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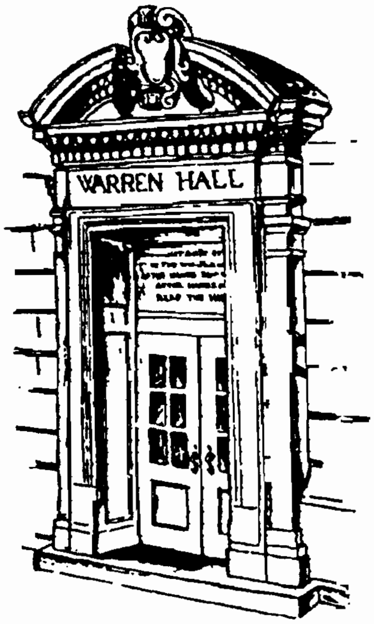

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MODELING THE EFFECTS OF CLIMATE CHANGE ON GRAIN PRODUCTION IN THE US: AN EXPERIMENTAL DESIGN APPROACH

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ABSTRACT

Climate places an important constraint on agriculture. Climate change will alter the production possibility frontier (PPF) for agricultural activities through the effects on yields. Farmers respond to new PPF by changing cropping patterns. The optimal cropping pattern is jointly determined by PPF and relative prices. A thorough investigation of the effects of climate change, therefore, requires an inderdisciplinary approach integrating climatic, agronomic, and economic processes.

In this paper, response surfaces are developed using data generated from a complex computer model to provide a single-equation summary of the physical and economic relationships embodied in the integrated model. An orthogonal design is chosen for the generation of the data. Analysis of variance is performed to evaluate the relative contribution of climatic, agronomic and economic variables to the variability of yield of four grain crops, average production, and farm net return in the midwestern United States. Due to the orthogonal design, total variability can be partitioned uniquely among these variables.

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The results of the analysis of variance indicate that agro-climatic variables dominate economic variables regarding crop yields. However, both agro-climatic and economic variables influence net return and total production. Although temperature is the most important variable for production, test statistics show that economic variables also have significant effects. The price of sorghum is important for net return because sorghum is typically the only crop that performs well under adverse climates. Not surprisingly, the most important economic variable is the own price for the production of each crop.

The estimated main effects and interactions of temperature and precipitation are used to predict yield, production, and net return under different climatic conditions presented in the literature. In comparison, this study shows that yield is more sensitive to warmer temperatures and less sensitive to drier conditions than other studies.

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The threat of global climate change, caused by increased concentration of greenhouse gases (GHG), has major implications for agriculture. An urgent policy issue is whether food production will be sufficient to sustain the world population in the future. Research efforts to analyze the influence of weather on crop yield were initiated by crop scientists during the late 1960's (Thompson 1969a, 1969b and 1970). Studies by economists have recently emerged to examine the economic impacts of climate change on agriculture at the international level (Kane et al. and Rosenzweig et al.), at the national level (Adams et al. and Mendelsohn et al.), at the regional level (Crosson, Katz and Wingard), and at the farm level (Kaiser et al.). While these studies have provided preliminary results, they have failed to develop a modeling framework which 1) establishes explicit linkages between production and agro-climatic constraints; and 2) simplifies the way in which effects of climate change are aggregated spatially.

This research examines the effects of climate change on agriculture in the midwestern United States by developing response surfaces for an integrated computer model of a representative grain farm (Kaiser et al.). The response surfaces provide a single-equation summary of the complex climatic, agronomic, and economic relationships embodied in the computer model. By establishing a linkage between farmers' decisions and the agro-climatic constraints on production, this approach is convenient for assessing the effects of climate change on grain production in an integrated way.

A complete factorial design is chosen for the generation of computer data because it not only allows for independent estimation of all main effects and interactions, but also preserves orthogonality among inputs. Analysis of variance is performed for the response surfaces using regression technique to evaluate the relative contributions of different climatic, agronomic, and economic variables to the variability of yields, production, and net farm return. Due to the orthogonal design, the total variability of these variables can be partitioned uniquely among the input variables using regression techniques.

Section 1 compares three alternative methods for generating computer data. Section 2 specifies the input variables for the computer model and the regression model for fitting response surfaces. The simulation procedure is also described. Section 3 analyzes the computer data for yield, production, and net return. Analysis of variance is performed to show the relative importance of the agro-climatic and economic variables. Section 4 takes a closer look at the effects of temperature and precipitation. In Section 4.1, the main effects for temperature and precipitation and the interaction from the original model are used to predict responses under the scenarios specified in two other studies of climate change. Results from these studies are compared. Section 5 gives a summary and the conclusions.

1. A Comparison of Alternative Experimental Designs

The general approach to approximating a complex model is to generate a data set of output values for different input configurations, and then use regression techniques to fit response surfaces. Methods differ by the procedure used to determine values of the inputs. To select an appropriate sampling procedure for this study, three alternative designs are compared: pseudo data techniques, factorial designs, and Latin hypercube designs.

1.1 Pseudo Data Techniques

Pseudo data (Griffin 1977, 1978, and 1982; Hertel and Preckel) are the solutions to any computer model describing a set of economic, technological , or social activities. The technique requires the identification of the input variables of interests and their ranges of values. Typically, data are generated according to a one-factor-at-a-time design in which one variable is varied incrementally holding all others constant. An advantage of the pseudo-data technique is that input variation is made orthogonal, which allows complete separation of effects among inputs using regression methods. A major shortcoming of the technique is that the method does not deal with interactions between inputs, because the one-factor-at-a-time sampling procedure excludes simultaneous variations among inputs. There are many alternative designs which do consider interactions, but pseudo-data technique has enjoyed popularity among economists. Maddala and Roberts are one exception (Maddala and Roberts, 1980 and 1981), and they have made a number of criticisms of the approach.

1.2 Factorial Designs

Factorial designs (Box, Hunter and Hunter; Montgomery; Myers) sample a set of combinations of the levels of the factors. A major advantage of a complete factorial design is that it is possible to partition the explained variability of the model among the explanatory variables (This is not possible in a typical regression model with correlated regressors). However, as the number of factors or levels increases, the number of runs required by the design rapidly outgrows the resources of most experiments. This difficulty has led to the popularity of a special case, the two-level factorial (2^k), in applications. A complete two-level factorial design involving k factors requires 2^k

observations. This design has two attractive features. First, it allows for estimation of all main effects and interactions. Second, the method ensures orthogonality among all of the explanatory variables. A disadvantage of such designs is that they are inadequate for estimating the shapes of the surfaces because only two levels of each factor are sampled.

1.3 Latin Hypercube Designs

The Latin hypercube sampling (Iman and Conover; McKay, Conover and Beckman; Welch, Buck, Sacks, Wynn, Mitchell and Morris) covers the entire range of input variables. The range of each input variable is divided into intervals, and one observation of the input variable is determined using random sampling to select an interval. The observations for other inputs are randomly selected to form the input set for a run. Depending on the number of runs needed, this process can go on until all observations are generated. A Latin hypercube design represents the complete range of values for all inputs in a fully stratified manner and ensures that the entire range of each input is equally likely to be sampled. By matching input levels randomly, the sample contains simultaneous movements in input levels. As a consequence, the procedure is able to estimate both main effects and interactions. A major advantage of the procedure is that it does not require as many runs as a complete factorial design. This is especially practical for the situation where a response is determined by a large number of variables. However, a disadvantage of the procedure is that it does not preserve exact orthogonality.

1.4 Choosing An Appropriate Design

Although the pseudo-data technique gives direct estimates of the marginal effects of each input, it is inappropriate for this research because it ignores interactions among inputs (e.g., plants may need higher rainfall if temperatures increase). In contrast, both factorial design and Latin hypercube allow for estimates of all main effects and interactions. Two-level factorial designs exhibit orthogonality between main effects and pairwise interactions, and, therefore, makes it possible to partition the explained variability of the regression among input variables and the interactions, but they are inadequate for estimating the shape of the surface. A Latin hypercube requires fewer observations and provides better information about the shapes of surfaces. However, it does not preserve exact orthogonality and is less suitable for assessing the relative importance among variables. Since we are more interested in the relative importance of variables in this research, a two-level factorial design is chosen for the analysis. Higher level factorial designs are rejected because the sample size would be too large. The analysis described in this paper uses k=9 inputs, and for a two-level factorial, there are 512 observations.

2. The Specification of Input Levels

2.1 Background

The Kaiser et al. model has three component models: climatic, agronomic, and economic. The climatic component is a stochastic weather generator (WGEN) initially introduced by Richardson and Wright, which characterizes weather through cosine functions and stochastic processes. The agronomic component is the General Purpose Atmospheric Plant Soils model (GAPS), developed by Buttler and Riha. The economic component is a LP farm-management model developed by Kaiser. Figure 2.1 illustrates how each component relates to one another.

While both WGEN and the LP model are relatively fast to solve, GAPS is computationally expensive because it tracks crop growth on an hourly basis for the length of growing season through integration of soil, plant, and near-plant atmospheric processes. A typical simulation requires users to specify a "cultivar", which, in this study, is determined by three attributes: a planting date, a harvest date, and the maturity type of a particular crop[1]. Although an annual run takes 15 seconds on a 486/33 IBM compatible computer, the economic model requires 30 yield observations for each "cultivar". Furthermore, in order to trace out the production frontier implied by supply relationships, a large set of "cultivars" must be simulated to allow for the possibility of crop substitutions within the model. The large choice of cultivars overcomes a serious limitation of many other studies on climate change which assumes that the same crops will be grown in the same places in the same ways, regardless of how the climate may change. However, an adverse consequence of this is it costs more in terms of computational time since a complete run now involves annual simulations for many different cultivars for each crop.

The high computing cost of GAPS limits the number of variables and levels to be specified for the computer simulations. According to a two-level factorial design, an extra variable will double the number of runs. Therefore, even though germination, tasseling, and maturation are critical stages in grain production, it is not possible to consider the climate at each of the stages separately. As a result, climatic variables are considered at a more time-aggregated level in terms of the average values for the growing season.

The objective now is to determine two levels for the input variables that provide for sufficient variability but are realistic for the midwestern United States. Consequently, the range of values observed in this region with two very different soils are adopted for the agro-climatic variables, and the levels for grain prices are based on large movements away from the historical mean values.

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[1] The conventional definition of a cultivar does not include planting and harvest date. This alternative definition is used in this study to facilitate exposition.

2.2 The Climatic Component

The four climatic variables identified as inputs are the average values of temperature, solar radiation, precipitation, and precipitation variability for the growing season[2]. Temperatures (in terms of maximum and minimum daily values) and solar radiation in WGEN are represented by cosine functions which exhibit annual cycles. The characteristics of the cosine functions are determined by three parameters : the phase angle (ϕ), the mean (c_o) and the amplitude (c_1). The phase angle for temperatures is 203 days. The range of input values for solar radiation refers to observed values for a broader region (the midwest and the southeast). The phase angle for solar radiation is 172 days. The random variability around the mean represented by a cosine function is determined by values for the standard deviations (sd)[3].

Daily precipitation is determined by a first-order Markov chain specified by two transition probabilities (p_{01}, the probability of a wet day following a dry day, and p_{11}, the probability of a wet day following a wet day) which change from month to month. These transition probabilities control whether a particular day is wet (rain occurs) or dry (rain does not occur). A mathematically equivalent parameterization of the occurrence process is to use the two parameters, $\pi=p_{01}/(1+p_{01}-p_{11})$, the unconditional probability of a wet day, and $d=p_{11}-p_{01}$, the "dependence parameter" which measures the strength of the persistence, or auto-correlation (d is the 1-day lagged autocorrelation of the occurrence series, Katz 1985). Precipitation amounts, given that precipitation occurs, are determined by the parameters of the gamma distribution (α, the shape

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2 Temperature variability is not considered here because it is not believed to be important, even though its value can be specified in the model.

3 Actual realization of temperature is presented as a deterministic mean value (determined by the cosine function) plus an autoregressive Gaussian random variable with zero mean and the standard deviations equal to sd. The standard deviations also exhibit annual cycles that are represented by separate cosine functions.

parameter, and β, the scale parameter). All parameters are listed in Tables 2.1 through 2.7.

Given these parameters, the means and variances of these processes can be determined. For N days, the conditional mean for temperature for the dry or wet days is

$$T_c = \frac{1}{N}\int_t^{t+N}\{c_0 + c_1 \times \cos[\frac{2\pi(t-203)}{365}]\}dt. \tag{2.1}$$

By substituting appropriate parameters into Equation 2.1, the mean can be derived for maximum temperature for the dry days ($T_{max,dry}$), maximum temperature for the wet days $T_{max,wet}$, minimum temperature for dry days ($T_{min,dry}$), and minimum temperature for the wet days ($T_{min,wet}$). The unconditional mean, therefore, is:

$$T = (1-\pi)\times(\frac{T_{max,dry} + T_{min,dry}}{2}) + \pi\times(\frac{T_{max,wet} + T_{min,wet}}{2}). \tag{2.2}$$

The conditional mean for solar radiation for the dry or wet days is:

$$S_c = \frac{1}{N}\int_t^{t+N}\{c_0 + c_1 \times \cos[\frac{2\pi(t-172)}{365}]\}dt. \tag{2.3}$$

By substituting appropriate parameters, the mean of solar radiation can be derived for the wet days (S_{wet}) and for the dry days (S_{dry}). The unconditional mean is:

$$S = (1-\pi)\times S_{dry} + \pi\times S_{wet}. \tag{2.4}$$

The mean for monthly precipitation is

$$P = N\pi\alpha\beta, \tag{2.5}$$

and the monthly variance is

$$P_v \cong N\pi\alpha\beta^2[1+\alpha(1-\pi)(1+d)/(1-d)]. \qquad (2.6)$$

Once these input variables are identified, the design requires that two levels be specified for each input. Tables 2.1 through 2.3 show the parameter values for temperature and solar radiation at different sites. The range of input values for temperature refers to observed values among these sites in the United States. The high (marked by *) and low (marked by #) values are used as input levels for the two-level factorial design. For example, the observed values of c_0 at Redwood Falls, Minnesota and Lincoln, Nebraska are chosen to represent, respectively, the low level and the high level for the maximum temperature. The amplitude (c_1) of Napoleon, Ohio (marked by ~) is selected to represent the typical continental climate for the midwest. The standard deviations for the cosine functions are represented by the observed values at Redwood Falls, Minnesota (Table 2.4).

Since the value of $\alpha\beta$ in Equation 2.5 is proportional to the mean value of precipitation for given π and N, this measure is used for determining the input levels for precipitation (Table 2.7). The observed values from Vicksburg and Redwood Falls are chosen to represent the high level and the low level. The variance for precipitation is determined jointly by two parameters, π and d (Equation 2.3). It is maximized when π is 0.5 and d approaches 1. The low and the high levels for precipitation variability are represented by the observed values from Napoleon and Vicksburg for π (Table 2.5) and those from Vicksburg and Napoloen for d (Table 2.6). The values of p_{01} and p_{11} implied by the selected π and d are shown in Table 2.8 for the growing season.

There is a complicating factor, however, for determining the mean and variability of precipitation simultaneously because the two are interdependent. Equation 2.1 indicates the mean involves π, a function of p_{01} and p_{11}, which in turn contributes to the variance. To keep the mean precipitation constant as the variance changes, either α (the shape parameter) or β (the scale parameter) needs to be compensated. In this study, α is kept constant while β is adjusted. The high and low values used in the design are shown in Table 2.9. The implied average values for the variances of the growing season are shown in Table 2.10.

2.3 The Agronomic Component

While a typical simulation of a "cultivar" in GAPS requires the specification of soil type and daily values of maximum temperature, minimum temperature, solar radiation, and precipitation, temperature is the most important variable for yield because it determines the lengths of growing seasons through its impact on the accumulation of heat units. Generally speaking, early maturing cultivars would do better than late maturing cultivars under low temperatures because maturing speed is important for success in shorter growing seasons. Shorter growing seasons are also more demanding on the timing for planting. Crops planted too early will face frost kill, while those planted too late will have too little time to fully mature. Under higher temperatures, the growing seasons are longer, and planting time does not need to be as precise. When growing seasons are long, late cultivars are expected to do well because they can take full advantage of the long growing time.

Since true supply relationships must reflect the production frontier, only the highest yielding cultivars need to be simulated for each crop. A practical problem is that it is not known *a priori* which cultivar will generate the highest yield for given agro-climatic conditions. If computation cost is not limiting, one can avoid making these judgments by simulating yields for all possible cultivars and let the model determine which cultivars result in highest yields. A more computationally efficient strategy is to focus on a smaller set of cultivars by eliminating those which obviously do not make sense (e.g., maize planted too early when there is still a high probability of frost).

To determine a smaller set of cultivars, the daily values for the low temperature and the high temperature are generated and compared with the observed temperatures for Redwood Falls, Minnesota and Lincoln, Nebraska (Figures 2.2 and 2.3). The figures indicate that the daily values for the low temperature and high temperature are similar to the observed values of Redwood Falls, Minnesota and Lincoln, Nebraska, respectively. As a result, the observed planting and harvest schedules for the two sites (Minnesota Agricultural Statistics; Nebraska Agricultural Statistics) are used to determine realistic sets of cultivars for the high and low temperature simulation. The schedules are shown in Table 2.11. Note that MZ, SB, SG, SW and WW stand for maize, soybean, sorghum, spring wheat and winter wheat, respectively. Three varieties (early, medium, and late) are simulated for each crop. To further reduce computation time, the set of "cultivars" specified for one level of temperature are assumed to be inappropriate for the other level, and no corresponding simulation is needed. This amounts to a total of 54 distinct "cultivars" (27 for each level of temperature). Although GAPS is capable of simulating double cropping, it is not appropriate in this study because the range of values for temperature refer to observed values in the midwestern United States with short growing seasons.

Since nutrients are not limiting in GAPS, soils matter for yield to the extent that they differ in the water-holding capacity. Ves Composite, a deep soil, with good water-holding capacity, and Dickman, a shallow, sandy soil, are chosen to represent the high and low values for the soil variables. The two soils encompass a reasonable range of soil quality for the grain-producing counties in the midwest.

2.4 The Economic Component

The economic component is a linear programming based on Hazell's MOTAD formulation, which can be interpreted as a linear approximation of a quadratic programming model. The objective is to maximize the difference between the expected net revenue and the total absolute deviations from the mean multiplied by a risk coefficient (ε). The basic formulation is:

Maximize	$C'X - \varepsilon\Phi Ld,$	(2.7)
subject to	$AX \leq B,$	(1)
	$DX + Id \geq 0,$	(2)
and	$X, d \geq 0,$	(3)

where X, A, B, and C represent activity levels, resource uses, resource availabilities, and gross margin expectations. Elements of D, the deviation matrix, consists the difference between the observed net return and the net return expectation. The vector, **d**, represents yearly negative deviations from expected net return summed over 30 years by **L**, a row vector of ones, to give a measure of summed total negative deviation over 30 years. The sum is translated into an estimate of standard deviation by multiplication by the constant Φ[4] . The trade-off between expected revenue and risk is represented by the risk aversion coefficient, ε. Parameterization of ε gives the efficient set of plans. A 30×30 identity matrix is shown as I. Constraint (1) restricts the use of farm labor and acres planted to endowed levels. Constraint (2) is an accounting constraint which defines negative deviation from expected net return. Constraint (3) is the standard non-negativity constraint. Three sources of risk are the observed variability of field time, crop yields, and grain drying costs from GAPS. Activities are constrained by the availability of field time, labor, and land. In an empirical study, Brink and McCarl found that 76% of the cornbelt farmers sampled had the risk

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3 Φ equals $(\frac{2}{s})\sqrt{\frac{s\pi}{2(s-1)}}$ where s is the sample size (for s=30, Φ=0.085). The factor outside the square root sign converts total negative deviation to mean absolute deviation (MAD), and the square root converts the MAD to an estimate of the standard deviation.

aversion coefficients within a narrower range (0 to 0.5). For this study, the risk coefficient is fixed at 0.25.

The input values of crop prices (Table 2.12) are determined using time-series data from 1975 through 1990 (Agricultural Statistics, 1992). The values 25% above the average values are used to be the high levels, and those 25% below the average values are used as the low levels (Table 2.13). Since all prices changes are mutually orthogonal by design, the approach probably exaggerate the importance of variability of prices. In reality, prices tend to move together due to substitution in demand.

2.5 The Response-Surface Model and Its Properties

In the last section, a high level and a low level are specified for a total of nine variables including four climatic variables: average values of temperature, precipitation, solar radiation, and precipitation variability for the growing season; one agronomic variable: soil; and four economic variables: the prices for maize, sorghum, soybean, and wheat (Table 2.14). A two-level factorial design requires that there be 32 runs for the 5 agro-climatic (physical) variables (2^5) and 16 runs for the 4 economic variables (2^4). There are 10 possible pairwise interactions (C_2^5) among physical variables, 6 (C_2^4) among economic variables, and 20 interactions between the two groups of variables (4×5). All together, there are 46 variables (an intercept, 9 main effects and 36 pairwise interactions) and 512 observations (32×16). To simplify the way inputs are represented, the low level and the high level for each input are coded to be 1 and -1, respectively. The full model in scalar notation can be written as

$$y_{pe} = \alpha + \sum_{i=1}^{5} \beta_{xi} x_{ip} + \sum_{j=1}^{4} \beta_{zj} z_{je} + \sum_{i>k}^{10} \gamma_{xxik} x_{ip} x_{kp} + \sum_{j>k}^{6} \gamma_{zzjk} z_{je} z_{ke} + \sum_{i>j}^{20} \gamma_{xzij} x_{ip} z_{je} + \varepsilon_{pe} \quad (2.8)$$

for p=1,2,...,32, e=1,2,...,16, $E[\varepsilon_{pe}]=0$, $Var[\varepsilon_{pe}]=\sigma^2$, and $Cov[\varepsilon_{pe}, \varepsilon_{p'e'}]=0$ for $p \neq p'$ and $e \neq e'$, where p=index for physical (agro-climatic) variables;

e=index for economic variables;

α=the intercept;

x_{ip}=a physical variable;

β_{xi}=the main effect for x_{ip};

z_{je}=a economic variable;

β_{zj}=the main effect for z_{je};

$x_{ip}x_{kp}$=the product of two physical variables, x_{ip} and x_{kp};

γ_{xxik}=the interaction effect between x_{ip} and x_{kp};

$z_{je}z_{ke}$=the product of two economic variables, z_{je} and z_{ke};

γ_{zzjk}=the interaction effect between z_{je} and z_{ke};

$x_{ip}z_{je}$=the product of a physical variable (x_{ip}) and an economic variable (z_{je});

γ_{xzij}=the interaction effect between x_{ip} and z_{je};

y_{pe}=the dependent variable, and

e_{pe}=an error term.

Equation 2.8 can be generalized to a standard regression model if variables are treated the same without regard to the classification of main effects, interactions, physical variables and economic variables. The model then becomes

$$y_t = \beta_0 + \sum_{i=1}^{45} \beta_i x_{it} + \varepsilon_t \text{ (scalar notation)} \tag{2.9a}$$

where $E(\varepsilon_t) = 0$, $Var(\varepsilon_t) = \sigma^2$, and $Cov(\varepsilon_i, \varepsilon_j) = 0$ for $i \neq j$ and t=1,2,...,512, or

$$Y_{512\times1} = X_{512\times46}\beta_{46\times1} + U_{512\times1} \text{ (matrix notation)} \tag{2.9b}$$

where $E(U_{512\times1}) = 0_{512\times1}$ and $Var(UU') = \sigma^2 I_{512\times512}$. The matrix X consists of 1's and -1's, depending on the level of the variables. Due to the orthogonal design , the matrix (X'X) is diagonal and equals $512\times I$, where I is a 512×512 identity matrix. The OLS estimator is

$$\hat{\beta} = (X'X)^{-1}X'Y = \frac{X'Y}{512},$$

and the total sum of squares is

$$\sum_{i=1}^{512}(y_i - \bar{y})^2 = 512\sum_{i=1}^{45}\hat{\beta}_i^2 + \sum_{i=1}^{512}\hat{\mu}_i^2 \text{ where } \bar{y} = \frac{1}{512}\sum_{i=1}^{512}y_i \text{ (scalar notation)}, \qquad (2.10a)$$

or

$$Y'Y = \hat{\beta}'X'X\hat{\beta} + \hat{U}'\hat{U} = 512\hat{\beta}'\hat{\beta} + \hat{U}'\hat{U} \text{ (matrix notation)}. \qquad (2.10b)$$

Equation 2.10 demonstrates the key feature of the orthogonal model. The term on the left is the total variability of the dependent variable around its mean. The first term on the right-hand side is the variability accounted for by the 9 main effects and 36 pairwise interactions. The second term is the portion which is not accounted for by the model. Due to the orthogonal design, the matrix (X'X) is diagonal, and total variability of the regression is completely partitioned among the individual regressors.

2.6 The Simulation Procedure

Since the error structure in the regression model specified in Equation 2.9 requires that a total of 512 simulations be generated independently (2^9), 512 distinct random seeds[5] were used for the weather generator to produce uncorrelated daily climatic data. Since 30 annual observations are needed by the economic model for each of the 27 cultivars, the two-level factorial design for the nine factors implies 72 days of continuous running of GAPS on a 486/33 IBM compatible machine[6]. To put this into perspective, an extra variable would require 144 days, and an extra level for nine variables would require 7 years and 212 days.

The 512 sets of data on yields, grain moisture and field time were then prepared in a spreadsheet format for the economic model which used a linear programming package (LP87). The solution to the LP program consists of optimum net return and acreage allocations to each cultivar. Production is obtained by summing up the products of the yield of each individual cultivar and its corresponding acreage for each crop. The computer time involved in WGEN and in the LP model is trivial compared to the time required for GAPS.

3. Statistical Results

3.1 The Yields of Individual Cultivars

a Background

Yields were generated through GAPS for each individual cultivar using the orthogonal two-factor design and ranges of the nine inputs specified in Section 2. Under this specification, there are 256 observations for yield at each temperature level.

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5 A sequential random number is required by the weather generator for each run. Climatic data generated with the same set of parameter values but different random numbers will exhibit similar characteristics with random variations.

6 It takes 15 seconds for GAPS to complete the simulation of a cultivar. Therefore, 512×30 runs for 27 cultivars require $512 \times 30 \times 27 \times 15$ seconds (72 days) of computer time.

Since crops in GAPS are simulated under ideal field conditions, these yields predicted by GAPS are larger than the average observed yields under typical field conditions (Moen, Kaiser and Riha). A common practice is to scale the simulated yields downward to observed levels. The scaling factors used by Kaiser *et al.* in their study (Table 3.1) are adopted for this study to scale the simulated yields. The yields for the low temperature and the high temperature were multiplied by the scaling factors for Redwood Falls, Minnesota and Lincoln, Nebraska, respectively[7]. The maximum and minimum yields from GAPS (scaled yields and potential yields) are recorded in Table 3.2. The scaled yields for individual cultivars were then normalized to 1 through 10 corresponding to 10 equal intervals between the maximum and the minimum observed yields for each crop. Table 3.3 shows the means, the variances, the C-V[8] coefficients, and the frequencies at each of the 10 levels for the normalized yields.

Note that MZ, SB, SG, SW, and WW are abbreviated crop names, and the three digits following each crop name denote planting period, harvest period, and maturity types, respectively. Nine periods are used for planting and harvest activity (Table 2.11), and three maturity types are simulated for each cultivar (1=early, 2=medium, and 3=late).

Under the low temperature, the early maturing cultivars of maize (MZ181 and MZ281) have the highest yields (Table 3.3). As expected, the yields are much lower for the medium and the late cultivars. Furthermore, these decreases in mean are accompanied by increases in variances. The deterioration of performance for later maturing cultivars is also illustrated by the declines in the C-V coefficients. Within

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7 It has been shown in Section 3.4.2 that the growing season for the low temperature (high temperature) exhibits similar behavior to that for Minnesota (Nebraska).

8 A C-V coefficient is defined as the ratio of the mean to the standard deviation of a given distribution. Since the C-V value is unit free, this coefficient is commonly used in economics to measure return potential of an activity relative to the risk.

each maturity group, the cultivars planted earlier (i.e., MZ181) have higher yields and lower variances than those planted later (i.e., MZ281). The cultivars grown under the high temperature, also as expected, have much more stable yields across-the-board than the cultivars grown under the low temperature. Although the means for yields are comparable, cultivars grown under the high temperature have much smaller variances. The improving performance due to higher temperature is indicated by the increases in the corresponding C-V coefficients. The length of growing season probably accounts for this behavior in maize yield. The early maturing cultivars showed superior performance under the low temperature because they are well-adapted to the short growing periods and limited heat units. Within the same maturity group, the cultivars planted later had lower yield because the problem of insufficient heat units is aggravated by the delay in planting. In the extreme case, 72% of MZ283, a late variety which was also planted late, result in zero yield, probably due to failure to mature. The high temperature, however, implies a longer growing season and plenty of heat units. As a result, very few zero yields are observed. Furthermore, the late cultivars have relatively high yields due to their ability to draw the maximum benefits from a long growing season.

Soybeans grown in the low temperature are relatively sensitive to planting time. While a large number of zero yields are observed for the cultivars planted in period 1 and period 3, the cultivars planted in period 2 seem to have normal yields. Frost kill early in the growing season probably causes the zero yields for the cultivar of period 1, and failure to mature is the reason for the zero yields for the cultivars of period 3. Compared to these cultivars, the cultivars of period 2 have higher means and smaller variances in yield, and larger C-V's. Soybean benefits significantly from a warmer climate. Not only does the high temperature increase the means for yields, it also reduces the variances of yield across all cultivars. As a result, the C-V coefficients for yields under the high temperature are larger than those under the low temperature.

As expected, the late cultivars exhibit the best performances under the high temperature.

Similar to maize, the early cultivars of sorghum (SG181, SG281) exhibit the best performance among cultivars grown in the low temperature. The medium cultivars (SG182, SG282) have lower means and larger variances in yield. The late cultivars (SG183 and SG283) have only zero yields. The yields of sorghum under the high temperature, on the other hand, have much higher values for mean and similar values for variance. The C-V coefficients for yields under the high temperature, therefore, are larger than those for yield under the low temperature. The better performance due to a higher temperature is consistent with the fact that sorghum is more commonly-grown in the southern midwest.

In contrast to soybean, wheat seems insensitive to planting time. The means and the variances for yield are comparable among all cultivars at each temperature level. However, the means in yield for winter wheat (grown in the high temperature) are much higher than the means for spring wheat (grown in the low temperature). The variances in yield for winter wheat are higher too. The increases in variance for winter wheat may be due to winter damage.

b The Regression Model for Yield

The model for yield is characterized by Equation 3.1. In comparison with the full model (Equation 2.8), this specification has four variables (precipitation, precipitation variability, solar radiation, and soil), and does not have temperature and the economic variables (four prices). Prices are excluded because only agro-climatic variables matter for yield. Furthermore, separate analysis is done for each temperature level because different cultivars were simulated at different temperatures. As a result, the model for yield has four main effects (soil, precipitation variability, precipitation and solar radiation), six pairwise interactions, and 16 runs (2^4). The dependent variable is the mean value of 16×30=480 annual yields[9] for 54 individual cultivars.

$$y_p = \alpha + \sum_{i=1}^{4} \beta_{xi} x_{ip} + \sum_{i>k}^{6} \gamma_{xxik} x_{ip} x_{kp} + e_p \tag{3.1}$$

for p=1,2,..16, $E[\varepsilon_p]=0$, $Var[\varepsilon_p]=\sigma^2$, and $Cov[\varepsilon_p,\varepsilon_{p'}]=0$ for $p \neq p'$ where

α=the intercept;

x_{ip}=a physical variable;

β_{xi}=the main effect for x_{ip};

$x_{ip}x_{kp}$=the product of x_{ip} and x_{kp};

γ_{xxik}=the interaction effect between x_{ip} and x_{kp}, and

ε_p=an error term.

A more generic representation of Equation 3.1 is

$$y_t = \beta_0 + \sum_{i=1}^{10} \beta_i x_{it} + \varepsilon_t \tag{3.2}$$

where $E(\varepsilon_t) = 0$, $Var(\varepsilon_t) = \sigma^2$, and $Cov(\varepsilon_i, \varepsilon_j) = 0$ for $i \neq j$ and t=1,2,...,16.

Since all inputs, by design, are orthogonal to one another, the total sum of squares of the regression can be written as

$$\sum_{i=1}^{16} (y_i - \bar{y})^2 = 16 \sum_{i=1}^{10} \hat{\beta}_i^2 + \sum_{i=1}^{16} \hat{\mu}_i^2 \text{ where } \bar{y} = \frac{1}{16} \sum_{i=1}^{16} y_i \,. \tag{3.3}$$

9 To recall, 30 annual yields are required for the economic model.

After simple manipulation (divide through by the left-hand-side quantities and multiplying by 100%), Equation 5.3 becomes

$$100\% = \frac{16\sum_{i=1}^{10}\hat{\beta}_i^2}{\sum_{i=1}^{16}(y_i - \bar{y})^2} + \frac{\sum_{i=1}^{16}\hat{\mu}_i^2}{\sum_{i=1}^{16}(y_i - \bar{y})^2}. \tag{3.4}$$

Equation 3.4 shows that the total variability of the regression is uniquely allocated in percent among the four main effects and six pairwise interactions.

c Results for the Analysis of Variance

The regression was conducted using the yield model specified in Equation 3.2. Results for the analysis of variance based on Equation 3.4 are reported in Tables 3.4 through 3.7. These results are conditional on the choice of low or high temperature. The yield model performed quite well. Except for the soybean cultivars grown in the low temperature, more than 95% of the yield variability is explained by the four main effects and the interactions.

Soil and precipitation are the most influential variables on the yield for maize (Table 3.4). Soil is particularly important for early maize but relatively less important for medium and late maize. On the contrary, precipitation is more important for medium and late maize yields than for early maize yields. Solar radiation has much smaller effects. Precipitation variability for the range observed in the midwestern United States does not seem to matter. The most important interaction is that between soil and precipitation (X1*X3). This means that maize yields are sensitive to precipitation (soil types), given soil types (the level of precipitation).

Precipitation variability and solar radiation are the most important main effects for soybean yields (Table 3.5). Solar radiation is more important under the high temperature than under the low temperature. The interactions for precipitation variability-solar radiation (X2*X4) and for precipitation variability-precipitation (X2*X3) show large effects on most soybean cultivars for the low temperature.

The estimated model for sorghum yields is dominated by solar radiation (Table 3.6), which explains more than 85% of the variability for all cultivars. The effect of precipitation variability is the next important but this is much smaller. Sorghum yield is not sensitive to soil, precipitation, or any of the interactions.

The most important main effects for wheat yields are soil and precipitation (Table 3.7), and the most important interaction is between soil and precipitation (X1*X3). Soil is relatively more important for spring wheat yields (under the low temperature) than for winter wheat yields (under the high temperature). The interaction, however, has larger effects on winter wheat than on spring wheat.

Table 3.8 provides a qualitative summary of the analysis-of-variance results by crop. For maize yields, soil and precipitation are important under both temperature levels. The interaction between soil and precipitation is important for maize yields in the high temperature. Soybean yields in the low temperature are dominated by precipitation variability and the interaction between precipitation variability and precipitation. The interaction between precipitation variability and solar radiation shows some effects. Soybean yields in the high temperature, however, are primarily determined by solar radiation. Precipitation variability has secondary effects. For sorghum, solar radiation has the largest effect on yield. Precipitation has much smaller effects for sorghum yields in the low temperature. Soil and precipitation are the most important main effects for wheat yields. The interaction between soil and precipitation also has secondary impacts on winter wheat yields under the high temperature.

3.2 Best Yield and Net Return

Estimates of yields for individual cultivars, grain moisture, and field hours are used as inputs for the economic model. Based on the agronomic information and prices, the economic model determines net return and acreages for individual cultivars. While net return are directly observable in the solution set, the best yield representing a particular crop depends on which cultivars of that crop are selected in the solution set of the economic model. When none of the cultivars are selected, it is not clear which cultivars should be used to represent the yield for the crop, and the observation on the best yield is missing. To complete the data set for the best yield, the weighted average yields (Table 3.9) for all the non-zero observations on acreage in the solution set are used as imputed values for yields.

The best yield and net return were analyzed using the full model specified in Equation 2.8 which includes four prices of grains and temperature as well as the 4 agro-climatic variables used in the model for individual cultivars. The analysis of variance is based on Equation 2.10. The results are shown in Table 3.10 based on the full sample of 512 observations. Hypothesis tests are conducted to see whether economic variables and associated interactions matter for the best yield. The null hypothesis is that prices have zero impact. The degrees of freedom are 466 and 436 for the full model and the restricted model.

The model fits well for the best yield (except for soybean) and net return. Due to the orthogonal design structure, the total variability for the best yield and for farm net return is uniquely allocated between agro-climatic variables and prices. The main effects of agro-climatic factors account for most of the variability for the best yield. Temperature has large effects on the yields of soybean, sorghum, and wheat, but a small effect on the yield of maize. Soil and precipitation are important for maize. Not surprisingly, none of the economic variables matter for yield. For net return, the main effect of temperature dominates and, as expected, the effects of economic variables are more important than they are for yields. Since sorghum is the least sensitive to adverse conditions, it is typically selected in the LP model when conditions are bad, regardless of price levels. Therefore, net return depend strongly on the price of sorghum.

Hypothesis tests are performed to see whether the economic variables and the associated interactions matter. The restricted model has 16 variables: an intercept, five main effects, and 10 interactions. The critical F-value for all tests is 1.46 at a 5% significance level. None of the test statistics are significant for the best yield, indicating that only agronomic variables matter for the best yield. However, the F-statistic is highly significant for net return, indicating, as expected, that economic variables do matter for net return.

3.3 Crop Production and Acreage Allocation

While the models for the best yield and net return exhibit satisfactory performance, preliminary results indicate that the production models do not work nearly as well as the yield models. Table 3.11 compares the R-squared statistics for the best yield, net return, acreage and production. It is obvious that best yield and net return fit well (for all but soybean). This is not true for acreage and production. However, it seems unlikely that the true unexplained variability could be so high. One possibility is that the poor fit is caused by the addition of the 4 price variables which may bring in new complexity into the model and make higher-order interactions important. To verify this hypothesis, the original model is augmented by adding 3-way interactions[10]. However, the addition of 3-way interactions does not improve the fit very much (except for sorghum). What is causing the problem with production? Some diagnostic measures are called for.

The problems with the production model are caused by the existence of "corner solutions" in acreage. The acreage allocation to a crop is the solution to a linear

[10] Since the model has 9 main effects, there are 84 distinct 3-way interactions.

programming model of a typical farm, and is constrained to be between 0 (the LP solution space) and 800 (the available land in the farm). Since four crops compete for 800 acres of farm land, the solution is often characterized by a dominating crop which uses up almost all of the land and subordinate crops which use little or no land at all. As a result, the acreage data are filled with extreme observations. Table 3.12 indicates that the number of extreme observations (either 0 or 800) on acreage ranges from 287 for sorghum to 422 for soybean out of a total of 512 observations.

This is exactly the truncated-data problem discussed in the econometric literature. When a large number of truncated observations are involved, OLS estimation becomes inappropriate because the truncation causes the true error terms to have non-zero means, violating the standard assumption of OLS estimation. Figure 3.1 shows that the corner solutions for acreage cause OLS to be biased. Not surprisingly, the truncation problem with acreage extends to production, since production is simply the product of acreage and yield.

While a new estimation method has been developed to deal with the truncation problem and to correct for bias, the corner solutions destroy the orthogonal structure of the original design. As a consequence, the models for production can no longer allocate variability uniquely among different agro-climatic and economic variables. In addition, the coefficients, or the marginal effects, for some variables can no longer be estimated (some of the regressors become linearly dependent on others). This is unfortunate because the marginal effects for the production of individual crops are of great interest. There is no simple way to resolve this problem because the data do not contain sufficient information to estimate all of the coefficients if there are too many corner solutions in the data set. The alternative method of estimation for corner solution is discussed in a separate paper.

For completeness, analysis of variance is performed for production by crop using OLS even though the method may generate biased estimates due to problems of corner solutions. Therefore, the results should be interpreted as descriptive measures of fit. The results are shown in Table 3.13.

The analysis of variance indicates that temperature is the most important climatic variable for the production of sorghum and wheat. Temperature, soil and precipitation are equally important for the production of maize. Solar radiation has the largest, but still small, effect on soybean. Not surprisingly, own price is the most important economic variable for the production of each crop. Cross prices are secondary. Relatively speaking, the most important cross prices are the price of sorghum for the production of soybean and wheat. Data for production indicate that, for the dry and hot scenario, sorghum is a substitute for soybean and wheat. In aggregate, interactions have an important role in production.

While the physical effects are larger than the economic effects in aggregate, the economic effects, not surprisingly, are more important for production than for the best yield. Test statistics indicate that economic variables clearly have significant influence for production.

Given the double truncation of production data (Figure 3.1), the observed means of production resemble the shape of a logistic curve. As an alternative to analyzing production directly, OLS is performed for a logistic transformation of production[11]. An advantage the transformation is it conforms with the observed means, and OLS becomes less biased. However, a disadvantage is that a logistic transformation of production may not be as interesting a variable as production itself. The results of the analysis of variance are shown in Table 3.14.

Surprisingly, the logistic transformation of production does not improve the fit significantly, but it does change the coefficient estimates. With the transformation, temperature becomes more important for maize, soybean, and wheat, but it becomes

[11] Let P be the production of a particular crop, p_{max} be the maximum production, and ε be a small number, the logistic transformation of P is $\ln[\frac{(p+\varepsilon)/p_{max}}{(1-(p+\varepsilon)/p_{max})}]$.

less important for sorghum. Furthermore, the own price effects are more important for the production of all crops. The changes of coefficients suggest that there are considerable biases associated with the coefficient estimates for the original production. In both cases, test statistics indicate that economic variables have significant effects.

3.4 Average Production

Another solution to the problem of corner solutions is to analyze the average grain production (sum up the production for the four crops and divide by the total acreage) instead of the production for individual crops. Since at least one crop is grown on the farm for each observation, this composite measure overcomes corner solutions and allows for the estimation of marginal effects. The average grain production (in terms of volume, weight, and calories) has been analyzed using OLS estimation. The bushel-pound conversion factors are 56, 60, 56, 60, respectively, for maize, soybean, sorghum, and wheat (Doane's Facts and Figures for Farmers), while the conversion factors for 100 grams of grain to calorie are 348, 403, 332, and 330 (Handbook of the Nutritional Contents of Foods).

The analysis-of-variance results for average production (Table 3.15) show different characteristics from those for the best yield and farm net return. While temperature is the most important variable for average production, the effects are distributed more evenly among the agro-climatic and the economic variables, and interactions are more important. A larger portion of the variability is unexplained for average production than for yield or net return. This may be due to adding the economic component of the model and making the overall the results more complex. Consequently, results can not be explained simply in terms of main effects. Second-order and third-order interactions matter, and probably, higher-order interactions account for part of the unexplained variability.

4. A Comparison with Other Studies

4.1 Previous Research Results

A common assumption in studies of global warming is that overall agricultural productivity will decrease in middle-latitude countries (such as the United States) and increase in higher-latitude countries (such as Canada and Russia) under the climate warming induced by a doubling of greenhouse gases. For example, according to Kane et al., a 3.71 °C increase in the median temperature in the summer months reduced average yields in the United States for maize, soybean, and winter wheat by 23.8%, 34.6%, and 16.0%, respectively. Crop model simulations showed similar responses in the study by Rosenzweig et al.. Since these two studies dealt with world agriculture, yield effects were specified at the country level.

In a national study of United States agriculture by Adams et al., the yield effects of climate change were estimated for different regions through simulations of crop models under two scenarios (with CO_2 fertilization effects). Under Scenario I (a 4.32 °C increase in monthly average temperature and a 7.20 mm increase in monthly average precipitation), crop yields generally increased for most states in the midwestern United States. The percentage change in yield from the mean in this region were typically between 10% and 49% for maize, 20% and 49% for soybean, and 0% and 10% for wheat. However, yields for all three crops decreased in the south. Under Scenario II (5.09 °C warmer and 2.40 mm drier), yields generally decreased (the only increase is the yield of soybean in the upper midwest). These results are summarized in Table 4.1.

Kaiser et al. examined the adaptability issue under three scenarios of climate change through crop simulations for a southern Minnesota farm using the same basic model as the one used for this research. Their results indicate that, under a mildly warmer (2.5 °C) and wetter (7.30 mm per month increase in precipitation) scenario, the yield for soybean and for sorghum increased by approximately 15%. The yield for maize showed small fluctuations around the mean. Under a mildly warmer (2.5 °C) and drier (7.30 mm per month decrease in precipitation) scenario, the yields for soybean and sorghum are 15% higher, while the yield for maize declined a little. A more severe scenario (5 °C warmer and 14.60 mm per month decrease in precipitation) further reduced maize yield, but had little impact on soybean and sorghum. Farm net return increased in all scenarios, due, in part, to incorporating a price response to changes of yield. See Table 4.2 for a summary of their results.

4.2 The Effects of Temperature and Precipitation

Earlier in this section, the models for the best yield, average production, and net return were estimated with regression techniques using data generated from the climate/agronomic/economic model. The design allows for independent estimates of all main effects and interactions. The main effects are marginal effects because they reflect the change in the dependent variables in response to a unit change in the independent variables (levels of each input are scaled to be -1 or +1). The estimated main effects and interactions for temperature and precipitation are shown in Table 4.3.

Based on these main effects and interactions for temperature and precipitation, responses of the dependent variables are computed for different levels of these two variables (Table 4.4). The observed means are used to predict the responses under the base point (all inputs are at kept at the average values).[12] The predictions show up as 0% change from the mean in the center cells of blocks of nine cells in Table 4.4. Going up (down) from the center increases (decreases) temperature. Going right (left)

[12] According to the two-level factorial design, simulation is required for the high value (1 in coded unit) and the low value (-1 in coded unit) for any given input but not required for the average value (0). The predictions from the existing fitted modles for the base point are tested with actual simulations (to test for linearity within the ranges of the variables used for the analysis-of-variance). Only two of the 12 cases tested fall outside the 95% confidence interval (four yields plus net return plus average production for two soils).

increases (decreases) precipitation. The corner cells show the net results of the main effects and the interactions, and correspond to observations in the data set.

For all variables, higher temperature and higher precipitation have positive effects, and lower temperature and lower precipitation have negative effects. For a higher temperature and lower precipitation, the yield for maize decreases as expected. However, this hot and dry scenario has little effect on all other crops. The implication is that moderately warmer and drier weather in this region of the United States may not be as harmful as is commonly assumed in the literature of climate change. The non-linearity due to the interaction variable is relatively large for average production where the negative effect of low temperature and low precipitation is about twice as large in absolute value as the positive effect of high temperature and high precipitation.

4.3 Comparisons of Results

For comparison purposes, the effects of temperature and precipitation are used to predict responses under the levels specified in other studies of climate change. Since the interaction is multiplicative (the product of the two main effects), its value tends to change fast if the levels of temperature and precipitation are both outside the observed ranges of values (see Figure 4.1). As an alternative, the interaction effects are linearized to make predictions.

The results are generally consistent with that of Kaiser et al. for Scenarios I and II (Table 4.2). Under these two scenarios, the predicted changes in yield for maize and soybean are similar to Kaiser et al.'s estimates. The discrepancy for sorghum is probably due to revisions undergone by updating the version of the sorghum model used in the GAPS model. The predictions are different for Scenario III. This is an indication that yield responses are non-linear in GAPS. The predicted increases in net return are small compared to Kaiser et al.'s. Note that in this study, prices are held constant, but this is not the case in Kaiser et al.'s study where a supply response is incorporated. Nevertheless, an important consistency between the two studies is that yield is more sensitive to warmer temperatures than it is to drier conditions. All three scenarios are shown in Figure 4.2, and it can be seen that Scenario III is considerably different from the ranges used in this analysis.

The results are less consistent with those in Adams et al's study (Table 4.1). While the predicted change in yield for maize in Scenario II (-9% versus -15% for most states) and soybean in Scenario I (26% versus 20%-29% for most states) are close, the other predictions are not consistent. A more fundamental difference between the two studies is the way yield responds to precipitation in a warmer climate. According to Adams et al., yield is much lower under Scenario II (warmer and drier) than under Scenario I (warmer and wetter). The implication is that yield is very sensitive to moisture under a warmer climate. In contrast, the results of this study (and Kaiser et al.'s) show that production and yields (except for maize) are relatively insensitive to precipitation differences over the range observed in the midwest. Furthermore, the difference in precipitation used by Adams et al. is quite small compared to the observed range (Figure 4.2).

5. Conclusions

Response surfaces are developed using data generated from a complex computer model to provide a single-equation summary of the physical and economic relationships embodied in the integrated model. An orthogonal design is chosen for the generation of the data. Analysis of variance is performed to evaluate the relative contribution of 4 climatic, 1 agronomic and 4 economic variables to the variability of yield of four grain crops, production, and farm net return in the midwest. Due to the orthogonal design, total variability can be partitioned uniquely among these variables. A total of 256 observations were simulated for 27 different cultivars at high temperature condition and another 27 cultivars at low temperature condition. Each observation required data for 30 years to incorporate uncertainties into the criterion for selecting a cropping pattern.

The yields for the individual cultivars are well-accounted for by the 4 agro-climatic variables and the 6 pairwise interactions. In most cases, more than 99% of the yield variability was explained by the regression models. The results of analysis of variance indicate that soil and precipitation are important for maize under both temperature levels, and the interaction between soil and precipitation is important in the high temperature. Soybean in the low temperature is dominated by precipitation variability and the interaction between precipitation variability and precipitation, and the interaction between precipitation variability and solar radiation also shows some effects. Soybean, however, is primarily determined by solar radiation. Precipitation variability has secondary effects. Solar radiation is also the most important variable for sorghum, and precipitation has much smaller effects in the low temperature. For wheat, soil and precipitation exhibit the largest main effects. The interaction between soil and precipitation also has secondary impacts on winter wheat under the high temperature.

For the best yield, climatic variables explain more than 70% of the variability in all cases. In particular, temperature dominates the yield of soybean, sorghum and wheat, but soil and precipitation have the largest effects on the yield of maize. In contrast, economic variables account for only 3% of the variability.

While only agro-climatic variables matter for crop yields, both agro-climatic and economic variables matter for net return and production. Temperature and the price of sorghum, together, explain 75% of the total variability for net return. The price of sorghum is important because sorghum has much more tolerance to adverse climate conditions than the other crops, and is often grown under these bad conditions regardless of the price. Therefore, changes in sorghum price have a direct impact on net return.

The data generated for the production of individual crops have many corner solutions. As a result, OLS may generate biased estimates for the production of individual crops, and the results should be interpreted with caution. Nevertheless, the analysis of variance indicates that temperature is the most important variable for the production of sorghum and wheat. Temperature, soil and precipitation are equally important for the production of maize. Not surprisingly, the most important economic variable is the own price for the production of each crop. When average production is analyzed (a measure adopted to overcome corner solutions), the analysis-of-variance results show that the effects are more evenly distributed among the agro-climatic and the economic variables, and interactions are more important than they are with the models for best yield. Furthermore, a relatively large portion of the variability for average production is unexplained.

The main effects of temperature and precipitation and the interactions are used to predict yield, production, and net return under scenarios used in other published studies of grain production in the US. The results of this study are generally consistent with the results of Kaiser et al. for slightly warmer scenarios. The predictions are different for a much warmer and drier scenario because the model does not account for non-linearities. Nevertheless, an important consistency between the two studies is that yield is more sensitive to warmer temperatures than it is to drier conditions over the range of values used. The results agree less with those in Adams et al.'s study. The most fundamental difference between the two studies is the way yield responds to precipitation in a warmer climate. While a relatively small reduction in precipitation causes large decreases in yield in Adams et al.'s study, this study finds that production and yields (except for maize) are relatively insensitive to precipitation differences over the range observed in the midwest. In summary, the results of this study imply that moderate climate warming is unlikely to have an adverse effect on agriculture in the midwest region. Maize production may suffer, but increased production from other crops will compensate.

Appendix 1 Tables

Table 2.1 Cosine Parameters for the Average Maximum Temperatures (°C)

	Dry		Wet	
	c_0	c_1	c_0	c_1
Redwood	13.33#	17.97	11.51#	17.56
Lincoln	16.50*	15.30	13.30	16.10
Napoleon	16.22	15.46~	16.04	13.71~
Indianapolis	16.83	14.67	16.67*	13.06
Madison	13.89	16.17	13.28	15.28

Table 2.2 Cosine Parameters for the Average Minimum Temperatures (°C)

	Dry		Wet	
	c_0	c_1	c_0	c_1
Redwood	1.08#	16.06	2.46#	16.18
Lincoln	4.80	14.50	4.60	14.50
Napoleon	3.78	12.65~	5.93*	11.91~
Indianapolis	5.72*	12.56	5.72	12.56
Madison	1.67	13.67	1.67	13.67

Table 2.3 Cosine Parameters for Average Solar Radiation ($MJ / m^2 \times day$)

	Dry		Wet	
	c_0	c_1	c_0	c_1
Redwood	16.60	10.10	10.30	7.00
Lincoln	17.50	9.70	11.10	7.85
Napoleon	15.90#	9.80*	9.60#	6.90*
Tarboro	17.70	7.50	10.50	7.00
Salisbury	17.80	7.50	10.60	7.00
Tifton	18.06*	6.80	11.10*	6.50
Lagrange	18.00	7.10	10.70	6.70
Vicksburg	18.20	7.10	10.20	6.40
Starkville	18.00	7.30	10.30	6.60
Memphis	17.08	8.30	10.00	6.90

Table 2.4 Standard Deviations for the Cosine Functions at Redwood Falls, Minnesota (°C)

	Dry		Wet	
	c_0	c_1	c_0	c_1
Maximum Temperature	5.03	-1.18	5.08	-1.48
Minimum Temperature	4.88	-1.16	4.53	-1.48
Solar Radiation	4.10	1.10	4.70	2.10

Table 2.5 Unconditional Probability of Rain Occurrence (π) for the Growing Season

	Apr	May	June	July	Aug	Sept	Oct	Sum
Redwood	0.30	0.34	0.36	0.29	0.30	0.27	0.20	2.05
Lincoln	0.04	0.35	0.35	0.30	0.26	0.25	0.15	1.70
Napoleon	0.37	0.34	0.32	0.28	0.28	0.28	0.25	2.12*
Tarboro	0.26	0.31	0.28	0.35	0.31	0.25	0.24	2.02
Salisbury	0.28	0.29	0.30	0.31	0.28	0.21	0.21	1.89
Tifton	0.22	0.26	0.31	0.42	0.34	0.29	0.18	2.02
Lagrange	0.28	0.27	0.31	0.38	0.30	0.25	0.20	1.98
Vicksburg	0.25	0.24	0.25	0.28	0.22	0.23	0.20	1.67#
Starkville	0.30	0.27	0.27	0.33	0.25	0.25	0.20	1.88
Memphis	0.34	0.29	0.29	0.29	0.26	0.24	0.20	1.91

Table 2.6 Persistence Strength Factor (d) for the Growing Season:

	Apr	May	June	July	Aug	Sept	Oct	Sum
Redwood	0.22	0.18	0.13	0.03	0.13	0.22	0.26	1.17
Lincoln	0.48	0.19	0.22	0.12	0.16	0.24	0.22	1.63
Napoleon	0.18	0.21	0.15	0.12	0.13	0.15	0.21	1.15#
Tarboro	0.16	0.17	0.15	0.20	0.17	0.29	0.26	1.40
Salisbury	0.22	0.21	0.21	0.19	0.21	0.30	0.23	1.57
Tifton	0.18	0.27	0.23	0.18	0.18	0.30	0.34	1.68
Lagrange	0.17	0.26	0.25	0.23	0.23	0.29	0.35	1.78
Vicksburg	0.25	0.19	0.16	0.17	0.19	0.30	0.30	1.56
Starkville	0.26	0.26	0.27	0.19	0.25	0.28	0.30	1.81*
Memphis	0.20	0.25	0.21	0.16	0.22	0.25	0.26	1.55

Table 2.7 Precipitation Index (αβ) for the Growing Season

	Apr	May	June	July	Aug	Sept	Oct	Sum
Redwood	6.80	7.30	8.60	10.50	9.60	7.70	7.70	58.20#
Lincoln	7.70	8.80	11.40	9.30	9.20	8.50	7.40	62.30
Napoleon	7.90	8.30	9.40	11.60	10.20	8.10	8.00	63.50
Tarboro	9.20	9.80	13.00	11.10	14.30	14.40	9.90	81.60
Salisbury	10.10	10.60	11.60	11.50	11.50	13.20	12.70	81.20
Tifton	15.10	12.30	11.10	10.20	11.40	10.20	9.60	79.90
Lagrange	15.50	11.30	10.60	12.30	10.30	12.30	11.10	83.40
Vicksburg	16.70	19.30	12.00	10.30	11.70	11.60	18.80	100.30*
Starkville	16.80	13.20	10.70	12.50	11.60	12.10	13.70	90.60
Memphis	13.70	14.10	11.00	11.20	11.50	11.40	11.50	84.30

Table 2.8 Conditional Probabilities for the Growing Season

	April	May	June	July	Aug	Sept	Oct
			Low Variability				
p_{01}	0.27	0.25	0.23	0.23	0.21	0.20	0.18
p_{11}	0.53	0.51	0.50	0.42	0.46	0.48	0.48
			High Variability				
p_{01}	0.21	0.19	0.21	0.24	0.19	0.19	0.16
p_{11}	0.39	0.40	0.36	0.36	0.32	0.34	0.37

Table 2.9 Gamma Parameters for the Growing Season (Adjusted to Maintain Constant Means for Precipitation)

	April	May	June	July	Aug	Sept	Oct
			High Precipitation/High Variability				
α	0.77	0.90	0.84	0.76	0.86	0.88	0.67
β	21.62	21.41	14.31	13.55	13.62	13.21	27.99
			High Precipitation/Low Variability				
α	0.77	0.90	0.84	0.76	0.86	0.88	0.67
β	31.22	31.19	18.18	13.89	16.91	16.32	35.43
			Low Precipitation/High Variability				
α	0.85	0.83	0.74	0.72	0.70	0.82	0.74
β	5.54	6.05	9.11	14.27	11.00	7.58	8.22
			Low Precipitation/Low Variability				
α	0.85	0.83	0.74	0.72	0.70	0.82	0.74
β	8.00	8.82	11.58	14.63	13.66	9.36	10.40

Table 2.10 Average Values for the Variances of Precipitation in the Growing Season (mm^2)

		Precipitation Level	
		Low	High
Precipitation Variability	Low	1011.54	3655.76
	High	1600.78	4998.37

Table 2.11 Planting and Harvest Schedules

	MZ	SB	SG	SW	WW	MZ	SB	SG	SW	WW
	Planting					Harvest				
	Low Temperature (based on Redwood Falls)									
1. Apr 23-May 11	x	x	x	x						
2. May 12-May 31	x	x	x	x						
3. June 1-June 8		x								
4. July 25-Aug 10										
5. Aug 11-Aug 31									x	
6. Sep 1-Sep 15										
7. Sep 16-Sep 30										
8. Oct 1-Oct 16							x			
9. Oct 17-Oct 31						x		x		
	High Temperature (based on Lincoln)									
1. Apr 20-May 10	x		x							
2. May 11-May 20	x	x	x							
3. May 21-June 10		x	x							
4. June 25-July 4										x
5. July 5-Aug 1										x
6. Sep 15-Sep 25										
7. Sep 6-Oct 20					x		x	x		
8. Oct 21-Dec 1						x				

Table 2.12 Historical Prices for Crops ($/bushel)

Year	Maize	Soybean	Sorghum	Wheat
75	2.54	4.92	4.21	3.98
76	2.15	6.81	3.63	2.68
77	2.02	5.88	3.25	2.45
78	2.25	6.66	3.59	2.89
79	2.52	6.28	4.18	3.59
80	3.27	7.61	5.39	4.05
81	2.47	6.07	4.01	3.73
82	2.55	5.71	4.41	3.54
83	3.21	7.83	4.89	3.72
84	2.63	5.84	4.15	3.53
85	2.23	5.05	3.45	3.38
86	1.50	4.78	2.45	2.54
87	1.94	5.88	3.04	2.62
88	2.54	7.42	4.05	3.77
89	2.36	5.69	3.75	3.61
90	2.30	5.75	3.75	......
Average	2.41	6.14	3.89	3.34

Table 2.13 Input Values for Prices

	maize	sorghum	soybean	wheat
Average	2.41	3.89	6.14	3.34
High	3.01	4.86	7.68	4.18
Low	1.81	2.92	4.61	2.51

Table 2.14 Range of Values for All Variables

	High	Low	Range/2
Temperature (Celsius)	17.69	13.79	1.95
Soil (from Dickman to Ves)	Ves	Dickman	N/A
Precipitation variability[1]	Large	Small	N/A
Precipitation (mm)	133.99	60.84	36.58
Solar ($MJ / m^2 \times day$)	19.28	18.00	0.64
Price of maize ($/bushel)	3.01	1.81	0.60
Price of soybean ($/bushel)	7.68	4.61	1.54
Price of sorghum ($/bushel)	4.86	2.92	0.97
Price of wheat ($/bushel)	4.18	2.51	0.84

Table 3.1 Scaling Factors used by Kaiser et al.

Location	Maize	Sorghum	Soybean	Wheat
Redwood Falls, MN	120/184	60.2/108	36.1/48	35/86.2
Lincoln, NE	92/186	100/122	30/52	55/83

Table 3.2 Observed Yield Range

	Scaled Yield		Potential Yield	
	Minimum	Maximum	Minimum	Maximum
Maize	0.00	205.30	0.00	338.72
Sorghum	0.00	137.31	0.00	167.52
Soybean	0.00	58.15	0.00	84.68
Wheat	0.00	81.73	0.00	115.98

[1] Defined jointly by p_{01}, the probability of a wet day following a dry day, and p_{11}, the probability of a wet day following a wet day. The average values of p_{01} and p_{11} for the growing season are 0.22 and 0.48 for the large variability, and 0.20 and 0.36 for the small variability. The two probabilities for the large variability always imply a larger variance than those for the small variability for given precipitation.

Table 3.3 Distribution of Normalized Yields by Cultivar (% ocurrances)

Temperature	Cultivar	1	2	3	4	5	6	7	8	9	10	mean	variance	C-V[2]
	MZ181	6.60	7.70	10.30	14.70	16.80	14.10	12.50	12.80	4.40	0.10	41.10	4473.90	0.60
	MZ281	13.30	8.80	12.00	16.40	16.90	12.70	12.40	7.30	0.20	0.00	34.00	5114.20	0.50
L	MZ182	17.20	10.40	11.80	15.00	16.00	11.30	8.10	5.70	3.80	0.80	32.60	5804.90	0.40
o	MZ282	37.60	10.90	11.60	12.70	12.20	7.00	4.30	2.70	0.90	0.00	20.80	7922.30	0.20
w	MZ183	45.40	10.40	10.80	10.80	10.30	5.50	3.70	1.70	1.10	0.30	17.90	8111.80	0.20
	MZ283	72.00	7.90	6.90	5.10	4.60	2.00	0.80	0.40	0.20	0.00	7.50	3453.00	0.10
	MZ181	0.50	3.60	8.20	16.10	35.50	32.90	3.30	0.00	0.00	0.00	39.50	1873.80	0.90
H	MZ281	0.60	4.40	8.40	14.70	34.40	32.80	4.70	0.10	0.00	0.00	39.60	1925.50	0.90
i	MZ182	0.70	3.60	7.40	13.60	28.80	35.10	10.40	0.50	0.00	0.00	41.60	1923.20	0.90
g	MZ282	1.20	4.50	7.40	13.20	26.60	34.30	12.00	0.80	0.00	0.00	41.40	2103.70	0.90
h	MZ183	0.80	4.90	7.60	10.60	24.20	31.60	18.10	2.10	0.10	0.00	43.10	2301.30	0.90
	MZ283	1.80	6.10	8.30	11.60	23.60	30.20	16.00	2.60	0.00	0.00	41.70	2518.50	0.80
	SB171	45.10	0.10	0.60	3.10	11.50	26.30	10.30	2.70	0.20	0.00	27.00	20231.90	0.20
	SB271	5.90	7.80	19.70	29.50	27.00	9.70	0.30	0.00	0.00	0.00	29.40	2116.30	0.60
	SB371	38.20	37.60	17.70	5.60	0.90	0.00	0.00	0.00	0.00	0.00	9.30	1794.60	0.20
L	SB172	45.10	0.10	0.20	0.30	2.40	20.10	20.50	9.30	1.90	0.10	31.60	26684.60	0.20
o	SB272	5.50	1.40	4.20	12.90	30.20	41.30	4.50	0.10	0.00	0.00	40.40	2454.20	0.80
w	SB372	26.20	19.20	23.70	19.80	9.50	1.60	0.00	0.00	0.00	0.00	17.20	3439.30	0.30
	SB173	45.10	0.10	0.10	0.30	0.40	6.90	18.00	20.70	7.30	1.10	35.90	34543.50	0.20
	SB273	5.30	0.60	2.10	4.60	9.70	44.80	29.10	3.70	0.10	0.00	48.30	2141.40	1.00
	SB373	18.20	16.00	19.00	17.70	16.90	11.20	0.80	0.00	0.00	0.00	23.60	4183.70	0.40
	SB171	0.80	0.00	0.00	6.90	13.50	57.30	21.50	0.00	0.00	0.00	49.00	934.10	1.60
H	SB271	0.00	0.30	9.50	44.70	39.40	4.70	1.40	0.00	0.00	0.00	34.30	1137.50	1.00
i	SB172	0.90	0.00	0.00	0.00	1.90	34.00	60.80	2.40	0.00	0.00	55.90	1077.20	1.70
g	SB272	0.00	0.00	0.30	7.90	70.90	20.70	0.10	0.00	0.00	0.00	41.20	487.80	1.90
h	SB173	0.90	0.00	0.00	0.00	0.10	8.50	71.40	18.90	0.20	0.00	60.50	449.10	2.90
	SB273	0.00	0.00	0.00	0.40	30.00	65.00	4.60	0.00	0.00	0.00	47.40	822.60	1.70

[2] the ratio of the mean value to the standard deviation.

Table 3.3 (continued)

	SG181	0.60	2.10	12.30	29.80	42.60	12.40	0.20	0.00	0.00	0.00	35.00	1411.20	0.90
L	SG281	2.20	9.50	30.70	36.30	19.30	2.00	0.00	0.00	0.00	0.00	26.70	1548.90	0.70
o	SG182	2.50	9.70	30.50	34.20	20.40	2.60	0.00	0.00	0.00	0.00	26.80	1638.50	0.70
w	SG282	8.30	28.50	40.90	17.90	4.30	0.10	0.00	0.00	0.00	0.00	18.20	1376.00	0.50
	SG183	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	N/A
	SG283	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	N/A
	SG171	0.00	1.10	0.00	0.00	0.00	0.20	7.40	34.70	43.10	13.50	75.60	1315.80	2.10
	SG271	0.00	1.10	0.10	0.00	0.00	0.40	12.60	39.70	38.60	7.50	73.30	1340.50	2.00
H	SG371	0.00	0.00	0.00	0.00	0.00	2.20	26.80	43.30	25.60	2.10	69.90	1423.70	1.90
i	SG172	0.00	1.20	0.00	0.00	0.00	0.30	10.30	38.30	41.00	8.90	74.10	1318.00	2.00
g	SG272	0.00	0.80	0.40	0.00	0.00	0.70	17.90	43.70	32.30	4.10	71.40	1329.30	2.00
h	SG372	0.00	0.00	0.00	0.10	0.20	4.70	37.20	41.80	15.50	0.50	66.90	1316.80	1.80
	SG173	0.00	0.90	0.30	0.00	0.00	1.00	19.80	44.20	30.20	3.70	71.00	1334.10	1.90
	SG273	0.00	0.10	1.10	0.00	0.10	3.60	33.50	42.30	18.30	1.10	67.40	1353.70	1.80
	SG373	0.00	0.10	0.10	0.20	3.50	18.90	45.90	27.40	4.00	0.00	60.90	1188.70	1.80
	SW151	0.00	0.20	4.30	31.10	59.90	4.60	0.00	0.00	0.00	0.00	36.50	950.70	1.20
	SW251	0.00	0.20	1.60	34.20	59.60	4.40	0.00	0.00	0.00	0.00	36.60	968.30	1.20
L	SW142	0.00	0.40	5.70	28.30	49.20	16.50	0.00	0.00	0.00	0.00	37.60	1133.80	1.10
o	SW252	0.00	0.00	2.40	30.60	51.00	15.70	0.00	0.00	0.00	0.00	37.90	1089.10	1.10
w	SW153	0.00	0.60	5.90	28.20	21.70	42.10	1.50	0.00	0.00	0.00	40.30	2689.20	0.80
	SW253	0.00	0.40	2.80	29.80	24.10	40.80	2.10	0.00	0.00	0.00	40.80	2521.30	0.80
	WW741	2.00	0.00	0.20	2.00	6.50	2.80	8.00	63.90	14.60	0.00	65.90	1696.60	1.60
H	WW751	2.00	0.00	0.20	2.00	6.50	2.80	8.00	63.90	14.60	0.00	65.90	1696.60	1.60
i	WW742	2.00	0.00	0.40	1.30	8.60	3.70	2.70	22.00	52.50	6.80	70.90	3498.20	1.20
g	WW752	2.00	0.00	0.40	1.30	8.60	3.70	2.70	22.00	52.50	6.80	70.90	3498.20	1.20
h	WW743	2.00	0.70	1.00	8.60	6.80	2.80	3.30	46.50	28.30	0.00	64.10	4146.00	1.00
	WW753	2.00	0.70	1.00	8.50	6.80	2.80	3.30	46.40	28.30	0.00	64.00	4165.90	1.00

Note: MZ, SB, SG, SW and WW are abbreviated crop names (see Chapter 4). The three digits following each crop name denote planting stage, harvest stage, and maturity types (1=early, 2=medium, 3=late), respectively.

Table 3.4 Average Yield of Maize: Allocation of Variability in Percent

			Low Temperature			
Variable\Cultivars	MZ181	MZ281	MZ182	MZ282	MZ183	MZ282
Soil (X1)	53.53	56.40	36.79	38.72	21.41	16.66
Precipitation variability (X2)	0.13	0.26	0.09	0.06	0.48	5.82
Precipitation (X3)	35.91	35.37	52.83	54.06	68.32	61.27
Solar radiation (X4)	4.69	3.88	5.01	3.18	4.89	8.62
X12	0.03	0.03	0.11	0.18	0.20	0.02
X13	4.63	1.90	2.48	0.50	0.28	0.01
X14	0.04	0.00	0.00	0.00	0.00	0.03
X23	0.05	0.02	0.13	0.36	0.73	0.87
X24	0.02	0.01	0.00	0.00	0.10	0.03
X34	0.80	1.89	2.06	2.59	2.76	1.49
Unexplained	0.18	0.23	0.51	0.37	0.83	5.18
Sum	100.00	100.00	100.00	100.00	100.00	100.00
Cutoff value	**0.14**	**0.18**	**0.42**	**0.29**	**0.66**	**4.14**
			High Temperature			
Soil (X1)	44.65	49.84	36.14	39.00	27.76	28.90
Precipitation variability (X2)	0.44	0.54	0.82	0.92	0.97	0.64
Precipitation (X3)	39.39	36.05	47.30	45.57	55.66	55.18
Solar radiation (X4)	5.36	5.69	5.91	6.36	6.29	7.66
X12	0.18	0.31	0.16	0.29	0.17	0.24
X13	8.28	5.44	8.39	5.85	7.99	5.13
X14	0.01	0.02	0.02	0.07	0.06	0.05
X23	0.01	0.00	0.00	0.00	0.02	0.07
X24	0.02	0.02	0.03	0.03	0.03	0.02
X34	0.75	0.91	0.45	1.06	0.59	1.27
Unexplained	0.91	1.18	0.79	0.86	0.46	0.83
Sum	100.00	100.00	100.00	100.00	100.00	100.00
Cutoff value[3]	**0.73**	**0.94**	**0.63**	**0.69**	**0.37**	**0.67**

3 Corresponds to the level which makes the regression coefficient significant at the 5% level.

Table 3.5 Average Yield of Soybean: Allocation of Variability in Percent

				Low Temperature					
Variable\Cultivars	SB171	SB271	SB371	SB172	SB272	SB372	SB173	SB273	SB373
Soil (X1)	4.66	9.84	0.00	3.19	3.22	0.00	1.99	0.03	0.00
Precipitation variability (X2)	31.94	24.11	4.63	30.05	20.88	20.07	28.69	17.24	17.27
Precipitation (X3)	1.52	11.46	0.43	0.88	7.55	2.71	0.55	2.93	2.35
Solar radiation (X4)	0.23	3.99	59.33	1.17	31.20	42.81	2.04	61.41	57.41
X12	2.20	4.20	0.00	1.67	1.53	0.00	1.19	0.06	0.00
X13	0.25	0.29	0.00	0.19	0.02	0.00	0.15	0.04	0.00
X14	4.28	10.67	0.00	2.76	3.73	0.00	1.63	0.16	0.00
X23	30.91	12.39	3.72	30.87	7.10	2.82	31.85	0.15	3.19
X24	17.39	5.15	27.98	23.82	12.24	20.66	27.40	12.18	17.70
X34	0.60	4.11	3.82	0.91	0.20	10.15	0.94	0.47	1.98
Unexplained	6.02	13.79	0.08	4.51	12.33	0.80	3.56	5.34	0.10
Sum	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Cutoff value	**4.82**	**11.03**	**0.07**	**3.60**	**9.87**	**0.64**	**2.85**	**4.27**	**0.08**
				High Temperature					
Variable\Cultivars	SB271	SB371	SB272	SB372	SB273	SB373			
Soil (X1)	0.05	0.00	0.04	0.01	0.03	0.01	N/A	N/A	N/A
Precipitation variability (X2)	26.92	10.98	24.32	15.60	23.45	12.65	N/A	N/A	N/A
Precipitation (X3)	3.21	0.37	5.33	0.33	3.75	0.56	N/A	N/A	N/A
Solar radiation (X4)	65.24	82.14	62.56	81.64	65.00	83.25	N/A	N/A	N/A
X12	0.00	0.00	0.00	0.00	0.00	0.00	N/A	N/A	N/A
X13	0.00	0.00	0.00	0.01	0.00	0.01	N/A	N/A	N/A
X14	0.01	0.00	0.01	0.01	0.01	0.01	N/A	N/A	N/A
X23	0.37	4.85	0.28	0.60	0.81	1.86	N/A	N/A	N/A
X24	0.04	0.51	0.88	0.13	1.00	0.34	N/A	N/A	N/A
X34	3.07	0.22	6.25	0.20	5.11	0.10	N/A	N/A	N/A
Unexplained	1.10	0.91	0.34	1.48	0.85	1.21	N/A	N/A	N/A
Sum	100.00	100.00	100.00	100.00	100.00	100.00	N/A	N/A	N/A
Cutoff value	**0.88**	**0.73**	**0.27**	**1.18**	**0.68**	**0.97**	N/A	N/A	N/A

N/A: unavailable because yields were not simulated.

Table 3.6 Average Yield of Sorghum: Allocation of Variability in Percent

				Low Temperature					
Variable\Cultivars	SG181	SG281	SG182	SG282	SG183	SG283			
Soil (X1)	0.00	0.00	0.00	0.00	*	*	N/A	N/A	N/A
Precipitation variability (X2)	7.49	7.08	10.02	8.64	*	*	N/A	N/A	N/A
Precipitation (X3)	0.10	0.23	0.33	0.72	*	*	N/A	N/A	N/A
Solar radiation (X4)	91.66	91.99	88.53	89.38	*	*	N/A	N/A	N/A
X12	0.00	0.00	0.00	0.00	*	*	N/A	N/A	N/A
X13	0.00	0.00	0.00	0.00	*	*	N/A	N/A	N/A
X14	0.00	0.00	0.00	0.00	*	*	N/A	N/A	N/A
X23	0.03	0.07	0.00	0.05	*	*	N/A	N/A	N/A
X24	0.09	0.15	0.01	0.01	*	*	N/A	N/A	N/A
X34	0.01	0.11	0.08	0.34	*	*	N/A	N/A	N/A
Unexplained	0.62	0.37	1.04	0.86	*	*	N/A	N/A	N/A
Sum	100.00	100.00	100.00	100.00	*	*	N/A	N/A	N/A
Cutoff value	**0.50**	**29.75**	**0.83**	**0.69**	*	*	N/A	N/A	N/A
				High Temperature					
	SG171	SG271	SG371	SG172	SG272	SG372	SG173	SG273	SG373
Soil (X1)	0.25	0.21	0.00	0.29	0.22	0.00	0.23	0.17	0.00
Precipitation variability (X2)	4.12	4.99	3.46	4.91	4.33	3.40	4.32	4.30	3.56
Precipitation (X3)	0.63	0.54	0.00	0.56	0.38	0.00	0.38	0.23	0.01
Solar radiation (X4)	87.30	87.73	96.29	86.56	88.71	96.25	88.81	90.11	96.06
X12	0.28	0.24	0.00	0.28	0.21	0.00	0.22	0.18	0.00
X13	1.97	1.64	0.00	2.07	1.57	0.00	1.61	1.23	0.00
X14	0.28	0.24	0.00	0.28	0.21	0.00	0.22	0.18	0.00
X23	0.37	0.31	0.09	0.37	0.44	0.09	0.54	0.40	0.20
X24	1.54	1.27	0.00	1.25	1.28	0.02	1.00	0.87	0.00
X34	0.36	0.25	0.03	0.36	0.04	0.10	0.10	0.01	0.07
Unexplained	2.90	2.58	0.13	3.08	2.61	0.14	2.59	2.34	0.10
Sum	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Cutoff value	**2.32**	**2.07**	**0.10**	**2.46**	**2.08**	**0.11**	**2.07**	**1.87**	**0.08**

*: not estimable due to zero yields.

Table 3.7 Average Yield of Wheat: Allocation of Variability in Percent

			Low Temperature			
Variable\Cultivars	SW151	SW251	SW152	SW252	SW153	SW253
Soil (X1)	78.43	81.21	81.76	85.37	83.57	88.81
Precipitation variability (X2)	0.53	1.17	0.34	0.91	0.23	0.75
Precipitation (X3)	14.28	12.09	13.03	9.97	13.04	8.19
Solar radiation (X4)	0.54	0.70	0.56	0.72	0.58	0.55
X12	0.05	0.04	0.06	0.01	0.06	0.01
X13	4.31	2.59	2.87	1.30	1.54	0.44
X14	1.26	1.41	0.74	0.93	0.36	0.57
X23	0.04	0.00	0.02	0.01	0.00	0.00
X24	0.21	0.16	0.19	0.16	0.13	0.14
X34	0.01	0.16	0.00	0.11	0.00	0.05
Unexplained	0.34	0.47	0.43	0.52	0.49	0.49
Sum	100.00	100.00	100.00	100.00	100.00	100.00
Cutoff value	**0.27**	**0.37**	**0.34**	**0.41**	**0.39**	**0.39**
			High Temperature			
Variable\Cultivars	WW741	WW751	WW742	WW752	WW743	WW753
Soil (X1)	32.08	32.08	35.59	35.59	38.79	38.80
Precipitation variability (X2)	0.03	0.03	0.04	0.04	0.01	0.01
Precipitation (X3)	30.98	30.98	31.60	31.60	32.88	32.87
Solar radiation (X4)	2.26	2.26	1.87	1.87	1.46	1.45
X12	0.17	0.17	0.09	0.09	0.03	0.03
X13	25.47	25.47	25.48	25.48	24.43	24.43
X14	3.03	3.03	1.74	1.74	0.64	0.64
X23	0.42	0.42	0.25	0.25	0.17	0.17
X24	0.03	0.03	0.02	0.02	0.01	0.01
X34	2.56	2.56	1.73	1.73	1.09	1.09
Unexplained	2.96	2.96	1.59	1.59	0.49	0.50
Sum	100.00	100.00	100.00	100.00	100.00	100.00
Cutoff value	**2.37**	**2.37**	**1.27**	**1.27**	**0.40**	**0.40**

Table 3.8 Summary of Important Variables for Yield

	Maize	Low Temperature Soybean	Sorghum	Wheat
Soil (X1)	xx			xx
Precipitation Variability (X2)		xx	x	
Precipitation (X3)	xx			x
Solar Radiation (X4)			xx	
X12				
X13				
X14				
X23		xx		
X24		x		
X34				
		High Temperature		
Soil (X1)	xx			xx
Precipitation Variability (X2)		x		
Precipitation (X3)	xx			xx
Solar Radiation (X4)		xx	xx	
X12				
X13	x			x
X14				
X23				
X24				
X34				

Table 3.9 Weights by Cultivar for Non-Zero Observations of Yield

Low Temperature								
MZ181	MZ281	MZ182	MZ282	MZ183	MZ282			
0.96	0.03	0.01	0.00	0.00	0.00			
SB171	SB271	SB371	SB172	SB272	SB372	SB173	SB273	SB373
0.00	0.00	0.00	0.01	0.00	0.00	0.06	0.92	0.00
SG181	SG281	SG182	SG282					
1.00	0.00	0.00	0.00					
SW151	SW251	SW152	SW252	SW153	SW253			
0.06	0.10	0.05	0.09	0.36	0.34			
High Temperature								
MZ171	MZ271	MZ172	MZ272	MZ173	MZ272			
0.09	0.02	0.35	0.02	0.50	0.02			
SB271	SB371	SB272	SB372	SB273	SB373			
0.00	0.00	0.00	0.00	1.00	0.00			
SG171	SG271	SG371	SG172	SG272	SG372	SG173	SG273	SG373
0.83	0.00	0.00	0.17	0.00	0.00	0.00	0.00	0.00
WW741	WW751	WW742	WW752	WW743	WW753			
0.17	0.17	0.17	0.17	0.17	0.17			

Table 3.10 Analysis-of-Variance for the Best Yield and Net Return: Allocation of Variability in %

	Maize	Soybean	Sorghum	Wheat	Return
Main Effects					
Temperature (degree Celsius)	2.02	71.47	94.45	67.59	53.98
Soil (Dickman v.s. Ves)	37.61	0.06	0.02	14.47	0.67
Precipitation variability	0.28	0.16	0.08	0.06	0.19
Precipitation (mm)	33.87	0.07	0.00	5.08	0.54
Solar $(MJ/m^2 \times day)$	4.31	1.73	3.37	0.14	0.93
Price of maize (dollars)	0.02	0.04	0.00	0.04	1.02
Price of soybean (dollars)	0.00	0.42	0.01	0.00	0.03
Price of sorghum (dollars)	0.00	0.01	0.00	0.01	21.71
Price of wheat (dollars)	0.00	0.07	0.01	0.00	0.14
Pairwise interactions					
Agro-climatic	12.72	0.78	0.32	4.35	3.35
Economic	0.23	1.90	0.08	0.36	0.34
Cross	0.33	0.39	0.01	0.06	10.73
Unexplained	8.61	22.92	1.65	7.85	6.36
Total	100.00	100.00	100.00	100.00	100.00
F statistic[2]	1.31	1.44	1.00	0.96	31.24

Table 3.11 R-Squared Statistics from OLS Estimation

	Maize	Soybean	Sorghum	Wheat
Best Yield	0.91	0.73	0.98	0.92
Acreage	0.62	0.51	0.74	0.53
Production	0.64	0.50	0.84	0.53
Acreage (+ 3-way)	0.72	0.70	0.85	0.67
Production (+ 3-way)	0.74	0.71	0.92	0.66

* The R-squared for return is 0.94.

[2] Test statistics are obtained under the null hypothesis that prices have zero impact. The critical F-values at 5% and at 1% significance level are 1.46 and 1.70, respectively.

Table 3.12 Number of Extreme Observations in the Acreage Data

Acreage	Maize	Soybean	Sorghum	Wheat
0	317	414	138	393
0<y<800	170	90	225	117
800	25	8	149	2
Total	512	512	512	512

Table 3.13 Analysis-of-Variance for Production: Allocation of Variability in %

	Maize	Soybean	Sorghum	Wheat
Main Effects				
Temperature (degree Celsius)	10.88	0.03	60.70	21.77
Soil (Dickman v.s. Ves)	11.84	0.66	1.40	2.04
Precipitation variability	0.03	0.06	0.17	0.24
Precipitation (mm)	10.41	0.02	1.95	0.02
Solar $(MJ / m^2 \times day)$	0.77	4.40	4.67	0.14
Price of maize (dollars)	8.46	0.65	0.85	0.62
Price of soybean (dollars)	0.07	11.17	0.51	0.72
Price of sorghum (dollars)	2.16	8.41	8.41	3.93
Price of wheat (dollars)	0.48	0.13	0.34	5.25
Pairwise interactions				
Agro-climatic	9.97	3.19	1.63	3.17
Economic	1.14	9.77	0.69	6.34
Cross	8.22	11.85	3.09	8.86
Three-way interactions	9.19	20.18	7.72	13.31
Unexplained	26.39	29.47	7.87	33.59
Total	100.00	100.00	100.00	100.00
F statistic[3]	4.01	7.62	9.81	4.12

[3] The null hypothesis is that all prices and associated interactions have zero coefficients. The critical F statistics are 1.28 (1.42) at 5% (1%) significance level.

Table 3.14 Analysis-of-Variance for the Logistic Transformation of Production: Allocation of Variability in %

	Maize	Soybean	Sorghum	Wheat
Main Effects				
Temperature (degree Celsius)	22.08	1.79	28.17	29.06
Soil (Dickman v.s. Ves)	7.08	0.69	7.94	1.01
Precipitation variability	0.00	0.00	0.33	0.10
Precipitation (mm)	6.08	0.34	4.03	0.25
Solar $(MJ / m^2 \times day)$	0.88	3.87	3.86	0.02
Price of maize (dollars)	13.48	1.01	1.23	0.32
Price of soybean (dollars)	0.13	16.04	0.37	0.08
Price of sorghum (dollars)	3.14	7.57	17.28	2.60
Price of wheat (dollars)	0.39	0.11	0.22	8.79
Pairwise interactions				
Agro-climatic	5.39	2.67	3.63	2.19
Economic	1.05	9.43	0.53	1.22
Cross	5.99	9.54	5.74	15.16
Three-way interactions	10.75	16.53	9.95	11.21
Unexplained	23.56	30.40	16.72	28.00
Total	100.00	100.00	100.00	100.00
F statistic	5.35	7.19	7.62	4.98

Table 3.15 Analysis-of-Variance for the Average Production: Allocation of Variability in %

	Volume	Weight	Calories
Main Effects			
Temperature (degree Celsius)	26.33	25.98	26.33
Soil (Dickman v.s. Ves)	7.57	7.82	7.57
Precipitation variability	0.08	0.07	0.08
Precipitation (mm)	3.70	3.76	3.70
Solar $(MJ / m^2 \times day)$	1.61	1.54	1.61
Price of maize (dollars)	3.44	3.41	3.44
Price of soybean (dollars)	0.60	0.56	0.60
Price of sorghum (dollars)	0.86	0.73	0.86
Price of wheat (dollars)	0.57	0.66	0.57
Pairwise interactions			
agro-climatic	17.06	17.47	17.96
economic	1.22	1.22	1.14
cross	6.91	6.95	7.10
3-way interactions	8.13	8.06	7.94
Unexplained	21.93	21.76	22.93
Total	100.00	100.00	100.00

Table 4.1 Results of Adams et al. and Projections by this Study for the Midwest: Percent Change from the Mean

Studies	Adams et al. (mid-point values)						This Study Average Midwest Climate	
Regions	Upper midwest		Central midwest		Lower midwest			
Scenarios	I	II	I	II	I	II	I	II
Yield								
Maize	45	-15	15	-15	-15	-5	-5	-9
Soybean	45	5	25	-5	25	-5	26	30
Sorghum	N/A	N/A	N/A	N/A	N/A	N/A	87	87
Wheat	5	-25	5	-25	-5	-25	47	52
Production	N/A	N/A	N/A	N/A	N/A	N/A	47	55
Return	N/A	N/A	N/A	N/A	N/A	N/A	102	121

Scenario I is 4.32 °C warmer and 7.20 mm per month wetter;
Scenario II is 5.09 °C warmer and 2.40 mm per month drier;
N/A refers to unavailability;
Upper midwest: Minnesota, Wisconsin, Michigan;
Central midwest: Iowa, Illinois, Indiana, Ohio, and Missouri;
Lower midwest: Kentucky.

Table 4.2 Results of Kaiser et al. and Projections by this Study: Percent Change from the Mean

Studies	Kaiser et al.			This Study Average Midwest Climate		
Regions	A Typical Midwest Farm					
Scenarios	I	II	III	I	II	III
Yield						
Maize	0	-4	-11	-2	-6	-13
Soybean	14	16	12	15	15	30
Sorghum	15	16	7	43	43	74
Wheat	N/A	N/A	N/A	28	24	48
Production	N/A	N/A	N/A	27	27	55
Return	139	173	173	59	60	119

Scenario I: 2.50 °C warmer and 7.30 mm per month wetter;
Scenario II: 2.50 °C warmer and 7.30 mm per month drier;
Scenario III: 5.00 °C warmer and 14.60 mm per month drier.

Table 4.3 Estimated Effects of Temperature and Precipitation

	Maize	Soybean	Sorghum	Wheat	Production	Return
	Percent change from the mean					
Temperature	-3.16	11.54	33.34	20.17	21.11	46.02
Precipitation	13.16	-0.33	-0.03	5.65	8.03	4.59
Interaction	-2.45	0.63	0.26	2.97	-8.65	-5.87
	Pounds or dollars/Acre					
Temperature	-181.58	236.42	1474.85	597.71	978.38	90.41
Precipitation	757.12	-6.69	-1.13	167.46	372.26	9.02
Interaction	-141.18	13.00	11.64	87.98	-401.03	-11.53

Table 4.4 Effects of Temperature and Precipitation under Different Levels: Percent Change from the Mean

			Precipitation		
			Low	Center	High
		High	-13.86	-3.16	7.55
Maize		Center	-13.16	0.00	13.16
		Low	-12.45	3.16	18.77
		High	11.23	11.54	11.85
Soybean	Temperature	Center	0.33	0.00	-0.33
		Low	-10.58	-11.54	-12.50
		High	33.11	33.34	33.58
Sorghum		Center	0.03	0.00	-0.03
		Low	-33.06	-33.34	-33.63
		High	11.55	20.17	28.79
Wheat		Center	-5.65	0.00	5.65
		Low	-22.85	-20.17	-17.49
		High	21.73	21.11	20.49
Production		Center	-8.03	0.00	8.03
		Low	-37.79	-21.11	-4.42
		High	47.30	46.02	44.74
Return		Center	-4.59	0.00	4.59
		Low	-56.48	-46.02	-35.56

Table 4.5 Crop Prices Used in Original and New Simulations (dollar/bushel)

	Maize	Soybean	Sorghum	Wheat
Original prices	2.41	6.15	3.89	3.35
New prices	3.03	5.38	2.92	4.60

Appendix 2. Figures

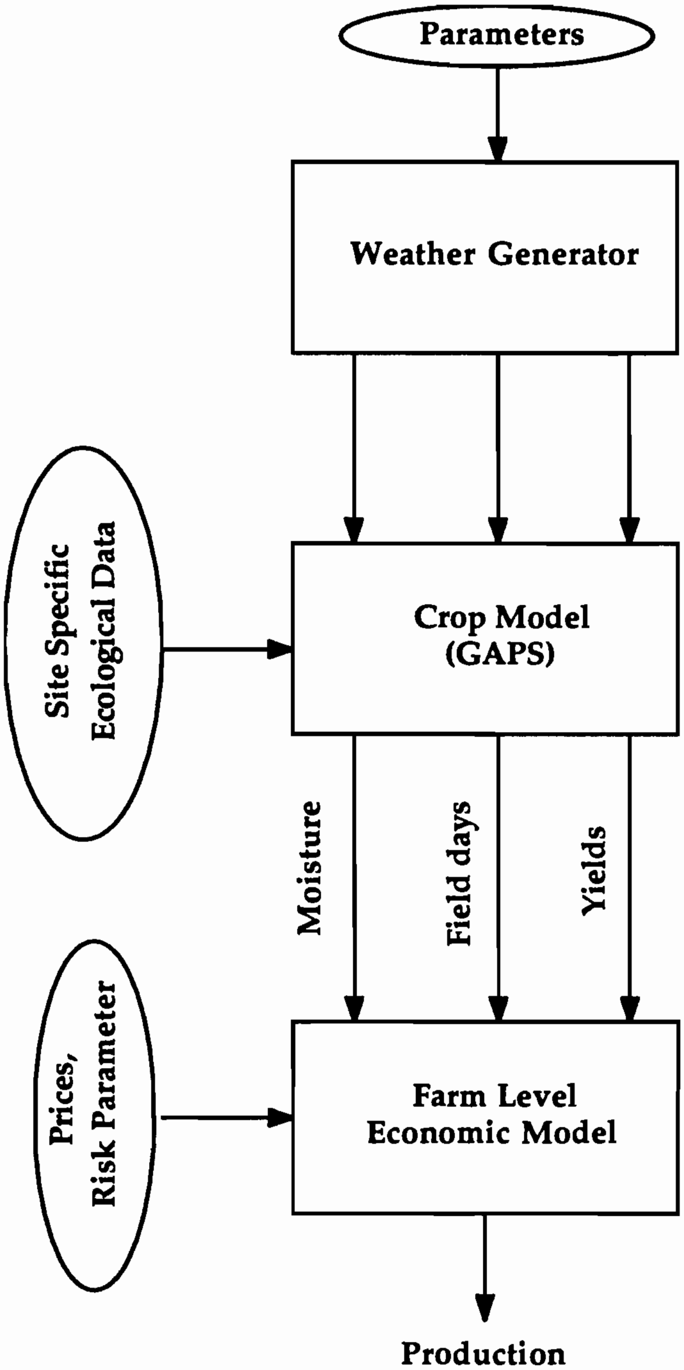

Figure 2.1 The Structure of the Kaiser-Riha-Wilks Model

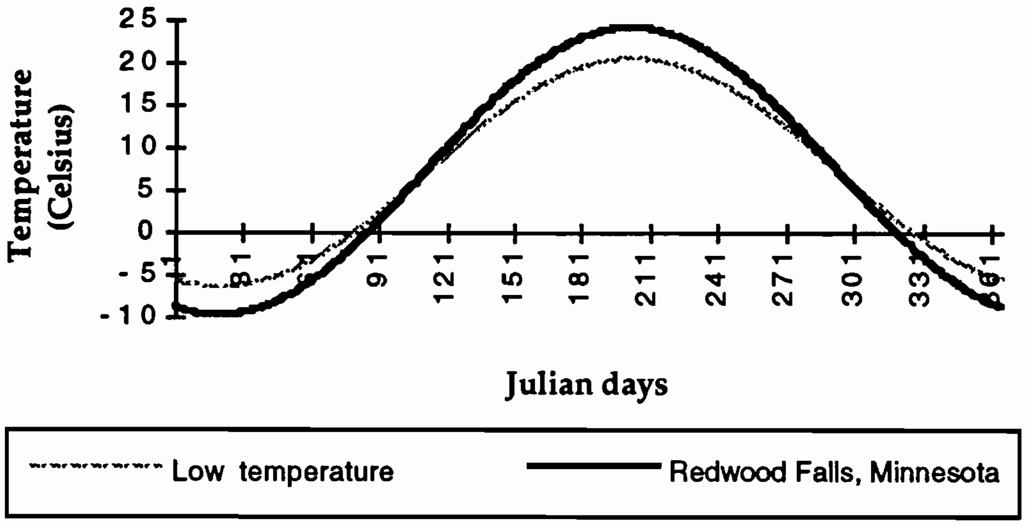

Figure 2.2 Comparison of Daily Temperature for the Low Temperature and for Redwood Falls, Minnesota

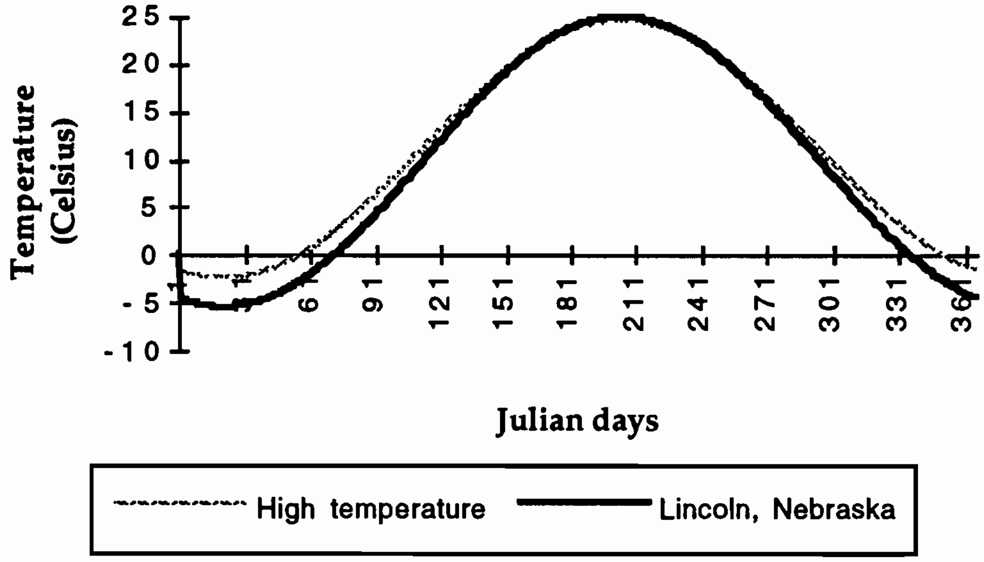

Figure 2.3 Comparison of Daily Temperature for the High Temperature and for Lincoln, Nebraska

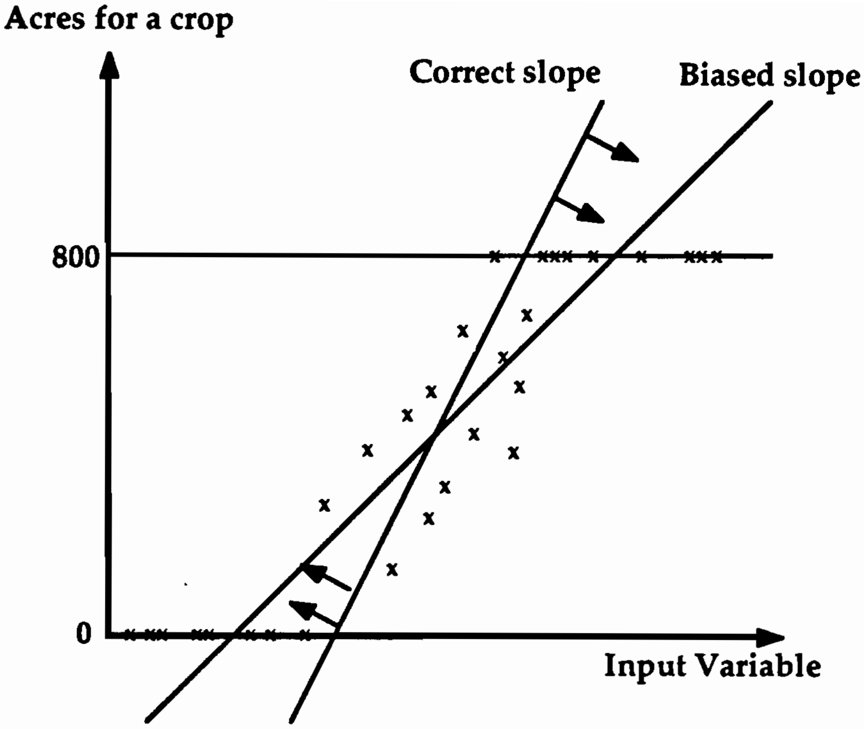

Figure 3.1 Corner Solutions in Acreage and Implications for OLS Estimation

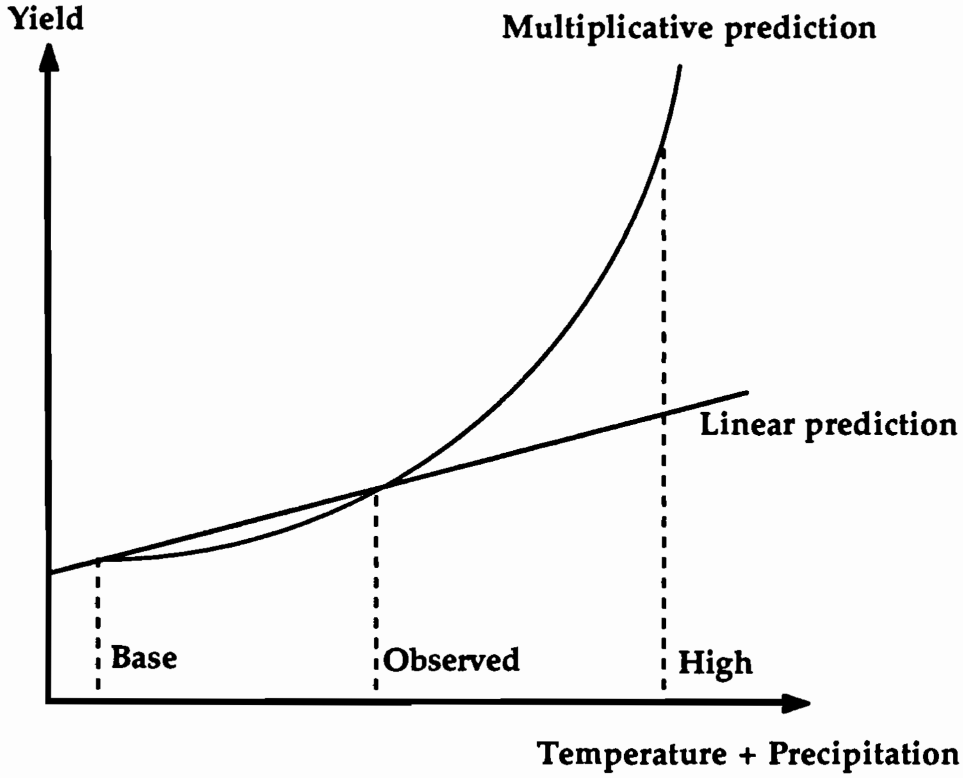

Figure 4.1 Alternative Methods for Prediction

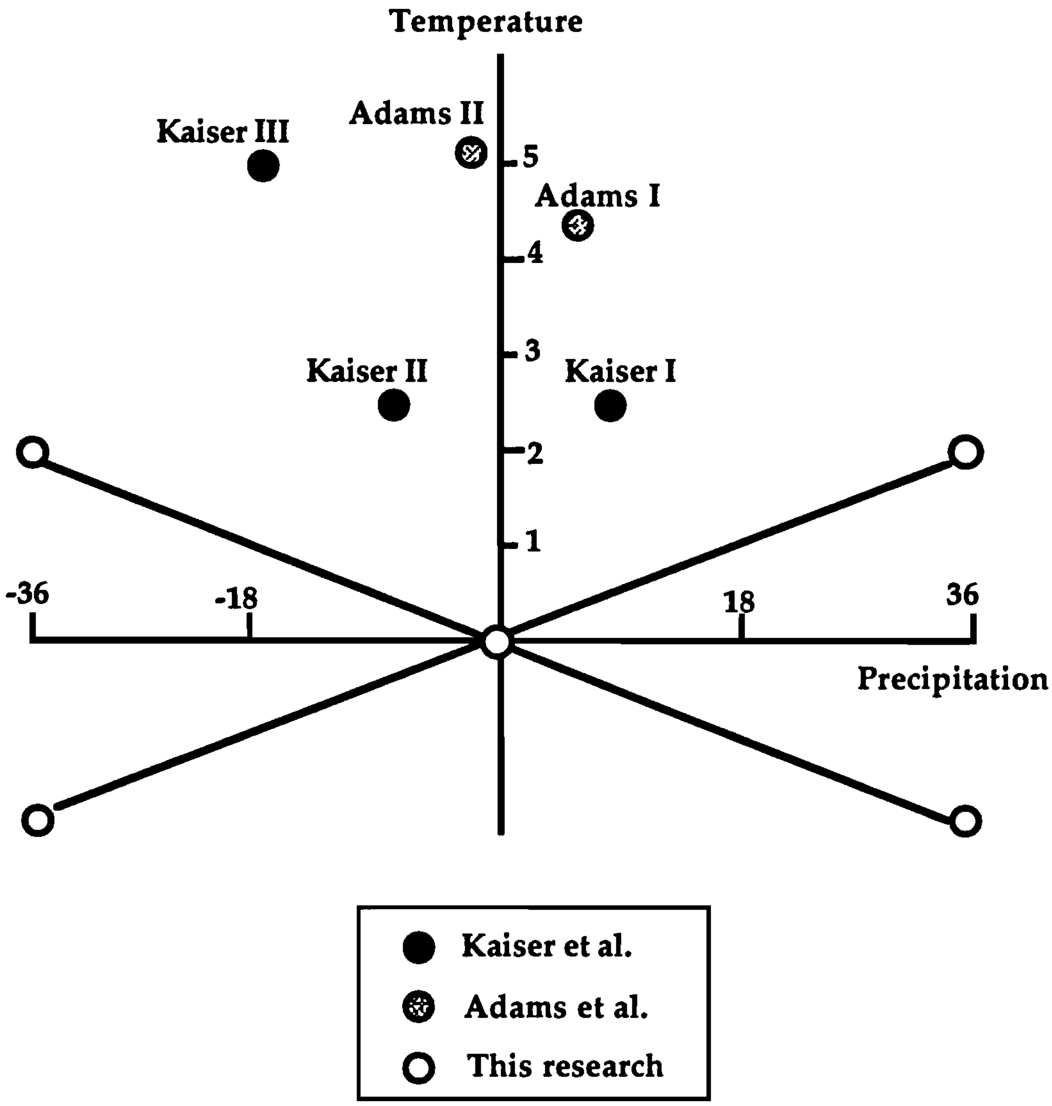

Figure 4.2 Alternative Scenarios of Temperature and Precipitation

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