

The World's Largest Open Access Agricultural & Applied Economics Digital Library

# This document is discoverable and free to researchers across the globe due to the work of AgEcon Search.

Help ensure our sustainability.

Give to AgEcon Search

AgEcon Search http://ageconsearch.umn.edu aesearch@umn.edu

Papers downloaded from **AgEcon Search** may be used for non-commercial purposes and personal study only. No other use, including posting to another Internet site, is permitted without permission from the copyright owner (not AgEcon Search), or as allowed under the provisions of Fair Use, U.S. Copyright Act, Title 17 U.S.C.

# The Relationship Between Economically and Environmentally Marginal Land

John Deal Manchester College E-mail:jldeal@manchester.edu

May 31, 2006

Selected Paper prepared for presentation at the American Agricultural Economics Association Annual Meeting, Long Beach, California, July 23-26, 2006

© 2006 by John Deal. All rights reserved. Readers may make verbatim copies of this document for non-commercial purposes by any means, provided that this copyright notice appears on all such copies.

# Abstract

Concerns have frequently been raised regarding the impact of federally-subsidized crop insurance and agricultural subsidy payments on land allocation and crop mix choices. If the reduction in production risk encourages farmers to plant on economically marginal land, it has often been asserted that this will lead to increases in environmental damage, including increases in soil erosion rates. This paper investigates the "conventional wisdom" that economically marginal land is also environmentally fragile, as defined by higher levels of inherent soil erodibility. We address this issue by looking at the distribution of crop yields for 4 major crops across National Resource Inventory (NRI) erodibility classes and by performing regression analysis. Our results indicate that land with higher levels of soil erodibility exhibit lower mean crop yields, a proxy for economic marginality, which lends support to the conventional wisdom.

### 1 Introduction

Recent research undertaken to explore the relationship between government programs, e.g., crop insurance, and acreage allocation decisions (see Wu (1999) and Goodwin, Vandeveer, and Deal (2004), for example) was motivated, in part, by concerns that increases in acreage or changes in input use would lead to a decline in environmental amenities. It has generally been assumed that the reductions in production risk associated with the availability of insurance and income subsidies encouraged production on economically marginal land. In this context, economically marginal land can be thought of as land that would not be cultivated at current output and input prices without the availability of government support programs. The "conventional wisdom" is that economically marginal land is also environmentally fragile, i.e., highly erodible (Goodwin, Vandeveer, and Deal (2004). This assumed positive correlation between economically marginal land and environmentally fragile land has rarely been questioned. In one of the few attempts to address this issue, Heimlich (1989) concluded that there was a relatively weak correlation between economically and environmentally marginal land.

For given output and input prices, land productivity (i.e., potential crop yield) determines whether or not land should be considered economically marginal. If input prices decrease, output prices increase, or the provision of government programs reduces production risk, economically marginal land may be brought into production. If this land is also highly erodible, the increase in cultivated cropland will potentially lead to greater levels of soil erosion, habitat destruction, and water quality degradation. As a result, the environmental impact of the provision of government income support and risk reduction programs depends on the direction and the magnitude of the link between economically marginal and environmentally fragile land.

It has generally been assumed that land retired from production due to its inherent erodibility or erosion history will not entail the sacrifice of high levels of production since erodible land is thought to be less productive than nonerodible land.<sup>1</sup> If there is not a significant negative relationship between land erodibility and productivity, efforts to take highly erodible land out of production (e.g., the Conservation Reserve Program (CRP)) could result in higher levels of foregone production than originally thought. As a result, the opportunity costs, in terms of foregone production, incurred by society when attempting to reduce soil erosion will again depend on the direction and magnitude of the link between economically and environmentally marginal land.

In a comprehensive study of the relationship between risk management policies and environmen-

 $<sup>^{1}</sup>$ In addition to the inherent erodibility of the soil, the impact on productivity will also depend on the tolerance of the land to soil loss. Our measure of erodibility includes the T factor, the measure of tolerance to productivity decreases due to soil loss.

tal outcomes, Soule, Nimon, and Mullarkey (2000) concluded that "the hypothesis that economically marginal land is also environmentally marginal is largely untested" (p.2) and that "research efforts need to be broadened to determine the environmental vulnerability of economically marginal cropland" (p.26). The limited research conducted in this area occurred primarily during the 1980s. Recent changes in federal risk management programs (e.g., increases in federal crop insurance subsidy levels) provide increased incentives for farmers to expand crop acreage on economically marginal land. If the land brought into production is also environmentally fragile, these policies may result in higher levels of environmental damage. Therefore it is increasingly important to explore the relationship between economically and environmentally marginal land.

Contrary to the concerns expressed by many (see Plantinga (1996)) as to the susceptibility of less productive land to soil erosion, one can also provide a reasonable argument that less productive land may be less susceptible to soil erosion (i.e., less erodible). For example, lower land productivity may result from low levels of soil permeability which inhibits the transport of water from rainfall to the rooting zone of the plant. As a result, one would expect to obtain lower crop yields. At the same time, lower soil permeability is associated with lower levels of soil erosion since less permeable soils, such as clay, are less susceptible to wind- or water-induced soil erosion. Therefore, it is theoretically possible that less productive land may be associated with less erodible soil. While "conventional wisdom" would indicate that economically marginal land (i.e., land with lower productivity) should also exhibit higher levels of soil erodibility, this is an open empirical question that deserves further study.

The potential environmental impact of land brought into production can be seen by looking at differences in soil erodibility by changes in land use. Table 1 contains the mean soil erodibility levels of land brought into cultivation during the period from 1982 to 1997.<sup>2</sup> The table designates the land use prior to cultivation and the data indicates the level of soil erodibility as measured after the land was brought under cultivation.<sup>3</sup> Noncultivated cropland and pasture that was brought into cultivation during the period.<sup>4</sup> For example, pasture brought into production during the 1982-1987 period exhibited a level of soil erodibility that was almost twice as large (15.8609 vs.)

 $<sup>^{2}</sup>$ The changes in land use designation are contained in the National Resources Inventory. The NRI contains a number (recordid) that allows one to link data from multiple points in time to one sample site. While data exists at five year intervals, these changes do not take into account changes that may have occurred during the five year inventory period.

 $<sup>^{3}</sup>$ The NRI does not provide measures of erodibility for land (e.g., pastureland) that is not designated as cropland (cultivated or noncultivated) or Conservation Reserve Program land. While the erodibility index was therefore not available for the beginning land use for pastureland, alternative analysis of cultivated and noncultivated cropland indicates that the soil erodibility index values were similar when using the previous or ending year measure.

<sup>&</sup>lt;sup>4</sup>Noncultivated cropland includes land used for horticulture (e.g., fruit or nuts), grass/hay/legume rotations, or land not used for crop production (e.g., corn or cotton) during the previous three years.

8.0736) as the land that remained under cultivation from 1982 to 1987. It is likely that the increases in soil erodibility associated with the cultivation of previously noncultivated cropland and pastureland reflect initial efforts, such as plowing, needed to prepare the land for planting. If agricultural risk management policies encourage farmers to bring pasture and noncultivated cropland into cultivation, this will increase the mean soil erodibility of land under cultivation, at least during the initial periods of cultivation.

Previous Land Use	Soil Erodibility		
	1982-1987	1987-1992	1992-1997
Cultivated	8.0736	7.6931	9.2827
Noncultivated	11.8492	11.8115	16.7845
Pasture	15.8609	13.5452	26.5619

Table 1. Soil Erodibility by Land Use Change

This study attempts to explore this relationship by extending the framework employed by Heimlich (1989). To capture the idea of economic marginality, we equate this concept with land productivity. As with Heimlich's study, we use mean crop yields as a measure of productivity. In contrast to Heimlich, we look at the yields of multiple crops in our study. Heimlich used a measure of soil erodibility (the Erodibility Index) based on the factors contained in the Universal Soil Loss Equation (USLE).<sup>5</sup> While the erodibility index employed by Heimlich only accounted for water-induced erodibility, we also take into account the impact of wind-induced erodibility in our study.

We employ two methodological approaches in our study. First, we analyze the distribution of mean crop yields across different levels of erodibility. A finding that mean crop yields decrease as erodibility levels increase would lend support to the conventional wisdom. Second, we employ multiple regression analysis to determine the contribution of our measure of soil erodibility to the variation in our measures of land productivity. We also include measures of inherent land productivity, climate, and management practices to capture other factors that affect crop yield and yield variability. While many of these factors are relatively stable over time, they can often exhibit a high degree of cross-sectional variability. We employ data from the 1992 NRI and the Soil Record Interpretation (SOILS-5) data in this study. Since the study uses data from one year only, all of the variation in the model is cross-sectional.

This study is organized as follows. Section 2 presents a brief discussion of the literature. Section

<sup>&</sup>lt;sup>5</sup>The USLE predicts the long-run average soil loss associated with runoff from fields with specific characteristics and under specified cropping and conservation practices.

3 presents a discussion of the methodology employed to test the relationship between economic and environmental marginality. In addition, we also discuss the data and the theoretical issues associated with the measures of economic and environmental marginality employed in this study. The presentation and discussion of the results is provided in section 4, while a summation of the findings and concluding remarks are presented in the final section.

# 2 Literature

As previously stated, there has been very little research conducted to explore the relationship between productivity and soil erodibility. In an early effort, Bills (1985)examined the relationship between the yields for two crops - corn silage and hay - and the level of soil erodibility on New York cropland. He used both SOILS-5 and state generated estimated crop yields in the study.<sup>6</sup> Using the  $RKLS^7$  components of the Universal Soil Loss Equation (USLE) to define the inherent physical capacity of the soil to erode, he found that SOILS-5 yields for both crops exhibited a weak negative correlation (ranging from -.093 to -.106) with the level of soil erodibility.

Heimlich's study (1989) is the most comprehensive effort to date to explore the relationship between land productivity and erodibility. In addition, his basic approach forms the starting point of the approach employed in this study. As a result, a detailed discussion of his methodology and results is warranted. Heimlich's purpose was to test the "hypothesis that highly erodible soils are less productive than less erodible soils and empirically investigate the overlap between physically and economically marginal U.S. cropland" (Heimlich (1989), p.1.). He used data from the 1982 NRI survey and the Soil Survey Interpretations Record (SOILS-5) to obtain productivity and soil erodibility measures.<sup>8</sup> The study was national in scope since it used all nonirrigated sample points in the NRI data where at least one of the eight crops used in the study was grown.

His methodological approach consisted of presenting the correlations between measures of productivity and soil erodibility, the distributions of productivity measures by erodibility levels, and regression results obtained by regressing measures of productivity on measures of erodibility. He

<sup>&</sup>lt;sup>6</sup>Soil Interpretation Record (SOILS-5) data is a collection of soil survey attribute information. Among other things, it contains information on physical and chemical soil properties, land use, and estimated crop yields. This data can be linked to the NRI sample sites by a key or pointer (nriptr) contained in both datasets.

<sup>&</sup>lt;sup>7</sup>The RKLS components of the USLE account for the soil and climate variables that affect potential soil erosion. The R variable accounts for the impact of rainfall and runoff on potential soil erosion, the K variable accounts for inherent soil erodibility, and the L and S variables account for the impact of slope length and steepness on potential soil erosion.

<sup>&</sup>lt;sup>8</sup>The SOILS-5 data contains estimated crop yields that can be linked to NRI site data. This allows the researcher to avoid aggregating the NRI data to a level, e.g. county, where crop yield data is available. The crop yields in the SOILS 5 data are estimated to approximate "leading commercial farmers at the management level that tends to produce the highest economic returns per acre" (Heimlich (1989). Therefore the estimated yields may be slightly larger than those obtained over a wide range of farm sizes and management practices.

used the Bills-Heimlich soil erodibility classification system as the measure of soil erodibility.<sup>9</sup> He used corn grain yield and average net revenue from field crops as measures of soil productivity.<sup>10</sup> Dummy variables for USDA land capability classes and subclasses and USDA prime farmland designation were included in the regression equations as independent variables to proxy for measures of inherent land productivity.

In the correlation results, Heimlich found that the relationship between the Bills-Heimlich erodibility measure and both productivity measures (i.e., corn yield and net revenue) was negative and not significantly different from zero (-.110 and -.059, respectively). While the signs were consistent with the hypothesis that less erodible land is more productive, the magnitudes of the correlations were relatively small. He also found a weak and negative relationship between land capability class and both productivity measures. The relationship between the prime farmland designation and both productivity measures was positive, but also weak. In terms of the independent variable correlations, the Bills-Heimlich measure of soil erodibility was not highly correlated with either of the inherent land productivity independent variables, with a .318 correlation with USDA land capability classes and a -.187 correlation with the USDA prime farmland designation.

When analyzing corn grain yield by level of erodibility and land capability class, Heimlich found that yields were higher on nonerodible land for land capability classes 1-3, but were lower (except for wind erodible land) for capability classes 4-8. Even in capability classes 1-3, crop yields were almost as high (96 bushels/acre) on moderately erodible land as on nonerodible land (99 bushels/acre). The same pattern held when analyzing corn yields by erodibility and prime farmland designation. For example, corn yields on nonprime farmland in the moderately erodible class (83 bushels/acre) were higher than those in the nonerodible class (76 bushels/acre). Similar results were generated when net crop revenue was used as the measure of productivity. Results for both measures of productivity indicate that the conventional wisdom that productivity is lower on highly erodible lands may not be accurate.

Heimlich used multiple regression analysis to decompose the impact of soil erodibility classifications on productivity. Specifically he regressed the two measures of productivity on the following independent variables: Bills-Heimlich soil erodibility classes, USDA land capability classes, USDA land capability subclasses, and the USDA prime farmland designation. The measures of inherent land productivity (i.e., the prime farmland designation and the class/subclass designations) were

 $<sup>^{9}</sup>$ The Bills-Heimlich classification system used the *RKLS* components of the USLE to partition cropland into three classes - highly erodible, moderately erodible, and nonerodible - based on its physical characteristics and the type of cropping activities conducted on the land.

<sup>&</sup>lt;sup>10</sup>The net revenue measure was calculated as the gross revenue of eight major field crops minus their variable costs of production. This measure was employed as an alternative to corn yields since previous research indicated that crop yields on the same land are often not highly correlated. Therefore the use of one indicator crop may bias the results to the degree that it may not represent the yield-land erodibility relationship for all crops.

included to capture the impact of land characteristics, excluding land erodibility, on the dependent variables. The independent variables were all discrete categorical variables that were represented by dummy variables. The coefficients on these regressors indicated how much that attribute added or subtracted from mean crop yield and net revenue. The estimated yields were generated by summing the coefficient estimates on each regressor.

In general, highly erodible land added more to corn grain yield and net revenue than did nonerodible land. Highest yields were generated on highly erodible land, while lowest yields were generated on wind erodible land and nonerodible land. For example, nonerodible land added 137.3 bushels to corn grain yield, while highly erodible land added 142.4 bushels. Land capability subclass *e* where potential soil erosion was deemed to be the primary limiting factor to agricultural production subtracted 12.5 bushels from corn grain yields. While this *e* subclass result lends support to the view that erodible land is less productive, the results for the land capability classes were not as definitive. For both measures of productivity, land capability classes 1-3 exhibited higher productivity than classes 4-8, but productivity did not decrease for each increasing class level. For example, land in LCCs 4 and 5 subtracted more from corn grain yield than did land in LCCs 6 and 7.

In a study of the use of productivity measures to target conservation programs, Runge, Larson, and Roloff (1986) compared a measure of erosion potential, i.e., land erodibility, with a measure of land productivity. Runge et al. used the Bills-Heimlich measure of soil erodibility, while the productivity index was constructed to incorporate the factors that lead to suitable root growth.<sup>11</sup> They conducted their study for six Major Land Resource Areas (MLRAs) in the Midwest using 1982 NRI and SOILS-5 data. While MLRAs with low erosion potential generally had high values for the productivity index, the third highest value for the productivity index occurred in a MLRA with the most erodible land. In addition, the most productive land was not found in the MLRA with the least erodible land. Exploring the relationship between air pollution and crop yield, Westenbarger and Frisvold (1995) found a negative relationship between corn and soybean yields and the Bills-Heimlich measure of soil erodibility.

Most efforts to test the relationship between economic and environmental marginality fail to take into account differences that may exist across crops and geographic regions. <sup>12</sup> Little research

<sup>&</sup>lt;sup>11</sup>The adequacy of root growth is considered to be essential to potential plant growth. Among the factors included in the productivity index were the sufficiency of available water capacity and the sufficiency of bulk density.

<sup>&</sup>lt;sup>12</sup>While Heimlich's net revenue measure did take into account differences in crops, the choice of revenue as a proxy for land productivity masked the fundamental relationship between crop yield and soil erodibility. For instance, land with highly erodible soil may be associated with low crop yields. At the same time, an increase in output prices or reduction in input prices may yield higher revenue on the same highly erodible soil. The first case generates a negative relationship between erodibility and productivity, while the second yields a positive relationship. Unless output and input prices are site-specific, revenue may not capture the direct relationship between soil productivity and soil erodibility.

has been conducted during the last decade to take advantage of improvements in the statistical reliability of the NRI data used in many of these studies. Given greater data reliability, the potential environmental impacts of government policy-induced expansions in production, and the potential opportunity costs associated with acreage reduction programs, this relationship deserves a more comprehensive and updated analysis.

# **3** Methodology and Estimation

#### 3.1 Measures of Economic Marginality

The first step in undertaking this study is the development of empirical measures of economic and environmental marginality. The concept of economic marginality is state dependent. Land that could not be economically cultivated under some level of output (input) prices and policy regimes may come under cultivation under some other price and policy regime. Holding prices and government policies constant, an increase in the productivity of the land increases the likelihood that a particular field will be brought into cultivation. Assuming that price and policy changes are not specific to geographic location, differences in economic marginality across space would be highly dependent on differences in land productivity. Since the data used in this study varies across space (not time), differences in land productivity will determine which land should be identified as economically marginal. We use mean crop yield as our measure of productivity in this study.<sup>13</sup>

While previous studies used one or two indicator crops (see Bills (1985), Heimlich (1989), and Westenbarger and Frisvold (1995)) to proxy for land productivity, different crops exhibit complex interactions with soil characteristics and climate that vary during the period of the growing season. In particular, different crops may require different types of soil for growth. For example, corn and soybeans grow best on high-quality finely-textured soils, while wheat grows best on deep fertile soils (Wu and Segerson (1995)). By looking at only one crop, it may be difficult to capture the different impacts of soil erodibility on crop productivity across different types of soil. Motivated by this potential concern, we include equations to model mean yield for the following crops: corn, soybeans, cotton, and grain sorghum. The inclusion of these four crops ensures that a variety of different soil types and characteristics are studied.

The mean crop yield data we use in this study comes from two different sources - SOILS-5 estimated crop yields and NASS county-level crop yields. Following the approach employed by Heimlich, we use the SOILS-5 estimated mean crop yields in the site-specific portion of our study.

<sup>&</sup>lt;sup>13</sup>Differences in crop yield may result from differences in the physical, chemical, and biological characteristics of the soil. It may also capture substitution of other inputs, e.g., fertilizers, for land.

This data was collected and analyzed by the USDA's Soil Conservation Service (SCS), which later became the Natural Resources Conservation Service (NRCS). In addition to collecting data on estimated crop yields, the NRCS collects data on soil characteristics (e.g., texture, organic matter content, and water holding capacity), climate characteristics (e.g., mean rainfall and temperature), and physiographic characteristics (e.g., slope and land cover) for individual soil mapping units.<sup>14</sup>

The crop yields are estimated for a series of benchmark soils. Yield estimates for other soils are then made by comparing the key soil properties (e.g., pH levels and water holding capacity) of the soil in question with the soil properties of similar benchmark soils. In addition, differences in climate between the mapping units are taken into account when assigning estimated yields to each site. These soil property comparisons and the estimated crop yields are based on the judgments of soil scientists, agronomists, and conservationists. A number of sources of crop yield information are used to develop the SOILS-5 yield estimates for the benchmark soils. These estimates are based on yield measurements from all of the following: (1) commercial farm fields, (2) field trials for particular farming practices, and (3) small research plots at experiment stations and other research institutions. Crop yields are estimated for soils on which the particular crop is most commonly grown.<sup>15</sup>. Attempts are made to employ ten years of data, if available, when estimating crop yields.

Crop yields are estimated assuming that the farmer employs a high level of management. The National Soil Survey Handbook defines a high level of management as "a level obtained by leading farmers that produce the highest economic returns per acre. It includes the best varieties; balancing plant populations and added nutrients to the potential of the soil; control of erosion, weeds, insects, and diseases; maintenance of optimum soil tilth; adequate soil drainage; and timely operations."<sup>16</sup> Given the level of management assumed for the crop yield estimates, those yield estimates should represent the upper end of the yield distribution.

NASS county-level mean crop yields are used for the aggregate portion of our study.<sup>17</sup> While these yields are not directly attributable to the individual NRI sample points (and thus may mask the heterogeneity between sites), they are constructed from historical crop yield data, and thus provide an alternative to the SOILS-5 estimated crop yields.

Since two sources of crop yield data are employed in this study, a comparison of the summary statistics of the two measures is warranted. Table 2 provides summary statistics comparing the

 $<sup>^{14}</sup>$ A soil mapping unit is a collection of areas that are defined in terms of their soil components or miscellaneous areas, where miscellaneous areas are areas that contain no recognizable soil but share common observable surface features, such as rock formations and vegetation.

 $<sup>^{15}</sup>$ Crop yields are not reported on soils where they are too low to be economically feasible or where they are economically feasible but not competitive with other potential crops (Heimlich (1989))

<sup>&</sup>lt;sup>16</sup>The National Soil Survey Handbook acts as a guideline for soil scientists when collecting soil samples, measuring soil characteristics, and estimating crop yield data.

<sup>&</sup>lt;sup>17</sup>See http://www.usda.gov/nass/nassinfo/estimate.html for a description of NASS data collection methods.

NASS mean crop yields (N) and the SOILS-5 estimated crop yields (S). To provide a direct comparison to the NASS data, the SOILS-5 data were aggregated to the county level before the calculation of the summary statistics.<sup>18</sup>

Crop	Summary Statistics					
	Obs.	Mean	St. Dev.	Median	Correlation	
Corn(N)	2490	91.3699	25.9118	89.4100	.2661	
$\operatorname{Corn}(S)$	1724	90.3162	30.9964	95.4650	(.0242)	
Cotton(N)	624	544.3834	197.0318	537.7506	.5627	
$\operatorname{Cotton}(S)$	366	552.5802	211.0526	599.5283	(.0532)	
Soybeans(N)	1998	28.3325	6.1780	27.7800	.4356	
Soybeans(S)	1338	32.7754	9.2410	34.0861	(.0274)	
Sorghum(N)	1512	55.5006	15.9962	54.4000	.3095	
Sorghum(S)	456	47.7991	21.2240	47.4724	(.0474)	

Table 2. Comparison of NASS and SOILS-5 Mean Crop Yields

The standard errors of the correlation coefficients are in parentheses.

Differences are readily apparent when comparing the NASS and SOILS-5 data. While the SOILS-5 yields were estimated to reflect the implementation of a "high" level of management, and therefore should reflect the upper end of the yield distribution, the NASS mean yields were higher for 2 of the 4 crops. With respect to the median yield, the SOILS-5 data yielded higher median yields for 3 of the 4 crops. One possible reason that the SOILS-5 mean yields were not consistently higher than the NASS mean yields was that the optimal choice for a profit-maximizing farmer may have been to employ the "high" level of management practices assumed in the construction of the SOILS-5 estimates. Alternatively, the differences between the NASS and SOILS-5 data may simply reflect problems associated with the subjective nature of the SOILS-5 crop yield estimation process.

The correlations between the NASS and SOILS-5 mean yields range from .266 for corn to .563 for cotton.<sup>19</sup> Finally, the sample size is consistently lower for the SOILS-5 data, which indicates that actual production was undertaken in counties where SOILS-5 yield estimates were not reported. This result is somewhat surprising since the SOILS-5 estimates are provided for each mapping unit if the crop can be produced in an economically viable manner on the land, whether or not the crop was actually grown on the land.

<sup>&</sup>lt;sup>18</sup>The SOILS-5 crop yields can be linked to each NRI site and then aggregated to the county level by the use of the NRI weighting factor (*xfact*) which accounts for the acreage represented by each NRI site.

<sup>&</sup>lt;sup>19</sup>The correlation coefficients presented are the Fisher's Z transformation of Pearson correlation coefficients. We used this transformation to calculate standard errors that could be used to calculate confidence intervals.

#### 3.2 Measure of Environmental Marginality

To act as a proxy for environmental marginality in this study, we construct a soil erodibility index from the water and wind erodibility indices contained in the NRI data. The erodibility index EIis a numerical value that expresses the potential for a soil to erode by considering the properties of the soil (chemical and physical) and the climatic conditions where the soil is located. The EI does not take into account cropping or conservation management practices, so it measures the "inherent physical erodibility" of the soil. The higher the EI value, the more susceptible the soil is to erosion and the greater the investment needed to maintain production on the soil. A value of EI greater than 8 is the criteria that is employed by the USDA to denote a plot of land as being "highly erodible."

The erodibility index employed in this study is constructed as the sum of the numeric values associated with the wind and water erodibility indices.<sup>20</sup> The water-induced erodibility index is based on use of the RKLS components of the Universal Soil Loss Equation (USLE), where K is an inherent soil erodibility factor, R is a rainfall erosivity factor, L is a slope-length factor, S is a slope-steepness factor. The K factor value for a particular soil type is determined from an equation that includes the following variables: silt percent, sand percent, organic matter content, structure (e.g., fine granular soil), and permeability . The K factor is assumed to be constant for each soil type, regardless of the production practices undertaken on the soil or the climatic differences associated with the geographic location of the soil. The rainfall erosivity factor R accounts for the soil erosivity associated with the impact of rain drops on the soil and the resulting runoff associated with the impact. It is a function of the kinetic energy associated with the rain drop impact and the maximum 30 minute intensity of the rainfall (Mitchell and Bubenzer (1980)).

The RKLS measure expresses the level of sheet and rill erosion that would occur if the field were maintained in clean-tilled fallow (Lee and Goebel (1986)). The index is adjusted (i.e., RKLS/T) to take into account the tolerance of the soil to maintain productivity in the presence of inherent soil erodibility. The T value is defined as the "the maximum rate of annual soil erosion that may occur and still permit a high level of crop productivity to be obtained economically and indefinitely" (Lee and Goebel (1986), p. 42). Wind-induced soil erodibility is measured as (C \* I/T), where Cmeasures the climatic components (e.g., windspeed and duration), I measures the susceptibility of the soil to wind erosion, and T measures soil tolerance. The I component is primarily a function of the surface cover and soil texture, including particle size (clods vs. fine granular) and ridge height and length, which is primarily a function of tillage practice.

<sup>&</sup>lt;sup>20</sup>These indices account for factors that affect the erodibility of the land without regard to the usage or production practices employed on that land.

In summation, we employ two measures of land productivity (mean crop yield and the coefficient of variation of mean crop yield) to proxy for economic marginality. The mean crop yield measure used in the site-specific research is the SOILS-5 estimated crop yield, while NASS county-level mean crop yield data were used in the aggregate portion of this study. Since the SOILS-5 data contain no measure of crop yield variability, the coefficient of variation of mean crop yield could be constructed only for the NASS data. We employ an erodibility index that incorporates the impact of water and wind on soil erodibility to proxy for environmental marginality. A list of variables and summary statistics for the site-specific data can be found in Table 9, while a list of variables and summary statistics for the aggregate data can be found in Table 10.<sup>21</sup>

#### 3.3 Site-Specific Yield Model

Past research (Kaufmann and Snell (1997), for example) has shown that any model attempting to explain crop yield should contain the following factors: management practices, climate, and soil characteristics.<sup>22</sup> Crop yield response models have typically been estimated in a single-equation framework with a linear model specification (Dixon et. al. (1994)). Hansen (1991) concluded that "commonly estimated yield functions are linear across most inputs with quadratic or logarithmic measures of particular inputs with nonconstant marginal products." He tested alternative functional forms (logarithmic and translog) for corn and soybean crop yield equations and found that the linear model performed better. We use a linear specification of the crop yield equations in our study.

We use ordinary least squares (OLS) to estimate multiple regression equations with crop yield as the dependent variable and the aforementioned factors as regressors. While including rainfall, temperature, soil characteristics, and management practice variables in each equation, we estimate a separate equation for each of the crops in our study. The general form of the crop yield model is given by the following equation:

$$YLD_{i} = b_{0} + b_{1} \cdot TEMP + b_{2} \cdot SQTEMP + b_{3} \cdot PRECIP + b_{4} \cdot SQPRECIP + b_{5} \cdot TEMP * RAIN + b_{6} \cdot EI + b_{7} \cdot AWC + b_{8} \cdot CFACT + \epsilon_{i}$$

$$(1)$$

where  $YLD_i$  is the yield of crop *i*, *TEMP* is monthly mean temperature, *SQTEMP* is the square of monthly mean temperature, *PRECIP* is monthly mean precipitation, *SQPRECIP* is the square of monthly mean precipitation, *TEMP* \* *RAIN* is an interaction term between mean monthly temperature and precipitation, *EI* is the measure of soil erodibility, *AWC* is average water holding capacity, *CFACT* is the cropping management factor, and  $\epsilon_i$  is an error term.

 $<sup>^{21}</sup>$ The summary statistics for the squared climate variables and the temperature/precipitation interaction terms are not included in the tables.

<sup>&</sup>lt;sup>22</sup>Crop yield response models that employ time-series data should also include a variable to capture technological change. While technology adoption differs across space, the major impact occurs over time.

Crop yields for soybeans, upland cotton, grain sorghum, and corn were used in this study. The yield data are the estimated yields contained in the SOILS-5 dataset. Even though crop yields were estimated for land defined as "noncultivated" cropland in the NRI if the soil could sustain production, we use data only from land defined as "cultivated cropland." This makes the comparison with the NASS county-level data more reasonable since actual yield data would have been collected only for land that was under cultivation. Since the SOILS-5 yields reported in 1992 (the data employed in this study) were estimated from data collected, when available, over the previous ten year period, we included all sites that were classified as "cultivated cropland" in either the 1987 or 1992 NRI. In the SOILS-5 data, crop yields were estimated for both irrigated and nonirrigated cropland. We ran regressions using both irrigated and nonirrigated crop yield data for this study, though only the results from the nonirrigated yields are presented.<sup>23</sup>. We include a variable, the percentage of nonirrigated cropland in the county, in the aggregate portion of our study to account for differences in nonirrigated and irrigated yields since we use total (irrigated and nonirrigated) yields from the NASS data. We chose to use total crop yield data since NASS fails to report irrigated and nonirrigated yields for a large number of counties.

To capture the inherent productivity of the soil, we include the average water holding capacity (AWC). Average water holding capacity, the ability of the soil to store and supply water for plant use, is critical for plant development, particularly in areas that have limited and/or variable precipitation. The AWC was constructed from data contained in the SOILS-5 dataset. The maximum and minimum values for the variable are reported for individual soil layers. To construct measures that could be linked to the NRI site data, the minimum and maximum values of the AWC were averaged for each soil layer. The resulting mean value was then multiplied by the number of inches in that soil layer. The resulting sum was then summed over all soil layers down to a predetermined soil depth. The resulting sum was then divided by the number of inches to the predetermined soil depth; therefore, the final value of the variable was reported per inch of soil. We used a soil depth of 30 inches in this study to construct our soil productivity measure.

Although the impact of weather variables on crop yield has generally been recognized (for example, see Runge(1968); Thompson (1969); and Teigen and Thomas (1995), the complex interactions among weather, biological and chemical processes, and technological factors make it difficult to separate the crop yield impact of weather from those associated with the other variables (Metcalfe and Elkins (1980)). Even with this limitation, the importance of including weather variables in any crop yield model can be demonstrated by noting that Teigen and Thomas found that over 90%

 $<sup>^{23}</sup>$ The results were robust to the choice of irrigated or nonirrigated yield. We present the nonirrigated yield data to facilitate comparisons with the results found in (Heimlich (1989)

of the variability of corn and soybean yields in the United States between 1950 and 1994 could be explained by variations in monthly temperature and rainfall.

While Kaufmann and Snell (1997) used rainfall and temperature data that corresponded to the phenological stages of crop development, they were looking at only one crop (i.e., corn) and one geographic area (i.e., the Corn Belt).<sup>24</sup> The more typical approach is to include average temperature and rainfall measures over the growing season (e.g., Westenbarger and Frisvold) or include monthly measures of those variables for some or all months over the growing season (e.g., Dixon and Segerson (1999)). Ideally we would like to model climate variables in a manner that corresponds to the phenological stage of crop development rather than in a manner that corresponds to calendar designations, i.e., months. However, the scope of this study (i.e., the large geographic area and number of crops under study) and the limitation of available data prohibited a detailed modeling of the impact of climate variables on the phenological stages of crop development. To attempt to capture the impact of climate on crop yield, we include mean temperature (TEMP)and mean precipitation (PRECIP) for the critical months during the year. For the crops in our study, adequate precipitation and temperature in the months of May, June, July, and August are crucial for plant growth. Since the weather data is not site-specific, we assign the county averages to each NRI site within the county. Since crop yields have not been found to be a linear function of climate variables, a quadratic term was included for temperature (SQTEMP) and precipitation (SQPRECIP) to capture those nonlinear effects. A negative (positive) sign on the quadratic term would indicate a(n) diminishing (increasing) marginal impact of climate on crop yield. In addition, the impact of temperature on crop yield is highly dependent on the presence of rainfall (and vice versa). For example, the effect of above average temperatures may be mitigated with higher than average rainfall. We include an interaction term between the temperature and precipitation variables in each month to capture this effect.

While differences in input usage can account for differences in crop yield across space, data on chemical usage (expenditure) or capital intensity/technology adoption do not exist at the NRI site level. In an effort to capture the impact of these factors, we include a NRI variable, the C factor (CFACT), which is designed to capture the impact of cropping management practices.<sup>25</sup> Among other things, the C factor incorporates the impact of cover, cropping sequence, residue management, conservation tillage, growing season length, and cultural practices on crop production (Mitchell and

<sup>&</sup>lt;sup>24</sup>The phenological stages of crop development indicate the different stages of plant growth.

 $<sup>^{25}</sup>$ The C factor is calculated as the ratio of soil loss from a specific combination of cropping practices to the soil loss associated with land in a tilled, continuous fallow condition. While the C factor directly addresses the impact of management practice on soil loss, its component factors also contribute to differences in yield. Given the lack of site-specific input and management practice data with respect to crop yield, the C factor provides a reasonable proxy measure.

Bubenzer (1980). The lower the C factor, the less soil loss that should occur from a given set of cropping management activities; therefore, a lower C factor would indicate the implementation of more intensive management practices with respect to the reduction in soil loss.<sup>26</sup> While these practices (e.g., conservation tillage) may enhance productivity in the long-run, it is likely that crop yields may decline in the short-term. Therefore, a higher C factor value may be associated with higher crop yields, at least in the short-run.

#### 3.4 Aggregate Models

For the aggregate portion of the study, mean crop yields were constructed as ten-year (1983-1992) crop yield averages using NASS county-level yield data.<sup>27</sup> The site-specific variables contained in the NRI data were aggregated to the county level to correspond to the NASS data.<sup>28</sup> The NRI contains a weighting factor (xfact) that is equivalent to the number of acres that each NRI sample point represents. The xfacts are summed for each county to give the total number of acres represented by the NRI sample points. The attribute value (e.g., C factor) is multiplied by the xfact, and then summed over all NRI sites within the county. Finally, the value obtained by summing the weighted attribute values was divided by the sum of the xfacts for the county in which the sites reside to obtain a county average for the attribute in question. County averages of the soil erodibility measure EI (AGEI), C factor (AGCFACT), and average water holding capacity (AGAWC) were constructed in this manner. While the SOILS-5 data provided yields for irrigated and nonirrigated land, we constructed a variable (PERNIRR) for the aggregate portion of the NRI study to capture the percentage of nonirrigated cropland within the county. All data from the NRI used to construct the county-level aggregate measures were limited to those sites associated with the cultivated cropland designation.

While differences in crop yield and yield variability across time and space are functions of input use and technological change, data limitations complicate their inclusion within our empirical framework. For example, crop-specific chemical usage or expenditure data are not available on the scale (i.e., county-level) employed in this study.<sup>29</sup> While technological change (e.g., precision farming and genetically engineered crops) has led to increases in crop yields over time, our focus is on

 $<sup>^{26}</sup>$ The inclusion of the C factor and the erodibility index in our regression equations raises a potential issue of collinearity. One could expect that higher inherent soil erodibility would encourage farmers to undertake cropping practices, e.g., conservation tillage, to reduce potential soil loss. Pearson correlation coefficients that range from -.115 (SOILS-5) to -.140 (NASS) indicate that the inclusion of both variables does not pose a major problem.

 $<sup>^{27}</sup>$ For each crop model, we used only those counties where the crop in question accounted for 10% or more of the total planted acres in the county.

 $<sup>^{28}\</sup>mathrm{The}$  temperature and precipitation data were already reported at the county level.

 $<sup>^{29}</sup>$ An alternative model specification that included county-level total chemical expenditures was estimated. Given the lack of crop-specific expenditures, the results were difficult to interpret, and their inclusion did not change the relationship between crop yield (yield variability) and soil erodibility.

differences in crop yield across space. As a result, differences in technology adoption across space are more relevant to our study. Though a body of research (see Daberkow and McBride (1998); Khanna, Epough, and Hornbaker (1999); and El-Osta and Mishra (2001)) have demonstrated a positive correlation between technology adoption and size of the farming operation (e.g., average number of acres comprising the farm), farm size could also represent a number of other influences, including economies of scale.<sup>30</sup> Finally, the rapid technological change of the 1990s occurred after our period of study. To avoid the lack of crop-specific chemical expenditure data and the difficulties associated with modeling technology adoption, we included the county average C factor (AGCFACT) to account for cropping management choices.

While crop yields are a proxy measure for economic marginality, the variation in crop yields may also play a significant role in the farmer's perception of the desirability of initiating or maintaining crop production on a particular plot of land. To account for this, we develop a measure of yield variability from the NASS time-series data. We construct the coefficient of variation of the tenyear average (1983-1992) of mean crop yields at the county level as our measure of yield variability. Many of the factors that contribute to crop yield should also contribute to yield variability. As a result, we include the same explanatory variables in the crop yield variability model as we did in the county-level crop yield model.

#### 3.5 Data

This study makes use of data collected from a number of sources. In particular, we make extensive use of 1982, 1987, and 1992 NRI data (see chapter 1 for a general discussion of the NRI). Among other things, the measure of soil erodibility (EI) and the cropping management factor (CFACT)were contained in the NRI data. The soil productivity measure (AWC) was obtained from the Soil Survey Interpretations Record (SOILS-5) data. The estimated crop yields used in the site-specific portion of the study were also obtained from the SOILS-5 data, while the county-level mean crop yield data (and the constructed coefficient of variation data) were obtained from the NASS agency of the USDA.

In addition to the site-characteristic and yield data, our study required data on other variables that have an impact on crop yield. Monthly mean temperature and precipitation data were obtained from the PRISM database created from research undertaken by the USDA and Oregon State University. The data used in this study were 30 year (1961-1990) averages of precipitation and temperature for all counties in the United States (excluding counties in Alaska and Hawaii). The

<sup>&</sup>lt;sup>30</sup>An alternative model specification that included farm size was estimated, but the results were difficult to interpret. In addition, their inclusion did not change the relationship between crop yield (yield variability) and soil erodibility.

data on the measure of scale (i.e., average farm size in acres) was taken from the 1992 USDA Agricultural Census, while data on average chemical expenditures was constructed from 1987-1992 chemical expenditure data contained in the Regional Economic Information System (REIS) database from the Bureau of Economic Analysis (BEA). Data on these variables were collected at the county level.

# 4 Results

#### 4.1 Acreage Distributions

The fact that cropland was not cultivated at a point in time indicates that the land was economically marginal at the existing input/output prices and government policy parameters. To determine if economically marginal land is also environmentally fragile, we can compare the measures of erodibility of cultivated and noncultivated cropland. If there is a positive relationship between economic marginality and environmental marginality, the erodibility measures should be higher on the noncultivated (i.e., economically marginal) cropland. We find a positive relationship in our data for the erodibility index in 1992, with the EI having a value of 12.623 on noncultivated cropland and a value of 7.028 on cultivated cropland.

Erodibility Classes	Cropland		
ETOuroning Chasses	Cultivated	Noncultivated	
EI<2	20.6	20.5	
$2 \le EI < 5$	34.2	24.2	
$5 \le EI < 8$	19.4	15.9	
$8 \le EI < 10$	7.3	7.2	
$10 \le EI < 15$	9.0	11.7	
$EI \ge 15$	9.5	20.5	

Table 3. Distribution of Cropland Acreage by Erodibility Class (1992)

The distribution of acreage across erodibility classes can also provide a clue as to the relationship between economic and environmental marginality. If a positive relationship exists, one would expect that noncultivated cropland (since it is economically marginal) would contain a higher proportion of land in the higher erodibility classes than would cultivated cropland. The results are displayed in Table 3. Within the cultivated cropland data, 74.2% of the acreage falls in the 3 classes associated with the lowest degree of soil erodibility, while the remaining 25.8% falls in the 3 classes of highest erodibility. Within the noncultivated cropland data, only 60.6% of the acreage falls in the lowest 3 erodibility classes, while the remaining 39.4% falls in the 3 highest classes. In particular, 20.5% of the acreage in noncultivated cropland falls in the class with the highest erodibility index value, while only 9.5% of the acreage in cultivated cropland exhibits the highest measure of erodibility. The results indicate that noncultivated cropland contains a higher percentage of more erodible soil than cultivated cropland, which gives some support to the conventional wisdom.

Erodibility Classes	Land Use			
	Cultivated	Noncultivated	CRP	
EI<2	84.41	14.23	1.37	
$2 \le EI < 5$	87.00	9.40	3.60	
$5 \le EI < 8$	82.60	10.40	7.00	
$8 \le EI < 10$	79.16	9.81	11.03	
$10 \le \text{EI} < 15$	72.92	12.53	14.55	
$EI \ge 15$	64.14	18.78	17.08	

Table 4. Land Use Distribution within Erodibility Classes (1992)

Alternatively, one could look at the distribution of land use within each erodibility class. Recall that the NRI erodibility index is only reported on land that is designated as cropland (cultivated or noncultivated) and land that is enrolled in the Conservation Reserve Program. The results in Table 4 i ndicate that the percentage of cultivated cropland generally decreases over the range of erodibility classes. As expected, the percentage of land enrolled in the CRP increases over the range of erodibility classes. While the changes in noncultivated cropland are not as dramatic as those in the CRP, land in the two highest erodibility classes contain a higher percentage of noncultivated cropland than do lower erodibility classes, except for the EI < 2 class. These results indicate that the percentage of corpland that is noncultivated or enrolled in CRP (as opposed to cultivated) increases as the level of soil erodibility increases. Again, this lends some support to the conventional wisdom that economically marginal land is associated with higher levels of soil erodibility.

#### 4.2 Site-Specific Crop Yield Distributions

If economically marginal land is also highly erodible, we would expect to find a decrease in mean crop yields (and an increase in crop yield variability) as the level of soil erodibility increases. Table 5 presents data on the mean crop yield (and standard deviation of crop yield) across classes of the soil erodibility index. The erodibility classes were chosen to coincide with the categories employed by the NRCS in reporting their summary findings for the NRI. The highest estimated mean yield for each crop occurs on land where the erodibility index (EI) is less than 2, and the yields generally

decline as the erodibility index takes on larger values. In addition, the standard deviation of mean crop yields tends to increase as the erodibility class increases.

Crop	Erodibility Classes						
Crop	EI<2	$2 \le \mathrm{EI} < 5$	$5 \le \mathrm{EI} < 8$	$8 \le EI < 10$	$10 \le \mathrm{EI} < 15$	$EI \ge 15$	
Cotton	649.559	638.379	478.161	435.233	439.357	433.237	
Cotton	(135.568)	(175.926)	(189.460)	(181.219)	(195.095)	(211.240)	
Corn	118.022	103.986	88.432	87.555	92.779	92.382	
Com	(28.230)	(30.371)	(34.412)	(35.856)	(34.264)	(28.283)	
Sorghum	75.803	67.462	50.831	43.729	40.481	38.149	
Sorghum	(17.224)	(16.378)	(17.282)	(16.973)	(19.043)	(21.191)	
Soybeans	40.390	37.210	34.762	35.007	34.937	33.118	
Soybeans	(8.046)	(7.984)	(8.954)	(9.234)	(9.062)	(8.684)	
C factor	0.270	0.253	0.244	0.242	0.248	0.223	
	(0.106)	(0.096)	(0.100)	(0.105)	(0.121)	(0.128)	

Table 5. Site-Specific Mean Crop Yield by Erodibility Class (1992)

The standard deviations of mean crop yield and C Factor are in parentheses.

While the general trend supports the view that land productivity and soil erodibility are inversely related, crop yields do not decrease as erodibility levels increase for all of the crops. Mean crop yields for sorghum decline over the entire range of erodibility classes, but the results for soybeans, cotton, and corn are mixed. For example, mean corn yields decline for the 4 lowest erodibility classes, but the fifth class  $(10 \le \text{EI} < 15)$  exhibits higher yields than land in the fourth class ( $8 \le \text{EI} < 10$ ). Even in cases where the yield generally declines over the range of erodibility classes, the magnitudes of the differences are quite small. For example, the soybean yield ranges from 35.007 to 33.118 over the four classes exhibiting the highest levels of erodibility classes. This indicates that more intensive cropping management practices with respect to the reduction in soil loss (for example, a higher percentage of land under conservation tillage) are conducted as the erodibility of the land increases. As previously discussed, a decline in the C factor may actually be expected to decrease crop yields in the short-run as cropping management practices are undertaken to reduce soil erosion.

#### 4.3 Aggregate Crop Yield Distributions

Table 6 presents data on the mean crop yield (and standard deviation of crop yield) across classes of the soil erodibility index for the NASS data. In contrast to the findings for the SOILS-5 data, most of the crops do not exhibit their largest yields on land in the lowest erodibility class. Mean corn yields are highest in erodibility class 5 ( $10 \le EI < 15$ ), while soybean yields are highest in erodibility class 6 ( $EI \ge 15$ ). In addition, the crop yields do not generally decline over the entire range of erodibility classes. For example, the lowest cotton yields occur in classes 3, 4, and 5, while the highest yields occur in classes 1, 2, and 6.

Cron	Erodibility Classes						
Crop	EI<2	$2 \le \mathrm{EI} < 5$	$5 \le \mathrm{EI} < 8$	$5 \le EI < 8$	$10 \le \mathrm{EI} < 15$	$EI \ge 15$	
Cotton	599.666	593.667	482.803	430.329	447.485	584.364	
Cotton	(191.575)	(164.976)	(172.262)	(139.194)	(198.929)	(267.261)	
Corn	86.869	91.874	89.173	93.283	93.347	92.382	
Com	(28.606)	(2.849)	(25.266)	(27.366)	(28.739)	(24.689)	
Sorghum	55.725	56.129	56.145	55.998	54.070	53.762	
Sorghum	(17.631)	(14.264)	(14.756)	(16.359)	(16.341)	(17.396)	
Soybeans	25.722	28.671	27.630	28.566	28.869	29.331	
Soybeans	(5.780)	(6.643)	(7.081)	(6.979)	(6.546)	(6.271)	
C factor	0.256	0.254	0.229	0.228	0.235	0.218	
Clactor	(0.120)	(0.084)	(0.079)	(0.084)	(0.091)	(0.112)	

Table 6. Aggregate Mean Crop Yields by Erodibility Class (1992)

The standard deviations of mean crop yield and C factor are in parentheses.

As in the SOILS-5 data case, the reduction in the C factor, and thus the implementation of more intensive cropping management practices with repsect to the reduction in soil loss, over the range of erodibility classes may actually reduce crop yields in the short-run, so the lack of a uniform decrease of crop yields over the erodibility classes may even be more pronounced if cropping management practices are excluded. Therefore, these results lend little support to the view that there is a close link between economic marginality (as measured by mean crop yield) and economic marginality (as measured by soil erodibility).

#### 4.4 Site-Specific Crop Yields

The erodibility coefficient estimates, standard errors, and adjusted R-squares for the regressions using the mean estimated crop yields from the SOILS-5 data are presented in Table 7.<sup>31</sup> A negative coefficient on the erodibility index indicates that an increase in soil erodibility (environmental marginality) leads to a decrease in crop yields, which indicates an increase in economic marginality. Therefore a negative sign on the erodibility coefficient implies a positive relationship between economic and environmental marginality.

 $<sup>^{31}</sup>$ Complete regression results for all of the models can be found in Tables 11 through 14.

The coefficients on the EI variable were negative for all of the crops in the study. In addition, the coefficient estimates were statistically significant at the 1% level for all of the crops. The adjusted R-squares ranged from .388 (soybeans) to .661 (sorghum), which indicates that the model has good explanatory power for cross-sectional data.

Crop	Erodibility Index			
Crop	Coefficient Estimates	Adjusted $\mathbb{R}^2$		
Cotton	-4.596	.624		
Cotton	(0.111)			
Corn	-0.541	.547		
	(0.008)			
Sorghum	-0.582	.661		
Sorghum	(0.010)			
Soybeans	-0.229	.388		
	(0.003)			

Table 7. OLS Results: SOILS-5 Crop Yields (1992)

The standard errors for the coefficient estimates are in parentheses. The coefficient estimates in bold are significant at the  $\alpha$ =.01 level.

The elasticities of the crop yields with respect to the erodibility index were inelastic in all cases. The elasticities ranged from -.041 for corn to -.087 for sorghum.<sup>32</sup> Given these elasticities, an increase in the soil erodibility index from its mean value of 7.79 (near the 70th percentile) to the value at the 80th percentile (10.6), a 36% increase, would result in decreases in yield ranging from 1.48% for corn to 3.13% for sorghum. If the soil erodibility index increased to the value at the 90th percentile (16.4), a 111% increase, crop yield reductions would range from 4.55% for corn to 9.66% for sorghum, respectively. The regression results for the SOILS-5 data provide support for the belief that there is a positive relationship between economic and environmental marginality.

Land productivity, as proxied by the average water holding capacity (AWC), should be positively related to crop yield since the ability of the soil to retain and transport water is essential for plant growth. As expected, the coefficient on AWC was positive and statistically significant in all cases. The C factor (CFACT) variable captures the impact of cropping management practices on soil loss (and indirectly crop yield). Since a lower C factor indicates more intensive cropping management activities designed to reduce soil loss, a priori expectations were that a higher value for the C factor would be associated with higher crop yields. As expected, the coefficient on CFACTwas significant and positive in all cases. Since the C factor incorporates management activities

 $<sup>^{32}</sup>$ All of the elasticities in this study were calculated at the mean values of the erodibility index and crop yields.

designed to mitigate potential soil loss, this positive relationship may indicate that these cropping management activities, such as cover and crop rotation, lead to reductions in short-term yield in an effort to protect the long-term productivity of the land.

Finally, the coefficients on the temperature, precipitation, squared terms of those variables, and interaction terms were of mixed sign and statistical significance. No discernible pattern exists across crops with respect to the climate variables, though higher precipitation in August is associated with higher crop yields in all cases. There was also a high degree of collinearity (as expected a priori) between all of the climate variables, which made the estimates of the standard errors and t-statistics unreliable. Since these variables were not the focal point of the study, all of the temperature, precipitation, squared terms, an interaction terms were retained in the estimating equations. The same problems existed with respect to the climate variables in both of the aggregate models.

#### 4.5 Aggregate Crop Yields

The erodibility coefficient estimates, standard errors, and adjusted R-squares for the regressions using the mean estimated crop yields from the NASS data are presented in Table 8.<sup>33</sup> Again a negative coefficient on the erodibility measure would indicate support for the belief that there is a positive relationship between economic and environmental marginality. Consistent with the findings with the SOILS-5 data, the coefficient signs are negative in all cases, with only the coefficient in the cotton yield equation being insignificant at the 10% level.

Crop	Erodibility Index			
Crop	Coefficient Estimates	Adjusted $R^2$		
Cotton	-0.292	.778		
Cotton	(1.095)			
Corn	-0.142	.622		
Com	(0.052)			
Sorghum	-0.407	.549		
Sorghum	(0.165)			
Soybeans	-0.057	.815		
Soybeans	(0.017)			

Table 8. OLS Results: NASS Crop Yields (1992)

The standard errors of the coefficient estimates are in parentheses.

The coefficient estimates in bold are significant at the  $\alpha = .10$  level.

The elasticities of the crop yields with respect to the erodibility index were inelastic, ranging

<sup>&</sup>lt;sup>33</sup>Complete regression results for all of the models can be found in Tables 15 through 18.

from -.013 for corn to -0.062 for sorghum. The magnitudes of the elasticities would indicate that changes in the level of soil erodibility would have a slightly smaller impact on crop yields than was evidenced in the SOILS-5 case. An increase in the erodibility index from the mean value of 8.48 (near the 60th percentile) to the value at the 80th percentile (12.30), a 45% increase, would result in yield decreases of between .23% (cotton) to 2.79% (sorghum). Even an increase to the 90th percentile (16.38), a 93% increase in the erodibility index, would result in decreases in yield ranging from .47% for cotton to 5.77% for sorghum. In both the SOILS-5 and NASS cases, an increase in the soil erodibility index would have a more pronounced impact on sorghum yields than it would for the yields of the other crops. The adjusted R-squares ranged from .549 (sorghum) to .815 (soybeans), which indicates that the models have good explanatory power for cross-sectional data. The regression results using the NASS yield data provides evidence to corroborate the findings in the site-specific portion of the study. Both support the conventional wisdom that there is a strong, positive relationship between economic and environmental marginality.

As expected, the percentage of nonirrigated cropland (*PERNIRR*) exhibited a statistically significant negative relationship with all mean crop yields. As with the SOILS-5 data, the coefficient on average water holding capacity (*AGAWC*) was positive, though it was not significant in the cotton and sorghum yield equations. The coefficient estimates on county-level average C factor (*AGCFACT*) were positive for corn and cotton, though negative for soybeans and sorghum. The soybean and sorghum results were inconsistent with those contained in the site-specific portion of the study. As with the results from the SOILS-5 data, the coefficients on the temperature, precipitation, squared and interaction terms are of mixed sign and statistical significance. The results varied by crop within each sample (SOILS-5 or NASS). For example, increases in May rainfall are associated with decreases in corn and sorghum yields and increases in corton and soybean yields using the SOILS-5 data. In addition, the results are not consistent for each crop across samples. For example, increases in precipitation in May are associated with lower corn yields in the SOILS-5 data and with higher corn yields in the NASS data. Again it should be noted that these variables are highly collinear and that separating out the individual effects may be impossible.

## 5 Conclusions

Conventional wisdom has long held that economically marginal land is also environmentally marginal (i.e., fragile). Very little research has been conducted to test this belief, with the few studies that have been conducted yielding mixed results. To test this relationship, we use site-specific (SOILS-5) and county-level (NASS) data on measures on economic marginality (crop yield and yield variability) and environmental marginality (the NRI soil erodibility index).

We employ two methodological approaches in our study. First, we analyze the distribution of our productivity measures across different levels of erodibility. The mean crop yields (SOILS-5 and NASS) generally diminished as the level of erodibility increased, though higher yields were often found in classes exhibiting higher levels of erodibility. While the coefficient of variation of mean crop yields generally increased as the level of erodibility increased, low yield CV's were also found at high levels of soil erodibility. These results are somewhat consistent with Heimlich's findings that mean yield and soil erodibility are weakly associated, though the general trend of diminishing (increasing) mean yields (yield variability) as levels of soil erodibility increase provide some support to those espousing the conventional wisdom.

Second, we conduct a more detailed analysis by regressing our measure of economic marginality (mean crop yield) on the erodibility index and a set of conditioning variables. This analysis yields consistent results in support of the conventional wisdom that economically marginal land is also likely to be environmentally fragile, at least with respect to increasing levels of soil erodibility. Although the estimated coefficients were negative and significant, the elasticities were generally small, though increases in the erodibility index from the mean value to values at the 80th and 90th percentile of the index distribution resulted in reductions in yields that ranged from .5% to 5.8% in the SOILS-5 data.

Our results do not confirm previous findings that indicate a weak relationship between economic marginality (crop productivity) and environmental marginality (soil erodibility). While the crop yield distribution results provide only weak support for the conventional wisdom, our regression results indicate that there appears to be a significant negative relationship between mean crop yield and soil erodibility. This would support the assertion that there is a positive association between economic and environmental marginality. This raises concerns that government policies that encourage production on economically marginal land (i.e., land with low mean crop yields) may lead to increases in soil erosion as more erodible soil is brought into production. As a result, it is important to consider the impact of government income support and risk management policies on acreage allocation decisions.

#### References

- Daberkow, S.G. and W.D. McBride. "Socio-Economic Profiles of Early Adopters of Precision Agriculture Techniques," *Journal of Agribusiness*, 16(Fall 1998): 151-168.
- Dixon, B. and K. Segerson. "Impacts of Increased Variability on the Profitability of Midwest Agriculture," Journal of Agricultural and Applied Economics, 31(December 1999): 537-549.
- Dixon, B., S. Hollinger, P. Garcia, and V. Tirupattur. "Estimating Corn Yield Response Models to Predict Impacts of Climate Change," *Journal of Agricultural and Resource Economics*, 19(July 1994): 58-68.
- El-Osta, H. and A. Mishra. "Adoption and Economic Impact of Site-Specific Technologies in U.S. Agriculture," Selected Paper, AAEA Annual Meeting, Chicago, Ill., August 5-8, 2001.
- Goodwin, B.K., M. Vandeveer, and J. Deal. "An Empirical Analysis of Acreage Effects of Participation in the Federal Crop Insurance Program," *American Journal of Agricultural Economics*, 86(November 2004): 1058-77.
- Hansen, L. "Farmer Response to Changes in Climate: The Case of Corn Production," Journal of Agricultural economics and Resources, 43(Fall 1991): 18-25.
- Heimlich, R. "Productivity and Erodibility of U.S. Cropland," Agricultural Economic Report 604, Economic Research Service, Washington, D.C., 1989.
- Kaufmann, R. and S. Snell. "A Biophysical Model of Corn Yield: Integrating Climatic and Social Determinants," American Journal of Agricultural Economics, 79(February 1997): 178-190.
- Khanna, M., O. Epough, and R. Hornbaker. "Site-Specific Crop Management: Adoption Patterns and Incentives," *Review of Agricultural Economics*, 21(Fall/Winter 1999): 455-472.
- Lee, L. and J. Goebel. "Defining Erosion Potential on Cropland: A Comparison of the Land Capability Class-Subclass System with RKLS/T Categories," *Journal of Water and Soil Conservation*, (Jan./Feb. 1986): 41-44.
- Metcalfe, D. and D. Elkins. Crop Production: Principles and Practices, 4th edition, MacMillan Publishing Company, New York, 1980.
- Mitchell, J. and G. Bubenzer. "Soil Loss Estimation" in M.J. Kirby and R.P.C. Morgan, eds., *Soil Erosion*, John Wiley and Sons, 1980: 17-62.
- Plantinga, A. "The Effect of Agricultural Policies on Land Use and Environmental Quality," American Journal of Agricultural Economics, 78(November 1996): 1082-1091.
- Runge, C., W. Larson, and G. Roloff. "Using Productivity Measures to Target Conservation Programs: A Comparative Analysis," *Journal of Soil and Water Conservation*, (Jan./Feb. 1986): 45-49.
- Runge, E. "Effects of Rainfall and Temperature Interactions During Growing Season on Corn Yield," Agronomy Journal, 60(September 1968): 503-507.
- Soule, M., W. Nimon, and D. Mullarkey. "Risk Management and Environmental Outcomes: Framing the Issues," Technical Report, ERS-USDA, Washington, D.C., September, 2000.
- Tiegen, L. and M. Thomas, Jr. "Weather and Yield, 1950-94: Relationships, Distributions, and Data," Commercial Agricultural Division Staff paper 9527, USDA-ERS, Washington, D.C., 1995.
- Thompson, L. "Weather and Technology in the Production of Corn in the U.S. Corn Belt," Agronomy Journal, 61(May 1969): 453-456.
- Westenbarger, D. and G. Frisvold. "Air Pollution and Farm-Level Crop Yields: An Empirical Analysis of Corn and Soybeans," Agricultural and Resource Economics Review, (October 1995): 156-165.
- Wu, J. "Crop Insurance, Acreage Decisions, and Non-Point Source Pollution," American Journal of Agricultural Economics 81(May 1999):305-320.

Variable	Definition	Mean	Std. Dev.
Cotton (cotton_nirryld)	cotton non-irrigated yield (pounds)	557.6100	201.6164
Corn (corn_nirryld)	corn non-irrigated yield (bushels)	101.5986	32.8398
Soybeans (soybean_nirryld)	soybean non-irrigated yield (bushels)	37.0791	8.6245
Sorghum (sorghum_nirryld)	sorghum non-irrigated yield (bushels)	52.2528	21.3799
Erodibility Index (EI)	average of 1987 and 1992 NRI soil erodibility indices	7.7879	10.4136
Soil Water-Holding Capacity (AWC)	average water holding capacity per inch of soil	0.1701	0.0374
C Factor (CFACT)	average of 1987 and 1992 NRI C Factors	0.2496	0.1071
May Rainfall (MAYRN)	average rainfall in ml. (1961-1990)	91.4313	28.0494
June Rainfall (JUNRN)	average rainfall in ml. (1961-1990)	91.5546	25.9204
July Rainfall (JULRN)	average rainfall in ml. (1961-1990)	86.1122	31.1798
August Rainfall (AUGRN)	average rainfall in ml. (1961-1990)	80.2113	28.5049
May Temp. (MAYTEMP)	average temperature 1961-1990 (Celsius degrees)	16.5793	3.2858
June Temp. (JUNTEMP)	average temperature 1961-1990 (Celsius degrees)	21.4217	2.9472
July Temp. (JULTEMP)	average temperature 1961-1990 (Celsius degrees)	23.9495	2.5841
August Temp. (AUGTEMP)	average temperature 1961-1990 (Celsius degrees)	22.8749	2.6965

Table 9. Variable Definitions and Summary Statistics for Site-Specific Data.

Variable	Definition	Mean	Std. Dev.
Cotton (cotton_mean)	county mean cotton yield (pounds)	535.2885	195.6828
Corn (corn_mean)	county mean corn yield (bushels)	91.3328	25.7158
Soybeans (soybean_mean)	county mean soybean yield (bushels)	28.3265	6.7262
Sorghum (sorghum_mean)	county mean sorghum yield (bushels)	55.4756	15.6972
$Cotton (cotton_cv)$	county CV of cotton yield (pounds)	25.6442	10.6225
$Corn (corn_cv)$	county CV of corn yield (bushels)	22.0148	9.4693
Soybeans (soybean_cv)	county CV of soybean yield (bushels)	19.6661	7.4606
Sorghum (sorghum_cv)	county CV of sorghum yield (bushels)	20.3083	10.3797
Nonirrigated Land (PERNIRR)	nonirrigated portion of cultivated cropland	0.8564	0.2723
Erodibility Index (AGEI)	county average soil erodibility index	8.4780	7.1384
Soil Water-Holding Capacity (AGAWC)	county average water holding capacity per inch of soil	0.1454	0.0306
C Factor (AGCFACT)	county average C Factor	0.2378	0.0893
May Rainfall (MAYRN)	average rainfall in ml. (1961-1990)	96.8731	28.9933
June Rainfall (JUNRN)	average rainfall in ml. (1961-1990)	93.7055	28.5065
July Rainfall (JULRN)	average rainfall in ml. (1961-1990)	92.8586	36.6809
August Rainfall (AUGRN)	average rainfall in ml. (1961-1990)	86.5090	32.6247
May Temp. (MAYTEMP)	average temperature 1961-1990 (Celsius degrees)	17.2492	3.8390
June Temp. (JUNTEMP)	average temperature 1961-1990 (Celsius degrees)	21.7377	3.4182
July Temp. (JULTEMP)	average temperature 1961-1990 (Celsius degrees)	24.1287	2.9621
August Temp. (AUGTEMP)	average temperature 1961-1990 (Celsius degrees)	23.2933	3.1102

Table 10. Variable Definitions and Summary Statistics for Aggregate Data.

Variable	Estimate	Standard Error	t-Ratio
INTERCEPT	-2969.8183	168.3181	$-17.64^{*}$
EI	-4.5960	0.1107	$-41.50^{*}$
AWC	767.5961	23.3254	$32.91^{*}$
CFACT	73.3343	5.8076	$12.63^{*}$
MAYRN	27.4431	0.6280	$43.70^{*}$
JUNRN	-2.2715	1.6431	-1.38
JULRN	-30.6302	1.2335	$-24.83^{*}$
AUGRN	60.5550	1.8551	$32.64^{*}$
MAYTEMP	523.8830	21.8830	$23.94^{*}$
JUNTEMP	-592.6994	41.6895	$-14.22^{*}$
JULTEMP	415.3241	44.1756	$9.40^{*}$
AUGTEMP	-206.4125	38.0388	$-5.43^{*}$
SQMAYTEMP	-10.1609	0.4723	$-21.52^{*}$
SQJUNTEMP	12.0352	0.7892	$15.25^{*}$
SQJULTEMP	-10.4937	0.8013	$-13.10^{*}$
SQAUGTEMP	7.9043	0.6958	$11.36^{*}$
SQMAYRN	0.0042	0.0015	$2.74^{*}$
SQJUNRN	-0.0058	0.0018	$-3.18^{*}$
SQJULRN	-0.0236	0.0010	$-24.38^{*}$
SQAUGRN	-0.0055	0.0013	$-4.23^{*}$
MAYRNTEMP	-1.3143	0.0328	$-40.07^{*}$
JUNRNTEMP	0.0954	0.0672	1.42
JULRNTEMP	1.5117	0.0479	$31.53^{*}$
AUGRNTEMP	-2.2151	0.0680	$-32.57^{*}$

Table 11. OLS Estimates of SOILS-5 Cotton Yields.

<b>X</b> 7 • 11			- D - L'
Variable	Estimate	Standard Error	t-Ratio
INTERCEPT	-14.0091	11.9566	-1.17
EI	-0.5412	0.0075	$-71.96^{*}$
AWC	277.4048	1.7479	$158.71^{*}$
CFACT	20.5848	0.6507	$31.64^{*}$
MAYRN	-0.1777	0.0432	$-4.11^{*}$
JUNRN	-2.3444	0.0740	$-31.67^{*}$
JULRN	0.7935	0.0638	$12.45^{*}$
AUGRN	3.6606	0.0643	$56.97^{*}$
MAYTEMP	78.3865	1.4139	$55.44^{*}$
JUNTEMP	-88.8716	3.1794	$-27.95^{*}$
JULTEMP	44.1034	3.7463	$11.77^{*}$
AUGTEMP	-16.2867	2.7832	$-5.85^{*}$
SQMAYTEMP	-2.2875	0.0396	$-57.74^{*}$
SQJUNTEMP	2.6242	0.0746	$35.20^{*}$
SQJULTEMP	-1.6104	0.0787	$-20.45^{*}$
SQAUGTEMP	0.5928	0.0593	$10.00^{*}$
SQMAYRN	0.0009	0.0002	$3.73^{*}$
SQJUNRN	0.0005	0.0002	$2.11^{*}$
SQJULRN	-0.0002	0.0001	-1.47
SQAUGRN	-0.0006	0.0001	$-4.30^{*}$
MAYRNTEMP	-0.0174	0.0025	$-7.10^{*}$
JUNRNTEMP	0.1032	0.0036	28.40*
JULRNTEMP	-0.0378	0.0028	$-13.56^{*}$
AUGRNTEMP	-0.1212	0.0029	$-41.20^{*}$
			11.20

Table 12. OLS Estimates of SOILS-5 Corn Yields.

Estimate	Standard Error	t-Ratio
-246.8643	9.2412	$-26.71^{*}$
-0.5824	0.0104	$-55.76^{*}$
92.5393	2.3087	$40.08^{*}$
0.0270	0.5551	0.05
-0.3502	0.0451	$-7.76^{*}$
0.1379	0.0727	$1.90^{*}$
-0.2231	0.1056	$-2.11^{*}$
5.6854	0.1163	$48.88^{*}$
-4.2249	1.3185	$-3.20^{*}$
-22.4714	2.6571	$-8.46^{*}$
28.2760	3.9683	$7.13^{*}$
3.9975	3.2931	1.21
0.3340	0.0310	$10.78^{*}$
0.1175	0.0569	$2.06^{*}$
-0.3149	0.0748	$-4.21^{*}$
0.0162	0.0630	0.26
-0.0005	0.0001	$-3.27^{*}$
0.0003	0.0001	$2.56^{*}$
-0.0048	0.0002	$-26.26^{*}$
0.0025	0.0002	$12.23^{*}$
0.0394	0.0022	$18.00^{*}$
-0.0025	0.0033	-0.77
0.0591	0.0041	$14.29^{*}$
-0.2478	0.0045	$-54.80^{*}$
	$\begin{array}{c} -246.8643\\ -0.5824\\ 92.5393\\ 0.0270\\ -0.3502\\ 0.1379\\ -0.2231\\ 5.6854\\ -4.2249\\ -22.4714\\ 28.2760\\ 3.9975\\ 0.3340\\ 0.1175\\ -0.3149\\ 0.0162\\ -0.0005\\ 0.0003\\ -0.0048\\ 0.0025\\ 0.0394\\ -0.0025\\ 0.0591\end{array}$	$\begin{array}{cccccccccccccccccccccccccccccccccccc$

Table 13. OLS Estimates of SOILS-5 Sorghum Yields.

VariableEstimateStandard Errort-RatioINTERCEPT $-92.1451$ $4.4868$ $-20.54^*$ EI $-0.2294$ $0.0027$ $-84.50^*$ AWC $85.2804$ $0.5611$ $151.99^*$ CFACT $3.6567$ $0.2166$ $16.88^*$ MAYRN $0.0806$ $0.0155$ $5.20^*$ JUNRN $-0.4460$ $0.0273$ $-16.34^*$ JULRN $-0.1044$ $0.0223$ $-4.69^*$ AUGRN $1.2487$ $0.0215$ $58.17^*$ MAYTEMP $2.9081$ $0.5026$ $5.79^*$ JUNTEMP $9.3564$ $1.0643$ $8.79^*$ JULTEMP $-17.1989$ $1.2548$ $-13.81^*$ AUGTEMP $13.4301$ $0.9358$ $14.35^*$ SQMAYTEMP $-0.0681$ $0.0146$ $-4.67^*$ SQJUNTEMP $-0.0637$ $0.0247$ $-2.58^*$ SQJUNTEMP $-0.2383$ $0.0198$ $-12.01^*$ SQAUGTEMP $-0.0001$ $0.0001$ $-1.42$ SQJULRN $-0.0001$ $0.0000$ $-2.99^*$ SQAUGRN $-0.0026$ $0.0013$ $16.35^*$ JUNRNTEMP $-0.0234$ $0.0009$ $-27.25^*$ JUNRNTEMP $0.0266$ $0.0011$ $5.32^*$ AUGRNTEMP $-0.0437$ $0.0010$ $-45.18^*$				
EI $-0.2294$ $0.0027$ $-84.50^*$ AWC $85.2804$ $0.5611$ $151.99^*$ CFACT $3.6567$ $0.2166$ $16.88^*$ MAYRN $0.0806$ $0.0155$ $5.20^*$ JUNRN $-0.4460$ $0.0273$ $-16.34^*$ JULRN $-0.1044$ $0.0223$ $-4.69^*$ AUGRN $1.2487$ $0.0215$ $58.17^*$ MAYTEMP $2.9081$ $0.5026$ $5.79^*$ JUNTEMP $9.3564$ $1.0643$ $8.79^*$ JULTEMP $-17.1989$ $1.2548$ $-13.81^*$ AUGTEMP $13.4301$ $0.9358$ $14.35^*$ SQMAYTEMP $-0.0681$ $0.0146$ $-4.67^*$ SQJUNTEMP $0.0260$ $9.50^*$ SQAUGTEMP $-0.2383$ $0.0198$ $-12.01^*$ SQJUNRN $-0.0001$ $0.0001$ $-1.42$ SQJULRN $-0.0001$ $0.0000$ $-2.99^*$ SQAUGRN $-0.0022$ $0.0000$ $-4.91^*$ MAYRNTEMP $-0.0234$ $0.0099$ $-27.25^*$ JUNRNTEMP $0.0266$ $0.0013$ $16.35^*$	Variable	Estimate	Standard Error	t-Ratio
AWC $85.2804$ $0.5611$ $151.99^*$ CFACT $3.6567$ $0.2166$ $16.88^*$ MAYRN $0.0806$ $0.0155$ $5.20^*$ JUNRN $-0.4460$ $0.0273$ $-16.34^*$ JULRN $-0.1044$ $0.0223$ $-4.69^*$ AUGRN $1.2487$ $0.0215$ $58.17^*$ MAYTEMP $2.9081$ $0.5026$ $5.79^*$ JUNTEMP $9.3564$ $1.0643$ $8.79^*$ JULTEMP $-17.1989$ $1.2548$ $-13.81^*$ AUGTEMP $13.4301$ $0.9358$ $14.35^*$ SQMAYTEMP $-0.0681$ $0.0146$ $-4.67^*$ SQJUNTEMP $0.2470$ $0.0260$ $9.50^*$ SQAUGTEMP $-0.2383$ $0.0198$ $-12.01^*$ SQJULRN $0.0001$ $15.35^*$ SQJULRN $-0.0001$ $0.0000$ $-2.99^*$ SQAUGRN $-0.0002$ $0.0000$ $-4.91^*$ MAYRNTEMP $-0.2344$ $0.0009$ $-27.25^*$ JUNRNTEMP $0.0266$ $0.0113$ $16.35^*$	INTERCEPT	-92.1451	4.4868	$-20.54^{*}$
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	EI	-0.2294	0.0027	$-84.50^{*}$
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	AWC	85.2804	0.5611	$151.99^{*}$
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	CFACT	3.6567	0.2166	$16.88^{*}$
JULRN $-0.1044$ $0.0223$ $-4.69^*$ AUGRN $1.2487$ $0.0215$ $58.17^*$ MAYTEMP $2.9081$ $0.5026$ $5.79^*$ JUNTEMP $9.3564$ $1.0643$ $8.79^*$ JULTEMP $-17.1989$ $1.2548$ $-13.81^*$ AUGTEMP $13.4301$ $0.9358$ $14.35^*$ SQMAYTEMP $-0.0681$ $0.0146$ $-4.67^*$ SQJUNTEMP $-0.0637$ $0.0247$ $-2.58^*$ SQJULTEMP $0.2470$ $0.0260$ $9.50^*$ SQAUGTEMP $-0.2383$ $0.0198$ $-12.01^*$ SQMAYRN $0.0012$ $0.0001$ $15.35^*$ SQJULRN $-0.0001$ $0.0000$ $-2.99^*$ SQAUGRN $-0.0002$ $0.0000$ $-4.91^*$ MAYRNTEMP $-0.0234$ $0.0099$ $-27.25^*$ JUNRNTEMP $0.0206$ $0.0013$ $16.35^*$ JULRNTEMP $0.0056$ $0.0011$ $5.32^*$	MAYRN	0.0806	0.0155	$5.20^{*}$
AUGRN1.24870.021558.17*MAYTEMP2.90810.50265.79*JUNTEMP9.35641.06438.79*JULTEMP-17.19891.2548-13.81*AUGTEMP13.43010.935814.35*SQMAYTEMP-0.06810.0146-4.67*SQJUNTEMP-0.06370.0247-2.58*SQJULTEMP0.24700.02609.50*SQAUGTEMP-0.23830.0198-12.01*SQJUNRN0.00120.000115.35*SQJULRN-0.00010.0000-2.99*SQAUGRN-0.00020.0000-4.91*MAYRNTEMP-0.02340.0009-27.25*JUNRNTEMP0.02660.001316.35*JULRNTEMP0.02660.00115.32*	JUNRN	-0.4460	0.0273	$-16.34^{*}$
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	JULRN	-0.1044	0.0223	$-4.69^{*}$
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	AUGRN	1.2487	0.0215	$58.17^{*}$
JULTEMP-17.19891.2548-13.81*AUGTEMP13.43010.935814.35*SQMAYTEMP-0.06810.0146-4.67*SQJUNTEMP-0.06370.0247-2.58*SQJULTEMP0.24700.02609.50*SQAUGTEMP-0.23830.0198-12.01*SQMAYRN0.00120.000115.35*SQJULRN-0.00010.0000-2.99*SQAUGRN-0.00020.0000-4.91*MAYRNTEMP-0.02340.0009-27.25*JUNRNTEMP0.02060.001316.35*JULRNTEMP0.00560.00115.32*	MAYTEMP	2.9081	0.5026	$5.79^{*}$
AUGTEMP13.43010.935814.35*SQMAYTEMP-0.06810.0146-4.67*SQJUNTEMP-0.06370.0247-2.58*SQJULTEMP0.24700.02609.50*SQAUGTEMP-0.23830.0198-12.01*SQMAYRN0.00120.000115.35*SQJULRN-0.00010.0001-1.42SQJULRN-0.00010.0000-2.99*SQAUGRN-0.0020.0000-4.91*MAYRNTEMP-0.02340.0009-27.25*JUNRNTEMP0.02060.001316.35*JULRNTEMP0.00560.00115.32*	JUNTEMP	9.3564	1.0643	$8.79^{*}$
$\begin{array}{llllllllllllllllllllllllllllllllllll$	JULTEMP	-17.1989	1.2548	$-13.81^{*}$
SQJUNTEMP         -0.0637         0.0247         -2.58*           SQJULTEMP         0.2470         0.0260         9.50*           SQAUGTEMP         -0.2383         0.0198         -12.01*           SQMAYRN         0.0012         0.0001         15.35*           SQJULRN         -0.0001         0.0000         -2.99*           SQAUGRN         -0.0002         0.0000         -4.91*           MAYRNTEMP         -0.0234         0.0009         -27.25*           JUNRNTEMP         0.0206         0.0013         16.35*	AUGTEMP	13.4301	0.9358	$14.35^{*}$
$\begin{array}{ccccccc} SQJULTEMP & 0.2470 & 0.0260 & 9.50^* \\ SQAUGTEMP & -0.2383 & 0.0198 & -12.01^* \\ SQMAYRN & 0.0012 & 0.0001 & 15.35^* \\ SQJUNRN & -0.0001 & 0.0001 & -1.42 \\ SQJULRN & -0.0001 & 0.0000 & -2.99^* \\ SQAUGRN & -0.0002 & 0.0000 & -4.91^* \\ MAYRNTEMP & -0.0234 & 0.0009 & -27.25^* \\ JUNRNTEMP & 0.0206 & 0.0013 & 16.35^* \\ JULRNTEMP & 0.0056 & 0.0011 & 5.32^* \\ \end{array}$	SQMAYTEMP	-0.0681	0.0146	$-4.67^{*}$
SQAUGTEMP         -0.2383         0.0198         -12.01*           SQMAYRN         0.0012         0.0001         15.35*           SQJUNRN         -0.0001         0.0001         -1.42           SQJULRN         -0.0001         0.0000         -2.99*           SQAUGRN         -0.0002         0.0000         -4.91*           MAYRNTEMP         -0.0234         0.0009         -27.25*           JUNRNTEMP         0.0206         0.0013         16.35*           JULRNTEMP         0.0056         0.0011         5.32*	SQJUNTEMP	-0.0637	0.0247	$-2.58^{*}$
SQMAYRN0.00120.000115.35*SQJUNRN-0.00010.0001-1.42SQJULRN-0.00010.0000-2.99*SQAUGRN-0.00020.0000-4.91*MAYRNTEMP-0.02340.0009-27.25*JUNRNTEMP0.02060.001316.35*JULRNTEMP0.00560.00115.32*	SQJULTEMP	0.2470	0.0260	$9.50^{*}$
SQJUNRN-0.00010.0001-1.42SQJULRN-0.00010.0000-2.99*SQAUGRN-0.00020.0000-4.91*MAYRNTEMP-0.02340.0009-27.25*JUNRNTEMP0.02060.001316.35*JULRNTEMP0.00560.00115.32*	SQAUGTEMP	-0.2383	0.0198	$-12.01^{*}$
SQJULRN-0.00010.0000-2.99*SQAUGRN-0.00020.0000-4.91*MAYRNTEMP-0.02340.0009-27.25*JUNRNTEMP0.02060.001316.35*JULRNTEMP0.00560.00115.32*	SQMAYRN	0.0012	0.0001	$15.35^{*}$
SQAUGRN-0.00020.0000-4.91*MAYRNTEMP-0.02340.0009-27.25*JUNRNTEMP0.02060.001316.35*JULRNTEMP0.00560.00115.32*	SQJUNRN	-0.0001	0.0001	-1.42
MAYRNTEMP-0.02340.0009-27.25*JUNRNTEMP0.02060.001316.35*JULRNTEMP0.00560.00115.32*	SQJULRN	-0.0001	0.0000	$-2.99^{*}$
JUNRNTEMP0.02060.001316.35*JULRNTEMP0.00560.00115.32*	SQAUGRN	-0.0002	0.0000	$-4.91^{*}$
JULRNTEMP 0.0056 0.0011 5.32*	MAYRNTEMP	-0.0234	0.0009	$-27.25^{*}$
	JUNRNTEMP	0.0206	0.0013	$16.35^{*}$
AUGRNTEMP -0.0437 0.0010 -45.18*	JULRNTEMP	0.0056	0.0011	$5.32^{*}$
	AUGRNTEMP	-0.0437	0.0010	$-45.18^{*}$

Table 14. OLS Estimates of SOILS-5 Soybean Yields.

Variable	Estimate	Standard Error	t-Ratio
INTERCEPT	4816.2418	1951.8351	$2.47^{*}$
AGEI	-0.2917	1.0953	-0.27
AGCFACT	-160.0767	73.7431	$-2.17^{*}$
PERNIRR	-280.2744	31.6038	$-8.87^{*}$
AGAWC	410.7842	403.4304	1.02
MAYRN	-18.7258	6.7747	$-2.76^{*}$
JUNRN	4.1674	12.4238	0.34
JULRN	-14.9681	15.4890	-0.97
AUGRN	37.9711	16.7521	$2.27^{*}$
SQMAYRN	0.0368	0.0149	$2.47^{*}$
SQJUNRN	0.0350	0.0186	$1.88^{*}$
SQJULRN	-0.0095	0.0081	-1.48
SQAUGRN	0.0249	0.0168	1.04
MAYTEMP	538.4492	342.3026	1.57
JUNTEMP	-1886.7849	804.5096	$-2.35^{*}$
JULTEMP	552.0553	1227.6480	0.45
AUGTEMP	453.0247	927.9176	0.49
SQMAYTEMP	-10.6537	7.6830	-1.39
SQJUNTEMP	34.0365	15.6353	$2.18^{*}$
SQJULTEMP	-9.0963	21.6172	-0.42
SQAUGTEMP	-6.8037	16.6999	-0.41
MAYRNTEMP	0.5728	0.3228	$1.77^{*}$
JUNRNTEMP	-0.4222	0.5222	-0.81
JULRNTEMP	0.7828	0.5602	1.40
AUGRNTEMP	-1.5250	0.6307	$-2.42^{*}$
A 1 . 1.		10	11 1 1

Table 15. OLS Estimates of NASS Cotton Yields (Mean).

		~	
Variable	Estimate	Standard Error	t-Ratio
INTERCEPT	31.8053	71.5759	0.44
AGEI	-0.1423	0.0517	$-2.75^{*}$
AGCFACT	14.7014	4.7349	$3.10^{*}$
PERNIRR	-32.7562	2.0656	$-15.86^{*}$
AGAWC	153.7956	15.7651	$9.76^{*}$
MAYRN	1.8827	0.1992	$9.45^{*}$
JUNRN	-1.1391	0.2685	$-4.24^{*}$
JULRN	-0.2196	0.3393	-0.65
AUGRN	0.3356	0.3100	1.08
SQMAYRN	-0.0066	0.0010	$-6.50^{*}$
SQJUNRN	0.0053	0.0010	$5.12^{*}$
SQJULRN	0.0033	0.0004	$7.81^{*}$
SQAUGRN	0.0020	0.0007	$3.04^{*}$
MAYTEMP	-5.5233	7.7653	-0.71
JUNTEMP	-0.2215	18.0865	-0.01
JULTEMP	-21.1120	23.4481	-0.90
AUGTEMP	28.0794	18.2400	1.54
SQMAYTEMP	-0.3257	0.2216	-1.47
SQJUNTEMP	0.8714	0.4222	$2.06^{*}$
SQJULTEMP	0.3090	0.4937	0.63
SQAUGTEMP	-0.8341	0.3991	$-2.09^{*}$
MAYRNTEMP	-0.0236	0.0122	$-1.94^{*}$
JUNRNTEMP	-0.0031	0.0153	-0.20
JULRNTEMP	-0.0225	0.0135	$-1.67^{*}$
AUGRNTEMP	-0.0123	0.0131	-0.94
Asterisks indicat	te statistical sign	if is a negative of the $\alpha = .10$ o	r smaller level

Table 16. OLS Estimates of NASS Corn Yields (Mean).

Variable	Estimate	Standard Error	t-Ratio
INTERCEPT	-1174.1765	335.0947	$-3.50^{*}$
AGEI	-0.4074	0.1649	$-2.47^{*}$
AGCFACT	-29.6441	7.7322	$-3.83^{*}$
PERNIRR	-14.0862	2.7606	$-5.10^{*}$
AGAWC	40.6809	31.9521	1.27
MAYRN	-0.1977	0.5954	-0.33
JUNRN	-2.0449	0.9500	$-2.15^{*}$
JULRN	3.3612	1.4762	$2.28^{*}$
AUGRN	1.9268	1.2890	1.49
SQMAYRN	0.0040	0.0013	$3.16^{*}$
SQJUNRN	0.0027	0.0012	$2.21^{*}$
SQJULRN	-0.0036	0.0014	$-2.63^{*}$
SQAUGRN	0.0016	0.0023	0.69
MAYTEMP	19.2757	23.9546	0.80
JUNTEMP	-61.6379	70.1259	-0.88
JULTEMP	339.8309	86.4700	$3.93^{*}$
AUGTEMP	-222.9388	61.9475	$-3.60^{*}$
SQMAYTEMP	-0.7542	0.5816	-1.30
SQJUNTEMP	1.6941	1.4601	1.16
SQJULTEMP	-6.3871	1.6183	$-3.95^{*}$
SQAUGTEMP	4.3453	1.1561	$3.76^{*}$
MAYRNTEMP	-0.0285	0.0280	-1.02
JUNRNTEMP	0.0694	0.0394	$1.76^{*}$
JULRNTEMP	-0.1008	0.0523	$-1.93^{*}$
AUGRNTEMP	-0.0698	0.0499	-1.40

Table 17. OLS Estimates of NASS Sorghum Yields (Mean).

Variable	Estimate	Standard Error	t-Ratio
INTERCEPT	-17.6266	40.6845	-0.43
AGEI	-0.0571	0.0171	$-3.32^{*}$
AGCFACT	1.8319	1.2287	1.49
PERNIRR	-2.1530	0.5231	$-4.12^{*}$
AGAWC	54.7830	4.1258	$13.28^{*}$
MAYRN	0.7967	0.0735	$10.84^{*}$
JUNRN	-0.5336	0.1009	$-5.29^{*}$
JULRN	0.0201	0.1274	0.16
AUGRN	0.1655	0.0978	$1.69^{*}$
SQMAYRN	-0.0020	0.0003	$-5.84^{*}$
SQJUNRN	-0.0012	0.0003	$-3.65^{*}$
SQJULRN	0.0002	0.0001	1.13
SQAUGRN	0.0000	0.0001	0.64
MAYTEMP	-16.3109	3.1258	$-5.22^{*}$
JUNTEMP	30.7008	7.1925	$4.27^{*}$
JULTEMP	-1.2581	8.4366	-0.15
AUGTEMP	-13.9638	5.5194	$-2.53^{*}$
SQMAYTEMP	0.2922	0.0873	$3.35^{*}$
SQJUNTEMP	-0.4784	0.1952	$-3.00^{*}$
SQJULTEMP	-0.0665	0.1674	-0.40
SQAUGTEMP	0.2633	0.1140	$2.31^{*}$
MAYRNTEMP	-0.0159	0.0032	$-4.95^{*}$
JUNRNTEMP	0.0335	0.0050	$6.70^{*}$
JULRNTEMP	-0.0030	0.0053	-0.57
AUGRNTEMP	-0.0034	0.0039	-0.87
		1	11 1 1

Table 18. OLS Estimates of NASS Soybean Yields (Mean).