

Chapter 1 Introduction

1.1 Brief overview of the Problem

Pests are a common problem of all agricultural producers. The term “pests” applies to all categories of organisms that cause damage to crops. Pests include insects, weeds, fungi, bacteria, and nematodes as well as different disease-inciting viruses. To reduce the damage caused by pest infestations in crops, researchers have long recommended the use of pesticides as well as biological and cultural control methods. The term “pesticides” refers to biologically active chemicals used to repel, kill, or debilitate specific targeted pests (Fernandez-Cornejo). Pesticides can be of different types depending on their specific targets and include insecticides, fungicides, and herbicides. The use of different pesticides has been responsible for increasing crop yields and net returns to farmers (Norton and Mullen), and many studies have shown that pesticide use has increased over the years (Taylor *et al.*, and Wetzstein *et al.*). Although pesticides increase crop yields, the increased use of pesticides, particularly the more toxic ones, may have negative effects on the environment (EPA; Babcock and Flickinger; Kovach *et al.*; Higley and Wintersteen) as well as on human health (Georghiou & Taylor; Infante *et al.*; Pimentel *et al.*; Rola and Pingali; Antle and Pingali).

1.2 Problem Statement

There are two broad categories of the problem to be considered in the context of increased pesticide usage, namely, the potential damage from chemical pesticides to the environment and human health, and second, the impact of information to farmers on the use of toxic chemicals. The first part of the problem is related to the toxic content of each pesticide used. All pesticides are compounds of one or more chemically active ingredients (a.i.s), and can be classified into different groups according to their respective a.i. contents. The toxicity of different pesticides varies with their chemical content. The problem therefore is to determine not just whether the application of pesticides has increased, but also whether or not the aggregate toxicity of pesticide applications has increased. The economic returns from using different pesticides depend, not only on the market price of the pesticides and the value of increased output resulting from pesticide use, but also on the external effects that the pesticides may have on the environment and health of people. Since the cost of these health and environmental effects is not reflected in pesticides' market prices, pesticide overuse may result when considering these external effects (Fernandez-Cornejo). In other words, pesticide costs including environmental damages may exceed pesticide benefits at the margin.

Potential environmental damages can be calculated based on a number of characteristics of each pesticide. The most important physical and chemical properties of pesticides related to health and environmental risks are toxicity, persistence, and mobility. Toxicity is defined as “the quality or degree of being poisonous or harmful to plant, animal,

or human life” (Cohrssen and Covello: p.374), and can be either acute (short term) or chronic (long term). A standard measure of chronic toxicity is based on the number of units of Reference Dose¹ contained in a pound of a.i., while a measure of acute toxicity is based on the acute oral lethal dose fifty or LD₅₀, that is, the amount of dosage in mg per kg of body weight that will kill 50 percent of the laboratory test animals if a single dose is given by mouth (Weaver, p.28). Persistence is the tendency of a pesticide a.i. to resist degradation and is often expressed in terms of half-life, that is, the number of days it remains chemically active in the environment in a form able to cause significant harm. Generally, pesticides with higher half-lives, usually over 100 days (Fernandez-Cornejo), have a higher probability of appearing as residues in groundwater or on agricultural commodities. An index formed by multiplying the measure of toxicity by the measure of persistence for each pesticide a.i., and then summing over all a.i.s contained in the pesticide generally defines the “aggregate toxicity” of a pesticide. Mobility of pesticides determines their ability to leach into the ground or runoff into surface water (Fernandez-Cornejo). Many researchers “have created specialized data sets of pesticide effects on the environmental parameters” (Levitan, Merwin and Kovach, p.157). In 1990, Phillips and Shabman created pesticide risk indices based on the toxicity and mobility of pesticides for the Chesapeake Bay Region of Virginia (Phillips and Shabman).

The second part of the problem is to see if the above information is recognized by farmers and their advisors such as extension agents in order to minimize environmental damages from pesticide residues subject to achieving farmers’ profit objectives. The influence of information can be observed by the effects that scouting and other advisory services have on the use of toxic pesticides among farmers. Farm advisors are one of the direct disseminators of information to farmers about the products or inputs that they use. Failure on the part of the advisors to impart basic information, such as the potential risk involved in using certain pesticides, could be harmful to both the farmers and the final consumers.

Farm advisors and farm advisory services refer to a broad category of people who disseminate information to farmers. These can be hired staff, extension agents trained at universities and research stations, chemical dealers, and/or scouting personnel. Traditionally, scouting personnel have been responsible for spotting and reporting pest problems. Their services therefore may not have much impact on the choice of chemicals that farmers use, but scouts could have a lot of influence on the quantity of chemicals used by the farmers. Hired staff, extension agents and chemical dealers may have considerable influence on both the choice and the quantity of chemicals used by farmers.

Finally, the use of advisory services may be reflected in the cost of pesticides used in the fields. If farmers reduce the quantity of pesticides following advice of the farm-advisory services, then it is likely that the expenditure on pesticides may also go down unless more expensive pesticides are being used at lower levels. Any reduction in pesticide

¹ Reference Dose is defined by the EPA as an estimate of the maximum daily exposure of human beings to the active ingredient in milligrams per kilogram of body-weight, which, if consumed per day, will not pose a risk of any deleterious effects over their lifetime.

expenditures will, in many cases, lead to a reduction in the total cost of production for the farmer. Therefore, the advice from the advisory services may also increase farmers' profits.

Because farmers (or farm-operators) are responsible for all the activities that go on in the fields, it is essential that they be educated about the most current pest control technology that may reduce costs, increase net returns, and reduce environmental damages. For the past 20 years or more, numerous studies have been undertaken on the different effective methods of pest control under Integrated Pest Management (or IPM). According to Hall and Duncan (p.625, 1984), "IPM is a complex, knowledge- and information-intensive technology". It is a combination of four different methods to control, rather than eradicate, the pest population. These methods include (i) biological control which uses beneficial organisms against pests; (ii) cultural control that involves altering practices such as planting date, row spacing, and crop rotations; (iii) legal control, such as, abiding by state and federal regulations that prevent the spread of pests; and (iv) chemical control, that is, the judicious use of pesticides and other chemicals in a responsible manner (Osteen, Bradley, and Moffitt). IPM recommends the use of more benign chemicals on farms to ward off pests, but the main aim has been to reduce the use of pesticides in general (Norton and Mullen). The USDA has proposed a goal of the use of IPM on 75 percent of the US farmland by the year 2000 (Fernandez-Cornejo). The Regional IPM Grants Program (RIPM) contains a budget of \$3,335,909 for the fiscal year 1997.

Evaluations of IPM have focused on IPM's effects on pesticide expenditures but have ignored the implication of scouting and extension agents' advice or information on the aggregate toxicity of pesticides used on crops. Farmers' knowledge and contact with extension agents as explanatory variables have been used before for the study of the adoption of IPM. For example, in 1986, while trying to determine the relative importance of socio-economic factors which influence the adoption of IPM, Napit stated the hypothesis that adoption of IPM is positively correlated with the education level of the farm operator and the frequency of contacts with extension agents. His model included as explanatory variables, education level of the farm operator and frequency of contacts with extension agents. He tested his hypothesis using a trichotomous logit model. However, Napit used these socio-economic variables just to determine whether they had any impact on the adoption of IPM techniques in general. Less is known about whether the educational level of the farmer or the contacts with extension agents is having any effect on the aggregate toxicity of chemical use. In 1992, Bosch *et al.* conducted a survey of Chesapeake Bay Watershed area farms to study water quality problems due to agricultural operations. Their findings suggested that although farmers are concerned about water pollution they do not agree that their own activities on the farm are likely to be a cause of pollution even in areas of high soil leaching and erosion (Bosch *et al.*).

Much literature exists about methods of evaluating costs and farm level returns of using IPM programs. However, less empirical work has been done to evaluate the total economic benefits resulting from reductions in pesticide use (Norton and Mullen). Assuming that the farmer's goal is profit maximization, any reduction in pesticide expenditures may suggest a proportional benefit both to the farmer in terms of increased

profits as well as to society in terms of less negative ‘externalities’. Taylor and Lacewell, Napit, and Rola and Pingali were among the authors who evaluated the economic benefits of IPM based on reduced pesticide costs.

1.3 The Albemarle-Pamlico Watershed

This study will evaluate the effects of farm-advisory services on the toxicity of pesticides used in the cultivation of cotton and peanuts in the Albemarle-Pamlico watershed of Virginia and North Carolina. The Albemarle-Pamlico study area covers 27,500 square miles of southern Virginia and northeastern North Carolina. About 25 percent of the area is agricultural land with the majority of farms cultivating corn, soybeans, cotton, peanuts, tobacco, and wheat. About one-fourth of the agricultural land is classified as highly erodible and about 36 percent as having a high to very high leaching potential respectively (USDA). This Watershed was one of the four areas chosen in 1992 by the Economic Research Service (ERS), the National Agricultural Statistics Service (NASS), and the Natural Resource Conservation Service (NRCS) to study the potential environmental problems due to the region’s significant cropland and agricultural chemical use levels. Of the major crops in 1992, cotton was produced on 316,911 acres and peanuts on 222,830 acres in the watershed, with the yield per acre for these crops being 687 pounds and 3,100 pounds respectively (USDA).

Cotton was chosen for this study because it is a pesticide intensive crop that is growing in importance in the study area. Out of the 22 studies on cotton IPM programs evaluated by Norton and Mullen, nine showed that IPM caused pesticide use to increase. Cotton pest problems include bollweevils, considered to be one of the most severe pests, as well as fleahoppers, aphids, spider mites, lygus bugs, pink bollworms, and others. Disease and weed problems have also affected cotton in the past. Peanuts are another particularly important and pesticide-intensive crop in the region, and have therefore been included in this study.

1.4 Objectives

The objectives of this study are as follows:

- (1) To evaluate the effects of advisory services, and socio-economic and physical characteristics on the aggregate toxicity of pesticides applied to cotton and peanuts in the Albemarle-Pamlico Watershed.
- (2) To evaluate the effects of advisory services, and socio-economic and physical characteristics on the aggregate expenditures on pesticides applied to cotton and peanuts in the Albemarle-Pamlico Watershed.

Advisory services include: hired staff, extension agents, chemical dealers and scouting personnel; socio-economic characteristics include: education level, age, and years of farming experience of the farm-operator, as well as the annual farm sales; and physical characteristics include: distance of crop site from nearest water source, soil leaching characteristics, soil erosion potential, and productivity of the soil at the farm site.

Through achieving these objectives, farm-advisory services may be found to be helpful in determining the level of aggregate toxicity of chemical pesticides being used. A finding that advisory services have a major influence will have important implications for pest management strategies such as IPM. For example, more advisory services will be recommended to the farmers if these services reduce toxicity of pesticides used on crops. These services may also be subsidized by the government, if such subsidies can increase their use and lead to a decrease in the aggregate toxicity of pesticides being used. Also, by evaluating the importance of a farmer's educational level on the use of toxic pesticides, it will be possible to determine whether farm educational services will help reduce pesticide use. For example, if farmers with lower education are more likely to use pesticides with a higher aggregate toxicity, they can be targeted for special educational services.

1.5 Evaluation of Pesticide Impacts

Carson recognized as early as the late 1950s that the use of pesticides produces externalities. In her book *Silent Spring* she warned of the imminent dangers of the ever-increasing volume of pesticides being annually introduced into the environment (Carson, 1962). However, the post 1962 period did not see any decrease in the production of pesticides. By the mid 1970s social scientists realized that the evaluation of IPM benefits would have to incorporate environmental and social costs, but little was done in the actual calculations of such costs until the early 1980s. Most early studies attempted to evaluate social benefits of IPM based on the reduction of pesticide use per acre, increase in yields, and/or increase in farmers' net returns.

In 1980 Pimentel *et al.* made one of the first attempts at calculating environmental costs of pesticide use, but their method of arriving at such estimates was ad-hoc. However, in recent years increased attention has been focused on the estimation of actual environmental effects of pesticide use. In 1992, Kovach *et al.* divided the environmental effects into different components such as farmer, worker, consumer, and ecological components, and weighted these components with their respective reaction to different pesticides. They derived toxicity measures of pesticides from a variety of databases. This method of weighting led them to develop what they called the "environmental impact quotient" (EIQ) of the pesticides. However, Kovach *et al.* did not separately evaluate the economic implications of the different EIQ values of the different components. Higley and Wintersteen (1992) did a similar study but also attempted to place a value on the external benefits of pesticide-use by using a method known as "contingent valuation" (CV). The CV method is a survey-based technique that asks respondents how much they would be willing to spend to avoid particular risks from pesticide applications (Norton and Mullen). In 1995,

Teague, Bernardo, and Mapp derived an environmental risk index for pesticides where they used specific weights for chemicals lost in percolation (affecting ground water) and for chemicals lost in runoff (affecting surface water), respectively. In their indexing scheme, they used a pesticide's lifetime HAL (Health Advisory Limit)², set by the EPA, as a proxy for threats to human health through ground water, and a pesticide's acute lethal concentration fifty or LC₅₀ (acute toxicity to fish for 96 hours of exposure) as a proxy for threats to aquatic life in surface water. However, their assumption that risk from a particular pesticide does not change when combined with other pesticides may not be justified. Moreover, they concluded in their paper that "indices involve value judgments and simplifications of reality, ... and the specific weights to place on various forms of pollution is debatable" (Teague, Bernardo, and Mapp, p.18).

1.6 Data, and Techniques Involved in the Study

1.6.1 Data Sources and Indexing

The majority of the data used in the study have been collected by the United States Department of Agriculture (USDA) as part of the Area Studies Survey which will henceforth be referred to as the Area Studies data. The Area Studies data set selected for this study has three years of data from 1990 to 1992 for the Albemarle-Pamlico region of Virginia and North Carolina. This data set includes three data files, one relating to the general information on farms and farm activities as well as cultural practices on a randomly selected crop or pasture site, the second relating to information on pesticide products and their active ingredients used on a randomly selected crop or pasture site, and the third relating to fertilizers used on a randomly selected crop or pasture site. Of these three data files, the first and the second are relevant for this thesis. Apart from the Area Studies data sets, four other data sets were used for the study. The first of these was the data file "NRI82" containing information on the different physical characteristics of the region, such as distance of a sample point from a water-source, and land cover. The second was the "Soils 5" data set containing information on soil characteristics in the region. The third data file used in the study was one that contained pesticides expenditures for cotton and peanuts during the year 1992. The pesticide data had expenditures shown separately for insecticides, fungicides, and herbicides for each farm. The fourth was the data required for construction of the aggregate toxicity index for the chemically active ingredients applied to cotton and peanuts and was obtained from the Economic Research Service (ERS) division of the USDA.³ The aggregate toxicity index developed in this thesis is a slight modification of the one developed by Charles Barnard of the ERS.

² The EPA defines four levels of drinking water Health Advisories (HAs): One-day HA, Ten-day HA, Long-term HA, and Lifetime HA. Lifetime HA is defined as the concentration of a chemical in drinking water that is not expected to cause any adverse non-carcinogenic effects over a lifetime of exposure, with a margin of safety (<http://www.epa.gov/OST/Tools/dwstds.html>).

³ The data were obtained from Charles Barnard of ERS at the USDA.

1.6.2 Hypotheses

The major hypotheses of the study are as follows:

- (i) The aggregate toxicity of pesticides applied to a cotton or a peanut site is not related to the use of farm-advisory services.
- (ii) The aggregate toxicity of pesticides applied to a site is not related to the age of farmers.
- (iii) The aggregate toxicity of pesticides applied to a site is not related to the education level of farmers.
- (iv) The aggregate toxicity of pesticides applied to a site is not related to the level of farming experience of farmers.
- (v) The aggregate toxicity of pesticides applied to cotton or peanut sites is not related to the farm's distance from nearest surface water source.
- (vi) The aggregate toxicity of pesticides being applied to cotton or peanut sites is not related to the potential of the site to leach.
- (vii) The aggregate toxicity of pesticides applied to a site is not related to the amount of farm sales.
- (viii) The aggregate toxicity of pesticides applied to a site is not related to the productivity of soils.
- (ix) The aggregate toxicity of pesticides applied to a site is not related to the erosion potential of the site.
- (x) The aggregate pesticide expenditures for a cotton or a peanut site are not related to the use of farm-advisory services.
- (xi) The aggregate pesticide expenditures for a cotton or a peanut site are not related to the age of farmers.
- (xii) The aggregate pesticide expenditures for a cotton or a peanut site are not related to the education level of farmers.
- (xiii) The aggregate pesticide expenditures for a cotton or a peanut site are not related to the level of farming experience of farmers.
- (xiv) The aggregate pesticide expenditures for a cotton or a peanut site are not related to the farm's distance from nearest surface water source.
- (xv) The aggregate pesticide expenditures for a cotton or a peanut site are not related to the potential of the site to leach.
- (xvi) The aggregate pesticide expenditures for a cotton or a peanut site are not related to the amount of farm sales.
- (xvii) The aggregate pesticide expenditures for a cotton or a peanut site are not related to the productivity of soils.
- (xviii) The aggregate pesticide expenditures for a cotton or a peanut site are not related to the erosion potential of the site.

1.7 Conclusion

This chapter has presented a brief outline of the problems in agriculture relating to pesticide use and has introduced the rationale for this study. Chapter II will present the conceptual and empirical literature on the use of pesticides in agriculture. The methods for analyzing the data will be discussed in Chapter III. Chapter IV will contain a descriptive analysis of the data, the estimated models, and the results of the hypothesis tests. Finally, Chapter V will summarize the thesis and discuss some of the policy implications based on the results obtained in Chapter IV.

Chapter 2 A Review of Conceptual and Empirical Literature on Pesticide Use

2.1 Introduction

This chapter explores the background of pesticide use in cotton and peanut farming in the Albemarle-Pamlico watershed. The chapter also lays a conceptual foundation for the study, which will be accomplished by reviewing past literature on the problems that have already been encountered in the area of toxic pesticide use as well as by discussing the problem theoretically.

2.2 Literature Review

2.2.1 A Brief Background of Pesticides

Pesticides have been used since ancient times to control different pest populations. As early as 1000 BC, sulfur was found useful as a prophylactic treatment against plant diseases (Tschirley). However, "the sudden rise and prodigious growth of an industry" manufacturing synthetic chemicals with insecticidal properties was a phenomenon of the post Second World War period, and came about in the process of using insects to test for deadly chemicals in laboratories during the Second World War (Carson, p.16). The resulting synthetic insecticides were derived from different minerals and plant products and were compounds of arsenic, copper, lead, as well as some other chemicals like pyrethrum, nicotine sulfate, and rotenone. Although inorganic chemicals were slowly being replaced by the organic (carbon compound) ones in the production of pesticides after the Second World War, there still existed some pesticides whose basic ingredients were arsenic and lead, both known for their highly toxic properties.

Modern insecticides may be classified into six or seven different groups or families according to their chemical structure. However, the most widely used groups are the chlorinated hydrocarbons (including methoxychlor, heptachlor, and chlordane), organic phosphate insecticides (including parathion, malathion, demeton, and phorate), and the organic carbamate insecticides (including carbaryl, carbofuran, aldicarb, and oxamyl). These insecticides are called "organic" because they are made from carbon atoms which form the basis of life on earth, but ironically they are also some of the most toxic pesticides, capable of being fatal to humans if used indiscriminately.

The widescale acceptance of these insecticides in agriculture led to new chemical products including fungicides, herbicides, and nematicides being synthesized and developed for numerous uses. The production of synthetic pesticides in the United States increased more than five-fold between 1947 and 1960 and in the early 1970's more than 32,000 pesticide products containing nearly 1,000 chemicals were registered for use (Carson; Tschirley).

Pesticides are an integral and indispensable part of agriculture not only in the United States but also all over the world. According to Ware, plants that provide most of the world's food are susceptible to 80,000 to 100,000 diseases caused by viruses, bacteria, mycoplasma-like organisms, fungi, algae, and parasitic higher plants. Also, of the 30,000 species of weeds in the world, approximately 1,800 species cause serious economic losses. Some 3,000 species of nematodes attack crops, and over 1,000 of these cause severe damage. Among the 800,000 species of insects, about 10,000 plant-eating species are responsible for a devastating loss of crops throughout the world. Pimentel and Levitan estimated that total worldwide food losses from pests amount to about 45 percent, of which the preharvest losses from insects, plant pathogens, and weeds are 30 percent and post-harvest losses from microorganisms, insects, and rodents range from 10 to 15 percent. Ware showed that in the United States alone, crop losses due to pests are about 30 percent or \$20 billion annually, despite the use of pesticides and other control methods. Pimentel and Levitan concluded that in economic terms, for the \$3 billion invested in the United States in controlling pests through the use of pesticides, about \$12 billion are returned on the investment.

In summary, the benefits of proper use of pesticides are enormous. Nevertheless, there are significant risks associated with widespread and indiscriminate use of these chemicals. Much attention has been focused on the social and environmental risks associated with pesticide use ever since the publication of Rachel Carson's *Silent Spring* in 1962.

2.2.2 Externalities from Chemical Pesticide Use

Pesticide use may involve negative externalities. Using Pigou's terminology, an externality can be said to be present when there is a divergence between private and social cost. This divergence can be interpreted to mean that "when all voluntary contractual arrangements have been entered into by market transactors, there still remain some interactions that ought to be internalized but which the market forces left to themselves cannot cope with" (Dahlman, p.141). It is important to note that externalities may be positive or negative, but in the case of indiscriminate use of pesticides it is generally recognized that mostly negative externalities are generated. That is, there are some additional costs associated with the use of certain pesticides, which the market does not take into account. It will be useful to look at some of these extra costs.

Mellor and Adams pointed out that human poisonings are clearly the highest price paid for using pesticides. They estimated a total of about 3,000 to 4,000 annual pesticide poisonings in Central America whereas Pimentel and Levitan estimated 45,000 annual human poisonings worldwide (Young). Mullen did a contingent valuation (CV) survey and calculated environmental risks for most continental states of the US by dividing the environment into eight different categories and using willingness to pay (WTP) estimates (represented by an increase in either a person's grocery bills in \$/month or her federal

taxes in \$/year to avoid pesticide risks). His categories included acute human, chronic human, groundwater, surface water, aquatic species, avian species, mammalian species, and arthropods. The risk estimates that he obtained were then divided into three levels: high, medium, and low. Mullen found that the mean WTP estimates for risk reduction were highest for chronic human health and ground water categories across all three risk levels. His estimates were also consistent across all the states evaluated in his study.

It is estimated that less than 0.1 percent of the pesticides applied to crops actually reach the target pests implying that most of what is applied enters the environment, contaminating the soil, water, air, and perhaps poisoning or adversely affecting non-target organisms (Pimentel and Levitan). Contamination is confirmed by studies by the Environmental Protection Agency (EPA) showing that 17 pesticides were detected in the ground water of 23 states in the US in 1986 compared to 12 pesticides found in 18 states in 1984 (Sun).

Pesticides can also have a detrimental effect on the environment by disrupting natural controls (Mellor and Adams). For example, the destruction of a certain fungi may unleash damaging outbreaks of foliage-feeding caterpillars that the fungi may otherwise have prevented. So, additional control treatments become necessary as outbreaks of new pests occur.

Another serious consequence related to the widespread use of pesticides is the rapid appearance of insecticide resistance. By 1980, 260 species of agricultural arthropod pests had developed insecticide-resistant strains, compared to 68 for disease vectors (Brattsten *et al.*).

The recognition that pesticides pose risks to or have negative external effects on human health and the environment is the reason for undertaking research programs to minimize these risks and negative externalities. No amount of research can eliminate all the uncertainties associated with assessing the risks of exposure to potentially hazardous chemicals. The concept of minimum or optimal level of externality can be identified and explained with the help of the diagram in figure 2.1 (Pearce and Turner).

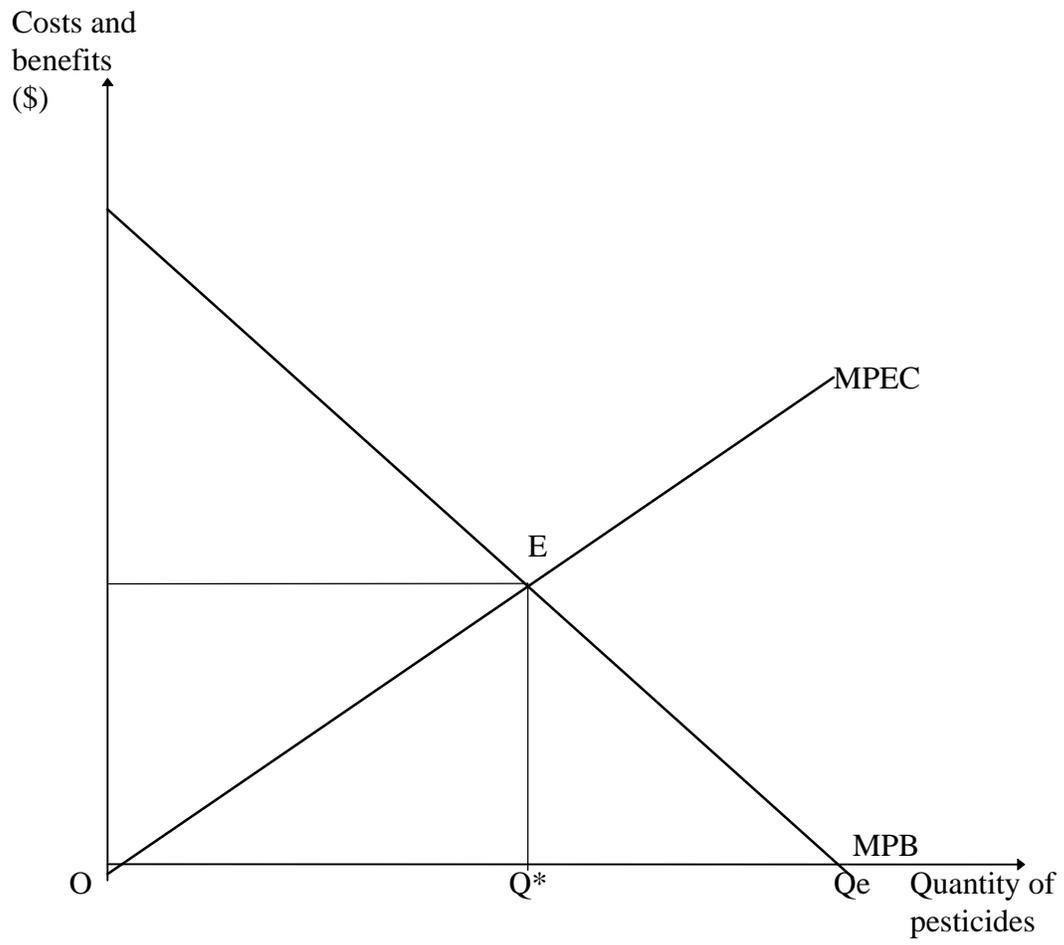


Figure 2.1. Optimum externality in agriculture.

In figure 2.1, costs and benefits are measured on the vertical axis and the amount of pesticides used is shown on the horizontal axis. The curve MPB represents the marginal private benefit of pesticides to the farmer where the private benefit is the additional revenues from use of the pesticides. The MPB therefore measures the extra benefit from increasing the level of pesticides by one unit. The MPEC schedule represents the marginal private and external cost, that is, the value of the farmer's private costs of using pesticides as well as of the external damage done by using one more unit of pesticide on the farm.

The optimal level of externality can now be identified by referring to the point of intersection of the MPB and MPEC curves. Starting from point O, where the difference between MPB and MPEC is greatest, the area between these two curves diminishes as more pesticides are used in farming, shown in the figure by moving to the right along the horizontal axis. It is, however, possible to expand production until the marginal private and external costs equal the marginal private benefits, that is until the point Q* is reached. But once production is increased beyond Q*, although the farmer still has some positive benefits until he reaches point Q_e, the marginal private and external costs become greater than his private benefits making use of additional toxic pesticides economically and socially non-optimal. The area OEQ* can be described as the optimal level of external and private costs.

2.2.3 Environmental Risk Indices for Hazardous Chemical Pesticides

The derivation of an optimal level of externality is possible only if these external effects are measurable. One effort to partially quantify external effects has been through the use of indices.

Metcalf's ratings of insecticides published in 1975 (Metcalf) was one of the first composite indices of pesticide hazards used to determine which insecticides were suitable for IPM. Metcalf's model is written algebraically as:

$$\text{Environmental Impact} = H + (B + F + HB)/3 + P \quad (2.1)$$

H is the acute toxicity to human beings and domestic animals; B is oral acute toxicity to birds; F is lethal concentration for fish; HB is contact toxicity to honey bees; and P is persistence in the soil.

Metcalf's concept of measuring pesticide hazards was later used in 1992 by Kovach *et al.*, who measured the environmental impact of pesticides using the environmental impact quotient (EIQ) method. They divided the environment into different components, namely, farm-worker, consumer, and ecological components, which are comprised of fish, birds, bees, and other beneficial arthropods. They then defined the formula for determining the EIQ value as follows:

$$EIQ = \{ [C(DT*5)+(DT*P)] + [(C*(S+P)2*SY)+(L)] + [(F*R)+(D*((S+P)/2)*3)+(Z*P*3)+(B*P*5)] \} / 3 \quad (2.2)$$

DT is dermal toxicity; C is chronic toxicity; D is bird toxicity; S is soil half-life; SY is systemicity; Z is bee toxicity; F is fish toxicity; L is leaching potential; R is surface loss potential; P is plant surface half-life; and B is beneficial arthropod toxicity. The data that Kovach *et al.* used for the environmental effects of specific pesticides as well as the data for toxicology, leaching, and surface loss potentials were derived from a variety of sources including the “EXTOXNET” on the Internet⁴.

In 1995, Teague, Bernardo, and Mapp developed an environmental risk index for pesticides based on the one built by Kovach *et al.*, in the following way:

$$EIP = (PPERC * HA * 0.5) + (PRUNOFF * LC * 0.5) \quad (2.3)$$

EIP is the Environmental Impact Parameter; PPERC is the quantity of pesticide lost in percolation; and PRUNOFF is the quantity of pesticide lost in runoff. They used specific weights for chemicals lost in percolation and for chemicals lost in runoff, respectively. HA is based on a pesticide’s lifetime Health Advisory Limit set by the EPA, and was used as a proxy for threats to human health through ground water. LC was based on a pesticide’s acute Lethal Concentration Fifty or LC₅₀ (acute toxicity sufficient to kill 50 percent of the fish after 96 hours of exposure), and was used as a proxy for threats to aquatic life in surface water.

There have been numerous other attempts at measuring environmental impacts of pesticides by constructing different kinds of indices. Warner cites examples of these indices including: (i) the Potential Environmental Hazard (PEH) index by Weber; (ii) the Environmental Harm Coefficient (EHC) by Dixon, Dixon, and Miranowski; and (iii) the Environmental Exposure Index (EEI) by Alt. The more recent indices were basically improved versions of the earlier ones, the improvements having come about by the inclusion of more than one parameter of toxicity and soil leaching characteristics.

Charles Barnard of the Economic Research Service at the USDA developed a toxicity index based on toxicity and persistence. Toxicity measures potential harm to one or more species. Persistence refers to the length of time until the active ingredient is broken down in the environment. Different adjustment factors are used to account for variations in toxicity and persistence among individual pesticide a.i.s. The index is then created by multiplying the number of units of Reference Dose or of oral LD₅₀ contained in each pound of pesticide a.i. with the number of days that an application of the specific a.i. remains chemically active in the environment. The Reference Dose is used only in case of determining chronic toxicity, while the oral LD₅₀ is used for determining acute toxicity.

⁴ The EXtension TOXicology NETwork (EXTOXNET) is an information base created by a joint effort of University of California at Davis, Oregon State University (OSU), Michigan State University, and Cornell University, and is accessible from the OSU World Wide Web (WWW) server at: <http://ace.ace.orst.edu/info/extoxnet/>

Multiplying this index number of each a.i. by the total pounds of each respective a.i. contained in the pesticide yields the toxicity/persistence units (TPUs) for that individual a.i. All individual a.i. TPUs can then be summed to obtain the index for the aggregate toxicity of a pesticide.

As an illustration, the aggregate TPU index for the pesticide “Bicep” will be constructed here. Bicep is a herbicide, a compound of two chemicals (or a.i.s) , namely, Metolachlor⁵ and Atrazine⁶. Both chemicals can be absorbed into the bloodstream through oral, dermal, and inhalation exposure. There are two different measures of toxicity, namely acute (short term) and chronic (long term). Farmers, farm-workers, and pesticide applicators will probably be more interested in the measure of acute toxicity since they are likely to be more susceptible to direct or acute exposure. The closest approximation of acute toxicity to humans posed by these chemicals can be calculated using the acute oral lethal dose fifty or LD₅₀ in rats. The acute oral LD₅₀ in rats for technical grade metolachlor is approximately .032 oz. per pound of a rat’s body weight, and the acute oral LD₅₀ for atrazine in rats is about .029 oz per pound of a rat’s body weight. Apart from the actual toxicity measure, a measure of persistence for both the chemicals is also required in order to construct the index of aggregate TPUs in a gallon of Bicep. Persistence of a chemical is defined in terms of half-life, and is the number of days required for one half of the active ingredient to disappear. Metolachlor has an average soil half-life of 32 days, and atrazine has an average soil half-life of 80 days.⁷

Given that every gallon of Bicep contains 3.33 lbs of metolachlor and 2.67 lbs of atrazine, the index of individual pesticide toxicity-persistence units (TPUs) for Bicep can be constructed in the following manner:

The TPU index for the a.i. metolachlor is given by multiplying the inverse of the acute LD₅₀ contained in one pound of the chemical (1/.032 oz.) by the number of days it remains active in the soil (32 days) and then multiplying that by the total number of pounds of metolachlor contained in a gallon of Bicep. So the TPU index for this a.i. is [(1/.032) * 32 * 3.33] or 3,330.

The TPU index for the a.i. atrazine is constructed in the same manner as described above for metolachlor and is therefore given by [(1/.029) * 80 * 2.67] or 7,365. The Aggregate TPU index for one gallon of Bicep is then derived by simply summing over the two individual a.i. TPUs, and is therefore given by (3,330 + 7,365) or 10,695.

⁵ Information obtained from the web site <http://ace.ace.orst.edu/info/extoxnet/pips/metolach.p93>

⁶ Information obtained from the web site <http://ace.ace.orst.edu/info/extoxnet/pips/atrazine.p93>

⁷ The product “Bicep” was chosen arbitrarily and the data for the half-life and LD₅₀ for both its active ingredients were taken from the EXTOKNET site on the Internet.

2.2.4 Influence of Socio-Economic Factors and Farm-advisory Services on Pesticide Use - Some IPM Studies

The increased-reliance on pesticides by farmers after the World War II to meet the increasing demand for food and the resulting damage to the environment led researchers to develop alternative pest-control technologies, which would be more effective and have fewer negative impacts on the environment and human health (Dahlsten). Although Integrated Pest Management (IPM)⁸ emerged as a concept in the 1950s to abate damage inflicted by pests to agricultural crops by resorting to biological control, crop rotations, and other non-pesticide alternatives, it gained in importance only in the 1970s as awareness of the external effects of pesticides became more widespread and intensified (Frisbie and Walker). So it has only been since the 1970s that a lot of studies have been conducted to determine the impact of IPM on farmers' behavior and on the environment.

In 1973, Stern noted that “when there is no yield/density information available, the decision to use chemicals to combat a real or an imaginary pest population is then left to the grower (p.262).” He was also of the opinion that, although the farmers are good at handling sophisticated farm equipment, or at making good decisions on the use of fertilizers, or in selecting the best plant varieties, or transacting the sale of farm products, they are “generally unprepared to cope with the ever-increasing complexity of applied entomological problems and must seek the advice of a chemical company representative, farm advisor, or supervised control entomologist (p.262).” Since there is a definite relationship of pest numbers (or pest density) to potential crop damage, Stern further noted that a better, more sophisticated knowledge of economic thresholds of pest species is required in order to optimize pesticide use as well as reduce indiscriminate use of pesticides.

In 1988, Napit *et al.* conducted a study on different states or regions of the United States to determine the relative importance of socioeconomic factors that influence the adoption of IPM. The explanatory variables they used in their adoption analysis were age, gender, farming experience, education level of the farm operator, race, value of products sold annually, frequency of contacts with the extension agents, percent of family income from farming, risk, and the number of hectares farmed. They found frequency of contact with extension agents and higher level of education to be positively related to IPM adoption. They found farm size to be positively correlated with IPM adoption in three of the nine states. They also found age to be positively related to adoption in one state and negatively related in another.

In another study of IPM adoption among Texas cotton growers in 1990, Thomas, Ladewig, and McIntosh demonstrated that age and level of education of the farmer as well as gross farm sales were positively related to adoption while the percentage of acreage irrigated was negatively related to IPM adoption. Their results also showed that “cotton growers' sources of information involving interpersonal communication were

⁸ See Chapter I for definition of IPM.

more important than sources of printed materials in influencing IPM beliefs and adoption” (p.406).

As part of their study on peanut producer adoption of IPM in Georgia, McNamara *et al.* found that age, education, farm income as percent of total income, yield, quota, and extension requests were some of the explanatory variables that had positive impacts on IPM adoption. Tjornhom looked at some factors that might affect pesticide misuse. She defined “misuse” along the lines of Heong, Escalada, and Lazaro to mean “incorrect adoption of pesticide technology (p.45).”⁹ She concluded that age, education, and access to IPM training had a negative influence on pesticide misuse as explanatory variables whereas a visit by an agricultural technician to discuss IPM had a positive impact on misuse.

Heimlich and Ogg conducted a study in 1979 using a linear programming model to evaluate soil erosion and pesticide-exposure control strategies in the Chowan-Pasquotank river basin of North Carolina. They measured the potential harm from pesticide exposure by characteristics of pesticides such as toxicity, longevity, and bioaccumulation. They used two different forms of pesticide exposure indices, one reflecting terrestrial exposure and the other reflecting aquatic exposure, to aggregate the effects of pesticide applications for no-till and conventional till systems. Their “WEBER2” index, derived from Weber’s original index, took into account the longevity, LC₅₀ toxicity, and bioaccumulation, and was considered to be a measure of potential harm to aquatic environments from pesticide applications. They also used Alt’s index, which considers longevity and LD₅₀ toxicity, to reflect potential harm to terrestrial organisms. However, their indices did not take into account the transportation of the pesticides (in the form of soil leaching or runoff) or of the interactions due to erosion or run-off. They concluded through their study that erosion-control strategies, as simulated by a cost-minimizing linear-programming model, are compatible with pesticide-exposure control at high levels of erosion control, and also that greater reductions of pesticide exposure with comparable levels of erosion control are achievable at a relatively low cost.

2.3 Economic Incentives for Pesticide Use

The problem presented in the current study concerns the influence of farm-advisory services on the use of toxic pesticides in cotton and peanut farming. However, the major concern is excessive use of toxic pesticides, that is, in terms of Figure 2.1, use at points where $MPEC > MPB$. In order to understand and address the problem it is worthwhile to analyze potential causes of excessive use.

⁹ According to Heong, Escalada, and Lazaro “when a pesticide is used for the wrong target or at the wrong time or both, it can be considered to be misused” (Heong, Escalada, and Lazaro, p.6).

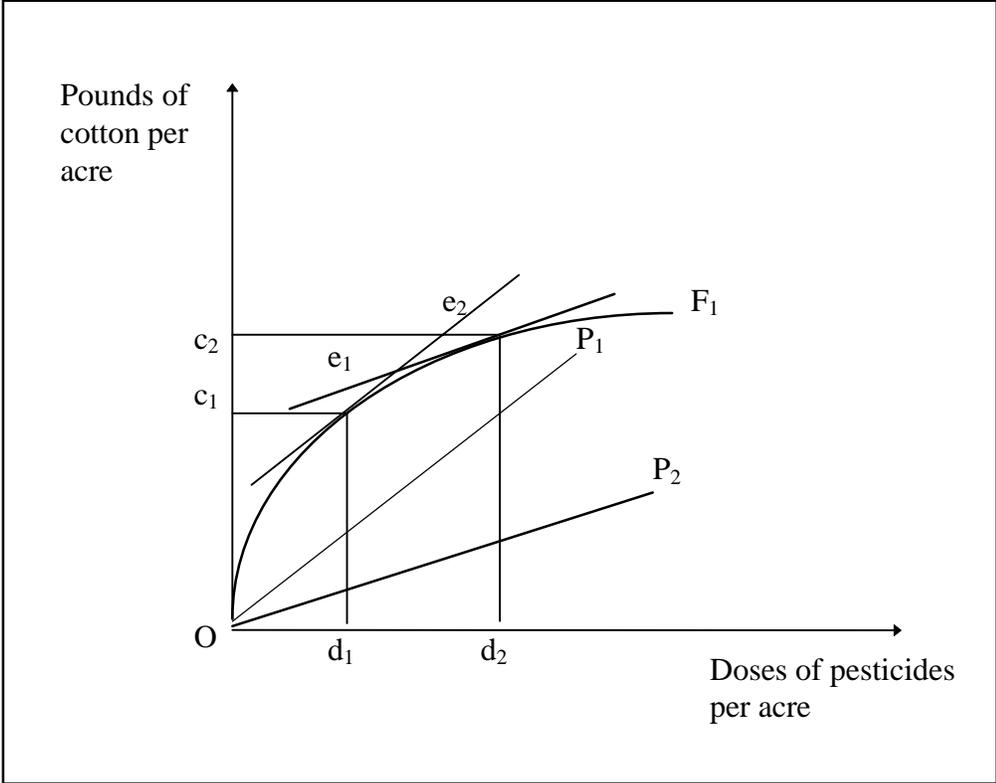


Figure 2.2. Change in pesticide use due to change in relative price of cotton.

Farmers have traditionally used pesticides as an input in order to increase their crop yields and maximize farm profits. However, as mentioned in Chapter I, pesticides may be toxic and so the use of such toxic pesticides may lead to externalities such as negative health and environmental effects.

The problem can be analyzed from different perspectives. First, the production function will be used as a tool to analyze use of pesticides for the production of either cotton or peanuts. Since the problem is similar for both crops, the example of cotton can be taken to explain and illustrate the case at hand. Here, if it is assumed that the farmer's production of cotton is a direct function of the doses of a given pesticide applied for plant protection, then the relationship can be illustrated with the help of Figure 2.2, where F_1 is the farmer's production function. Given the market prices of a pound of cotton and of each dose of pesticide combination used, the initial price ratio (price of pesticide dose to price of cotton) can be denoted by the slope of the line P_1 . The farmer therefore maximizes his profits by operating at the point where the slope of the production curve is parallel to the price line (that is, at e_1). Now, if all other things remain constant, then an increase in the price of cotton relative to the price of the pesticide, shown by a clockwise rotation of the price line from P_1 to P_2 , will make the farmer switch from producing at e_1 to the point e_2 , which now corresponds to the new maximum profits. If the production function is relatively flat in the area of initial use, then the pesticide use may be relatively unresponsive to increased cotton prices. It is evident that such behavior of the farmer will increase the production and supply of cotton but will also increase the doses of pesticides. However, not all things may remain constant as price changes. For instance, the production technology may change in the sense that it may now be possible to produce more pounds of cotton for the same doses of pesticides as before.

The doses of pesticides can now be expressed in terms of the externality, namely, toxicity. Figure 2.3 shows that toxicity can be affected by changes in the dosage of a given pesticide or by changes in the types of pesticides. First, toxicity may increase with each and every additional dose of a given pesticide combination used for plant protection, as denoted by a movement along the line T_1 . However, the second effect of a technology change may be represented by lower toxicity than in T_1 for each additional dose of pesticides. This effect can be illustrated by rotating the line T_1 to T_2 and then to T_3 , each of which represents a successively less toxic combination of pesticides.

The preceding two graphical explanations can now be linked to demonstrate the relation between the movements in toxicity relative to movements in the price of cotton, as shown by the supply curve S_1 in Figure 2.4. *Ceteris paribus*, as the price of cotton increases relative to the price of pesticides, the supply of the external product *toxicity* also increases.¹⁰ However, not all other things remain constant as price changes. A better technology may be developed that requires fewer doses of toxic pesticides. Or less toxic pesticides could be developed that produce lower aggregate toxicity. In other words,

¹⁰ At some point, no additional cotton yield is achieved with further pesticide increases. At that point, further price increases will not increase toxicity and the supply curve in Fig. 2.4 becomes flat.

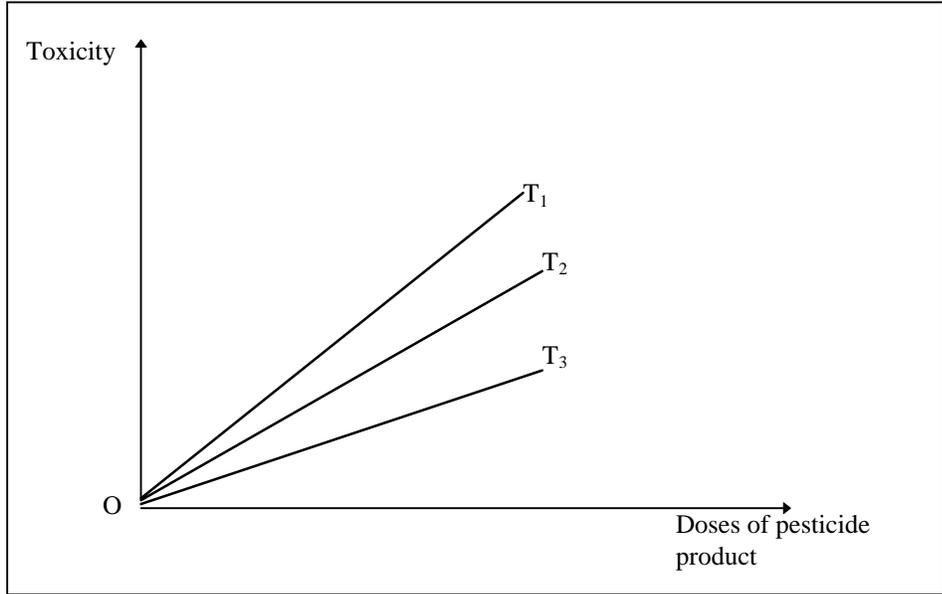


Figure 2.3. Relationship between pesticide-doses and toxicity.

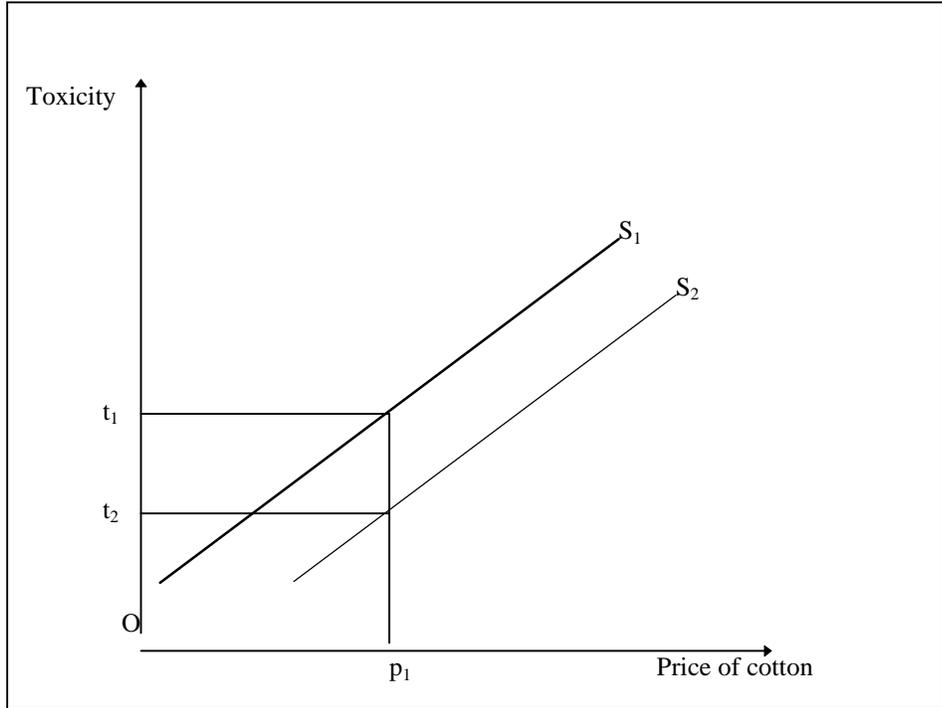


Figure 2.4. Relationship between price of cotton and toxicity.

aggregate toxicity may be lowered by either reducing the doses of toxic chemicals, or by substituting less toxic chemicals for the more toxic ones.

The change in technology can be effective in reducing toxicity only if the information regarding technology-change is disseminated to the farmer, and provided the farmer is willing to adopt the new technology. Advisory services can play an important role in making farmers aware of changes in technology that might enable him/her to earn higher profits by simultaneously reducing aggregate toxicity. A farmer's behavioral characteristics may also determine to what extent he/she will adopt the new technology. For example, a farmer may be doubtful of the new technology and might prefer to hold on to his initial production technology. It has been shown in a survey conducted at Michigan State University that most farmers were not only unaware of the environmental and health hazards posed by some chemical pesticides but also doubted the same fact when they were informed about it (Owens, Swinton, and Ravenswaay).¹¹

Thus, the supply curves may shift from S_1 to S_2 depending on how fast the new technology is adopted by farmers. S_1 represents a higher amount of aggregate toxicity for every cotton price than does S_2 . This shift is shown in Figure 2.4 by holding price constant at p_1 , which corresponds to aggregate toxicity levels t_1 and t_2 for the curves S_1 and S_2 , respectively. As better technologies represented by lower dose requirements or by lower toxic chemical requirements emerge, the toxicity supply curve will shift to the right. The important catalysts involved in shifting the supply curve are: (i) the development of new technologies that substitute less toxic chemicals or other alternatives for more toxic chemicals; (ii) information from farm advisory services that make farmers aware of new technologies and encourage adoption; and (iii) farmers' behavioral characteristics that condition their receptiveness to new technologies.

Finally, in Figures 2.5 and 2.6 a change in technology is analyzed holding output prices constant. Figure 2.5 illustrates how an initial technology can be replaced by a more productive technology that not only uses fewer doses of pesticides but in fact uses more scouting labor than before, given that the ratio of scouting labor price to pesticide price has not changed. Given the ratio of pesticide price to scouting costs represented by the line P_1 , the farmer could produce a quantity of cotton given by Q_1 using a combination e_1 representing d_1 doses of pesticides and l_1 units of labor. However, the new technology given by Q_1' allows him to use a combination e_2 which represents d_2 doses of pesticides and l_2 units of labor to produce the same quantity of cotton as before. The new technology must be made available to the farmers through information, and information costs are not included in this framework.

¹¹ The survey was conducted using simulation of a market for corn herbicide formulations similar to atrazine except that the new version of atrazine would be non-carcinogenic, non-leachable, and non-toxic to fish.

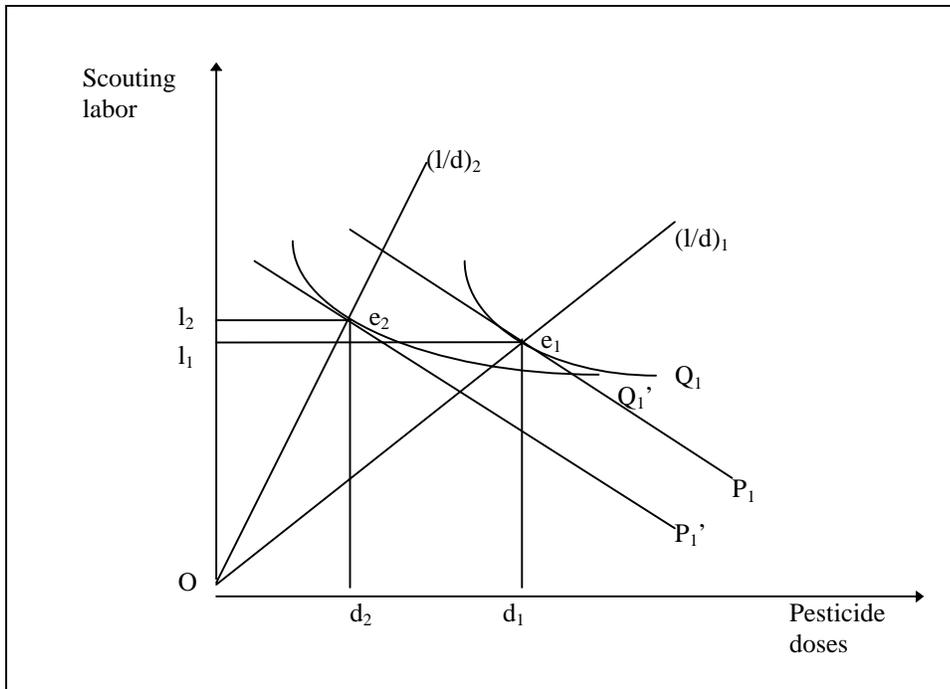


Figure 2.5. Change from pesticide-intensive to scouting-intensive technology.

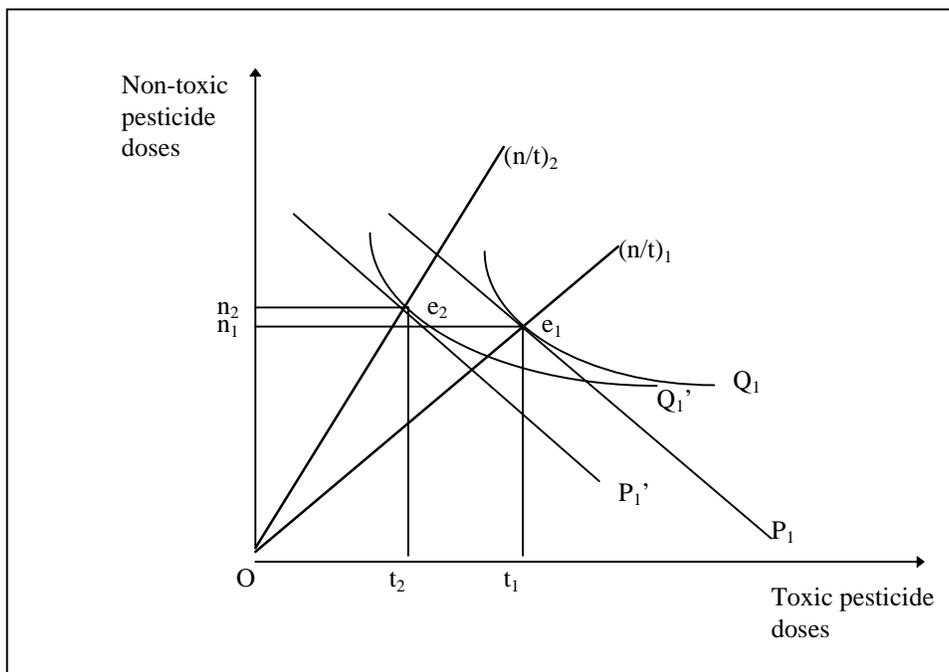


Figure 2.6. Change from toxic pesticide-intensive to non-toxic pesticide-intensive technology.

Technology can also change toxicity of effective pesticides as illustrated in Figure 2.6, which shows a tradeoff between a toxic and a non-toxic pesticide. The arguments are very similar to those presented in Figure 2.5 except that the technology change now allows a farmer to use fewer doses of the toxic pesticide and more doses of the non-toxic pesticide to produce the same quantity of cotton given the same price ratio as before. The technology is shown here again by an inward shift of the isoquant from Q_1 to Q_1' and a movement of the farmer's input bundle from e_1 to e_2 .

Figures 2.5 and 2.6 can now better explain Figures 2.3 and 2.4. The change in technology suggested by Figure 2.5 indicates a movement along any one of the curves T_1 , T_2 , or T_3 in figure 2.3 depending on the toxicity levels of the doses of pesticides used. Thus, a movement from e_1 to e_2 in Figure 2.5 would mean a movement toward the origin along the curve T_1 in Figure 2.3 if fewer doses of toxic pesticides were used. However, a movement from e_1 to e_2 in Figure 2.6 indicates a shift of the curves from T_1 to T_2 or T_3 as shown in Figure 2.3 since more non-toxic pesticides are now being used to replace toxic pesticide doses. Information plays an important part in the movement along the curves as well as in the shifting of the curves T_1 through T_3 in figure 2.3. If farmers are aware of and are willing to adopt scouting and other pesticide alternatives, they can move down along any of the curves T_1 through T_3 toward the origin and use fewer doses of pesticides. On the other hand, if the farmers are aware of and have access to non-toxic pesticides that are cheaper and as effective as the toxic ones, then they can move from T_1 to T_2 or T_3 . In both cases, information about scouting and other pesticide alternatives or about the effectiveness of non-toxic pesticides has to be communicated to the farmers. This information, however, has a cost that has to be borne either by farmers or by society, or by both. Sources of information regarding the changes in different technologies include chemical dealers, extension agents and hired staff.

2.4 Concluding Remarks

Pesticide use is an important tool to address pest problems. However, in view of the different environmental and human health hazards posed by toxic pesticides, it is useful to explore the alternatives to chemical pesticide use or to find ways to reduce the current use of toxic pesticides. Economic incentives that a farmer faces play an important role in his choice of inputs (including pesticides) in agriculture. Hence, research on less toxic pesticides and pesticide alternatives can be helpful in lowering toxic pesticide use. However, any new breakthroughs in agricultural technology that allow farmers to earn larger profits by simultaneously reducing use of toxic chemicals have to be communicated to the farmers. Lack of information or awareness among farmers may be one of the primary causes in the use of toxic chemicals beyond the point of profit maximization resulting in the exacerbation of the environmental problem. If farmers are kept well informed and equipped to realize the benefits from the economical use of toxic chemicals, not only will they be able to increase their profits but at the same time environmental problems can also be reduced. In this aspect the role of farm-advisory services is very important since these advisors act as liaisons between researchers and

farmers. By distributing and disseminating the right kinds of information at the right times, farm advisory services will not only help increase farmers' profits but also help reduce the extent of potential damages that can be caused to the environment and to human health from use of agricultural chemicals.

Chapter 3 Empirical Procedures

3.1 Introduction

In this chapter the procedures for analyzing the data will be described. However, before the stepwise description of the methods and analytical tools, it is also important to recognize the different data sources and methods used for collection of the data for this study. The identification of the sources will shed some light on the relevance and importance of the problems considered in this study, while the methods used to collect data will indicate the nature and degree of accuracy of the data.

3.2 Procedures and Relevance of Data Collection for the Study

The United States Department of Agriculture (USDA) initiated the collection of information about agricultural activities including chemical use in different regions of the United States as part of the President's Water Quality Initiative launched in 1989. The Economic Research Service (ERS), the National Agricultural Statistics Service (NASS), and the Natural Resource Conservation Service (NRCS) conducted the Area Studies Survey. Areas for sampling were selected to correspond to watersheds identified by the United States Geological Survey (USGS) for potential water quality problems. In 1992 the Albemarle-Pamlico Drainage (North Carolina and Virginia) was among the four a million sample sites. different sites selected.

Iowa State University (ISU) designed the sampling plan for the survey. The sample was selected from the NRCS area frame used in the National Resource Inventory (NRI) every five years. The NRI is based on a stratified random sampling design in which soil, water, and related natural resource data are collected at nearly Choosing the sample point to coincide with the NRI points insures that information on soil properties will be available and provides for a valid statistical aggregation. Iowa State University selected a total of 1,462 primary sampling units (PSU's) ranging in size from 100 to 160 acres for the Albemarle-Pamlico Drainage area, and one site was selected randomly from each PSU for the survey.

The NRCS provided NASS with the name of the operator, address, and a map with the PSU's marked to enable the enumerator to identify the PSU and the sample site within the PSU and to locate the farm operator of this point.

The questionnaire was finalized after input from USGS, Environmental Protection Agency (EPA), NRCS, agricultural economists from several universities, and numerous analysts and statisticians within ERS and NASS. A field-level questionnaire was designed to collect information on chemical use and farming practices on the field containing the sample site for the previous three years. Some information for the whole farm and about the operator was collected as well. The questions were tailored mainly to accommodate

row crop operations because the sampling design was based on an area frame. Although this design was thought to be most appropriate for measuring chemical use and farming activities associated with row crops, crops such as vegetables and fruits and confined livestock operations are poorly represented in the sample at the current sampling rate.

Data were collected in the fall of 1992 for the 1992, 1991, and 1990 crop years. This data collection process resulted in three data files, namely, Main, Fertilizer, and Pesticide, of which the first and the last were used for this study. These two files contained the following general types of information:

Main: This file contains all data about farming practices on the site, and characteristics of the farm and operator except that which was collected on the fertilizer table and the pesticide table. There is one record in the data set for each sample point for which data were obtained in the survey.

Pesticide: This file contains data on pesticide usage such as day, month, and year of application, names of products and active ingredients (a.i.), amount of each a.i. contained in the product, and application rate of the product. This data file, however, does not contain any information on pesticides expenditures. There is one record for each completed line of the table. There is also one record for each year where applications were either not made or not reported.

Four other data files were used for the current study. The first of these was the National Resource Inventory (NRI) data file, which was contained in the file NRI82 and had information on the physical characteristics of a sample site such as soils and land use that were collected in 1982. The Natural Resource Conservation Service (NRCS) collects the NRI data every five years. The sample for the 1982 NRI data was selected with particular attention to Major Land Resource Areas. The sample for the 1982 NRI consists of nearly 350,000 PSUs in the U.S., with the number of sample points selected within a PSU being fixed at three.

The second data file used was the SCS Soil Interpretation Records (“Soils 5”) data file containing information on soil characteristics in the region. This data file is like a dictionary for soils with expert assessments of physical attributes of each soil type. The third data file used in the study contained expenditures on pesticides used for the year 1992. The pesticide data has expenditures shown separately for insecticides, fungicides, and herbicides for each farm. However, since this data file contains summaries by “sample” and “crop”, there is more than one observation corresponding to each record in the Main data file. Finally, the data required for construction of the toxicity index for the chemicals applied to cotton and peanut farms were obtained from the Economic Research Service (ERS) division of the USDA.¹² These data were comprised of the “half-life” and “reference dose” values for chemicals used in the Northern Plains as assigned by the Environmental Protection Agency (EPA), the Office of Pesticide Programs (OPP), and/or

¹² These data were obtained from Charles Barnard of the ERS division at the USDA.

the World Health Organization (WHO).

3.3 The Procedures for Data Analysis

As mentioned earlier, this study is concerned with the impact of socioeconomic variables on the use of toxic chemicals in Cotton and Peanuts grown in the Albemarle-Pamlico drainage area. Based on the hypotheses and the conceptual framework laid out for the present study in Chapters I and II respectively, two different regression models can be specified. The hypotheses in Chapter I can be tested by using the results of the following regression models:

$$(AGGINDEX)_j = f(s, c, e, p) \quad (3.1)$$

$$(EXPEND)_j = f(s, c, e, p) \quad (3.2)$$

AGGINDEX in equation (3.1) refers to the aggregate toxicity from using pesticides for crop *j* (where *j* is either cotton or peanuts), and the dependent variable *EXPEND* in equation (3.2) refers to the expenditure on pesticides for crop *j*. The explanatory variables on the right hand side of both the equations can be grouped under the categories *s* (representing social characteristics such as age, education level, and years of farming experience of the farmers); *c* (representing contact with extension agents, chemical dealers, scouting personnel, and/or hired staff and rankings of the most important advisory service by the farmers); *e* (representing economic variables such as annual farm sales, and number of labor hours worked off the farm); and finally *p* (representing physical and locational characteristics such as productivity of the soil, leaching potential of the soil, distance of farm from surface water source, and state where the farm is located). The parameters of all the variables in all the categories will be estimated separately.¹³

Having specified the regression models, the next step was to isolate the required variables from the different data sets mentioned earlier in order to run the regressions and estimate their respective coefficient parameters. Although most variables were taken from the data sets in their original forms, three of the variables for the two models, *AGGINDEX*, *EXPEND*, and *LEACH*, were constructed using variables from one or more of the data sets. The data had to be sorted according to farms growing cotton and/or peanuts, and two or more data files had to be merged by common farms (that is, those growing cotton and peanuts) so as to get all the above mentioned variables in the same data file. The *Main* and *Pesticide* data files were first used to create a subset of the data containing only sample points which showed either cotton or peanuts or both grown in each of the three years. A subset of sample (or farm) sites where cotton and/or peanuts was grown at least once during the three years was first obtained from the *Main* data set for each of the three years. The variables in the data set corresponding to crops grown in 1992, 1991, and 1990 were given respectively by “*CTCROPI*” through “*CTCROPS*”,

¹³ All variables used in these two models have been defined and explained in Table 4.1 in Chapter IV.

“*CTCROP6*” through “*CTCROP10*”, and “*CTCROP11*” through “*CTCROP15*”. A value of “8” for any of these variables implied that cotton was grown on that site for that year, whereas a value of “16” implied similarly that peanuts were grown. Hence any other value that appeared in any observation for any year was deleted. Each of these subsets was then merged with the *Pesticide* data by common sample points (farms) so that pesticide application information for only the cotton and/or peanut growing sites would be available. So, finally three different files were obtained for each of the three years containing information on the type and amount of pesticides applied in cotton and/or peanut farming.

3.3.1 Procedure for Construction of the AGGINDEX Variable

In the current study, the aggregate toxicity of a chemical product was constructed based on procedures used by Barnard as described in Chapter II. Data from the EPA, the OPP, and/or the WHO were used for persistence (half-life) and toxicity (reference dose)¹⁴. Copper hydroxide, copper resinate, and sulfur were not required to have a “tolerance” and were not assigned any reference dose value by the above-mentioned sources. These chemicals were all assigned an index value of zero implying that they are non-toxic.

The toxicity index (*AGGINDEX*) was then constructed in the following manner:

$$(AGGINDEX_k) = \sum_j [\sum_i (RFD_ERS_i * HALF-LIFE_i * AIAMT_i)] * (ASTDRATE_j) \quad (3.3)$$

RFD_ERS is the reference dose of an a.i. (measure of chronic toxicity of an a.i.) in milligrams per kilogram of human bodyweight; *HALF-LIFE* is the number of days an a.i. remains active in the environment to be able to cause potential harm (measure of persistence of an a.i.); *AIAMT* is defined as the amount of chemical active ingredient in pounds per pound or gallon of a pesticide product; and *ASTDRATE* is the rate of application of the pesticide product in pounds per acre (for dry products) or gallons per acre (for liquid products).

AGGINDEX is first summed over all active ingredients (a.i.s) ($i = 1$ to m) in a single product and is then summed over all products ($j = 1$ to n) used at a particular site k . The reference dose (*RFD_ERS*) for each chemical given in milligrams per kilogram of body-weight (in the ERS data set) was calculated for an average man weighing 70 kgs. The toxicity for that individual chemical was then derived in terms of pounds per unit mg of human body-weight by multiplying the number of mgs (of reference dose) by the factor converting mg to pounds (.0000022046).¹⁵ So the *RFD_ERS* multiplied by 70 times 0.0000022046 would give the toxicity for a 70-kg man in pounds. The toxicity amount

¹⁴ The reference dose value for the chemicals was used in this study instead of their LD₅₀ value, implying that in this study more importance was given to the chronic rather than the acute effects of toxic chemicals.

¹⁵ The conversion from kg to pound was used here: (1 kg = 2.2046 lbs.)

contained in one pound of the chemical a.i. would then be 1 divided by ($RFD_ERS * 70 * 0.0000022046$). This value when multiplied by the half-life gives the toxicity contained in one pound of a.i. of the pesticide. However, some of these values turned out to be very large (in millions) and so they were all scaled down dividing by 1,000,000 to obtain “giga doses” of toxicity. The calculation of the toxicity can be illustrated using the following example.

The product “Temik TSX” is comprised of three a.i.s, namely, “Aldicarb”, “PCNB”, and “Etridiazole”. Each of these a.i.s was contained in the product in amounts denoted by $AIAMT1$, $AIAMT2$, and $AIAMT3$, respectively. These ingredients along with the “ $HALF-LIFE$ ” and “ RFD_ERS ” for the a.i.s, and the application rate ($ASTDRATE$) for the product are given in Table 3.1.

Table 3.1. Toxicity and Persistence of Active Ingredients of Temik TSX.^a

active ingredient	$HALF-LIFE$ (days)	RFD_ERS (mgs/kg)	$AIAMT1^b$ (lbs/lb)	$AIAMT2$ (lbs/lb)	$AIAMT3$ (lbs/lb)
Aldicarb	30	0.001	0.05		
PCNB	21	0.003		0.1	
Etridiazole	103	0.036			0.025

^a $ASTDRATE$ for Temik TSX = 5.0 pounds per acre.

^b Pounds of active ingredient per lb. of formulated product.

The toxicity index values for a given a.i. of a product ($INDEX$) can now be calculated using slight modifications over the formula in equation (3.3), shown as follows:

$$INDEX = [1/(RFD_ERS_i * 70 * .0000022046)] * HALF-LIFE_i * (AIAMT_i) * (1/1000000).$$

Based on the above,

$$INDEX1 = [1/(.001 * 70 * .0000022046)] * 30 * .05 * (1/1000000) = 9.72$$

$$INDEX2 = [1/(.003 * 70 * .0000022046)] * 21 * .1000 * (1/1000000) = 4.54$$

$$INDEX3 = [1/(.036 * 70 * .0000022046)] * 103 * .025 * (1/1000000) = 0.46$$

The index for a particular product is then the sum of all the individual a.i. indices times the application rate of the product:

$$PRODINDEX_j = \sum_i(INDEX_i) * (ASTDRATE_j) \quad (3.4)$$

The aggregate index for “Temik TSX” would then be:

$$\begin{aligned} \text{PRODINDEX} &= [\text{INDEX1} + \text{INDEX2} + \text{INDEX3}] * \text{ASTDRATE} \\ &= [9.72 + 4.54 + 0.46] * 5.0 \\ &= 14.72 * 5.0 \\ &= 73.6 \end{aligned}$$

Once the individual chemical indices were constructed, the aggregate chemical toxicity for each site was then constructed by first sorting the data by sample and then by summing over the index values of all the products used on a particular site. So $\text{AGGINDEX} = \sum_j(\text{PRODINDEX}_j)$ represents the aggregate toxicity from all chemical products ($j = 1$ to n) used on a particular sample site. The sample farm sites were then sorted according to crops (that is, cotton and peanuts) and the variable $(\text{AGGINDEX})_j$ referred to the aggregate toxicity from pesticide use for the crop j (where $j =$ cotton or peanuts).

The next step was to merge the subset data obtained earlier with the data file containing the toxicity index calculated for each of the chemicals.¹⁶ The merged data set, however, contained sample sites with one or more missing values. For instance, there were two sites showing a pesticide product code “9114” but this code was not listed with the EPA, and so these two sites were dropped assuming a typo during data entry.¹⁷ One site showed a product code “9117” but no other information, and was dropped too. Seventeen sites had missing *ASTDRATE*s for one or more products applied to the site. If the same site used two products or less with missing *ASTDRATE*, then the recommended rate was used for the product on that particular site. There were six different farm sites that appeared twice or less with missing *ASTDRATE*s. The products corresponding to these sites were “Storm”, “Harvade 5F”, “Bravo S (EC)”, “Dropp (50WP)”, “Def 6”, and “Sonalan (3EC)”. However, the remaining eleven sites showing missing *ASTDRATE*s appeared more than twice and were dropped from the analysis altogether.

3.3.2 Construction of LEACH for representing the leaching potential of the soil

The Soils 5 and the NRI82 data files were merged and the proxy variable *LEACH* was constructed for each sample site using the variables *AWCH* and *AWCL* (showing, respectively, the maximum and minimum water holding capacity in inches per inch of soil for each layer of soil), *LAYDEPH* and *LAYDEPL* (denoting, respectively, the upper and lower bounds of each layer of the soil), and *LAYERNUM* (denoting the layer number).

¹⁶ Table B1 in Appendix B shows the list of pesticide products along with their corresponding chemical active ingredients and toxicity indices used in the study.

¹⁷ The EPA-assigned product code for each pesticide product was used in the survey and therefore appears in the data set.

First an average of the water-holding capacity of the soil (in fractions of an inch of water per inch of soil) was taken and was denoted by *HOLD* ($HOLD = (AWCH + AWCL)/2$). Then the depth of each layer in inches was calculated and denoted by *THICK* ($THICK = (LAYDEPH - LAYDEPL)$). The third step was to construct the leaching potential for each layer of the soil, which was done in the following manner: $LEACH = HOLD * THICK$. Finally the values of *LEACH* were added up for all the layers of each sample.

3.3.3 Construction of the EXPEND variable for pesticide expenditures

The second model in this study, namely (3.2), required expenditures on pesticides to be the dependent variable. However, since the *Pesticide* data contained information only by each type of pesticide, the ERS collected a separate set of information on the expenditure on different pesticides by farmers. This information was compiled into a data set to show the dollar values spent separately per acre on insecticides, herbicides, and fungicides (*I_DOLLAR*, *H_DOLLAR*, and *F_DOLLAR* respectively), for each sample and crop. Based on this data set, the variable *EXPEND* was then constructed for each sample site by adding up the dollar values spent on each of these pesticide types. More specifically, $EXPEND = I_DOLLAR + H_DOLLAR + F_DOLLAR$.

3.4 Potential Estimation Problems and Suggested Remedies

The data used for this study were cross-sectional data of different farms. Five assumptions were made for estimating the two models specified in equations (3.1) and (3.2). The first assumption is that the data for all continuous variables followed a Normal Distribution pattern. Secondly, it was assumed that all conditional means (that is, the conditional expectation function as well as the parameters) were linear. The third assumption was that the variances of coefficient estimates and the error terms were invariant to the independent variables implying homoscedasticity. The fourth assumption was that all data observations were identically and independently distributed. Finally, it was assumed that the parameters were stable. Based on these assumptions, the estimators of the independent variables in both models could be either Ordinary Least Square (OLS) or Maximum Likelihood (ML) estimators.

Problems may arise from the violation of any of the assumptions of the model (or, in other words, from model misspecification), leading to different kinds of biases and/or errors in the estimates. Since the five major assumptions (normality, linearity, homoskedasticity, independence and parameter stability) were made about both models in the study (represented by equations 3.1 and 3.2), the consequences of violating any one or more of those assumptions can be examined and necessary corrections recommended.

First, the violation of the normality assumption implies that the OLS estimator will still be the best linear unbiased estimator but will be only relatively efficient implying that asymptotic tests will yield close but not exact results compared to actual

tests. However, if the sample size is small, asymptotic results would not produce any significant results either. Two different methods can be used as remedies to problems arising from violation of normality. First, a more suitable distribution may be specified by looking at the data, but is often difficult to do in reality. Second, normality can be induced in the data by resorting to some kinds of transformations. Several kinds of transformations are possible of which the most widely used is taking logarithms of the data. Misspecification of normality can be tested using the Bera-Jarque skewness (3rd moment of the distribution) or kurtosis (4th moment of the distribution) tests and/or the D'Agostino Pearson (asymptotic) tests (Spanos).

The violation of the second assumption, that is, linearity, results in more severe consequences than violating normality. The OLS estimator of the variable coefficients becomes biased and inconsistent, and the bias does not diminish even as the sample size increases. Violation of linearity can be tested using the second order Kolmogorov-Gabor (KG2) or the 2nd or 3rd order Reset tests (Spanos).

When regression results indicate heteroskedasticity in the data, different methods can be used to correct for the heteroskedasticity, namely, Generalized Least Squares (GLS) estimation or “White’s correction” on the parameters estimated from OLS (Spanos). The GLS method requires the estimation of OLS on a transformed model. Since heteroskedasticity implies that the variance of the error term is not constant, transformation by division of the error term (and all other variables, dependent or independent) of the regression by the standard deviation of the error term in fact induces homoskedasticity. Transformations may also involve dividing all variables by the continuous independent variable that exhibits any kind of relation with the error term.

The other method used for correcting heteroskedasticity, referred to as “White’s correction” involves certain stages. First the error terms (or residuals) from the OLS estimation need to be preserved and then a similar model has to be estimated by regressing the square of these residuals on the square of the explanatory (independent) variables. The parameters obtained would be homoskedastic. As a result of doing the GLS estimation or “White’s correction”, the sign of the parameter estimates of the independent variables in the regression should remain the same, or else it would indicate the existence of some other problem besides heteroskedasticity (Spanos).

The violation of the independence assumption leads to true autocorrelation, which means that the errors of the estimated regression equation follow some kind of pattern. The error pattern may be due to one of at least two causes. One cause of autocorrelation is when certain variables are omitted. To overcome this problem an attempt was made to include as many variables as possible in each model. Secondly, measurement errors may also give rise to autocorrelation. Although most of the explanatory variables in these two models are dummies, there may be a possibility of having measurement errors in the variables constructed for the study, namely, both dependent variables, *AGGINDEX* and *EXPEND*, as well as the variables that quantify the leaching potential of the soil, the distance of farm from water source, and the farm sales. These errors are assumed to be

small and will be ignored.

Parameter instability may arise if the probabilistic data are not identically distributed leading to varying values of one or more of the parameters with each estimation of the regression equation. This problem can be corrected using recursive least squares estimates or by resorting to “window” estimation techniques.

The violation of any one or more of the five distributional assumptions of a regression model may also be tested by the Joint Conditional Mean tests or the Joint Conditional Variance tests. The joint conditional mean test assumes that normality, homoskedasticity, and stability of the variance conditions are satisfied by the model to be tested. This joint test determines whether the model satisfies the assumptions of (coefficient) parameter stability, linearity, and independence. The joint conditional variance test is similar to the joint conditional mean test but differs only in that it assumes that normality is valid, and that the conditional mean is properly specified in the model to be tested. The joint conditional variance test then tests for the presence of stability of the variance, and static as well as dynamic heteroskedasticity.

A final problem that may be of some concern in a regression analysis is that of multicollinearity among explanatory variables. The literature on IPM has shown evidence of the existence of collinearity among variables such as “education level of the farmer” and “farm sales”, and linear dependence is also expected to exist between “age”, “education”, “years of farming experience”, and “contact with the extension agent”. However, exclusion of these variables will lead to omitted variable bias, and so the risk of multicollinearity is in a way unavoidable.

There are two ways to deal with the collinearity problem. One is to collect and use more “well-conditioned” data. However, in most cases additional data collection would involve spending large amounts of additional money and time and is therefore infeasible. The other method is to use Bayesian techniques by which subjective information about the data can be put to use by the researcher to conduct tests rather than relying on hypothesis testing using significance levels. The Bayesian procedure is therefore more acceptable than additional data collection in avoiding multicollinearity, but has limitations because of its subjectivity.

3.5 Limitations of the Model

A possible study limitation concerns the advisory-services variable. Farmers were asked to respond yes or no to questions in the survey about their contact with hired staff, extension agents, chemical dealers, and scouting personnel. Hence, only dummy variables could be used in the models to represent a contact or otherwise of the farmers with the farm-advisors. The second limitation concerns the *AGGINDEX* variable. This variable represents aggregate toxicity only in the potential rather than the actual sense since it does not incorporate soil or weather characteristics which affect actual pesticide runoff and

leaching. The variable indicates hazard only to human beings rather than the whole environment. Moreover, the index for toxicity does not account for drift or volatilization. The third limitation involves the construction of the *LEACH* variable. Although *LEACH* was constructed to take into account potential leaching to the underground aquifer, actual leaching depends on subsoil characteristics between the edge of the root zone and the aquifer. Another major problem concerned the assumption that all farms faced the same pesticide prices. The data were not adequate to indicate whether some farms may have actually faced lower pesticide prices due to volume discounts on pesticide-purchases. Finally, the analysis applies only to one single watershed and so it is difficult to state how transferable these results are to other watersheds.

3.6 Concluding Remarks

This chapter has described the procedures adopted for the regression analysis. The data that were collected for this study are not sufficient for testing models of all the economic concepts presented in Chapter II. Results of the analysis of the data will be presented in Chapter IV.

Chapter 4 Distribution of Data and Regression Results

4.1 Frequency Distributions of the Explanatory Variables in the Model

The explanatory or independent variables used in the regression models in this study, as briefly mentioned in Chapter III, were divided into four different categories, namely: contact with and rankings of the different advisory services; social characteristics; economic characteristics; and physical and locational characteristics. The final data set contained 135 observations, of which 80 were for cotton and the remaining 55 for peanuts. The description and frequency distributions of these variables by crop are shown in Table 4.1 and will be discussed subsequently.

The variable *PMRANK1* was used to construct dummy variables *HSI*, *EXI*, *CDI*, and *SPI*, under the category of contact with and rankings of different advisory services. In the survey, farmers were asked to respond to ‘yes’ or ‘no’ type questions as to whether they used hired staff (*PM575*), university extension services (*PM576*), chemical dealer advice (*PM577*), and/or scouting personnel help (*PM578*) for pest management in the sampled fields. The variable *PMRANK1* represented which of these four different services was ranked as the most important service by the farmer (1=hired staff; 2=extension agents; 3=chemical dealers; and 4=scouting personnel). If *PMRANK1* equaled 1, then *HSI* was set equal to 1, while if *PMRANK1* was not equal to 1, *HSI* was set equal to zero. A similar procedure was used for the other dummies as can be seen in Table 4.1.

The obvious assumption here is that the farmer, who ranked any of these services as most important in influencing his/her decisions, had also used it, that is, had answered ‘yes’ to the particular question in the survey asking whether that service was used. There were slight discrepancies in the number of farmers reporting hired staff and extension services as being the most important service and the number of farmers who reported using these services. Table 4.2 gives the detailed statistics of the farmers’ choice of the different services and their rankings of the most important service.¹⁸

Among the nine farmers who ranked hired staff as the most important service in cotton farming, only six said ‘yes’ to using hired staff advice, while among the eleven farmers who ranked extension advice to be the most important service, ten reported actually using extension services. Similar discrepancies were seen in the farmers’ usage and in his/her ranking as the most important service of hired staff and chemical dealer advice in peanut farming. Given that there were relatively few discrepancies, only the information variable *PMRANK1* was used to create the advisory service dummies *HSI*, *EXI*, *CDI*, and *SPI*. Those who ranked any of the four advisory services as being the most important in terms of influencing their pesticide usage decisions were also assumed

¹⁸ The actual survey questions have been listed in Appendix C. Moreover, hired staff in the Area Study survey was used to refer to farm consultants and pest management advisors other than scouting personnel.

Table 4.1. Description of the explanatory variables used in the study for constructing Model 1 (eqn. 3.1) and Model 2 (eqn. 3.2) specified in Chapter III.

Variable	Frequency or Mean ^a		Description of Variable
	<u>Cotton</u>	<u>Peanuts</u>	
<i>PM575</i>	[0] = 53 [1] = 27	[0] = 46 [1] = 9	Whether farmer used hired staff advice (1 = yes; 0 = no).
<i>PM576</i>	[0] = 38 [1] = 42	[0] = 37 [1] = 18	Whether farmer used extension service (1= yes; 0 = no).
<i>PM577</i>	[0] = 44 [1] = 36	[0] = 36 [1] = 19	Whether farmer used chemical dealer advice (1=yes; 0 = no).
<i>PM578</i>	[0] = 35 [1] = 45	[0] = 41 [1] = 14	Whether farmer used scouting personnel (1= yes; 0= no).
<i>PMRANK1</i>	[1] = 9 [2] = 11 [3] = 11 [4] = 36	[1] = 5 [2] = 6 [3] = 12 [4] = 12	What the farmer ranked as most important service in influencing his decision of pesticide usage (1 =hired staff; 2 = extension; 3 = chemical dealer; 4 = professional scouting).
<i>PMADVICE</i>	[1] = 13 [2] = 37 [3] = 15	[1] = 1 [2] = 17 [3] = 16	Advice affect pesticide usage (1 = increased; 2 = decreased; 3 = no effect).
<i>BPAGE</i>	46.10 (10.22)	51.76 (10.55)	Age of farm-operator.
<i>BPYROP</i>	21.44 (10.29)	27.35 (11.34)	Number of years operating farm/ranch.
<i>BPWORK</i>	22.79 (71.20)	14.59 (54.73)	Number of days worked off farm.
<i>BPEDUC</i>	[1] = 4 [2] = 37 [3] = 1 [4] = 24 [5] = 11 [6] = 3	[1] = 11 [2] = 22 [3] = 2 [4] = 9 [5] = 10	Formal education of operator (1 = less than high school; 2 = high school; 3 = vocational training; 4 = some college; 5 = completed college; 6 = graduate school).
<i>IGSALES1</i>	460366.67 (280464.65)	351759.26 (296167.19)	Value of annual farm sales (in dollars). ^b
<i>CLASS</i>	[1] = 14 [2] = 41 [3] = 22 [4] = 2 [5] = 1	[1] = 11 [2] = 37 [3] = 7	Land capability class (Ratings for soils range from 1 through 8. Class 1 soil has few restrictions that limit its use, class 8 soil has severe limitations that make it less productive for agriculture).

^a Frequency distributions of discrete (dummy) variables, and mean as well as standard deviations (figures in parentheses below each mean) for continuous variables have been shown in the table.

^b See text and Table 4.3 for details.

Table 4.1 (contd.). Description of the explanatory variables used in the study for constructing Model 1 (eqn. 3.1) and Model 2 (eqn. 3.2) specified in Chapter III.

<i>USLE</i>	3.88 (3.29)	3.77 (2.86)	Estimated average soil movement due to sheet and rill erosion (tons per acre per year).
<i>DIST4</i>	2022.55 (2438.71)	2545.98 (2842.89)	Distance in feet from point to nearest occurrence of water.
<i>LEACH</i>	5.05 (3.34)	5.75 (4.08)	Leaching potential of the soil (inches of plant-available water holding capacity).
<i>STATE</i>	[37] = 65 [51] = 15	[37] = 31 [51] = 24	State code (51 = Virginia; 37 = North Carolina).

The dummy variables for the model were defined as follows:

<i>LH</i>	[0] = 76 [1] = 4	[0] = 44 [1] = 11	if <i>BPEDUC</i> = 1 then <i>LH</i> = 1; else <i>LH</i> = 0;
<i>HS</i>	[0] = 43 [1] = 37	[0] = 33 [1] = 22	if <i>BPEDUC</i> = 2 then <i>HS</i> = 1; else <i>HS</i> = 0;
<i>VT</i>	[0] = 79 [1] = 1	[0] = 53 [1] = 2	if <i>BPEDUC</i> = 3 then <i>VT</i> = 1; else <i>VT</i> = 0;
<i>SC</i>	[0] = 56 [1] = 24	[0] = 46 [1] = 9	if <i>BPEDUC</i> = 4 then <i>SC</i> = 1; else <i>SC</i> = 0;
<i>CC</i>	[0] = 69 [1] = 11	[0] = 45 [1] = 10	if <i>BPEDUC</i> = 5 then <i>CC</i> = 1; else <i>CC</i> = 0;
<i>HSI</i>	[0] = 71 [1] = 9	[0] = 50 [1] = 5	if <i>PMRANK1</i> = 1 then <i>HSI</i> = 1; else <i>HSI</i> = 0;
<i>EXI</i>	[0] = 69 [1] = 11	[0] = 49 [1] = 6	if <i>PMRANK1</i> = 2 then <i>EXI</i> = 1; else <i>EXI</i> = 0;
<i>CDI</i>	[0] = 69 [1] = 11	[0] = 43 [1] = 12	if <i>PMRANK1</i> = 3 then <i>CDI</i> = 1; else <i>CDI</i> = 0;
<i>SPI</i>	[0] = 44 [1] = 36	[0] = 43 [1] = 12	if <i>PMRANK1</i> = 4 then <i>SPI</i> = 1; else <i>SPI</i> = 0;
<i>PROD1</i>	[0] = 66 [1] = 14	[0] = 44 [1] = 11	if <i>CLASS</i> = 1 then <i>PROD1</i> = 1; else <i>PROD1</i> = 0;
<i>PROD2</i>	[0] = 39 [1] = 41	[0] = 18 [1] = 37	if <i>CLASS</i> = 2 then <i>PROD2</i> = 1; else <i>PROD2</i> = 0;
<i>PROD3</i>	[0] = 58 [1] = 22		if <i>CLASS</i> = 3 then <i>PROD3</i> = 1; else <i>PROD3</i> = 0; ^c
<i>VA</i>	[0] = 65 [1] = 15	[0] = 31 [1] = 24	if <i>STATE</i> = 51 (Virginia) then <i>VA</i> = 1; else <i>VA</i> = 0;

^c The dummy variable *PROD3* was constructed only for cotton.

Table 4.2. Farm-advisory services: Most important rank and effect on pesticide usage.

Advisory Service	Farmer's Rank of Most Important Service and Effect of Advice on Pesticide Usage	Cotton (no. of obs)	Peanuts (no. of obs)
Hired Staff (HSI)			
	<i>HSI</i> =1 (Used Hired Staff) ^a	27	9
	<i>PMRANKI</i> =1 (Ranked <i>HSI</i> as most important service)	9	5
	<i>PMRANKI</i> =1 and <i>HSI</i> =1 (Used <i>HSI</i> and ranked it as most important) ^b	6	3
	<i>PMADVICE</i> =1 (<i>HSI</i> advice increased usage)	2	0
	<i>PMADVICE</i> =2 (<i>HSI</i> advice decreased usage)	4	3
	<i>PMADVICE</i> =3 (<i>HSI</i> advice had no effect)	2	2
Extension Advice (EXI)			
	<i>EXI</i> =1 (Used Extension Advice)	42	18
	<i>PMRANKI</i> =2 (Ranked <i>EXI</i> as most important service)	11	6
	<i>PMRANKI</i> =2 and <i>EXI</i> =1 (Used <i>EXI</i> and ranked it as most important) ^b	10	6
	<i>PMADVICE</i> =1 (<i>EXI</i> advice increased usage)	1	0
	<i>PMADVICE</i> =2 (<i>EXI</i> advice decreased usage)	9	4
	<i>PMADVICE</i> =3 (<i>EXI</i> advice had no effect)	1	2
Chemical Dealer (CDI)			
	<i>CDI</i> =1 (Used Chemical Dealer's Advice)	36	19
	<i>PMRANKI</i> =3 (Ranked <i>CDI</i> as most important service)	11	12
	<i>PMRANKI</i> =3 and <i>CDI</i> =1 (Used <i>CDI</i> and ranked it as most important) ^b	11	11
	<i>PMADVICE</i> =1 (<i>CDI</i> advice increased usage)	1	1
	<i>PMADVICE</i> =2 (<i>CDI</i> advice decreased usage)	1	5
	<i>PMADVICE</i> =3 (<i>CDI</i> advice had no effect)	8	6
Scouting Personnel (SPI)			
	<i>SPI</i> =1 (Used Scouting Personnel's Advice)	45	14
	<i>PMRANKI</i> =4 (Ranked <i>SPI</i> as most important service)	36	12
	<i>PMRANKI</i> =4 and <i>SPI</i> =1 (Used <i>SPI</i> and ranked it as most important) ^b	36	12
	<i>PMADVICE</i> =1 (<i>SPI</i> advice increased usage)	9	0
	<i>PMADVICE</i> =2 (<i>SPI</i> advice decreased usage)	23	5
	<i>PMADVICE</i> =3 (<i>SPI</i> advice had no effect)	4	6

^a Used the indicated information service in the sampled field for pest management.

^b Said "yes" they used the indicated advisory service and ranked it as most important.

to have used that particular service. Table 4.1 gives a detailed description of the construction of these dummies using *PMRANK1* as well as the relevant statistics involved.

It should be noted that not all farmers ranked an advisory service according to the data. Thirteen cotton farmers and 20 peanut farmers did not answer the questions in the survey regarding their use and rankings of advisory services. In this study, lack of response from farmers is assumed to mean that those particular farmers had not used any of the advisory services. Thus, these farmers are the reference against which other advisory services are compared. However, if the lack of response is due to interviewer or data coding error, then the results of the econometric modeling will be misleading.

In cotton farming, most farmers ranked scouting personnel advice as the most important service (36 out of 80 responses). Chemical dealers and extension advice were tied for second place (11 responses), while use of hired staff came last (nine responses). In the case of peanut farming, however, scouting and chemical dealers' advice were ranked the highest by farmers (12 responses), while extension agents and hired staff were ranked as the most important service by fewer farmers. The above findings point to the high potential influence of advice by scouting personnel and chemical dealers on the farmers' use of pesticides. The regression analysis in a later section will help to shed more light on the effects of advice on pesticide expenditures and chemical toxicity.

The frequency distribution for the variable *PMADVICE* in both Tables 4.1 and 4.2 shows the farmers' views of the effect that different services had on their use of pesticides. A majority of the farmers in cotton reported a decrease in pesticide usage due to advice from scouting personnel (23 out of 36) and from extension agents (9 out of 11). Most farmers using chemical dealers' advice (8 out of 11) reported that the service had no effect on their usage of pesticides in cotton farming. Based on the results shown in Table 4.2, a negative correlation between aggregate toxicity and the use of extension as well as scouting personnel advice, at least in cotton farming, might be expected.

In the case of peanut farming, however, the response of the farmers was mixed. For most of the advisory services, almost as many farmers reported a decrease in pesticide usage as the ones reporting no change as a result of these services. While there were 13 farmers in cotton farming who reported an increase in their pesticide usage due to advice from the service they ranked as most important, there was only one farmer who reported an increase in pesticide use in peanut farming as a result of advice. The results of the regression analysis will be given and discussed in a later section in this Chapter. The following variables were categorized as social characteristics of the farmers in the survey: *BPAGE* (representing age of the farm-operator), *BPEDUC* (representing the type of educational level achieved by the farmer), *BPYROP* (denoting the years of farming experience of the farmer), and *BPWORK* (the number of days that the farmer worked off the farm). Table 4.1 indicates that the mean age of farmers was over 45, and that their mean farming experience was over 20 years. The age and farming experience of the farmers were greater in peanut farming compared to cotton. This younger age of cotton

farmers is possibly a reflection of the greater willingness of younger farmers to try out cotton which was a relatively new crop in the Albemarle-Pamlico watershed during the years 1990-1992.

Table 4.1 also describes the variable *BPEDUC* as well as the dummy variables constructed using its values. The frequency results indicate at least several farmers at each level of educational achievement except for “vocational training” (one in cotton and two in peanut farming) and “graduate school” education (three in cotton and none in peanut farming). The statistics given in table 4.1 lead to some potential concern regarding the variable *BPWORK* because of its extremely high standard deviation. A more detailed analysis of this variable will be discussed in a later section.

In the initial data, *IGSALES* had one value representing each of the twenty ranges of annual farm sales values, as shown in Table 4.3. However, in order to have a continuous variable in the model, the mid-point of each of these ranges was taken to construct the variable *IGSALES1*. Most of the observations for *IGSALES* were concentrated in some of the highest ranges, and consequently, the same was true of *IGSALES1*. As a result, the standard deviation of this variable turned out to be really high, as shown in Table 4.1, leading to similar concerns as with the variable *BPWORK*.

Finally, in the category describing physical and locational characteristics, the variable *CLASS*, which represented a progressively lower physical productivity of the soil denoted by values 1 through 8, had observations with values 1 through 5 for the cotton data, and values 1 through 3 for the peanut data in this study. Dummy variables *PRODI*, *PROD2*, (for both cotton and peanuts) and *PROD3* (only for cotton) were therefore constructed as shown in Table 4.1.¹⁹ The locational variable *STATE* was used to construct a dummy variable (*VA*, where *VA* = Virginia) to study the nature of influence (if any) of regional characteristics on the aggregate toxicity of pesticides. The variables *USLE* and *DIST4* were used as in the original data with a slight modification for *DIST4*. The variable *DIST4* denoted the distance of the farm sample site from the nearest water source. The NRI82 survey data used the value 9999 as a code for all distances that were a mile or more. The observations corresponding to the values 9999 were made to correspond to 5,280 feet. The variable *LEACH* in this category, denoting the leaching potential of the soil, was constructed from some of the other variables in the data as already discussed and shown in Chapter III. *USLE* indicates the estimated average soil movement in tons per acre per year based on the Universal Soil Loss Equation (Wischmeier and Smith).

¹⁹ Since there was just one observation for the *CLASS* rating of 5 in the cotton data, both classes 4 and 5 were used as references against three dummies.

Table 4.3. Values assigned to *IGSALES* and *IGSALES1* along with their frequency distribution and average values for cotton and peanuts.^a

<i>IGSALES</i>	Annual Farm Sales (\$)	<i>IGSALES1</i> (\$)	Cotton (no. of obs)	Peanuts (no. of obs)
1	0	0	1	
2	1 - 999	500		
3	1000 - 2499	1,250		
4	2,500 - 4,999	3,750		
5	5,000 - 9,999	7,500		
6	10,000 - 14,999	12,500	1	
7	15,000 - 19,999	17,500		2
8	20,000 - 24,999	22,500		1
9	25,000 - 29,999	27,500		
10	30,000 - 34,999	32,500		1
11	35,000 - 39,999	37,500		1
12	40,000 - 49,999	45,000		2
13	50,000 - 59,999	55,000	1	
14	60,000 - 79,999	70,000	1	3
15	80,000 - 99,999	90,000	1	2
16	100,000 - 174,999	137,500	8	8
17	175,000 - 249,999	212,500	8	9
18	250,000 - 499,999	375,000	28	11
19	500,000 - 999,999	750,000	20	11
20	1,000,000 and over	1,000,000	6	3
Average of <i>IGSALES1</i> :			460,366.67	351,759.26

^a *IGSALES* had a value of 0 for 5 observations in cotton and 1 in peanuts indicating missing values and were ignored.

4.2 Description of the Dependent Variables

The dependent variables in each of the two basic regression models in the study had continuous values. The first model for cotton and peanuts had *AGGINDEX*, and the second model for both cotton and peanuts had *EXPEND* as their respective dependent variables. Both these variables have been listed in Table 4.4 with their respective means and standard deviations. The mean and standard deviation for *AGGINDEX* indicates the existence of large values with high variability. The chemical active ingredients of the pesticide products were sorted according to their respective toxic values after taking into consideration the rate of application of the product per acre of cultivation for each crop. Table 4.5 shows the ten most toxic chemicals separately for cotton and for peanuts. As mentioned earlier, every pesticide product can contain a maximum of three chemicals (*AICODE1*, *AICODE2*, and *AICODE3*). Because the pesticides used in this study had mostly one active ingredient in them, the contribution of *AICODE1* was the most in terms of toxicity. Table 4.5, however, takes into account the mean of all individual chemicals whether *AICODE1*, *AICODE2*, or *AICODE3*.

The variable *EXPEND*, shown in Tables 4.4 and 4.6, indicates that the expenditures on pesticides on the whole were relatively more for peanuts than for cotton. Table 4.6 lists the breakdown of expenditures on the different forms of pesticides, namely, insecticides, herbicides, and fungicides. It also provides a rough comparison between the 1992 mean pesticide expenditures as given in the Area Studies data used in this study and those estimated by the Virginia Cooperative Extension Service for the cotton and peanut farmers of southeastern Virginia. This table indicates that the Area Studies expenditures for all forms of pesticides used in this study were far below those estimated for the Virginia farms.

It is worth noting here that while the Area Studies conducts extensive surveys to get maximum information directly from the farmer, the Extension Budgets are based on recommended values based on interviews with production scientists, extension experts, and progressive farmers. Hence, there is a possibility that while the recommended quantities and rates of application of pesticides may be higher, the farmers may actually be using much lower quantities and applying pesticides at rates much lower than recommended, especially because of the high prices of some of the pesticides. This discrepancy between recommended quantities and rates of application of pesticides and the actual use by farmers may therefore have been reflected in the discrepancy between the Area Studies and the Virginia Budget total expenditure on the different forms of pesticides.

Table 4.4. Distribution of the dependent variables in the regression models.

Variable	Cotton			Peanuts		
	N	Mean	Std Dev	N	Mean	Std Dev
<i>AGGINDEX</i> ^a	74	4666.40	9133.71	55	3078.97	8278.23
<i>EXPEND</i> ^b	78	31.24	20.56	55	62.48	38.65

^a See Chapter III section 3.3.1 for definition and construction of *AGGINDEX*.

^b See Chapter III section 3.3.3 for definition and construction of *EXPEND*.

Table 4.5. The ten most toxic chemicals in this study used on each crop, after including the rate of application of the respective pesticide products for which they are active ingredients.

Cotton			Peanuts		
Chemical code	Chemical name	Mean Toxicity Index	Chemical code	Chemical name	Mean Toxicity Index
41101	Ethoprop	64799.57	41101	Ethoprop	13499.91
6801	Arsenic acid	34135.49	57801	Diazinon	3911.03
29001	Dichloropropene	7123.11	100601	Fenamiphos	1943.99
74801	Tribufos	2105.99	57201	Phorate	816.48
57801	Diazinon	2059.20	74801	Tribufos	607.82
57201	Phorate	622.08	61601	Paraquat	542.77
105001	Terbufos	261.66	32501	Disulfoton	486.00
41701	Fonofos	142.56	39003	Metam-sodium	144.20
59101	Chlorpyrifos	127.98	41404	Vernolate	126.39
35506	Linuron	97.20	35506	Linuron	124.12

Table 4.6. Comparison of mean expenditures per acre on pesticide applications to cotton and peanuts in the Area Studies data and in the Virginia Cooperative Extension Budget^a.

Crop	Mean Expenditures on Insecticides (\$/acre)			Mean Expenditures on Herbicides (\$/acre)			Mean Expenditures on Fungicides (\$/acre)			Total Expenditures (\$/acre)		
	Area Studies		Virginia	Area Studies		Virginia	Area Studies		Virginia	Area Studies		Virginia
	N. Carolina	Virginia	Extension Budget	N. Carolina	Virginia	Extension Budget	N. Carolina	Virginia	Extension Budget	N. Carolina	Virginia	Extension Budget
Cotton	15.60	11.30	24.71	15.25	12.05	18.16	1.95	0.76	28.77	32.80	24.10	71.64
Peanuts	16.01	15.85	51.83	33.13	26.80	42.60	15.70	16.79	48.52	64.84	59.44	142.95

^a The mean expenditures on pesticides for the VA data are based on the 1992 Crop Budget Guide for South-Eastern Virginia prepared by Guy Sturt of the Virginia Cooperative Extension Service. The expenditures for cotton in Sturt's budget are based on a 650 lb. lint yield and those for peanuts are based on a 3,000 lb. yield.

Another reason for the lower pesticide expenditures may be that the Area Studies data took into account a sample of farms from both Virginia and North Carolina and Table 4.1 shows that the sample of North Carolina farms was much larger than that of Virginia, both for cotton (65 against 15) and peanuts (31 against 24). Moreover, since cotton was a relatively new crop in 1992, there were probably fewer acres devoted to cotton farming in Virginia than in North Carolina. Also, farmers in Virginia, being newly introduced to cotton farming during the years 1990-1992, were probably still learning to grow cotton with larger pesticide requirements (such as applications for pre-plant and pre-emergence of weeds and other pests). Another reason for the understatement of the pesticide expenditures in the Area Studies data may have been because of errors in prices used or because not all quantities of pesticides were recorded. The Area Studies expenditure data were derived by multiplying the pounds per acre of each chemical applied by the dollars per pound of the corresponding chemical for each sample site in the survey. The prices of chemicals in the Area Studies data may have been different from those assumed in the Virginia extension budgets.

4.3 Regression Analysis

The regression analysis in this section has been divided into two parts - one for cotton and the second for peanuts. The analysis for each crop has again been subdivided into two separate analyses for the two different models specified in Chapter III, namely, the model for estimating the influence of socioeconomic, physical, and locational factors on the aggregate toxicity of chemicals, and the model for estimating the influence of the same socioeconomic and other factors on the aggregate expenditures on pesticides.

The significance of the parameter estimates of these models are then tested using Student's t-tests. For example, a null hypothesis ($H_0: \alpha_1 = 0$), implying that the coefficient estimate of the variable *BPAGE* is not significant in explaining the model, can be tested against the alternative hypothesis ($H_1: \alpha_1 \neq 0$), implying that the coefficient estimate is significant. Normally, a p-value equal to or less than 0.05 leads to a rejection of the null hypothesis, leading one to conclude that the estimate is significant at a five percent level. In other words, the prediction about the estimate would prove to be correct 95 percent of the time, with only a five percent chance of error. Similarly, one percent (p-value < or = 0.01) and ten percent (p-value < or = 0.10) significance levels are also used in predictions of the coefficient estimates. In this study, a 10 percent significance level (p < or = 0.10) will be used.

4.3.1 Results for Cotton

Model 1: Factors affecting aggregate toxicity of pesticides in cotton farming.

The model for estimating the influence of socioeconomic, physical, and locational factors on the aggregate toxicity of pesticides used in cotton farming can be written as

follows:

$$\begin{aligned}
 AGGINDEX = & CONST + \alpha_1 BPAGE + \alpha_2 BPYROP + \alpha_3 LH + \alpha_4 HS + \alpha_5 VT + \\
 & \alpha_6 SC + \alpha_7 CC + \alpha_8 HSI + \alpha_9 EXI + \alpha_{10} CDI + \alpha_{11} SPI + \alpha_{12} IGSALES1 + \alpha_{13} \\
 & PROD1 + \alpha_{14} PROD2 + \alpha_{15} PROD3 + \alpha_{16} USLE + \alpha_{17} LEACH + \alpha_{18} DIST4 + \alpha_{19} VA
 \end{aligned}
 \tag{4.1}$$

where: *CONST* is the intercept, and $\alpha_1, \alpha_2, \dots, \alpha_{19}$ are the coefficients of the independent explanatory variables to be estimated as presented in Table 4.1.

The model specified above had several estimation problems. Three of the variables, *AGGINDEX*, *BPWORK*, and *IGSALES1*, were not normally distributed. Moreover, *AGGINDEX* had extremely large values leading to scaling problems. The normality problem can usually be solved by resorting to transformations of the variables such as taking the natural logarithms. However, although taking the natural logarithm of *AGGINDEX* (and renaming it as *LAGG*) resulted in a normally distributed variable, the logarithmic transformations of *BPWORK*, and *IGSALES1* were not normal. Another problem was that the variables *IGSALES1* and *LEACH* had many missing values (five and twenty, respectively) for the cotton data. Since GAUSS fails to execute its computational procedures in the presence of missing observations, inclusion of these variables in the regression would tend to give biased estimates. Hence, the variables *BPWORK*, *IGSALES1* and *LEACH* were dropped from the regression model. So the model that was finally estimated had *LAGG* as its dependent variable and is given as follows:

$$\begin{aligned}
 LAGG = & CONST + \alpha_1 BPAGE + \alpha_2 BPYROP + \alpha_3 LH + \alpha_4 HS + \alpha_5 VT + \alpha_6 SC \\
 & + \alpha_7 CC + \alpha_8 HSI + \alpha_9 EXI + \alpha_{10} CDI + \alpha_{11} SPI + \alpha_{12} PROD1 + \alpha_{13} PROD2 + \alpha_{14} \\
 & PROD3 + \alpha_{15} USLE + \alpha_{16} DIST4 + \alpha_{17} VA
 \end{aligned}
 \tag{4.2}$$

The results of the regression for equation 4.2 for cotton are shown in Table 4.7. The estimates of the variables in this model were obtained using 74 observations (6 observations were missing for the original *AGGINDEX* and consequently for the *LAGG* variable, and were omitted by GAUSS). The model F-test result (probability of the F-statistic = .005) indicates that the model did explain the variations in the log of aggregate toxicity. The R-square value of 0.436 is a reasonably high estimate of the correlation coefficient for cross-sectional data analysis. The results in Table 4.7 indicate that the coefficient estimates of *BPYROP*, *HSI*, *EXI*, *SPI*, *PROD1*, *PROD2*, *PROD3*, and *VA* are significant at the 0.10 level. No conclusive evidence can be reached regarding the coefficient estimates of the remaining variables since the p-values (the probability > |t|, where t is the test statistic) are much greater than 0.10 in most cases.

Table 4.7. Results of regressing the log of aggregate toxicity of pesticides used in cotton farming on socio-economic, and physical, and advisory services variables as represented by equation 4.2.

Dependent variable:	<i>LAGG</i>					
Valid cases:	74	Degrees of freedom:	56			
R-squared:	0.436	Rbar-squared:	0.265			
Std error of est:	1.720					
F(17,56):	2.547	Probability of F:	0.005			
Durbin-Watson:	1.761					
Variable	Estimate	Standard Error	t-value	Prob > t	Standardized Estimate	Cor with Dep Var
<i>CONST</i>	-1.603828	2.557879	-0.627015	0.533	---	---
<i>BPAGE</i>	0.058396	0.037133	1.572595	0.121	0.290598	-0.063987
<i>BPYROP</i>	-0.075217	0.038302	-1.963774	0.055	-0.393393	-0.156251
<i>LH</i>	-2.105737	1.597833	-1.317870	0.193	-0.239031	-0.272051
<i>HS</i>	0.757581	1.497835	0.505784	0.615	0.190083	-0.069984
<i>VT</i>	-0.467175	2.271810	-0.205640	0.838	-0.027078	-0.058606
<i>SC</i>	1.358000	1.432371	0.948079	0.347	0.302749	0.279890
<i>CC</i>	-0.320277	1.418744	-0.225747	0.822	-0.057196	-0.087241
<i>HS1</i>	2.816475	0.948938	2.968029	0.004	0.439030	0.111167
<i>EX1</i>	1.467118	0.783940	1.871468	0.067	0.262001	0.034387
<i>CD1</i>	1.189646	0.868345	1.370015	0.176	0.204164	-0.038828
<i>SP1</i>	1.495751	0.655762	2.280936	0.026	0.374884	0.024820
<i>PROD1</i>	5.804173	1.559934	3.720782	0.000	1.141172	0.098756
<i>PROD2</i>	5.148093	1.500314	3.431343	0.001	1.292169	-0.143324
<i>PROD3</i>	5.976418	1.536016	3.890857	0.000	1.352570	0.184482
<i>USLE</i>	0.017992	0.067358	0.267109	0.790	0.030351	-0.147499
<i>DIST4</i>	0.000004	0.000183	0.023189	0.982	0.002753	0.120339
<i>VA</i>	1.549607	0.626240	2.474463	0.016	0.286734	0.062849

Additional tests were conducted to verify the validity of the distributional assumptions of the model. These tests also called misspecification tests, as defined in Chapter III, led to results that have been summarized in Table 4.8. More detailed description of the GAUSS misspecification test procedures and results have been given in Appendix D.²⁰ Table 4.8 shows that the cotton model with *LAGG* as the dependent variable, as defined by equation 4.2, passed all model assumption tests since all p-values turned out to be much greater than .05.

Returning to the parametric estimates of the model (Table 4.7), the signs of these estimates are of importance in this context. With a negative sign for the coefficient of *BPYROP*, the hypothesis that “the years of farming experience of the farmer is inversely related to the use of more toxic chemicals” cannot be rejected. This finding, however, seems to contradict the findings of Napit whose studies on Texas cotton indicated that as cotton farming experience increases, the adoption of IPM decreases. Assuming that adoption of IPM and use of toxic chemicals are inversely related, Napit’s inverse relationship would imply more aggregate toxicity. The aggregate toxicity of chemicals used by farmers, however, turned out to be positively related to the farmers’ age, their contact with hired staff, extension agents, and scouting personnel, as well as with the productivity of the soil, and finally, with farming in Virginia. The relationship between aggregate toxicity and age of the farmer in these results also seems to contradict Napit’s findings, assuming that greater IPM adoption corresponds to less use of toxic chemicals.

The most surprising results, however, are regarding the advisory services and aggregate toxicity. The frequency results of Tables 4.1 and 4.2 indicated that most farmers viewed scouting personnel and extension agents as reducing their use of pesticides on cotton. However, the regression results in Table 4.7 may indicate otherwise. However, it is difficult to infer a cause and effect relationship between information services and pesticide use from cross sectional data. Farmers may actually have reduced their use of chemicals based on advice. Other unobserved variables may actually have led to higher pesticide use among farmers who used extension or scouting. Another reason for the positive relationship between advice and toxicity might be the fact that farmers substitute more toxic chemicals as a result of extension advice. So, even if individual farmers reduce the quantities of their chemicals, the aggregate toxicities increase, if these farmers are advised to use chemicals that are more effective but also more toxic.

²⁰ The null hypotheses in these tests (stating that the model has been misspecified with respect to a particular assumption), however, are rejected if the p-values are greater than .05.

Table 4.8. Summary of results from misspecification tests^a conducted on the regression models of Chapter IV^b.

Mis specification Tests		p - values					
		Cotton			Peanuts		
		<i>LAGG</i>	<i>EXPEND</i>	<i>EXPENDI</i>	<i>LAGG</i>	<i>EXPEND</i>	<i>EXPENDI</i>
Normality	Bera-Jarque test	0.95	0.00	0.46	0.65	0.51	0.32
	D'Agostino Pearson test	0.93	0.00	0.34	0.44	0.46	0.20
	D'Agostino Skewness test	0.37	0.00	0.11	0.24	0.23	0.07
	D'Agostino Kurtosis test	0.41	0.00	0.21	0.14	0.16	0.16
Linearity	RESET test of order 2	0.20	0.41	0.66	0.58	0.45	0.86
Homoskedasticity	RESET test of order 2	0.13	0.01	0.30	0.73	0.05	0.07
Independence	Autocorrelation test	0.18	0.91	0.77	0.11	0.43	0.48
Joint Tests	Conditional mean test	0.56	0.85	0.85	0.92	0.03	0.19
	Trend F-test	0.95	0.89	0.60	0.94	0.04	0.13
	Reset Linearity F-test	0.17	0.34	0.69	0.92	0.12	0.98
	Residual autocorrelation F-test	0.25	0.66	0.72	0.38	0.49	0.29
	Conditional variance test	0.19	0.92	0.58	0.31	0.16	0.96
	Trend F-test	0.29	0.40	0.31	0.49	0.99	0.98
	Reset static HC F-test	0.09	0.00	0.40	0.18	0.01	0.93
	Dynamic HC F-test	0.20	0.53	0.55	0.30	0.89	0.45

^a The misspecification tests were conducted using the GAUSS software and the procedures written in GAUSS jointly by Anya McGuirk and John Robertson, Associate Professor and former graduate student, respectively, in the Department of Agricultural and Applied Economics at Virginia Tech.

^b The regression models have been represented by the respective dependent variables for each crop.

Model 2: Factors affecting aggregate pesticide expenditures in cotton farming.

The model for estimating the influence of socioeconomic, physical, and locational factors on the aggregate pesticide expenditures was similar to the model estimating the influence of these different factors on aggregate toxicity, with the difference that the dependent variable was *EXPEND* instead of *LAGG*. Equation 4.2 now can be rewritten as follows:

$$\begin{aligned} EXPEND = & CONST + \alpha_1 BPAGE + \alpha_2 BPYROP + \alpha_3 LH + \alpha_4 HS + \alpha_5 VT + \alpha_6 \\ & SC + \alpha_7 CC + \alpha_8 HSI + \alpha_9 EXI + \alpha_{10} CDI + \alpha_{11} SPI + \alpha_{12} PROD1 + \alpha_{13} PROD2 + \\ & \alpha_{14} PROD3 + \alpha_{15} USLE + \alpha_{16} DIST4 + \alpha_{17} VA \end{aligned} \quad (4.3a)$$

Table 4.9 lists the estimates of the parameters for the above regression. The p-values of the coefficients of the variables *HSI* and *SPI* turned out to be less than 0.10 (that is, significant at ten percent). However, a closer look at the model statistics revealed that the model was not really explaining anything since the probability of the F-statistic was greater than 0.05 and also the R-square was a low 0.278.

The misspecification tests conducted on this cotton model with *EXPEND* as its dependent variable, represented by equation 4.3a, showed in detail some of the problems encountered by the model. The results in Table 4.8 indicated that the model failed to satisfy the assumptions of normality and homoskedasticity. A closer look at the data

Table 4.9. Results of regressing aggregate pesticide expenditures in cotton farming on socio-economic, physical, and advisory services variables as represented by equation 4.3a.

Dependent variable:	<i>EXPEND</i>					
Valid cases:	74	Degrees of freedom:	56			
R-squared:	0.278	Rbar-squared:	0.059			
Std error of est:	20.152					
F(17,56):	1.267	Probability of F:	0.248			
Durbin-Watson:	1.846					
Variable	Estimate	Standard Error	t-value	Prob > t	Standardized Estimate	Cor with Dep Var
<i>CONST</i>	-7.944142	29.974111	-0.265033	0.792	---	---
<i>BPAGE</i>	0.310836	0.435140	0.714335	0.478	0.149373	0.086072
<i>BPYROP</i>	-0.347402	0.448837	-0.774004	0.442	-0.175458	0.053541
<i>LH</i>	-5.387767	18.723958	-0.287747	0.775	-0.059059	-0.130602
<i>HS</i>	11.382297	17.552149	0.648485	0.519	0.275787	0.049122
<i>VT</i>	-14.064991	26.621849	-0.528325	0.599	-0.078723	-0.094633
<i>SC</i>	15.021455	16.785013	0.894933	0.375	0.323388	0.111169
<i>CC</i>	0.593230	16.625330	0.035682	0.972	0.010230	-0.104510
<i>HS1</i>	26.395168	11.119982	2.373670	0.021	0.397321	0.108891
<i>EX1</i>	0.586647	9.186474	0.063860	0.949	0.010117	-0.199082
<i>CD1</i>	10.939816	10.175571	1.075106	0.287	0.181301	-0.083296
<i>SP1</i>	18.029198	7.684448	2.346193	0.023	0.436358	0.255310
<i>PROD1</i>	18.902126	18.279840	1.034042	0.306	0.358881	-0.014712
<i>PROD2</i>	18.973277	17.581201	1.079180	0.285	0.459880	-0.033349
<i>PROD3</i>	22.707782	17.999563	1.261574	0.212	0.496276	0.115511
<i>USLE</i>	-0.984035	0.789328	-1.246674	0.218	-0.160297	-0.208566
<i>DIST4</i>	-0.003250	0.002141	-1.518483	0.135	-0.203995	-0.023104
<i>VA</i>	0.823338	7.338495	0.112194	0.911	0.014712	-0.114199

revealed the existence of two isolated observations with very high expenditures. An additional dummy variable “*DUM*” was therefore created to incorporate the effects of these two isolated observations. The regression of a modified version of equation 4.3a (by adding *DUM* to equation 4.3a) was then conducted using the following equation:

$$EXPENDI = CONST + \alpha_1 BPAGE + \alpha_2 BPYROP + \alpha_3 LH + \alpha_4 HS + \alpha_5 VT + \alpha_6 SC + \alpha_7 CC + \alpha_8 HSI + \alpha_9 EXI + \alpha_{10} CDI + \alpha_{11} SPI + \alpha_{12} PROD1 + \alpha_{13} PROD2 + \alpha_{14} PROD3 + \alpha_{15} USLE + \alpha_{16} DIST4 + \alpha_{17} VA + \alpha_{18} DUM \quad (4.3b)$$

Table 4.10 lists the estimates and other model statistics from the above regression. The model showed a fairly high R-square value of 0.753 and since the probability of F for the model was 0, the estimates obtained from the regression could be considered reliable. The model misspecification tests also reconfirmed the validity of the regression results of equation 4.3b since all the p-values listed under the column of *EXPENDI* in cotton in Table 4.8 were all much greater than 0.05.

Table 4.10 showed that the coefficient estimates of *BPAGE*, *BPYROP*, *SPI*, *PROD2*, *PROD3* and *DUM* were significant at ten percent. The positive coefficient for *SPI* (scouting personnel) seems to be in line with the findings of Norton and Mullen whose research of the 19 different studies conducted in the United States since 1975 for the cotton crop showed an increase in pesticide costs with IPM for five of those studies.

A Pearson product-moment correlation coefficient matrix was obtained for *LAGG* and *EXPEND* as shown in Table 4.11. The correlation coefficient turned out to be 0.435 which indicates a moderately positive relation between *LAGG* and *EXPEND*. Hence, the lack of a strong positive correlation between these two variables probably leads to different outcomes from regressing each of them separately on the same advisory services, socio-economic variables and physical explanatory variables in the model.

The results obtained from the regression models represented by equations 4.2 and 4.3b have been summarized and matched against the hypotheses listed in Chapter I in the Table 4.12. Hired staff, extension agents and scouting personnel turned out to have a positive influence on aggregate toxicity in cotton while scouting had a positive influence on aggregate pesticide expenditures in cotton. Farmer experience seemed to have a negative effect on both aggregate toxicity as well as aggregate pesticide expenditures in cotton, while age seemed to have a positive effect on aggregate pesticide expenditures in cotton. Soil productivity seemed to have a positive effect on aggregate toxicity and aggregate pesticide expenditures compared to the least productive soil (except that the effect of the most productive soil on aggregate pesticide expenditures was not significant). The effect of all other variables was statistically insignificant.

Table 4.10. Revised results of regressing aggregate pesticide expenditures in cotton farming on socio-economic, physical, and advisory services variables as represented by equation 4.3b.

Dependent variable:	<i>EXPENDI</i>					
Valid cases:	74	Degrees of freedom:	55			
R-squared:	0.753	Rbar-squared:	0.672			
Std error of est:	11.886					
F(18,55):	9.327	Probability of F:	0.000			
Durbin-Watson:	2.069					
Variable	Estimate	Standard Error	t-value	Prob > t	Standardized Estimate	Cor with Dep Var
<i>CONST</i>	-3.626738	17.684624	-0.205079	0.838	---	---
<i>BPAGE</i>	0.446813	0.256999	1.738580	0.088	0.214717	0.086072
<i>BPYROP</i>	-0.476482	0.265035	-1.797809	0.078	-0.240651	0.053541
<i>LH</i>	-12.246318	11.064044	-1.106857	0.273	-0.134241	-0.130602
<i>HS</i>	-1.139584	10.424015	-0.109323	0.913	-0.027612	0.049122
<i>VT</i>	-16.702786	15.704474	-1.063569	0.292	-0.093487	-0.094633
<i>SC</i>	-0.403767	10.013075	-0.040324	0.968	-0.008692	0.111169
<i>CC</i>	-8.622166	9.846909	-0.875622	0.385	-0.148691	-0.104510
<i>HS1</i>	6.331527	6.842377	0.925340	0.359	0.095307	0.108891
<i>EX1</i>	1.412263	5.419058	0.260610	0.795	0.024355	-0.199082
<i>CD1</i>	3.905172	6.040643	0.646483	0.521	0.064719	-0.083296
<i>SP1</i>	13.839676	4.550759	3.041180	0.004	0.334960	0.255310
<i>PROD1</i>	14.671168	10.789842	1.359720	0.179	0.278551	-0.014712
<i>PROD2</i>	21.757996	10.373459	2.097468	0.041	0.527377	-0.033349
<i>PROD3</i>	18.389102	10.624981	1.730742	0.089	0.401891	0.115511
<i>USLE</i>	-0.504747	0.467892	-1.078769	0.285	-0.082222	-0.208566
<i>DIST4</i>	-0.000055	0.001300	-0.042207	0.966	-0.003444	-0.023104
<i>VA</i>	1.504581	4.328976	0.347560	0.729	0.026885	-0.114199
<i>DUM</i>	96.440495	9.368645	10.293964	0.000	0.758126	0.769638

Table 4.11. Pearson product-moment correlation matrix for *LAGG* (log of aggregate pesticide toxicity) and *EXPEND* (aggregate pesticide expenditures) on cotton sites.^a

<u>Cotton</u>		
Pearson Correlation Coefficients		
Prob > R under Ho: Rho=0 / N = 74		
	<i>LAGG</i>	<i>EXPEND</i>
<i>LAGG</i>	1.00000 (0.0)	0.43546 (0.0001)
<i>EXPEND</i>	0.43546 (0.0001)	1.00000 (0.0)

^a The figures in parentheses denote the probability for testing the null hypothesis that the product-moment correlation coefficient (rho) between *LAGG* and *EXPEND* in cotton is zero.

Table 4.12. Summary of the hypotheses in Chapter I and the corresponding results obtained in Chapter IV.

	Hypothesis	Results at 10 %	
		Cotton	Peanuts
1	H0: Aggregate toxicity of pesticides is not related to the use of the following farm advisory services: Hired Staff Extension Agents Chemical Dealers Scouting Personnel	Reject (+) Reject (+) Do not reject Reject (+)	Do not reject Do not reject Reject (+) Reject (+)
2	H0: Aggregate toxicity of pesticides is not related to the age of the farmer.	Do not reject	Reject (+)
3	H0: Aggregate toxicity of pesticides is not related to the more farmer experience.	Reject (-)	Do not reject
4	H0: Aggregate toxicity of pesticides is not related to the education level of the farmer. <i>LH</i> <i>HS</i> <i>VT</i> <i>SC</i> <i>CC</i>	Do not reject Do not reject Do not reject Do not reject Do not reject	Do not reject Reject (+) – Reject (+) Do not reject
5	H0: Aggregate toxicity of pesticides is not related to a farm's distance from the nearest water source.	Do not reject	Do not reject
6	H0: Aggregate toxicity of pesticides is not related to the potential of the site to leach.	Did not test	Did not test
7	H0: Aggregate toxicity of pesticides is not related to the erosion potential of the farm sample site (<i>USLE</i>).	Do not reject	Do not reject
8	H0: Aggregate toxicity of pesticides is not related to annual farm sales.	Did not test	Did not test
9	H0: Aggregate toxicity of pesticides is not related to soil productivity levels: <i>PROD1</i> <i>PROD2</i> <i>PROD3</i>	Reject (+) Reject (+) Reject (+)	Do not reject Do not reject –

^a The hypothesis that hired staff as the farmer's most important service does not have any influence on aggregate pesticide toxicity in cotton has been rejected at ten percent level of significance, and the conclusion is that it does have a positive effect on aggregate toxicity as indicated by the "+" sign in the parentheses. Similarly, other hypotheses have been rejected leading to a conclusion of positive (+) or negative (-) effect of the variable being tested on aggregate pesticide toxicity.

^b 'Do not reject' means that the coefficient estimate for the indicated variable was not statistically significant at the 0.10 level.

Table 4.12 (contd.). Summary of the hypotheses in Chapter I and the corresponding results obtained in Chapter IV.

	Hypothesis	Results at 10 %	
		Cotton	Peanuts
10	H0: Aggregate pesticide expenditures are not related to the use of the following farm advisory services: Hired Staff Extension Agents Chemical Dealers Scouting Personnel	Do not reject Do not reject Do not reject Reject (+)	Reject (+) Do not reject Do not reject Reject (+)
11	H0: Aggregate pesticide expenditures are not related to the age of the farmer.	Reject (+)	Do not reject
12	H0: Aggregate pesticide expenditures are not related to the education level of the farmer. <i>LH</i> <i>HS</i> <i>VT</i> <i>SC</i> <i>CC</i>	Do not reject Do not reject Do not reject Do not reject Do not reject	Do not reject Do not reject – Do not reject Do not reject
13	H0: Aggregate pesticide expenditures are not related to the more farming experience.	Reject (-)	Did not test
14	H0: Aggregate pesticide expenditures are not related to a farm's distance from the nearest water source.	Do not reject	Do not reject
15	H0: Aggregate pesticide expenditures are not related to the potential of the site to leach.	Did not test	Did not test
16	H0: Aggregate pesticide expenditures are not related to the erosion potential of the farm sample site (<i>USLE</i>).	Do not reject	Do not reject
17	H0: Aggregate pesticide expenditures are not related to annual farm sales.	Did not test	Did not test
18	H0: Aggregate pesticide expenditures are not related to soil productivity levels: <i>PROD1</i> <i>PROD2</i> <i>PROD3</i>	Do not reject Reject (+) Reject (+)	Reject (-) Do not reject –

^c This implies a failure of the test to reject the hypothesis that hired staff as the farmer's most important service does not have any influence on aggregate pesticide expenditures in peanuts (at a ten percent level of significance) leading to inconclusive results regarding the effect of the variable being tested (hired staff) on aggregate pesticide expenditures.

^d 'Do not reject' means that the coefficient estimate for the indicated variable was not statistically significant at the 0.10 level.

4.3.2 Results for Peanuts

Model 1: Factors affecting the aggregate toxicity of pesticides in peanut farming.

The basic model for peanuts is the same as that for cotton, that is, equation 4.2, except that there were fewer observations (54 compared to 74 in cotton) and there were two less variables to estimate. The variable *BPEDUC* had only five values with a positive number of observations in peanuts, and since only four dummies could be used here, *VT* was dropped from the regression. Moreover, the dummy *PROD3* contained no observations for peanuts. Hence the aggregate toxicity index model for the peanuts sample estimated 15 variables (and an intercept) as against 17 in the case of cotton as shown by equation 4.4 below:

$$LAGG = CONST + \alpha_1 BPAGE + \alpha_2 BPYROP + \alpha_3 LH + \alpha_4 HS + \alpha_5 SC + \alpha_6 CC + \alpha_7 HSI + \alpha_8 EXI + \alpha_9 CDI + \alpha_{10} SPI + \alpha_{11} PROD1 + \alpha_{12} PROD2 + \alpha_{13} USLE + \alpha_{14} DIST4 + \alpha_{15} VA \quad (4.4)$$

The regression results for equation 4.4 have been given in Table 4.13. The model statistics revealed that the variations in the error term were well explained by the model (an R-square value of 0.469 with the probability of F being 0.023). The misspecification tests on the model assumptions also confirmed the validity of the model results. The p-values under *LAGG* in peanuts are much greater than 0.05 in Table 4.8 indicating that the model represented by equation 4.4 satisfied all the assumptions.

In the case of peanut farm samples, the coefficient estimate of only *BPAGE*, *HS*, *SC*, *CDI*, and *SPI* were significant at ten percent. The positive sign on all these estimates indicated a positive correlation between aggregate toxicity of chemicals applied by farmers and farmers' age, farmers' use of advice from chemical dealers and scouting personnel, and also farmers with only high school as well as those with some college education. The reference value is vocational training, and thus education had mixed effects on pesticide toxicity. One of the points to note here is that although high school and some college education are both significant in increasing aggregate toxicity, some amount of college education increases toxicity less than high school education. This result is in line with Napit's findings for Georgia peanut growers in 1984, which concluded that farmers' adoption of IPM increased (implying aggregate toxicity decreased) with their level of education. However, as noted in section 4.1.1 earlier, almost none of the farmers reported an increase in pesticide usage in peanut farming due to the different advisory services. Possibly farmers substitute more toxic chemicals but use smaller amounts as a result of such advice. So although they may apparently end up using lesser pesticides, the aggregate toxicity goes up. Another possibility is that unobserved variables contribute to higher pesticide use by farmers using advisory services.

Table 4.13. Results of regressing the log of aggregate toxicity of pesticides used in peanut farming on socio-economic, physical, and advisory services variables as represented by equation 4.4.

Dependent variable:	<i>LAGG</i>					
Valid cases:	54	Degrees of freedom:				38
R-squared:	0.469	Rbar-squared:				0.259
Std error of est:	1.441					
F(15,38):	2.235	Probability of F:				0.023
Durbin-Watson:	1.570					
Variable	Estimate	Standard Error	t-value	Prob > t	Standardized Estimate	Cor with Dep Var
<i>CONST</i>	0.216243	1.724685	0.125381	0.901	---	---
<i>BPAGE</i>	0.075640	0.036049	2.098289	0.043	0.476769	0.282259
<i>BPYROP</i>	0.003655	0.033333	0.109654	0.913	0.024767	0.245045
<i>LH</i>	0.418079	1.330791	0.314158	0.755	0.101537	-0.184883
<i>HS</i>	2.239213	1.224149	1.829200	0.075	0.663464	0.204695
<i>SC</i>	2.123763	1.262957	1.681580	0.101	0.477276	0.068064
<i>CC</i>	0.985821	1.224618	0.805003	0.426	0.230919	-0.039461
<i>HS1</i>	0.301682	0.884237	0.341177	0.735	0.052731	-0.024738
<i>EX1</i>	-0.175858	0.826142	-0.212866	0.833	-0.033327	-0.240752
<i>CD1</i>	1.188194	0.657663	1.806692	0.079	0.297878	0.137845
<i>SP1</i>	1.074010	0.591792	1.814845	0.077	0.260840	0.200172
<i>PROD1</i>	-0.475609	0.573556	-0.829229	0.412	-0.115509	-0.157758
<i>PROD2</i>	-0.167708	0.766790	-0.218715	0.828	-0.033969	0.030293
<i>USLE</i>	0.124153	0.084094	1.476356	0.148	0.212572	0.009595
<i>DIST4</i>	0.000147	0.000158	0.927136	0.360	0.138140	0.258756
<i>VA</i>	-0.608691	0.529308	-1.149975	0.257	-0.182389	-0.179378

Model 2: Factors affecting aggregate pesticide expenditures in peanut farming.

The model for estimating the influence of different socioeconomic and other factors on the aggregate pesticide expenditures for peanuts was given by equation 4.5a shown below:

$$EXPEND = CONST + \alpha_1 BPAGE + \alpha_2 BPYROP + \alpha_3 LH + \alpha_4 HS + \alpha_5 SC + \alpha_6 CC + \alpha_7 HSI + \alpha_8 EXI + \alpha_9 CDI + \alpha_{10} SPI + \alpha_{11} PROD1 + \alpha_{12} PROD2 + \alpha_{13} USLE + \alpha_{14} DIST4 + \alpha_{15} VA \quad (4.5a)$$

The results of the regression for equation 4.5a applied to peanuts have been shown in Table 4.14. The p-value for the model F-statistic being very high at 0.215, the model estimates did not seem reliable. Model misspecification test results shown in Table 4.8 confirmed the suspicions about the validity of the model represented by equation 4.5a. The model failed to satisfy the individual homoskedasticity test and some of the joint tests, having p-values lower than 0.05.

The model represented by equation 4.5a was therefore modified in order to correct for the heteroskedasticity. First, an investigation into the error term diagnostics revealed that the error was in fact positively related to the variable *BPYROP*, and so each observation on each of the variables in equation 4.5a was divided by the corresponding value of *BPYROP*. The new variables were renamed by adding *I* at the end of their previous names except for *HS* (the dummy for High School education) and *HSI* (dummy for Hired Staff service) which were renamed by adding *II* at the end of each of them. The intercept term, on the other hand was dropped since the old *BPYROP* was converted to *CONST* after the modification. Hence, the model that was finally estimated for aggregate peanut expenditures is given in equation 4.5b below:

$$EXPENDI = CONST + \alpha_1 BPAGEI + \alpha_2 LHI + \alpha_3 HSII + \alpha_4 SCI + \alpha_5 CCI + \alpha_6 HSI + \alpha_7 EXII + \alpha_8 CDII + \alpha_9 SPII + \alpha_{10} PRODI + \alpha_{11} PROD2I + \alpha_{12} USLEI + \alpha_{13} DIST4I + \alpha_{14} VAI \quad (4.5b)$$

The regression results for equation 4.5b are shown in Table 4.15. The model F-test now had a probability value of zero and a high R-square value of 0.725. Hence nearly 75 percent of the variation of the error term could be explained by the model. The validity of the model was further confirmed by the results of the misspecification tests shown in the last column of Table 4.8. The model represented by equation 4.5b satisfied all the model assumptions as seen by the p-values (all greater than 0.05) in Table 4.8.

Table 4.14. Results of regressing aggregate pesticide expenditures in peanut farming on socio-economic, physical, and advisory services variables as represented by equation 4.5a.

Dependent variable:	<i>EXPEND</i>					
Valid cases:	54		Degrees of freedom:	38		
R-squared:	0.350		Rbar-squared:	0.093		
Std error of est:	36.648					
F(15,38):	1.364		Probability of F:	0.215		
Durbin-Watson:	1.491					
Variable	Estimate	Standard Error	t-value	Prob > t	Standardized Estimate	Cor with Dep Var
<i>CONST</i>	-15.703014	43.866540	-0.357972	0.722	---	---
<i>BPAGE</i>	0.539021	0.916880	0.587885	0.560	0.147749	-0.005220
<i>BPYROP</i>	-0.037261	0.847805	-0.043950	0.965	-0.010980	-0.027226
<i>LH</i>	19.801463	33.848044	0.585011	0.562	0.209135	-0.157741
<i>HS</i>	46.268577	31.135663	1.486032	0.146	0.596173	0.140760
<i>SC</i>	48.770829	32.122704	1.518267	0.137	0.476637	0.083522
<i>CC</i>	30.818498	31.147573	0.989435	0.329	0.313933	-0.006255
<i>HS1</i>	42.341409	22.490146	1.882665	0.067	0.321846	0.217654
<i>EX1</i>	-6.412726	21.012522	-0.305186	0.762	-0.052849	-0.212815
<i>CD1</i>	16.317847	16.727350	0.975519	0.335	0.177901	-0.006866
<i>SP1</i>	26.507654	15.051942	1.761079	0.086	0.279964	0.207297
<i>PROD1</i>	-33.343409	14.588124	-2.285654	0.028	-0.352160	-0.316912
<i>PROD2</i>	-6.034749	19.502946	-0.309428	0.759	-0.053157	0.154882
<i>USLE</i>	2.067368	2.138889	0.966562	0.340	0.153933	0.161835
<i>DIST4</i>	-0.000584	0.004019	-0.145271	0.885	-0.023941	0.043938
<i>VA</i>	5.377147	13.462706	0.399411	0.692	0.070068	-0.051423

Table 4.15. Results of regressing aggregate pesticide expenditures in peanut farming on socio-economic, physical, and advisory services variables as represented by equation 4.5b.

Dependent variable:	<i>EXPEND1</i>					
Valid cases:	54	Degrees of freedom:				39
R-squared:	0.725	Rbar-squared:				0.626
Std error of est:	1.613					
F(14,39):	7.331	Probability of F:				0.000
Durbin-Watson:	1.623					
Variable	Estimate	Standard Error	t-value	Prob > t	Standardized Estimate	Cor with Dep Var
<i>CONST</i>	0.516440	0.727922	0.709472	0.482	---	---
<i>BPAGE1</i>	0.475691	0.714196	0.666051	0.509	0.332191	0.535678
<i>LH1</i>	-4.910424	33.710303	-0.145665	0.885	-0.031386	-0.144182
<i>HS11</i>	20.286006	27.757031	0.730842	0.469	0.383059	0.553839
<i>SC1</i>	28.172118	28.248899	0.997282	0.325	0.200729	0.087771
<i>CC1</i>	28.737866	28.247555	1.017358	0.315	0.520206	0.023619
<i>HS111</i>	57.266401	21.096657	2.714477	0.010	0.356859	0.369249
<i>EX11</i>	-9.657936	18.622084	-0.518628	0.607	-0.169374	-0.104655
<i>CD11</i>	6.320349	15.855154	0.398631	0.692	0.052379	0.000331
<i>SP11</i>	29.399107	15.240485	1.929014	0.061	0.184881	0.136805
<i>PROD11</i>	-31.250209	12.006975	-2.602671	0.013	-0.580802	-0.144726
<i>PROD21</i>	-15.155180	18.126256	-0.836090	0.408	-0.116626	0.229565
<i>USLE1</i>	2.026968	2.010125	1.008379	0.319	0.257506	0.503454
<i>DIST41</i>	-0.000530	0.004283	-0.123710	0.902	-0.019221	0.175161
<i>VA1</i>	-6.821123	12.752538	-0.534884	0.596	-0.165287	0.352417

Table 4.15 indicates that the variables *HS111*, *SP11* and *PROD11* were significant at ten percent. Of these three variables, the sign of the coefficient estimate of *PROD1* turned out to be negative while those of the other two variables were positive.

Hence, it can be concluded that the results in this model seem to satisfy those found in 1975 by Von Rumker *et al.*, and in 1986 by Napit *et al.*, both of which showed a percentage increase in pesticide costs due to scouting. Also, the more productive the soil the lower the expenditures on toxic pesticides.

The Pearson product-moment correlation coefficients for *LAGG* and *EXPEND* in the peanut models can be compared again just as in cotton. Table 4.16 shows the matrix of the correlation coefficient obtained for these two dependent variables in peanuts. A value of 0.447 for rho, indicates that the relation between *LAGG* and *EXPEND* in peanuts is moderately positive, just as obtained in cotton. Hence, it may be concluded again that the lack of a strong positive correlation between *LAGG* and *EXPEND* in peanuts, just as in cotton, is probably responsible for different regression results when these two dependent variables are each regressed on the same explanatory variables in the peanut model.

The summary of results given in Table 4.12 for the comparison of regression models in peanuts to the hypotheses in Chapter I shows that chemical dealers and scouting personnel have positive effects on the aggregate pesticide toxicity while hired staff and scouting personnel have positive effects on the aggregate pesticide expenditures. Age had a positive effect on the aggregate toxicity as did farmers with high school and some college education compared to those who had vocational school education. Moreover, the most productive level of soil turned out to have a negative effect on aggregate pesticide expenditures. All other hypotheses stating no influence of the variable to be tested were failed to be rejected by the t-tests on the relevant coefficient. The influence of annual farm sales or leaching could not be tested since it was not possible to include the variable into the model due to estimation problems discussed earlier in section 4.2.

4.4 Concluding Remarks

All information services variables, namely, hired staff, extension agents, chemical dealers, and scouting personnel, seemed to positively affect aggregate toxicity either for cotton or for peanuts or for both crops. One possible conclusion that may be drawn in view of the results obtained so far is that farmers may have been advised to apply chemicals in the production of cotton or peanuts that, although lower in quantity, led to more aggregate toxicity. Another possibility is that the unobserved variables which are correlated with use of information services affect toxicity of pesticides used. On the other hand, the aggregate expenditures on the chemicals applied may be an insignificant part of the farmers' budgets for them to pay much heed to the nature of chemicals applied. Some of the variables like the number of days worked off the farm by the farmer, the annual farm sales and the soil leaching index could not be tested in the models in this study due to data problems discussed in this chapter.

Table 4.16. Pearson product-moment correlation matrix for *LAGG* and *EXPEND* on peanut sites.^a

<u>Peanuts</u>		
Pearson Correlation Coefficients		
Prob > R under Ho: Rho=0 / N = 55		
	<i>LAGG</i>	<i>EXPEND</i>
<i>LAGG</i>	1.00000 (0.0)	0.44718 (0.0006)
<i>EXPEND</i>	0.44718 (0.0006)	1.00000 (0.0)

^a The figures in parentheses denote the probability for testing the null hypothesis that the product-moment correlation coefficient (ρ) between *LAGG* and *EXPEND* in peanuts is zero.

Chapter 5 Summary, Conclusions, and Policy Implications

5.1 Brief Summary of this Study

The research undertaken in this study was concerned primarily with the cotton and peanut farm samples obtained from the Area Studies Surveys conducted by the Economic Research Service of the United States Department of Agriculture in the Albemarle-Pamlico Watershed of Virginia and North Carolina. The main problems discussed in this study relate to the use of farm-advisory or information services in agriculture in the above mentioned region applied to the use of pesticides that may in turn lead to environmental and human health hazards. The primary objectives of this study involved the evaluation of the effects of advisory services (such as hired staff, extension agents, chemical dealers and scouting personnel), of socio-economic factors (such as the farmer's age, education and farming experience), and physical characteristics (such as distance of farm from nearest water source, productivity of farm soil, leaching potential of the farm soil) on the aggregate toxicity of pesticides and on the aggregate expenditures of pesticides applied to cotton and peanut farms.

The formulation of an aggregate toxicity index is a unique feature of this study and has been useful in comprehending, at least partially, the relationship between farmers' use of different farm-advisory services and the toxicity of pesticides used for cotton and peanuts. In Chapter III, a detailed construction of the aggregate toxicity index was presented. The aggregate toxicity index, defined as *AGGINDEX* in this study, was a combination of several factors such as the chronic toxicity measure (measured by reference dose of the chemical active ingredient or a.i.), persistence (measured by half-life of the chemical a.i.), and the rate of application of a pesticide per acre. The formula for constructing *AGGINDEX* was adapted from the toxicity index formulated by Charles Barnard of ERS. *AGGINDEX*, therefore, resulted from an aggregation over all chemicals in a pesticide, and then over all pesticides applied in a sample cotton or peanut crop site in the Albemarle-Pamlico region.

The influence of farm-advisory services, socio-economic and physical variables on the aggregate pesticide expenditures was also determined by constructing an aggregate pesticide expenditure variable (*EXPEND*), which was a summation of the dollars per acre spent on insecticides, herbicides and fungicides for all pesticides applied on a sample cotton or peanut farm in the Albemarle-Pamlico region.

As mentioned in the limitations of this study in Chapter III, the data obtained from the USDA were mostly cross-sectional farm level data for the year 1992, and so only the qualitative nature of the relationship between the choice of farm-advisors and the toxicity of chemicals could be obtained, as described in Chapter IV. For example, it was possible to compare the influence of each of the farm-advisory services, namely, hired staff, extension agents, chemical dealers, and scouting personnel on the aggregate toxicity of chemicals in both cotton and peanut farming. However, the data were not sufficient to

indicate a causal relationship between information services and pesticide toxicity or expenditures.

Farmers tended to indicate that advice from chemical dealers had no effect on pesticide use while scouting personnel, extension, and hired staff reduced their pesticide use. However, advice from hired staff, scouting personnel, and extension agents is associated with increased aggregate toxicity in the case of cotton farming. Chemical dealers' advice and scouting personnel advice are associated with increased toxicity on peanut farms. Scouting personnel advice is associated with increased pesticide expenditures for cotton and peanuts, while hired staff is positively associated with peanut pesticide expenditures. Further investigation of the relationship between pesticide toxicity, expenditures, and advisory services is needed.

5.2 Conclusions and Some Policy Implications

Farmers usually rely on different sources like hired staff, extension agents, chemical dealers, and scouting personnel for information regarding various pest-control technologies and methods. The information that these types of farm advisors communicate to the farmers regarding use of particular pesticides may have important implications in terms of environmental and health concerns. From society's point of view, the decision to use toxic pesticides has to involve not just the market price of the pesticides and their effectiveness in increasing crop yields, but also health and environmental costs. So in view of the negative externalities that toxic pesticide use may produce, an evaluation of the corresponding external costs and the consequent economic trade-offs between toxic pesticide use and environmentally friendly alternatives needs to be made.

Because farmers are guided by the profit motive, it is reasonable to believe that they may fail to take into account the external costs of toxic pesticide use. In fact, some farmers may not even be aware that certain chemicals that they use as pesticides on their farms are extremely hazardous to life, both human and non-human. Under such circumstances, farm-advisory services may be of immense help in conveying information on toxicity to farmers by communicating directly with them.

The results in this study indicate, however, that farmers who reported using one or more of the farm-advisory services had higher aggregate toxicity index than those who did not. If these farm advisors are in fact leading to greater toxicity of pesticide use on farms, then the possible policy implication would be for the government to spend more resources in training the advisors to consider toxicity as they develop pest management programs. The research undertaken in this study explains that aggregate toxicity is a combination of different factors such as reference dose and half-life of the chemical, as well as the rate of application of pesticide products. Hence, information about these factors and the potential adverse effect they may have on the farmer and on the environment should be made common knowledge to both farm advisors as well as

farmers. Training farm advisors on the methods of disseminating important information relating to toxicity and publicizing the aggregate toxicity of products on pesticide packages are some of the possible recourses the government can take. The government could also fund research on less toxic yet effective pesticides. Subsidies could also be provided to farmers for less toxic pesticides.

The basic motive of this study was not to advocate the elimination of pesticides but rather to imply judicious use of these inputs so as not to pose any health hazards to farmers and consumers of agricultural products or any damage to the environment in general. The concept of the aggregate toxicity index used in this study helps shed light not only on the hazards of using chemical pesticides but also on the importance of considering more effective and environmentally friendly alternatives to pest management. Some of the limitations of this study also indicate the need for collection of more in-depth data from farmers, which will help relate pesticide toxicity to socio-economic and physical characteristics and farm advisory services not only in the United States but also throughout the world.

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Appendices

Appendix A: SAS Code for Organizing Data and Creating Variables Used in the Study.

```
/* ===== */
/* Creating a subset of cotton and peanut growing farms from the Main file */
/* =====*/

DATA NEW; SET ERS.ALBPAM_M;
DROP SAMPLE;

DATA NEW1; SET NEW;
SAMPLE=OLDSMPLE;

DATA NU; SET ERS.ALBPAM_P;
DROP SAMPLE;

DATA NU1; SET NU;
SAMPLE=OLDSMPLE;

MACRO VARS SAMPLE BPAGE BPEDUC BPYROP LOTOTAC IGSALES IGAC3 IGQUOTA1
          PM575 PM576 PM577 PM578 PCHERB PCINSECT PCFUNG PCOTHER
          FISTREAM FILAKE CTCROP1 CTCROP2 CTCROP3 CTCROP4
          CTCROP5 CTCROP6 CTCROP7 CTCROP8 CTCROP9 CTCROP10
          CTCROP11 CTCROP12 CTCROP13 CTCROP14 CTCROP15 %
MACRO VARS3 SAMPLE YEARP PRODCODE ASTDRATE AICODE1 AICODE2
          AICODE3 AIAMT1 AIAMT2 AIAMT3 %

DATA ONE; SET NEW1;
KEEP VARS;

PROC IML;

USE ONE VAR{VARS};
READ ALL INTO X;
CLOSE;

T=NROW(X);
COUNTER=J(T,1,0);

DO I=1 TO T;
  COUNTER[I,]=I;
END;

X=COUNTER||X;

DO I=1 TO T;
  MARKER = 0;

  IF (X[I,19]=8 | X[I,19]=16) THEN DO;
    Y=Y//X[I,];
    MARKER=1;
  END;
  IF MARKER=0 THEN DO;
    IF (X[I,20]=8 | X[I,20]=16) THEN DO;
      Y=Y//X[I,];
      MARKER=1;
    END;
  END;
  IF MARKER=0 THEN DO;
    IF (X[I,21]=8 | X[I,21]=16) THEN DO;
      Y=Y//X[I,];
      MARKER=1;
    END;
  END;
```

```

END;
IF MARKER=0 THEN DO;
  IF (X[I,22]=8 | X[I,22]=16) THEN DO;
    Y=Y//X[I,];
    MARKER=1;
  END;
END;
IF MARKER=0 THEN DO;
  IF (X[I,23]=8 | X[I,23]=16) THEN DO;
    Y=Y//X[I,];
    MARKER=1;
  END;
END;
IF MARKER=0 THEN DO;
  IF (X[I,24]=8 | X[I,24]=16) THEN DO;
    Y=Y//X[I,];
    MARKER=1;
  END;
END;
IF MARKER=0 THEN DO;
  IF (X[I,25]=8 | X[I,25]=16) THEN DO;
    Y=Y//X[I,];
    MARKER=1;
  END;
END;
IF MARKER=0 THEN DO;
  IF (X[I,26]=8 | X[I,26]=16) THEN DO;
    Y=Y//X[I,];
    MARKER=1;
  END;
END;
IF MARKER=0 THEN DO;
  IF (X[I,27]=8 | X[I,27]=16) THEN DO;
    Y=Y//X[I,];
    MARKER=1;
  END;
END;
IF MARKER=0 THEN DO;
  IF (X[I,28]=8 | X[I,28]=16) THEN DO;
    Y=Y//X[I,];
    MARKER=1;
  END;
END;
IF MARKER=0 THEN DO;
  IF (X[I,29]=8 | X[I,29]=16) THEN DO;
    Y=Y//X[I,];
    MARKER=1;
  END;
END;
IF MARKER=0 THEN DO;
  IF (X[I,30]=8 | X[I,30]=16) THEN DO;
    Y=Y//X[I,];
    MARKER=1;
  END;
END;
IF MARKER=0 THEN DO;
  IF (X[I,31]=8 | X[I,31]=16) THEN DO;
    Y=Y//X[I,];
    MARKER=1;
  END;
END;
IF MARKER=0 THEN DO;
  IF (X[I,32]=8 | X[I,32]=16) THEN DO;
    Y=Y//X[I,];
    MARKER=1;
  END;
END;

```

```

IF MARKER=0 THEN DO;
  IF (X[I,33]=8 | X[I,33]=16) THEN DO;
    Y=Y//X[I,];
    MARKER=1;
  END;
END;
END;

NAMES={COUNT VARS};

CREATE SUBSET FROM Y[COLNAME=NAMES];
APPEND FROM Y;

/* ===== */
/* Separating out farms that grew only cotton and/or peanuts and nothing else in the year 1992 */
/* ===== */

DATA TWO; SET SUBSET;

IF CTCROP1=8 AND CTCROP2=4 OR CTCROP2=6 OR CTCROP2=20 OR CTCROP2=22
OR CTCROP2=25 OR CTCROP2=26 OR CTCROP2=31 OR CTCROP2=32 OR CTCROP2=33
OR CTCROP2=34 OR CTCROP2=111 OR CTCROP2=131 OR CTCROP2=303 OR
CTCROP2=304 THEN DELETE;
IF CTCROP1=8 AND CTCROP3=4 OR CTCROP3=6 OR CTCROP3=20 OR CTCROP3=22
OR CTCROP3=25 OR CTCROP3=26 OR CTCROP3=31 OR CTCROP3=32 OR CTCROP3=33
OR CTCROP3=34 OR CTCROP3=111 OR CTCROP3=131 OR CTCROP3=303 OR
CTCROP3=304 THEN DELETE;
IF CTCROP1=8 AND CTCROP4=4 OR CTCROP4=6 OR CTCROP4=20 OR CTCROP4=22
OR CTCROP4=25 OR CTCROP4=26 OR CTCROP4=31 OR CTCROP4=32 OR CTCROP4=33
OR CTCROP4=34 OR CTCROP4=111 OR CTCROP4=131 OR CTCROP4=303 OR
CTCROP4=304 THEN DELETE;

IF CTCROP1=16 AND CTCROP2=4 OR CTCROP2=6 OR CTCROP2=20 OR CTCROP2=22
OR CTCROP2=25 OR CTCROP2=26 OR CTCROP2=31 OR CTCROP2=32 OR CTCROP2=33 OR
CTCROP2=34 OR CTCROP2=111 OR CTCROP2=131 OR CTCROP2=303 OR CTCROP2=304
THEN DELETE;
IF CTCROP1=16 AND CTCROP3=4 OR CTCROP3=6 OR CTCROP3=20 OR CTCROP3=22
OR CTCROP3=25 OR CTCROP3=26 OR CTCROP3=31 OR CTCROP3=32 OR CTCROP3=33 OR
CTCROP3=34 OR CTCROP3=111 OR CTCROP3=131 OR CTCROP3=303 OR CTCROP3=304
THEN DELETE;
IF CTCROP1=16 AND CTCROP4=4 OR CTCROP4=6 OR CTCROP4=20 OR CTCROP4=22
OR CTCROP4=25 OR CTCROP4=26 OR CTCROP4=31 OR CTCROP4=32 OR CTCROP4=33 OR
CTCROP4=34 OR CTCROP4=111 OR CTCROP4=131 OR CTCROP4=303 OR CTCROP4=304
THEN DELETE;

IF CTCROP1=4 OR CTCROP1=6 OR CTCROP1=20 OR CTCROP1=22 OR CTCROP1=25 OR
CTCROP1=26 OR CTCROP1=31 OR CTCROP1=32 OR CTCROP1=33 OR CTCROP1=34 OR
CTCROP1=110 OR CTCROP1=111 OR CTCROP1=131 OR CTCROP1=168 OR CTCROP1=303
OR CTCROP1=304 THEN DELETE;

/* ===== */
/* Merging the subset file containing cotton and/or peanut growing farms with the Pesticide file */
/* ===== */

DATA THREE; SET NU1;
KEEP VARS3;
PROC IML;
USE TWO VAR{VARS};

```

```

READ ALL INTO X2;
CLOSE;
USE THREE VAR{VARS3};
READ ALL INTO X3;
CLOSE;

T2=NROW(X2);
T3=NROW(X3);

DO I=1 TO T2;
DO J=1 TO T3;
IF X2[I,1]=X3[J,1] THEN DO;
  Y=Y//X3[J,];
  END;
END;
END;

NAZWY={VARS3};

CREATE FOUR FROM Y[COLNAME=NAZWY];
APPEND FROM Y;

DATA TWO1; SET TWO; PROC SORT; BY SAMPLE;
DATA THREE1; SET THREE; PROC SORT; BY SAMPLE;

DATA FIXED;
MERGE TWO1 THREE1; BY SAMPLE;

/* ===== */
/* Appending new observations in the "Index" file and then renaming and sorting all observations */
/* ===== */

DATA ELEVEN; SET SONALI.OUT;
DATA ADD;
INPUT AI_CODE AI_NAME $21. HALFLIF2 HALFLIFE RFD_ERS RFDINDEX;
CARDS;
32501 DISULFOTON      43.2714  30 .0004 7009855414
122809 FLUAZIFOP-P-BUTYL      21.6404  15 .01  14022760
99801 ETHEPHON        14.4270  10 .005  18697014;
PROC APPEND BASE=ELEVEN DATA=ADD;
DATA TWELVE(KEEP=AI_CODE RFD_ERS HALFLIFE); SET ELEVEN;
PROC SORT DATA=TWELVE; BY DESCENDING AI_CODE;

/* ===== */
/* Merging the data set "Fixed" with the "Index" file using only "aicode1" */
/* ===== */

DATA FINAL1; SET FIXED;
IF COUNT=. THEN DELETE;
DATA FINAL11(KEEP=SAMPLE CTCROP1-CTCROP5 PRODCODE AICODE1 AIAMT1
ASTDRATE);

SET FINAL1;
PROC SORT DATA=FINAL11; BY DESCENDING AICODE1;

DATA THRIFT1; SET TWELVE;
RENAME AI_CODE=AICODE1;

DATA FINALS1; MERGE FINAL11 THRIFT1; BY DESCENDING AICODE1;

IF SAMPLE=. THEN DELETE;
IF PRODCODE<0.001 THEN DELETE;

```

```

IF PRODCODE=0 THEN DELETE;
IF PRODCODE=. THEN DELETE;
IF PRODCODE=9114 THEN DELETE;
IF PRODCODE=9117 THEN DELETE;

IF ASTDRATE=. THEN DO;

    IF SAMPLE=30832 THEN DELETE;
    IF SAMPLE=30992 THEN DELETE;
    IF SAMPLE=31073 THEN DELETE;
    IF SAMPLE=32463 THEN DELETE;
    IF SAMPLE=33352 THEN DELETE;
    IF SAMPLE=33371 THEN DELETE;
    IF SAMPLE=35433 THEN DELETE;
    IF SAMPLE=36093 THEN DELETE;
    IF SAMPLE=37952 THEN DELETE;
    IF SAMPLE=38503 THEN DELETE;
    IF SAMPLE=39761 THEN DELETE;

IF SAMPLE=31661 THEN ASTDRATE=1.5;
IF SAMPLE=32492 THEN ASTDRATE=.5;
IF SAMPLE=32602 THEN ASTDRATE=4.25;
    IF SAMPLE=34762 AND PRODCODE=9049 THEN ASTDRATE=1.00;
    IF SAMPLE=34762 AND PRODCODE=9046 THEN ASTDRATE=0.2;
    IF SAMPLE=34852 AND PRODCODE=9049 THEN ASTDRATE=1.00;
    IF SAMPLE=34852 AND PRODCODE=9046 THEN ASTDRATE=0.2;
IF SAMPLE=39691 THEN ASTDRATE=1.5;

END;

/* ===== */

/* Calculating Index1 for aicode1 */

/* ===== */

DATA CHILL1; SET FINALS1;
INDEX1= HALFLIFE/(RFD_ERS*70*0.000022046*1000000)*(AIAMT1);
PROC SORT DATA=CHILL1; BY PRODCODE;

/* ===== */

/* Merging the data set "Fixed" with the "Index" file using only "aicode2" */

/* ===== */

DATA FINAL2; SET FIXED;
IF COUNT=. THEN DELETE;
DATA FINAL22(KEEP= SAMPLE PRODCODE CTCROP1-CTCROP5 AICODE2 AIAMT2
                                                    ASTDRATE);

SET FINAL2;
PROC SORT DATA=FINAL22; BY DESCENDING AICODE2;

DATA THRIFT2; SET TWELVE;
RENAME AI_CODE=AICODE2;

DATA FINALS2; MERGE FINAL22 THRIFT2; BY DESCENDING AICODE2;

IF SAMPLE=. THEN DELETE;
IF PRODCODE<0.001 THEN DELETE;
IF PRODCODE=0 THEN DELETE;
IF PRODCODE=. THEN DELETE;
IF PRODCODE=9114 THEN DELETE;
IF PRODCODE=9117 THEN DELETE;

IF ASTDRATE=. THEN DO;

```

```

IF SAMPLE=30832 THEN DELETE;
IF SAMPLE=30992 THEN DELETE;
IF SAMPLE=31073 THEN DELETE;
IF SAMPLE=32463 THEN DELETE;
IF SAMPLE=33352 THEN DELETE;
IF SAMPLE=33371 THEN DELETE;
IF SAMPLE=35433 THEN DELETE;
IF SAMPLE=36093 THEN DELETE;
IF SAMPLE=37952 THEN DELETE;
IF SAMPLE=38503 THEN DELETE;
IF SAMPLE=39761 THEN DELETE;

IF SAMPLE=31661 THEN ASTDRATE=1.5;
IF SAMPLE=32492 THEN ASTDRATE=.5;
IF SAMPLE=32602 THEN ASTDRATE=4.25;
  IF SAMPLE=34762 AND PRODCODE=9049 THEN ASTDRATE=1.00;
  IF SAMPLE=34762 AND PRODCODE=9046 THEN ASTDRATE=0.2;
  IF SAMPLE=34852 AND PRODCODE=9049 THEN ASTDRATE=1.00;
  IF SAMPLE=34852 AND PRODCODE=9046 THEN ASTDRATE=0.2;
IF SAMPLE=39691 THEN ASTDRATE=1.5;

END;

/* ===== */

/* Calculating Index for aicode2 */

/* ===== */

DATA CHILL2; SET FINALS2;
INDEX2= HALFLIFE/(RFD_ERS*70*0.000022046*1000000)*(AIAMT2);
IF INDEX2=. THEN DO;
  IF PRODCODE^=7103 THEN INDEX2=0;
  IF PRODCODE=7103 THEN INDEX2=.;
END;
PROC SORT DATA=CHILL2; BY PRODCODE;

/* ===== */

/* Merging data sets with Index1 and Index2 by the product code */

/* ===== */

DATA TEST1; MERGE CHILL1 CHILL2; BY PRODCODE;

/* ===== */

/* Merging the data set "Fixed" with the "Index" file using only "aicode3" */

/* ===== */

DATA FINAL3; SET FIXED;
IF COUNT=. THEN DELETE;
DATA FINAL33(KEEP=SAMPLE PRODCODE CTCROP1-CTCROP5 AICODE3 AIAMT3 ASTDRATE);

SET FINAL3;
PROC SORT DATA=FINAL33; BY DESCENDING AICODE3;

DATA THRIFT3; SET TWELVE;
RENAME AI_CODE=AICODE3;

DATA FINALS3; MERGE FINAL33 THRIFT3; BY DESCENDING AICODE3;

IF SAMPLE=. THEN DELETE;
IF PRODCODE<0.001 THEN DELETE;
IF PRODCODE=0 THEN DELETE;
IF PRODCODE=. THEN DELETE;

```

```

IF PRODCODE=9114 THEN DELETE;
IF PRODCODE=9117 THEN DELETE;

IF ASTDRATE=. THEN DO;

    IF SAMPLE=30832 THEN DELETE;
    IF SAMPLE=30992 THEN DELETE;
    IF SAMPLE=31073 THEN DELETE;
    IF SAMPLE=32463 THEN DELETE;
    IF SAMPLE=33352 THEN DELETE;
    IF SAMPLE=33371 THEN DELETE;
    IF SAMPLE=35433 THEN DELETE;
    IF SAMPLE=36093 THEN DELETE;
    IF SAMPLE=37952 THEN DELETE;
    IF SAMPLE=38503 THEN DELETE;
    IF SAMPLE=39761 THEN DELETE;

IF SAMPLE=31661 THEN ASTDRATE=1.5;
IF SAMPLE=32492 THEN ASTDRATE=.5;
IF SAMPLE=32602 THEN ASTDRATE=4.25;
    IF SAMPLE=34762 AND PRODCODE=9049 THEN ASTDRATE=1.00;
    IF SAMPLE=34762 AND PRODCODE=9046 THEN ASTDRATE=0.2;
    IF SAMPLE=34852 AND PRODCODE=9049 THEN ASTDRATE=1.00;
    IF SAMPLE=34852 AND PRODCODE=9046 THEN ASTDRATE=0.2;
IF SAMPLE=39691 THEN ASTDRATE=1.5;

END;

/* =====*/

/* Calculating Index for aicode3 */

/* =====*/

DATA CHILL3; SET FINALS3;
INDEX3= HALFLIFE/(RFD_ERS*70*0.000022046*1000000)*(AIAMT3);
IF INDEX3=. THEN INDEX3=0;
PROC SORT DATA=CHILL3; BY PRODCODE;

/* =====*/

/* Merging the data set containing Index1 and Index2 with the data set containing Index3
and calculating the Aggregate Index for each farm for the year 1992 */

/* =====*/

DATA CHILL; MERGE TEST1 CHILL3; BY PRODCODE;
DATA BEST; SET CHILL;
INDEX = (INDEX1+INDEX2+INDEX3)*ASTDRATE;
PROC SORT DATA=BEST; BY SAMPLE;

RUN;

PROC SUMMARY DATA=BEST;
    CLASS SAMPLE;
    VAR INDEX;
    OUTPUT OUT=AGGIND SUM=AGGINDEX;
DATA INDEX1(KEEP=SAMPLE AGGINDEX); SET AGGIND;
IF SAMPLE=. THEN DELETE;

DATA SOIL1(KEEP=NRIPTR AWCH AWCL LAYDEPH LAYDEPL LAYERNUM);SET ERS.LAYER;
PROC SORT DATA=SOIL1; BY NRIPTR;

DATA SOIL2(KEEP=SAMPLE NRIPTR CLASS DIST4 USLE); SET ERS.NRI82;
PROC SORT DATA=SOIL2; BY NRIPTR;

```

```

DATA JOIN1; MERGE SOIL1 SOIL2; BY NRIPTR;
PROC SORT DATA=JOIN1; BY SAMPLE;

DATA ADD2; SET JOIN1;
HOLD=(AWCH+AWCL)/2;
THICK=LAYDEPH-LAYDEPL;
TOTAL=HOLD*THICK;

PROC SUMMARY DATA=ADD2;
  CLASS SAMPLE;
  VAR TOTAL;
  OUTPUT OUT=LEACH SUM=LEACH;
DATA LEACH1(KEEP=SAMPLE LEACH); SET LEACH;
IF SAMPLE=. THEN DELETE;

DATA MERGER1; MERGE JOIN1 LEACH1; BY SAMPLE;
  IF FIRST.SAMPLE;
KEEP SAMPLE CLASS DIST4 USLE LEACH;

DATA MAIN; SET BEST; BY SAMPLE;
  IF FIRST.SAMPLE;
KEEP SAMPLE CTCROP1 CTCROP2 PRODCODE INDEX1 INDEX2 INDEX3 INDEX ASTDRATE;

DATA MAIN2; MERGE MAIN INDEX1; BY SAMPLE;

DATA MERGER2; MERGE MERGER1 MAIN2; BY SAMPLE;

DATA MERGER3; MERGE MERGER2 FIXED; BY SAMPLE;
IF SAMPLE=. THEN DELETE;

DATA MAIN3; SET MERGER3; BY SAMPLE;
  IF FIRST.SAMPLE;
KEEP SAMPLE STATE CTCROP1 CTCROP2 BPAGE BPEDUC BPYROP BPWORK IGSALLES
  PM575 PM576 PM577 PM578 PMRANK1 PMRANK2 PMADVISE DIST4 USLE
  CLASS LEACH PRODCODE INDEX1 INDEX2 INDEX3 ASTDRATE INDEX AGGINDEX;

DATA EXPEND1; SET ERS.SMITRA;
IF I_DOLLAR=. AND H_DOLLAR=. AND F_DOLLAR=. THEN DELETE;
PROC SORT DATA=EXPEND1; BY SAMPLE;

PROC SUMMARY DATA=EXPEND1;
  CLASS SAMPLE;
  VAR I_DOLLAR H_DOLLAR F_DOLLAR;
  OUTPUT OUT=EXPEND2 SUM=IDOL HDOL FDOL;

DATA EXPEND3; MERGE EXPEND1 EXPEND2; BY SAMPLE;
  IF FIRST.SAMPLE;
KEEP SAMPLE IDOL HDOL FDOL CROP;

DATA EXPEND; SET EXPEND3; BY SAMPLE;
EXPEND=IDOL+HDOL+FDOL;

DATA MERGER4; MERGE MAIN3 EXPEND; BY SAMPLE;
PROC SORT DATA=MERGER4; BY CTCROP1;

DATA MAIN4; SET MERGER4;
IF CTCROP1=. THEN DELETE;

RUN;

```

Appendix B: Reference Doses, Half-lives, and Toxicity Indices for Pesticide Active Ingredients Used in this Study.

Table B1. Pesticide products with their respective chemical active ingredients (a.i.), reference dose, half-life, and toxicity index values as obtained from the Economic Research Service (ERS) division of USDA.

Product code	Product Name	a.i. Code	a.i. Name	Reference dose	Half-life	Chemical Toxicity Index
1001	Ambush 25W	109701	Permethrin	0.05	30	5607884
1002	Ambush (2EC)	109701	Permethrin	0.05	30	5607884
1004	Asana XL (.66EC)	109303	Esfenvalerate	0.025	35	13078414
1009	Counter (15G)	105001	Terbufos	0.00013	5	359557970
1018	Sevin 80S	56801	Carbaryl	0.1	10	934851
1033	Di-Syston 15% G	32501	Disulfoton	0.00004	30	7009855414
1037	Dyfonate II 10-G	41701	Fonofos	0.002	40	186635276
1039	Dyfonate 4EC	41701	Fonofos	0.002	40	186635276
1043	D-z-n Diazinon 14G	57801	Diazinon	0.00009	40	4147450589
1046	Diazinon AG500 (4E)	57801	Diazinon	0.00009	40	4147450589
1047	Diazinon 14G	57801	Diazinon	0.00009	40	4147450589
1053	Furadan 15G	90601	Carbofuran	0.005	50	92891842
1064	Lannate LV (2.4 lbs.)	90301	Methomyl	0.025	30	11215769
1066	Larvin 3.2	114501	Thiodicarb	0.03	7	2181318
1068	Lorsban 15G	59101	Chlorpyrifos	0.003	30	93464739
1069	Lorsban 4E	59101	Chlorpyrifos	0.003	30	93464739
1080	Mocap 10G	41101	Ethoprop	0.000015	25	15580217970
1082	Mocap EC (6 lbs.)	41101	Ethoprop	0.000015	25	15580217970
1096	Nemacur 15G	100601	Fenamiphos	0.00025	50	1857836836
1097	Nemacur 3E	100601	Fenamiphos	0.00025	50	1857836836
1102	Orthene 75 S	103301	Acephate	0.004	3	7011380
1105	Pounce 1.5G	109701	Permethrin	0.05	30	5607884
1107	Pounce 3.2EC	109701	Permethrin	0.05	30	5607884
1113	Proxol 80 SP	57901	Trichlorfon	0.002	10	46742536
1124	Temik 15G	98301	Aldicarb	0.001	30	280394217
1127	Thimet 20-G	57201	Phorate	0.0005	60	1105276207
1133	Ammo 2.5EC	109702	Cypermethrin	0.01	30	28039422
1134	Ammo WSB (39%)	109702	Cypermethrin	0.01	30	28039422
1135	Cymbush 3E	109702	Cypermethrin	0.01	30	28039422
1151	Furadan 5G	90601	Carbofuran	0.005	50	92891842
1170	Scout X-TRA (0.9 lb EC)	121501	Tralomethrin	0.0075	27	33651758
1172	Sevin 50W	56801	Carbaryl	0.1	10	934851
1246	Baythroid 2 (EC)	128831	Cyfluthrin	0.025	30	11215769
1252	Karate (1EC)	128867	Lambdacyhalothrin	0.005	30	56078843
1256	Thimet 15-G	57201	Phorate	0.0005	60	1105276207
1257	Temik TSX **	98301	Aldicarb	0.001	30	280394217
1257	Temik TSX	56502	PCNB	0.003	21	65439167
1257	Temik TSX	84701	Etridiazole	0.036	103	24453504

Table B1(contd.).

Product code	Product Name	a.i. Code	a.i. Name	Reference dose	Half-life	Chemical Toxicity Index
1258	Orthene 90 S	103301	Acephate	0.004	3	7011380
1314	Mocap Plus 4-2 EC *	41101	Ethoprop	0.000015	25	15580217970
1314	Mocap Plus 4-2 EC	32501	Disulfoton	0.00004	30	7009855414
1316	Orthene Tobacco Insect Spray	103301	Acephate	0.004	3	7011380
4003	2, 4-D/Weedar 64	30001	2, 4-D	0.01	10	9348507
4006	Aatrex 4L	80803	Atrazine	0.035	60	15789660
4007	Aatrex 80W	80803	Atrazine	0.035	60	15789660
4016	Balan EC	84301	Benefin	0.3	40	1244235
4019	Basagran (4L)	103901	Bentazon	0.0025	20	74787818
4021	Bicep 6L *	108801	Metolachlor	0.1	90	7907668
4021	Bicep 6L	80803	Atrazine	0.035	60	15789660
4022	Bladex 4L	100101	Cyanazine	0.002	14	65439550
4027	Bullet (4EC) *	90501	Alachlor	0.01	15	14022760
4027	Bullet (4EC)	80803	Atrazine	0.035	60	15789660
4038	Devrinol 50-WP	103001	Napropamide	0.1	70	6367683
4041	Atrazine 4L	80803	Atrazine	0.035	60	15789660
4042	Atrazine 5L	80803	Atrazine	0.035	60	15789660
4051	Dual (8E)	108801	Metolachlor	0.1	90	7907668
4055	Evik 80W	80801	Ametryn	0.009	60	61404234
4060	Fusilade 2000 (1EC)	122809	Fluazifop-p-butyl	0.01	15	14022760
4065	Hoelon 3EC	110902	Diclofop-methyl	0.002	30	140197108
4069	Lasso (4EC)	90501	Alachlor	0.01	15	14022760
4070	Lasso II (15G)	90501	Alachlor	0.01	15	14022760
4074	Linex 4L	35506	Linuron	0.002	60	276319052
4076	Lorox L (4 lbs.)	35506	Linuron	0.002	60	276319052
4081	Poast (1.5 EC)	121001	Sethoxydim	0.09	5	519362
4084	Princep 4L	80807	Simazine	0.005	60	110527621
4086	Prowl (4EC)	108501	Pendimethalin	0.04	90	19769169
4093	Roundup (4L)	103601	Glyphosate	0.1	47	4373612
4100	Sonalan (3EC)	113101	Ethafuralin	0.04	60	13815953
4104	Sutan+ 6.7E	41405	Butylate	0.05	13	2430612
4107	Tillam 6E	41403	Pebulate	0.007	14	18697014
4108	Treflan EC (4lbs.)	36101	Trifluralin	0.0075	60	73685080
4109	Treflan 5 (EC)	36101	Trifluralin	0.0075	60	73685080
4110	Treflan MTF (4EC)	36101	Trifluralin	0.0075	60	73685080
4111	Treflan TR-10 (10G)	36101	Trifluralin	0.0075	60	73685080
4112	Trilin (4EC)	36101	Trifluralin	0.0075	60	73685080
4139	Harmony Extra (DF) *	128845	Thifensulfuron	0.013	12	8629391
4139	Harmony Extra (DF)	128887	Tribenuron-methyl	0.008	12	14022761
4144	MSMA 4 Plus	13803	MSMA	0.01	10	9348507
4146	Blazer 2L	11402	Acifluorfen	0.013	14	10067623
4147	MSMA 6.6 (EC)	13803	MSMA	0.01	10	9348507

Table B1(contd.).

Product code	Product Name	a.i. Code	a.i. Name	Reference dose	Half-life	Chemical Toxicity Index
4154	Bronco (4EC) *	90501	Alachlor	0.01	15	14022760
4154	Bronco (4EC)	103601	Glyphosate	0.1	47	4373612
4158	Butoxone 200 (2EC)	30819	2, 4-DB	0.008	10	11685634
4159	Butyrac 175 (1.75EC)	30819	2, 4-DB	0.008	10	11685634
4160	Butyrac 200 (2EC)	30819	2, 4-DB	0.008	10	11685634
4161	Canopy (75DG) *	101101	Metribuzin	0.025	40	14930822
4161	Canopy (75DG)	128901	Chlorimuron-ethyl	0.02	40	18663528
4167	Classic (25DG)	128901	Chlorimuron-ethyl	0.02	40	18663528
4176	Cotoran 4L	35503	Fluometuron	0.013	85	58009126
4177	Cotoran 80W	35503	Fluometuron	0.013	85	58009126
4178	Cotoran DF	35503	Fluometuron	0.013	85	58009126
4189	DSMA Liquid (3.6 lbs.)	13802	DSMA	0.01	1000	208968219
4194	MSMA 6 Plus	13803	MSMA	0.01	10	9348507
4218	Gemini (60DG) *	35506	Linuron	0.002	60	276319052
4218	Gemini (60DG)	128901	Chlorimuron-ethyl	0.02	40	18663528
4230	Lariat (4F) *	90501	Alachlor	0.01	15	14022760
4230	Lariat (4F)	80803	Atrazine	0.035	60	15789660
4231	Lasso Micro-Tech (4E)	90501	Alachlor	0.01	15	14022760
4232	2, 4-D/Lithate	30001	2, 4-D	0.01	10	9348507
4236	Meturon 4L	35503	Fluometuron	0.013	85	58009126
4237	Meturon DF (80%)	35503	Fluometuron	0.013	85	58009126
4249	Princep Caliber 90	80807	Simazine	0.005	60	110527621
4250	Probe (WP)	106001	Methazole	99999	14	0
4254	Pursuit (2EC)	128982	Imazethapyr	0.25	90	3163067
4255	Pursuit Plus (EC) *	108501	Pendimethalin	0.04	90	19769169
4255	Pursuit Plus (EC)	128982	Imazethapyr	0.25	90	3163067
4267	Scepter OT (2.5L) *	128848	Imazaquin	0.25	60	2210552
4267	Scepter OT (2.5L)	11402	Acifluorfen	0.013	14	10067623
4269	Squadron (EC) *	108501	Pendimethalin	0.04	90	19769169
4269	Squadron (EC)	128848	Imazaquin	0.25	60	2210552
4272	Storm *	103901	Bentazon	0.0025	20	74787818
4272	Storm	11402	Acifluorfen	0.013	14	10067623
4277	Sutazine+ (EC) *	41405	Butylate	0.05	13	2430612
4277	Sutazine+ (EC)	80803	Atrazine	0.035	60	15789660
4289	Vernam 10-G	41404	Vernolate	0.001	12	112182087
4290	Vernam 7-E	41404	Vernolate	0.001	12	112182087
4296	2, 4-D/Weedone 638	30001	2, 4-D	0.01	10	9348507
4298	2, 4-D/Weedone LV4	30001	2, 4-D	0.01	10	9348507
4310	Zorial Rapid 80 (DF)	105801	Norflurazon	0.04	30	7009855
4311	Butoxone (1.75EC)	30819	2, 4-DB	0.008	10	11685634
4314	Gramoxone Extra (2.5L)	61601	Paraquat	0.0045	1000	464373819

Table B1(contd.).

Product code	Product Name	a.i. Code	a.i. Name	Reference dose	Half-life	Chemical Toxicity Index
4334	Poast Plus (1EC)	121001	Sethoxydim	0.09	5	519362
4352	Partner WDG	90501	Alachlor	0.01	15	14022760
4360	Prowl 3.3 EC	108501	Pendimethalin	0.04	90	19769169
4378	Paarlan E.C.	100201	Isopropalin	0.015	100	57358697
7007	Bravo 500 (4.17EC)	81901	Chlorothalonil	0.015	30	18692948
7008	Bravo 720 (6EC)	81901	Chlorothalonil	0.015	30	18692948
7011	Bravo W-75	81901	Chlorothalonil	0.015	30	18692948
7027	Ridomil 2E	113501	Metalaxyl	0.074	70	8604977
7032	Rovral 4 Flowable	109801	Iprodione	0.04	14	3271977
7034	Sulfur Wettable Powder (95%)	77501	Sulfur	999998	1	0
7035	Terraclor 10% Granular	56502	PCNB	0.003	21	65439167
7060	Kocide 606 (Liq)	23401	Copper hydroxide	999998	2	0
7093	Super Six	77501	Sulfur	999998	1	0
7100	Tenn-Cop 5E	23104	Copper resinate	999998	2	0
7103	Top Cop with Sulfur *	77501	Sulfur	999998	1	0
7103	Top Cop with Sulfur	8101	Basic copper sulfate			
7107	Ridomil PC 11G	56502	PCNB	0.003	21	65439167
7107	Ridomil PC 11G	113501	Metalaxyl	0.074	70	8604977
7120	Terraclor Super X Granular (12.5%) *	56502	PCNB	0.003	21	65439167
7120	Terraclor Super X Granular (12.5%)	84701	Etridiazole	0.036	103	24453504
7123	Vitavax-3F	90201	Carboxin	0.1	3	280455
7125	Bravo S (EC) *	77501	Sulfur	999998	1	0
7125	Bravo S (EC)	81901	Chlorothalonil	0.015	30	18692948
7126	Kocide 404S *	77501	Sulfur	999998	1	0
7126	Kocide 404S	23401	Copper hydroxide	999998	2	0
9008	Royal MH-30 (1.5EC)	51503	Maleic hydrazide	0.5	30	560788
9011	Telone II	29001	Dichloropropene	0.0003	10	311616908
9012	Vapam (3.18EC)	39003	Metam-sodium	0.01	7	6543955
9013	Vorlex *	68103	Methyl isothiocy	999999	7	0
9013	Vorlex	29001	Dichloropropene	0.0003	10	311616908
9038	Pix Plant Regulator	109101	Mepiquat chloride	0.03	1000	69656073
9039	Prep 6EC	99801	Ethephon	0.005	10	18697014
9045	Desiccant L-10	6801	Arsenic acid	0.0042	10	556069472
9046	Dropp (50WP)	120301	Thidiazuron	0.036	10	2596808
9047	Folex 6EC	74801	Tribufos	0.00003	10	3116169077
9048	Harvade - 5F	118901	Dimethipin	0.02	120	49279262
9049	Def 6	74801	Tribufos	0.00003	10	3116169077
9080	Starfire (1.5L)	61601	Paraquat	0.0045	1000	464373819
9100	Prime+	123001	Flumetralin	0.03	20	6232318
9114		79029		.	.	.
9117				.	.	.

Appendix C: Questions Related to the Use of Farm Advisory Services.

Questions used in the Albemarle-Pamlico Area Study survey to get information from farmers regarding farm advisory services for pest management:

1. During the past three years have you used hired staff for pest management in this field? (Include only those trained in pest management, entomology, etc.)

YES - [Enter code 1] NO []

2. During the past three years have you used the local extension service (university, state, federal) for pest management in this field?

YES - [Enter code 1] NO []

3. During the past three years have you used chemical dealers, suppliers or stores for pest management in this field?

YES - [Enter code 1] NO []

4. During the past three years have you used professional scouting for pest management in this field? (Exclude scouting provided by a chemical supplier.)

YES - [Enter code 1] NO []

5. [Skip to item 7 if items 1-4 are all NO.]

Which of these was the most important for pest management on your operation?

[Enter code.] [CODES: 1 - HIRED STAFF, 2 - LOCAL EXTENSION SERVICE (University, State, Federal), 3 - CHEMICAL DEALER, SUPPLIER OR STORE, 4 - PROFESSIONAL SCOUTING]

[]

a. Which would you say was the next most important? []

6. Considering what you would have done without this advice, would you say the advice you received:

[1 - INCREASED YOUR PESTICIDE USAGE?, 2 - DECREASED YOUR PESTICIDE
USAGE?, 3 - HAD NO EFFECT ON THE AMOUNT OF PESTICIDE YOU USED?]

[]

Appendix D: GAUSS Code Used for Ordinary Least Squares (OLS) Regression and for Misspecification Testing of the Models in the Study.

The following GAUSS code was used to test the parameters of the model represented by equation 4.3b and reported in Table 4.10:

```

new ;
_flag = 1 ;
format /rd 9,3 ;

output file = i:\thes12.out reset;
"Thesis Output" ; ? ;

/* Loading data from the disk */
load D[74,20] = i:\data11.txt;

/* Naming variables according to the respective column of the data set */
obs = D[.,1]; expend = D[.,3] ; bpage = D[.,4] ;
bpyrop = D[.,5] ; lh = D[.,6] ; hs = D[.,7] ; vt = D[.,8] ; sc = D[.,9] ; cc = D[.,10] ;
hs1 = D[.,11] ; ex1 = D[.,12] ; cd1 = D[.,13] ; sp1 = D[.,14] ;
prod1 = D[.,15] ; prod2 = D[.,16] ; prod3 = D[.,17] ;
usle = D[.,18] ; dist4 = D[.,19] ; va = D[.,20] ;

/* Creating a dummy variable DUM with a value of 1 at observation numbers 32 and 53 */
z1=zeros(31,1); z2=zeros(20,1); z3=zeros(21,1); o1=ones(1,1);
dum = z1|o1|z2|o1|z3;

xp = rows(expend);
t = seqa(1,1,xp);
const = ones (74,1) ;
x = const~bpage~bpyrop~lh~hs~vt~sc~cc~hs1~ex1~cd1~sp1~prod1~prod2~prod3~usle~dist4~va~dum;

xmc = bpage~bpyrop~lh~hs~vt~sc~cc~hs1~ex1~cd1~sp1~prod1~prod2~prod3~usle~dist4~va~dum;
y = expend;
beta = inv(x'x)*x'y;
nam = "const" | "bpage" | "bpyrop" | "lh" | "hs" | "vt" | "sc" | "cc" | "hs1" | "ex1" | "cd1" | "sp1" |
      "prod1" | "prod2" | "prod3" | "usle" | "dist4" | "va" | "dum" | "expend" ;

/* Ordinary Least Square (OLS) Regression */

_olsres = 1 ;

__altnam = "const" | "bpage" | "bpyrop" | "lh" | "hs" | "vt" | "sc" | "cc" | "hs1" | "ex1" | "cd1" | "sp1" |
          "prod1" | "prod2" | "prod3" | "usle" | "dist4" | "va" | "dum" | "expend" ;

{nam, cov, b, stdb, vc, stderr, s, cor, rsq, resid, dw } = ols ( "" , y , x )?;

/* Residual analysis */

u = resid;
s2 = u'u/(xp-cols(x));

```

The following code and procedures were written in GAUSS for testing model misspecifications by Anya McGuirk and

John Robertson (Associate Professor and former graduate student, respectively, in the Department of Agricultural and Applied Economics at Virginia Tech):

```
/* Testing for Normality */  
normal(u);  
xy(t,u);
```

```
/* Testing for Linearity */  
lreset(y,const,xmc,beta,u,2);
```

```
/* Testing for Homoskedasticity */  
hreset(y,x,beta,u,2);
```

```
/* Testing for Independence */  
AC(y,const,xmc,u,4);
```

```
/* Joint Conditional Mean Test */  
lag = 1;  
reset = 2;  
ntr = 2;  
jmean(y,xmc,beta,u,lag,reset,ntr);
```

```
/* Joint Conditional Variance Test */  
vlag = 1;  
vreset = 2;  
vtr = 2;  
jvar(y,xmc,beta,u,vlag,vreset,vtr);
```

Vita

Sonali Mitra was born in Calcutta on April 5, 1970. She started her education in a boarding school, called Pine Mount, in Shillong in the state of Meghalaya, India, where she spent the four most formative years of her life. She then traveled with her parents to Iraq where she stayed two years and had one of the most interesting times in her life, experiencing the pleasures of travel combined with the horrors of war. She then completed the rest of her high school and college education in the city of Calcutta, India. She received her Bachelor of Science degree in Economics from Lady Brabourne College (University of Calcutta) in 1992, and her Master of Arts degree in Economics from Jadavpur University (Calcutta, India) in 1994. Sonali set foot on the United States of America for the first time on September 18, 1994. She spent her first year in the US doing coursework in the Economics department at Central Michigan University. She then came to Blacksburg (Virginia) in the fall of 1995 to get her Master's degree in Agricultural and Applied Economics at Virginia Polytechnic Institute and State University.