Evaluating the performance of the soil productivity index (PI) model in Cascade County, Montana
by Kristin Elva Sorensen Gerhart

A thesis submitted in partial fulfillment of the requirements for the degree of Master of Science in Earth Sciences
Montana State University

Abstract:
The Productivity Index (PI) model developed by Pierce and associates at the University of Minnesota for initial use in the Corn Belt is evaluated for application in the northern Great Plains. In the project's first phase, the PI model is used in conjunction with the USDA Soil Conservation Service SOILS-5 data base to generate soil productivity ratings for agricultural soils in Cascade County, Montana. These PI values are regressed against small grain yield data from SOILS-5 and the Cascade County Area Soil Survey to test the model's ability to estimate actual soil productivity. The regression results indicate that the existing model is not as successful as it was in the Corn Belt, explaining only 40% (average r2 = .40) of the variation in Cascade County barley, spring wheat and winter wheat crop yields. The project's second phase explores potential additions to the PI model. Four factors known to be important yield determinants are examined in conjunction with PI values using multiple regression analysis to investigate how well they improve the explanation of crop yield variations. These analyses did improve the r2 values to greater than .50 for spring wheat and barley.

Several aspects related to the quality and consistency of input data, the model's current design and the need for model extensions are discussed. However, from the results of the multiple regression analyses it is concluded that the model's success in the northern Great Plains requires the addition of other parameters to account for climatic, topographic, and calcium carbonate effects on soil productivity. Overall, the PI model appears to be a promising tool for extensive soil productivity and soil erosion studies in Montana and the northern Great Plains.

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ABSTRACT

The Productivity Index (PI) model developed by Pierce and associates at the University of Minnesota for initial use in the Corn Belt is evaluated for application in the northern Great Plains. In the project's first phase, the PI model is used in conjunction with the USDA Soil Conservation Service SOILS-5 data base to generate soil productivity ratings for agricultural soils in Cascade County, Montana. These PI values are regressed against small grain yield data from SOILS-5 and the Cascade County Area Soil Survey to test the model's ability to estimate actual soil productivity. The regression results indicate that the existing model is not as successful as it was in the Corn Belt, explaining only 40% (average $r^2 = .40$) of the variation in Cascade County barley, spring wheat and winter wheat crop yields. The project's second phase explores potential additions to the PI model. Four factors known to be important yield determinants are examined in conjunction with PI values using multiple regression analysis to investigate how well they improve the explanation of crop yield variations. These analyses did improve the r^2 values to greater than .50 for spring wheat and barley.

Several aspects related to the quality and consistency of input data, the model's current design and the need for model extensions are discussed. However, from the results of the multiple regression analyses it is concluded that the model's success in the northern Great Plains requires the addition of other parameters to account for climatic, topographic, and calcium carbonate effects on soil productivity. Overall, the PI model appears to be a promising tool for extensive soil productivity and soil erosion studies in Montana and the northern Great Plains.

CHAPTER ONE

INTRODUCTION

Scope and Purpose

Soil erosion represents the disturbance and transport of surface soil by wind and/or water. Rates of soil formation match the pace of surface soil removal (about 3-4 cm per 1,000 years) and soil depth is maintained in environments free of human disturbance over long periods of time (Beckman and Coventry, 1987). Although rates of erosion fluctuate over shorter time scales in these undisturbed environments, rates of soil formation show little change, and periods of net loss are offset by periods of net gain. However, many types of human land use cause accelerated erosion rates several times greater than the natural rates of soil displacement and soil formation. Hence, the balance between rates of soil formation and removal is lost, leading inevitably to shallow and less productive soils.

Accelerated erosion rates are cause for concern because productive soil is an essential resource which contributes to the nation's economic development and the general well-being of its people. Our modern agricultural activities make intense demands on our soil resources, and in doing so, lead to the removal of valuable topsoil faster than it can be replaced. These losses of topsoil are accompanied by losses of organic matter, favorable soil structure, water holding capacity, nutrients and rooting depth, and they often produce soils which are less productive. Thus farmers are presented with the problem of maintaining or increasing soil productivity, or yield per unit area, over extended periods of time. Although it is possible for erosional processes to alter the soil profile in a positive manner, most commonly the effect is negative. The farmer then must choose between accepting lower crop yields or replacing lost nutrients in order to maintain previous productivity levels. The result, through either product scarcity and/or higher food production costs, is higher food prices.

Crosson (1983, p. 41) defines the concept of productivity as "ratio of output of product or services to the input of resources used per unit of time to produce the output." However, in a specifically soil-related study such as this one, a more precise statement defines productivity as "the capacity of a soil in its normal environment for producing a specified plant or sequence of plants, under a specified system of management" (Meyer et al., 1985, p. 219).

Several approaches toward quantifying the effect of soil erosion on soil productivity have been formulated over the past fifty years. The United States Department of Agriculture (USDA) has been the most consistent sponsor of this research, and the Soil Conservation Service (SCS) recently named quantification of the erosion/productivity relationship as its top priority (Sharpe, 1984). In 1980, the Secretary of Agriculture appointed a National Soil Erosion - Soil Productivity Research Planning Committee to investigate and define the factors, issues and methods involved with this relationship.

A number of scientists have described the deficiencies of past and present studies and have also argued the need for more rigorous and conclusive assessments (Flach and Johannsen, 1981; Meyer et al., 1985; Larson, 1986; Daniels et al., 1987). For example, Crosson (1983, p. 44) states that the earlier studies "do not permit valid general statements of how much national agricultural productivity has been, or is being, lost to erosion." Similarly, Poincelot (1986) notes that while yields and profits have continued to be adequate, they are based on an increase in technological inputs which support high yields, and thus yield decreases due to erosion tend to be overlooked.

Dudal (1981) suggested that research on achieving high levels of biologic productivity and on the land's ability to recover and maintain its productivity is necessary to guarantee the stability of our agriculture systems for future generations. The study presented here responds to Dudal's suggested research directions requiring investigations into the effects of erosion on long-term soil productivity. One approach involves the use of models to estimate soil productivity change over time. The Productivity Index (PI) model developed by Pierce and associates at the University of Minnesota (Pierce et al., 1983; 1984a; 1984b; 1984c) is precisely such a tool, and thus its application to Montana's soils and grain crops will be critically examined in this study. Although the Minnesota PI model investigations were performed using the soils and crops of the Corn Belt, their tentative conclusions regarding the PI model's performance with small grain crops provided cause for optimism when applying the model to a northern Great Plains environment.

The major objective of this project is to evaluate whether or not the PI model can be used to quantify the effects of erosion on soil productivity for the soils and crops found in Cascade County, Montana. The overall outcomes of this study will assist with the evaluation, and targeting of soil conservation efforts, as well as continued study of the agricultural soils that are vulnerable to erosion. Specifically, there are four reasons for evaluating the PI model's performance in Cascade County. First, because the PI values calculated by the model provide estimates of current soil productivity as well as future productivity conditions following simulated rates of soil loss, successful use of the model will provide a systematic, consistent method of identifying soils most susceptible to erosion-induced soil productivity losses. Second, the model becomes an "analytical tool" useful in locating land areas where it is most urgent and efficient to adopt conservation efforts (Runge et al., 1986, p. 46). Third, the model results will help with the compilation of erosion risk assessment maps as urged by Daniels et al. (1985), who criticized the current method of mapping erodible soils using small numbers of rainfall intensity measurements. Finally, soil vulnerability indices similar to those developed by Pierce et al. (1984b) could be produced from analyses of soil data using the PI model, perhaps in conjunction with the soil vulnerability maps.

Quantifying the Effect of Erosion on Soil Productivity

Assessments of soil erosion/soil productivity relationships require experimental designs based on complex considerations. First, studies must encompass soils of all productivity levels because erosion affects deep, shallow, rich and poor soils in different ways. This is because individual and combined soil horizons present different combinations of texture, structure, temperature, water storage, nutrients, salts, unweathered material, and physical impedance to root growth. For example, a study performed only on deep loess soils may not produce useful conclusions since productivity on such a soil will nearly always be high. The productivity of these soils is not sensitive to soil profile changes which occur during the erosion process. Thin, less favorable soils, being more sensitive to a loss of depth, would produce quite different results. Finally, soils of average depth and productivity fall somewhere between the two extremes. Therefore, research must incorporate a design which evaluates both deep, medium and shallow soils.

The problem of quantifying the effect of erosion on soil productivity is difficult for two additional reasons. First, studies must consider the complex interrelationships between soil productivity and variation in landscape positions, growing seasons and moisture availability regimes, as well as those between landscape position and erosion rate (Daniels et al., 1985). Second, rates of productivity losses may not be constant over time, meaning that a similar amount of erosion during the second ten years may reduce productive potential more than during the first ten years (Meyer et al., 1985). Experiment design thus presents a perplexing and intricate problem.

The first studies designed to explore the connection between erosion and soil productivity were carried out in the first half of this century (Crosson, 1983). These studies occurred at the time when incentives to boost crop yields were widespread, and the use of new technology in the form of fertilizers, pesticides and machinery disguised the actual effects of erosion on the soil itself. These complicating factors, combined with the problems of research expense, collection of large amounts of high quality data and the popular belief that farmers had largely succeeded in stabilizing soil movement through new tillage practices, limited the number of studies examining the productivity effects of erosion (Crosson, 1983). Most of the early research tested the effects of erosion on the soil's rooting environment in small simulation plots or actual field situations (e.g., Daniel and Langham, 1936; Finnel, 1948; Stallings, 1950).

Unfortunately, the limited scope of these microstudies did not provide an adequate basis for comprehensive deductions. Specifically, the results were derived from small scale, controlled environments and they required field verification (Meyer et al., 1985, p. 222). Additionally, Langdale and Schrader (1982, p. 44) warned that the results are outdated and cannot be used either for predicting modern crop yield responses to eroded soils or for comparison with the results of current studies. Nevertheless, the microstudies did uphold the important concept that repairing soil erosion damage depends on both the type of erosion and the characteristics of the damaged soil (Crosson, 1983).

The concept of soil loss tolerance (T) values also arose from the newly gathered information and study results of the 1940s (Crosson, 1983). Expressed in tons per acre per year, a T value represents the amount of soil which can be removed from the soil profile before a loss in productivity becomes evident. Soil scientists generally concur that there is little scientific basis for the T values which are assigned to soils according to their topsoil depths and depths to restrictive layers (Gibbon, 1984; Nowak et al., 1985). Indeed, Wischmeier and Smith (1962, p. 156) explain that the assignment of T values is "largely a matter of judgement based on observations." From a more current perspective, Larson et al. (1983) suggest that the rate of soil formation is commonly used to determine T values. However, McCormack and Young (1981) concluded that the criteria now used to determine T values are unsound, mainly because the effects of erosion on productivity are not well understood. Successful application of the PI model to Great Plains environments would increase knowledge of such effects and establish more valid criteria for specifying tolerable soil loss under Great Plains soil and crop conditions. Substitution of PI model results in place of T values has already been investigated for soils in the Corn Belt (Pierce et al., 1984a).

The discovery from these early studies that erosion adversely impacted soil productivity partly explains why research in the 1960s began to shift away from productivity effects of erosion to related aspects of soil erosion such as the measurement of erosion rates, minimizing wind and water energy over field surfaces, and formulating erosion control strategies (Meyer et al., 1985). In addition, further improvements in agricultural technology, which served to increase crop yields again, caused the soil erosion/soil productivity problem to lose urgency.

Soon it was recognized that better quantification and prediction of soil erosion effects were needed. This new interest was spurred by the improved availability of data on erosion rates, soil properties and yield, as well as by rising fuel and other farming costs. Research turned again to the soil erosion/soil productivity problem and focused upon a variety of new approaches. One procedure involved the removal of topsoil to examine the influence of shallower rooting zones (e.g., Tanaka et al., 1986). Another approach employed newly collected information on land capability subclasses and erosion rates (Krauss and Allmaras, 1982). A third method relies upon regression analysis of past yields and past erosion rates in an effort to predict how current erosion rates will affect future crop yields (e.g., Crosson, 1985).

During this period, the first U.S. National Resources Inventory (NRI) was completed in 1977 as required by the Soil and Water Resources Conservation Act (RCA), Public Law 95-192 (USDA-SCS, 1984a). It is reasonably suggested by Crosson (1983) that the enormous volume of data collected for the NRI and made available through computers spurred the creation of macrostudies. Two significant advances in research strategy were thus made possible by the NRI. First, it enabled a considerable extension in the geographic scope of research. Second, and more importantly, the NRI made it possible to incorporate analysis at the fundamental level of individual soil properties. None of the microstudies had the capability of assessing as much diverse information over such large geographic areas.

The first of the macrostudies, thoroughly described by Crosson (1983), was the Yield-Soil Loss Simulator or Y-SLS. Crop yields were predicted with the Y-SLS equation, as functions of the combined depths of topsoil and two subsoil horizons, average slope, land capability subclass, soil texture and use of irrigation. Separate Y-SLS equations were developed for the 1977 NRI to assess soil erosion/soil productivity relationships for ten major crops and 21 water resource regions throughout the nation. The results were viewed skeptically because the input data were thought to be questionable and the model itself had been developed under a very strict time schedule. Essentially, the Y-SLS was considered a learning experience and it has indeed served as "the point of departure" for two more comprehensive and sophisticated modeling efforts (Crosson, 1983, p. 45).

The first and more substantial of these efforts consists of the Erosion/Productivity Impact Calculator (EPIC) model. The development of EPIC was prompted by the USDA National Soil Erosion -- Soil Productivity Research Planning Committee and its completion was rushed in order to report on the impact of erosion on long-term soil productivity in the 1985 RCA Appraisal (Williams et al., 1984; 1985). The nine sets of inputs required by the EPIC model incorporate weather, hydrology, erosion and sedimentation, nutrient cycling, plant growth, tillage, soil temperature, economics and plant environmental control (Williams et al., 1984). The model is capable of simulating hundreds of years of erosion on a daily basis and, unlike much soil erosion/soil productivity research, it incorporates the effects of crop management changes and economic impacts. Its authors claim that EPIC has produced "reasonable results under a variety of climatic conditions, soil characteristics and management practices", and has also demonstrated "sensitivity to erosion in terms of reduced crop production" (Williams et al., 1984, p. 141). However, EPIC's data requirements are formidable and the model is perhaps best used as it is now, by government agencies which possess the necessary data and personnel resources for national scale assessments.

The second successful modeling effort following the Y-SLS has seen development and testing of the PI model by Larson, Pierce, and their associates at the University of Minnesota (Larson et al., 1983; Pierce et al., 1983; 1984a; 1984b; 1984c). Their model was derived from an earlier equation constructed by Kiniry et al. (1983) at the University of Missouri. Most of the modifications to the original model were made in order to take advantage of the USDA-SCS SOILS-5 data base (which supplies most of the input data) and to accommodate additional concepts relating to variable soil conditions (Pierce et al., 1984a).

Underlying the PI approach is the premise that crop yields are closely related to the rooting environment provided by the soil. The model focuses, therefore, on inherent soil properties and based on these variables, it calculates the productive capability of the soil represented by Productivity Index (PI) values ranging from 0.0 to 1.0. The model is capable of predicting future PI values as the soil profile is affected (lowered) by erosion over time, because it analyzes the different horizons in the soil profile.

It is necessary, however, to recognize the effect of site-specific factors which may strongly skew the calculated PI values. These factors, which are not evaluated by the PI model, include steeply sloping, depressional or frequently flooded lands, and soils with high organic contents. The University of Minnesota study (Pierce et al., 1984a) demonstrated that the relationship between PI and yield (measured by the coefficient of determination, r^2) is much improved by excluding these special cases from the regression analyses used for model verification. Therefore, the impact of these factors (and perhaps additional environmental factors) must be carefully considered, especially when applying the PI model to locations other than the Corn Belt.

The model has other limitations related to three basic assumptions made in order to hold a number of factors constant. First, climate variability within a study region and between study regions (i.e., the Corn Belt and Cascade County) was presumed to have no effect on the model's performance. This assumption means that PI values generated in dissimilar climatic regions cannot be compared with each other since regional climatic conditions exert different influences on soil productivity. Second, it was assumed that a high level of farming technology (machinery, biocides, fertilizers, etc.) was used in crop production and therefore, that farming technology could not account for variations in crop yields. Third, the NRI erosion rates were accepted as estimates of future erosion in the next 50 to 100 years. These assumptions might be viewed as model limitations since they introduce generalization.

The initial development and testing of the model by Pierce and his associates took place in the U.S. Corn Belt (Pierce et al., 1983). They found that high PI values correlated strongly with high crop yields and low PI values with low yields. The productivity indices generated by the model represented productivity loss per centimeter of soil and thus, when combined with a known rate of soil removal (in cm yr^{-1}), a rate of productivity loss or gain could be calculated. Pierce et al. (1984c) used their PI values in conjunction with the 1977 NRI soil erosion rates to estimate the productivity changes of individual Corn Belt soils after 25, 50, and 100 years of simulated erosion. Following these first tests on soils supporting corn crops, Pierce and his associates demonstrated that their model may perform well for soybeans, barley, spring wheat, sunflower and oat crops in Minnesota (Pierce et al., 1984b).

The relatively simple and explicit nature of the PI formula prompted the International Federation of Institutes for Advanced Study (IFIAS) to evaluate model performance in Nigeria, India, Mexico and Hawaii (Rijsberman and Wolman, 1985). The model lends itself to application in diverse regions since it is designed without a complicated equation and does not require complex data inputs and computations. Therefore, possible model modifications and deficiencies are more easily identified. Although IFIAS' international applications of the PI model might best be considered tentative, mainly because data quality and availability were not equivalent to the data used by the University of Minnesota researchers, Rijsberman and Wolman (1985, p. 354) did conclude that "the PI approach appears to be a promising tool" for areas other than the Corn Belt. As soil resource agencies extend and refine their data bases and data management systems, it is desirable to develop models such as the PI model to complement these agencies' efforts. Expanding the use of these data bases using models results in improved and more efficient management of soil resources.

Overall, the PI approach would appear to satisfy several important requirements for improved assessment of the soil erosion/soil productivity problem. As stressed by Meyer et al. (1985, p. 215) it uses "appropriate quantitative data" in "pertinent experiments" which produce quantitative rather than qualitative results. Further, major variables are "experimentally evaluated to determine their relative importance." It was against this background (and these advantages) that this model was chosen for this study, which examines the suitability of using the model to evaluate soil erosion/crop productivity in the northern Great Plains.

Description of Study Area

Situated in northcentral Montana, Cascade County is centered approximately on latitude 47°22'N, longitude 111°20'W and borders the eastern slopes of the Rocky Mountains (Figure 1). In general, the topography ranges from nearly flat or rolling plains in the north to benchlands and mountainous areas in the southwest and southeast.

Approximately the northern two thirds of the study area lies within the Brown Glaciated Plains Major Land Resource Area (MLRA 52), and the other one third is classified as Northern Rocky Mountain Foothills, MLRA 46 (USDA-SCS, 1982a; 1982b) (Figure 1). MLRAs are defined by the USDA as large land areas (i.e., geographic units) having similar soils, climate, water resources and land use characteristics (USDA-SCS, 1984a). Land use in both MLRA 52 and MLRA 46 is characterized by the production of small grains and livestock forage. MLRA 52, with lower elevations (650 to 1,300 m) and less rugged terrain than MLRA 46 (1,200 to 2,000 meters elevation), is more extensively farmed. In both areas most grain is dry-farmed, but many river valleys are irrigated. Rangeland supports short and mid-height grasses as well as some shrubs, while some of the

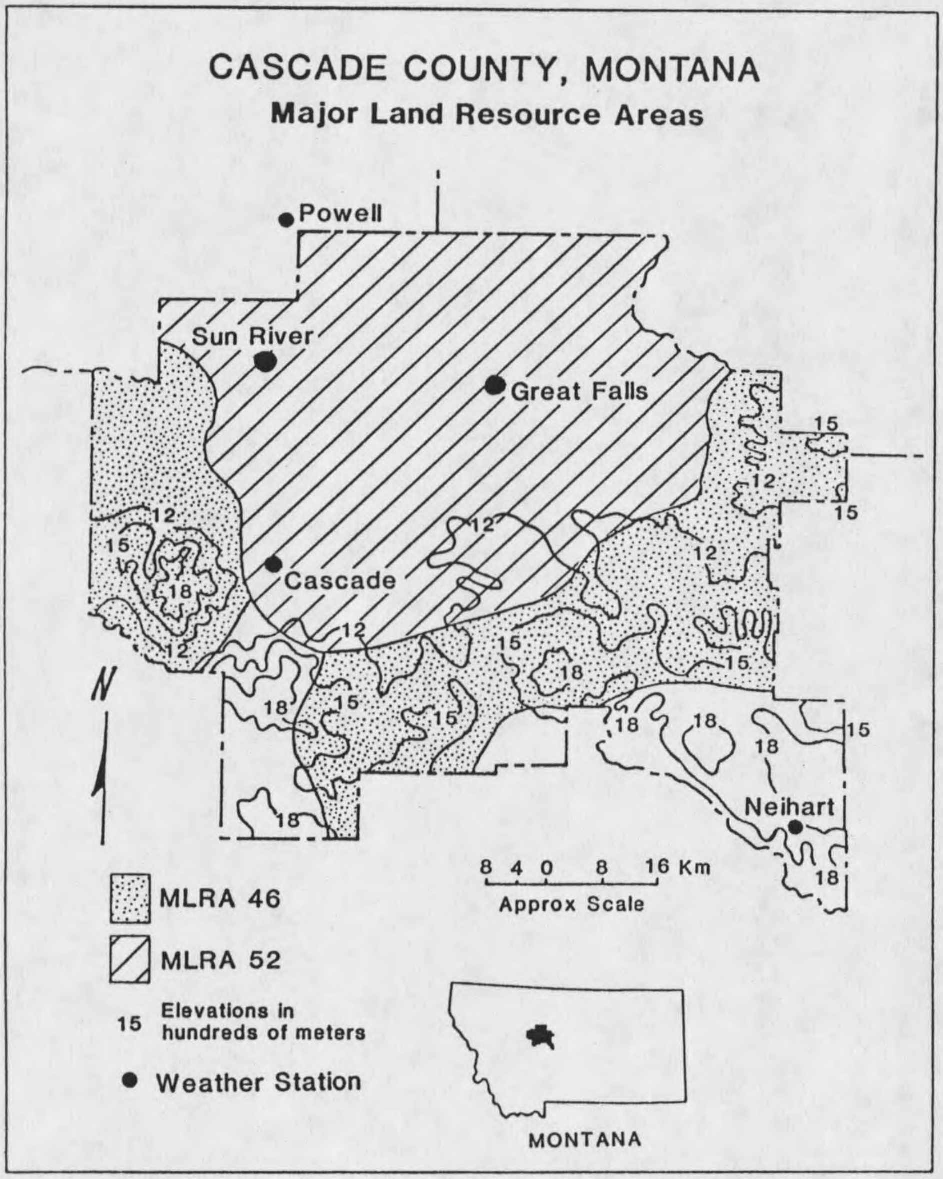

Figure 1. Location of Cascade County, Montana in relation to the Rocky Mountains and Major Land Resource Areas (USDA-SCS, 1982a; 1982b).

higher hills and low mountains are forested. Annual precipitation for both areas ranges from 25 to 43 cm (10 to 17 in), but higher elevations in MLRA 46 receive up to 76 cm (Figure 2). Subsurface glacial till yields ground water in moderate quantities, though in lesser quantities

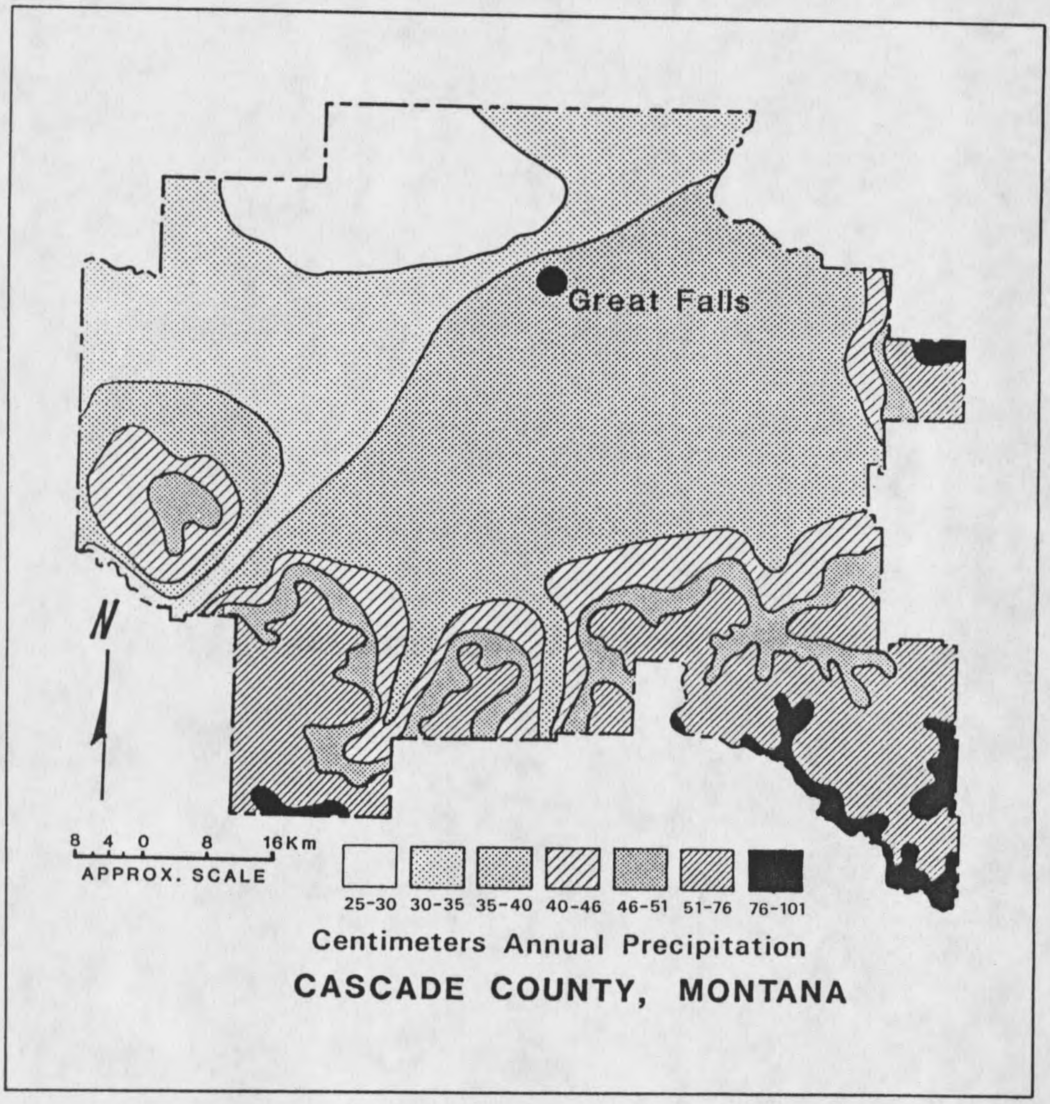

Figure 2. Average annual precipitation over Cascade County (unpublished map prepared by Cascade County Conservation District personnel, January 1987).

in MLRA 46. Soils of both areas are not strongly developed (haploborolls are common) and are often within the ustic soil moisture regime and frigid/cryic temperature ranges (Montagne et al., 1982).

These characteristics indicate cool/cold soils with inadequate plant available water for much of the year (Donahue et al., 1983). MLRA 46 contains mainly Alfisols, while MLRA 52 soils are mostly Mollisols, soils which are preferable for agriculture since they contain higher organic matter contents. Soils in MLRA 52 also commonly exhibit higher amounts of $CaCO_3$ (Calciborolls and Calciorthids) (Montagne et al., 1982; Donahue et al., 1983).

Overall, Cascade County's climate is characterized by low humidity, low winter and hot summer temperatures, and mostly sunny days. In this cool steppe environment precipitation amounts may be highly variable from year to year. By comparing regional topography and relative locations of climate stations (Figure 1) with precipitation data (Table 1, Appendix A, and Figure 2), it is evident that large year to year fluctuations in precipitation are compounded by area to area topographic variations within and adjacent to Cascade County. These data show that locations closer to mountain ranges experience greater precipitation variability than locations removed from the mountain-induced effects. Hence, the weather station at Cascade measured large precipitation fluctuations between 1974 and 1980 when compared to the weather station at Great Falls, located only 40 km to the northeast (Table 1 and Appendix A).

Winter precipitation, which originates in the Pacific mP air mass, falls mainly as snow. Typically snow occurs from November to March, but may fall as early as September or as late as July (Ruffner, 1978). The month of highest precipitation is June, which is then followed by occasional thunderstorms throughout the summer. Most of the summer

Table 1. Mean annual total precipitation (cm) and standard deviation for five weather stations in Cascade County, 1951-1980 (National Oceanic and Atmospheric Administration, 1951 through 1980).

	Climate Station				
	Cascade	Great Falls	Neihart*	Power*	Sun River
Mean Annual Precip.	38.7	37.7	50.7	27.6	31.0
Standard Deviation	10.6	8.5	12.0	6.8	8.6

* Less than thirty years of available data; see Appendix A.

moisture arrives from local thunderstorms and Gulf of Mexico maritime tropical air masses when pressure ridges over the southern Great Plains permit (Warrick, 1975).

Severe droughts lasting two to three years are infrequent. Warrick (1975) states that such dry periods result from development of abnormally persistent mid-continental high pressure ridges which can have the compound effect of both repelling invasion of moist Gulf of Mexico air, and of forcing hot, dry air northward from the southwestern deserts. Less lengthy, but nonetheless critical precipitation fluctuations are common in Cascade County (Table 1 and Appendix A).

The county's position in the lee of the Rocky Mountains imposes a marked rain shadow effect mainly in the northern half of the county (Figures 1 and 2). Here, many farm operations are forced to irrigate in order to obtain profitable crop yields. In the south, the higher elevation benchlands receive more precipitation and are cooler, thus maintaining a higher soil moisture supply. Further, the Little Belt mountain range, located in the southeast part of Cascade County, precludes development of a rainshadow by uplifting and cooling westerly air thus causing higher precipitation in that area of the county.

Cascade County temperatures range from mean monthly lows of -12^{o} C (10^{o} F) to mean monthly highs of 28^{o} C (82^{o} F). Frost-free periods range from 85 to 135 days, the average being 110 days (Montana Agricultural Experiment Station Farm Economics Division and USDA Economics Research Service, 1971). Growing degree days (GDD), another measure of growing season temperature, represent the cumulative number of degrees Fahrenheit over a designated threshold temperature achieved during a year. Based on a 50^{o}F threshold, Cascade County's GDDs range from 1,800 to 2,600 according to the Montana Agricultural Potentials System (MAPS) database developed by the Department of Plant and Soil Science at Montana State University.

Average wind speeds range between 17 and 26 km hr^{-1} and flow predominantly from the southwest (Ruffner, 1978). More importantly, the highest wind velocities occur in the fall and spring months when soil surfaces are exposed to erosive winds (Ruffner, 1978). In winter, strong, warm Chinook winds along the Rocky Mountain front have the detrimental effect of melting protective snow covers, thus leaving the soil open to wind dessication and removal by either wind or water.

Agricultural soils occur on the flat and sloping terrain of plains, fans, benches and terraces. Nearly all of these soils are classified as Mollisols, Aridisols and Entisols. The region's soils are primarily characterized as young soils because the cold, dry climate and relatively short time since the last glaciation contribute to very slow soil formation. Glaciation and glacial materials exert only a partial influence on soil characteristics since the county lies within both the glaciated and unglaciated plains (Montagne et al., 1982). Additional parent material consists of sandstone, limestone, dolomite and soft red and black shales (Montagne et al., 1982). The predominance of clayey soils reflects the presence of these extensive shale beds.

Cascade County farmers must contend with two productivity problems related to soil chemistry. First, all of the agricultural soils analyzed in this study contain at least slight $CaCO_3$ concentrations (observed HCl reactivity or effervescence) within 24 cm of the surface. In fact, 60% of all the soils contain higher concentrations (violent and extremely violent effervescence) at 18 cm or less. Second, although Cascade County soils are predominantly well-drained, annual precipitation does not sufficiently leach out soluble soil salts over time. Saline soils may contribute to the development of saline seeps when the effects of summer fallowing, water applications and subsoil drainage problems are not closely monitored. Recently, the number of saline seeps in Cascade County has increased at a rate of 8 to 10% per year (USDA-SCS, 1982c). Saline seeps are a serious concern to Cascade County farmers because excessive salts can affect soil productivity by inhibiting plant uptake of water, causing collapse of root cells, reducing activity of soil microorganisms and delaying seed germination (Summerfeldt and Rapp, 1982).

Other soil productivity problems in Cascade County soils are the result of their formation in water deposited materials (USDA-SCS, 1982c). Some cobbly and gravelly soils inhibit root development, cause excessive drainage and retain little water in the soil profile for subsequent use by crops. Another common problem is soil crusting (USDA-SCS, 1982c). This condition occurs in soils having a high proportion of fine sands and silts on the surface, underlain abruptly by a clayey subsoil. The resulting crusts and very durable clods adversely affect seedbed conditions and seedling emergence.

The regions's climatic conditions tend to aggravate the erosion hazard in Cascade County. In this important grain producing region, such a climate is a critical problem since the region is subject to constant dry valley and downslope winds from the Rocky Mountains. Comparing 1982 NRI erosion rates between MLRAs 46 and 52 indicates that the hazard is not uniform over the county area. Plains soils (MLRA 52), where most crop production takes place, are more susceptible to wind erosion (Table 2). Considering the 72 agriculturally valuable Cascade County soils evaluated in this study, only eight are classified in the very highly erodible or highly erodible wind erodibility groups, while 14 are moderately erodible, and the remaining 50 are slightly and very slightly erodible (USDA-SCS, 1982c). From these data it might be concluded that the soil's susceptibility to wind erosion is not especially severe. However, considering that wind in Cascade County is persistent and can impose substantial impacts on even the slightly erodible soils, the magnitude of the hazard increases. For example, in 1987 Cascade County ranked third among Montana's 56 counties for wind erosion damage with a total affected area of 22,500 ha (USDA-SCS, 1988a).

Cascade County's agricultural production is notable in spite of the soil conditions, erosion vulnerability and other climate-related risks

Table 2. 1982 estimated erosion rates (Mg ha^{-1}) for Montana and Cascade County cropland soils (USDA-SCS, 1984a).

		MLRA 46	MLRA 52	Montana
Cropland:				
	wind	10.1	16.4	18.7
	water	2.7	2.7	1.6
	total	12.8	19.1	22.3

so far described. The county forms the southern corner of Montana's "Golden Triangle", an area well-known for its prolific small grain crops. The northern half of the county contains the majority of cropland, although precipitation is generally lowest here. The southern half enjoys a more adequate moisture supply, but contains soils and topography less suited for grain crops and highly mechanized agriculture. Approximately 16% (101,000 ha) of the 607,000 non-forest hectares surveyed by SCS is used for dryland grain production while 2% (15,000 ha) supports irrigated crops (Montana Department of Agriculture and USDA National Agricultural Statistics Service, 1986).

Average dryland crop yields for the state and for the county are reported in Table 3. Additional figures reported by the Montana Department of Agriculture and the USDA National Agricultural Statistics Service (1986) lend perspective to Cascade County's rank among Montana's 56 counties. In 1984, the county ranked tenth for its $23.7 million in agricultural crop receipts, a total which excludes livestock receipts and government subsidies (Montana Department of Agriculture and USDA National Agricultural Statistics Service, 1987). In 1986, Cascade County ranked sixth for barley production, seventeenth for spring wheat

Table 3. Comparison of Cascade County with average state yields and market values (Montana Department of Agriculture, 1986; 1987).

Crop	Year	Yield: State	Yield: Cascade Co.	Value of Production: State	Value of Production: Cascade Co.	Percentage State Prod.
		(Mg ha^{-1})[a]		(millions of dollars)		
Barley						
	1984	6.2	6.6	141.2	4.8	3%
	1985	3.8	1.3	64.5	1.8	3%
	1986	9.3	9.9	111.1	5.4	5%
Spring wheat[b]						
	1984	5.1	6.0	126.9	2.5	2%
	1985	3.1	3.1	97.7	2.4	2%
	1986	4.5	9.1	172.4	4.5	2%
Winter wheat						
	1984	8.8	10.9	228.3	11.0	5%
	1985	5.1	4.7	76.2	3.5	5%
	1986	10.5	11.9	146.1	6.9	5%

[a] Conversion to metric from USDA Cooperative Extension Service, Montana State University (1982).
[b] Spring wheat figures exclude Durum wheat production.

production, fifth for winter wheat production, and eighth for all wheat production (Montana Department of Agriculture and USDA National Agricultural Statistics Service, 1987).

In summary, the somewhat harsh physical qualities of the region's agricultural environment demand the cultivation of cereal grains rather than other less hardy crops. In fact, because of the highly variable moisture supply, the region is designated by Parry (1978) as climatically marginal for agricultural purposes. Agriculture throughout the northern Great Plains region (which includes Cascade County) has been characterized by low yields (compared to national averages), high yield variability over time and occasional crop abandonment due to a variety of environmental factors (Montana Agricultural Experiment Station, 1971). However, the predominance of agriculture in Cascade County and consistent delivery of relatively high yields indicate that the agricultural environment has been and will continue to be valuable for food production (Montana Department of Agriculture and USDA National Agricultural Statistics Service, 1986). It would seem then that preserving the area's economic resources warrants investigation of a model designed to predicting soil productivity.

Thesis Organization

This introductory chapter has described the scope and purpose of this project and the theory upon which the work is based. The context of this study within the broader topic of soil erosion is established by summarizing both older and more recent research exploring soil erosion/ soil productivity relationships. The agricultural significance and erosion hazard in Cascade County are described in the final section to indicate why Cascade County was chosen for this evaluation of the Productivity Index (PI) model.

The second chapter explains the methods and data sources used to apply the Productivity Index model in Cascade County. The first section provides a more practical rather than theoretical explanation of the PI model. The second section describes the acquisition of data and computer software, the process and problems encountered in setting up the programs, the function of each program and the calculation of PI values. The third section deals with the verification of PI values, and the fourth section explains the selection of four terms for potential addition to the PI model, the sources of data for those new factors, and the multiple regression analysis used to evaluate their relation to yield variability.

Chapter Three presents the results of the model verification tests. The sequence of multiple regression models used to analyze each of the new terms with each of the three crops is generally explained. More specifically, each factor's changes in significance as a crop yield predictor and the increasing explanation of yield variability are described.

Chapter Four discusses the wider significance of the regression results as they relate to quality of data inputs, the existing PI model and the possibility of model alteration. The roles of the four new terms as potential model additions are examined with respect to their different effects on each crop's yield, their variable distribution over the study area and the considerations necessary for including them in the model. Finally, the overall success and relevance of this study are summed up in the conclusion.

CHAPTER TWO

METHODS AND DATA SOURCES

Productivity Index Model

The Productivity Index (PI) model developed by Pierce and associates at the University of Minnesota (Pierce et al., 1983; 1984a; 1984b; 1984c) and used in this study was derived from an earlier equation constructed by Kiniry et al. (1983) at the University of Missouri. Modification of the original model was accomplished mainly to take advantage of the SCS SOILS-5 and National Resources Inventory (NRI) data bases which together supply all of the required information on soil properties, erosion rates, and MLRA characteristics.

The Minnesota PI model can be written:

$$PI = \sum_{i=1}^{n} (A_i * C_i * D_i * WF_i)$$

where A_i is the sufficiency of available water capacity, C_i is the sufficiency of bulk density, D_i is the sufficiency of pH, WF_i is the weighting factor representing an idealized rooting distribution and n is the number of horizons in the depth of rooting (Pierce et al., 1984b; 1984c). The sufficiency curves are based on root response to each variable normalized over the range of 0.0 to 1.0 (Figure 3). Essentially a sufficiency value estimates how adequate (or deficient) a soil's environment is for optimum root development. The weighting factor modifies the "importance" of each horizon's PI values according to that

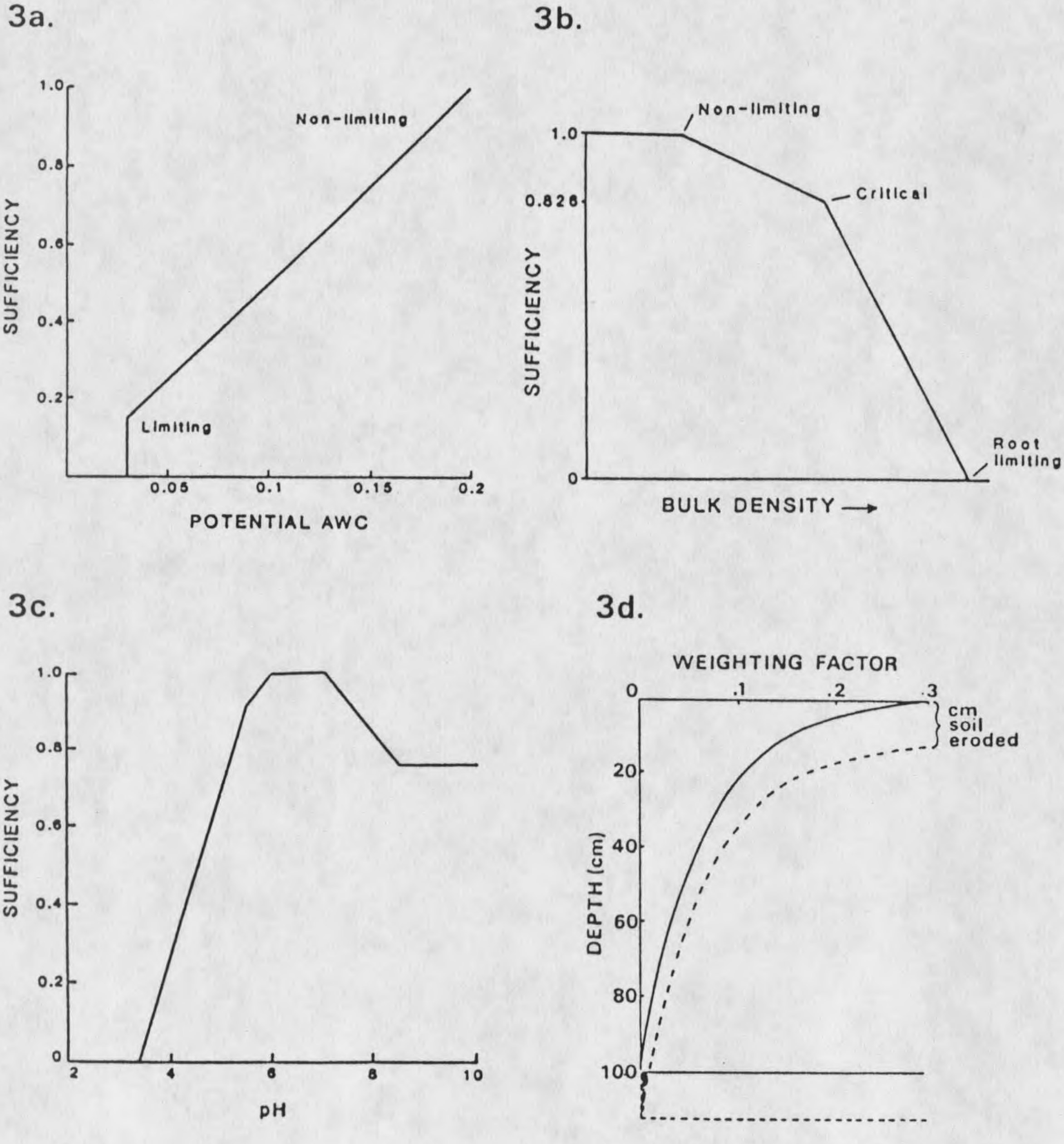

Figure 3. Sufficiency curves for (a) available water capacity, (b) bulk density, (c) pH and (d) the sliding weighting factor used by the PI model (Pierce et al., 1983; 1984a).

to that horizon's depth within the rooting zone (Figure 3d). The curve is designed to evaluate effects of erosion and root limiting layers in the soil. First, as the PI model simulates erosion the curve moves down the horizon depth axis (shown by the dashed line in Figure 3d) which adjusts the PI rating assigned to horizions in the soil profile. Equivalent horizons in a deeper, non-eroded soil profile receive higher PI ratings (shown by the solid line in Figure 3d). Second, if a root limiting layer is encountered in the profile, the portion of the curve below that layer is removed from the calculation of the PI value. This is because the soil below a root limiting layer is not available for plant use and such a condition, of course, lowers a soil's productive value.

It is necessary to note that the sufficiency of bulk density curve lacks units along the X axis because the bulk density data supplied to the model may be altered by the program according to soil texture (as described fully later in this chapter). Hence, the units along the bulk density axis may vary for each soil and cannot be graphically represented.

Underlying the PI approach is the premise that crop yields are closely related to the rooting environment provided by the soil. The model focuses, therefore, on inherent soil properties and based on these variables, it calculates the productive capability of the soil represented by PI values ranging from 0.0 to 1.0. By examining the physical and chemical characteristics of the soil profile as soil is removed, the PI method provides a quantitative evaluation of changes in a soil's rooting environment and overall productive value that occur in response to erosion processes.

Application of the PI Model to Cascade County

Copies of the PI model computer software and an accompanying manual were obtained from the Department of Soil Science at the University of Minnesota (Winkelman et al., 1984). An account was set up on Montana State University's Honeywell CP6 mainframe for accomplishing two data pre-processing operations. Several minor alterations were made to the two pre-processing programs, GENERS5 and GPIFORM, because the CP6 Pascal compiler would not accept some of the terms incorporated in the Minnesota versions of these programs. The Montana USDA-SCS SOILS-5 data base contained most of the soils data required to run the model and was provided on magnetic tape by the state SCS office.

The two data pre-processing programs (GENERS5 and GPIFORM) accomplish four complex operations. First, the required data are extracted from the magnetic tape. Second, the texture and clay content of each horizon are evaluated and translated into a textural code number (Figure 4). Third, the relationship between bulk density and the reported available water capacity (AWC), clay content and air-filled porosity (AFP) is checked in each horizon for bulk densities incompatible with these other measured parameters. AFP, AWC and percent clay are used to detect situations where soil stucture is highly developed. Since bulk density measurements are derived independently of soil structure, it is possible to obtain a very high density indicating a heavy, low porosity soil when, in fact, the soil structure is different. In these situations the original bulk density would be a

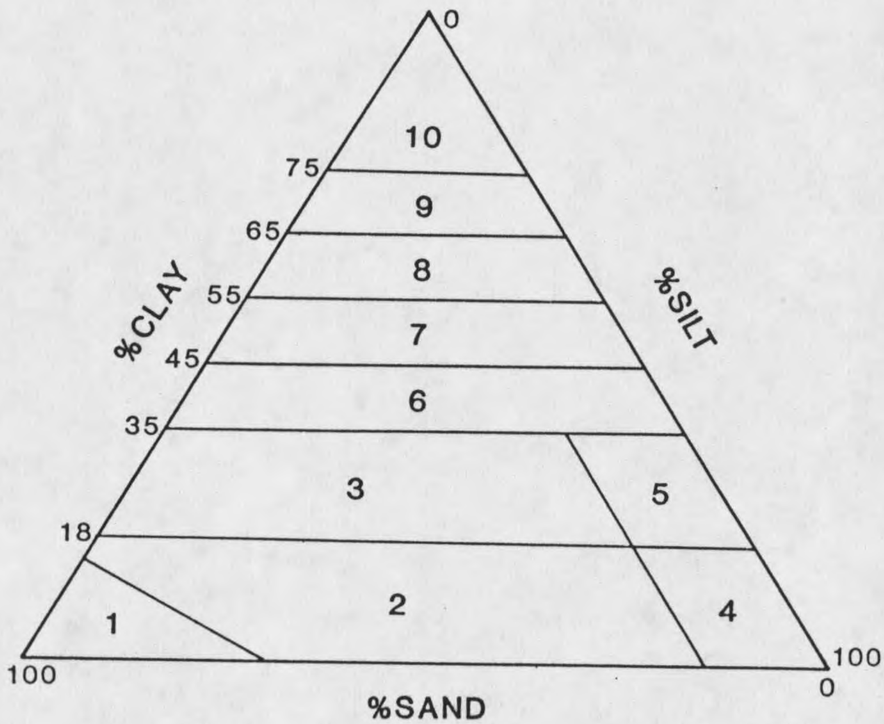

Figure 4. Soil family texture classes derived from <u>Soil Taxonomy</u> (USDA-SCS, 1975) and used in the PI program, GENERS5 (after Winkelman et al., 1984).

false indicator of actual porous qualities of the soil (Pierce et al., 1983). SOILS-5 bulk densities exceeding the "check bulk density" calculated by the program are flagged for identification and replaced with the lower value adjusted by the AWC, clay content and AFP measurements combined with soil family texture class (Pierce et al., 1983; Winkelman et al., 1984). Finally, soil data used in the PI model for each soil series (horizon number, SCS texture, texture code, horizon depth, available water capacity, bulk density, pH and permeability) are correctly formatted and linked with series name and phase number for downloading and subsequent analysis on an IBM-compatible personal computer.

Pre-processing revealed a critical gap in the USDA-SCS SOILS-5 data records because soil moist bulk density estimates were missing for approximately 95% of the soil series present in Cascade County. The National Soil Laboratory's moist bulk density triangle and program modifications in GENERS5 were used to estimate the missing bulk densities (Figure 5). Because this triangle is applied over a diverse range of soil types and environments, an adjustment for organic matter is used in conjunction with the triangle values in order to account for highly variable organic matter contents. An adjustment for coarse fragments is not necessary since laboratory measurements of bulk density exclude stones and cobbles (D. McLean, personal communication, 1989). The bulk density triangle was compiled by Robert Grossman and Otto Baumer from approximately 4,000 soil samples collected nationwide and thus, does not consider specifically the local climatic and geologic influences in Cascade County (W. Braker, personal communication, 1987). However, William Braker (SCS Soils Interpretations Specialist for Montana) checked the triangle values' accuracy by comparing them with known moist bulk density values which had been measured in a laboratory. He found the triangle values to be within plus/minus 0.1 gm cm^{-3} of the laboratory values and thus felt the estimates were close enough to justify use of the triangle (W. Braker, personal communication, 1989). Methods used by Evans (1982) to measure bulk density on Montana soils and by Mausbach and Gamble (1984) to assess North and South Dakota soils were examined and found to require substantial field and/or laboratory work or data that were otherwise unavailable. Therefore, the bulk density triangle proved to be the most convenient, rapid, and comprehen-

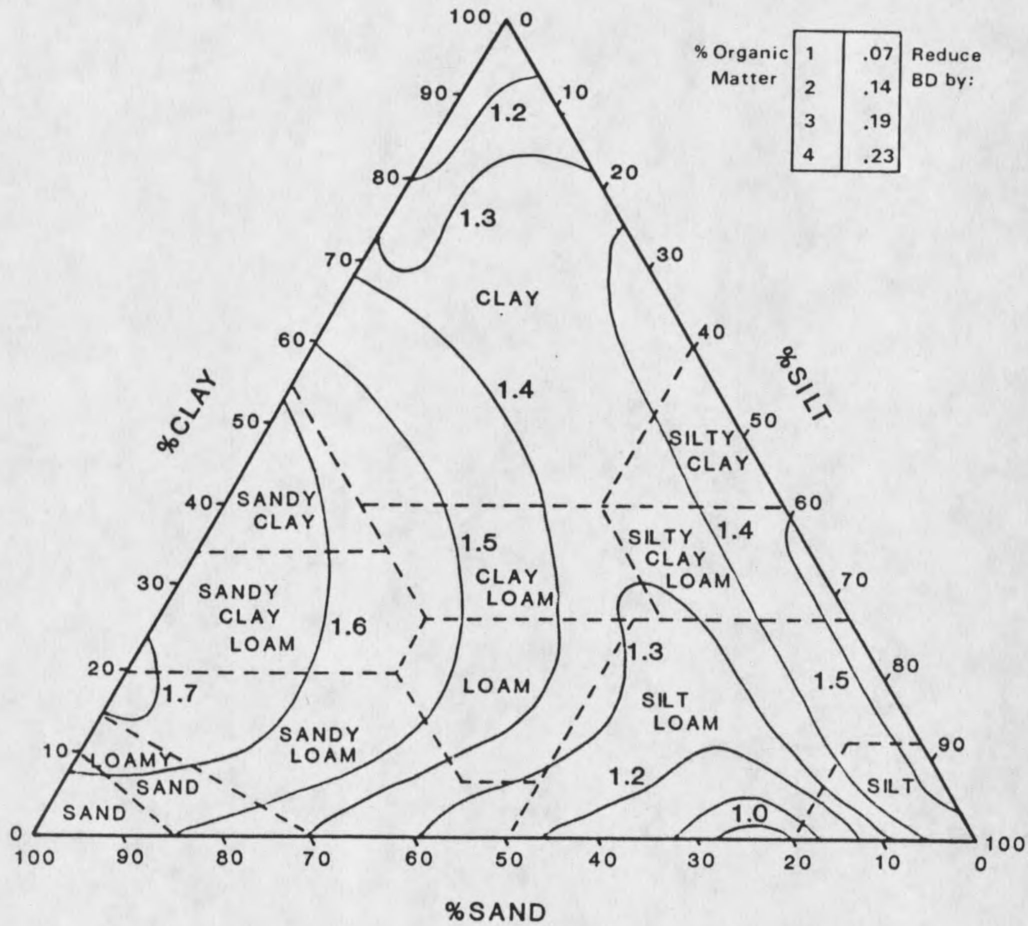

Figure 5. The moist bulk density triangle developed by Grossman and Baumer at the National Soil Science Laboratory in Lincoln, NE.

sive solution to the missing data problem.

The final task prior to downloading the soils data onto diskettes involved the selection and extraction of data for only the agricultural soils of Cascade County. This step was important to increase computational efficiency. A second data access problem to do with the selection of surface horizon textures for Cascade soil series was solved after these data were downloaded. The Cascade County Soil Survey produced by the USDA-SCS (1982c) was used to select and manually place the most appropriate surface textures in the shortened SOILS-5 records that were used in subsequent PI calculations.

The pre-processed and edited data were downloaded via modem from the MSU Honeywell mainframe to the hard drive of a Zenith Z-158 PC. These data were preserved on the Honeywell CP6 in addition to being stored separately on backup diskettes. After locating the correct Pascal compiler (version 3.0) for subsequent micro-computer operations, the TODIRECT program performed one more additional pre-processing step which consisted of simply converting the data file from sequential access to a direct (or random) access file format.

Subsequent analysis (i.e., the generation of PI values) was performed with the GRAPHPI2 program. This program generates several PI values for each soil series. First, a current productivity rating is calculated. Next, PI values are computed for successive soil profiles as computer-simulated erosion removes two centimeters of topsoil at a time. These calculations continue until 100 cm are removed or PI reaches zero. GRAPHPI2 also plots the sequence of PI values against centimeters eroded in standard graph format. Finally, the program displays the current PI values and PI values after 50 and 100 cm are lost, along with a vulnerability parameter expressing the rate at which productivity diminishes with decreasing profile depth.

Model Testing

Simple regressions of PI values versus current crop yields were used in the effort to evaluate the applicability of this model to Cascade County soils and crops. Pierce et al. (1984a) used a similar approach to demonstrate model performance in the Corn Belt, concluding that r^2 values of at least 0.70 demonstrated that PI values provided good estimates of soil productivity (Pierce et al., 1984a). A high degree of correlation between PI and crop yields was also used in this attempt to evaluate model performance in Cascade County.

However, the yield data had to be acquired differently from the Minnesota studies because GENERS5 was unable to access crop yield information in SOILS-5. Hence, yield data for barley, spring wheat and winter wheat were collected manually from SOILS-6, another data base maintained by SCS. (SOILS-6 yields are identical to those reported in SOILS-5 and so will be referred to as SOILS-5 data). Yield data for the same three crops were also taken from the Cascade County Area Soil Survey (USDA-SCS, 1982c). The two sets differ slightly due to the different origins of the data. The Soil Survey yields are developed directly from Cascade County producer information and soil scientists familiar with the area's soils, crops and growing conditions. The SOILS-5 data is acquired directly from soil series descriptions which reflect the growing conditions specific to the location where each series was first identified. For instance, the Montana SOILS-5 records contain numerous soil phases attributed to Colorado, Idaho, North Dakota, South Dakota and Wyoming. These inclusions are due in part to the slower progress made in mapping soils in a state as large as Montana.

The two sets of yield estimates meant there were two opportunities to test model performance. One set of simple regressions compared PI values and SOILS-5 barley, spring wheat and winter wheat yields, and the second set of regressions compared PI values and Cascade County Area Soil Survey yields. Since SOILS-5 data were used to calculate PI values, it was expected that the regressions using the SOILS-5 yield data would produce higher correlations. All of these regressions were performed on Montana State University's new VAX 8550 cluster with the Statistical Analysis System (SAS) package (Freund and Littell, 1986).

In order to improve their model's explanation of crop yield variability, Larson and his associates excluded histosols (soils with high organic matter contents) and soils that were steeply sloping, depressional or frequently flooded. With the exception of steeply sloping soils, these exceptional cases were not considered in this study simply because they do not occur in Cascade County. Slope factors were evaluated in a manner different from the Minnesota study as explained below.

Assumptions similar to those made in prior applications of the PI model are also made in this study. First, because regional climatic differences were excluded in the Corn Belt study, it is likewise presumed that climate has no effect on the model's performance in Cascade County. Initially, it is necessary to make this assumption because in order to determine whether or not climatic differences across the study area affect soil productivity, the model must be applied as it was originally (i.e., assume no climatic effects). Except for the exclusion of steeply sloping soils as explained below, the influence of landscape position (described by Onstad et al., 1985) is also ignored. It is assumed that a high level of farming technology was applied in crop production and therefore, that farming technology does not explain variations in crop yields. Finally, soil nutrients and moisture conditions are presumed to be adequate for crop growth. Such assumptions are necessary to create a controlled situation and thus avoid confounding the experiment and making it impossible to establish cause and effect relationships (Meyer et al., 1985).

In the interest of making these assumptions more reasonable, two choices were made. First, only non-irrigated crop yields were used to evaluate model performance, since data for irrigated crops were less abundant and, more importantly, because highly variable irrigation practices result in inconsistent yields and soil degradation unrelated to erosion. Second, a study region was selected where agricultural production was relatively high and also well established in the region's economy. From this is inferred a record of reliable yield data collection, an adequate supply of soil nutrients, and widespread local investment in high technology such as machinery and fertilizers.

Statistical Exploration of Potential Model Additions

The low r^2 values from the simple regressions (see Chapter Three) led to a search for additional variables which may strongly influence crop yields and yet are not included in the model. Several climate and topographic factors, as well as additional soils variables are known to affect yield (Langdale and Schrader, 1982; Larson et al., 1983; Pierce et al., 1984a; Meyer et al., 1985; Daniels et al., 1987; USDA-SCS, 1987b; Sandor, 1989). Data were gathered by soil series for several of these variables and four multiple regression equations were built for each crop in an attempt to better predict crop yield variability in

Cascade County. The new variables selected were water balance (Meyer et al., 1985), growing degree days (Pierce et al., 1984a), slope (Larson et al., 1983) and $CaCO_3$ (Sandor, 1989).

Data for annual precipitation and potential evapotranspiration (PET) were obtained for calculating a water balance factor. These data are not available on a soil series by soil series basis. They were closely approximated for each series using the typical profile location (range and township) described in the Cascade County Area Soil Survey (USDA-SCS, 1982c) and the Montana Agricultural Potentials System (MAPS) data base developed and maintained by Caprio, Nielsen and associates in MSU's Department of Plant and Soil Science. Precipitation is represented by annual average totals incorporating rain and snowfall. PET is defined as the rate at which moisture would evaporate and transpire from soil and vegetation given an unlimited supply of water. The MAPS data base expresses both factors in inches of water, and the water balance used in this study was obtained by subtracting PET from precipitation.

Growing degree days (GDD) are essentially a measure of growing season, but can affect soil temperature and PET. Each degree Fahrenheit above a daily mean threshold temperature equals one GDD, and reported GDD figures represent the cumulative total for one year. GDD data for this study were also obtained from MAPS, which uses $50^{o}F$ as the temperature threshold. Although GDD data using the $50^{o}F$ threshold more closely represents the needs of warm weather crops (and not northern Plains small grains), GDD data based on $40^{o}F$ was unavailable at the time of this study (J. Caprio, personal communications, 1988; 1989).

Slope classes for each soil series were gathered from the Cascade County Area Soil Survey (USDA-SCS, 1982c), although the slope ranges (e.g., 0-2%, 4-8%, etc.) were converted to single values (mid-points) for this study.

The $CaCO_3$ data were obtained from the ratings of soil reactivity with hydrochloric acid also reported in the Cascade County Area Soil Survey (USDA-SCS, 1982c). These ratings were translated to codes using the appropriate USDA-SCS technical guide (USDA-SCS, 1974). These data were expressed as the depth to the affected layer in inches.

These four variables and the PI values (representing the three variables incorporated in the model) were then used in a series of multiple regression models in an attempt to explain yield variation more completely than with PI values alone. When evaluating environmental parameters specific to Cascade County, only the Cascade County Area Soil Survey yields (USDA-SCS, 1982c) were used in the multiple regression analysis. This is because these yield data reflect the local growing conditions, making them compatible with the four new local variables.

The initial model regressed four primary independent variables (PI, water balance, GDD and slope) with the dependent variable (yield) for each of the three crops used in this study. The second model incorporated a fifth factor (labeled "TYPE" through the remainder of this thesis) which indicated whether or not a soil contains $CaCO_3$ within the top 20 cm of the profile (TYPE = 0 if it did, and TYPE = 1 if it did not). The TYPE variable served as an indicator variable which separated the entire data set into two groups. This setup was required to create the situation where presence or absence of $CaCO_3$ in the topsoil, rather than depth and/or concentrations of $CaCO_3$, could be analyzed. The third model incorporated four more independent variables representing the interaction effects occurring between the first four independent factors noted above and the TYPE variable, as well as the original five independent variables themselves. This arrangement meant that a total of nine independent variables were included in the third regression model. The fourth and final series of models included only those independent variables that displayed a statistically significant ability, by themselves, to explain yield variation. Hence, the combination of independent variables which satisfied the P <= T requirement (with 1 and 5% levels of significance) was allowed to vary in the case of each crop.

CHAPTER THREE

RESULTS

PI Model Evaluation

To discover whether the SOILS-5 and Cascade County Soil Survey sets of yield estimates differed significantly, matched pairs t tests were performed for barley, spring wheat and winter wheat. The results indicated that there was no statistically significant difference at the 1% (.01) significance level and the null hypothesis, that the two samples were drawn from the same population, was accepted.

Despite this conclusion, the sources of each yield data set suggest that each has a specific application in the statistical testing of the PI model. First, since the PI values were derived from SOILS-5 soil profile data, the accompanying SOILS-5 yields were used to evaluate whether or not PI values can be used to estimate soil productivity. Second, the Survey yields representing specific growing conditions in Cascade County were used to examine how other local factors (e.g., water balance, slope, temperature and lime content) affect soil productivity. It was assumed that applying each set in this manner would result in higher correlation coefficients.

Results of the simple bivariate regression of barley, spring wheat and winter wheat yields versus PI are presented in Table 4 and Figure 6.

Table 4. Bivariate regression results of PI value versus yield.

Crop	SOILS-5 Data			Soil Survey Data		
	r	r^2	n	r	r^2	n
Barley	.59	.35	70	.59	.35	69
Spring Wheat	.66	.44	65	.57	.32	65
Winter Wheat	.65	.42	68	.56	.31	62

By performing the same analysis with both yield data sets, the better match between SOILS-5 yields and data used for calculating PI is confirmed by the slightly higher correlations (Table 4). More importantly, it is seen that PI explains approximately 40% of the variation in crop yield. This result suggests that the PI model, as is, does not satisfactorily estimate soil productivity in Cascade County.

Pierce et al. (1984b) obtained similar correlation coefficients (r^2 values between .23 and .68 for corn) when they tested the PI model in Iowa, Indiana, South Dakota and Minnesota counties. However, they improved their correlations and obtained r^2 values between .70 and .77 by excluding histosols, frequently flooded, depressional and sloping soils from the subsequent model tests. This strategy could not be repeated in Cascade County for two reasons. First, three of the four exclusion cases (histosols, frequently flooded and depressional soils) do not occur in Cascade County and second, the scatterplots did not produce outliers which could be clearly ascribed to other special conditions (Figure 6).

Pierce et al. (1984b) suggested that the model may require alterations when applied in regions having crops, climatic conditions

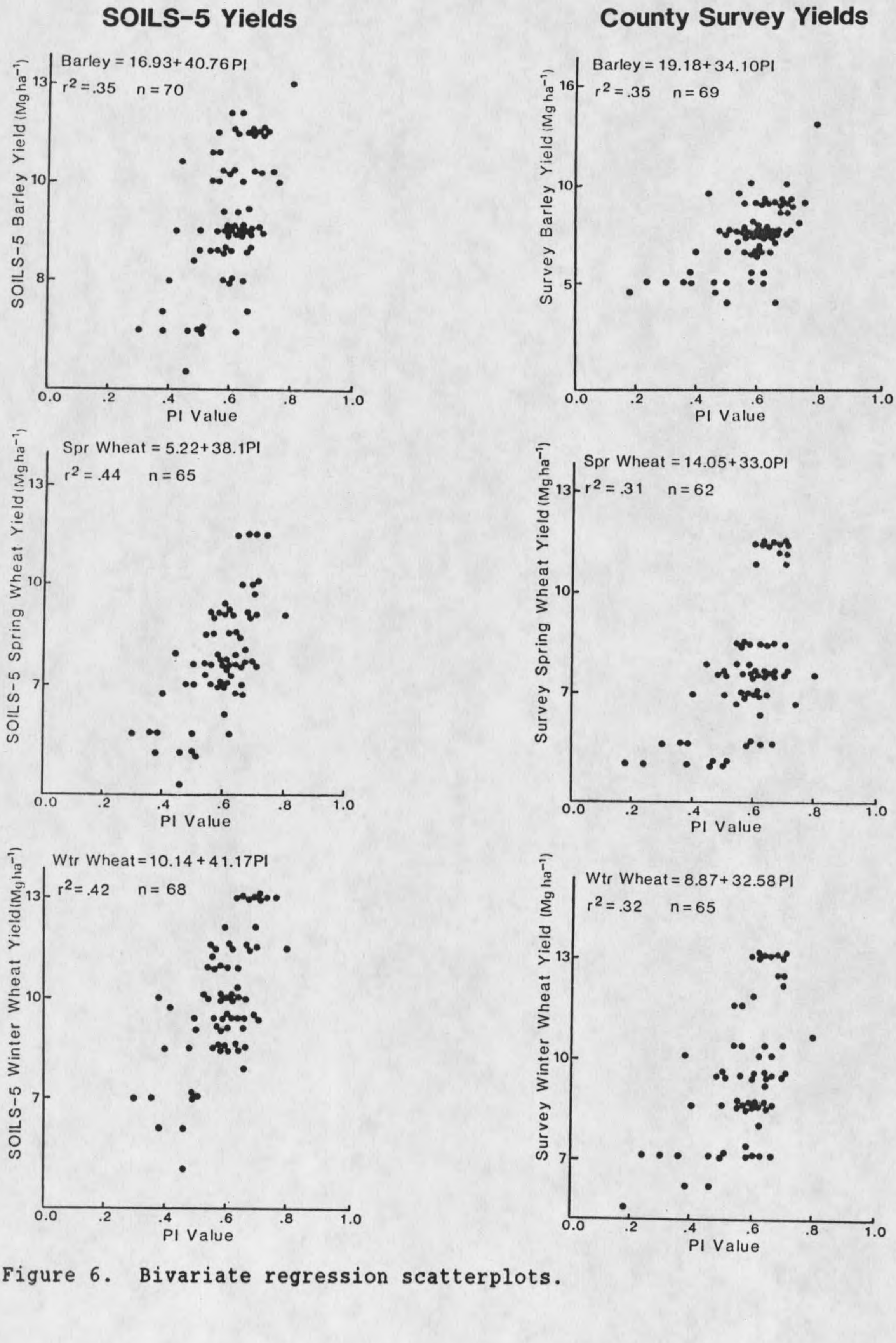

Figure 6. Bivariate regression scatterplots.

and soils different from those of the Corn Belt. Numerous studies indicate that many soil and non-soil factors in addition to those included in the PI model can affect crop yield. One USDA-SCS (1987b) study found high correlations between precipitation and yield. Pierce et al. (1984a) suggested the inclusion of sufficiency factors to account for the effects of growing degree days and moisture supply. Sandor (1989), who evaluated the PI model in two field-scale applications in Hill and Jefferson counties, Montana, tested new input variables previously identified as pertinent factors of soil productivity in Montana. His potential model alterations included eight topsoil variables (clay, sand, silt, $CaCO_3$ equivalent, pH, organic matter, AWC and family textural class), nine variables weighted throughout the profile (clay, sand, silt, $CaCO_3$ equivalent, pH, organic matter, family textural class and bulk density), three topographic variables (slope position, slope gradient and slope aspect) and four profile variables (rooting depth, AWC, depth to $CaCO_3$ concentrations in excess of 5% and rooting depth). Based on findings from these studies and data availability, four variables (slope gradient, water balance, growing degree days and presence of $CaCO_3$) were selected and their relationships to crop yield were explored with multiple regression analysis.

Multiple Regression Analysis

A two stage process is necessary when modifying the PI model. First the appropriate factors must be identified and second, the correct method for their inclusion in the model must be worked out. It was the intention of this part of my study to complete the first step of suggesting appropriate new factors. This evaluation of new parameters is accomplished in conjunction with PI values using regression analysis.

The factors selected for evaluation have been identified by research on small grains in Great Plains environments and/or were suggested in other PI model studies. Water availability was noted by Heilman et al. (1977), Meyer and Alston (1977), Rickman et al. (1977) and Pierce et al. (1984a) for its influence on crop yields. Growing degree days were studied as the basis for yield prediction by Sammis et al. (1985) and Williams et al. (1988). Pierce et al. (1984b) and Sandor (1989) included slope considerations in their research and Sandor (1989) made $CaCO_3$ a special focus of his work with the PI model because it had been shown by Schweitzer (1980) and Burke (1984) that crop yields are related to the presence or absence of $CaCO_3$ in the Ap horizon of Montana soils.

The approach for each of the three crops involved using these four new variables in addition to PI (representing the sufficiency of available water capacity, pH and bulk density within the rooting depth) as the independent variables in an effort to explain crop yield variation. This part of the analysis used only the Cascade County Soil Survey (USDA-SCS, 1982c) yield data for the reasons stated at the beginning of this chapter. Calcium carbonate was included as a categorical variable to investigate the possibility of interactions between lime and the other factors by creating an indicator ("dummy") variable in the second and subsequent regression models for the reasons described earlier in Chapter Two.

In general, this method involves sequential development of regression models (equations) in which the variables that are statistically non-significant as explanatory factors can be isolated and removed from each successive equation. Four such models were developed for each crop. A summary of these results and the variables that were included at each step are shown in Table 5, and the complete results from these models are presented in Tables 6 through 9.

During this development process, a key output examined after every run was the F Value (the model mean square divided by the error mean square). The F Value is used to test whether or not all of the regression coefficients (except for the intercept) equal zero. If all of them are zero, there is no relationship between any of the dependent and independent variables, indicating that the model is useless. Every model in this process, however, did produce statistically significant relationships.

The first set of models incorporated PI, water balance (WBAL), growing degree days (GDD), and slope as independent variables and raised r^2 values for all three crops compared to the simple regression results (Table 4 versus Table 5). The significance of PI and slope were very high (1% significance level) for all three crops and WBAL was significant at 5% for barley and winter wheat. GDD did not add significantly to the explanation of yield variation for any of the crops (Table 6).

The second set of models added the indicator variable TYPE to represent $CaCO_3$ in the top 20 cm of soil. This depth is recognized as the plow layer where root development and nutrient uptake by plants are most critical. TYPE was assigned the value "0" when calcium carbonate

Table 5. Summary results of multiple regression analysis.

Crop	Model 1[a]	Model 2[b]	Model 3[c]	Model 4[d]
	Multiple Regression Runs			
	r^{2e}	r^2	r^2	r^2
Barley	.48	.48	.55	.53[f]
Spring Wheat	.46	.49	.54	.54[g]
Winter Wheat	.45	.46	.49	.43[h]

[a] Independent variables = PI, WBAL, GDD, and slope.
[b] Independent variables = PI, WBAL, GDD, slope, and TYPE.
[c] Independent variables = PI, WBAL, GDD, slope, TYPE, PI*TYPE, WBAL*TYPE, GDD*TYPE, and slope*TYPE.
[d] Individual models were built for each of the three crops as indicated in footnotes e through g.
[e] r^2 values shown have been adjusted to overcome the objection that r^2 can be forced toward perfect goodness of fit by simply adding "superfluous" variables to the regression model (Freund and Littell, 1986, 23).
[f] Independent variables = PI, WBAL, GDD, slope, TYPE, and GDD*TYPE.
[g] Independent variables = PI, WBAL, GDD, slope, TYPE, and WBAL*TYPE.
[h] Independent variables = PI, WBAL, and slope.

was encountered within the top 20 cm and a value of "1" if it was not encountered. This model also retained GDD from the first model since the addition of a new variable (TYPE) could change the significance of the original variables. The correlation between the independent and dependent variables (r^2) increased for spring and winter wheat, but not for barley (Table 5). Significance of WBAL, slope and GDD diminished for all three crops, but slope was still statistically significant at 5%. Only PI remained significant at 1% for all three crops. For barley, the importance of TYPE was so low that one might have concluded

Table 6. Multiple regression results for Model 1.

Test 1
Dependent variable: Barley

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	4	1565.35177	391.33794224	16.705	0.0001
Error	64	1499.28591	23.42634238		
C Total	68	3064.63768			

Root MSE	4.840077	R Square	0.5108
Dep Mean	38.92754	Adj R-SQ	0.4802
C.V.	12.43356		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for Ho: Parameter=0	Prob>|T|
Intercep	1	18.03945460	11.94310494	1.510	0.1359
PIVAL	1	31.28547578	5.31281869	5.889	0.0001
Slope	1	-0.753799	0.19367235	-3.892	0.0002
WBAL	1	0.56639374	0.15858926	3.571	0.0007
GDD	1	0.005834709	0.004793179	1.217	0.2280

Test 2
Dependent variable: Spring Wheat

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	4	1404.72204	351.18050929	14.781	0.0001
Error	60	1425.49335	23.75822246		
C Total	64	2830.21538			

Root MSE	4.874241	R Square	0.4963
Dep Mean	27.67692	Adj R-SQ	0.4628
C.V.	17.61121		

Table 6. (Continued)

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for Ho: Parameter=0	Prob>|T|
Intercep	1	-11.9146	12.71926435	-0.937	0.3526
PIVAL	1	34.63739672	5.46598270	6.337	0.0001
Slope	1	-0.724646	0.20155950	-3.595	0.0007
WBAL	1	0.32617656	0.16438375	1.984	0.0518
GDD	1	0.01188809	0.00510436	2.329	0.0232

Test 3
Dependent variable: Winter Wheat

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	4	1386.85646	346.71411472	13.395	0.0001
Error	56	1449.50420	25.88400352		
C Total	60	2836.36066			

Root MSE	5.087632	R Square	0.4890
Dep Mean	33.16393	Adj R-SQ	0.4525
C.V.	15.34086		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for Ho: Parameter=0	Prob>|T|
Intercep	1	2.06524234	12.94490634	0.160	0.8738
PIVAL	1	33.43646724	5.80711199	5.758	0.0001
Slope	1	-0.832714	0.22198185	-3.751	0.0004
WBAL	1	0.42853497	0.17092242	2.507	0.0151
GDD	1	0.009294706	0.005307786	1.751	0.0854

that it could be rejected as a causal variable for barley (Table 7). In the case of spring wheat, the TYPE variable was a significant factor, but WBAL lost significance (Table 7). In fact, the large increase in the WBAL coefficient may be an indication of multicollinearity as

Table 7. Multiple regression results for Model 2.

Test 1
Dependent variable: Barley

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	5	1575.24189	315.04837794	13.326	0.0001
Error	63	1489.39579	23.64120304		
C Total	68	3064.63768			

Root MSE	4.86222	R Square	0.5140
Dep Mean	38.92754	Adj R-SQ	0.4754
C.V.	12.49044		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for Ho: Parameter=0	Prob>|T|
Intercep	1	17.78023740	12.00444137	1.481	0.1436
PIVAL	1	31.23060590	5.33780118	5.851	0.0001
Slope	1	-0.73308	0.19717791	-3.718	0.0004
WBAL	1	0.53297991	0.16748151	3.182	0.0023
GDD	1	0.005492282	0.004844128	1.134	0.2612
TYPE	1	0.84031136	1.29919465	0.647	0.5201

Test 2
Dependent variable: Spring Wheat

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	5	1497.77006	299.55401224	13.264	0.0001
Error	59	1332.44532	22.58381904		
C Total	64	2830.21538			

Root MSE	4.752244	R Square	0.5292
Dep Mean	27.67692	Adj R-SQ	0.4893
C.V.	17.17042		

Table 7. (Continued)

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for Ho: Parameter=0	Prob>|T|
Intercep	1	-12.1431	12.40142540	-0.979	0.3315
PIVAL	1	34.59957850	5.32920746	6.492	0.0001
Slope	1	-0.66572	0.19864740	-3.351	0.0014
WBAL	1	0.22525635	0.16780426	1.342	0.1846
GDD	1	0.01058176	0.005018044	2.109	0.0392
TYPE	1	2.60756718	1.28463758	2.030	0.0469

Test 3
Dependent variable: Winter Wheat

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	5	1419.63135	283.92627018	11.023	0.0001
Error	55	1416.72930	25.75871463		
C Total	60	2836.36066			

Root MSE	5.075304	R Square	0.5005
Dep Mean	33.16393	Adj R-SQ	0.4551
C.V.	15.30369		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for Ho: Parameter=0	Prob>|T|
Intercep	1	2.74412878	12.92755645	0.212	0.8327
PIVAL	1	33.53920978	5.79375659	5.789	0.0001
Slope	1	-0.768778	0.22858292	-3.363	0.0014
WBAL	1	0.35979780	0.18107020	1.987	0.0519
GDD	1	0.007949444	0.005427573	1.465	0.1487
TYPE	1	1.69362731	1.50144459	1.128	0.2642

suggested by Lewis-Beck (1980, p. 60). The occurrence of multicollinearity violates one of the assumptions necessary for correct application of multiple regression models, indicating that further refinement of the model was required. For winter wheat, TYPE was non-significant and a marked increase in the significance of GDD occurred, as well as slight drops in significance for the other three factors (Table 7). Considering the second model overall, the $CaCO_3$ variable (TYPE) by itself rather surprisingly did not appear to help explain variation in crop yields. This result coupled with the declines in the significance of the other parameters and the multicollinearity problem confirmed the need to continue with model development.

The first two models are fairly straight-forward because they did not include any interaction effects between TYPE and the other independent variables. The major innovations incorporated with the third series of models added variables to account for these interaction effects. Hence, four new variables which are the products of the indicator variable (TYPE) and the continuous variables were added in the third set of regression equations. This approach allowed interactions between TYPE and each of the other variables to be evaluated. For example, TYPE by itself was shown to be a non-significant variable in the second model (Table 7). However, by combining it with water balance to make a new variable, it may become evident that certain combinations of water availability and presence of $CaCO_3$ strongly influence yield variations. In effect, the use of TYPE in this fashion separates the data into two sets to be examined separately according to their $CaCO_3$ characteristics.

The resulting r^2 values from the third model, although high, are the product of a large number of variables, not all of which are significant (Tables 5 and 8). Further, careful analysis of these

Table 8. Multiple regression results for Model 3.

Test 1
Dependent variable: Barley

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	9	1875.12840	208.34759954	10.334	0.0001
Error	59	1189.50929	20.16117433		
C Total	68	3064.63768			

Root MSE	4.49012	R Square	0.6119
Dep Mean	38.92754	Adj R-SQ	0.5527
C.V.	11.53456		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for Ho: Parameter=0	Prob>|T|
Intercep	1	6.76179826	19.82864212	0.341	0.7343
PIVAL	1	12.58497327	13.12539485	0.959	0.3416
Slope	1	-0.927063	0.29106664	-3.185	0.0023
WBAL	1	0.96800773	0.36242253	2.671	0.0098
GDD	1	0.01818241	0.007166887	2.537	0.0138
TYPE	1	31.16786873	24.27044208	1.284	0.2041
PIVAL*TYPE	1	24.02873058	14.21408762	1.690	0.0962
Slope*TYPE	1	0.26063007	0.37431406	0.696	0.4890
WBAL*TYPE	1	-0.703762	0.40414587	-1.741	0.0868
GDD*TYPE	1	-0.0241146	0.009252812	-2.606	0.0116

Test 2
Dependent variable: Spring Wheat

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	9	1710.69556	190.07728498	9.338	0.0001
Error	55	1119.51982	20.35490581		
C Total	64	2830.21538			

Root MSE	4.511641	R Square	0.6044
Dep Mean	27.67692	Adj R-SQ	0.5397
C.V.	16.30109		

Table 8. (Continued)

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for Ho: Parameter=0	Prob>|T|
Intercep	1	6.99765473	19.92368242	0.351	0.7268
PIVAL	1	18.15809009	13.18830594	1.377	0.1741
Slope	1	-0.531734	0.29246175	-1.818	0.0745
WBAL	1	0.81133951	0.36415965	2.228	0.0300
GDD	1	0.009753898	0.007201238	1.354	0.1811
TYPE	1	-17.1611	25.27405481	-0.679	0.5000
PIVAL*TYPE	1	22.92222182	14.33631612	1.599	0.1156
Slope*TYPE	1	-0.329185	0.38398417	-0.857	0.3950
WBAL*TYPE	1	-0.745477	0.40871581	-1.824	0.0736
GDD*TYPE	1	-0.001047	0.009711025	-0.108	0.9145

<u>Test 3</u>
<u>Dependent variable: Winter Wheat</u>

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	9	1609.97985	178.88664956	7.439	0.0001
Error	51	1226.38081	24.04668254		
C Total	60	2836.36066			

Root MSE	4.903742	R Square	0.5676
Dep Mean	33.16393	Adj R-SQ	0.4913
C.V.	14.78637		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for Ho: Parameter=0	Prob>|T|
Intercep	1	24.36857687	22.72860482	1.072	0.2887
PIVAL	1	10.06782149	13.29363650	0.658	0.5133
Slope	1	-0.57097	0.34077099	-1.676	0.1000
WBAL	1	0.68639130	0.40181937	1.708	0.0937
GDD	1	0.005961166	0.008821281	1.676	0.5022
TYPE	1	-21.3541	27.52299432	-0.776	0.4414
PIVAL*TYPE	1	30.17882677	16.49529991	1.830	0.0732
Slope*TYPE	1	-0.45789	0.45021053	-0.017	0.3139
WBAL*TYPE	1	-0.434138	0.44958978	-0.966	0.3388
GDD*TYPE	1	0.0007812306	0.01111357	0.071	0.9437

results demonstrates that each crop's yield variations respond differently to the independent variables in the regression model (Table 8). By examining the changes in the significance of each variable in the first two models and comparing them to results from the aggregate (third) model, a fourth and final model was created for each individual crop. This set of models included only the variables that were significant in explaining variations in yield for that particular crop. The removal of non-significant terms in this way usually reduces r^2 values slightly.

Considering barley alone in the third model, three of the original factors (slope, WBAL and GDD) were significant causal variables at the .05 significance level (Table 8). TYPE, slope*TYPE and WBAL*TYPE were non-significant, apparently indicating that $CaCO_3$ both alone and interacting with slope and water availability has no effect on barley yield. Only GDD*TYPE was significant where calcium interaction is concerned. This result meant that both TYPE and GDD*TYPE were retained in the fourth model for barley (Tables 8 and 9). The TYPE variable remained in the model since it was a lower order term in a model that still includes one product term (Freund and Littel, 1986).

For spring wheat, PI, WBAL, slope and GDD were retained in the final model. Although slope was marginally non-significant (.07) and GDD also was non-significant, they were both previously useful, and it was felt that removal of their associated dummy variables (slope*TYPE and GDD*TYPE) would unclutter their relationship to yield (Table 8). Apparently WBAL*TYPE did not cloud the effect of WBAL as greatly, since WBAL was still significant. WBAL*TYPE itself was marginally significant

Table 9. Multiple regression results for Model 4.

Test 1
Dependent variable: Barley

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	6	1740.10027	290.01671221	13.575	0.0001
Error	62	1324.53741	21.36350658		
C Total	68	3064.63768			

Root MSE	4.622067	R Square	0.5678
Dep Mean	38.92754	Adj R-SQ	0.5260
C.V.	11.87352		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for Ho: Parameter=0	Prob>|T|
Intercep	1	-16.0271	16.68330016	-0.961	0.3405
PIVAL	1	31.13472758	5.07427410	6.136	0.0001
Slope	1	-0.730979	0.18744043	-3.900	0.0002
WBAL	1	0.45551534	0.16163295	2.818	0.0065
GDD	1	0.01993027	0.006943913	2.870	0.0056
TYPE	1	57.12990108	20.30083937	2.814	0.0065
GDD*TYPE	1	-0.0247032	0.00889269	-2.778	0.0072

Test 2
Dependent variable: Spring Wheat

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	6	1639.34655	273.22442448	13.307	0.0001
Error	58	1190.86884	20.53222134		
C Total	64	2830.21528			

Root MSE	4.531249	R Square	0.5792
Dep Mean	27.67692	Adj R-SQ	0.5357
C.V.	16.37194		

Table 9. (Continued)

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for Ho: Parameter=0	Prob>|T|
Intercep	1	12.05342	12.43334035	-0.165	0.8694
PIVAL	1	37.36915818	5.18968974	7.201	0.0001
Slope	1	-0.710855	0.19018800	-3.738	0.0004
WBAL	1	1.00537507	0.33743256	2.979	0.0042
GDD	1	0.01052892	0.004784732	2.201	0.0318
TYPE	1	-10.8046	5.25248780	-2.057	0.0442
WBAL*TYPE	1	-0.943609	0.35934743	-2.626	0.0110

Test 3
Dependent variable: Winter Wheat

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	3	1307.48289	435.82762926	16.249	0.0001
Error	57	1528.87777	26.82241698		
C Total	60	2836.36066			

Root MSE	5.179036	R Square	0.4610
Dep Mean	33.16393	Adj R-SQ	0.4326
C.V.	15.61647		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for Ho: Parameter=0	Prob>|T|
Intercep	1	23.18030020	4.79404053	4.835	0.0001
PIVAL	1	32.29314774	5.87396084	5.498	0.0001
Slope	1	-0.867868	0.22504402	-3.856	0.0003
WBAL	1	0.36823391	0.17042553	2.161	0.0349

and was therefore retained in the final equation as well. Although TYPE was highly non-significant in the aggregate model results, it was retained for the reasons noted earlier in connection with the results for barley.

The results for winter wheat were similar to barley and spring wheat in that the T values indicated that the same weakening effect caused by the addition of the product variables had occurred (Table 8). In fact, there were no significant variables for winter wheat using the aggregate model. Slope and WBAL maintained a small degree of significance, but only with a high probability of error (10%). The higher significance of PIVAL*TYPE compared with PIVAL may suggest an interaction effect between $CaCO_3$ and PI factors, but it was already seen in the first and second models that PIVAL without the addition of TYPE or product variables is highly significant at 1%. Hence only PI, WBAL, and slope were retained and GDD was dropped because it was non-significant from the start.

It is important to note that PI became highly non-significant for all three crops and PIVAL*TYPE was non-significant as well (Table 8). The dramatic shift in PI's coefficient once again indicated that a multicollinearity situation was generated by this particular combination of parameters. Since PI was a highly significant term in previous models, it was retained in the final equations for all three crops. The non-significant PIVAL*TYPE product variable was used to support the conclusion that interactions between calcium carbonate and PI had no relation to yield and thus PI*TYPE was dropped in order to clarify PI's relationship to yield.

Considering the aggregate (i.e., third) model, r^2 values for all three crops were of interest because they had increased over those of the previous model despite their inclusion of several non-significant terms (Tables 5 and 8). This result suggested that the creation and analysis of two soil types (shallow versus deep calcium soils) clearly improved the model's fit for barley and spring wheat. The coefficient of variation (C.V), at its lowest in the aggregate model results, supported this conclusion regarding the effect of calcium in explaining yield variation. Specifically, the addition of TYPE caused r^2 for barley to rise from .48 to .55 and r^2 for spring wheat increased from .46 to .54 (Table 5). For winter wheat, however, the addition of TYPE improved the explanation of yield variation only slightly, the r^2 rising only from .46 to .49 (Table 5).

After running each crop's final model, the r^2 results were not dramatically altered (Tables 5 and 9). In the cases of both barley and winter wheat the r^2 values actually declined (from .55 to .53 for barley and from .49 to .43 for winter wheat). This result was not surprising, considering the high number of variables used to achieve the maximum r^2 values in the third model. For spring wheat, r^2 stayed at .54 even with the removal of non-significant factors included in the previous model.

The overall finding with respect to barley is that growing season combined with $CaCO_3$ (TYPE*GDD) and $CaCO_3$ (TYPE) alone added substantially to the original four factors' ability to explain yield variability (Tables 6 and 9). In other words, interaction between growing degree days and $CaCO_3$ content affect barley yield. The conclusion for spring wheat is similar in that GDD and $CaCO_3$ (TYPE and WBAL*TYPE) were significant variables, though at lower confidence levels (Table 9). In the case of winter wheat, GDD was not a significant term as it was with barley and spring wheat probably because winter wheat's unique growing season includes a winter period of dormancy. Since the removal of the non-significant variables (GDD, TYPE and all four product variables) brought no improvement in winter wheat's r^2 value, it is apparent that some other variable or variables which influence winter wheat yields have yet to be identified (Table 9).

CHAPTER FOUR

DISCUSSION

Two major conclusions arise from the statistical analysis presented in Chapter Three. First, the existing PI model explains approximately 40% of the variation in crop yields. Second, by considering the relationships between yield and water balance, growing degree days, calcium carbonate, and slope it is shown that the addition of these factors to the PI model would improve its explanation of yield to greater than 50%. It is necessary now to examine the implications of these results as they relate to the PI model itself and to their role in further applications of the PI model in other northern Great Plains environments.

Four aspects of the existing PI model and the extensions tried in this study warrant further discussion. One involves a review of possible shortcomings concerning the input data. The second and third aspects concern the PI model structure and the yield data used to verify the model, and the final topic concerns the parameters that were added which may be unique to a northern Plains environment.

PI Model Input Data

The first consideration for improving model performance is the quality of the model's input data. When the PI model was first altered and tested by Pierce and associates at the University of Minnesota, the use of large, standardized USDA-SCS data bases was assumed as a key step in its implementation. By using these structured data collections not only are extensive calculations made possible and other computerized data manipulations made more efficient, but also questions of data validity, reliability and variability are largely put to rest. Several problems were, however, encountered and several questions are raised by the use of these data bases in this study.

One problem concerns the lack of moist bulk density estimates in the Montana SOILS-5 data base. As described in Chapter Two, the bulk density triangle developed by Grossman and Baumer (Figure 5) was used to estimate bulk density values for horizons where they were not reported. Bulk density is difficult to determine (especially in the surface horizon) and yet is the basis for inferences about resistance to root penetration and moisture movement (Erbach, 1987). Mausbach and Gamble (1984) agree that bulk density is not known by horizon for many soils and often the parameter is reported not as a precise value, but as a range inferred from textural data. Because the Grossman/Baumer triangle provides such bulk density estimates based on soil texture, it was assumed that it would generate bulk density input data.

Two problems associated with these moist bulk densities require mention. First, by using generalized bulk densities from the triangle which do not reflect soil development conditions in Montana, clarity of the actual soil/crop yield relationship may have been lost. Hence, using estimates from the bulk density triangle may be only a partial solution. Second, Pierce et al. (1984a; 1984b) found that the bulk density estimates that did appear in the SOILS-5 data base resulted in low PI values for fine textured, highly productive soils. Their reasoning for this inconsistency was that the soil was in fact porous in structure, and thus high yielding despite high bulk density values which did not reflect the actual quality of the rooting environment. They remedied this problem with an algorithm (described in Chapter Two) incorporated in the PI model.

Both the bulk density triangle and the PI adjustment may be inappropriate techniques for estimating soil bulk density in Cascade County because Mausbach and Gamble (1984) have found that in addition to soil texture, accurate bulk density measurements require separate analysis of soils according to their parent material (loess, glacial till, alluvium and residuum). Because the Corn Belt studies were performed primarily on loess soils (Pierce et al., 1984b, 132) and Cascade County soils are formed mainly from till and alluvium, the PI model's bulk density adjustments developed for the Corn Belt may not be applicable in Cascade County. Second, the Grossman/Baumer triangle does not account for parent material and thus is shown again to be an incomplete method of bulk density estimation.

Another consideration involving the SOILS-5 data is that the series descriptions are recorded using data from a single, typifying pedon (profile) location for the series or phase of a series. Thus the SOILS-5 data reflects environmental conditions of that particular location which may strongly affect soil development and productivity. This means that a soil occurring in Cascade County may have been first described in another part of Montana or even in another state, and hence the Cascade County environment is not always closely represented.

For purposes of testing the PI model, this problem is best dealt with by using the corresponding SOILS-5 yield estimates and not the Soil Survey estimates. The problem becomes more complex when the purpose is to examine soil-related issues and data (i.e., soil erosion rates) specific to a small area such as Cascade County.

Existing PI Model Structure

The question of whether or not the PI model is an appropriate tool for estimating soil productivity in the northern Great Plains must also be considered. The issue of adding new parameters to the model is dealt with later in this chapter in connection with the multiple regression analysis. This section discusses the three terms in the existing model. The two aspects which warrant further examination are the depth of rooting used with the weighting factor and the equal importance assigned to each of the inputs.

The weighting factor in the original model was based on corn rooting depth, and it is well-documented that wheat and barley rooting depths differ greatly from those of corn (Rickman, et al., 1977). Not only are the depths important, but patterns of root distribution and water use in the rooting zone differ from corn as well (Proffitt et al., 1985). Sandor (personal communication, 1988) determined that 178 cm rather than the original model's 100 cm serves to better duplicate wheat and barley rooting environments. However, Sandor also found that the model output (PI values) were not very sensitive to changes in rooting depth, since the weighting depth functions emphasize soil characteristics in the topsoil (Figure 3d). Hence, substituting a rooting depth of 178 versus 100 cm did little to alter PI values at the field scale at which he tested model performance. Based on his results, no further attempt was made to extend the rooting depth in this study.

Model performance may have been improved by varying the weightings of the three model parameters which are weighted equally in the original model. However, no efforts were made to alter this arrangement in this study because the desirability of incorporating additional parameters was still being examined and the effect of those additions on model performance and existing model structure are as yet unknown.

Yield Data Used for Model Testing

The yield data used for model verification in Cascade County may also have contributed to poor model performance. As suggested by Larson (personal communication, 1987) it is necessary to establish whether yields are collected from one typical year or whether they represent an average yield over many years. Long-term averages are preferred because they do not reflect the impacts of climate variations and new farming technology on crop yields. Cascade County data reported in the Soil Survey (USDA-SCS, 1982c) are long-term averages, but they do not represent the full range of yields that may be experienced on soils that are distributed widely throughout the county (R. Richardson, personal communication, 1988). This condition introduces uncertainty because one cannot know whether the "average" yields reported in the Soil Survey are actually high or low as a result of regional precipitation variability (Figure 2) and/or the experience of individual soil scientists contributing their opinions to the Soil Survey yield estimates. Cropping patterns also exert substantial influences on storage of soil water and therefore on crop yield from year to year. Carlson (1987; cited in Sandor, 1989) found that recropped fields were only 65% as productive as fallowed fields. Hence, Cascade County Survey yields may be highly specific to particular areas and farming practices.

At the other extreme, SOILS-5 yield estimates are highly generalized, reflecting very little of the local climatic, topographic, farming and soil development characteristics which influence yields in Cascade County. As previously described, the disparity between the two data sets was dealt with first by using the matched pairs t test to determine if they were statistically comparable and second, by testing PI values with the associated SOILS-5 data and performing multiple regression analysis of local site factors with local yield data.

With regard to verification of PI values, it would be worthwhile to discover another productivity measure with which to compare PI in Montana. Pierce et al. (1984a, 1984b) used Crop Equivalent Ratings (CERs) developed by Rust and Hanson (1975) in addition to corn for model verification (Pierce et al., 1984a). The CER represents "the relative net economic return per acre when managed for cultivated crops, permanent pasture or forestry, whichever use is computed as giving the highest net return" (Pierce et al., 1984a, 55). Their testing with both crop yields and CER indicates that Pierce and associates may have held some doubts regarding the consistency of yield estimates alone. It was unfortunate that Montana CER data were not available for testing PI model results and too, that shortcomings were present in the yield data. However, the SOILS-5 and County Survey crop yields were the best and most consistently compiled and researched data available.

Multiple Regression Outcomes

The results of the multiple regression analysis demonstrate the need to expand the model to better include Cascade County and northern Great Plains environmental factors which affect soil productivity. In the cases of barley and spring wheat, the addition of water balance, growing degree days, slope and lime factors to the three original PI factors generated higher correlation coefficients between PI values and yields. For winter wheat, only the additions of water supply and slope produced similar improvements. It was expected that growing degree days would not be a useful factor in the case of winter wheat since its growing season includes a period of dormancy over the winter unlike barley and spring wheat.

It was not necessary for the Minnesota studies to examine the effect of these northern Great Plains factors in great detail. They were able to deal with some of these variables, particularly climate-related factors, by separately evaluating soils in individual MLRAs. The effect of slope was managed by excluding soil phases exceeding a six per cent slope gradient. The crops they used to test the PI values were similar in growing season requirements and finally, Corn Belt soils are not adversely affected by lime content.

In the Corn Belt, where relatively homogeneous topography, elevation and vegetation contribute to a more spatially consistent climatic regime, the assumption of constant climate is reasonable. Cascade County, however, is known to have marked precipitation and growing season gradients (Figures 1 and 2). Thus climatic factors were expected to have a strong influence on yield, and hence, PI model performance.

The influences of climatic inputs on crop yield in the Plains are well-documented. Heilman et al. (1977), Meyer and Alston (1977), Rickman et al. (1977) and the USDA-SCS (1987b) all examined soil moisture and wheat yield, except for the USDA study which tested corn and soybeans in addition to wheat. All four studies discovered a strong connection between crop yields and moisture supply. Maturing time and total available heat (as measured by growing degree days) were closely correlated with spring wheat yields in research conducted by Williams et al. (1988). Burke (1984) also connected soil temperature (a function of GDD) and crop yield. Sammis et al. (1985) developed a yield prediction index based on growing degree days and Pierce et al. (1984a) suggest both growing degree days and water supply as means of controlling for effects of geographic location on yield (Figure 7).

Results from the regression analysis of water balance and growing degree days confirm this expectation by demonstrating that yield variability is better explained by PI in conjunction with these two factors than by PI alone (Table 5). This result shows why climate factors should be included in soil productivity models, such as the PI model, when they are applied across large geographic areas and/or within smaller regions which experience considerable spatial climatic variations. The different reactions of spring grains and winter wheat to climatic influences point out that two separate models may also be necessary. Crop responses to precipitation, potential evapotranspiration and growing degree days differ because each crop has different

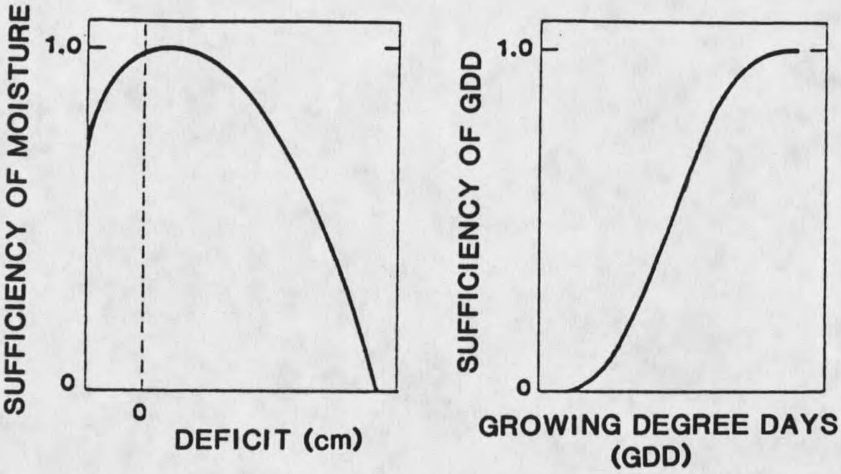

Figure 7. Generalized forms for water supply and growing degree day sufficiency curves proposed by Pierce et al. (1984a).

water use and maturing time requirements. Each crop's model would be unique by either including specific combinations of variables or by using the same combination, but weighting each variable differently to reflect its particular significance to individual crops.

When evaluating the multiple regression results from this study it was necessary to note that the relationships between the dependent and independent variables are not always linear. The models used in this study's multiple regression analysis were limited by that constraint. However, more complex regression equations could be designed to approximate a curvilinear relationship and thus give higher correlation coefficients. For example, referring back to earlier reviews of the PI model parameters, it is seen that their sufficiency curves are not linear and therefore that their relationships to soil productivity and crop yield cannot be linear either (Figure 3). It is therefore assumed that PI, water balance, slope, growing season and $CaCO_3$ may also have non-linear relationships with yield, possibly explaining why linear regression produced relatively low r^2 values. Pierce et al. (1984a) suggested relationships for water balance and GDD, but similar speculation for slope and $CaCO_3$ is beyond the scope of this thesis (Figure 7).

As with the Minnesota studies, multiple regression analysis in this study showed that slope was a significant yield determinant for all three Cascade County crops. Pierce et al. (1984b) indicated that sloping soils produced outlier points in their regressions of PI with yield, meaning that slope exerted a definite influence on yield which the PI model did not consider. In this study the outlying points were distributed randomly and could not be attributed consistently to the influence of slope, suggesting a non-linear relationship between yield and slope. The task of incorporating a slope factor in the PI model will require that a sufficiency curve be constructed and this is a complex undertaking for four reasons. First, it is likely that collinear relationships exist between slope and existing PI model variables, making it difficult to isolate the specific effects of slope on yield from other interrelationships. A second consideration is whether or not (and if so, how) the impacts of slope change with depth in the soil profile. Third, slope gradients within a soil phase can vary over large ranges (e.g., 8 to 15%, or 10 to 20% slope classes) thereby adding the problem of selecting one value to represent the entire range. Fourth, it may be that effects of sloping topography are most accurately represented by a factor which combines both slope gradient and location on a slope.

The multiple regression analysis showed that $CaCO_3$ is another important and yet complex crop yield factor. Other studies which confirm this finding have established two different effects of lime on soil productivity. First, lime is known to diminish phosphorus uptake by roots by inhibiting nutrient transport within the plow and fertilizer layer (G.A. Nielsen, personal communication, 1988). Second, the presence of lime, particularly in combination with high bulk densities, can increase soil strength and thus restrict root development (Sandor, 1989). Because both conditions occur in the surface horizon, 20 cm was selected as the key depth when constructing the TYPE variable (i.e., when $CaCO_3$ occurred within the top 20 cm TYPE was assigned the value "0" and assigned the value "1" if it did not). Although pH can be used as a general measure of soil lime content, pH alone does not cause nutrient deficiencies and/or other impediments in the rooting zone (Sandor, 1989). Sandor (1989) states that while increasing concentrations of $CaCO_3$ theoretically have no effect on soil pH, increasing $CaCO_3$ may impose serious negative effects on the rooting environment. Therefore the function of pH in the PI model cannot provide a measure of $CaCO_3$ since pH alone does not cause similar impediments in the rooting zone.

As with slope, building a sufficiency curve for $CaCO_3$ presents several problems. For example, there remains considerable controversy about the techniques that should be used to quantify lime and whether or not we should evaluate its effects by location in the profile, its concentration or both measurements (Sandor, 1989). In addition, the relationships between depth, concentration and crop yield in Montana are not well understood. For example, Sandor (1989) and Schweitzer (1980) reached different conclusions about the relationship between yield and $CaCO_3$ and Burke (1984) suggested several different conditions of $CaCO_3$

in the soil profile that can influence yield. The multiple regression results reaffirm this observation since the association of lime with growing degree days and with water balance exert different controls in the cases of spring wheat and barley, whereas in the present study, winter wheat was apparently insensitive to $CaCO_3$ altogether.

Conclusions

The comparison of PI values with crop yields in a Great Plains environment indicates that the existing PI model is not as successful as it was in the Corn Belt application. Literature describing this and other empirical models can often give the impression that such models can be applied anywhere as long as the appropriate data are correctly input. This is a simplistic concept, since testing and verification are certainly required in every situation. The study presented here emphasizes this need for thorough testing, especially in the complex environments of the northern Great Plains. In Cascade County, extensive model evaluation is even more essential since climate, climatic effects, topography and soil conditions are not spatially homogeneous even at the county level.

Although soil productivity and soil erosion studies have identified numerous factors which contribute to yield variability, the parameters examined in this study as potential extensions of the PI model are either critical aspects of northern Great Plains agriculture or were strongly suggested in other PI model research (Heilman et al., 1977; Burke, 1984; Pierce et al., 1984a; Williams et al., 1988; Sandor, 1989). Multiple regression analysis confirms that the addition of growing degree days, water balance, slope and $CaCO_3$ to PI values improves the statistical explanation of yield variation. Specifically, the explanation of barley yield variation improved by 34%, spring wheat by 17% and winter wheat by 2%. Overall, models were constructed in which different combinations of independent variables explained between 40 to 50% of the yield variations. This demonstrates that the PI model has much potential as a soil productivity estimator once the addition and proper configuration of new factors is complete.

Fortunately, data for soil productivity determinants in the northern Great Plains are available, and thus will permit further investigation of modifications to the PI model in these environments. Work by Sandor (1989) and the study presented here demonstrate that the PI model can potentially make use of these data and can be altered to benefit soil productivity research in Montana and the northern Plains as a whole.

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APPENDICES

APPENDIX A

Cascade County Precipitation Data

APPENDIX A

Table 10. Annual precipitation (cm) for five weather stations in or near Cascade County, 1951-1980.

Year	Weather Station				
	Cascade	Great Falls	Neihart	Power	Sun River
1951	49.5	54.9	NO DATA	NO DATA	46.0
1952	24.9	22.9			19.6
1953	46.0	52.6			40.9
1954	42.2	39.9		27.7	36.3
1955	34.5	49.8		36.6	43.2
1956	25.4	27.4		20.8	27.2
1957	43.2	41.1		28.7	34.0
1958	45.0	40.9		35.1	43.9
1959	31.8	34.5		24.4	29.0
1960	24.1	24.9		29.7	20.3
1961	26.7	26.7		19.3	19.8
1962	41.4	40.4		22.4	31.8
1963	30.0	30.2		19.3	21.8
1964	44.2	45.5		37.1	37.6
1965	49.3	46.7		29.5	44.5
1966	30.8	35.8	54.4	28.7	27.7
1967	45.0	47.5		29.0	41.7
1968	49.8	41.7	57.9	34.3	31.5
1969	36.6	31.5	51.3	24.1	29.7
1970	32.0	38.9	49.5	32.5	27.2
1971	30.5	29.2	29.7	22.1	22.4
1972	30.7	33.3	43.2	24.9	28.2
1973	29.7	31.0	36.8	19.3	16.8
1974	32.5	38.9	51.3	26.2	27.4
1975	66.0	35.1	53.3	25.9	24.6
1976	32.1	35.1	53.2	25.9	24.6
1977	39.6	38.1	59.9	30.0	30.2
1978	52.3	48.8	79.5	48.3	43.3
1979	33.0	25.2	37.3	16.5	22.9
1980	60.9	41.2	51.8	26.9	35.8

APPENDIX B

Regression Analysis Data

APPENDIX B

Table 11. Data used for model verification regression analysis.

Soil Map Unit No.[a]	PI Value	SOILS-5 Yields Barley	SOILS-5 Yields S-Wheat	SOILS-5 Yields W-Wheat	Soil Survey Yields Barley	Soil Survey Yields S-Wheat	Soil Survey Yields W-Wheat
		(Mg ha^{-1})			(Mg ha^{-1})		
1	.499	9.9	8.2	10.4	10.4	8.8	10.8
4	.541	11.7	9.8	12.4	10.4	9.8	11.7
11	.635	9.1	7.8	9.8	10.4	8.8	10.8
13	.807	14.4	10.4	13.0	16.2	8.8	12.1
15	.607	9.9	8.2	10.4	9.1	8.2	9.8
18	.598	10.4	8.8	10.8	10.4	8.8	10.8
24	.478	9.7	8.2	9.8	10.4	8.8	10.8
29	.709	12.0	13.0	14.7	12.0	13.0	14.7
33	.558	13.1	10.4	13.0	11.7	9.8	13.0
47	.622	13.1	10.4	13.0	12.0	13.0	14.7
48	.627	13.1	10.4	13.0	8.4	7.5	9.1
52	.653	9.9	8.2	10.4	6.5	6.5	8.2
54	.581	11.0	9.1	10.4	13.1	9.8	9.8
56	.568	10.4	8.8	10.8	10.4	8.8	10.8
58	.490	7.8	6.5	8.2	9.1	8.2	9.8
61	.189	999[b]	999	999	7.3	5.9	6.5
63	.371	7.8	5.9	7.2	7.8	5.9	7.2
64	.461	7.8	5.9	7.2	7.8	5.9	7.2
65	.620	11.0	8.5	11.4	12.0	13.0	14.7
71	.677	12.0	13.0	14.7	12.0	13.0	14.7
72	.578	9.1	8.2	9.8	9.1	8.2	9.8
74	.606	13.6	999	13.7	11.0	12.4	13.4
75	.700	13.1	11.1	13.7	13.1	9.8	11.7
78	.686	13.1	10.4	13.0	11.5	12.7	14.0
80	.702	13.1	10.4	13.0	11.5	12.7	14.0
85	.664	13.1	11.4	14.7	12.0	13.0	14.7
89	.602	9.1	8.2	9.8	9.1	8.2	9.8
90	.407	9.1	7.8	9.8	9.1	8.2	9.8
94	.599	10.4	8.8	11.4	10.4	8.8	999
95	.596	10.4	8.8	11.4	10.4	8.8	999
96	.659	10.4	999	11.4	999	999	999
97	.428	10.4	999	11.1	999	999	999
102	.626	10.4	8.8	10.8	999	999	999
103	.659	9.9	8.8	9.8	9.9	8.8	9.8
109	.509	10.4	8.8	10.8	10.4	8.8	10.8

Table 11. (cont'd)

Soil Map Unit No.[a]	PI Value	SOILS-5 Yields Barley	S-Wheat	W-Wheat	Soil Survey Yields Barley	S-Wheat	W-Wheat
		(Mg ha^{-1})			(Mg ha^{-1})		
114	.658	8.4	7.8	9.1	10.4	9.8	11.4
122	.547	12.5	8.8	11.4	12.3	9.1	999
123	.430	12.3	9.1	999	12.3	9.1	999
127	.355	7.8	6.5	8.2	7.8	6.5	8.2
139	.532	9.9	8.5	11.4	9.9	7.8	13.0
143	.450	6.8	4.9	5.9	7.8	5.9	8.2
148	.709	10.4	8.8	10.8	10.4	8.8	10.8
151	.606	9.1	7.2	9.8	9.1	8.2	9.8
155	.493	7.8	5.9	8.2	7.8	5.9	8.2
156	.638	11.7	9.1	12.4	9.1	8.2	9.8
161	.736	12.0	13.0	14.7	10.7	7.8	999
166	.657	10.4	8.8	10.8	10.4	8.8	10.8
168	.646	10.4	8.8	10.	10.4	8.8	10.8
171	.621	7.8	6.5	999	7.8	6.5	8.2
173	.595	12.0	10.8	11.4	12.0	13.0	14.7
175	.641	10.4	9.8	11.7	10.4	9.8	11.7
177	.647	10.4	999	9.8	10.4	999	9.8
182	.235	999	999	999	7.8	5.9	8.2
183	.764	11.7	999	14.7	11.7	999	999
184	.681	13.1	10.4	13.0	11.7	999	999
186	.572	12.0	10.4	12.4	10.4	9.1	9.8
189	.608	12.0	10.4	12.4	9.1	999	8.2
192	.594	10.4	8.8	10.8	10.4	8.8	10.8
195	.555	11.7	9.8	12.4	9.1	8.2	9.8
197	.495	7.8	5.9	8.2	6.5	5.9	8.2
201	.586	9.9	8.2	9.8	7.8	6.5	8.2
202	.550	9.9	8.2	9.8	10.4	8.2	9.8
205	.386	8.4	6.5	11.4	8.4	6.5	11.4
206	.579	9.9	8.2	10.4	8.4	6.5	8.5
207	.694	13.1	11.4	14.7	11.7	12.4	13.7
208	.694	13.1	11.4	14.7	12.0	13.0	14.7
211	.302	7.8	6.5	8.2	7.8	6.5	8.2
217	.559	12.5	10.4	13.0	10.4	9.8	11.7
220	.697	10.4	8.8	10.8	10.4	8.8	10.8
222	.630	13.6	13.0	14.7	12.0	13.0	14.7
227	.641	10.4	9.8	11.4	10.4	8.8	10.4
229	.620	10.4	9.8	11.4	10.4	9.8	11.4

[a] Map unit numbers identify each soil series (USDA-SCS, 1982c).
[b] The entry "999" indicates no data.

Table 12. Data for the four additional yield determinants analyzed by multiple regression.

Soil Map Unit #[a]	Slope Range[b]		$CaCO_3$ Rating[c]	Depth to $CaCO_3$[d]	Precip Range[e]		PET Range[f]		GDD Range[g]	
1	0	4	1	0	10	12	26.5	29.0	2200	2400
4	0	4	2	21	14	16	25.0	26.5	2200	2400
11	0	2	1	20	12	14	29.0	31.5	2200	2400
13	4	15	1	13	18	20	20.5	22.0	1800	2000
15	0	4	2	15	12	14	29.0	31.5	2200	2400
18	0	4	3	13	14	16	29.0	31.5	2200	2400
24	0	2	2	9	12	14	25.0	26.5	2000	2200
29	0	5	1	24	12	14	23.5	25.0	2000	2200
33	2	10	2	28	16	18	20.5	22.0	2200	2400
47	0	2	1	14	14	16	26.5	29.0	2400	2600
48	8	20	1	11	14	16	25.0	26.5	2200	2400
52	4	20	1	0	12	14	25.0	26.5	2000	2200
54	4	8	1	10	14	16	29.0	31.5	2200	2400
56	0	8	1	14	10	12	26.5	29.0	2200	2400
58	4	8	1	0	14	16	29.0	31.5	2400	2600
61	0	4	2	12	10	12	26.5	29.0	2200	2400
63	0	8	2	23	14	16	29.0	31.5	2200	2400
64	0	4	2	23	14	16	29.0	31.5	2200	2400
65	0	2	2	16	10	12	26.5	29.0	2200	2400
71	0	2	2	15	12	14	29.0	31.5	2200	2400
72	4	10	2	15	12	14	29.0	31.5	2200	2400
74	0	4	2	9	14	16	26.5	29.0	2200	2400
75	0	2	2	15	14	16	23.5	25.0	2200	2400
78	2	4	1	14	14	16	29.0	31.5	2200	2400
80	0	2	1	14	14	16	29.0	31.5	2200	2400
85	0	4	2	14	14	16	29.0	31.5	2400	2600
89	0	2	2	0	12	14	29.0	31.5	2200	2400
90	4	15	2	8	16	18	20.5	22.0	2200	2400
94	0	2	2	0	12	14	26.5	29.0	2200	2400
95	0	2	2	0	12	14	26.5	29.0	2200	2400
96	0	4	1	0	10	12	26.5	29.0	2000	2200
97	0	4	1	0	10	12	26.5	29.0	2000	2200
102	8	15	1	0	12	14	29.0	31.5	2200	2400
103	0	4	1	0	14	16	29.0	31.5	2200	2400
109	0	4	1	0	14	16	26.5	29.0	2200	2400
114	0	8	1	0	12	14	29.0	31.5	2400	2600
122	0	4	1	0	14	16	29.0	31.5	2400	2600
123	0	4	1	0	14	16	29.0	31.5	2400	2600
127	2	8	1	21	14	16	26.5	29.0	2200	2400

Table 12. (cont'd)

Soil Map Unit #[a]	Slope Range[b]		$CaCO_3$ Rating[c]	Depth to $CaCO_3$[d]	Precip Range[e]		PET Range[f]		GDD Range[g]	
139	0	8	1	0	14	16	29.0	31.5	2200	2400
143	0	8	1	0	10	12	29.0	31.5	2000	2200
148	2	10	999	999	16	18	20.5	22.0	2000	2200
151	0	15	1	0	12	14	26.5	29.0	2200	2400
155	0	4	2	17	10	12	26.5	29.0	2200	2400
156	8	20	2	12	16	18	22.0	23.5	2000	2200
161	2	8	2	13	12	14	23.5	25.0	2000	2200
166	0	2	1	0	10	12	25.0	26.5	2000	2200
168	0	2	1	0	10	12	25.0	26.5	2000	2200
171	0	2	2	8	10	12	26.5	29.0	2200	2400
173	0	2	2	16	14	16	29.0	31.5	2400	2600
175	2	10	1	14	14	16	25.0	26.5	2200	2400
177	2	10	999	999	16	18	23.5	25.0	1800	2000
182	0	4	999	999	14	16	23.5	25.0	2200	2400
183	0	2	2	10	14	16	23.5	25.0	2200	2400
184	0	2	2	10	14	16	23.5	25.0	2200	2400
186	0	8	1	14	14	16	29.0	31.5	2200	2400
189	0	8	1	14	14	16	29.0	31.5	2200	2400
192	0	15	2	17	10	12	26.5	29.0	2200	2400
195	2	15	2	15	14	16	26.5	29.0	2400	2600
197	0	10	1	4	10	12	26.5	29.0	2000	2200
201	8	15	2	7	14	16	29.0	31.5	2200	2400
202	2	10	2	7	14	16	29.0	31.5	2200	2400
205	0	6	1	17	14	16	29.0	31.5	2200	2400
206	0	4	1	12	14	16	26.5	29.0	2400	2600
207	2	8	1	13	14	16	23.5	25.0	2200	2400
208	0	2	1	13	14	16	23.5	25.0	2200	2400
211	0	2	2	21	12	14	29.0	31.5	2200	2400
217	2	15	2	7	14	16	23.5	25.0	2000	2200
220	2	20	3	21	20	30	18.0	20.5	2200	2400
222	0	15	3	22	14	16	22.0	23.5	2000	2200
227	4	15	1	0	12	14	25.0	26.5	2000	2200
229	0	2	1	0	12	14	25.0	26.5	2000	2200

[a] Map unit numbers identify each soil series (USDA-SCS, 1982c).
[b] The two slope figures represent the percent slope range (USDA-SCS, 1982c).
[c] $CaCO_3$ rating obtained from soil reaction to HCl (USDA-SCS, 1982c; 1974).
[d] Depth to effervescence (HCl reaction) in cm (USDA-SCS, 1982c).
[e] Low and high annual precipitation averages in inches.
[f] Low and high annual potential evapotranspiration in inches.
[g] Low and high annual growing degree days.
[h] The figure "999" indicates no data.