{u,c,s,j}\right)\Big|_{a^{LAND}_{u,c,s,j,g}>0} \\ &+\sum_{l}\left(a^{LUTR}_{u,l,g}\cdot LUTR_{u,l}\right)\Big|_{a^{LUTR}_{u,l,g}>0} \\ &+\sum_{k,i}\left(a^{LIVE}_{u,k,i,g}\cdot LIVE_{u,k,i}\right)\Big|_{a^{LIVE}_{u,k,i,g}>0} \\ &+\sum_{h}\left(a^{PROC}_{u,h,g}\cdot PROC_{u,h}\right)\Big|_{a^{PROC}_{u,h,g}>0} \end{aligned} \quad \text{for all u and g}$$

(10) $$\begin{aligned} SEQU_{u,g} = &\sum_{c,s,j}\left(a^{CROP}_{u,c,s,j,g}\cdot CROP_{u,c,s,j}\right)\Big|_{a^{LAND}_{u,c,s,j,g}<0} \\ &+\sum_{l}\left(a^{LUTR}_{u,l,g}\cdot LUTR_{u,l}\right)\Big|_{a^{LUTR}_{u,l,g}<0} \\ &+\sum_{k,i}\left(a^{LIVE}_{u,k,i,g}\cdot LIVE_{u,k,i}\right)\Big|_{a^{LIVE}_{u,k,i,g}<0} \\ &+\sum_{h}\left(a^{PROC}_{u,h,g}\cdot PROC_{u,h}\right)\Big|_{a^{PROC}_{u,h,g}<0} \end{aligned} \quad \text{for all u and g}$$

All equations described so far have defined the convex feasibility region for the set of agricultural activities. The purpose of this single equation is to determine the optimal level of all endogenous variables within the convex feasibility region. In ASMGHG a price-endogenous, welfare based objective function is used as proposed by McCarl and Spreen (1980) This equation is shown equation 11The left hand side of equation11 contains the unrestricted total agricultural welfare variable (WELF), which is to be maximized. The right hand side of equation equation11 contains several major terms, which will be explained in more detail below.

$$
\begin{aligned}
\text{Max WELF} = & \sum_{\mathrm{u,y}} \left[\int_{\mathrm{y}} p_{u,y}^{DOMD} \left(\mathrm{DOMD_{u,y}} \right) \mathrm{d}(\cdot) \right] \\
& - \sum_{\mathrm{u,n}} \left[\int_{\mathrm{n}} p_{u,n}^{INPS} \left(\mathrm{INPS_{u,n}} \right) \mathrm{d}(\cdot) \right] \\
& + \sum_{\mathrm{m,y}} \left[\int_{\mathrm{y}} p_{m,y}^{FRXD} \left(\mathrm{FRXD_{m,y}} \right) \mathrm{d}(\cdot) \right] \\
& - \sum_{\mathrm{m,y}} \left[\int_{\mathrm{y}} p_{m,y}^{FRXS} \left(\mathrm{FRXS_{m,y}} \right) \mathrm{d}(\cdot) \right] \\
& - \sum_{\mathrm{u,f}} \left(\mathrm{p_{u,f}^{INPS}} \cdot \mathrm{INPS_{u,f}} \right) \\
& - \sum_{\mathrm{r,\tilde{r},y}} \left(\mathrm{p_{r,\tilde{r},y}^{TRAD}} \cdot \mathrm{TRAD_{r,\tilde{r},y}} \right)
\end{aligned}
$$

The first term $\sum_{\mathrm{u,y}} \left[\int_{\mathrm{y}} p_{u,y}^{DOMD} \left(\mathrm{DOMD_{u,y}} \right) \mathrm{d}(\cdot) \right]$ adds the sum of the areas underneath the inverse U.S. domestic demand curves over all crops, livestock products, and processed commodities.

The second right hand side term $-\sum_{\mathrm{u,n}} \left[\int_{\mathrm{n}} p_{u,n}^{INPS} \left(\mathrm{INPS_{u,n}} \right) \mathrm{d}(\cdot) \right]$ subtracts the areas underneath the endogenously priced input supply curves for hired labor, water, land, and animal grazing units.

The following two terms $+\sum_{\mathrm{m,y}} \left[\int_{\mathrm{y}} p_{m,y}^{FRXD} \left(\mathrm{FRXD_{m,y}} \right) \mathrm{d}(\cdot) \right]$ and $-\sum_{\mathrm{m,y}} \left[\int_{\mathrm{y}} p_{m,y}^{FRXS} \left(\mathrm{FRXS_{m,y}} \right) \mathrm{d}(\cdot) \right]$ account for the areas underneath the foreign inverse excess demand curves minus the areas underneath the foreign inverse excess supply curves. Together these two terms define the total trade based Marshallian consumer plus producer surplus economic of foreign regions.

Finally, the terms $-\sum_{u,f}\left(p_{u,f}^{INPS}\cdot INPS_{u,f}\right)$ and $\sum_{r,\tilde{r},y}\left(p_{r,\tilde{r},y}^{TRAD}\cdot TRAD_{r,\tilde{r},y}\right)$ subtract the costs of exogenously priced production inputs and the costs for domestic and international transportation, respectively.

CHAPTER 6

PESTICIDE AND GREENHOUSE GAS EXTERNALITIES FROM US AGRICULTURE – THE IMPACT OF THEIR INTERNALIZATION AND CLIMATE CHANGE ON LAND USE, MANAGEMENT INTENSITIES, ECONOMIC SURPLUS, AND EXTERNALITY MITIGATION

6.1 INTRODUCTION

The build-up of greenhouse gas (GHG) concentrations in the earth' atmosphere, much of it driven by human activity, may have already started to affect global climate. In recognition of the GHG problem, the number of related scientific studies has increased exponentially over the last three decades. A substantial proportion of these studies analyze possible GHG impacts from land use and land use change (LULUCF). Many LULUCF related studies investigate important components of the complex interactions between agriculture, climate, and policies (Freibauer et al. 2004, Mall et al. 2006) and focus on climate change mitigation (Clemens and Ahlgrimm 2001, Smith and Almarez 2004), climate change impacts (Adams et al. 1994, Reilly et al. 2003), land management adaptation and technical progress (Olesen 2007, Alexandrov et al. 2002, Tubiello et al. 2002, Schneider et al. 2007, Schneider et al. 2010), and economic impacts of mitigation (Pautsch et al. 2001, Antle et al. 2003, De Cara et al. 2005, Lubowski et al. 2006, Schneider et al. 2007) However, none of the existing studies integrates in detail the entire spectrum of interactions between land use, society, and environment. Chapter 6 addresses this gap and contributes to a more comprehensive analysis of LULUCF impacts and opportunities under global change. This chapter extents previous studies by jointly assessing climate change impacts with greenhouse gas emission and pesticide externality mitigation options from US agriculture. The underlying research motivation for this integrated analysis is to find important synergies and tradeoffs between multiple political objectives, which may help to design more efficient regulations of LULUCF externalities.

Studies of climate change effects on pesticide applications are rare and cover only climate impacts on pesticide use (Chen and McCarl 2001; Koleva, et al. 2009), pesticide treatment cost (Chen and McCarl, 2003), pesticide external costs estimates Koleva and Schneider (2009) and impacts on agricultural sector welfare (Chen and McCarl, 2001). Chapter 5 introduces a hypothetical regulation of the pesticide externality in the US under current climate conditions and for different projections of climate change. In chapter 5 we analyze the impacts of climate change and regulations of the pesticide externality on pest management intensities. We find that, without external cost regulation, climate change benefits from increased agricultural production in the US may be more than offset by increased environmental costs. Higher production costs due to the internalization of the pesticide externalities increases farmers' income because of price adjustments and associated welfare shifts from consumers to producers. However, their estimates do not consider possible GHG emission regulations in the LULUCF sector.

This study builds on the analysis presented in chapter 5. Three major questions will be addressed each of which are relevant to researchers, policymakers, and the general public. First, is to quantify the impacts of pesticide externality and GHG emission regulations on the US agricultural sector including likely consequences for agricultural producers, consumers. Second, is to estimate if and how these climate adaptation impacts differ under projected changes in climate under different pest management options and across the periods. Third is to estimate how the individual and combined impacts of pesticide externality regulations and climate change mitigation policies, influenced producers' preferences pest and crop intensities. The expectations are that the answers to these questions will provide more insight into the ongoing debate about the scope, degree, and justification of environmental and climate change adaptation policies. To simultaneously portray the diverse spectrum of agricultural production options, feedback from national and international commodity markets, climate change impacts, and external effects of pesticides, and climate adaptation options we extend chapter 5, with climate change mitigation policy data.

Chapter 6 proceeds as follows. Section 2 describes the climate change mitigation policy data and ASMGHG modification. The estimated values of agricultural surplus, market shifts, and arable area changes and water use changes, associated with scenarios on climate change, climate policy, and pesticide policy are analyzed in section 3. Finally, section 4 concludes.

6.2 Climate policies and ASMGHG modification

This chapter uses the same methodology as chapter 5 and involves all major components described in section 5.2 Data and methods. Therefore this section draws only climate changes mitigation policies and ASMGHG modification.

Agricultural greenhouse mitigation policies can be designed in many different ways with varying levels of severity. Here is used a tax/subsidy hybrid system for internalizing emissions. In this study climate policies are internalized via exogenous carbon equivalent prices on all greenhouse gas accounts. The introduction of a carbon price acts as a tax on agricultural emissions and a subsidy on emission reductions. To address the uncertainty of future climate policies, a wide range of hypothetical price levels between $0 and $500 per mega gram carbon equivalent (MgCE) is used.

For the purpose of this study, the model ASMGHG (Schneider et al. 2007) is used. Descriptions of the model and model modifications are given in chapter 5 sections 5.2.5 and 5.5.1. Here are used the same modification as in chapter 5. Additionally carbon prices are added. For each carbon price, the model ASMGHG is solved, with and without the externality internalized.

6.3 Results

This section describes the empirical findings of ASMGHG simulations with different assumptions about greenhouse gas emission policies and pesticide externality regulations on the US agricultural sector Furthermore, is examined how the two distinct policies impact crop management regimes. A total of 240 scenarios which result from combinations of four time steps (2000, 2030, 2060, 2090), two climate projections (Canadian and Hadley), three internalization levels for the external costs of pesticide applications (0, 50, 100 percent) and ten greenhouse gas emission prices (0, 10, 20, 30, 50, 100, 200, 300, 400, 500 USD per metric ton of carbon) are considered. Here are used different internalization rates to address the uncertainty of the estimated external costs and carbon equivalent prices. For each scenario, is solved a modified version of the ASMGHG model. Due to the large model size, here are presented only selected aggregate measures of the simulated scenarios.

6.3.1 AGRICULTURAL MARKET AND WELFARE CHANGES

Adaptation to greenhouse gas emission and pesticide externality regulations affect agricultural markets. Table 6-1 shows quantitative projections of agricultural market and welfare indicators from ASMGHG simulations. The results from both climate change models are averaged. While climate change tends to increase production levels, the opposite effect is induced by greenhouse gas emission mitigation incentives and internalization of the pesticide externality. The results indicate that, for relatively low greenhouse gas prices, agricultural production decreases mostly due to pesticide externality internalization. For greenhouse gas prices above $100 per MgCE, the effects of different pesticide externality internalization are minor compared to the impacts of the greenhouse gas emission regulation.

Agricultural crop prices and trade volumes mirror the impacts on crop production. In absence of pesticide regulations and climate change mitigation policies, projected climate change decreases prices but increases pesticide use. The combined effect of the three drivers (climate change, pesticide regulations and greenhouse gas emission regulation) yields is more complex. For relatively weak greenhouse gas emission mitigation policies, the prices increase above 75 percent mostly due to pesticide externality internalization. If stronger greenhouse gas emission policies are used the prices increase 2 to 3 time relative to the base period. Note, however, that in the model the international crop supply functions are constant. If crop production outside the US would substantially decrease due to climate change, the decline in crop prices from increased US crop production would be smaller or reversed.

Table 6-1 also shows the distribution of agricultural surplus between US producers, US consumers, and foreign countries. Consumer surplus changes due to supply shifts are closely linked to price changes. The more prices increase, the higher are losses to US consumers. While consumers increasingly benefit from climate change the opposite effect is induced by climate and pesticide regulations. The strongest negative impacts on consumers occur under full internalization and high carbon prices.

Table 6- 1 Economic surplus and market effects in US agriculture in response to pesticide and greenhouse gas externality regulations

Projection	category		$0			$10			$20			$50			$100			$300		
			Carbon price under different pest managements																	
			Pesticide externalities internalization																	
	Sub category		none	50%	100%	none	50%	100%	none	50%	100%	none	50%	100%	none	50%	100%	none	50%	100%
2000	Production	Fisher Index	100	84.9	77.1	99.5	84.9	77.8	99.0	84.7	77.6	96.7	82.8	76.3	85.1	75.9	73.1	68.0	65.6	63.9
	Prices	Fisher Index	100	131.8	170.2	100.1	132.1	170.9	100.0	133.3	172.8	103.6	139.3	177.3	127.3	162.1	194.7	214.2	258.2	293.0
	Exports	Fisher Index	100	53.7	34.6	98.7	53.2	37.4	97.8	52.4	36.9	90.3	49.4	34.6	54.9	29.5	27.8	15.1	13.8	13.3
	Imports	Fisher Index	100	132.8	168.3	100.0	134.9	173.5	105.2	136.9	173.0	105.4	139.1	182.9	117.0	145.4	193.0	166.0	203.1	253.1
	US Producers	Billion $	0	-3.0	6.5	-1.2	-4.8	4.8	-2.3	-4.9	4.3	-2.6	-3.2	5.9	13.5	12.1	18.1	89.0	91.2	93.6
	US Consumers	Billion $	0	-18.6	-38.4	-1.1	-19.2	-39.3	-2.2	-21.3	-40.9	-7.9	-28.2	-47.8	-27.6	-46.5	-63.8	-88.3	-109.8	-125.5
	Foreign Surplus	Billion $	0	-2.3	-2.9	-0.1	-2.3	-2.7	0.0	-2.2	-2.7	0.0	-2.1	-2.5	-1.5	-2.7	-2.3	-5.4	-5.5	-5.0
2030	Production	Fisher Index	112.6	93.4	82.6	112.4	93.5	82.7	111.4	93.7	82.8	107.3	90.7	81.6	96.1	82.7	76.5	73.5	69.9	67.9
	Prices	Fisher Index	78.0	117.0	165.5	78.1	116.8	165.3	78.0	117.6	166.1	82.3	122.1	171.0	98.8	144.4	188.8	181.8	224.7	258.8
	Exports	Fisher Index	136.9	79.6	56.1	136.6	79.5	55.8	135.4	78.4	55.8	122.7	70.7	53.7	89.5	51.6	39.1	26.9	25.2	22.6
	Imports	Fisher Index	81.1	103.7	148.2	81.1	103.6	149.0	84.0	103.6	147.7	85.8	107.9	155.4	88.1	121.4	156.4	123.8	167.9	200.1
	US Producers	Billion $	-3.0	-4.2	11.3	-4.2	-6.3	8.9	-5.4	-6.9	8.0	-4.1	-5.8	9.6	8.8	10.5	21.8	88.0	86.4	86.7
	US Consumers	Billion $	10.6	-11.2	-36.7	9.5	-11.6	-36.7	8.3	-13.1	-38.0	2.0	-19.1	-45.0	-12.8	-12.8	-12.8	-75.0	-96.8	-111.3
	Foreign Surplus	Billion $	4.1	0.3	-1.4	4.2	0.4	-1.5	4.3	0.4	-1.4	3.7	0.2	-1.1	2.0	-0.8	-1.5	-3.8	-3.6	-3.5
2060	Production	Fisher Index	119.0	94.5	83.3	118.7	94.8	83.5	118.5	94.9	83.7	112.8	91.2	81.9	100.3	84.7	77.3	76.5	71.8	68.5
	Prices	Fisher Index	74.2	116.5	170.1	74.5	116.6	169.1	74.9	116.7	168.8	77.5	122.8	174.4	92.5	143.2	196.8	174.7	216.6	262.2
	Exports	Fisher Index	168.9	87.8	61.8	168.3	88.3	62.3	168.6	87.4	62.4	148.4	77.8	60.3	104.4	60.0	46.4	37.3	32.4	26.4
	Imports	Fisher Index	91.2	110.2	148.7	91.6	112.4	148.7	91.6	114.1	148.7	91.6	110.4	155.9	94.3	129.6	160.5	124.6	163.4	200.5
	US Producers	Billion $	-2.4	-3.3	15.1	-3.2	-5.4	12.7	-3.9	-6.1	11.2	-4.1	-4.4	13.6	8.5	11.7	26.9	89.5	85.5	89.5
	US Consumers	Billion $	11.9	-11.8	-40.0	10.4	-12.1	-40.1	8.9	-13.6	-40.7	3.7	-20.2	-48.5	-10.7	-37.9	-65.0	-72.5	-94.3	-113.4
	Foreign Surplus	Billion $	5.5	1.4	-0.4	5.5	1.5	-0.3	5.6	1.5	-0.3	5.5	1.4	0.1	4.2	0.6	-0.3	-2.6	-2.4	-2.5
2090	Production	Fisher Index	124.4	96.8	84.2	124.3	96.6	84.2	124.1	96.1	84.3	119.1	92.8	82.3	104.7	86.0	78.3	78.4	73.9	69.6
	Prices	Fisher Index	72.0	115.1	170.5	71.8	115.2	170.6	71.7	115.7	171.5	74.9	121.3	176.8	87.7	140.1	197.6	164.6	208.2	261.3
	Exports	Fisher Index	197.9	101.1	70.7	198.4	100.6	70.1	197.9	97.7	69.8	181.8	86.6	65.2	123.8	68.4	54.1	45.8	40.2	32.3
	Imports	Fisher Index	93.4	116.6	160.6	89.3	116.7	164.6	89.7	116.6	164.6	93.7	116.7	165.1	93.5	134.0	169.1	125.4	155.7	196.5
	US Producers	Billion $	0.1	-2.3	18.0	-1.1	-4.1	15.9	-2.1	-5.1	14.9	-1.9	-3.3	16.3	8.9	11.8	29.0	89.3	84.1	91.2
	US Consumers	Billion $	11.9	-12.0	-42.9	10.8	-12.7	-43.0	9.8	-13.9	-44.1	4.2	-20.5	-50.3	-9.4	-37.3	-66.8	-69.5	-91.1	-114.1
	Foreign Surplus	Billion $	6.4	2.6	1.5	6.4	2.8	1.3	6.4	2.9	1.3	6.3	2.8	1.1	5.8	2.2	1.3	-1.1	-1.1	-1.5

The effects of climate change, pesticide and greenhouse gas regulations on agricultural producers are potentially more diverse because price and supply impacts work in opposite directions regarding farm income. Particularly, supply increases lead to higher sales at lower prices and vice versa. The simulation results show that the supply enhancing impact of climate change projections do not benefit producers. A 50 percent internalization of pesticide externalities and relatively low carbon prices worsens producer surplus. However, for high carbon prices, this response reverses. The combined effect of full pesticide external costs internalization and carbon prices increases considerably farmers' income and for $300 MgCE the benefits change 7 to 8 times relative to the value under 2000 climate conditions, full pesticide internalization and $0 MgCE.

Foreign countries' surplus aggregates changes of foreign producer and consumer surplus. Results indicate that in absence of pesticide and climate regulations, the net effects on these surplus changes are moderately positive. Introduction of greenhouse gas emission strategies and pesticide external costs internalization individually and jointly, lower the net foreign surplus.

Details on the level of the pesticide externality from US agriculture in response to its internalization, climate change and greenhouse gas mitigation regulation are shown in Table 6 -2. In absence of pesticide and greenhouse gas externality regulations, climate change leads to substantial increases in total environmental and human health costs (TEHH). Particularly, these cost increase relative to total US agricultural revenue (TAR) from about one third in 2000 to about one half in 2090. The internalization of the external cost of pesticides increases moderately total US agricultural revenue and decreases substantially the total environmental and human health cost. At full internalization, agricultural revenues changes less than 8 percent but the pesticide externality decreases by 86 percent and more across all examined climate projections. The introduction of relatively low carbon equivalent prices has little impact on both total agricultural revenue and total environmental and human health costs. In absence of pesticide policy, high carbon equivalent emission prices above $ 100 MgCE decrease total environmental and human health cost and moderately increase the total agricultural revenue.

Table 6- 2 Absolute and relative pesticide externality from US agriculture in response to pesticide and greenhouse gas externality regulations and climate change projections

Carbon prices	Internalization rate of external pesticide impacts	Climate Projection	Total Environmental and Human Health Costs in US (TEHH)	Total Internalized Costs in the US	Total Agricultural Revenues in the US (TAR)	Absolute Change in TEHH	Absolute Change in TAR	TAR Levels Relative to Base	TEHH Levels Relative to Base
			- - - - - - - - in Billion US dollars - - - - - - - -					- - - in % - - -	
None Tax	*None*	2000	125.16	0.00	357.11	0.0	0.0	100	100
		2030	143.33	0.00	351.54	18.17	-5.57	98.44	114.51
		2060	156.33	0.00	350.52	31.17	-6.60	98.15	124.90
		2090	162.38	0.00	351.22	37.22	-5.89	98.35	129.73
	50%	2000	27.47	13.74	367.63	-97.69	10.51	102.94	21.95
		2030	32.14	16.07	363.99	-93.02	6.88	101.93	25.68
		2060	33.53	16.77	364.84	-91.63	7.73	102.16	26.79
		2090	33.80	16.90	365.74	-91.36	8.62	102.41	27.00
	100%	2000	18.09	18.09	380.23	-107.07	23.11	106.47	14.46
		2030	17.22	17.22	377.10	-107.94	19.98	105.60	13.76
		2060	17.40	17.40	380.08	-107.76	22.97	106.43	13.90
		2090	17.23	17.23	383.28	-107.93	26.17	107.33	13.77
$20	*None*	2000	125.09	0.00	357.05	-0.07	-0.07	99.98	99.94
		2030	142.20	0.00	351.39	17.04	-5.72	98.40	113.61
		2060	155.49	0.00	352.40	30.32	-4.72	98.68	124.23
		2090	161.87	0.00	351.76	36.71	-5.35	98.50	129.33
	50%	2000	27.51	13.76	369.26	-97.65	12.15	103.40	21.98
		2030	32.78	16.39	366.16	-92.39	9.05	102.53	26.19
		2060	33.84	16.92	366.32	-91.32	9.21	102.58	27.04
		2090	33.73	16.87	366.57	-91.43	9.46	102.65	26.95
	100%	2000	18.19	18.19	381.40	-106.97	24.28	106.80	14.53
		2030	17.40	17.40	378.44	-107.76	21.32	105.97	13.90
		2060	17.61	17.61	380.97	-107.56	23.86	106.68	14.07
		2090	17.44	17.44	384.47	-107.72	27.35	107.66	13.93
$100	*None*	2000	113.38	0.00	375.09	-11.78	17.98	105.03	90.59
		2030	131.41	0.00	365.07	6.24	7.96	102.23	104.99
		2060	141.52	0.00	365.54	16.35	8.43	102.36	113.07
		2090	146.28	0.00	365.36	21.12	8.24	102.31	116.87
	50%	2000	26.81	13.40	388.25	-98.36	31.14	108.72	21.42
		2030	32.55	16.28	380.73	-92.61	23.61	106.61	26.01
		2060	35.27	17.63	382.62	-89.89	25.51	107.14	28.18
		2090	36.51	18.26	382.24	-88.65	25.13	107.04	29.17
	100%	2000	18.22	18.22	397.73	-106.94	40.62	111.37	14.56
		2030	18.69	18.69	395.68	-106.48	38.56	110.80	14.93
		2060	17.94	17.94	398.96	-107.22	41.85	111.72	14.34
		2090	18.59	18.59	399.97	-106.57	42.86	112.00	14.85

Although, the environmental and human health costs increase due to climate change, they remain below the values without greenhouse gas emission and pesticide externality regulation. The combination of pesticide externalities internalization and high carbon prices increases the total agricultural revenue while total environmental and human health cost is little affected. This implies that supply reductions are more than compensated for by associated price changes.

6.3.2. PESTICIDE APPLICATION INTENSITIES

Greenhouse gas emission and pesticide externality regulations affect agricultural decisions in multiple ways. Farmers may grow different crops, use different rotations, and change the intensity of management related to irrigation, tillage, fertilization, and pesticide use. These adjustments are represented in ASMGHG. The simulated individual and combined effects of climate projections, externality regulation on pest management and greenhouse gas mitigation strategies are provided in Table 6- 3

Each section in Table 6 -3 shows the area allocated to different pesticide application intensities for different carbon equivalent prices and simulation periods. In absence of climate and pesticides externality regulations, agricultural producers prefer conventional pesticide intensities under all climate projections. The simulation results indicate that individually each of the three drivers (climate change, pesticide regulation and greenhouse gas emission regulation) reduce the total area with conventional pesticide management but increase the area with reduced pesticide management. The combined impact of climate change, pesticide and greenhouse gas emission regulations on cropping is stronger than individual effect. The strongest impact occurs for high carbon prices and full pesticide internalization under 2090 condition where the land share under conventional pesticide application intensity decreases above 60 percent with most of the land moving to zero pesticide use. Note, however that the impacts of the three drivers do not add up. For instance, under 2060 climate condition 50 percent pesticide internalization and $100 carbon price would reduce the cropped area under conventional pesticide application intensity by 55 percent. Equivalently, climate 2030 projections with full pesticide external costs internalization and without climate regulation would reduce cropping areas by 55 percent (columns 3 and 4 of Table 6-3).

Table 6- 3 Effect of climate projections, pesticide and greenhouse gas externality regulation on pesticide application rates

Pesticide Application Rate	Internalization rate of climate	Climate Projection	Internalization Rate of External Environmental Costs of Agricultural Pesticides					
			None (Base)		50 Percent		100 Percent	
			in million acres (in percent relative to base)					
			in million acres (share of total acreage)					
Conventional Pesticide Management	*None*	2000	330.1	100.0	193.8	58.7	165.2	50.0
		2030	310.7	100.0	177	53.6	158.4	48.0
		2060	316.3	100.0	172.4	52.2	153	46.3
		2090	309.8	100.0	171.1	51.8	149.5	45.3
	$20	2000	329.1	99.7	195.5	59.2	169	51.1
		2030	308.3	93.4	178.4	54.0	159	48.1
		2060	316.7	95.9	174.9	53.0	156	47.2
		2090	310	93.9	166	50.3	151	45.6
	$100	2000	281.5	85.3	177.9	53.9	160.8	48.7
		2030	264.9	80.2	159	48.2	148.8	45.1
		2060	258.6	78.3	147.6	44.7	140.3	42.5
		2090	258.1	78.2	139.6	42.3	130.6	39.6
Reduced Pesticide Management (50 Percent)	*None*	2000	0	0.0	73	22.1	64	19.5
		2030	55	16.6	71	21.4	57	17.3
		2060	39	11.7	65	19.5	46	14.0
		2090	35	10.7	56	17.0	37	11.3
	$20	2000	0	0.0	73	22.2	63	19.0
		2030	55	16.6	72	21.7	53	16.1
		2060	39	11.7	63	19.1	45	13.6
		2090	35	10.7	57	17.1	37	11.2
	$100	2000	0	0.0	56	17.0	53	16.0
		2030	55	16.6	60	18.3	51	15.4
		2060	39	11.7	62	18.9	45	13.7
		2090	35	10.7	56	17.1	39	11.8
Minimum Pesticide Management (0 percent)	*None*	2000	0	0.0	32	9.7	54	16.4
		2030	24	7.2	41	12.5	62	18.8
		2060	35	10.7	43	13.2	73	22.2
		2090	38	11.4	50	15.3	80	24.2
	$20	2000	0	0.0	32	9.8	61	18.4
		2030	24	7.2	41	12.5	70	21.2
		2060	35	10.7	46	13.9	76	23.2
		2090	38	11.4	53	16.1	81	24.5
	$100	2000	0	0.0	29	8.7	59	18.0
		2030	24	7.2	35	10.6	48	14.7
		2060	35	10.7	35	10.6	59	17.9
		2090	38	11.4	35	10.6	67	20.4

The simulation results from Table 3 represent weighted averages over major crop groups. Figures 6- 1 to 6- 3 shows the effect of climate change, different greenhouse gas emission mitigation strategies and full pesticide externality internalization on pesticide management for individual crop categories.

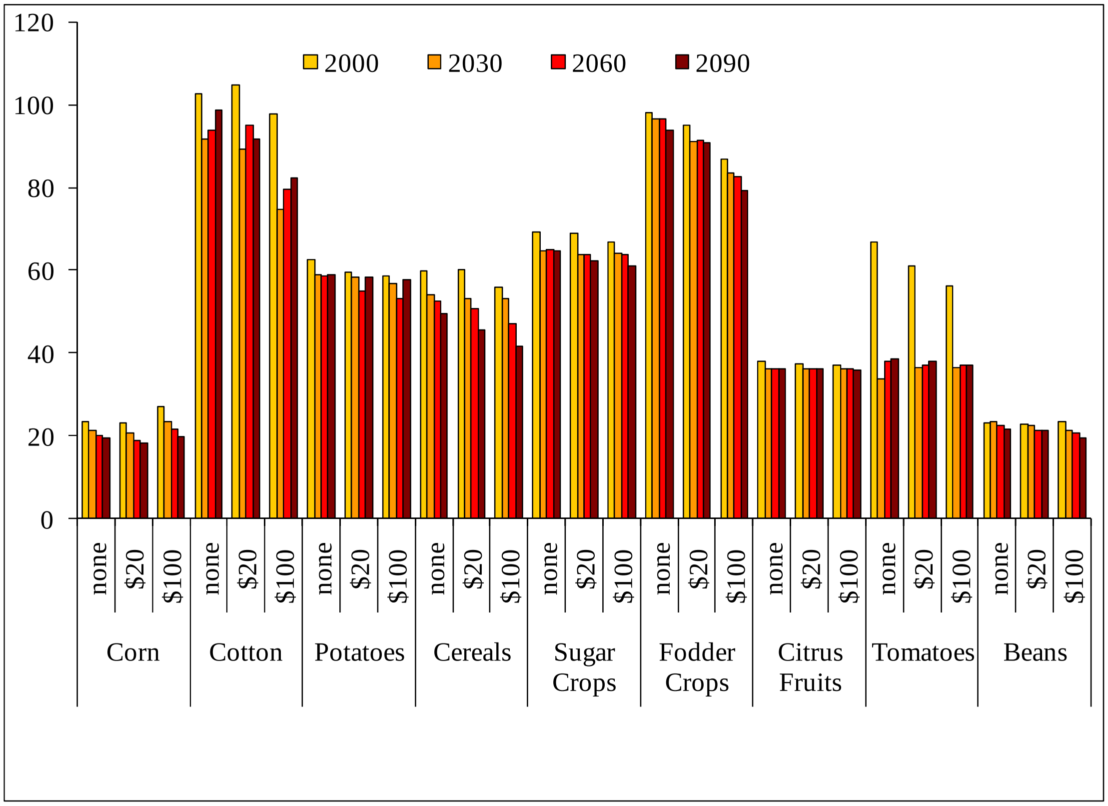

Figure 6- 1 Effect of projected climate change, carbon equivalent prices and 100%full internalization of external environmental cost of pesticides on area share (in percent) under conventional pesticide management by crop group

Although there is a substantial reduction in conventional pest management across simulated periods, under full pesticide internalization conventional pesticide rates dominate reduced rate strategies for all crops except for corn and beans. Sugar crops, fodder crops, and tomatoes show no or relatively little change in pesticide intensities. Carbon equivalent prices decrease the area shares for most crops with conventional pesticide intensities except for corn for which area share increases and citrus fruits, beans and potatoes, for which climate policies do not have substantial impacts on area shares.

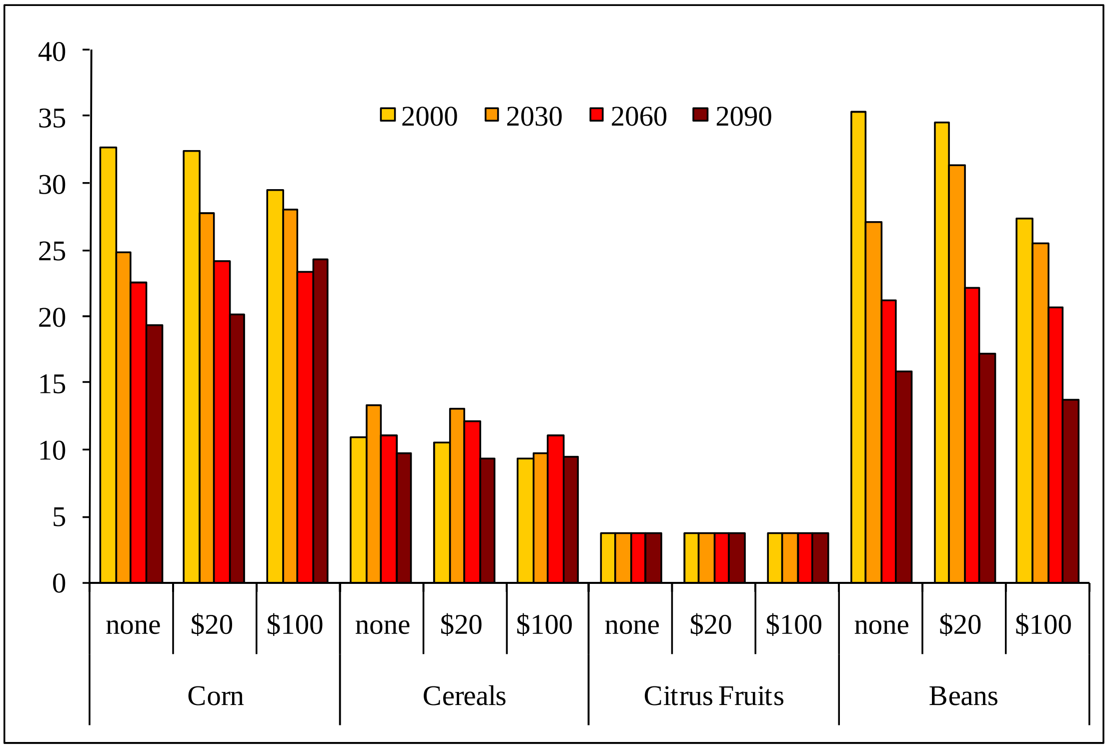

Figure 6- 2 Effect of projected climate change, carbon prices and 100%full internalization of external environmental cost of pesticides on area share (in percent) under reduced pesticide management by crop group

For reduced and zero pesticide application managements, greenhouse gas emission prices mostly decrease their area shares except citrus fruits, which show no changes for reduced pesticide application management and relatively little change for zero pesticide application management. Climate change projections affect the preferred pesticide intensities for corn and soybeans and lead to gradually increasing shares of pesticide free management at the expense of the area under reduced pesticide applications. For all other crop groups, climate change has relatively little impact on the examined non-conventional pesticide control strategies.

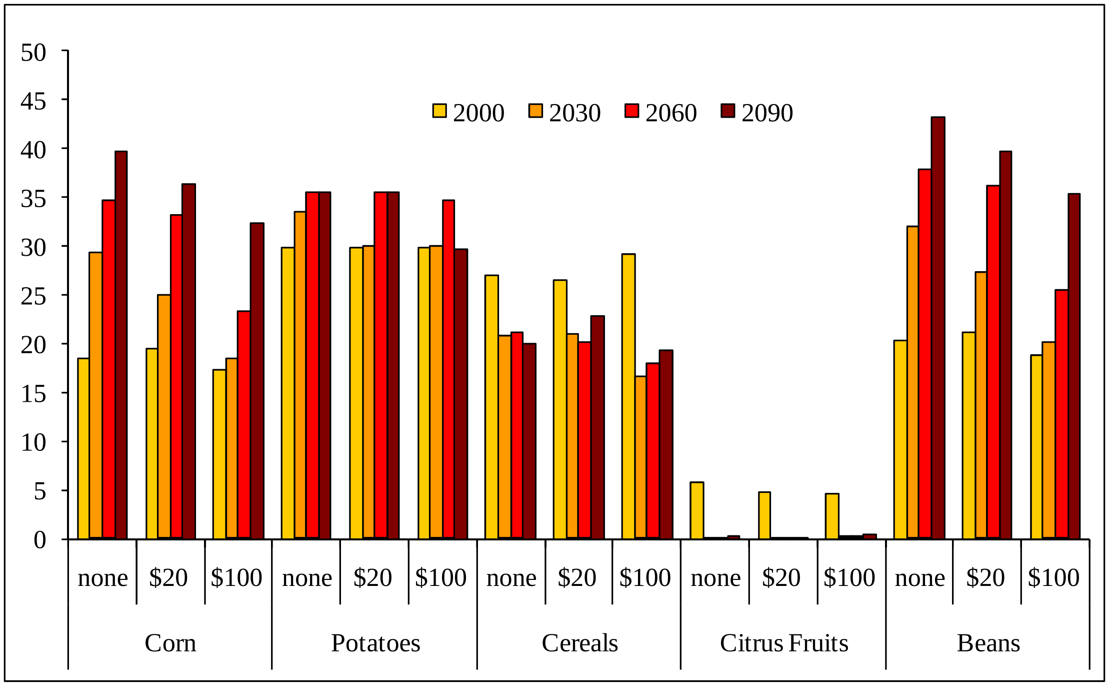

Figure 6- 3 Effect of projected climate change, carbon prices and 100% internalization of external environmental cost of pesticides on area share (in percent) under pesticide free management by crop group

6.3 WATER USE IMPACTS

This section summarizes irrigation water use changes due to pesticide and greenhouse gas externality regulation and climate change projections. Table 6-4 shows the impacts on the total area occupied by traditional crops and total water use. The water use per hectare is averaged over the entire area occupied by traditional crops (including irrigated and non-irrigated fields). Simulation results indicate that individually, climate change tends to increase the area occupied by traditional crop and decreases water use (Table 4, column 4). If carbon equivalent prices are used, both total land and water use decrease. Particularly, for $ 100 per MgCE and in absence pesticide regulation, the total area in 2090 is close to the base value, and water use decreases by 22 percent compare to the base level.

Table 6- 4 Effect of climate projections, greenhouse gas and pesticide externality regulation on total land and water use

Pesticide application rate	Internalization rate of climate change mitigation policies	Climate projection	Internalization rate of external environmental costs of agricultural pesticides: None (Base)		50 Percent		100 Percent	
			in million acres (in percent relative to base) / in million acres (share of total acreage)					
Total area	*None*	2000	330	100	299	90.5	284	50
		2030	389	123.8	289	87.6	278	48
		2060	390	122.4	280	84.9	273	46.3
		2090	383	122.1	278	84.2	267	45.3
	$20	2000	329	99.7	301	91.3	292	51.1
		2030	387	117.2	292	88.3	282	48.1
		2060	391	118.4	284	85.9	277	47.2
		2090	383	116	276	83.5	269	45.6
	$100	2000	282	85.3	263	79.5	273	48.7
		2030	344	104.1	254	77.1	248	45.1
		2060	333	100.8	245	74.2	245	42.5
		2090	331	100.3	231	70	237	39.6
Total water use			in cubic kilometers (in percent relative to base) / in cubic kilometers (share of total water use)					
	None	2000	106	100	109	103.6	110	104.5
		2030	96	90.6	99	93.3	101	95.5
		2060	92	86.8	94	88.8	98	92.3
		2090	91	85.7	93	87.7	96	90.9
	$20	2000	102	96.1	108	102.5	108	102.6
		2030	94	88.5	97	91.4	99	93.5
		2060	91	86.2	92	87.3	96	91.2
		2090	90	85.1	92	86.8	95	89.8
	$100	2000	97	91.9	105	99.8	106	100.5
		2030	87	82.7	91	86	96	90.8
		2060	84	79.8	86	81.2	91	86.2
		2090	83	78.8	85	80.3	87	82.8

The introduction of pesticide regulation substantially decreases the amount of total land use but increase total water use. While, the amount of total area decreases gradually to the level of pesticide internalization, the changes in total water requirements are minor.

For full pesticide internalization and $20 per MgCE the total land use in 2090 is below 50 percent while the total water use exceeds 89 percent of the base value. If high carbon price are used the effects are stronger.

Figures 6-4 to 6-7 display the water use in response to greenhouse gas emission incentives and different levels of the pesticide externality regulation for each simulated period. As shown, the assumed degree of climate policy has considerable impacts on water use preferred crop management. As carbon equivalent prices increase, the water use substantially decreases. Particularly, under 2090 and for $ 250 per Mg CE in 2090 water use is below 82 km^3 or one forth less compare to the base value. While climate change and greenhouse gas emission strategies tend to increase pesticide use and decrease water use pesticide externalities internalization induce opposite effect. Changes in levels of pesticide internalization affect differently water use crop managements across simulation periods. For example, under year 2000 the impacts of full and 50 percent pesticide internalization on water use crop management does not differ substantially while under year 2030 water use change proportionally to the level of pesticide internalization. For the last two simulation periods the, irrigation water use is higher for full pesticide internalization and carbon price below $300 per MgCE. If carbon prices are higher water use changes mostly due to greenhouse gas emission regulations. For instance for carbon above $300 per MgCE the water use in 2090 is the same or moderately differ for different degrees of pesticide externality internalization For carbon equivalent prices above $ 400 the changes in water use are minor across simulation periods, the likely reason is that, special mitigation measures such as afforestation and energy crop plantations increase at the expense of traditional crop production.

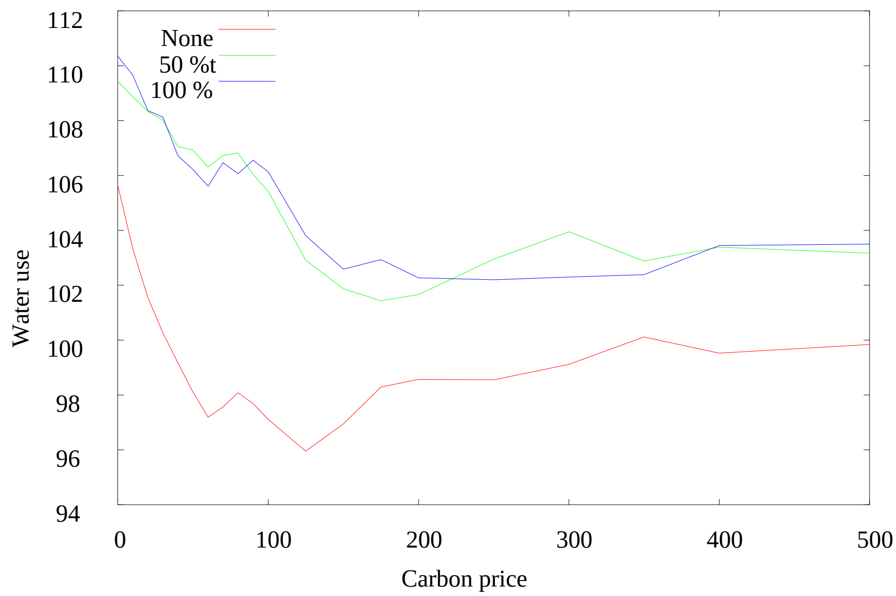

Figure 6- 4 Effect of climate adaptation andgreenhouse gas and pesticide internalization externality regulations on water use in 2000

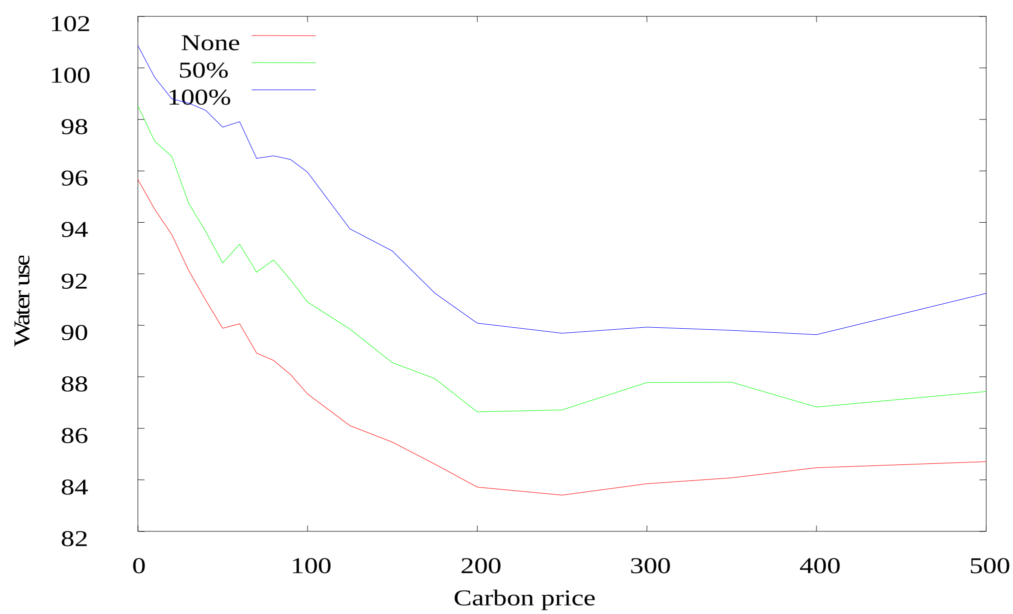

Figure 6- 5 Effect of climate adaptation andgreenhouse gas and pesticide internalization externality regulations on water use in 2030

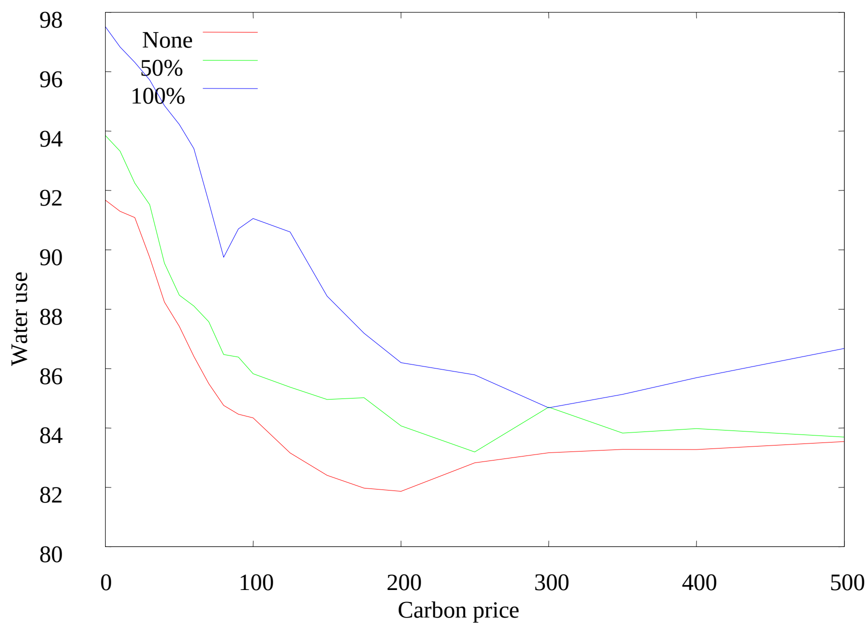

Figure 6- 6 Effect of climate adaptation andgreenhouse gas and pesticide internalization externality regulations on water use in 2060

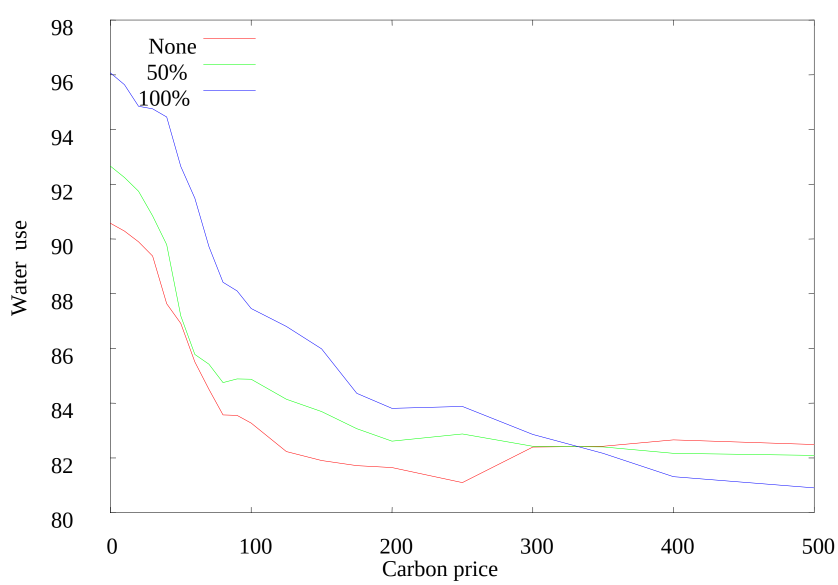

Figure 6- 7 Effect of climate adaptation andgreenhouse gas and pesticide internalization externality regulations on water use in 2090

6.4 CONCLUSIONS

This chapter examines alternative assumptions about regulations of external costs from pesticide applications in US agriculture under different climate conditions. The impacts of the internalization of the pesticide externality and climate change are assessed both independently and jointly. Without climate and pesticide externality regulations, climate change benefits from increased agricultural production in the US may be more than offset by increased environmental costs. While climate policy and pesticide externality internalization may increase substantially farmers' production costs, farmers are likely to benefit because of price adjustments and associated welfare shifts from consumers to producers. This chapter also illustrates that full consideration of pesticides' external costs and low carbon prices motivate farmers to substantially reduce pesticide applications for corn and soybeans and considerably for cereals and potatoes. For high emission prices and high pesticide externality taxes, farmers prefer conventional pesticide intensities for corn but reduced pesticide levels for other major crops. Although the additional impact of climate change on preferred pesticide intensities is marginal for most crops, it is substantial for corn and soybeans. The simulation results also show that full, pesticide externality regulation substantially increases the total water use for irrigation and decreases total area use while, greenhouse gas emission regulation leads to opposite effect on water use. Chapter 6 also illustrates that full consideration of pesticides' external costs and carbon prices motivate farmers to substantially reduce pesticide applications for corn and soybeans and considerably for cereals and potatoes.

The results from this study have important research and policy implications. First, this analysis quantifies the tradeoff among agricultural market surplus climate policies and external pesticide costs under different climate conditions. Estimated benefits from internalization may be contrasted with policy transaction costs, to judge whether combination of climate, pesticide externality and climate regulations is desirable. The examined pesticide and climate policy provide more insight into the ongoing debate about the scope, degree, and justification of environmental and climate change adaptation policies. Furthermore the results from chapter 6 could affect agricultural research programs because the expected social returns to research on alternative pest control strategies depend also on the expected external cost change. Additionally, this study can help to improve the mathematical representation of agricultural externalities in integrated assessment models. These models are increasingly used for the design and justification of climate and other environmental policies.

Several important limitations and uncertainties to this research should be noted. First, the findings presented here reflect agricultural management options for which data were available to us. Alternative pesticide management options are limited to three levels of application rates. In reality, farmers could adopt any application rate and could consider many other pest control adaptations which are not considered here. Second, the data for pesticide treatment costs, yield impacts, irrigation water requirements, and external costs involve regression analyses and mathematical simulation models. Thus, the certainty of the estimates presented here depends on the quality of these models and the certainty of all associated input data. Third, not monetized in this analysis were costs or benefits from reduced levels of other agricultural externalities, and costs or benefits of changed income distribution in the agricultural sector. Fourth, we operate with 32 crops mainly grains and not many fruits and vegetables which have higher contribution to the external cost of pesticide use. Fifth, the reductions in external costs due to regulation may be overstated because of leakage of pesticide intensive crops to other countries. Finally, all simulated results are derived from the optimal solution of the mathematical program and as such constitute point estimates without probability distribution.

CHAPTER 7

SUMMARY AND CONCLUSIONS

Some of the most important interactions between society and the environment occur in the agricultural sector. The complex linkages between food production, environment and climate change can only be understood within a long-term, interdisciplinary framework. This dissertation contributes to such investigations by providing an integrated economic analysis on climate change and US pesticide use. The analysis consists of four parts subsequently connected, that correspond to the aims of this thesis, which were set out in the first chapter, The realization of the aims of this thesis are summarized below, followed by a discussion of implications and limitations.

The first aim of the thesis, to establish the quantitative relationship between weather, climate and variable pesticide use, was achieved in the first part of the analysis (chapter 2). A panel data regression model for the US is used to find out how weather and climate differences influence agricultural pesticide application. The regression results confirm the existence of significant, mostly positive, impacts of temperature and precipitation variables on pesticide applications. Weather and climate variables have different effects on different crops, thus the changes in pesticide doses vary substantially. Notably, more rainfall increases plant protection needs for cereals, while higher temperatures increase pesticide doses applied to fruits and vegetables. Additionally, in this part (chapter 2), the regression results and downscaled climate change projections from the Canadian and Hadley climate models are combined to obtain future projections on pesticide use, which is the second aim of the thesis. The results indicate that for current crop area allocations, pesticide application rates increase, except for botanical pesticides, cyclohexanedione and inorganic pesticides. For those pesticides climate change is likely to decrease their applications. For fruits and vegetables, pesticide application doses increase the most due to climate change. Across the US geographic regions, pesticide application in southern US regions increases the most.

An increase in pesticide application, due to climate change, may cause substantial ramifications to society and the environment. An important issue is the aquatic environment. The third aim was to compute the potential risks for the aquatic species, based on the projection on pesticide applications and this was met in the second part of this analysis (chapter 3),with the focus on 13 US coastal states. In the second part it is estimated how climate change may affect the acute and chronic toxicity risk to algae, daphnia and fish, from agricultural pesticides. The projections on pesticide application from the Canadian and Hadley climate model, statistically estimated dependencies of pesticide applications to climate and weather variables in the first part of the analysis and the environmental risk indicator, REXTOX, developed by the OECD, was incorporated. On average, climate change is likely to increase the toxicity risk to aquatic species by 47 percent because of increased applications of agricultural pesticides. Daphnia and fish are more affected than algae. Across eight broad crop groups, pesticides used on fruits and vegetables contribute the most to aquatic risk. Within the thirty two US states examined, more than 90 percent of the climate change-induced pesticide pollution impact on the aquatic environment is caused by only thirteen states near the coast. Since projections on aquatic risk are based on uncertain regression coefficients with an error distribution, a Monte Carlo simulation is used to estimate the uncertainty of risk estimates. Our projections consider relatively long periods, using the 95% prediction intervals on pesticide applications for all projected dates and all regressions from part 1 (chapter 2), and we thus compute an uncertainty estimate for each aquatic risk category. Due to lack of information, not all possible pesticide pathways to the aquatic environment are considered in this study, but should be addressed in future studies.

To compute the impact of climate change on the external cost of pesticide applications, was the fourth aim of the thesis and this was achieved in the third part of this analysis (chapter 4). The Pesticide Environmental Accounting tool (PEA from Leach et al. 2008) is combined with the projections on pesticide use due to climate change (chapter 2). Using data from 32 US states, 49 crops and 339 pesticides, the current average external cost of pesticide use in US agriculture, is estimated to be $42 per hectare, per kilogram of active ingredient. In the absence of crop choice and crop management adaptations, climate change is likely to increase plant protection need and therefore the associated external environmental cost. In particular, the external cost might increase over all examined dates and reach $72 per kilogram of active ingredient per hectare by 2100. Thus, the current costs might increase by more than 50 percent. This increase in external costs comes mainly from pesticides applied to fruits and vegetables. Although a large amount of pesticide is used on cereals, the external costs of cereals remain at the lowest value, with and without climate change.

In the current situation, with about 500 million kilograms of pesticide applied to about 170 million hectares (USDA, 2001b), we calculate that social costs are about 12.5 billion dollars annually: 9.5 billion due to human health impact and the remaining 3 billion due to environmental damages. For the projected climate change, we estimate human health and environmental costs to reach 14.5 billion dollars and 5.3 billion dollars respectively in 2100. However, these estimations neglect possible agricultural adaptations regarding alternative pest management, major technological improvements in cropping systems or changes in planting crops. These factors might significantly change the use of pesticides and mitigate or enhance the external costs of pesticides. These issues are addressed in the last part of this analysis (chapter 5).

The fifth aim of the thesis, which was to use the projections on pesticide application and pesticide external costs and to examine alternative assumptions about regulations of external costs from pesticide applications in agriculture, was achieved in chapter 5. The results from the sections discussed above (part 1, part 3), together with data on climate change projections on yield and irrigation, are integrated with the Agricultural Sector and Mitigation of Greenhouse Gas (ASMGHG) model (Schneider et al. 2007), to examine alternative assumptions about regulations of external costs from pesticide applications in US agriculture. Two climate projections, provided by the Canadian and Hadley climate models, are used. The impact of the internalization of the pesticide externality and climate change is assessed, both independently and jointly. Results indicate that without external cost regulation, climate change benefits from increased agricultural production in the US may be more than offset by increased environmental costs. While the internalization of the pesticide externalities may increase farmers' production costs, they are likely to increase farm income because of price adjustments and associated welfare shifts from consumers to producers. The results also illustrate that full consideration of pesticide external costs motivate farmers to substantially reduce pesticide applications for corn and soybeans and considerably for cereals and potatoes. While the additional impact of climate change on preferred pesticide intensities is marginal for most crops, it is substantial for corn and soybeans.

The final aim of the thesis

The findings from this analysis have research and policy implications and may affect the optimal design and premiums of crop insurance programs. Overall increased negative externalities from pesticide applications could provide an argument for more mitigation, i.e. for stronger greenhouse gas emission control policies and improvement in existing pesticide regulations, which only prohibit pesticides but impose no charge on admitted ones. Related to this argument, the externality estimates can help to improve the scope of climate change impacts in integrated assessment and earth system models. These models are increasingly used for the design and justification of climate and other environmental policies. Furthermore, the results could affect agricultural research support programs because the expected social returns to research on various pest control strategies, depends on the expected external cost change as well.

In interpreting the empirical results of the study, a few words need to be said about existing limitations. Sources of errors relate to data inaccuracies, model structural assumptions and aggregation approximation errors. As outlined, the data used for this analysis were obtained from statistical, climate and environmental models. Thus, the validity of the estimates presented here depends on the quality of these models and associated data. Not monetized in this analysis are costs or benefits from reduced levels of other agricultural externalities and costs or benefits of changed income distribution in the agricultural sector. Another shortcoming of the presented analysis is that we do not explicitly account for climate change impact on pest populations. Furthermore, we do not consider all possible pest control alternatives such as enhanced mechanical control or genetically modified organisms. Finally, the reduction in external costs, due to regulation, may be overstated because of leakage of pesticide intensive crops to other countries.

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