Using the soil-crop yield database to evaluate and improve a productivity index (PI) model for small grains in Montana
by Scott Henry Lorbeer

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

Abstract:
Researchers and land managers need to quantify the relationship between soil properties and soil productivity for sustainable crop management. One tool that is adaptable to different regions and can measure soil productivity is the Productivity Index (PI) model. This model was applied to Montana sites using pH, bulk density and available water holding capacity (AWC) data from the Soil Interpretations Record (SIR) database. PI values generated from the model were compared to actual yield values from the Montana Soil-Crop Yield Database which contains over 300 yield records spanning six years, 26 counties and over 50 soil series. Barley, spring wheat, and winter wheat yield correlated weakly with PI. By including long-term precipitation, potential evapotranspiration and soil organic matter data, little improvement was found between PI and small grain yields. When further adjusted by annual precipitation data at county weather stations, a consistent, modest improvement was noted for barley and spring wheat, but not for winter wheat. These results indicate that the original PI model does not explain small grain yield variability, with the possible exception of spring wheat grown on fields fallowed the previous year. When long-term average and annual climate data and soil organic matter were used to modify the PI model, the relationship between PI and yield was increased, indicating that further model adjustments should consider adjusting long-term average precipitation with annual weather station data. Whereas an accurate PI model for dryland small grains in Montana should be able to measure soil productivity, monitor rate of deterioration due to degradation and erosion, and measure rate of soil improvement due to well planned management, the model at this stage of development cannot predict yields, the best estimate of soil productivity.

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of a thesis submitted by

Scott Henry Lorbeer

This thesis has been read by each member of the thesis committee and has been found to be satisfactory regarding content, English usage, format, citations, bibliographic style, and consistency, and is ready for submission to the College of Graduate Studies.

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ABSTRACT

Researchers and land managers need to quantify the relationship between soil properties and soil productivity for sustainable crop management. One tool that is adaptable to different regions and can measure soil productivity is the Productivity Index (PI) model. This model was applied to Montana sites using pH, bulk density and available water holding capacity (AWC) data from the Soil Interpretations Record (SIR) database. PI values generated from the model were compared to actual yield values from the Montana Soil-Crop Yield Database which contains over 300 yield records spanning six years, 26 counties and over 50 soil series. Barley, spring wheat, and winter wheat yield correlated weakly with PI. By including long-term precipitation, potential evapotranspiration and soil organic matter data, little improvement was found between PI and small grain yields. When further adjusted by annual precipitation data at county weather stations, a consistent, modest improvement was noted for barley and spring wheat, but not for winter wheat. These results indicate that the original PI model does not explain small grain yield variability, with the possible exception of spring wheat grown on fields fallowed the previous year. When long-term average and annual climate data and soil organic matter were used to modify the PI model, the relationship between PI and yield was increased, indicating that further model adjustments should consider adjusting long-term average precipitation with annual weather station data. Whereas an accurate PI model for dryland small grains in Montana should be able to measure soil productivity, monitor rate of deterioration due to degradation and erosion, and measure rate of soil improvement due to well planned management, the model at this stage of development cannot predict yields, the best estimate of soil productivity.

CHAPTER 1

INTRODUCTION

Productive soils, required for the food needs of the world's population, face the threat of degradation. Poor management practices lead to compaction and loss of soil structure. Wind and water erosion deteriorate soil quality and ultimately, soil productivity. Non-agricultural land uses such as urban development increasingly compete with agriculture for land as the population increases.

Modern technology has brought about changes in the way agricultural soils are managed. Some improvements have led to higher yields. Unfortunately, many modern farming practices expose the soil to erosion, and tons of the nation's topsoil have been lost. Other human impacts reduce the soil's ability to provide a rooting environment where plant roots can take up nutrients and water. Farming communities are dependent on the long-term productivity of their soils. A need exists for proven, economically practical methods of sustaining productive soils.

The soil's ability to grow crops is referred to as soil productivity, defined 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). Deteriorating soil productivity and loss of agricultural land to other uses may be tolerable in the short-term as new technologies such as improved crop species, fertilization and pest control practices have pushed yields higher. However, in the long-term, there is concern that technology cannot replace innate productivity, once the soil is lost or damaged. Soils with high productivity need to be recognized as such, in order to protect a vital resource. Land with unproductive soils ought to be identified so that it can be used for purposes that do not need high quality soil. Clearly then, having a method of evaluating soil productivity is vital to wise land use decisions.

A numeric productivity index would be an invaluable tool for comparative analysis of soils and subsequent land use decisions. Soil productivity is altered to some degree, by human and natural activities, thus a productivity index value must be able to be updated as conditions warrant. Factors other than soil also affect productivity, especially climate and management. Because of these factors, isolating soils for productivity trials becomes problematical, since locating test plots of different soils under identical climate and management is difficult. As distances between plots increase, climate and management variations increase as well. An ideal productivity index will measure productivity from soil parameters specifically, and also allow the inclusion of climate and management data to more completely describe productivity.

By definition, high productivity soils are more conducive to plant growth than low productivity soils. Thus, crop biomass information is the primary way to interpret the accuracy of productivity index values for agricultural soils. Small grain yield information is readily available from the Montana soil-crop yield (SCY) database. This database was established by a cooperative venture between the USDA Soil

Conservation Service (SCS) and Montana State University (MSU) to contribute soil and crop information from Montana to a national study. This multi-county, multi-year database was started in 1986, and contains information on soil, crop, climate and other attributes.

Thesis Objectives

This thesis describes research at MSU, where a productivity index model is being tested and improved by using actual small grain yield, management and climate data collected for six years throughout the state. The objectives are to 1) test the original, Minnesota version of the productivity index (PI) model for Montana conditions using measured barley, spring wheat, and winter wheat grain yields from the SCY database, and 2) identify soil and climate factors that will further explain variations in Montana small grain yield.

Literature Review

Threats to Soil Productivity

Soil productivity has been a concern of researchers for many years. In his treatise on land degradation, Barrow (1991) fears that land degradation is not adequately controlled, and that its unknown long-term effects may reverse the post-World War II crop production increases. Short-term gains in crop production can create an illusion of progress, while land degradation goes largely unheeded until the problem is severe. Land managers must weigh the short-term economic costs of degradation control efforts against possible long-term benefits. A decision to degrade and abandon some lands may make sense economically.

Soil degradation often results in the decline of productivity. Natural processes such as flooding, hurricanes and other storms, volcanic activity, mudslides, intense rainfall, drought and periodic invasions of destructive insects and other pests can dramatically impact productivity. The onset or severity of natural disasters may be exacerbated by human activity pushing the environment closer to a threshold, or triggering a disaster. Global biogeochemical cycles are facing unprecedented human impact which threatens soil productivity including the buildup of greenhouse gases, global climate and sea level changes, ozone depletion, and acid rain. Human activity can result in land degradation through industrial pollution, or unwanted side effects of agrichemicals. Localized degradation problems in the form of salinity and alkalinity problems also arise (Barrow, 1991).

One of the most pervasive types of soil degradation is erosion. Barrow (1991) believes the gradual loss of topsoil is one of the major threats to human well being, and in its early stages, may not be readily apparent. Soil erosion is widely recognized as a serious global problem that depletes soil productivity (Burnett and Hanks, 1981; Lal, 1988a,b). However, the dimensions are difficult to define. The extent, magnitude and rate of erosion, and its economic and environmental costs need to be known.

Poincelot (1986) cites the economic dilemma many farmers are in. Many are financially overextended and cannot afford the long-term investment needed for sustaining the soil. Schultz (1984) would disagree, claiming that farmers calculate the value of their soil resource to a fine degree. The large stake and self-interest farmers have in the economic value of their soil is the key to soil conservation.

Steiner (1990) echoes Poincelot in making a case for erosion control policy. He finds it difficult to convince farmers that erosion is a problem when they have seen their yields increase dramatically. Like Barrow's concern about degradation, Steiner's specific concern is that although soil erosion and declining productivity are recognized as problems, there is no simple way to evaluate the economics of conservation. Farmers face a dilemma if forced to decide whether to pursue maximum profits, or to sacrifice some short-term profit in the long-term interest of maintaining soil productivity by erosion prevention measures. The temptation to skip conservation expenses when erosion seems slight and monetary concerns are high, is a serious issue. A tool to quantify productivity would help clarify the decision.

Flach and Johannsen (1981) recognize the need to understand the impact of soil erosion on soil productivity. The amount of public and private funds used for soil conservation should be justified by the threat of lost soil productivity. Soil productivity needs to be measurable in order to document the nation's ultimate capability to produce food. Dudal (1981) raises the point that if more marginal lands are brought into production, less profit is made, and less money is available for conservation practices.

The impact of soil erosion on productivity is also addressed by Crosson (1983). He suggests that soil productivity losses from erosion be calculated in terms of lost crop production. This value would indicate the cost of erosion to the nation, and provide a criteria for judging when erosion-induced losses sufficiently justify national erosion-reducing policies.

In their introduction to "Proceedings of soil erosion and productivity workshop", Larson et al. (1990) state the prevailing view that no imminent threats exist to the U.S. domestic food production capability. However, soil productivity is a major concern when viewing world food needs. Sustaining current American food production levels into the future will be impossible if soil erosion continues unchecked. Demand for cropland could increase substantially in the future, especially if alternatives to fossil fuels or industrial chemicals are produced agriculturally, or if population, with its accompanying demand for food, continues to grow. These trends could dramatically increase the need for sustained productivity. For the survival of civilization, soil and water management must improve. Land management must make every acre contribute to national needs while conserving it for future generations.

Modeling Soil Productivity

Various soil productivity ratings have been used for many years. Huddleston (1984) has written an excellent overview on the development and use of soil productivity ratings. In turn of the century America, the first rating systems were qualitative, describing soils with a narrative or classifying them subjectively by agricultural suitability.

Quantitative rating systems were developed in the 1930s. They use objective criteria and can be described as inductive or deductive. Inductive rating systems do not directly use yield data in model establishment. Instead, they use various soil, climate and land properties to predict the yield potential of a soil. Large data sets are required for development and testing. Soil and other attributes generate the rating, which is then tested with yield values. Deductive productivity ratings are generated from crop yield data only, and do not take soil factors into account. The simplest consist of tables of soil series listed with the yields of major crops. The deductive ratings also require large amounts of yield data in order to cover all soil series for all possible crops (Huddleston, 1984).

To date, there are two well known models for estimating soil productivity, the erosion-productivity impact calculator (EPIC) and the productivity index (PI) model. EPIC is a powerful, complex model composed of nine major divisions: hydrology, weather, erosion, nutrients, plant growth, soil temperature, tillage, economics and plant environment zone. Each division contains complex equations requiring a variety of input data. Such a large model requires a tremendous amount of data, but some results show promise (Williams et al., 1984). The PI model is much simpler, only requiring values for three soil factors throughout the soil profile.

Productivity Index Model Studies

The original PI model was developed by Pierce et al. (1983) at the University of Minnesota after work done by Neill (1979). The model was designed to calculate changes in soil productivity as the soil surface erodes. It is based on the premise that soil provides an environment for root growth and is closely related to crop yield. The model assumes that nutrients are not limiting to plant growth and factors such as climate, management, and plant differences are constant.

In the original, Minnesota version of the model, three soil parameters, available water holding capacity (AWC), bulk density, and pH are used to quantify productivity (Pierce et al., 1983). Each parameter is normalized to give a dimensionless value between 0.0 and 1.0 called a sufficiency. Three sufficiencies were calculated for each soil layer. The sufficiencies and a weighting factor were multiplied together, and the products of each soil layer were summed as in Equation 1. This sum is the PI value:

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

where PI is the original productivity index, A_i is sufficiency of available water-holding capacity, C_i is sufficiency of bulk density, D_i is sufficiency of pH, WF_i is a weighting factor representing an idealized rooting distribution, n is the number of soil layers in the top 100 cm, and i represents each soil layer.

Sufficiency curves used in this model are shown in Figure 1. AWC indicates the amount of water the soil can store (Figure 1a). The AWC sufficiency increases linearly as the soil's ability to hold water increases. The vertical line in the curve indicates that below 0.03, the sufficiency is 0.0, a level considered too dry for root growth. Bulk density also impacts the rooting environment. Low bulk density soils are easily penetrated by roots, so the sufficiency value is 1.0 (Figure 1b). Higher bulk densities imply decreased pore space and increased difficulty for root penetration,

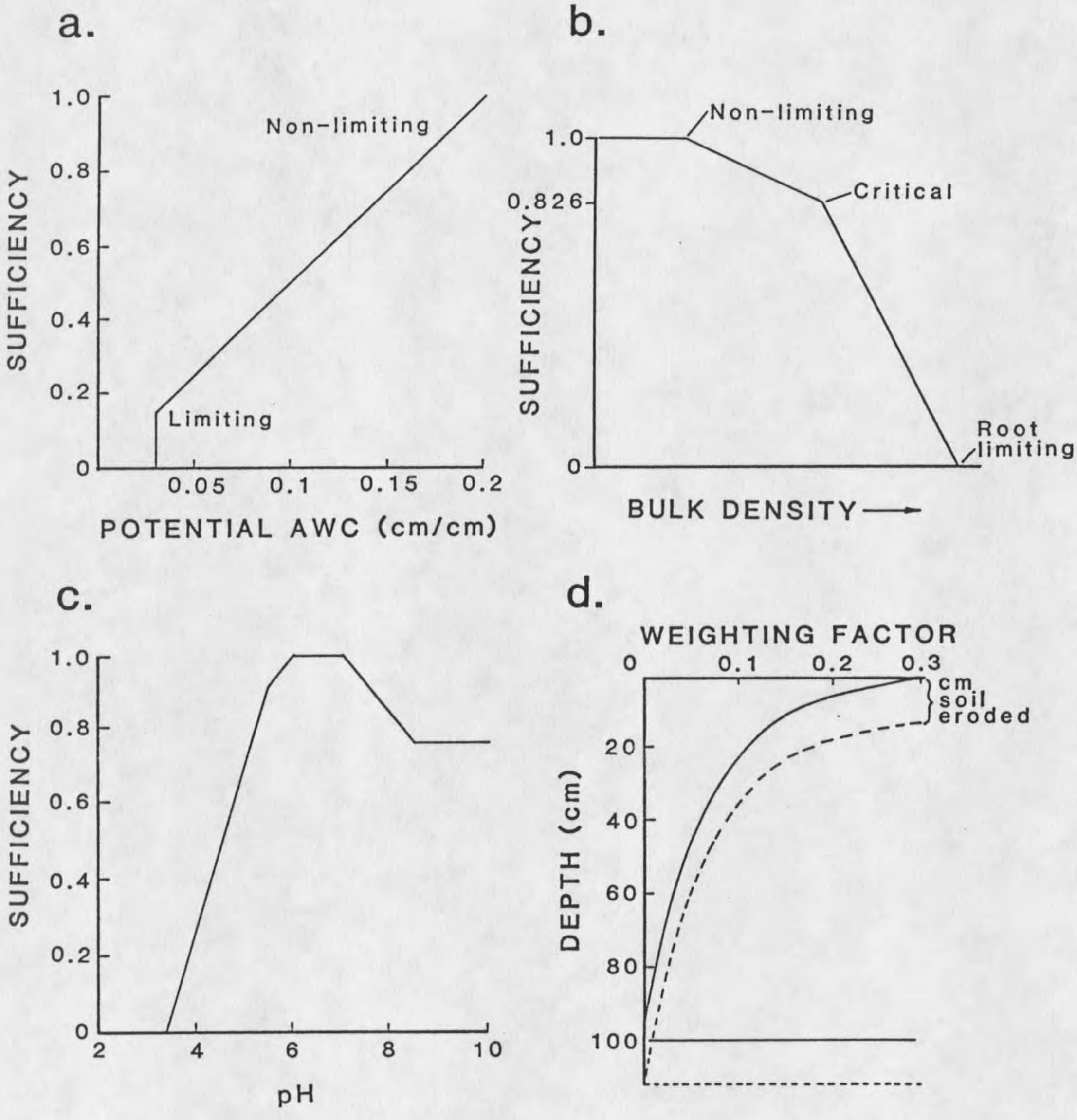


Figure 1. Sufficiency curves used in calculating PI. No units are reported on the X-axis in (b) because the non-limiting, critical and root-limiting bulk densities vary with soil family texture class (Wilson et al., 1992).

hence a lower sufficiency. The pH values in the neutral range are ideal for crops and therefore have a sufficiency of 1.0 (Figure 1c). Higher pH levels indicate higher concentrations of base cations and reduced solubility levels for some nutrients, often associated with reduced productivity. Lower pH levels similarly indicate higher concentrations of acidic cations and, in some cases, poorer nutrient availability. The model considers only the soil's top 100 cm. The soil layers closest to the surface are weighted more than the deeper layers, based on the assumption that surface layers have a greater influence on plant growth than deeper layers (Figure 1d).

The model was tested by Pierce et al. (1984) in the Corn Belt by comparing both crop equivalency ratings (CER) and yield estimates from county soil surveys with PI. Crop equivalency ratings represent the highest relative net economic return per acre, when managed for cultivated crops, permanent pasture, or forestry. In order to calculate PI, data from the USDA Soil Conservation Service's (SCS) Soil Interpretations Record (SIR) database was used (formerly named SOILS-5).

A simple linear regression gave correlation coefficients (R^2) ranging from 0.63 to 0.71 when PI was compared to soil survey yield estimates and CER. A second trial that excluded histosols, frequently flooded and depressional soils, and soils with slope exceeding 6% resulted in the R^2 range increasing to 0.79 to 0.90. Pierce et al. (1984) hypothesized in rationalizing the removal of these outliers, that "the model predicts a higher productivity for these soils because it fails to account for insufficient aeration during a portion of the growing season in the case of wet soils, and does not account for slope effects on yield in the case of more sloping soils."

Lindstrom et al. (1992) compared PI values calculated from SIR information with PI values calculated from field data for 12 sites in the North Central Region of the United States. The PI values calculated from SIR data are obtained from the midpoints of provided ranges. This step greatly simplifies data collection, but is not as accurate as using actual field data. They found that five sites had a 0-5% difference between SIR generated PI and field data PI, three sites had a 7-10% difference, two sites had a 16-18% difference and two sites had a 25-27% difference, with eight of the 12 PI values generated from SIR smaller than the field data PI values. They concluded that SIR data is an efficient method of characterizing soil productivity when field data are unavailable, but that the PI values for specific sites representing a soil series are difficult to estimate when using the midpoints of SIR soil characteristic ranges.

Rijsberman and Wolman (1985) found the PI model to be remarkably adaptive to soils around the world when the model's components are modified. They made several modifications that include a sufficiency for available nutrients in areas that lack resources for optimal soil fertility, gravel content for skeletal soils where gravel impedes root growth, and organic carbon content where comparisons need to be made between soils with relatively large soil organic matter (SOM) deep into the profile and those with virtually no SOM below 15 cm. Additional modifications include a sufficiency for electrical conductivity, and for penetrometer resistance to replace bulk density in estimating root growth for Hawaiian volcanic ash soils. They conclude that the PI model is a promising tool for soil productivity and erosion studies.

A Montana study compared PI with small grain yields in Hill and Jefferson counties (Sandor, 1989; Wilson et al., 1991). In each county, two fields were selected. A transect that sampled two to six soil series was established within each field. Sites along the transect were sampled for soil information and other attributes. These data were used to calculate PI (Equation 1). Grain yields were obtained by sampling the barley or spring wheat, at the transect sites. PI correlated fairly well with grain yield in three of four transects. In the fourth transect, no relationship between yield and PI was detected (R^2 = 0.64, 0.67, 0.63, and 0.01; average R^2 = 0.49). When a calcium carbonate sufficiency was included in the model, a higher relationship was found between yield and PI (R^2 = 0.72, 0.78, 0.62, and 0.39; average R^2 = 0.63). In addition, when an organic matter sufficiency was added to the previous test, even higher correlation was detected (R^2 = 0.77, 0.69, 0.60, and 0.75; average R^2 = 0.70). In a final model adaptation, differences in cropping history were examined. By including a variable in the model that increased the yields of recropped grains, compensating for increased moisture and nutrient content of fallowed fields, a strong correlation was found between PI and yield: R^2 equaled 0.69 and 0.75 for the original and modified forms of the model, respectively (Wilson et al., 1991).

Another Montana study tested the PI model in Cascade County (Gerhart, 1989; Wilson et al., 1992). Yield tables from SCS county soil surveys were compared with PI values calculated using SIR data. An average R^2 of 0.32 was obtained when PI was compared to barley, spring wheat and winter wheat yields using simple linear regression. The regression outliers suggested that factors other than those evaluated by PI were contributing to variability in the yield table of the Cascade County soil survey. Multiple regression was used to compare yield to PI, growing degree days (GDD), water balance, calcium carbonate, and slope. These parameters were chosen due to their likelihood of influencing small grain productivity in Montana. Calcium carbonate and slope data were obtained from SIR. Water balance was derived from precipitation and potential evapotranspiration, which along with GDD data, were obtained from the Montana Agricultural Potentials System (MAPS) database (Nielsen et al., 1990). The system divides Montana into 17,993 cells, each representing an area about 3.8 km by 5.6 km. The data consist of long-term averages and can be accessed by individual cell. The typical series location from the county soil survey was used as a representative site for each soil series' climate. The added parameters increased the correlation from an R^2 of 0.32 to 0.57.

Reliability of Yield Tables

In a recent study, Baker and Gersmehl (1991) examined yield values from SCS county soil surveys. They expected to find the more recently published soil surveys to have higher yields than earlier surveys, reflecting improved seed stock and management. They did find a trend of increasing yields from the late 1950s to the early 1970s. However, after 1972, they discovered reported yields that were essentially the same, even when SCS District Conservationists consistently reported in interviews that yields were increasing. Baker and Gersmehl (1991) hypothesized that instead of recalculating a realistic yield value for each county's soils, SCS personnel were taking values from the newly available databases. The researchers final conclusion is that yield estimates from the county soil surveys, particularly after 1972, "should be treated as suspect and used with caution". These conclusions raise questions about the validity of using yield data from county soil surveys in model testing. A more reliable source of crop yield data for individual soil series is desired.

Soil-Crop Yield Database

The SCY database has been used to further understand the relationship between soil, landscape, management and climatic properties and crop production in a semi-arid environment (Osman, 1988; Spencer, 1990). Over 60 variables have been collected from Montana soils. A national interagency soil-crop yield committee selected the majority of these variables collected in the database, and provided the methodology for data collection. Eleven additional variables have been added for Montana soils at the recommendation of the faculty of the Department of Plant and Soil Science at MSU. A sulfur soil test was discontinued as it appeared to have little impact on soil productivity for Montana dryland small grains. This database contains soil, crop, and management data from twenty-six counties throughout Montana.

In one study using data from 1986, Osman (1988) used multiple regression to investigate which factors from the database correlated with yield. He found strong correlation (R^2 =0.74) between winter wheat yield and moist soil depth. When soil test nitrate-nitrogen and potassium were included in the analysis, R^2 increased to 0.76. Spring wheat yields also correlated fairly well with factors in SCY. A multiple regression showed R^2 of 0.55 between yield and moist soil depth, increasing to 0.67 with soil test phosphorus included, and to 0.72 with elevation added as well. Barley yield had an R^2 of 0.51 compared to available water, increasing to 0.57 with the inclusion of elevation. Although the study covered only one year, Osman's work indicates that soil water is a major factor in predicting small grain yields in Montana.

Spencer (1990) completed a study similar to Osman (1988) using 1986 to 1989 SCY data. In multiple regression analysis of variables that had a clearly numerical basis, barley yield correlated positively with moist soil depth (R^2=0.22). The inclusion of soil organic matter (SOM) raised R^2 to 0.32. Elevation, A-horizon thickness and pH explained an additional 6% of barley yield variability (R^2=0.36). Spring wheat similarly correlated most strongly with moist soil depth (R^2=0.18). Inclusion of SOM raised R^2 to 0.30, and by including soil pH, R^2 increased to 0.37. Winter wheat also correlated strongest with moist soil depth (R^2=0.26). By including SOM, depth to $CaCO_3$, and elevation, R^2 increased to 0.32. Clearly, water continues to have a strong impact on crop yield, and a factor that measures plant available water would greatly increase the accuracy of a productivity index in Montana.

Both Osman (1988) and Spencer (1990) ran multiple regression tests between yield and a large group of factors. Although barley cannot be compared due to the methods Osman used, spring and winter wheat results can. Osman found a relationship of R^2 = 0.72 and 0.76 for spring and winter wheat, respectively. Spencer found a relationship of R^2 = 0.37 and 0.32 for spring and winter wheat respectively. The primary difference between the two studies is that Osman only used data from the

1986 crop year, and Spencer used crop data from 1986 to 1989. By including extra years in Spencer's equations, year to year yield variability was introduced which was reflected in decreased correlation between yield and soil, climate and management factors. Whereas 1986 was considered a normal rainfall year, 1987 and 1988 were considered drought years in much of the state. A decrease in water would lead to drought damage and perhaps other problems in susceptible fields. These fields would produce lower yields. Other less affected fields with more stored water would not be as dramatically affected by the drought, produce more normal yields, and thus, the range in yields would expand and R^2 values would be smaller.

Water and Small Grain Yields

Brown and Carlson (1990) also found a strong relationship between Montana small grain yields and water. They compiled equations that estimate yield for several crops based on stored soil water and anticipated growing season precipitation. Unfortunately, the difficulty in predicting growing season precipitation in a region where large annual precipitation variability exists, precludes the ability of highly accurate yield estimates. Brown and Carlson's model illustrates the crucial role water plays in Montana small grain yields.

Site Description

This study examines data for study sites contained in SCY. They were set up by SCS personnel in 1986. The participating counties are spread throughout Montana, with clusters primarily located in the northeastern, north-central, and south-central regions of the state (Figure 2). A wide variety of soil series exist throughout the state and many agricultural soils are represented in this study (Table 1). Originally, four soil series per county were selected that had potential for barley and wheat production and were extensively found in the county or state (Osman, 1988).

Much of the small grain production in Montana follows a crop-fallow rotation. In order to collect data from these series each year, pairs of fields on the same soil series, in close proximity, were identified. Each field was divided into three replicate plots for grain and soil sampling purposes. At the start of the study, 25 counties widely distributed throughout Montana participated. In 1987, one new county was added and several dropped out. As the study progressed, the number of fields and participating counties decreased. Some fields were lost to the Conservation Reserve Program (CRP), or to changes in land use by the farmer, and several counties were lost due to changes in the priorities at the SCS Field Offices. In 1991, 10 counties contributed data, and most tested fewer than four soils.

The paired field arrangement allowed yield data from virtually the same location (considered the same site) to be collected every year if the fields were in a crop-fallow rotation. Since many fields were lost to CRP after the 1986 crop, and more were lost after the 1987 crop, data on many soils were obtained every other year. In some cases, the SCS Field Office personnel had difficulty in coordinating harvest timing with the operators, so that a small but significant amount of yield data was lost due to the operators harvesting before SCS Field Office personnel sampled.

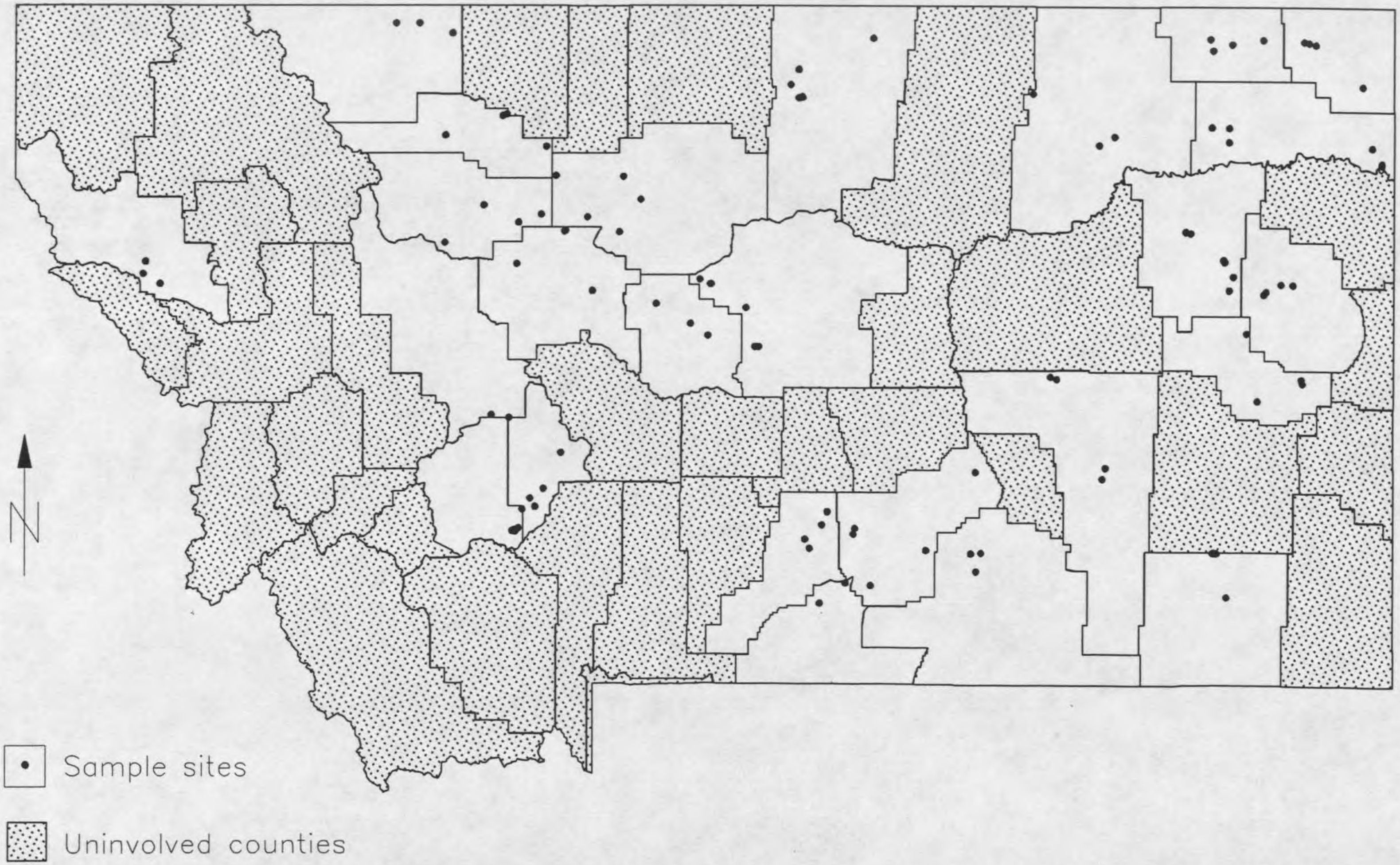


Figure 2. Counties that have contributed data to soil–crop yield study.

Table 1. Classification of soils in the 1986 to 1991 study.

Soil Series	Classification†
Absarokee	Fine, Montmorillonitic Typic Argiborolls
Amesha	Coarse-Loamy, Mixed Borollic Calciorthids
Bearpaw	Fine, Montmorillonitic Typic Argiborolls
Bonfri	Fine-Loamy, Mixed Borollic Haplargids
Brocko	Coarse-Silty, Mixed Borollic Calciorthids
Cambert	Fine-Silty, Mixed Frigid Typic Ustochrepts
Cherry	Fine-Silty, Mixed Frigid Typic Ustochrepts
Chinook	Coarse-Loamy, Mixed Aridic Haploborolls
Cushman	Fine-Loamy Mixed, Mesic Ustollic Haplargids
Danvers	Fine, Montmorillonitic Typic Argiborolls
Ethridge	Fine, Montmorillonitic Aridic Argiborolls
Fairfield	Fine-Loamy, Mixed Typic Argiborolls
Farland	Fine-Silty, Mixed Typic Argiborolls
Fort Collins	Fine-Loamy, Mixed, Mesic Ustollic Haplargids
Gilt Edge	Fine, Montmorillonitic, Mesic Haplustollic Natrargids
Gird	Coarse-Silty, Mixed, Frigid Typic Haploxerolls
Half Moon	Fine-Silty, Mixed Typic Eutroboralfs
Havre	Fine-Loamy, Mixed (Calcareous), Frigid Ustic Torrifluvents
Havrelon	Fine-Loamy, Mixed (Calcareous), Frigid Typic Ustifluvents
Hesper	Fine, Montmorillonitic, Mesic Ustollic Haplargids
Judith	Fine-Loamy, Carbonatic Typic Calciborolls
Keiser	Fine-Silty, Mixed Mesic Ustollic Haplargids
Kobar	Fine, Montmorillonitic Borollic Camborthids
Kremlin	Fine-Loamy, Mixed Aridic Haploborolls
Lambeth	Fine-Silty, Mixed (Calcareous), Frigid Ustic Torriorthents
Lonna	Fine-Silty, Mixed Borollic Camborthids
Marias	Fine, Montmorillonitic, Frigid Udorthentic Chromusterts
Martinsdale	Fine-Loamy, Mixed Typic Argiborolls
McCollum	Coarse-Loamy, Mixed, Frigid Typic Haploxerolls
McRae	Fine-Loamy, Mixed, Mesic Ustollic Camborthids
Musselshell	Coarse-Loamy, Carbonatic Borollic Calciorthids
Olney	Fine-Loamy, Mixed, Mesic Ustollic Haplargids
Pendroy	Very-Fine, Montmorillonitic, Frigid Udorthentic Chromusterts
Phillips	Fine, Montmorillonitic Borollic Paleargids
Rothiemay	Fine-Loamy, Mixed Aridic Calciborolls
Sappington	Coarse-Loamy, Mixed Aridic Argiborolls
Savage	Fine, Montmorillonitic Typic Argiborolls
Scobey	Fine, Montmorillonitic Aridic Argiborolls

Table 1, continued.

Soil Series	Classification†
Shaak	Fine, Montmorillonitic Abruptic Argiborolls
Shambo	Fine-Loamy, Mixed Typic Haploborolls
Shane	Very-Fine, Montmorillonitic Abruptic Argiborolls
Tally	Coarse-Loamy, Mixed Typic Haploborolls
Tanna	Fine, Montmorillonitic Aridic Argiborolls
Telstad	Fine-Loamy, Mixed Aridic Argiborolls
Turner	Fine-Loamy over Sandy or Sandy-Skeletal, Mixed Typic Argiborolls
Vanstel	Fine-Silty, Mixed Borollic Haplargids
Varney	Fine-Loamy, Mixed Aridic Argiborolls
Williams	Fine-Loamy, Mixed Typic Argiborolls
Winifred	Fine, Montmorillonitic Typic Haploborolls
Yamac	Fine-Loamy, Mixed Borollic Camborthids

†Soil Classification according to Soil Taxonomy (Soil Survey Staff, 1975) from Spencer (1990).

At other times, unforeseen circumstances such as severe snow or hail damage could cause the operator to reseed to a different crop, plow the field, or cut for hay, any of which could prevent the acquisition of a usable yield value.

Large climatic variability exists in Montana. Precipitation varies between 25 cm to over 100 cm. Winter mean minimum temperatures vary between -29°C to -7°C. Summer mean maximum temperatures vary between 20°C and 33°C (Caprio and Nielsen, 1992). The extreme cold and extreme high precipitation areas in Montana tend to occur in the most mountainous areas, unsuitable for cropping. The long-term average annual precipitation for the study sites ranges from 28 to 63.5 cm, with a mean of 35 cm. High variability exists within the agricultural areas and representative study sites spread across Montana.

CHAPTER 2

METHODS

SCY Data Collection and Management

Men and women across Montana have contributed many hours in collecting and compiling the data in the SCY database. In the counties where study sites were located, SCS Field Office personnel collected grain samples, pre-plant soil samples (except in 1986, when the soil sampling took place after harvest) and moist soil depth measurements. Soils were dried and mailed to MSU where they were ground and submitted to the Soil Analytical Laboratory. Grain samples were sent by Field Office personnel to the MSU Agricultural Experiment Stations for threshing and weighing. The grains were sent to MSU where test weight and thousand kernel weight were measured. The threshing and weighing were completed at MSU for sites close to the university, and when other problems arose. In several cases, experiment stations measured test weight and/or thousand kernel weight. The SCS Field Office personnel also measured moist soil depth with a Paul Brown probe each April and recorded site, soil, crop and management data on a modified SOI-1 data form. The form was then forwarded to MSU and entered into the database, along with soil test and grain data.

The software program dBase III Plus, marketed by Ashton-Tate, was used for the SCY database. The variables were assigned database fields, and each database record (or row) contains data from the three plots in a single field. An individual SCY data file was built every year. This study uses data from 1986 to 1991. The six individual year files were combined with each record identified by year. This procedure simplified the separation of barley, spring wheat, and winter wheat data and other data management processes.

Generating PI Values

Several computer programs were obtained from the University of Minnesota to extract the needed data out of the massive SCS database SIR, and to organize them into abbreviated soil series records or blocks. The program GRAPHPI2, calculates a PI value using these modified data blocks (Winkelman et al., 1984; Gerhart and Wilson, undated). In March, 1992, a current version of the SIR magnetic tape was obtained from the Statistical Lab at Iowa State University, Ames, Iowa. The tape contains a lengthy data record for over 500 soil series in Montana. The tape was loaded onto the VAX-8550 computer cluster at MSU. The program GENERMSU.PAS was run using the SIR tape and the file LOOKUPT as input. If the SIR record did not contain bulk density values, a value was added from LOOKUPT for each profile by estimating bulk density from texture, and adjusting for organic matter content. The output file contained an abbreviated record (a block) for each soil series on the tape.

Soil series, phase number and surface texture were extracted for each location in SCY in order to determine which SIR record is the best match for the site. A second program, GPIFORM.PAS was run using the output file from GENERMSU, and a list of soil series for which data is available in SCY. This procedure generated an output file containing blocks for the soil series in SCY.

In a few cases, the soil series recorded in SCY did not correlate to an SIR record. In these cases, Michael Hansen, Soil Data Manager at the Montana SCS State Office in Bozeman was consulted. Some of the soil series names had been changed since 1986 when the SCY soils were identified, and updating to the correct name was straightforward.

For most soils in Montana, several phases exist for each series. Each phase is identified by a phase number consisting of a two letter state abbreviation followed by a four digit number (e.g. MT0123). An abbreviated SIR record block was generated for each phase, hence, for almost every soil series, there was more than one corresponding block or phase. In several cases, the phase numbers from the SCY soil series did not match any of the phase numbers for a soil series in SIR. In these cases, the phase had been reassigned to another soil series after the SCY sites had been identified in 1986. Hansen's knowledge of soil series, phases and their characteristics plus additional information from SCY, provided an appropriate, precise SIR phase and series designation to match the SCY sites.

A soil series frequently contains soils with different surface textures. Each block contains a row of code for a group of possible surface textures. The surface texture from SCY was matched with the corresponding SIR block. The extra rows of code for unneeded textures were deleted. For each deleted row of data, a row of blank code was added to keep the number of rows in each block constant. In some cases, the surface texture at the SCY site did not match the available textures in the abbreviated SIR record block. It was found that in the GPIFORM.PAS procedure, the abbreviated record only lists one texture per row. In the actual SIR record, several textures correspond to the values in a row of the block. Hansen accessed additional information from SIR, and the correct surface texture row in the block could be matched to the SCY soils.

In SCY, several complexes are listed for soil series. The original soil scientists who set out the study sites assigned the sites a phase number. This number was matched to one of the series of the complex, and the appropriate abbreviated data block was generated.

When the editing was completed, the data were downloaded to an IBM-compatible personal computer, where all subsequent computer operations were completed. The program TODIRECT was run which changed the downloaded file to a direct access file, SOILS5.DAT. This final file became the designated input file for running GRAPHPI2. Here, PI values were calculated for each series-phase-texture combination from SCY. The appropriate PI value was then entered into a new database field in SCY for each record.

Testing Original PI

All Sites

Barley, spring wheat and winter wheat were compared separately, as the crop yields vary and cannot be directly compared. The three plot yields from each field were averaged. In several cases, only one or two plots of data were recorded for a field, in which case the plot value or an average of the two plots was used. In the first test, all records were included. Yields from multiple years were averaged for each site. Three simple linear regressions were run between the original PI and the average yield values for barley, spring wheat and winter wheat.

Removing Damage-Influenced Yields

The SCY database contains data from fields experiencing successful growing seasons, as well as fields that had a poor harvest or some level of crop damage. Using all the SCY sites would violate the PI model assumptions of constant climate, optimum management and optimum fertility. In previous studies, various strategies were used to avoid variations in climate. Soil survey yield tables were used by Pierce et al. (1984), Gerhart (1989), and Wilson et al. (1992), which took into account climate variability. Pierce et al. (1984) divided the study by MLRAs, so that sites from different MLRAs were not included in the same regression test. Sandor (1989), and Wilson et al. (1991), accounted for moisture variability by examining several soil series in the same field. In order to minimize the impact of management and climate variability in Montana, several different types of data points were removed. The first group of points removed was an attempt to control for yield damage, resulting from severe climatic conditions such as drought or hail, or unsuccessful management, resulting in losses to insects or weeds. Several forms of damage occurred to many fields in the study. SCS Field Office personnel recorded damage levels of slight, moderate or severe damage due to drought, hail, insects, weeds, water, and drainage, as well as a miscellaneous category to include items such as freezing or snow damage. The PI model assumes optimal nutrient levels and management, and constant climate. Since severe damage in a field results in lower yields, the yield values from damaged sites violate the assumption of constant management and climate. Sites that had severe damage in any category were removed. Sites with multiple yield values from more than one year had the yields averaged. Another set of simple linear regressions was run between PI and barley, spring wheat and winter wheat yields.

Controlling for Fertility Variability

A second group of points was removed in an attempt to control for yield variability due to differences in soil fertility. The PI model assumes that plant nutrients are not limiting. The data in SCY shows a large variation in available soil nutrient levels. The database records soil tests for available nitrogen (N), phosphorus (P) and potassium (K).

The SCY data suggests that K is not a limiting fertility factor in this study. Out of 875 plots, the mean K level is 368 ppm. Fertilizer guidelines do not recommend adding fertilizer K if soil test levels are over 200 ppm. (Lichthardt and Jacobsen, 1992). Nitrogen and P, however, are often limiting.

Nitrogen is essential to these crops (Brown and Carlson, 1990). However in the database, there did not appear to be a minimum N level where low soil test N fields with little fertilizer applied, if they were removed, would increase the correlation between PI and yield. Thus, no sites were removed due to low soil test N. Apparently, organic N mineralization was adequate for the available soil water in those years with low pre-plant soil test N, and made up for any potential N deficiencies.

Phosphorus (P) is also essential to these crops, and was not present in equal quantities across the sample sites. The soil test values of P for each plot were averaged. When Olsen-P was lower than 12 ppm, and less than 16.8 kilograms of P per hectare (15 lbs/ac) were added as fertilizer, the fields were removed from consideration. Two fields with missing soil test data were not removed because they had high P levels in previous years which indicates a high likelihood that these fields were well above the 12 ppm level.

After removing low P sites, yields following fallow were separated from yields following a crop. Linear regressions were calculated, both between PI and averaged yields following fallow and yields following a crop, for barley, spring wheat and winter wheat.

Modifying PI for Montana

Spatial Climate Variability

A large source of variability in yield may arise from the climatic variability of Montana. In the Corn Belt study (Pierce et al., 1984), climate variability was controlled by testing individual MLRAs separately. The Cascade County study (Gerhart, 1989; Wilson et al., 1992) found a large increase in correlation between PI and yield by including two climate variables, water balance and GDD. By accounting for moisture variability across a single county, an increase in correlation between PI and yields was detected. A study spanning Montana will contain even more moisture variability than a single county study (Caprio and Nielsen, 1992), indicating that the need to account for moisture variability will increase. Sandor (1989) and Wilson et al. (1990) experienced relatively constant climate and management because their study sites were within the same fields, and the four fields were compared to PI separately. Researchers have repeatedly demonstrated the key role water plays in crop yield in Montana (Osman, 1988; Gerhart, 1989; Brown and Carlson, 1990; Spencer, 1990; Wilson; 1992). To account for spatial variability of precipitation across the state, long-term average precipitation and PET data were obtained from MAPS for each study site.

Soil Organic Matter

Several Montana productivity researchers found SOM to correlate with soil productivity (Sandor, 1989; Spencer, 1990; Wilson et al., 1991). It is indicative of historical root growth, and therefore, indicates long-term water availability. Soil organic matter also holds water, contains nutrients, and contributes to soil structure. Although beneficial, plants do not require SOM to grow, hence, it enters the model by addition, which indicates productivity increases when organic matter is present, but does not necessarily lower productivity when it is absent. If it was multiplied into the model, soils with low organic matter would end up with greatly reduced PI values.

A modified PI was calculated using precipitation and PET data from MAPS, as well as SOM:

$$\text{Modified PI} = (\text{Original PI} \times \text{P/PET}) + (\%\text{SOM} \times 0.01) \qquad (2)$$

where P and PET are precipitation and Thornthwaite potential evapotranspiration from MAPS, respectively, and SOM is soil organic matter from a soil test in SCY. In one case that contained a large original PI value, and had P greater than PET, the final modified PI value was greater than 1.0. In this case, the modified PI was set equal to 1.0. Four linear regression models were run between modified PI and yield for each small grain crop. This time, the yields from the same site from multiple years were not averaged. The paired fields did not necessarily have the same SOM levels, and SOM levels from the same field varied slightly from year to year, giving different PI values.

Temporal Climate Variability

Since long-term average precipitation data does not account for temporal variability between years, another source of data was pursued. Annual precipitation data are not available for each study site, but annual precipitation data are collected at weather stations in each county (except Jefferson County) where the study sites are located. An annual water index was created for each county for each year, by dividing the particular year's annual precipitation, obtained from the 1987 to 1992 Montana Agricultural Statistics (Montana Agricultural Statistics Service, 1987; 1988; 1989;

1990; 1991; 1992) by the long-term average precipitation for that weather station's location (from MAPS). Thus, the water index will be greater than 1.0 for wetter years in that county, and less than 1.0 during drier years. In order to account for temporal variability, this annual water index was used to adjust the long-term average MAPS precipitation value for each year. The annual water index was multiplied by the long-term average precipitation (MAPS), and divided by PET. This water balance value was multiplied by the original PI and a SOM value was added to generate another modified PI:

$$\text{Modified PI} = (\text{Original PI} \times \text{AWI} \times \text{P/PET}) + (\%\text{SOM} \times 0.01) \qquad (3)$$

where AWI is annual water index, P and PET are precipitation and Thornthwaite potential evapotranspiration from MAPS, respectively, and SOM is soil organic matter from a soil test in SCY. In one case, where P was greater than PET, the final modified PI value was greater than 1.0. In this case, the modified PI was set equal to 1.0.

Four linear regression models were run between modified PI and yield for each small grain crop. No averaging of yields from different years at the same site occurred, since the annual water index generated different PI values for the same site depending on variations in precipitation at the county weather station. As with the original PI model testing, the first trial tested all sites. In the second trial, sites that indicated severe damage had occurred were removed. In the third trial, both severe damage sites and sites with low P levels were removed, and only those sites that were fallowed the previous summer were considered. In the last trial, damage and low P sites were removed, and only those sites that were cropped the previous growing season were considered. The same sequence of removing data points was followed as for the tests of the original PI model. Simple linear regressions were calculated and graphed.

CHAPTER 3

RESULTS AND DISCUSSION

Soil Water Variability

Soil water availability varies greatly across Montana. The long-term precipitation averages of weather stations in Montana counties involved in the SCY project range from 28 to 63.5 cm per year (Table 2). In addition, the year to year variation at the same site can be substantial. For example, a Dawson County weather station recorded 17.3 cm of precipitation in 1987, and 45.2 cm the following year. Similarly, Glacier County recorded 23 cm of precipitation in 1988, and the following year reported 49.5 cm. Teton County reported 23.5 cm of precipitation in 1988 and 51 cm in 1989. With the large variability in precipitation, and the evidence of moisture having tremendous impact on yield (Osman, 1988; Gerhart, 1989; Brown and Carlson, 1990; Spencer, 1990; Wilson et al., 1992), it is not surprising to see the large variability in yields in Table 3.

In testing the original PI model with small grain yields, the number of sites considered in each regression model vary with the criteria for each trial. Two sample sizes for the yields of each test are listed in Table 3. The first sample size (n_1) is the number of yields included in the sample. The second sample size (n_2) represents the number of sites where yields from different years are averaged. In examining the

Table 2. Long-term average annual (Nielsen, 1990) and yearly precipitation (Montana Agricultural Statistics Service, 1987-1992) by county.

County	Average	1986	1987	1988	1989	1990	1991
	cm						
Big Horn	38.1	48.1	39.2	n.p.[†]	37.2	26.8	n.p.
Blaine	33.0	52.1	n.c.[‡]	n.c.	n.c.	23.9	n.c.
Broadwater	27.9	31.5	n.c.	n.c.	n.c.	n.c.	n.c.
Carbon	27.9	n.p.	n.c.	n.c.	n.c.	28.1	40.7
Cascade	38.1	33.9	35.7	30.0	56.8	35.7	35.7
Chouteau	38.1	38.1	23.1	27.1	50.4	27.1	n.c.
Daniels	33.0	42.3	n.c.	26.0	27.8	23.4	42.8
Dawson	33.0	42.9	30.8	17.3	45.2	25.1	50.0
Fergus	43.2	44.7	41.1	32.5	n.p.	n.p.	n.c.
Glacier	27.9	36.0	30.6	23.0	49.5	23.3	38.4
Judith Basin	38.1	45.2	35.5	42.4	n.c.	n.c.	n.c.
Lewis & Clark	27.9	30.7	25.5	n.c.	n.c.	n.c.	n.c.
McCone	38.1	42.5	36.7	n.c.	24.2	19.1	n.c.
Pondera	33.0	36.1	32.2	23.6	50.2	24.2	40.3
Powder River	38.1	36.7	29.3	n.c.	34.3	n.c.	n.c.
Prairie	33.0	28.3	n.c.	n.c.	n.c.	n.c.	n.c.
Roosevelt	38.1	46.1	32.7	17.6	n.c.	n.c.	n.c.
Rosebud	27.9	53.9	32.4	21.5	35.5	25.7	45.0
Sanders	63.5	n.c.	39.4	52.6	59.8	n.c.	n.c.
Sheridan	38.1	39.2	30.0	21.7	n.c.	n.c.	n.c.
Stillwater	33.0	n.p.	n.c.	n.c.	n.c.	n.c.	n.c.
Teton	33.0	25.9	31.7	23.5	50.9	24.1	33.6
Valley	27.9	34.0	23.5	19.0	26.2	17.4	27.9
Yellowstone	33.0	36.2	31.6	n.c.	n.c.	n.c.	n.c.

[†] No precipitation data available.

[‡] No study sites in county that year.

Table 3. Sample sizes from test of original PI model before averaging yields from same site (n_1), sample sizes after averaging yields from same site (n_2), means and ranges of barley, spring wheat and winter wheat grain yields.

Crop	n_1	n_2	Minimum	Mean	Maximum
			------------- Mg ha^{-1} -------------		
Yield for all sites:					
Barley	74	47	0.06	2.31	5.47
Spring wheat	111	48	0.06	1.94	5.33
Winter wheat	132	59	0.32	2.45	5.26
Yield for sites without severe damage:					
Barley	64	42	0.10	2.48	5.47
Spring wheat	89	48	0.13	2.15	5.33
Winter wheat	119	54	0.81	2.51	5.26
Yield for sites following fallow without severe damage or low phosphorus:					
Barley	20	16	0.10	2.54	4.50
Spring wheat	23	23	0.35	2.38	5.33
Winter wheat	56	34	0.82	2.51	5.26
Yield for recropped sites without severe damage or low phosphorus:					
Barley	30	20	0.52	2.61	5.47
Spring wheat	27	19	0.80	2.34	3.79
Winter wheat	44	23	0.81	2.52	5.20

minimum yields obtained, even after severely damaged sites and low P sites were removed from consideration, there were still some very low yields, which may have been due to low plant available water. Barley yields following fallow were as low as 0.10 Mg ha^{-1}, spring wheat yields were as low as 0.35 Mg ha^{-1}, and winter wheat yields were as low as 0.82 Mg ha^{-1}. Recropped sites for barley and spring wheat had higher minimum yields, compared to the same crops following a fallow year, with winter wheat about the same. Lower minimum yields for recropped sites may be anticipated due to shorter time to capture soil water and lower fertility due to shorter time for SOM to mineralize. Management plays a major role in this, as the decision to recrop is usually made if the soil conditions, particularly soil water, are adequate. If the decision to recrop is made only when enough water is available, and fertilizer is added as needed, then recrop yields can be as high or higher than yields following fallow, particularly if soil conditions following fallow are not carefully managed.

Table 3 also illustrates that mean recropped barley and winter wheat yields are slightly larger than yields following fallow, with spring wheat following fallow yields slightly larger than recrop. Field experience suggests recropped yields are about 70% of yields following fallow. This study has a maximum of six years of data, which, in this case, does not show this anticipated long-term trend. Perhaps this result of surprisingly high recropped yields indicates careful management, or that recropping takes place in areas with increased precipitation, which allows larger yields.

The original version of the PI model was designed in the Corn Belt where annual precipitation of at least 100 cm is common. Consequently, the model component measuring plant available water is AWC, which accounts for the soil's ability to store water. Corn has a high water requirement relative to small grain crops, and the amount of water stored in the profile has a direct impact on plant growth and yield. In the semi-arid environment of Montana, the ability of the soil to store water makes little difference if the amount of precipitation is below the amount needed to charge the profile. In a semi-arid environment, AWC is much different than available water. Without any method to estimate plant available water, the original PI model performed understandably poorly.

Original PI Results

Average yield versus PI are shown for the three crops in Figure 3. The slopes of two of the three regression lines were negative, and R^2 values for barley and spring wheat were 0.01 or less. Winter wheat had an R^2 of 0.06, indicating that PI had a very small correlation with yield. Surprisingly, the slope was -1.10, which indicates that higher yields tended to be found on soils with a lower PI. Generally the points were scattered, with high and low yields reported for low, medium and high PI values. Regression lines with negative slope occur when low PI sites report relatively high yields, and high PI sites report relatively low yields. The high PI-lower yield sites are present as expected since this trial contains data from poor fertility sites and where severe damage occurred. The low PI-higher yield sites are more difficult to explain. Perhaps the producer knows these soils are not very productive and carefully monitors his management, or the soil's actual productivity is higher than the PI model predicts. Alternatively, these situations may represent extremes, where precipitation came along at the optimum time, producing a larger crop than normal.

In Figure 4, yields for sites that experienced severe damage were removed. Barley and winter wheat still had negative slopes. The R^2 value for barley remained

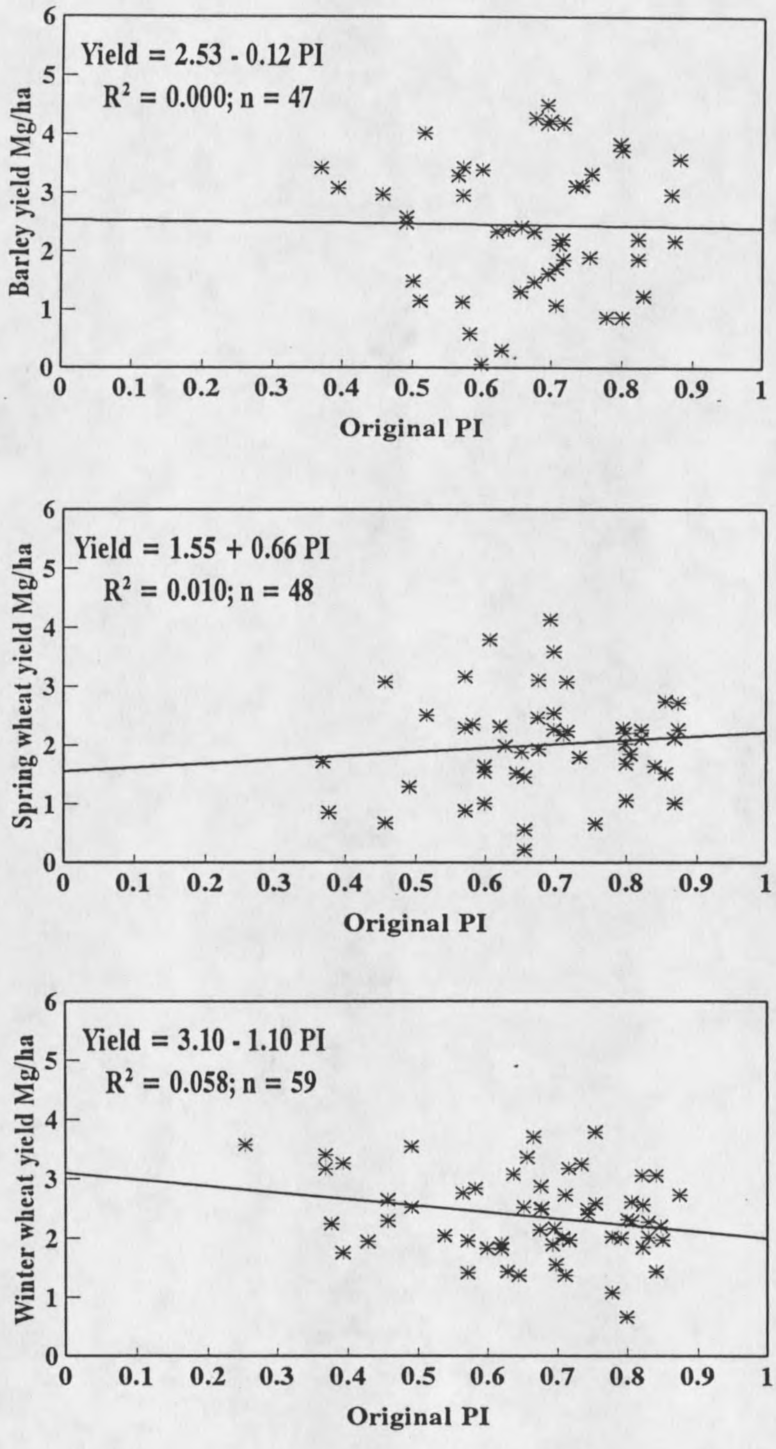
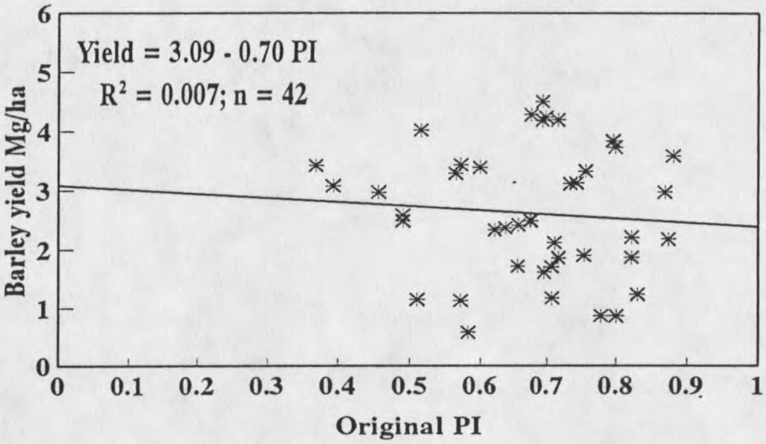
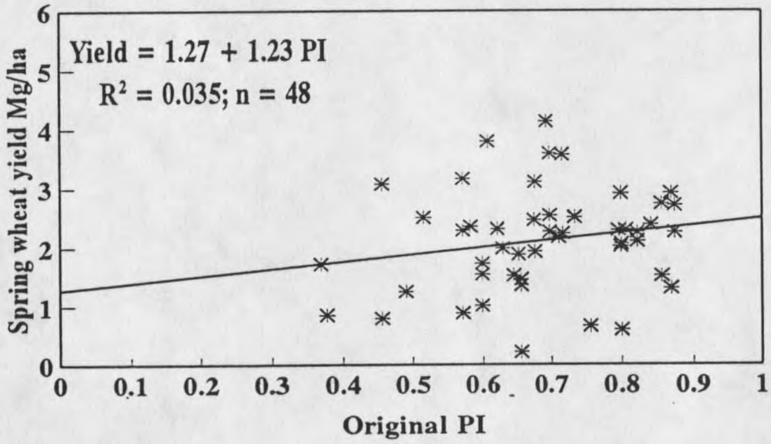


Figure 3. Small grain yields compared to original PI for all sites.





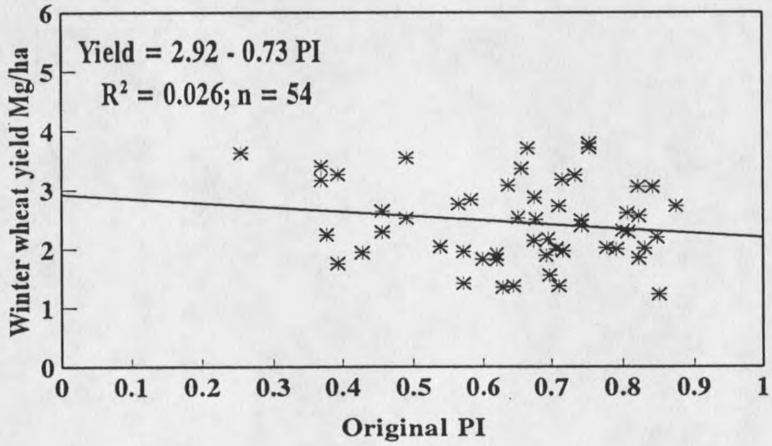


Figure 4. Small grain yields compared to original PI for sites without severe damage.

below 0.01, and for winter wheat decreased from 0.06 to 0.03. Spring wheat showed a minimal increase in correlation to PI by the removal of damaged yields and the slope increased from 0.66 to 1.23. It was expected that removing severely damaged yields would improve PI model performance, as low yields caused by damage do not necessarily reflect soil productivity. Only minimal improvement in model performance occurred for spring wheat, with no improvement for barley or winter wheat. Although some low yields were removed, other points that contributed to a trend of PI predicting yield were removed as well. The instructions for SCS Field Office personnel were to report the extent of damage, without specifying whether the damage occurred to the field as a whole or to individual plots. If, for instance, severe hail damaged half of a field, but the plots were unharmed, the SCY database may record severe damage. The yields from the plots would be unaffected by the damage to the rest of the field, but the data point would be discarded, as it is labeled as damaged. If good data points were discarded, the accuracy of model evaluation suffers.

Figure 5 shows the yields with damaged and low phosphorus (P) sites removed, following fallow. Barley showed no improvement. A relatively strong correlation was found between PI and spring wheat yields following fallow with an R^2 of 0.37 and a positive slope of 4.92. No improvement was noted for fallowed winter wheat.

In Figure 6, recropped yields with damaged and low P sites removed are shown. Barley has an R^2 of 0.01, with a slightly negative regression line.

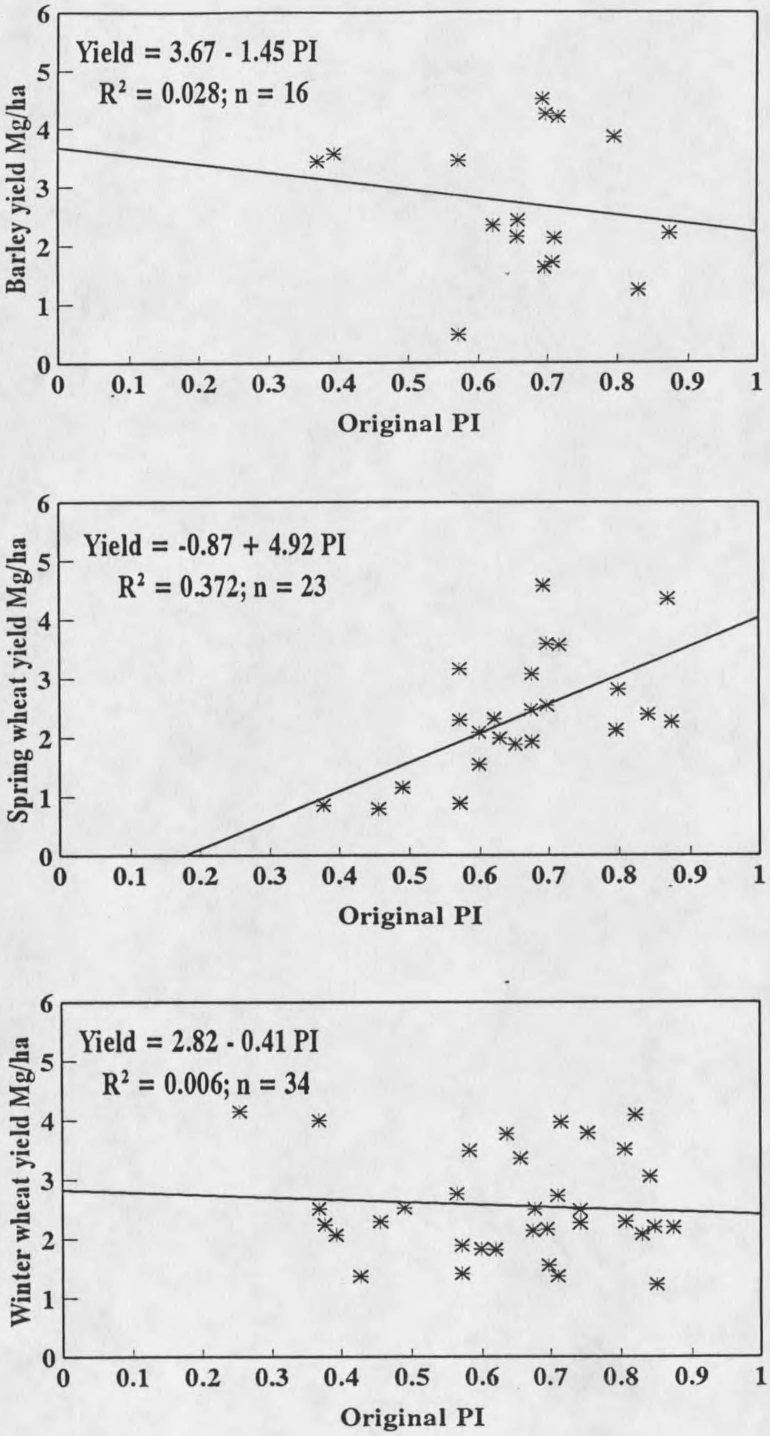


Figure 5. Small grain yields compared to original PI for sites without severe damage, without low P, following a fallow year.

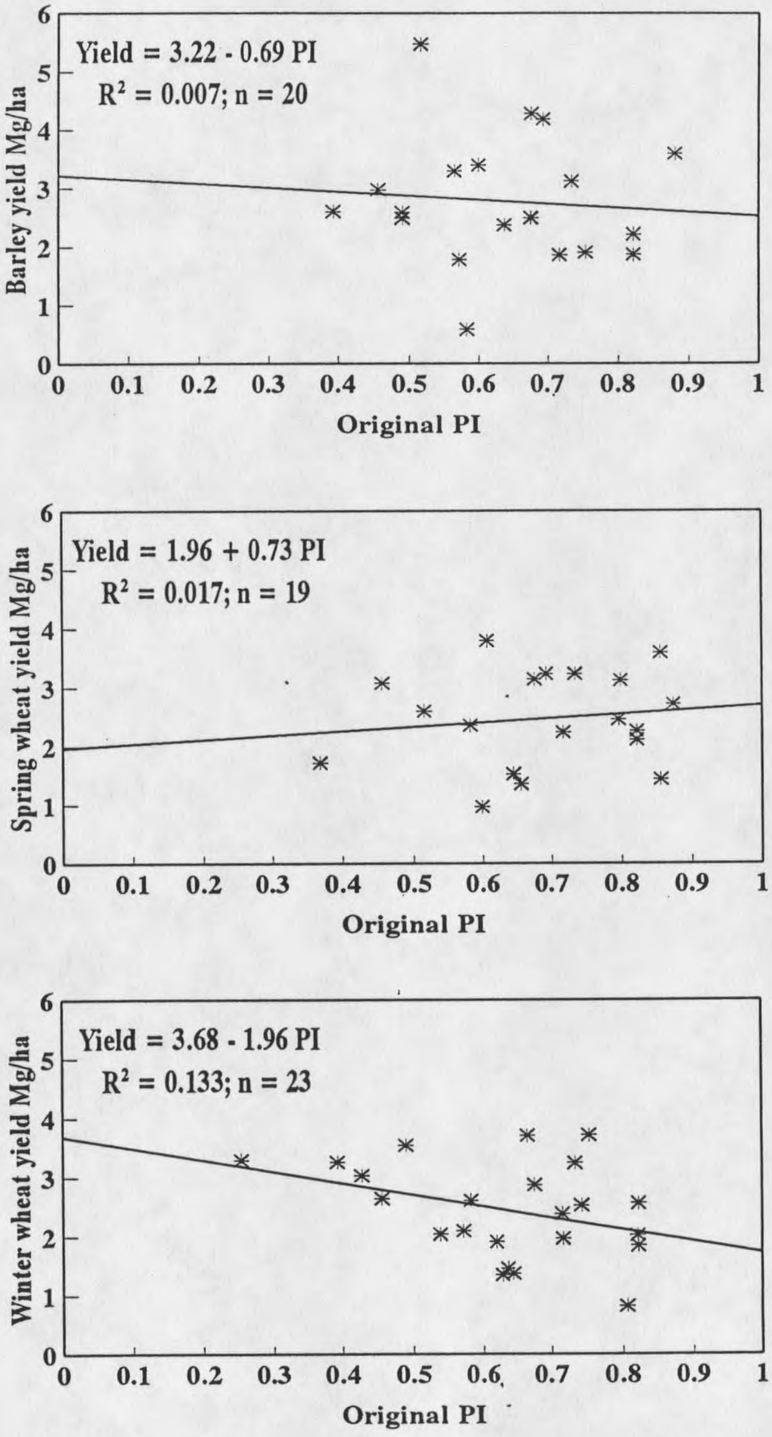


Figure 6. Small grain yields compared to original PI for sites without severe damage, without low P, following a cropped year.

Recropped spring wheat showed no correlation with PI ($R^2 = 0.02$). Recropped winter wheat showed a stronger negative slope of -1.96 with a larger R^2 of 0.13. While the PI model explains a portion of the spring wheat yields following fallow, it fails to explain recropped yields, and there is no uniformity in correlation for the different small grains. Gerhart (1989) and Wilson et al. (1992) found the original PI model explained an average 32% ($R^2 = 0.32$) of barley, spring wheat and winter wheat yields.

The results with spring wheat after a fallow year are encouraging. Sandor (1989) and Wilson et al. (1991) obtained R^2 values between 0.01 and 0.67, when comparing the original PI to small grain yields. Part of this higher correlation may be due to using actual field data to generate PI values, and making individual regressions for each field, which eliminates many climate and management differences. Gerhart (1989) and Wilson et al. (1992) used the SOILS-5 (currently called SIR) database to obtain the model parameters needed to calculate PI and obtained R^2 values between 0.31 and 0.34 for original PI and small grain yields. These values are similar to the spring wheat following fallow correlations found in this study.

Model performance for barley and winter wheat was much poorer. Winter wheat grows during one season, becomes dormant over winter, and then grows during a second. Thus, winter wheat has more variability, as the conditions of two growing seasons and a winter contribute to a high, medium or low yield. Spring wheat grows during one growing season only, and has less potential for variability. Perhaps this is why there is lower correlation with winter wheat than spring wheat.

Barley did not show any strong correlation to PI. Barley is often planted when a farmer feels he cannot get a good wheat crop, due to moisture or other conditions. Barley tends to be more tolerant of poor growing conditions, and perhaps is not as good an indicator of soil productivity as spring wheat.

Removing severely damaged sites is problematical. As mentioned before, interpretation of the instructions for recording damage is somewhat ambiguous. In addition, for each county in the study, different personnel are recording their subjective interpretation of crop damage. Multiply this by the high turnover at the Field Offices, and many different opinions of what comprises severe damage are represented in the database. Fortunately, the criteria for soil fertility is far more objective, as is separating the yields as to whether they are following fallow or recropped.

Modified PI Results

Long-Term Climate Averages

Modifying the original PI model by including precipitation and PET data from MAPS, and SOM data did not appreciably increase the efficacy of the PI model in predicting yield (Table 4). Barley showed no improvement. Although regression line slopes became slightly more positive, the low R^2 value makes slope less important.

The first two spring wheat trials had a slight increase in correlation. Spring wheat, all sites, increased slightly, and sites without damage had R^2 increase from 0.04 to 0.09. Spring wheat with damaged and low P sites removed, following fallow

Table 4. Correlation coefficient (R^2) and slope of regression line for relationships between small grain yields and PI.

Grain	Test		Productivity Index†		
			Equation 1	Equation 2	Equation 3
Barley	All sites	R^2:	0.00	0.02	0.10
		slope:	-0.12	1.30	2.68
	Damaged sites removed	R^2:	0.01	0.01	0.09
		slope:	-0.70	1.04	2.39
	After fallow; low P removed	R^2:	0.03	0.00	0.13
		slope:	-1.45	-0.34	2.95
	Recropped; low P removed	R^2:	0.01	0.01	0.02
		slope:	-0.69	0.77	1.13
Spring wheat	All sites	R^2:	0.01	0.03	0.21
		slope:	0.66	2.13	3.00
	Damaged sites removed	R^2:	0.04	0.09	0.33
		slope:	1.23	3.40	3.77
	After fallow; low P removed	R^2:	0.37	0.43	0.48
		slope:	4.92	8.05	4.96
	Recropped; low P removed	R^2:	0.02	0.00	0.11
		slope:	0.73	0.14	1.54
Winter wheat	All sites	R^2:	0.06	0.00	0.00
		slope:	-1.10	-0.04	-0.05
	Damaged sites removed	R^2:	0.03	0.00	0.00
		slope:	-0.73	0.20	-0.22
	After fallow; low P removed	R^2:	0.01	0.02	0.00
		slope:	-0.41	1.19	-2.18
	Recropped; low P removed	R^2:	0.13	0.01	0.00
		slope:	-1.96	-0.18	0.15

†Equation 1 is original Minnesota model; Equation 2 is modification using climate data from MAPS only; Equation 3 is modification using climate data from MAPS and Montana Agricultural Statistics.

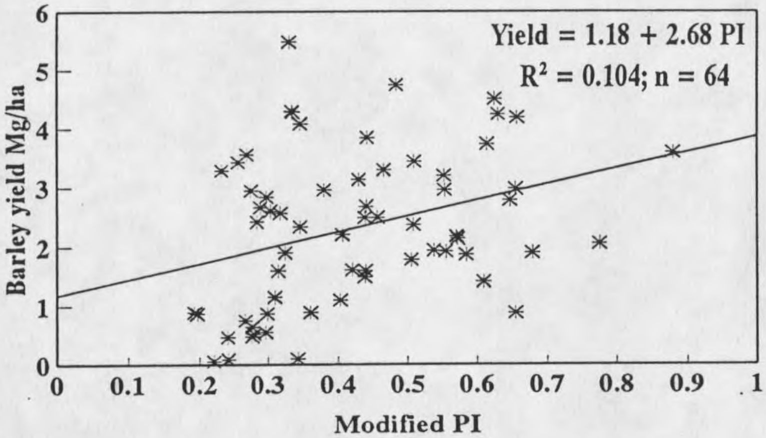
had R^2 increase from 0.37 to 0.43. The recropped field had R^2 decrease from 0.02 to 0.00. Regression line slopes, similar to the response of barley, became slightly more positive, with the exception of the recropped sites trial. Winter wheat showed virtually no response to the model modification.

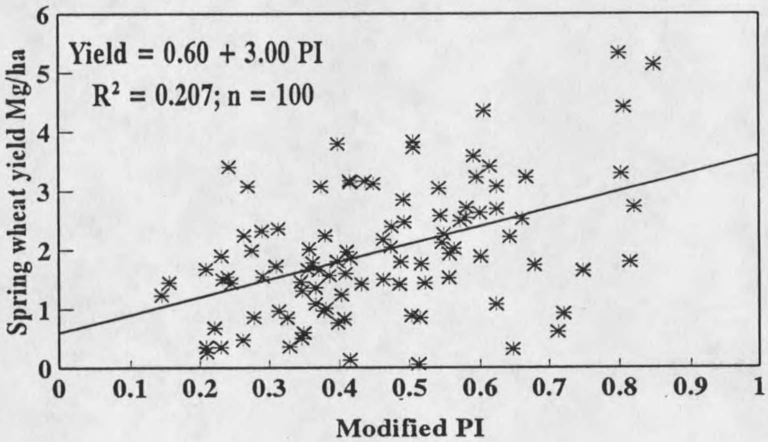
It appears that long-term averages as found in MAPS are insufficient to significantly improve the ability of the PI model to reflect annual yields and therefore, soil productivity. There is, perhaps, too much precipitation variability from year to year to use only long-term average climate data to predict the yields at a specific site. Nevertheless, some slight improvements were noted for barley, and three of four trials of spring wheat showed increased model performance.

<u>Averages Modified by Year</u>

By adding the temporal precipitation modification in the PI model, a modest, consistent improvement in model performance with regard to barley and spring wheat yields was achieved. Table 4 compares the three models, while Figures 7 to 10 show the actual scatter plots and regression lines for the second, final modification. Sample sizes for the second modification are slightly smaller than shown in Table 3 (n_1) because not every site has usable climate data.

In Figure 7, the barley, all sites trial R^2 increases to 0.10, with a more positive slope compared to the regression line from the previous models. Spring wheat, all sites, shows a strong improvement over the previous models with $R^2 = 0.21$, and a regression line with positive slope. Winter wheat has an R^2 of 0.00, and the regression





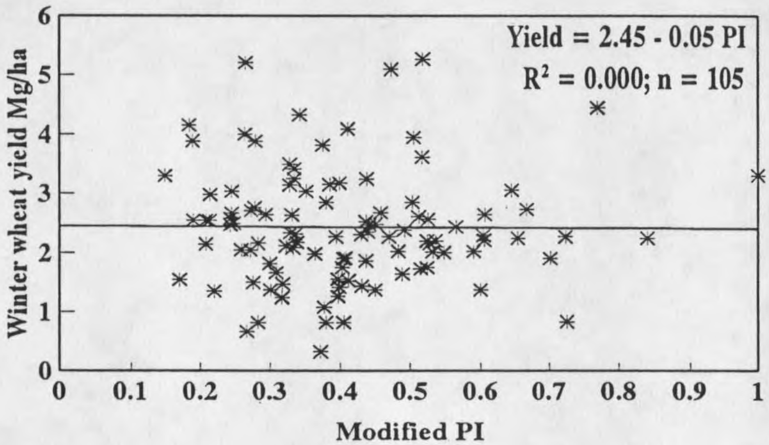


Figure 7. Small grain yields compared to PI modified for location and year for all sites.

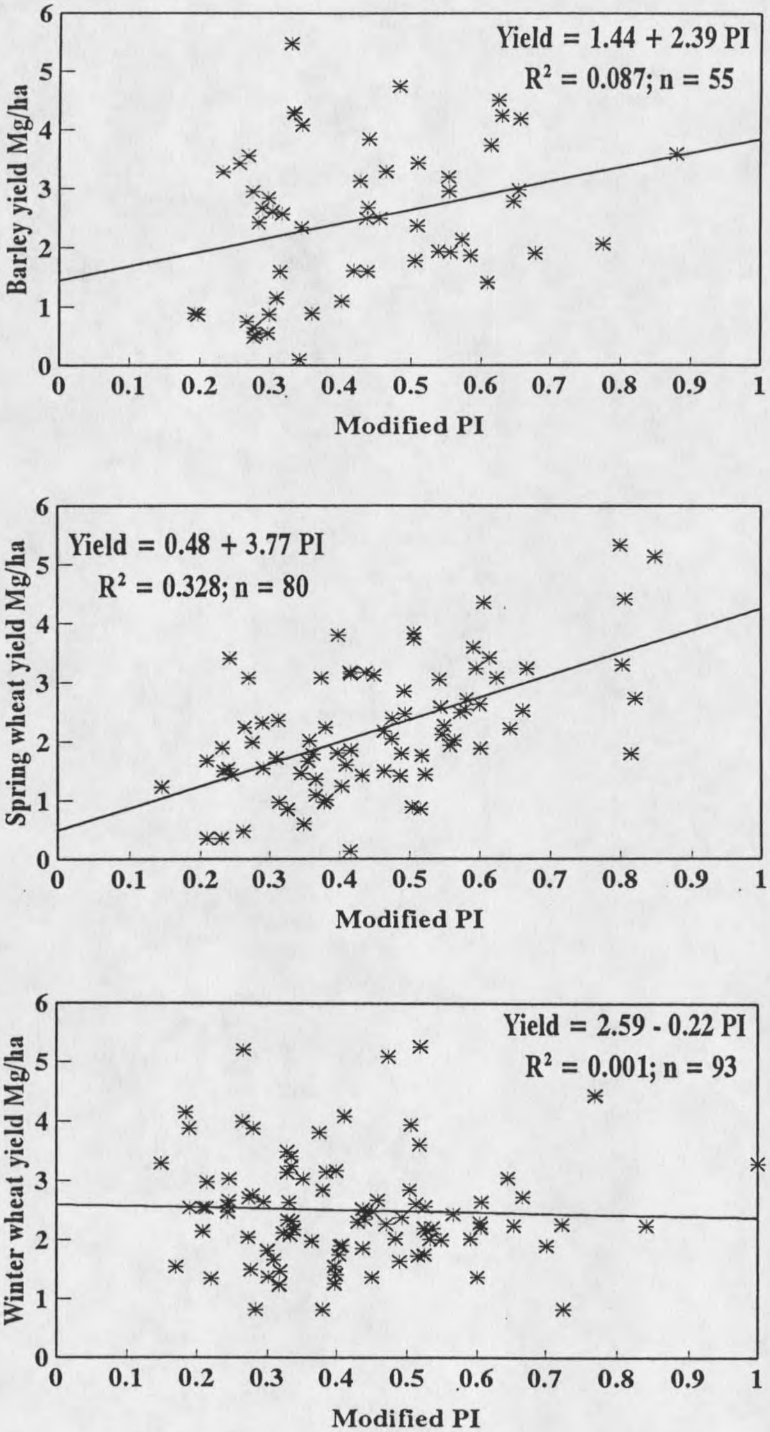


Figure 8. Small grain yields compared to PI modified for location and year for sites without severe damage.

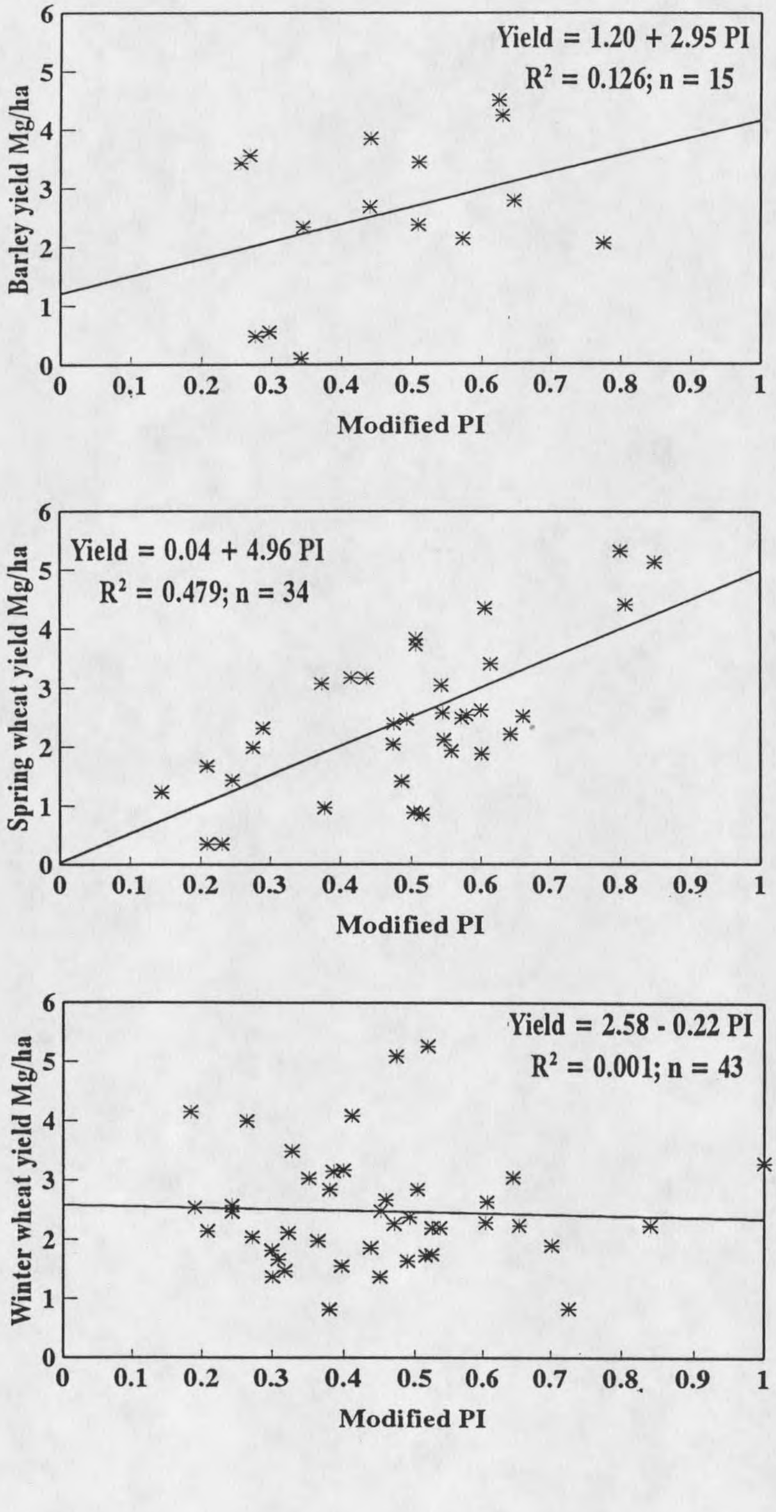


Figure 9. Small grain yields compared to PI modified for location and year for sites without severe damage, without low P, following a fallow year.

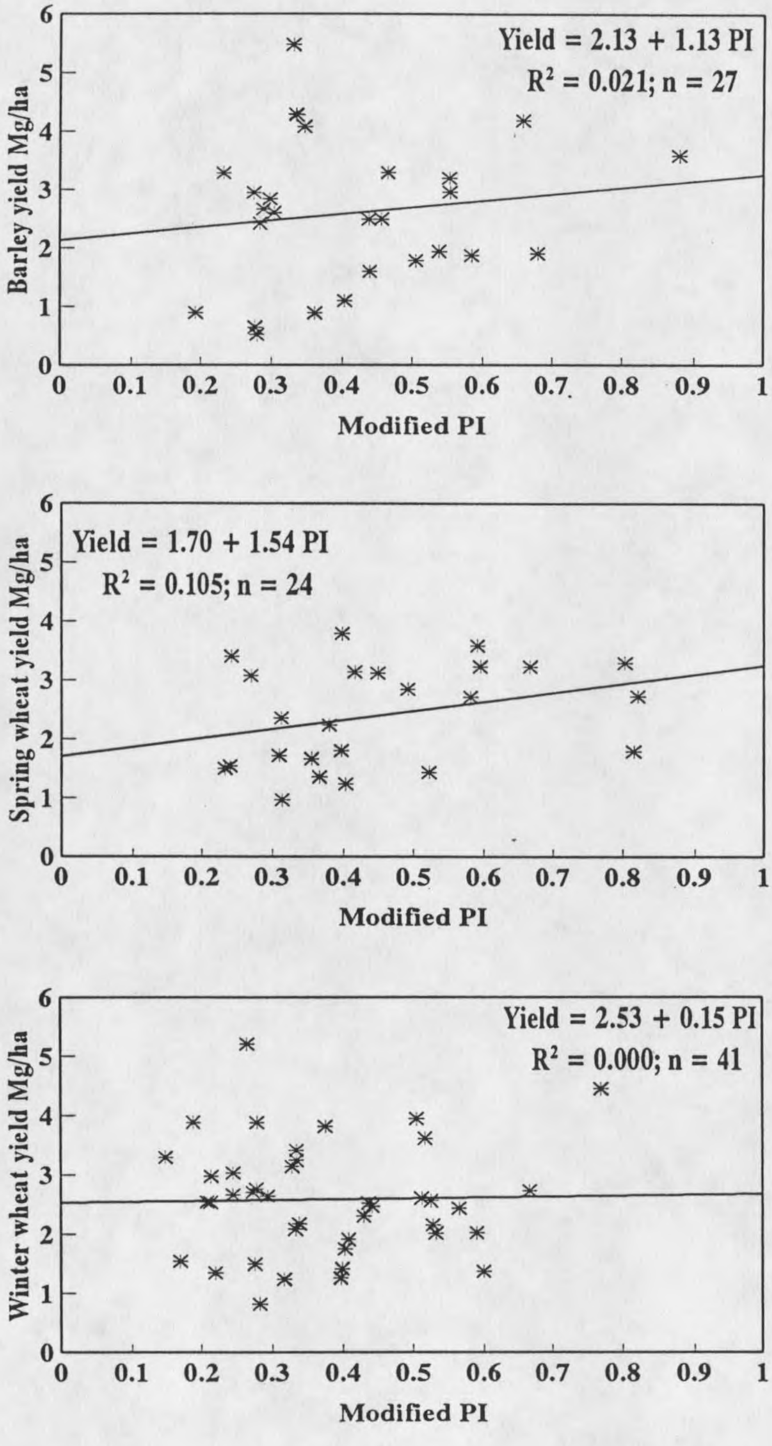


Figure 10. Small grain yields compared to PI modified for location and year for sites without severe damage, without low P, following a cropped year.

line is flat. Without removing damaged or low P sites, this improved model demonstrates dramatically how the annual water index improves model performance. Table 4 shows that barley, all sites, has a higher correlation than either of the previous models, even after the data sets were adjusted for inappropriate yields. Spring wheat yields, again, correlate the most with PI, and, again, winter wheat yields continue to be virtually unexplainable by the model.

Removing the damaged sites (Figure 8) from consideration has a mixed effect on model performance. Barley has little change. Spring wheat correlation increased 57% to $R^2 = 0.33$. Many low yield sites were removed, especially those with higher PI values, which increased the slope and correlation. Winter wheat showed no improvement.

In Figure 9, showing the trials with low P and damaged sites removed, following fallow, barley and spring wheat have the strongest correlations of the study. Barley has an R^2 of 0.13, spring wheat has an R^2 of 0.48. However, sample sizes are low at 34 and 15, respectively. Both regression line slopes are positive. The increase in correlation for these two grains is likely due to the removal of low P, which limits crop yield, and that summer fallow makes up for nutrient deficiencies as organic matter has time to mineralize and the profile is more likely to be charged with water. Winter wheat again has a negative slope and an R^2 of 0.00.

In Figure 10, the recropped yields show much poorer correlation with PI than the yields following fallow. Like the original model test of recropped yields (Figure 6), barley and winter wheat do not have a positive correlation with PI. The spring wheat trial has an R^2 of 0.11, the only recropped yield trial that demonstrates a positive correlation with the original or modified PI model.

By using the original PI value, adjusting it for annual and spatial differences of precipitation, including long-term averages of PET, and a factor for organic matter, the modified PI model more accurately portrays barley and spring wheat yields than the original model alone. However, the original PI model does not explain recropped small grain yields, or barley yields following fallow and winter wheat yields following fallow. The modified model is a step in the right direction, but raises the question, *"if the precipitation and PET variability of Montana could be completely controlled for, how accurately would the original PI model, consisting of bulk density, pH and AWC, explain small grain yields?"*

Recommendations for Future Research

Site PI Verification

This study used SIR records to calculate the original PI. The actual SCY sites were identified as to soil series, phase, and surface texture. The SIR database lists a range of values for pH, AWC and bulk density for each soil series phase. The PI model software uses the midpoint value for each range in calculating PI. This step introduces variation between the PI used in this study and a value that would be obtained if site specific data were available. The results in this study indicate that the modified PI model does not completely explain the small grain yields in Montana. The original PI equation is the backbone of the model. The question, *"would PI values,* *generated from data of on-site profile examinations, differ significantly from PI values generated using SIR data?*" ought to be answered. Lindstrom et al. (1992) found differences up to 27% between the PI values calculated from two data sources. Improvements in obtaining model parameters may need to be found, or else accurate yield estimates that match SIR in terms of climate and management generalization are needed. These are difficult to obtain given the current state of unreliability that Baker and Gersmehl (1991) found in county soil survey yield tables .

One practical method of comparing SIR generated PI values with site specific PI values is to gather soil profile data of the remaining sites in the SCY database. Each site where a soil pit is dug would relate to several years of previous yield data, providing an opportunity for comparing a site specific PI with the SIR generated PI, as well as testing both against yields. What results would have been obtained in this study if site specific PI values were available? Another method would be to generate PI values from SIR for the sites used in Sandor's (1989) study. Site specific PI values have already been generated for several fields, and could be compared with SIR values. Would his results differ much if only SIR data were employed?

Testing Management Variability

Another factor difficult to control for is management. Two hypothetical producers growing grain on adjacent fields of identical soil and climate conditions can make many different management decisions. These management decisions include fertilizer type, rate, placement and timing, planting time, seed variety, pest and stubble management, and use of available soil water. Different producers will differ in their response to the same weather forecasts and will have their own intuitive sense of the coming growing season. The variability in behavior leads to yield differences. Farmers operate in a volatile economic environment as well, and their management options are likely to reflect their budgets.

A long-term management factor would be a logical model parameter to consider. Perhaps it should be based on past performance of the producers, and the degree of economic limitation they are operating under. A producer with many years experience and a history of consistently growing optimum yields, with a flexible budget, would have a higher management sufficiency value than another producer who cannot perform as efficiently. Gathering the needed performance data would be challenging enough, without the potential strain on relationships between agricultural colleges, federal agencies and the farming community if management ability was estimated.

Annual Water Index Adjustment

The accuracy in using the annual water index to adjust MAPS data in estimating site specific precipitation should be determined and improvements made if possible. Accuracy of the annual water index could be compared with actual precipitation data available for a few SCY sites.

Long-term average MAPS data, adjusted with an annual water index is an improvement over MAPS data alone, particularly for spring wheat and barley.

However, using annual precipitation values that represent January to December precipitation does not reflect the water that the crops utilize. For example, the yield of a 1988 crop of recropped spring wheat would correlate more closely to precipitation that fell between harvest 1987 and harvest 1988 than total precipitation for 1988. The precipitation that arrived after harvest would be irrelevant to the crop. If spring 1988 was very dry, and fall 1988 exceptionally wet, the 1988 records may be average, but the crop may suffer from drought. Perhaps a more accurate approach would be to use September to August as the precipitation year for adjusting the MAPS long-term averages. Data processing would take more time in such a project, but the effort has the potential of improving model performance. Monthly precipitation data can be obtained from the National Oceanic and Atmospheric Administration Climatological Data publications. Winter wheat may require different climate considerations, and crops following fallow may need to take two years of precipitation, evaporation during fallow, and transpiration into account. Management also affects plant available water, because practices such as snow trapping, soil shading, weed suppression and cultivation directly influence soil water. Including an additional index for year to year variations in PET by developing annual PET estimates may also help the model explain crop growth.

Timing of Precipitation

Timing of precipitation may be more meaningful to small grain crops than the quantity of water. Heavy snow at planting time may shorten the growing season.

Frequent light rain throughout June and July might lead to record yields. Including a timing sufficiency that considers when precipitation occurs in relation to the crops' growth cycle may improve the relationship between PI and yield. One method of investigating this idea would be to use daily precipitation data, from the National Oceanic and Atmospheric Administration Climatological Data publications, to adjust MAPS precipitation data. The growth cycle of the crops would need to be monitored, perhaps with remote sensing, and a strategy devised to measure the deviation from optimum soil water for the crops during their growth. If the growth cycle is evaluated at the site, then rain gauges could be read at the same time.

PI Model Structure

The suggestions outlined above may allow compensation for climate and management variability. If and when those improvements are made, further work would need to be done to fine tune the sufficiency curves and weighting curve to more accurately reflect the biological realities of small grain crops in Montana.

CHAPTER 4

SUMMARY AND CONCLUSIONS

A productivity index model that accurately measures soil productivity in the semi-arid Great Plains would be advantageous to farmers and land managers. The ability to estimate productivity of land given several easily measured parameters would allow high productivity soils to be matched to appropriate land uses, would offer a method of monitoring and protecting soil productivity from decline due to erosion or other causes of degradation, would predict crop yields for fertilizer management, and aid in assessing fair land values.

The original PI model uses three soil parameters obtained or calculated from data in the SIR database: pH, bulk density, AWC, and a weighting factor to estimate soil productivity. Data sets for barley, spring wheat, and winter wheat were processed individually. Yields from all sites for each grain type were compared to original PI values. Three more trials were run for each grain type, with certain categories removed in order to more accurately control for climate and management variability. First, severely damaged yields were removed, then yields grown on soils with low soil test P, and then the yields were split depending on whether they were grown on fields following a fallow year or whether the fields were recropped. The correlation found between the original PI and Montana small grain yields was weak. The best correlation was with spring wheat following fallow (R^2 = 0.37). The other trials of spring wheat and other grains either had regression lines with negative slopes indicating a tendency for lower PI soils to produce higher yields, or did not correlate above an R^2 of 0.04.

A modified PI model incorporating SOM and climate data from MAPS was tested against measured yields. No appreciable improvement in model performance was found, except for the spring wheat following fallow trial (R^2 = 0.43, an increase of 16%). A further modification that adjusted long-term average precipitation with an annual precipitation index derived from data from nearby weather stations improved model performance for all four trials of spring wheat (R^2 = 0.11 to 0.48) and all four trials of barley (R^2 = 0.09 to 0.13).

Three earlier studies also compared the original PI model with small grain yields. Pierce et al. (1984), Sandor (1989) (also Wilson et al. (1991)), and Gerhart (1989) (also Wilson et al. (1992)) obtained average R^2 values of 0.67, 0.49, and 0.32 respectively. These values compare reasonably well with the spring wheat following fallow trial (R^2 = 0.37). However, all recropped yields and barley and winter wheat following fallow had no positive correlation with PI greater than an R^2 of 0.05.

Each of the earlier studies made different biologically justifiable modifications, and increased average correlation (R^2 = 0.85, 0.70 and 0.57, respectively). In this study, the final model modification increased correlation in the spring wheat following fallow trial 30% (R^2 = 0.48), comparing fairly well with the earlier studies. However, the barley following fallow trial also increased, but only to an R^2 of 0.13, and the recropped spring wheat trial increased to an R^2 of 0.11. These two results illustrate the difficulty in accounting for yield variation in Montana. Furthermore, winter wheat had no positive correlation, and neither did recropped barley. Whereas the earlier studies had fairly uniform results over their different trials, in this study, the trial with the best results compared fairly well, but the majority of the trials had very slight correlation between PI and yield.

The results presented in this study suggest that further refinements of the precipitation data could improve the correlation between a future model's PI values and yield. There is no question that tremendous variability in small grain yields occur in Montana. This variability is due to differences in soil properties, management practices and climatic conditions, and also in part to unknown factors and interactions, and biological variation. The SCY database has dramatically illustrated that variability. The original PI model explains only a small part of that variability in the semi-arid Montana environment. The second modification to the PI model indicates that research is proceeding in the right direction, though not yet improved enough for wide use by land managers and farmers. A future model may help land managers and farmers predict the ability of a soil to produce small grain crops, make more intelligent economic and conservation decisions, and monitor long-term soil productivity.

Management Variability

Montana farmers represent a diverse group of people. They differ in their skill level, experience and knowledge. Although presumably all farmers are trying to stay in business, they have different objectives, and there are different strategies to obtain them. Each farmer devises an economic survival strategy that includes generating enough income from crop yields amid price fluctuations, long-term land management, input cost control and various government programs. The variety of farmers and their circumstances, coupled with the tremendous spatial and temporal variability in precipitation, leads to highly variable yields. Whereas farmers may know what the ideal yields for their fields are, that target may only be reached once every five to ten years. Thus, the farmers need to be able to withstand the lean years and wisely use their income from plentiful years.

This story is richly illustrated in the SCY database, where extreme ranges of management are documented. For example, soil test levels of nitrogen in the top 61 cm of soil, range from 1.7 to 460 kg ha^{-1}. Soil test P levels range from 1.6 to 149 ppm in the plow layer. These soil fertility levels result in part from different fertilizer practices which also have wide ranges, 0 to 123 kg N ha^{-1}, and 0 to 103 kg P_2O_5 ha^{-1}. Most sites have evidence of root growth to at least 152 cm, but some only have roots to 57 cm. Due to the fluctuating climate, planting time in spring ranges from March 17 until May 20 for barley and spring wheat. Farmers choose different row spacing, anywhere from 15 cm to 51 cm, and plant anywhere from 28 to 130 kg ha^{-1} of seed. Soil chemistry varies too, with pH values ranging from 5.4 to 8.7. With the variety of conditions and management styles in Montana, the difficulty in indexing soil productivity becomes evident.

Farmers may be interested in the range of these characteristics found throughout Montana. Periodic soil testing is important in order to understand N and P levels particularly. Some farmers may be unaware of their low N and P levels. Others have far more N than can be used by the plants and are placing their ground water quality unnecessarily at risk. Other farmers may be unaware of their soil pH and may want to consider applying lime, for the more acidic soils, and fertilizers with acidic qualities to the more alkaline soils.

SCY Database Validity

Critics may take issue with the validity of the SCY database. The data set contains uneven distribution of records over the six years in the study. The combined number of data records for the first two years of the study is essentially equal to the combined number of records in the last four years. Nevertheless, it is unlikely that an even number of records for each year would have changed the results. The causes of variability between PI and yield, and between yields from different years would still remain.

One source of variability in SCY is due to the difficulty in sampling soil series every year that follow a crop-fallow rotation. In the original PI trial, nearby fields of the same soil series were considered the same site and averaged together, but they could differ considerably in terms of soil characteristics, management and landscape characteristics. It is unlikely that the poor model performance of the original PI model was due to the averaging of yields.

Certainly the database has some error in it. Many different people are involved in data collection, with different education, training, and time to devote to accuracy. Each SCS Field Office receives most of the management data from several different operators, who may or may not be accurate in their reporting due to their record keeping, poor memory, or hesitancy to be candid with a government agency. Reliable soil test information is dependent on Field Office personnel accurately locating the site and labeling it correctly. Soil testing lab personnel transcribe the sample numbers, run the tests and log the results. Again, these results are entered into the database. At harvest time, SCS Field Office personnel harvest representative rows from the three sites. A subjective decision locates and identifies the sample site, and the correct harvest is dependent on correct understanding of row spacing and good measurement technique. Most of the grain is sent to Agricultural Experiment Stations for threshing, weighing and recording. In this project, much effort has been made to insure the quality of the data. Certainly higher standards of quality control could be employed, but the cost of the study could rise by an order of magnitude or two. It is the opinion of this researcher that even if this kind of investment was made in the SCY database, very similar results to the ones in this study would be found. The large sample size of the SCY database is perhaps the strongest assurance that any error it may contain does not significantly distort the results.

LITERATURE CITED

Baker, B.D. and P.J. Gersmehl. 1991. Temporal trends in soil productivity evaluations. Prof. Geog. 43(3): 304-318.

Barrow, C.J. 1991. Land degradation: Development and breakdown of terrestrial environments. Cambridge Univ. Press. Cambridge, Great Britain.

Brown, P.L. and G.R. Carlson. 1990. Grain yields related to stored soil water and growing season rainfall. Montana Agric. Exp. Sta. Report 35.

Burnett, E. and R.J. Hanks. 1981. Semi-arid and arid regions: Conservation needs and technology on agricultural land. *In* W.E. Larson, L.M. Walsh, B.A. Stewart and D.H. Boelter [eds.] Soil and water resources: Research priorities for the nation. Soil Sci. Soc. Am. Madison, WI. pp. 41-61.

Caprio, J.M. and G.A. Nielsen. 1992. Climate atlas of Montana. EB 113. Montana State Univ., Bozeman.

Crosson, P.R. 1983. Productivity effects of cropland erosion in the United States. Resources for the Future, Inc. Wash., D.C.

Dudal, R. 1981. An evaluation of conservation needs. *In* R.P.C. Morgan [ed.] Soil Conservation: Problems and prospects. Wiley and Sons. Chichester, Great Britain. pp. 3-12.

Flach, K.W., and C. Johannsen. 1981. Land: Resource base and inventory. *In* W.E. Larson, L.M. Walsh, B.A. Stewart and D.H. Boelter [eds.] Soil and water resources: Research priorities for the nation. Soil Sci. Soc. Am. Madison, WI. pp. 21-40.

Gerhart, K.E.S. 1989. Evaluating the performance of the soil productivity (PI) model in Cascade County, Montana. M.S. thesis. Montana State Univ., Bozeman.

Gerhart, K.E.S and J.P. Wilson. undated. Instructions for running PI model at Montana State University. Departmental document. Department of Earth Sciences. Montana State Univ. Bozeman.

Huddleston, J.H. 1984. Development and use of soil productivity ratings in the United States. Geoderma. 32: 297-317.

Lal, R. 1988a. Soil erosion by wind and water. *In* R. Lal [ed.] Soil erosion research methods. Soil and Water Con. Soc., Ankeny, IA. pp. 1-6.

Lal, R. 1988b. Monitoring soil erosion's impact on crop productivity. *In* R. Lal [ed.] Soil erosion research methods. Soil and Water Con. Soc., Ankeny, IA. pp. 187-200.

Larson, W.E., G.R. Foster, R.R. Allmaras, and C.M. Smith [eds.] 1990. Proceedings of soil erosion and productivity workshop. Univ. of Minn., St. Paul, MN. p. xi-xvii.

Lichthardt, J.J. and J.S. Jacobsen. 1992. Fertilizer guidelines for Montana. EB 104. Montana State Univ., Bozeman.

Lindstrom, M.J., T.E. Schumacher, A.J. Jones, and C. Gantzer. 1992. Productivity index model comparison for selected soils in North Central United States. J. Soil Water Con. 47(6): 491-494.

Meyer, L.D., A. Bauer, and R.D. Heil. 1985. Experimental approaches for quantifying the effect of soil erosion on productivity. *In* R.F. Follet and B.A. Stewart [eds.] Soil erosion and crop productivity. Am. Soc. Agron., Crop Sci. Soc. Am., and Soil Sci. Soc. Am. Madison, WI. pp. 213-234.

Montana Agricultural Statistics Service. 1987. Montana Agricultural Statistics. Volume 24. October 1987. Helena, MT.

Montana Agricultural Statistics Service. 1988. Montana Agricultural Statistics. Volume 25. October 1988. Helena, MT.

Montana Agricultural Statistics Service. 1989. Montana Agricultural Statistics. Volume 26. October 1989. Helena, MT.

Montana Agricultural Statistics Service. 1990. Montana Agricultural Statistics. Volume 27. October 1990. Helena, MT.

Montana Agricultural Statistics Service. 1991. Montana Agricultural Statistics. Volume 28. October 1991. Helena, MT.

Montana Agricultural Statistics Service. 1992. Montana Agricultural Statistics. Volume 29. October 1992. Helena, MT.

Neill, L.L. 1979. An evaluation of soil productivity based on root growth and water depletion. Univ. of Missouri-Columbia, Department of Agronomy, M.S. Thesis.

Nielsen, G.A., J.M. Caprio, P.A. McDaniel, R.D. Snyder, and C. Montagne. 1990. MAPS: A GIS for land resource management in Montana. J. Soil Water Con. 45(4): 450-453.

Osman, H.F. 1988. Soil productivity (crop yield) data acquisition and analysis methods for Montana soil series. M.S. thesis. Montana State Univ., Bozeman.

Pierce, F.J., W.E. Larson, R.H. Dowdy, and W.A.P. Graham. 1983. Productivity of soils: Assessing long-term changes due to erosion. J. Soil Water Con. 38(1): 39-44.

Pierce, F.J., R.H. Dowdy, W.E. Larson, and W.A.P. Graham. 1984. Soil productivity in the Corn Belt: An assessment of erosion's long term effects. J. Soil Water Con. 39(2): 131-136.

Poincelot, R.P. 1986. Toward a more sustainable agriculture. AVI Pub. Co., Inc. Westport, CT.

Rijsberman, F.R. and M.G. Wolman. 1985. Effect of erosion on soil productivity: an international comparison. J. Soil Water Con. 40(4): 349-354.

Sandor, S.P. 1989. A productivity index model for Montana soils. M.S. thesis. Montana State Univ., Bozeman.

Schultz, T.W. 1984. The dynamics of soil erosion in the United States. *In* J. Baden [ed.] The vanishing farmland crisis. Univ. Press of Kansas. Lawrence, KS. pp. 45-57.

Soil Survey Staff. 1975. Soil Taxonomy: A basic system of soil classification for making and interpreting soil surveys. USDA-SCS Agric. Hdbk 436. U.S. Govt. Printing Office, Wash., D.C.

Spencer, L.A. 1990. Dryland cereal grain yield relationships with soil, environmental, and crop management factors in Montana. M.S. thesis. Montana State Univ., Bozeman.

Steiner, F.R. 1990. Soil conservation in the United States: Policy and planning. The John Hopkins Univ. Press. Baltimore, MD.

Williams, J.R., C.A. Jones, and P.T. Dyke. 1984. A modeling approach to determining the relationship between erosion and soil productivity. Trans. Am. Soc. Agric. Eng. 27(1): 129-144.

Wilson, J.P., S.P. Sandor, and G.A. Nielsen. 1991. Productivity index model modified to estimate variability of Montana small grain yields. Soil Sci. Soc. Amer. J. 55(1): 228-234.

Wilson, J.P., K.E.S. Gerhart, G.A. Nielsen, and C.M. Ryan. 1992. Climate, soil and crop yield relationships in Cascade County, Montana. Appl. Geog. 12: 261-279.

Winkelman, L.J., W.A.P. Graham, W.E. Larson, F.J. Pierce, and R.H. Dowdy. 1984. A program to display the effects of erosion on soil productivity. (Revision 3). St. Paul: Univ. of Minn. Dept. of Soil Science and USDA Agric. Res. Svc.