Agricultural Economics Report No. 345 1995

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Introduction

Crop insurance underwriters seek to price multiple peril crop insurance policies according to farmers' probabilities for yield loss, thereby reducing their firm's risk exposure to adverse selection. However, identifying the risk quality of various farm units is a complex task given the variety of agronomic methods farmers use.

In practice, underwriters evaluate a farm's risk quality using several approaches that range from highly subjective, informal methods to scoring devices based on sophisticated statistical analysis of the farmer's production history. Simple comparisons of a farm's yield history with peer farms in a given geographic area is the most common method of determining risk quality. Historical information on weather trends, especially patterns of hail and frost damage, supplement these yield deviation methods.

However, several additional characteristics of a farm unit may be linked, ex ante, to each farmer's probability of yield loss. Such characteristics may encompass seeding rates, fertility expense, management effort expended, and even the financial leverage of the farm operator. These farm characteristics can be referred to as risk quality factors. These major attributes of a farm operation must be appraised if potential adverse selection and moral hazard risks of crop

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insurance are to be minimized. Implementing such a risk-scoring procedure would broaden and diversify the scope of insured farms which comprise the risk pool.

The objective of this research was to develop a crop insurance risk assessment model by incorporating the agronomic, economic, and demographic characteristics of farm operations. Time series and cross-sectional record data from farm management services in Illinois and North Dakota, respectively, were used for the analysis. A survey of North Dakota farmers elicited soil productivity information to complement the analysis. The outcome of the modeling effort was a risk assessment tool that may serve several purposes: (1) distinguish between good and bad insurance risks; (2) evaluate risks for new applicants with minimal production history; (3) match premiums with expected yield variability; (4) identify insurance situations warranting increased monitoring, supervision, and control; and (5) assist in examining the quality of an underwriter's insurance portfolio.

Related Literature

In general, insurance is the pooling of many risks from diverse situations in order to reduce risk for the combined group. As the pool becomes larger, losses also can be predicted with more precision so that actual losses stay close to predicted losses. Crop insurance protects against economic loss from adverse events affecting the insured crop. Only those events and crops with a minimum opportunity for moral hazard and adverse selection are insurable (i.e., are actuarially sound). Moral hazard arises when the individual being insured has sufficient incentive to allow a preventable loss or to purposefully cause a loss. Adverse selection arises when there is a sufficient asymmetric information advantage so that the individual being insured can predict losses better than the insurer.

Moral Hazard

The moral hazard problem associated with individual crop insurance coverage has been documented (Chambers; Vandeveer and Loehman; Vercammen and van Kooten). To overcome the problems of moral hazard associated with individual farm-yield insurance plans, several alternative approaches have been proposed (Miranda; Skees and Reed; Carriker et al.). One alternative, based on the area-yield concept, that has received considerable attention is the Group Risk Plan (GRP) (Skees and Reed).

The GRP is based on the concept of group risk rather than individual risk. By making the group large enough that any one individual within the group cannot affect the outcome, the potential for moral hazard problems is avoided. In addition to reducing moral hazard, area-yield insurance would substantially reduce administration costs because individual production histories would not be required to record and verify.

The GRP is being tested as a pilot program covering a few crops in a small geographic area. Those farms whose yield variability do not track closely to the county average are encouraged to maintain individual coverage because indemnities are paid only if the group as a whole suffers a loss. Under current design, the group consists of all producers of that commodity within the county, making GRP an ideal product for widespread catastrophic loss. The group as a whole could suffer sufficiently that each insured unit would receive an indemnity payment and have one or more insured units who suffered no loss. The owners of these units would have their normal crop to sell and would also collect an insurance payment. Conversely, an individual within the group could be insured, suffer a loss, and not receive an indemnity payment because the group as a whole did not experience a sufficient loss to trigger payment. Consequently, many lenders will not accept GRP insurance as collateral, thus limiting its attractiveness to their borrowers.

Adverse Selection

Problems of adverse selection in crop insurance programs were documented decades ago (Halcrow; Lee). Present crop insurance programs are not actuarially sound because of the inability to tailor coverage to individual-yield-loss experience (Miranda). In principle, area-yield insurance is superior to individual farm-yield insurance because it reduces moral hazard, but is rather intractable in practice and may induce adverse selection. Under individual coverage plans, Goodwin found that the sole use of average yields to indicate probability of loss may result in adverse selection. This occurs because the relationship between average yield and yield distribution is tenuous; and hence, little can be known about the probability of loss among farms with the same average yield. Therefore, a more beneficial means of predicting expected risk would be a direct measure of yield variability (Goodwin).

A common assumption in rating crop insurance is that yields are normally distributed with standard deviations equal to 25 percent of the mean of a particular distribution (Botts and Boles; Driscoll). This method has been criticized because coefficients of variation do not remain fixed across crops or across aggregated groups of the same crop, and perhaps a calculated measure of variation should be used to classify farms instead of average yields (Skees and Reed; Goodwin). Although the coefficient of variation describes well the instability about the mean of a data group, it is not a good measure of the riskiness of an activity (Fleisher). Risk can be both the possibility of gain or loss; however, it is the possibility of loss (downside risk) that is of concern in selecting and rating insurance. Furthermore, if the assumption of normal distribution of yields is relaxed, coefficient of variation becomes even less useful in measuring risk (Goodwin; Nelson).

In addition to an improved measure of yield variability, other farm characteristic information may improve the risk rating of crop insurance. Goodwin suggested and tested "... whether observable farm characteristics could be used to improve measurement of yield risk in rating insurance." By measuring risk with the coefficient of variation and regressing it upon individual farm characteristics, such as size and chemical use, Goodwin was able to grant "... a degree of support for current FCIC practices that apply discounts for farms with higher average yields." This support was based on his results that show a significant inverse relationship between average yield and coefficient of variation.

Classification Procedures

The methodology of applying classification procedures to farmer-attributed data to limit risk from adverse selection has been applied to problems in agricultural lending with considerable success. Objective statistical methods for evaluating farm borrowers have been proposed since the 1960s. Betubiza and Leatham, and Chhikara provide excellent summaries of this research. Agricultural credit assessment models have been used to evaluate potential borrowers (credit screening) and to evaluate existing borrowers (credit scoring). Credit screening and credit scoring require two different approaches. Credit screening relies on information from the initial loan application to discriminate between loans which are expected to be successful (Reinsel and Brake; Bauer and Jordan; Evans; Dunn and Frey). Credit scoring relies on recent financial information to identify variables which indicate the quality of unmatured loans (Johnson and Hagan; Hardy and Weed; Lufburrow, Barry, and Dixon; Turvey). Credit scoring analyses are most suitable for periodic evaluations of portfolio quality and loan pricing. Ellinger, et al. reported about present lender usage of credit scoring concepts.

Quality assurance decisions related to risk management in banking are similar to those in the insurance industry. Lenders utilize methods of credit assessment for two purposes. First, credit customers are screened by their risk characteristics to determine if they are worthy of receiving credit. Credit applicants are rated, and ratings are compared to a predetermined index. If the rating is above a minimum level, the applicant is accepted for a loan. Second, if they are determined to be credit worthy, the interest rate (price) that is applied to their loan is based on the amount of risk each customer represents.

Research on credit granting has applied classification procedures to customer attributes and developed classification models to assign group membership (Srinivasan and Kim). Customer group classifications can include acceptable with minimal loan supervision, acceptable with regular supervision, questionable, and unacceptable (Kohl). Credit scoring of this type is not meant to circumvent subjective loan evaluation, but should be used in conjunction with a lender's own knowledge of borrower characteristics (Baltezore and Gustafson). However, the benefits engendered to banks from developing and using credit scoring models include improved support for loan acceptance decisions, more equitable loan pricing, monitoring of existing loans, and quality appraisals of loan portfolios (Ellinger).

The crop insurance industry faces similar tasks. First, underwriters must determine which policies to hold. Second, they must price policies commensurate with the perceived risks involved. Insurance applicants are selected and classified based on their individual downside yield variability. Agents and companies must decide if the applicant is an acceptable risk based on the applicant's risk score. After the applicant has been selected for insurance, the rating process begins.

Insurance companies must classify and select applicants to remain competitive and to reduce adverse selection. Webb, Harrison, and Markham explained:

> The insurer must actively select those applicants it desires to insure. Otherwise, prospective policyholders will purchase the insurer's products at bargain prices relative to their exposure to loss. The selection process enables the insurer to ration its available capacity to obtain the optimum spread of loss exposures by geographic distribution, class, and line of business.

Multi-variate procedures of risk scoring have only recently been applied to crop insurance. Calvin examined farmer's demand for Federal multi-peril insurance. By applying logit analysis to respondents of a USDA's Farm Cost and Returns Survey, she found that crop insurance and other risk-management strategies were considered substitutes. However, because no policy level data were available, her study was limited by a "lack of data on individual yields and policies (which) prevent addressing the issue of adverse selection as a determinant of participation."

This purpose of this study was to identify farm production and management characteristics of individual farmers that could be used to develop a risk-screening tool similar to that used in agricultural lending. Thus, an improved classification procedure was developed.

Theoretical Development

Under present individual crop insurance plans, policy income (π_f) at the farm level can formally be expressed as:

$$\Pi_f = \sum_{c=1}^{n} \left[\max\left[0, P_c(HY_c \cdot LD_c - AY_c - IP_c^{FCIC})\right] \right] \tag{1}$$

where

c denotes each crop on the farm,
P_c is the indemnity price election for crop c,
HY_c is the insured yield of crop c,
LD_c is the insured portion of crop c (1 - percent deductible),
AY_c is the actual yield of crop c, and
IP_c^{FCIC} is the crop-specific insurance premium set by FCIC.

Further, IP_c^{FCIC} is assumed to be equal to the actuarially fair crop-specific insurance premium, IP_c* which is exactly equal to expected indemnities such that

$$IP_c^{FCIC} = IP_c^* \equiv \text{expected indemnities} \tag{2}$$

Under current FCIC actuarial procedures, this assumption of equality in equation (2) may not hold, causing low-risk farmers to be overcharged and high-risk farmers undercharged. For IP_c^{FCIC} to be actuarially fair, average yields must accurately reflect the likelihood of loss. There is considerable evidence (Goodwin; Skees and Reed; Nelson) that this relationship is extremely weak. Consequently, moral hazard and adverse selection problems are not avoided, allowing for asymmetric information where the insured has superior knowledge to the writer of the policy about the impending probability of low yield. To further understand why IP_c^{FCIC} is not actuarially fair, reviewing how IP_c^{FCIC} is determined is helpful.

In practice the premium charged on an individual insurance unit is established by a two-step process (Goodwin). The first step is to establish a county-wide span of rates (CR) for the crop, and the second step is to classify the individual unit (IUC) as to which specific rate in the span applies. Thus, the insurance premium set by FCIC, IP_c^{FCIC}, can be expressed as:

$$IP_c^{FCIC} = f(CR, IUC) \tag{3}$$

where

CR = the span of county premium rates, and
IUC = the individual unit risk classification.

Moreover the county rates or first step can be expressed as:

$$CR = f(clf, cy, ps, lr) \tag{4}$$

where

CR = the span of county premium rates,
clf = catastrophic loading factor,
cy = county average harvested yield,
ps = proportional spanning of risks, and
lr = legal requirements.

The catastrophic loading factor is determined by evaluating the 20-year loss history for a given county. The largest losses are grouped in a pool and spread across the entire state. A smoothing procedure is applied to reduce the possibility of large differences in insurance rates for neighboring farms. This smoothing and loss-spreading practice may induce adverse selection because low-loss-risk counties are penalized because they share the risk of high-risk counties.

The historical county average yields also impact county rates. Rates are inversely adjusted with the NASS yields so that counties with low average yields are assigned higher rates than counties with high average yields.

Once the loss history and historical county average yields have been evaluated, the county rate is spread over a span of nine discrete risk categories using a proportional spanning procedure. These categories or R-spans are inversely related to average yield so that high yields are assigned a lower risk category than are low yields.

Federal regulations also impact the county rates. These regulations cap annual rate increases at 20 percent maximum, and cups yield decreases at 5 percent, thus reducing the flexibility of rate adjustments.

The second step or classification of the individual unit can be expressed as:

$$IUC = f(APH) \tag{5}$$

where

IUC = individual unit classification, and
APH = actual production history.

The IUC is used to classify the unit to determine which of the nine R-spans apply. The classification is determined by the actual production history (APH) of the farm. A minimum of four years (and maximum of ten years) of actual yields are needed to verify the APH. A procedure of using weighted ASCS program yields as a proxy to determine a transitional yield

(T-yield) is followed for farms with less than the four years of required historical farm yield data. The premium charged depends on the R-span for which the unit qualifies.

As discussed in the review of literature, these procedures for determining premium rates do not adequately address the problem of adverse selection. In fact, the Botts and Boles assumption that yields are normally distributed with a constant standard deviation of 25 percent across all crops and all yields could encourage participation by high-risk farmers because their premiums are artificially discounted. Because the historical average yield of a unit is not a perfect predictor of expected loss, average yield cannot alone adequately determine the risk classification of the unit.

Other easily observable characteristics beyond production history can be identified and may more accurately represent the risk class of a farm than the sole use of average yields. For example, the actuarially fair insurance premium can be expressed as:

$$IP_c^* = f(AGR,DEM,ECON) \tag{6}$$

where

AGR represents various agronomic variables on the farm,
DEM represents certain demographic variables associated with the farm operator, and
ECON is the economic and financial characteristics associated with the farm operation.

Statistical verification of this relationship may improve risk classification of individual units. Consequently, premiums charged would be more actuarially sound than current premium setting procedures because of the additional information.

The farm-level agronomic, demographic, and economic characteristics represented in equation (6) consist of the variables listed in Table 1. Agronomic variables consist mainly of crop production expense variables that represent how individual farm managers use inputs. A higher level of use of these variables may reduce downside risk.

Demographic variables (including age of the farm operator and soil productivity of farmland) contain information about individual farm operators and the operating environment in which they work. A more conducive operating environment was believed to foretell less downside risk. Mature farm operators were proposed to have greater experience in dealing with various production situations that may threaten yields. The productive capacity of the farmer should increase and the variability of production should decrease as the quality and fertility of the farm soil increases.

Economic variables contain information about the farm's financial efficiency and profitability. These variables provide information about the farm's financial and business position. This set of variables was postulated to allow the important relationships between financial and business performance and yield performance to be delineated.

Model Construction

The hypothesis of this study was that farm production and management characteristics can be related to yield performance. While prior management studies (Sonka and Thorpe) have identified the business characteristics of high-performing farm operators, they have not related these business characteristics exclusively to classifying yield performance. In this study, three criteria were used to measure yield performance. One criterion developed was based on the coefficient of variation (CV) as the dependent variable. Another criterion used was the observed probability of yields falling below a coverage level yield. The third performance criterion was the loss ratio.

Coefficient of Variation Model

The first model developed was based on the coefficient of variation (CV) as the dependent variable. The coefficient of variation is often used in risk analysis because it provides a basis for comparison when the expected returns of two alternatives are not the same. The coefficient of variation is expressed as:

$$CV = \frac{\sigma}{\mu} \tag{7}$$

where:
σ = standard deviation of yield
μ = expected yield or average yield.

All analyses for this model are on a per acre basis.

Probability of Loss Model

The second performance criterion used was the observed probability of yields falling below a coverage level yield. This analysis differed from that using the coefficient of variation (CV) as the dependent variable in a very important way. Coefficient of variation analysis assumes a normal distribution of yields in the absence of knowing the exact distribution, which implies that the probability of a below-average yield is equal to the probability of an above-average yield. However, there is sufficient evidence to support the assertion that yield data may not be normally distributed, but in fact is skewed (Vandeveer and Loehman; Gallagher; Nelson; Goodwin). This creates a condition where the probability of an above-average yield is not equal to the probability of a below-average yield.

When a normal distribution is assumed, crop insurance risk is overestimated if the actual distribution is positively skewed (mode < mean) and underestimated if the actual distribution is negatively skewed (mode > mean). The more critical of the two is negative skewness because that is the case where insurance coverage is underpriced and adverse selection is encouraged. For this reason, yield performance that is below average or to the left of the mean is of more importance than above-average performance. Moreover, not having sufficient data on individual farmers to determine the actual distribution of each yield necessitated developing an alternative procedure to measure their performance.

The observed probability of loss was calculated with the following formula:

$$\rho((AY_i - HY) < 0) \tag{8}$$

where

AY_i = the actual yield realized in year i, and
HY = the insurance guaranteed coverage in crop units.

The yield guarantee was calculated as 65 percent of the maximum of either the mean farm level yield or the county average for the year of insurance. The 65 percent coverage level was chosen because it has been the most popular coverage level selected by purchasers of Federal crop insurance. The system used to calculate yield guarantees was developed to approximate the current actual production history method of calculating average farm level yields. Analyses for this model were performed on a whole farm rather than a per acre basis.

Loss Ratio Dependent Variable Model

A loss ratio (LR) measure of crop insurance performance at the crop level for each producer was calculated by dividing the cumulative indemnity paid to the producer on that crop by the cumulative premium:

$$LR = \frac{\sum_{i}^{n} Indemnity_{i}}{\sum_{i}^{n} Premium_{i}} \tag{9}$$

where:

LR = loss ratio, and
i = individual farm operation.

This measure, called the loss ratio, is a commonly used measurement in the crop insurance industry. The crop loss ratios were used as dependent variables and were regressed against the independent variables from the farm level data set on a whole farm basis.

Procedures

To improve classification and selection of crop insurance applicants these methods were established to capture yield variations as demonstrated in equations (7)-(9). Once these measures were established, regression analysis was performed to estimate relationships between agronomic, demographic, and economic characteristics of farms to those yield histories.

Models for North Dakota and Illinois were developed to explain yield variations among farmers. North Dakota data emphasized small grain and cross-sectional relationships, whereas Illinois data were primarily used to investigate row crop and time-series relationships. Information was not available to construct models based on crop insurance history.

The results of these models were used to develop a risk quality measurement tool. This tool formulates an index that rates the importance of each risk quality factor. The index can be compared to a chart of index numbers that indicate cutoff points for varied risk levels. The data used to develop and verify these models are discussed in the next section, and the models are presented in the two subsequent sections of this report.

Data Sources

Illinois

The Illinois Farm Business Farm Management Association (FBFM) data set contains records for 7,200 farms. These records include detailed information about the farm business, such as revenue, yields, expenses, and tenure information and were screened by the association's professional field staff to eliminate incomplete files. In 1992, 3,700 farm records were considered usable, i.e., the record was complete enough for statistical analysis. However, only 1,401 farm records were classified as usable from 1982 through 1992.

The FBFM collects data on farm balance sheets. Completed balance sheets were available for 313 of the 1,401 farms from 1988 through 1992. The agronomic data from the

1,401 farms with 11 years of data were analyzed, and the combined agronomic and financial data were analyzed for the subset of 313 farms with 5 years of completed records.

The Illinois FBFM data set was constructed from information gathered from members of the association. Therefore, it is not a random sample of Illinois farms. The FBFM farmers are compared to National Agricultural Statistical Service (NASS) statistics on Illinois in Table 2. The FBFM members farmed an average of 707 acres from 1982 through 1992, while NASS reported the average size farm over the same period was 319 acres, a 121 percent difference. Net farm income of FBFM members averaged $72,557.14, over the study period while NASS statistics indicated net farm income averaged $12,825.08. The relative larger size and higher net farm income of FBFM members was attributed to most members' being full-time farm operators, while NASS statistics include part-time farm operators. The average age of farmers in the two data sets was closer, 49.4 years for FBFM members and 50.4 years from NASS (in 1987).

North Dakota

North Dakota farm level data used were taken from the North Dakota Farm Business Management Education Program (NDFBMEP). The NDFBMEP uses the FINPACK analysis package for record keeping and analysis. Prior to 1992, another software program was utilized for data compilation and analysis. Consequently, only a single year of information was available for this study. The program was organized to assist farmers in developing a record-keeping system and to compile a database of farm records. This database comprises three sub-databases of crop, livestock, and composite farm records. Only the crop sub-database was used in this study.

This cross-sectional database contained a total of 428 farm operators in crop sub-database. A separate record was made for each field within the operator's farm. The total number of field records in the crop database was 6,532. The average number of records per farm operator was 15.

The database contained a variety of crops (Table 3). Spring wheat was the most common crop, comprising 21 percent of the records. Barley, durum, and alfalfa hay together made up another 20 percent of the records. However, many crops had relatively few observations.

For various reasons, a number of crops were eliminated from the database. For example, if the number of observations of a crop code was too few for regression analysis, the crop was eliminated. Other crops lacked a real production variable, such as set-aside acres, rented out acres, and CRP (conservation reserve program) acres, and were eliminated. Other variables (such as cash crop #1) were developed as catch-all variables. Some of the FINPACK codes for crops not grown in North Dakota (rice or cotton) were used by program participants to classify crops grown in North Dakota (crambe) for which no code was available in FINPACK. The total number of crops eliminated was 28, which resulted in the loss of 2,072 records. The eliminated records caused only one farm operator to be eliminated from the data set.

The remaining 4,460 records in the database contained 19 different crops. To further improve the regression analysis, the crop codes of grass hay, mixed hay, fescue hay, and other forage were combined to form the code of all other hay. Likewise, the codes of dry beans and pinto beans were combined to form the dry edible beans code. Consequently, only 15 crops remained for analysis.

FCIC

Because the NDFBMEP database did not contain the identity of farm operators, farm operators enrolled in the program were surveyed to allow their identity to be attached to their farm data for this research project. The response rate was 109 out of 427 operators or 25.5 percent. Crop insurance records obtained from the Federal Crop Insurance Corporation were matched to individual farm data using the names from the participant survey.

FCIC records were available at the individual crop unit level. These data were aggregated to the crop level for each insured and the three performance measures were calculated. The crop-level performance measures were then matched with the like crops in the NDFBMEP database. Although the NDFBMEP contains individual field data, it does not contain information about the location of that field. Therefore, it was impossible to match each field to its specific crop insurance unit. Using this procedure, 51 producer records were successfully cross-referenced to their FCIC insurance history, resulting in a total of 631 observations.

Independent Variables

The regression model used to estimate crop insurance risk quality factors had 18 explanatory variables separated into three general categories. The agronomic explanatory variables were primarily crop expense items. The economic variables were farm financial measures recommended by the Farm Financial Standards Task Force (FFSTF) to determine financial position and performance of farm businesses. The demographic explanatory variables identified non-business characteristics of farm operations that were important in determining yield.

Agronomic Variables. Agronomic practices, such as fertilizer application, seeding rates, and other chemical usages, vary from crop to crop, from region to region, and among farmers. For instance, wheat growers in central North Dakota may differ considerably in the amount of wheat seed they plant, and they may also apply fertilizer and other chemicals in differing quantities. Some of this variation can be explained by the variety of growing conditions that can exist among wheat growers within this region. However, much of the variation may be attributed to different farm management practices. Differing management practices may come about from the variety of knowledge and experiences possessed by farmers.

Among the specific agronomic characteristics of farms used in this study, seed expense, fertilizer expense, and other chemical expenses were selected for their immediate and direct impact on yield performance. Higher expenses for seed, fertilizer, or other chemicals imply that the farmer must have some knowledge or experience that causes him or her to believe that high application rates will either improve yields or reduce the possibility of low yields. Therefore, it was expected that greater expenses for these items would be associated with better yield performance and lower yield risk.

Based on the same approach, it was expected that farmers would not invest heavily in power and equipment, and miscellaneous farm inputs if they did not have some prior notion of positive yield response associated with that investment. Furthermore, the quantity of outside labor employed by farmers was expected to be directly associated with improved yields, or labor would not have been employed.

The total taxes paid by farmers were expected to be directly linked to yield performance, because higher yields generally mean higher income. Furthermore, total taxes can indicate behavior such as purchasing patterns and quality of farm and. Thus, a linkage between taxes and yields could be expected.

Farmland tenure was included in the regression models to test for possible differences in yield performance between rented, crop shared, and owned land. No prior knowledge of these relationships was postulated.

Economic Variables. The socioeconomic and financial position of a farm business can be directly associated with past yield performance that may go beyond what is indicated by a 10-year series of average yields. A farm in good financial standing is generally perceived to have gotten to that position by being economically efficient and employing good farm business management practices. The measures recommended by the Farm Financial Standards Task

Force were divided into five categories based on what financial aspects were being measured.[2] One measure from each of the categories was selected over using them all, because some of the ratio measures within a group sum to one, which would lead to multicolinearity in the regression analysis. The measures used were chosen based on their individual strength of association to yield performance, and careful consideration of model design.

Demographic Variables. Demographic and other nonbusiness characteristics of farms, such as age of operator, vary greatly among farms. It was expected that certain groups would out perform others.

The age of a farm operator was expected to be positively associated with yield performance. The basis for this expectation was the fact that older farmers tend to have more years of farming experience, and thus may in fact have a better knowledge of how to make decisions in various production situations.

The total number of crop acres was also expected to be positively related to yield performance. Larger farms may be able to take advantage of economies of scale in equipment and capitalization. It was expected that higher yields would result from this more efficient use of inputs.

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[2]For a discussion of FFSTF measures and categorical descriptions, see Baltezore, Gustafson, and Swenson, 1993.

In addition to the three sets of independent explanatory variables, dummy variables were used when more than one crop type was included in a regression model. In these cases, wheat was used as the base crop in North Dakota and corn was used as the base in Illinois.

Soil Productivity Index

The USDA Soil Conservation Service (SCS) has developed productive ratings for soil types in North Dakota. SCS soil maps of North Dakota were used to identify soil types located within a farm from the NDFBMEP data set. Soil productivity indexes were then developed based on the most productive soil in the county.

Because the NDFBMEP database did not contain information on the geographic location of specific farms, farm operators enrolled in the program were surveyed as to the primary location of their farm real estate. The response rate was 109 out of 427 operators or 25.5 percent. County soil surveys were then used to determine the soil types that were within the farm unit.

A soil productivity index was then calculated for each section of land identified by survey respondents as:

$$PI = \frac{\sum_{i}^{n} ACRES_i \times BU_i}{BEST \times TOTACRES} \tag{10}$$

where:

PI	= the productivity index for a section of land,
$ACRES_i$	= the number of acres of soil type i within the section,
BU_i	= the average yield for wheat (in bushels) on soil type i,

BEST = the average yield for wheat (in bushels) on the most productive soil in the county, and
TOTACRES = number of acres in the section sample.

This index was based on a sample of 32 acres from within the section. The productivity of the soil found in the sample was indexed to the most productive soil in the county. Each section was given a score ranging from 0 to 100 based on its relative productivity to that of a section comprised entirely of the most productive soil in the county.

Farm operators were allowed up to four sections in which to identify the primary location of the major portions of their crop land real estate. Composite indexes were generated for all farms from the section indexes so that a single soil productivity rating could be used in the study. Each section within a farm was given a weight based on the percentage contribution to the total crop acres of the farm. The composite farm productivity index was calculated as:

$$CFPI = \sum_{s}^{n} (PI_s \times WEIGHT_s) \tag{11}$$

where:

CFPI = the composite farm productivity index
PI_s = the productivity index for section s
$WEIGHT_s$ = the portion of total farm acres that are within section s

Because all farms did not possess soil productivity information, a subset of the NDFBMEP data set was developed for the survey respondents. These farms had soil productivity data, which would be used as an explanatory variable in the regression analysis.

Illinois Results

Over the course of the 11 years of Illinois data, the 1,401 farms varied the crops the grew each year (Table 4). The annual average number of farmers who grew corn was 1,382, or 98.6 percent of all farms in the data set. Soybeans were slightly less common, with an average of 92.1 percent (1,290) of farms growing them in any given year. Wheat and oats were minor crops compared to corn and soybeans, 37.5 percent and 15.3 percent respectively.

Coefficient of Variation Results

The coefficient of variation was calculated for each producer's yields over the years in which the crop was grown. It was used as a representation of yield risk for the individual producer, and a dependent variable in the regression analysis. The average coefficient of variation of yields for the 1,401 corn growers in the data set was 25.19 percent.

Following the procedure developed by Goodwin to estimate a model of farm characteristics to the coefficient of variation of yields, average values of observable agronomic and demographic characteristics over the period were used as independent variables in the regression analysis. These variables were measured on a per acre basis. A stepwise regression analysis was performed on the four major crops in the Illinois data set.

Results from these models varied by crop. The model for corn yield coefficient of variation was most successful in terms of identifying statistically significant relationships. The model for soybean yield coefficient of variation was most successful in explaining the variation in the dependent variable compared to the other crop models. For example, variables entered the wheat model at the 5 percent significance level and only power and equipment expenses entered the oats model.

All independent variables that were significant in the corn model carried a negative sign except seed expense per acre (Table 5). This implies that as fertilizer expense per acre, power and equipment expense per acre, soil productivity, or the total number of crop acres increases from farm to farm, the relative variation of yields about the mean farm yield tends to decrease.

Probability of Loss Results

A second crop yield performance measure was developed to simulate the use of default rates in credit screening and scoring models. The probability of loss due to low yields was calculated for each farm in the Illinois FBFM data set. The variables were measured on a whole farm basis. The total number of growing seasons where observed yields fell below 65 percent of a maximum of either farm level mean yield or county yields was divided by the total number of years the crop was grown. This measure estimates the probability that a farm would collect an indemnity on a crop insurance contract.

This variable was calculated for all 1,401 Illinois farms with complete agronomic and demographic data from 1982 through 1992. The observed corn yields fell below the estimated coverage level 12.1 percent of the time, with a range for individual farms from 0 to 54 percent. Soybean yields, on the average, were below coverage levels 6.9 percent of the time and ranged for individual farms from a low of 0 to a high of 100 percent. It was possible for a lower than coverage yield to occur 100 percent of the time because yield guarantees could be based on county average yields when farm yields were low. This situation was allowed to develop to simulate a situation where transitional yields (used by the FCIC when little or no yield history is available for a farmer) are greater than farm yields. Probability of yield losses for wheat and oats both ranged from 0 to 100 percent and averaged 11.6 and 16.9 percent, respectively.

The probability of yield loss variables were regressed against the set of agronomic and demographic characteristics (Table 6). Following the procedure used by Goodwin to estimate a model of farm characteristics to the coefficient of variation of yields, average values of observable agronomic and demographic characteristics over the period 1982 to 1992 were used in the regressions.

Results from these models found very few characteristics to be significantly related to probability of losses. The most notable results were the consistently significant negative relationship between probability of yield losses and soil productivity. The interpretation of these results are that greater soil productive capacity reduces the probability of yield losses. Additionally, significant negative relationships were found between probability of yield losses and power and equipment expenses in the corn and soybean models. This implies that for corn and soybeans a greater use of power and equipment can reduce the probability of yield losses. Farm taxes were estimated to have a significant positive relationship to probability of yield losses for corn and soybeans. Chemical expenses were found to have a decreasing effect on the probability of yield losses for soybeans.

A second probability of yield loss model was estimated with average farm level yields as an additional explanatory variable. A linear relationship was found to exist between average yields and soil productivity, thus creating a multicolinearity problem. This problem was overcome by removing the soil productivity variable from the regression formula.

The ability to explain variability in the probability of yield losses variable was substantially enhanced by the inclusion of historical average yields. The R^2 measure increased from an average of .05 per model to .33 per model when historical average yield was among the explanatory variables (Table 7).

The number of significant relationships remained low in these models. However, significant negative relationships between historical average yields and probability of yield losses were found for all crops. These results support the practice of lower premium rates for farmers with higher average yields.

Results from the subset of Illinois farms with completed balance sheet information brought forth few significant variables. Average power and equipment expenses were significant for corn and soybeans. Depreciation expense ratio was significant for soybeans, and no variables entered either the wheat or oats models. These results were due partially to the small size of the subsetted data.

Illinois Conclusions

Attempts to test relationships between yield performance criteria and agronomic, economic, and demographic characteristics of Illinois farms were successful in that statistically significant effects were found for some characteristics. Most notably, soil productivity proved to have a statistically measurable consistent relationship over time and across different modeling approaches. The productive capacity of a farm's soils had a risk reducing impact in all but two of the models where it was used as an explanatory variable. This demonstrates that soil productivity could be used as a preliminary measure of yield risk when there is insufficient actual production history.

Power and equipment expenses of row crop producers were relatively consistent in their relationship to yield performance criteria. Generally, higher power and equipment expenses were associated with improved yield performance. This implies that greater use of capital technology reduces yield risk among row crops in Illinois.

North Dakota Results

Loss Ratio Results

Loss ratios were calculated from crop insurance records obtained from the FCIC for producers who participated in the NDFBMEP program as described earlier. Each producer had a separate loss ratio for each crop produced. The crop loss ratio was then associated with each of that crop produced. The loss ratio variable was used to represent risk yield loss of that crop as a dependent variable in regression analysis. The variables were measured on a whole farm basis.

Since only one year of data was available, actual values of agronomic and demographic characteristics were used as independent variables in place of mean values (such as in the Goodwin procedures) over the period for which the loss ratio was calculated. Additionally, dummy variables were used to account for possible differences in crops. A stepwise regression analysis was used to identify statistically significant relationships between the risk variable, loss ratio, and the independent farm characteristics and crop dummy variables.

The loss ratio records were cross referenced with 667 NDFBMEP records. The average loss ratio among this set was 124.29 percent, which means that on average this set of producers collected $1.24 for every $1.00 they paid in crop insurance premiums.

Stepwise regression results generated eight significant variables (Table 8). Fertilizer expense, chemical expense, and return on farm equity all had positive parameter estimates. This implies that these characteristics are directly associated with increased loss ratios across farms. The positive association with chemical expense could appear counter intuitive. However, high chemical expenses that are higher than average often are an indication of either infestations that are costly to control without crop damage, or undesirable management practices that create conditions requiring multiple applications.

Rent expense, total crop acres on the farm, and depreciation expense had negative parameter estimates. Also, the hay crop dummy variable was significant and had a positive parameter estimate which indicates that this crop was significantly more risky than the base crop, wheat. The soybean dummy variable was significant and had a negative parameter estimate.

Crop Insurance Scorecard Development: Three Examples

The relationships identified by this study provide necessary background for the development of a risk screening/scoring tool. Parameter estimates from the regression models were used to identify significant statistical relationships, as well as the magnitude and sign of these relationships. This information was then transformed into scorecards that were used to classify farms according to their relative risk.

Crop insurance scorecards were developed for two models using Illinois data and one using North Dakota data. Illinois scorecards were developed for the coefficient of variation (Table 5) and probability of loss (Table 6) dependent variable models for farms with complete financial information. The loss ratio dependent variable model (Table 8) for farms with soil productivity data was used to develop the North Dakota scorecard. These models were chosen for their relative ability to explain variation of the dependent variable and their broad inclusion of data from each of the data sets. However, scorecards can be constructed with little difficulty for the remaining regression models reported in the study.

Univariate statistical analysis for significant independent variables from each sample model was performed. Quartile values were used to create ranges of the independent variables. Point scores (ranging from 3 to 0) were attached to the ranges, with higher points associated with favorable values of the independent variable. For example, a positive parameter estimate for fertilizer expense in the Illinois corn probability of loss model meant that greater fertilizer use received higher points. If a farm spent more than $33,500 on fertilizer it received 3 points; whereas, if less than $14,500 were spent on fertilizer, no points were awarded. The opposite situation occurred with debt-to-asset ratios in that same model. Debt-to-asset ratios under 14 percent were awarded 3 points, while farms with debt-to-asset ratios over 50 percent received 0 points (see scorecards for Illinois corn producers and North Dakota producers for other variables and point ranges).

Model estimates for dependent variables were calculated with observed values of independent variables in the two data sets. Mean dependent variable estimates were calculated, along with mean contributions from independent variables (Table 9). Absolute values for mean contributions were summed and percentages of the total were calculated for each. The proportion that each independent variable contributed to the total absolute value multiplied by 10 was the weight assigned to that variable in the total score calculation. For instance, 14.4 percent of the total absolute value of contributing independent variables came from the fertilizer expense variable in the Illinois coefficient of variation model. Therefore, .144 (the proportion) multiplied by 10 equals 1.4, the weight assigned to fertilizer expense variable on the Illinois coefficient of variation scorecard.

A composite total score was calculated by multiplying the contributing weights by the point scores and summing. A maximum score of 30 was possible on either scorecard, which would result from a perfect score of three in each scoring category multiplied by the category weights which summed to 10. The minimum score was zero for all scorecards, and would occur if observed characteristics were such that zero points were awarded in all scoring categories.

The score evaluation ranges were established by calculating scores for the observations in the two data sets from the examples. Again, univariate statistical analysis was used to obtain quartile values for the scores in each example. Ranges were developed from the quartile values and four classifications were established.

Critical evaluation of the range scores can be found in the "code explanation" sections of each scorecard example. These explanations are themselves examples and do not represent the only evaluations possible. Based on insurer experience more in-depth explanations of classifications could be established. Furthermore, additional classifications or subclassifications could be added to increase the detail and improve the accuracy of the scorecard system. Just as was noted in the review credit screening/scoring, crop insurance scorecards should not circumvent subjective application evaluation by insurers, but rather scorecards should be used in conjunction with the knowledge of the insurer.

The scorecard was designed such that higher total scores would result from favorable combinations of observed characteristics from individual producers, not withstanding the sign on the corresponding regression parameter estimate. Thus, having been developed directly from the identified relationships in the regression analysis, the accuracy of the scorecards depends upon the ability of the regression models to explain dependent variable variation. R^2 statistics for the example models were .12 and .11 for the Illinois models, and .18 for the North Dakota model. These relatively low values indicate that accuracy of the example scorecards could be a concern. However, the accuracy could be improved with further investigation of statistical relationships and additional data.

CROP INSURANCE SCORECARD
FOR
ILLINOIS CORN PRODUCERS

Based on Coefficient of Variation Dependent Model

Instructions: Award point scores in the following seven categories according to data provided by individual producers. Multiply point scores for each category by their corresponding weights in the *composite score* section. Then sum the composite scores, comparing the total score to the classified ranges given in the *score evaluation* section.

SCORING SECTIONS.

A. Seed Expense

Score points based on per acre seed expense.

	Score
Greater than $16.75	3
$14.25 to $16.75	2
$11.75 to $14.24	1
Less than $11.75	0

B. Fertilizer Expenses

Score points for per acre fertilizer expenses of farm.

Greater than $34.50	3
$28.30 to $34.50	2
$23.30 to $28.29	1
Less than $23.30	0

C. Power and Equipment Expense

Score points for per acre power and equipment expenses from production.

Greater than $73.00	3
$55.60 to $73.00	2
$44.25 to $55.59	1
Less than $44.25	0

SCORING SECTIONS (CONTINUED).

D. Soil Productivity Index

Score points based on the general soil productivity of the farm.

	Score
Greater than 91	3
81 to 91	2
66 to 80	1
Less than 66	0

E. Total Acres

Score points according to the farm's size.

Greater 920 acres	3
630 acres to 930 acres	2
425 acres to 629 acres	1
Less than 425 acres	0

COMPOSITE SCORE.

Multiply point scores from sections A through E by their corresponding weights and round the total score to the nearest whole number.

Section A. points	___	x	1.0	=	___
Section B. points	___	x	1.4	=	___
Section C. points	___	x	0.7	=	___
Section D. points	___	x	6.6	=	___
Section E. points	___	x	0.3	=	___

TOTAL SCORE (Maximum = 30) ________

SCORE EVALUATION.

Find the range in which the total score falls. The code corresponding to that range is the classification of the farm.

	Code
21 to 30 points	Green
15 to 20 points	Yellow
10 to 14 points	Orange
Less than 10	Red

CODE EXPLANATION.

The following explanations coincide with the classification code in the *score evaluation* section.

Green:	Insurance applicant is most likely an above average producer. The applicant is a good risk and qualify for premium discounts.
Yellow:	Insurance applicant is likely above average or close to average producer. The applicant is an average risk. Regular premiums are appropriate.
Orange:	Insurance applicant is likely an average to slightly below average producer. The applicant in a questionable risk. Premium loads are necessary until an insurance history can be developed.
Red:	Insurance applicant risk most likely a below average producer. The applicant is a high risk. Denial of insurance is recommended.

CROP INSURANCE SCORECARD
FOR
ILLINOIS CORN PRODUCERS

Based on Probability of Loss Dependent Model

Instructions: Award point scores in the following seven categories according to data provided by individual producers. Multiply point scores for each category by their corresponding weights in the *composite score* section. Then sum the composite scores, comparing the total score to the classified ranges given in the *score evaluation* section.

SCORING SECTIONS.

A. Fertilizer Expense — Score

Score points based on total farm fertilizer expense.

	Score
Greater than $33,500	3
$21,000 to $33,500	2
$14,500 to $20,199	1
Less than $14,500	0

B. Herbicide, Insecticide, and Other Chemical Expenses

Score points for total chemical expenses of farm.

	Score
Less than $8,750	3
$8,750 to $13,300	2
$13,301 to $21,750	1
Greater than $21,750	0

C. Total Farm Taxes

Score points based on the total taxes of the farm.

	Score
Less than $8,250	3
$8,250 to $11,500	2
$11,501 to $16,200	1
Greater than $16,200	0

	Score
D. Power and Equipment Expense	
Score points for power and equipment expenses from production.	
Greater than $47,200	3
$32,200 to $47,200	2
$22,900 to $31,199	1
Less than $22,900	0
E. Soil Productivity Index	
Score points based on the general soil productivity of the farm.	
Greater than 91	3
85 to 91	2
84 to 75	1
Less than 75	0
F. Debt-to-Asset Ratio	
Score points according to the farm's debt-to-asset ratio.	
Less than 14 percent	3
14 percent to 31 percent	2
32 percent to 50 percent	1
Greater than 50 percent	0
G. Return on Farm Equity	
Score points based on the return to farm equity.	
Greater than 15 percent	3
9 percent to 15 percent	2
5 percent to 8 percent	1
Less than 5 percent	0

COMPOSITE SCORE.

Multiply point scores from sections A through G by their corresponding weights and round the total score to the nearest whole number.

Section A. points	___	x	0.4	=	___
Section B. points	___	x	0.2	=	___
Section C. points	___	x	0.5	=	___
Section D. points	___	x	6.5	=	___
Section E. points	___	x	1.8	=	___
Section F. points	___	x	0.1	=	___
Section G. points	___	x	0.5	=	___

TOTAL SCORE (Maximum = 30) __________

SCORE EVALUATION.

Find the range in which the total score falls. The code corresponding to that range is the classification of the farm.

	Code
21 to 30 points	Green
15 to 20 points	Yellow
10 to 15 points	Orange
Less than 10	Red

CODE EXPLANATION.

The following explanations coincide with the classification code in the *score evaluation* section.

Green: Insurance applicant is most likely an above average producer. The applicant is a good risk and qualify for premium discounts.

Yellow: Insurance applicant is likely above average or close to average producer. The applicant is an average risk. Regular premiums are appropriate.

Orange: Insurance applicant is likely an average to slightly below average producer. The applicant in a questionable risk. Premium loads are necessary until an insurance history can be developed.

Red: Insurance applicant risk most likely a below average producer. The applicant is a high risk. Denial of insurance is recommended.

CROP INSURANCE SCORECARD
FOR
NORTH DAKOTA PRODUCERS

Based on Loss Ratio Dependent Variable Model

Instructions: Award point scores in the following four categories according to data provided by individual producers. Multiply point scores for each category by their corresponding weights in the *composite score* section. Then sum the composite scores, comparing the total score to the classified ranges given in the *score evaluation* section.

SCORING SECTIONS.

	Score
A. Fertilizer Expenses	
Score points for per acre fertilizer expenses of farm.	
Less than $5.00	3
$5.00 to $9.00	2
$9.00 to $16.00	1
Greater than $16.00	0
B. Chemical Expenses	
Score points for per acre chemical expenses of the farm.	
$20.00 or less	3
More than $20.00	0
C. Rent Expense	
Score points for the per acre rent expense of the farm.	
Greater than $47.00	3
Less than $47.00	0
D. Total Crop Acres	
Score points based on the number of crop acres on the farm.	
Greater than 2,000	3
1,370 to 2,000	2
925 to 1,999	1
Less than 925	0

E. Return on Equity Score	Score
Score points for the return on equity of the farm (%).	
Greater than 17	3
9.3 to 17	2
-1.4 to 9.3	1
Less than -1.4	0
F. Depreciation Expense	
Score points for depreciation expense per acre of the farm.	
Greater than $7.00	3
$4.30 to $7.00	2
$1.5 to $4.29	1
Less than $1.50	0
G. Hay Crop	
Score points based on if the farm raises a hay crop.	
If no hay crop	3
If hay crop is grown	0
H. Soybeans	
Score points based on if the farm raises soybeans.	
If soybean crop is grown	3
If no soybean crop is grown	0

COMPOSITE SCORE.

Multiply point scores from sections A through H by their corresponding weights and round the total score to the nearest whole number.

Section A. points	___	x	0.9	=	___
Section B. points	___	x	3.3	=	___
Section C. points	___	x	1.7	=	___
Section D. points	___	x	2.4	=	___
Section E. points	___	x	0.1	=	___
Section F. points	___	x	0.7	=	___
Section G. points	___	x	0.4	=	___
Section H. points	___	x	0.5	=	___

TOTAL SCORE (Maximum = 30) ________

SCORE EVALUATION.

Find the range in which the total score falls. The code corresponding to that range is the classification of the farm.

	Code
19 to 30 points	Green
14 to 18 points	Yellow
11 to 13 points	Orange
Less than 11	Red

CODE EXPLANATION.

The following explanations coincide with the classification code in the *score evaluation* section.

Green: Insurance applicant is most likely an above average producer. The applicant is a good risk and qualify for premium discounts.

Yellow: Insurance applicant is likely above average or close to average producer. The applicant is an average risk. Regular premiums are appropriate.

Orange: Insurance applicant is likely an average to slightly below average producer. The applicant in a questionable risk. Premium loads are necessary until an insurance history can be developed.

Red: Insurance applicant risk most likely a below average producer. The applicant is a high risk. Denial of insurance is recommended.

Implications for Practical Application of Crop Insurance Scorecards

The scorecard approach to crop insurance farm classification was developed following the procedures used in agricultural credit screening/scoring. The concept has been successful in this application, with widespread use of credit screening/scoring devices.[3] Furthermore, the concept of classifying has been used in the insurance industry. Property and casualty insurers classify insureds by characteristics related to probabilities of loss. In crop insurance, rate makers classify farms based on historical average yield, and insurers classify policies for reinsurance purposes.

Benefits expected from further development and practical application of crop insurance scorecards include: (1) improved rate classifying, (2) improved selection of insurance applicants, (3) improved underwriter portfolio analysis, and (4) improved identification of policies warranting audits or cancellation. Crop insurance rate makers will benefit by the designation of additional characteristics by which premium discounts and increases could be made thus improving actuarial soundness. Firms selling crop insurance who make use of scorecards will be able to make better and faster decisions about whether or not to insure new applicants. Completed scorecards for all clients would allow managers of crop insurance firms to quickly analyze the profitability of an underwriter's portfolio by examining the percentage of clients with ratings in each classification. Insurance auditors will benefit from scorecards by having a quick and simple method of identifying existing policies that require auditing or cancellation.

[3]For a discussion of credit assessment in North Dakota, see Baltezore and Gustafson, "Credit Assessment Methods and Applications: North Dakota Agricultural Banks," Staff Paper AE91007, Department of Agricultural Economics, North Dakota State University, Fargo, 1991.

Some additional analysis is recommended before practical adaptation of a crop insurance scorecard system is possible. Namely, the system needs to be tailored to individual needs. The data used to develop the two examples presented in this study in some cases may be too broad and in others may be too specific. In the former case, additional data regarding the particular area, insurance pool, and other farm characteristics may be necessary to create a scorecard that has an adequate rate of correct prediction. In the latter case, the data used may not be considered representative of the universe of farmers. Thus, the relationships developed may not be representative of the true relationships, and some relationships may not have even been identified. Again, additional data may be needed to overcome this problem. If these recommendations are followed, a crop insurance scorecard system with considerable accuracy could be developed for an individual company or by the Federal Crop Insurance Corporation for use in setting rates.

The drawbacks related to developing and implementing a scorecard classifying system center around data requirements. The Actual Production History Plan for crop insurance is perceived as complex and burdensome in its informational requirements from farmers and insurance agents. Scorecard systems will require even more data to be collected. This however, was not perceived by the investigators of this project as an insurmountable obstacle to further investigation and use of such a system. The incentives of premium reductions should encourage farmers to gather this data on their own behalf. For crop insurance firms, the incentive of improved profitability acquired from a more accurate analysis of insurance risk should encourage their involvement. Secondary sources could also prove to be excellent providers of necessary data. For example, Geographic Information Systems (GIS) have developed to the point where reliable and detailed information on specific tracts of land will be easily accessable. For these reasons and the fact that agricultural lenders have been gathering this type information, it is believed that crop insurance scorecards could be successfully implemented.

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TABLE 1. AGRONOMIC, DEMOGRAPHIC, AND ECONOMIC VARIABLES USED IN THE YIELD DEVIATION MODEL

AGRONOMIC	ECONOMIC	DEMOGRAPHIC
Seed Expense	Current Ratio	Soil Productivity
Fertilizer Expense	Debt to Asset Ratio	Total Crop Acres
Chemical Expense	Return on Farm Equity	Age of Operator
Taxes	Term Debt and Capital Replacement Margin	
Power and Equipment Expense	Depreciation Expense Ratio	
Labor Costs		
Miscellaneous Expenses		
Land Tenure		

TABLE 2. AVERAGE FARM SIZE AND AVERAGE NET FARM INCOME FOR ILLINOIS FARMERS, FBFM DATABASE AND NASS, 1982 - 1992

YEAR	FBFM DATABASE FARM SIZE	FBFM DATABASE NET FARM INCOME	NASS FARM SIZE	NASS NET FARM INCOME
	-acres-	-dollars-	-acres-	-dollars-
1982	628	60,688.41	276	8,719.23
1983	643	54,436.22	287	(4,762.00)
1984	661	46,358.68	299	10,603.13
1985	680	67,664.71	309	17,030.11
1986	697	60,169.21	315	15,596.70
1987	714	83,889.64	321	14,950.56
1988	729	60,054.76	325	8,998.86
1989	737	89,314.01	331	22,868.61
1990	754	95,642.03	343	17,650.60
1991	768	70,972.23	348	8,629.27
1992	771	108,938.64	351	20,972.84

Source: National Agricultural Statistics Service.

TABLE 3. ELIMINATED CROPS, NORTH DAKOTA FARM BUSINESS MANAGEMENT EDUCATION PROGRAM CROP DATABASE, 1992

ELIMINATED CROPS	OBSERVATIONS	RETAINED CROPS	OBSERVATIONS
MILLET	23	FEED CORN	271
OTHER GRAIN #1	3	FEED OATS	174
BUCKWHEAT	4	BARLEY	644
HAYLAGE	3	ALFALFA HAY	239
CORN SILAGE	154	SPRING WHEAT	1,353
OATLAGE	34	WINTER WHEAT	25
SORGHUM SILAGE	10	GRASS HAY*	256
STOVER	5	MIXED HAY*	119
SET ASIDE	792	OTHER FORAGE*	119
AFTERMATH GZ	5	FESCUE HAY*	13
OTHER SILAGE	3	SOYBEANS	241
SMALL GRAIN SILAGE	15	DRY BEANS**	14
RICE	6	PINTO BEANS**	9
COTTON	1	DURUM WHEAT	375
STRAW	6	OIL SUNFLOWERS	392
BUCKWHEAT	3	FLAX	58
CRP	156	RYE	13
CASH CROP #1	27	CONFECTIONERY SUNFLOWERS	42
CASH CROP #2	16	SUGARBEETS	28
CASH CROP #3	6		
PEAS	2		
CLOVER SEED	1		
FESCUE SEED	1		
PASTURE	417		
FALLOW	362		
TURFGRASS	1		
CUSTOM HIRE	6		
RENTED OUT	10		
TOTAL	2,072	TOTAL	4,460

*Crops were combined to form Other Hay.
**Crops were combined to form Dry Edible Beans.

TABLE 4. NUMBER OF FARMS WITH CORN, SOYBEANS, WHEAT, AND OATS IN THE ILLINOIS FARM BUSINESS FARM MANAGEMENT ASSOCIATION DATASET 1982 - 1992

YEAR	CORN	SOYBEANS	WHEAT	OATS
		-farms-		
1982	1,393	1,248	535	251
1983	1,305	1,224	512	223
1984	1,390	1,260	591	212
1985	1,393	1,278	478	232
1986	1,390	1,307	408	216
1987	1,396	1,307	494	244
1988	1,379	1,297	542	185
1989	1,397	1,312	606	253
1990	1,385	1,312	640	209
1991	1,389	1,322	556	155
1992	1,386	1,324	410	183
Average	1,382	1,290	525	215

TABLE 5. STEPWISE REGRESSION PARAMETER ESTIMATES* FOR ILLINOIS COEFFICIENT OF VARIATION DEPENDENT VARIABLE MODEL--PER ACRE BASIS

VARIABLE	CORN	SOYBEANS	WHEAT	OATS
R2	0.12	0.17	**	0.02
INTERCEPT	41.52714811 (1.26195338)***	40.81760868 (1.28919780)		38.39578917 (2.51958309)
Seed Exp	0.13442050 (0.06657067)			
Fertilizer Exp	-0.09879251 (0.02599489)			
Chemical Exp		-0.23226121 (0.03577712)		
Power & Equip Exp	-0.02172694 (0.00687296)			-0.08408026 (0.02808331)
Soil Prod Index	-0.17053468 (0.01442952)	-0.19037131 (0.01571826)		
Total Crop Acres	-0.000809336 (0.00040539)	-0.00216320 (0.00043146)		

*Parameter estimates significant at the 5% level.
**No variables were significant at the 5% level.
***Numbers in parentheses are the standard errors.

TABLE 6. STEPWISE REGRESSION PARAMETER ESTIMATES* PROBABILITY OF LOSS DEPENDENT VARIABLE--WHOLE FARM BASIS

VARIABLE	CORN	SOYBEAN	WHEAT	OATS
R2	0.06111032	0.12705764	0.00500156	0.02133515
INTERCEPT	0.26186925 (0.01523468)**	0.26126742 (0.01572504)	0.17367451 (0.02903403)	0.44284667 (0.08010718)
Seed Exp				
Fertilizer Exp				
Chemical Exp		-0.00000147 (0.0000005)		
Taxes	0.00000216 (0.00000052)	0.00000149 (0.00000064)		
Power & Equip Exp	-0.00000074 (0.00000012)	-0.00000041 (0.00000014)		
Labor Exp				
Misc Exp				
Soil Prod Index	-0.00169369 (0.00019872)	-0.00219816 (0.00020671)	-0.00078439 (0.00038994)	-0.00343594 (0.00099228)
Total Crop Acres				
Part Owned				
Rented				

*Parameter estimates significant at the 5% level.
**Numbers in parentheses are the standard errors.

TABLE 7. STEPWISE REGRESSION PARAMETER ESTIMATES* PROBABILITY OF LOSS DEPENDENT VARIABLE--AVERAGE YIELD SCENARIO

VARIABLE	CORN	SOYBEAN	WHEAT	OATS
R2	0.28049426	0.32681584	0.2884418	0.40669637
INTERCEPT	0.43551114	0.42819162	0.48486577	0.6989228
	(0.01362185)**	(0.01477221)	(0.02252276)	(0.02890047)
Seed Exp				
Fertilizer Exp				
Chemical Exp				
Taxes	0.00000407	0.00000202	0.00000706	
	(0.00000041)	(0.00000046)	(0.000001)	
Power & Equip Exp	-0.00000077			
	(0.00000009)			
Labor Exp				
Misc Exp				
Historical Average Yield	-0.00260456	-0.00847712	-0.00728490	-0.00747454
	(0.00011414)	(0.0003654)	(0.00040391)	(0.00038495)
Total Crop Acres		-0.00003810	-0.00005712	
		(0.00000584)	(0.00001159)	
Part Owned				
Rented				

*Parameter estimates significant at the 5% level.
**Numbers in parentheses are the standard errors.

TABLE 8. STEPWISE REGRESSION PARAMETER ESTIMATES* FOR NORTH DAKOTA LOSS RATIO DEPENDENT VARIABLE MODEL

VARIABLE	PARAMETER ESTIMATE
R2	0.18014632
INTERCEPT	1.23215900 (0.16273009)**
Fertilizer Expense	0.01919832 (0.00892613)
Chemical Expense	0.07511868 (0.00860973)
Rent Expense	-0.01379172 (0.00280670)
Total Crop Acres	-0.00021497 (0.00008692)
Return on Equity	0.00043093 (0.00018996)
Deprection Expense	-0.02214936 (0.00655077)
Hay Crop Dummy	0.47154662 (0.18685058)
Soybean Crop Dummy	-0.73829727 (0.23451586)

*Parameter estimates significant at the 5% level.
**Numbers in parentheses are the standard errors.

TABLE 9. MEAN OF ESTIMATED DEPENDENT VARIABLES, MEAN CONTRIBUTING INDEPENDENT VARIABLES, ABSOLUTE VALUE OF CONTRIBUTING VARIABLES, AND COMPOSITE WEIGHTS FOR CROP INSURANCE SCORECARDS

Variable	Mean Contribution	Absolute Value of Mean Cont.	Percent Contribution	Assigned Weight
		--Illinois - Coefficient of Variation Model--		
INTERCEPT	41.53	*	*	*
Seed Expense	1.96	1.96	9.7	1.0
Fertilizer Expense	-2.93	2.93	14.4	1.4
Power & Equipment	-1.40	1.40	6.9	0.7
Soil Index	-13.36	13.36	66.0	6.6
Total Acres	-0.60	0.60	3.0	0.3
TOTAL	25.20	20.25	100.0	10.0
		--Illinois - Probability of Loss Model--		
INTERCEPT	-26.32	*	*	*
Fertilizer Expense	6.08	6.08	3.85	0.4
Chemical Expense	-3.16	3.16	2.00	0.2
Farm Taxes	-8.08	8.08	5.12	0.5
Power & Equipment	102.02	102.02	64.67	6.5
Soil Productivity	28.67	28.67	18.17	1.8
Debt-to-Asset Ratio	-2.20	2.20	1.41	0.1
Return to Equity	7.55	7.55	4.78	0.5
TOTAL	104.56	157.76	100.00	10.0
		--North Dakota of Loss Ratio Model--		
INTERCEPT	1.23	*	*	*
Fertilizer Expense	0.12	0.12	9.3	0.9
Chemical Expense	0.42	0.42	32.6	3.3
Rent Expense	-0.22	0.22	17.1	1.7
Total Acres	-0.31	0.31	24.0	2.4
Return in Equity	-0.02	0.02	1.5	0.1
Depreciation Expense	-0.09	0.09	7.0	0.7
Hay Crop Dummy	0.05	0.05	3.9	0.4
Soybeans Dummy	-0.06	0.06	4.6	0.5
TOTAL	1.12	1.29	100.0	10.0

*Intercepts were not used to calculate weights for scorecards.

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APPENDIX A

Yield Deviation Dependent Variable Model Construction

Due to the limitations of the dependent variables in the three models detailed in the report, an additional model was developed to address these shortcomings. In this model, deviations from the county average yield were regressed upon farm production and management characteristics. Thus, farms were automatically classified into above and below county average by the sign of the yield deviation variable.

This analysis differes from that using the coefficient of variation (CV) as the dependent variable in a very important way. Recall, coefficient of variation analysis assumes a normal distribution of yields, which implies that the probability of a below-average yield is equal to the probability of an above-average yield, causing a condition where the probability of an above-average yield is not equal to the probability of a below-average yield. Also recall, not having sufficient data on individual farmers to determine the actual distribution of each yield necessitated developing a procedure to measure their performance relative to the county average.

Because of this variability, a fourth criterion was used to measure yield performance based on farm yields relative to county average yields such that:

$$DV_i = AY_i - CY \tag{A1}$$

where

DV_i = the farm yield deviation for the i^{th} farm, measured in units,
AY_i = the actual farm yield for the i^{th} farm, and
CY = the NASS county average annual harvested yield for the crop.

Yield deviations (DV_i) can be either negative (indicating farm yield below county average) or positive (farm yield above county average). This measure allowed for the classification of farms into two groups: above-average producers and below-average producers.

Procedures

To improve classification and selection of crop insurance applicants a method had to be established to capture downside yield variations as demonstrated in equation (A1). Once this measure was established, regression analysis was performed to estimate relationships between agronomic, demographic, and economic characteristics of farms to those yield deviations. The variables were measured on a whole farm basis.

Models for North Dakota and Illinois were developed to explain yield variations among farmers. Studying only farmers who participated in the Federal crop insurance program may subject the insurance screening model to biases resulting from the possibility that FCIC participants do not characterize the universe of risk.

Regression Model Design - North Dakota

The NASS county average yields per harvested acre were subtracted from farm level yields per acre contained in the NDFBMEP database using the procedure described in equation (A1). The resulting differences were used as dependent variables in the regression model. These differences or deviations above and below the county averages created a generalized variable that allowed the comparison of farming practices across the state by removing the known difference in regional production standards. The yield deviations were divided by the county averages to create a percentage deviation variable, thus removing the unit measurement of each crop. This allowed inter-county comparisons of farming practices, and comparisons across crop varieties.

A wide variety of deviations were found to exist in the North Dakota data (Table A.1). Average deviations and the percentage deviation variable were measured for all crops. These averages were interpreted as the mean deviation from county averages. Each crop mean deviation was measured in the units used to report that the crop. For example, the average deviation among corn growers was 2.05 bushels below county average harvested yields. However, wheat growers in the database had mean deviations above county harvested yields per acre in spring, winter, and durum wheat. The mean percentage deviation was 10 percent above county averages.

The minimum deviation for oats was 86.7 bushels below the county average, while the minimum deviation for all other hay was 1.65 tons below county average. The minimum percentage deviation was 100 percent below county averages, implying a zero yield. Maximum deviations were the highest values observed in the deviation variables. The maximum percentage deviation was 250.18 percent above county average. This does not necessarily represent the highest yield in the data set, but rather the greatest positive deviation from a county average.

Soil Productivity Index

By specifying the dependent variables as deviation variables, inter-county differences in production capacity were overcome. However, intra-county differences in production capacity still remain unexplained. As explained in the main report, SCS soil maps of North Dakota were used to identify soil types located within a farm from the NDFBMEP data set. Soil productivity indexes were then developed based on the most productive soil in the county. The development of the soil productivity index is presented in the report as equations (10) and (11).

Results - NDFBMEP Data Set

Three modeling approaches were taken to test for cross sectional relationships between crop performance criteria and agronomic, economic, and demographic farm characteristics. First, a regression model was developed for each crop in the data set; second, crops were categorized into small grains, row crops, and forage crops; and third, all crops were combined using the percentage deviation variable to compensate for differences in crop unit measurements. These models were then estimated using the NDFBMEP data set and the subset of farms with soil productivity data.

Individual Crop Models

Stepwise regression models were estimated for the 15 crops in the NDFBMEP data set (Table A.2). This approach was designed to identify statistically significant relationships between yield deviations and farm characteristics. The sign on parameter estimates indicates how a farm characteristic influences whether farm yields were above or below county average. A positive parameter estimate signifies that higher observed values of the characteristic are less likely to be associated with below county average yields. Conversely, a negative parameter estimate denotes that should higher values of a particular characteristic be observed on a farm there would be an increased likelihood of below county average yields.

A general consistency of significance and sign for parameter estimates across crop models was considered an indication that the characteristic displayed a good degree of useability as a means of classifying crop insurance farms. Significant statistical relationships between yield deviations and agronomic expense characteristics generally were not consistent in significance across crops. At most, a characteristic was significant in three out of the fifteen models. However, when a characteristic appeared as significant in more than one model, it was generally consistent in sign. For instance, although fertilizer and chemical expenses were significant in only three models apiece, each time they appeared, the sign on the parameter estimate was positive.

Crop insurance expenses were significant in only one crop model, oil sunflowers. Interestingly though, the parameter estimate was positive. This denotes a direct association between crop insurance expenditures and above county average producers. This result was opposite of what might be expected if moral hazard were to exist. However, this isolated incidence does not indicate that moral hazard does not exist in crop insurance.

Power and equipment expenditures by corn and barley producers had a significant positive relationship to above county average yields. It was inferred that high power and equipment expenditures were an indication of a greater level of mechanized capitalization. The relatively isolated incidence of statistical significance shown here does not strongly support the notion that greater capitalization results in above county average production.

The greatest consistency among the individual crop models was the significant relationship of share cropped land to above county average yields. A positive parameter estimate was estimated for 13 of 15 crop models. In the confectionery sunflowers and sugarbeets models share cropping was not significant. The implication of such a strong relationship was that share cropping demonstrated a tendency to be related to above county average yields.

More mature farm operators were assumed to have more farming experience. While this is not an absolute, generally speaking inexperienced farm operators tend to be younger than the experienced. Thus stated, the regression results did not indicate with consistency that farming experience relates to above county average yields. The age of farm operators was significant in only 3 crop models (corn, dry edible beans, and rye) and furthermore, parameter estimates were not consistent in sign.

Financial or economic characteristics of NDFBMEP farms did not have an overwhelmingly stable relationship with yield deviations. The ratio of current assets to current liabilities (called the current ratio) was significant in four crop models, but the sign on the parameter estimates was not significant. However, parameter estimates associated with debt-to-asset ratios were consistent in their significant negative relation ship to yield deviations. Thus, in the four models where debt-to-asset ratios were significant, high degrees of leverage were associated with below county average yields. Additionally, the amount of revenue a farm had available for debt service and retirement was significant in seven models, but parameter estimates were not consistent.

In general the regression models developed to identify relationships between yield deviations and county average yield explained relatively little of total variability in the dependent variables. The R^2 statistics for the individual crop models ranged from a low of .035 for other hay varieties to a high of .884 for dry edible beans. The mean R^2 was .379, thus on the average our models explained 38 percent of the variability in farm yield deviations about the county average yield. One model, sugarbeets, did not generate any statistics with a 95 percent or greater significance.

Combined Crops and All Crop Models

To further test for relationships between yield deviations from county average and farm level characteristics crops were combined to form groups that contained crops with similar production situations. The groups were small grains (oats, barley, spring wheat, winter wheat, durum, flax and rye), row crops (corn, soybeans, dry edible beans, oil sunflowers, confectionery sunflowers, and sugarbeets), and forage crops (alfalfa and other hay). Creating the combined crop models increased the number of observations per model, thus improving the reliability of the relationships identified.

The final model design used with the NDFBMEP data included all crops. Crop unit measures were removed by dividing yield deviations by their respective county averages. This resulted in a proportional deviation from county average yields, but the sign indicating positive or negative deviation was able to be retained.

In order to pick up differences between crops in the crop group models and the all crops model, dummy variables were added as explanatory variables. Therefore, crops with greater variability had a compensating measure.

The stepwise regression models were estimated for the crop group models and the all crop model (percentage deviation). Interpretation of parameter estimates for these models was identical to that of the individual crop models. That is, a positive parameter identifies a relationship such that higher values for the characteristic were associated with above county average yield, and the opposite scenario for a negative parameter.

Fertilizer expenses were significant in all models, and chemical expenses were significant in all but forage crops (Table A.3). In all cases fertilizer and chemical expense parameter estimates were consistent in positive sign. These results support the earlier results where a relatively weaker association was developed. Labor expenses were significant with a positive parameter estimate in the small grains and percentage deviation model. The large representation of small grains in the data set may have influenced the identification of a significant relationship across all crops. The strong share crop relationship recognized in the individual crop models carried through to the combined and all crop models with the exception of row crops. Farming experience as measured by age of the farm operator was significant in only the small grains model. The inconsistent relationships recognized between the current ratio and yield deviations was not carried forward in the combined and all crop models. However, the significant and consistent relationship of debt-to-asset ratio with the dependent variable was recognized in the summarized models. Return on farm equity and term debt and capital replacement margin were significant with positive parameters in the small grains model. Additionally, a relationship was acknowledged for depreciation expense ratio that was not previously brought out in the individual crop models.

Overall the identification of relationships between yield deviations above and below county average yields and farm characteristics were supported from the individual crop models. However, explanation of variability of the dependent variables was not enhanced by the combined or all crop models.

Farms With Soil Productivity Data

The above analysis was repeated for a subset of farms where soil productivity indexes were developed. The same regression procedures and models were estimated with the inclusion of soil productivity indexes as an additional explanatory variable. This additional analysis was necessary to test the hypothesis that the productive capacity of soils within a county may influence whether a farm had above or below county average yields.

Stepwise regression models were again estimated for the 13 crops in the NDFBMEP data set (Table A.4). Two crops, winter wheat and rye, were not represented in the subset data. However, in each of the remaining models the explanatory power increased. The R^2 statistics increased, indicating that the inclusion of soil productivity indexes improved the explanatory power of the models.

Soil productivity indexes were significant in 5 models with consistently positive parameter estimates. These results indicate that soils that have been rated by the USDA Soil Conservation Service as having greater productive capacity were likely to produce above county average yields.

Results from the combined and all crop models support the same conclusions (Table A.5). Again, in each model the R^2 statistic increased when soil productivity data was included as an explanatory variable. The soil productivity indexes were significant in all models except forage crops, and signs on the parameter estimates were consistently positive. This supports the conclusion that productive capacity of soil was directly related to increased likelihood of above county average yields.

North Dakota Conclusions

The NDFBMEP database contained sufficient data at the field level for successful cross-sectional analysis. Statistical relationships identified in the individual crop models proved to be relatively consistent when aggregated. Aggregation was to combine like crops and then to combine all crops.

By far, the most distinguishing results of this analysis was the strong and consistently positive relationship found to exist between soil productivity and yield performance (measured by deviations from the county average). Other consistent and significant relationships were share cropping, operator's age, and current ratio.

Regression Model Design - Illinois

NASS county average yields were subtracted from observed farm yields in each of the 11 years of data to obtain the yield deviation variables. On the average farm level corn yields were 9.13 bushels greater than county yields in 1982 (Table A.6). Annual average yield deviations for corn ranged from a low of 4.75 bushels above county averages in 1983 to a high of 10.09 bushels above county averages in 1984. Annual average yield deviations were positive in all but one case, wheat in 1990. Generally speaking this indicates that farm yields in the data set maintained a relatively constant relationship to county average yields over the study period.

Stepwise regression models were estimated for corn, soybeans, wheat, and oats (Table A.7). This procedure allowed only significant relationships between yield deviations and farm characteristics to be recognized. Dummy variables for crop years were added with 1982 as a base year. This was done to isolate situations that were unique to a particular year within the time series.

Fertilizer expense was significant for corn, soybeans, and wheat. The consistently positive parameter estimates indicate that greater fertilizer expenses are associated with a reduced probability of below average yield. Chemical expenses were significant with a positive parameter estimate in the soybean model only. Taxes paid by farmers had a negative association with reduced yield deviations in the corn and soybean models, and a positive association in the oats model. Power and equipment expenses were significant and positively associated in the corn, soybean, and oats models. Labor expenses had a significant negative association in the corn model, but was not significant in any other model. Miscellaneous farm expenses were significant in a positive relationship with yield deviations in the soybean model. The most significant and striking results were the positive associations of soil productivity indexes in all models. The total number of crop acres on a farm were negatively associated in the soybean and oats models, indicating that larger farms had an increased chance of having below average yields. The same was true if a soybean farm rented crop acres.

The relatively low values for R^2 statistics indicate that the models do not explain a high degree of variation of yield deviations. However, the f-tests performed for goodness of fit of the general models were all significant at the 95 percent level.

The stepwise regression analysis was repeated for a subset of 313 farms that had completed balance sheets from 1988 through 1992. Annual average yield deviations for this subset of data were relatively consistent to those of the larger sample (Table A.8).

The purpose for subsetting the Illinois FBFM data was to test for relationships between financial characteristics of farm operations and yield deviations. Additionally, the age of the principle farm operator was obtained for the subset. Relationships previously developed between agronomic characteristics and yield deviations remained relatively unchanged for the subset with the exception of some minor changes (Table A.9). The current ratio and depreciation expense ratio were not significant in any model. Debt-to-asset ratio and return on farm equity were both significant for corn and soybeans. Debt-to-asset ratio parameter estimates were negative in both cases, indicating that higher leverage on farms was associated with a reduction in yields relative to the county average yield. Return on farm equity was positively associated with yield deviations in both corn and soybeans. The age of the principle farm operator was not significant for any crop.

CROP INSURANCE SCORECARD
FOR
NORTH DAKOTA PRODUCERS

Based on Yield Deviation Dependent Variable Model

Instructions: Award point scores in the following four categories according to data provided by individual producers. Multiply point scores for each category by their corresponding weights in the *composite score* section. Then sum the composite scores, comparing the total score to the classified ranges given in the *score evaluation* section.

SCORING SECTIONS.

A. Share Cropping — Score

Score points based on whether the farm share crops.

	Score
Farm Share Crops	3
Farm Does Not Share Crop	0

B. Operator's Age

Score points based on principle farm operator's age.

	Score
Over 45 years old	3
39 to 45 years old	2
34 to 38 years old	1
Under 34 years old	0

C. Soil Productivity Index

Score points for the general soil productivity of the farm.

	Score
Greater than 77	3
63 to 77	2
48 to 62	1
Less than 48	0

D. Current Ratio

Score points based on the current ratio of the farm.

	Score
Less than 1.1	3
1.2 to 2.3	2
2.4 to 5.2	1
Greater than 5.2	0

COMPOSITE SCORE.

Multiply point scores from sections A through D by their corresponding weights and round the total score to the nearest whole number.

Section A. points	___	x	1.3	=	___
Section B. points	___	x	1.7	=	___
Section C. points	___	x	3.2	=	___
Section D. points	___	x	3.8	=	___

TOTAL SCORE (Maximum = 30) ________

SCORE EVALUATION.

Find the range in which the total score falls. The code corresponding to that range is the classification of the farm.

	Code
19 to 30 points	Green
14 to 18 points	Yellow
11 to 13 points	Orange
Less than 11	Red

CODE EXPLANATION.

The following explanations coincide with the classification code in the *score evaluation* section.

Green: Insurance applicant is most likely an above average producer. The applicant is a good risk and qualify for premium discounts.

Yellow: Insurance applicant is likely above average or close to average producer. The applicant is an average risk. Regular premiums are appropriate.

Orange: Insurance applicant is likely an average to slightly below average producer. The applicant in a questionable risk. Premium loads are necessary until an insurance history can be developed.

Red: Insurance applicant risk most likely a below average producer. The applicant is a high risk. Denial of insurance is recommended.

TABLE A1. MEAN, STANDARD DEVIATION, MINIMUM AND MAXIMUM VALUES FOR DEPENDENT VARIABLES

Variable	Units	Observations	Mean	Standard Deviation	Minimum	Maximum
Corn	bu	271	-2.05	29.30	-66.07	168.10
Oats	bu	174	-2.35	41.46	-86.70	193.73
Barley	bu	644	5.28	28.54	-68.30	157.86
Spring Wheat	bu	1,353	6.16	18.21	-53.00	148.90
Winter wheat	bu	25	3.91	19.56	-37.40	68.22
Durum	bu	375	7.13	17.26	-33.40	81.49
Alfalfa	tons	239	-0.02	1.29	-2.67	8.80
Other Hay	tons	582	0.01	1.14	-1.65	19.39
Soybeans	bu	241	3.93	13.89	-21.00	98.56
Dry Edible Beans	bu	22	1.54	11.16	-11.46	30.01
Oil sunflowers	cwt	392	1.79	6.51	-16.58	42.86
Confectionery Sunflowers	cwt	42	0.49	4.35	-8.30	12.23
Flax	bu	58	0.42	11.30	-23.00	34.23
Rye	bu	13	4.61	30.11	-29.37	78.46
Sugarbeets	tons	28	-4.52	9.54	-19.55	15.97
Percentage deviation	**	4,459	0.10	0.68	-1.00	25.18

TABLE A2. STEPWISE REGRESSION PARAMETERS* FOR NDFBMEP DATA SET, INDIVIDUAL CROP MODELS

Variable	Corn	Oats	Barley	Spring Wheat	Winter Wheat
R^2	0.38894521	0.15194127	0.30574271	0.3387213	0.71736507
Intercept	8.0546667 (8.1791903)**	1.53105255 (5.75449057)	-13.91263092 (1.93969271)	1.40767414 (1.281449)	-0.78685485 (6.8434688)
Seed Exp				-0.48984562 (0.18079609)	-2.90252478 (1.32761801)
Fertilizer Exp	0.36175465 (0.13758593)		0.99543406 (0.1808654)		
Chemical Exp	0.84511127 (0.18810834)			0.36143054 (0.10654983	
Crop Ins Exp					
Irrigation Exp					
Farm Taxes					
Power & Equip Exp	0.00102349 (0.00037539)		0.00109899 (0.00048942)		
Labor Exp				0.21361458 (0.07231819)	
Miscellaneous Exp					
Share Crop	32.16166479 (3.82748589)	45.28190324 (8.49215487)	32.71894361 (2.12309239)	23.04932634 (0.97512601)	21.12954176 (0.04065898)
Rented					
Age of Operator	-0.62995248 (0.14434061)				
Total Crop Acres					
Current Ratio	-0.00047212 (0.00017261)				
Debt-to-Asset Ratio	-0.27861338 (0.0605539)	-0.21661344 (0.10592473)			
Return on Farm Equity				0.00653569 (0.0011623)	
Term Debt and Capital Replacement Margin	-0.00005162 (0.00002349)		0.00004524 (0.00001623)		
Depreciation Exp Ratio					

*All parameter estimates significant to the 95 percent level.
**Numbers in parentheses are standard errors.
***No variable met the 0.05 significance level for entry into the model.

TABLE A2. (CONTINUED)

Variable	Durum	Alfalfa	Other Hay	Soybeans	Dry Beans
R^2	0.38536111	0.19257111	0.03506176	0.3051543	0.88376748
Intercept	-0.86684008	-0.22968634	-0.05320674	0.19601792	-17.14995864
	(1.10445287)	(0.09438913)	(0.04842483)	(0.85782745)	(3.82284396)
Seed Exp		-0.02925019			
		(0.00928629)			
Fertilizer Exp		0.04187373			
		(0.01401502)			
Chemical Exp					
Crop Ins Exp					
Irrigation Exp					
Farm Taxes					
Power & Equip Exp					
Labor Exp	0.51616337	0.05755927			
	(0.16031553)	(0.02489129)			
Miscellaneous Exp	0.0019212				
	(0.00086536)				
Share Crop	21.55065216	1.54654713	0.66046813	18.18742499	21.26804277
	(1.52255013)	(0.30528869)	(0.17233913)	(1.81490394)	(2.51209723)
Rented					
Age of Operator					0.55559086
					(0.08615984)
Total Crop Acres					
Current Ratio	0.00011501			-0.0002822	-0.00012383
	(0.00005791)			(0.00011993)	(0.00004937)
Debt-to-Asset Ratio					-0.13274611
					(0.02777983)
Return on Farm Equity				0.00444973	
				(0.00224858)	
Term Debt and Capital Replacement Margin	0.00005563	0.00000272	-0.00000166		
	(0.00001771)	(0.00000124)	(0.00000072)		
Depreciation Exp Ratio	-0.23764287				
	(0.04021209)				

TABLE A2. (CONTINUED)

Variable	Oil Sunflowers	Confectionery Sunflowers	Flax	Rye	Sugarbeets
R^2	0.33352201	0.31132563	0.25640451	0.70014800	***
Intercept	0.1895989 (0.72978975)	-4.70235255 (1.36576204)	-6.42908074 (2.20395599)	92.14567613 (42.58672476)	
Seed Exp					
Fertilizer Exp					
Chemical Exp		0.3257507 (0.09465872)			
Crop Ins Exp	0.1821616 (0.07654653)				
Irrigation Exp					
Farm Taxes					
Power & Equip Exp					
Labor Exp		0.15722463 (0.07333731)			
Miscellaneous Exp					
Share Crop	7.7513814 (0.62030421)		8.44731922 (2.82279699)	40.2747266 (12.62126101)	
Rented					
Age of Operator				-2.19290404 (0.93367098)	
Total Crop Acres					
Current Ratio					
Debt-to-Asset Ratio	-0.03665768 (0.01050258)				
Return on Farm Equity					
Term Debt and Capital Replacement Margin	0.00001283 (0.00000588)		0.00006146 (0.0000256)		
Depreciation Exp Ratio					

TABLE A3. STEPWISE REGRESSION PARAMETERS* FOR NDFBMEP DATA SET, CROP CATEGORY MODELS AND PERCENTAGE DEVIATION MODEL

Variable	Small Grains	Row Crops	Forage Crops	Percentage Deviation
R^2	0.2994055	0.31808929	0.03044392	0.15572703
Intercept	-0.08178325	-0.30021649	-0.05177354	-0.01322756
	(0.04732014)**	(0.06863705)	(0.04304047)	(0.02783132)
Seed Exp	-0.01194921			-0.00583814
	(0.00368338)			(0.00242268)
Fertilizer Exp	0.00443526	0.00710338	0.02270841	0.00807273
	(0.00146465)	(0.00200374)	(0.00960048)	(0.00148559)
Chemical Exp	0.00926491	0.00551508		0.00703555
	(0.00219512)	(0.00188773)		(0.00189598)
Crop Ins Exp				
Irrigation Exp				
Farm Taxes				
Power & Equip Exp				
Labor Exp	0.00480662			0.00603625
	(0.00156128)			(0.00170582)
Miscellaneous Exp				
Share Crop	0.56330771		0.68490727	0.60469415
	(0.01857661)		(0.15025679)	(0.02314222)
Rented				
Age of Operator	0.00218314			
	(0.000934)			
Total Crop Acres				
Current Ratio				
Debt-to-Asset Ratio		-0.00263724		-0.00135069
		(0.00051328)		(0.0031176)
Return on Farm Equity	0.00011792			
	(0.00002219)			
Term Debt and Capital Replacement Margin	0.00000073			
	(0.00000014)			
Depreciation Exp Ratio	-0.00298719	-0.00556448		-0.00297125
	(0.00074545)	(0.00246088)		(0.00090006)
Crop #1				-0.30162480
				(0.04984226)
Crop #2	-0.08707965			
	(0.03397778)			
Crop #3	-0.09537156			-0.07399632
	(0.01989678)			(0.02787731)

*All parameter estimates significant to the 95 percent level.
**Numbers in parentheses are standard errors.

TABLE A3. (CONTINUED)

Variable	Small Grains	Row Crops	Forage Crops	Percentage Deviation
Crop #55				
Crop #56				
Crop #203				
Crop #10				
Crop #107				0.09345959 (0.03203452)
Crop #200				
Crop #201				
Crop #204				
Crop #231				
Crop #207	-0.15480886 (0.05480854)			
Crop #208				
Crop #232				-0.62551539 (0.15955452)

TABLE A4. STEPWISE REGRESSION PARAMETERS* FOR NDFBMEP DATA SET FARMS WITH SOIL PRODUCTIVITY INDEXES, INDIVIDUAL CROP MODELS

Variable	Corn	Oats	Barley	Spring Wheat	Winter Wheat
R^2	0.40340676	0.311785	0.38320142	0.46028797	***
Intercept	-56.28481782	-14.9770987	-30.85816618	-6.9642745	
	(25.96491434)**	(5.43631151)	(6.32782679)	(2.42436219)	
Seed Exp				-0.87792727	
				(0.28803758)	
Fertilizer Exp			1.19397696		
			(0.52262105)		
Chemical Exp					
Crop Ins Exp				0.67837442	
				(0.28900101)	
Irrigation Exp					
Farm Taxes					
Power & Equip Exp					
Labor Exp					
Miscellaneous Exp					
Share Crop	38.06491665	72.43419841	39.13806237	26.1560367	
	(11.48130092)	(14.51098084)	(5.85222032)	(1.87461879)	
Rented					
Age of Operator					
Total Crop Acres					
Soil Prod. Index	81.17943411		33.31150396	20.353826	
	(37.48545975)		(12.79447791)	(3.81790726)	
Current Ratio				0.00014608	
				(0.00006028)	
Debt-to-Asset Ratio					
Return on Farm Equity				0.00953566	
				(0.00365432)	
Term Debt and Capital Replacement Margin					
Depreciation Exp Ratio			-.55863413	-0.34007786	
			(0.26183657)	(0.09543494)	

*All parameter estimates significant to the 95 percent level.
**Numbers in parentheses are standard errors.
***Farms with soil productivity indexes did not grow winter wheat.

TABLE A4. (CONTINUED)

Variable	Durum	Alfalfa	Other Hay	Soybeans	Dry Beans
R^2	0.65925595	0.42366185	0.24227955	0.48836979	0.89502501
Intercept	-27.75924218	-2.10634978	-0.16763954	-1.14257339	4.10506443
	(8.16626870)	(0.53613998)	(0.07149807)	(2.42743321)	(2.04016191)
Seed Exp					
Fertilizer Exp					
Chemical Exp	1.31631097				
	(0.43352035)				
Crop Ins Exp			0.12132266		
			(0.05387016)		
Irrigation Exp					
Farm Taxes					
Power & Equip Exp					
Labor Exp					
Miscellaneous Exp					
Share Crop	20.30996116		1.47934141	26.06233843	24.92058962
	(2.45820218)		(0.35804979)	(3.15263037)	(3.81679344)
Rented					
Age of Operator	0.66551191				
	(0.19434736)				
Total Crop Acres		0.00066406			
		(0.00024395)			
Soil Prod Index		2.42866857			
		(0.9470911)			
Current Ratio	1.19922179		-0.00000744		
	(0.31032677)		(0.00000311)		
Debt-to-Asset Ratio				0.08877751	
				(0.03318532)	
Return on Farm Equity			-0.0052159		
			(0.00141102)		
Term Debt and Capital Replacement Margin					
Depreciation Exp Ratio	-0.90888286				
	(0.28983487)				

TABLE A4. (CONTINUED)

Variable	Oil Sunflowers	Confectionery Sunflowers	Flax	Rye	Sugarbeets
R^2	.44887369	***	***	****	***
Intercept	-16.02770934 (3.46226319)				
Seed Exp					
Fertilizer Exp					
Chemical Exp					
Crop Ins Exp					
Irrigation Exp					
Farm Taxes					
Power & Equip Exp					
Labor Exp					
Miscellaneous Exp					
Share Crop	5.18722443 (1.07348533)				
Rented					
Age of Operator	0.1631451 (0.06152306)				
Total Crop Acres	0.0039787 (0.00091664)				
Soil Prod. Index	7.13767605 (3.11066512)				
Current Ratio					
Debt-to-Asset Ratio					
Return on Farm Equity					
Term Debt and Capital Replacement Margin					
Depreciation Exp Ratio					

***No variable met the 0.05 significance level for entry into the model.
****Farms with soil productivity indexes did not grow rye.

TABLE A5. STEPWISE REGRESSION PARAMETERS* FOR NDFBMEP DATA SET FARMS WITH SOIL PRODUCTIVITY INDEXES, CROP CATEGORY MODELS AND PERCENTAGE DEVIATION MODEL

Variable	Small Grains	Row Crops	Forage Crops	Percentage Deviation
R^2	0.38345219	0.36864871	0.23455184	0.31328237
Intercept	-0.37650666 (0.09362186)**	-0.80875473 (0.21768024)	0.04678089 (0.09446138)	-0.5048092 (0.08283508)
Seed Exp				
Fertilizer Exp				
Chemical Exp				
Crop Ins Exp				
Irrigation Exp				
Farm Taxes				
Power & Equip Exp				
Labor Exp			0.03701973 (0.01175747)	
Miscellaneous Exp	0.00004515 (0.00002125)			
Share Crop	0.69365571 (0.039227)	0.74201255 (0.07455183)	1.34564603 (0.25174981)	0.71396641 (0.03871393)
Rented				
Age of Operator	0.00453053 (0.00165809)	0.00685539 (0.00286052)		0.00452737 (0.00152295)
Total Crop Acres				
Soil Prod. Index	0.45694518 (0.08262896)	0.87683549 (0.22520347)		0.52779845 (0.07452769)
Current Ratio			-0.00000686 (0.00000221)	-0.00000207 (0.00000103)
Debt-to-Asset Ratio	-0.00156904 (0.00054669)		-0.00426107 (0.00171869)	
Return on Farm Equity			-0.00447144 (0.0011939)	
Term Debt and Capital Replacement Margin				
Depreciation Exp Ratio	-0.00781796 (0.00202596)			
Crop #1				
Crop #2				
Crop #3	-0.08154696 (0.03737282)			
Crop #55				
Crop #56				

TABLE A5. (Continued)

Variable	Small Grains	Row Crops	Forage Crops	Percentage Deviation
Crop #203				
Crop #10				
Crop #107				
Crop #200				
Crop #201				0.43413952 (0.18457635)
Crop #204				
Crop #231				
Crop #207				
Crop #208				
Crop #232				

*All parameter estimates significant to the 95 percent level.
**Numbers in parentheses are standard errors.

TABLE A6. AVERAGE FARM YIELD DEVIATIONS FROM COUNTY YIELD FOR ILLINOIS FARM BUSINESS FARM MANAGEMENT ASSOCIATION, 1982 - 1992

YEAR	CORN	SOYBEANS	WHEAT	OATS
		-bushels-		
1982	9.13	3.68	2.95	4.13
1983	4.75	2.68	3.92	9.50
1984	10.09	4.16	4.07	9.01
1985	9.18	3.41	2.84	5.22
1986	9.81	3.93	1.26	5.69
1987	6.36	3.71	2.64	4.61
1988	6.07	2.48	3.72	6.08
1989	7.30	3.80	2.50	7.84
1990	5.70	3.26	-0.07	4.19
1991	7.90	4.51	0.91	2.87
1992	6.01	2.79	1.55	3.43

TABLE A7. STEPWISE REGRESSION PARAMETER ESTIMATES* AGRONOMIC AND DEMOGRAPHIC VARIABLES (N=1,401) WITH TIME SERIES DUMMY VARIABLES

VARIABLE	CORN	SOYBEANS	WHEAT	OATS
R2	0.10493732	0.05836717	0.04407285	0.05309233
INTERCEPT	-24.6524471	-1.49957072	-8.7264520	-22.8033956
	(1.00175454)**	(0.37597201)	(0.82161042)	(3.67687931)
Seed Exp				
Fertilizer Exp	0.00008749	0.00003956	0.00004437	
	(0.00001414)	(0.00000574)	(0.00000847)	
Chemical Exp		0.00002104		
		(0.00000836)		
Taxes	-0.00019568	-0.00005166		0.00039516
	(0.000034)	(0.00001339)		(0.00017109)
Power & Equip Exp	0.00016227	0.00005962		0.00015511
	(0.00000961)	(0.00000321)		(0.00002793)
Labor Exp	-0.00013042			
	(0.00001447)			
Misc Exp		0.00007779		
		(0.00003235)		
Soil Prod Index	0.38289747	0.05329800	0.15040918	0.32381582
	(0.01271797)	(0.00485355)	(0.01159583)	(0.04542815)
Total Crop Acres		-0.00274308		-0.01563139
		(0.00029819)		(0.00326033)
Part Owned				
Rented		-0.46342687		
		(0.12618912)		
Yr83	-0.260053	-1.25890105	1.56883822	4.07090007
	(0.54552308)	(0.19446615)	(0.56649017)	(1.58171060)
Yr84			1.50980108	3.82749261
			(0.53333479)	(1.61444486)
Yr85		-0.67020711		
		(0.1909426)		
Yr86	1.34071527			
	(0.53121219)			
Yr87	-1.63881507			
	(0.53219872)			
Yr88	-1.80085947	-1.14374682	1.36060519	
	(0.53300985)	(0.19028504)	(0.55244556)	
Yr89				3.84323448
				(1.49841407)
Yr90	-2.5335363	-0.57836275	-2.8123104	
	(0.53182582)	(0.1907629)	(0.51618304)	
Yr91		0.73293156	-1.7418527	
		(0.19321306)	(0.54697929)	
Yr92	-1.80493953	-1.01265423		
	(0.536397)	(0.19346792)		

*Parameter estimates significant at the 5% level.
**Number in parentheses is standard error.

TABLE A8. AVERAGE FARM YIELD DEVIATIONS FROM COUNTY YIELD FOR ILLINOIS FARM BUSINESS FARM MANAGEMENT ASSOCIATION--FARMS WITH COMPLETE FINANCIAL INFORMATION, 1982 - 1992

YEAR	CORN	SOYBEANS	WHEAT	OATS
		-bushels-		
1988	6.26	2.51	2.95	4.00
1989	11.03	4.13	3.53	17.93
1990	6.69	3.66	-1.64	-3.59
1991	7.97	4.04	1.26	6.89
1992	7.71	2.00	0.01	0.60

TABLE A9. STEPWISE REGRESSION PARAMETER ESTIMATES* FOR FARMS WITH COMPLETE FINANCIAL INFORMATION--WITH TIME SERIES DUMMY VARIABLES

VARIABLE	CORN	SOYBEANS	WHEAT	OATS
R2	0.11191601	0.10907021	0.04060180	0.35268710
INTERCEPT	-26.31523084	-2.49907921	-0.20185753	3.1838724
	(5.0431671)**	(1.68643866)	(1.3111121)	(6.97225567)
Seed Exp				
Fertilizer Exp	0.00024203		0.00008549	0.00077459
	(0.00006519)		(0.00003958)	(0.00032262)
Chemical Exp	-0.00019675			
	(0.00009027)			
Taxes	-0.00061463	-0.00020866		
	(0.00013662)	(0.00003793)		
Power & Equip Exp	0.0027454	0.00006463		
	(0.00004486)	(0.00001426)		
Labor Exp		0.00008994		0.00084652
		(0.00002828)		(0.00031408)
Misc Exp		0.00025068		
		(0.00012698)		
Soil Prod Index	0.35063022	0.05130739		
	(0.05905657)	(0.01858169)		
Total Crop Acres				-0.05438501
				(0.01159979)
Part Owned				
Rented				22.97399487
				(6.97331005)
Age of Farm Operator				
Current Ratio				
Debt-to-Asset Ratio	-6.6531247	-2.94382472		
	(2.45734645)	(0.79287812)		
Return on Farm Equity	23.44858181	8.52661307		
	(4.52564516)	(1.47717598)		
Depreciation Expense Ratio				
Yr89				22.34740985
Yr90			-3.86570888	
			(1.42669814)	
Yr91				
Yr92		-2.55700308		
		(0.46446271)		

*Parameter estimates significant at the 5% level.
**Numbers in parentheses are the standard error.

TABLE A10. MEAN OF ESTIMATED YIELD DEVIATION DEPENDENT VARIABLES, MEAN CONTRIBUTING INDEPENDENT VARIABLES, ABSOLUTE VALUE OF CONTRIBUTING VARIABLES, AND COMPOSITE WEIGHTS FOR CROP INSURANCE SCORECARDS FOR NORTH DAKOTA PRODUCERS

Variable	Mean Contribution	Absolute Value of Mean Cont.	Percent Contribution	Assigned Weight
INTERCEPT	-0.50	*	*	*
Crop Share	0.13	0.13	13.30	1.3
Operator's Age	0.18	0.18	17.47	1.7
Soil Productivity	0.32	0.32	31.59	3.2
Current Ratio	-0.38	0.38	37.64	3.8
Crop #201	-0.00**	*	*	*
TOTAL	-0.25	1.01	100.00	10.0

*Intercept and Crop #201 were not used to calculate weights for scorecard.
**Mean contribution to estimate was greater than -0.00, but was significant.