Risk Management in Precision Agriculture

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Risk Management Tools in Precision Agriculture

Introduction

One of the primary responsibilities of the farm manager is making decisions. These decisions are typically based on profit maximization (Boehlje and Eidman). While many factors influencing this goal can be controlled by the farm manager, such as economically efficient input use, other factors cannot. These uncontrollable events introduce a great deal of uncertainty into the farm business. This uncertainty makes the inclusion of risk in the decision-making process a necessity for producers to reach their goal of profit maximization.

By identifying the appropriate risk statistics, this study will examine three methods for mapping risk using precision agriculture by creating a break-even probability, a coefficient of variation (CV), and a mean-variance (E-V) map. Break-even probabilities calculate the percent chance that break-even production levels, the minimum yield required for net returns over specified costs to equal zero, will occur, based on historic production levels. Thus, the higher the break-even probability, the lower the risk. The CV reports the distribution variation; the larger the CV, the greater the variability, thus the more “risky”. Finally, an E-V framework is used to adjust net returns according to defined levels of risk aversion. Comparing results among these maps provides producers useful information on the level of risk faced in agricultural production.

Calculating these measures for decisions depends on gathering accurate farm information. The use of precision agriculture (PA) technologies allows producers to collect and analyze information on a spatial basis. This information can then be used to aid producers in their ability to make decisions on a spatial basis, such as calculating the various levels of risk across a field.

The role of PA in the decision-making process will be the focus of this study. Few decision aids have been developed to help PA practitioners make decisions from the data they
The overall purpose of this study is present risk assessment tools useful to users of PA. Specifically, this objective will be achieved through the following procedures: 1) identify key statistics for measuring risk which will reflect changes in temporal risk, 2) develop procedures using Geographical Information Systems (GIS) software and yield monitor data to visually identify this temporal risk spatially throughout a field, and 3) provide an empirical application and interpretation of the resulting risk maps using crop insurance as an example.

Theoretical Framework

The first step in developing risk management tools using PA data is outlining the underlining risk theory. This section will begin that discussion, including E-V, break-even analysis and CV. Following the risk framework will be a presentation of the current literature regarding the role PA has played in risk management.

The USDA defines five types of risk in agriculture: production risk, market risk, financial risk, institutional or social risk, and human risk (Harwood et al.). Production risk is particularly relevant to agriculture because of its susceptibility to the weather. Many events that affect production, such as drought, flooding, or disease, are caused by unfavorable weather conditions. While all areas of risk affect decision making, production risk will be main focus of this study.

The evolution of risk in decision making began with the game theory work of Von Neumann and Morgenstern. It was their work which dictated that the decision maker uses expected utility to make their “best” choice (Day). In making decisions, one must chose among a set of alternatives with varying degrees of risk and a set of probability distributions. A decision is based on finding the alternative which maximizes expected utility (Freund).

The next evolutionary step in risk theory stated that decisions could be based on only the mean and variance of the models (Varian; Boisvert and McCarl). Markowitz began the development of E-V analysis, looking at investment strategies (Varian). The E-V model states that decisions are based on the mean and variance of net returns, preferring a higher mean and
lower variance. It has been found that E-V analysis is a proper tool to use, as being consistent with expected utility modeling, when the stochastic variables differ only by location and scale (Meyer) such as when returns are normally distributed (Boisvert and McCarl). The framework for E-V analysis is as follows:

\[
\text{Max: } EV = \sum \bar{r}_i \times x_i - \Phi \times Var_y
\]

where \( EV \) is the risk adjusted net returns, \( \bar{r} \) is the average rate of return, \( x_i \) is the dollar amount invested, \( \Phi \) is the risk aversion parameter, and \( Var_y \) represents the variance of net returns.

Difficulty in applying E-V analysis arises because the risk aversion coefficient (RAC) must be known. McCarl and Bessler developed an approach to calculate a level of risk aversion when the utility function is not known. Their formula for calculating RACs is as follows:

\[
\Phi = \frac{2Z \alpha}{S_y}
\]

where \( \Phi \) is the risk-aversion coefficient, \( Z \alpha \) is the standardized normal Z value of \( \alpha \) level of significance and \( S_y \) is the relevant standard deviation. When applied to Equation 2, the RAC gives the level at which the producer is affected by risk, represented by the variance of net returns. Dillon, Oriade, and Parsch used a similar method in analyzing production risk in soybean rental arrangements in Arkansas. This approach will again be employed in this study.

Farm management texts (e.g. Kay and Edwards) discuss other, more simplified, methods for measuring risk. The literature confirms the use of statistics such as the CV and break-even analysis for measuring risk. The CV has been identified in several studies as a method for measuring risk, such as the sustainability of agricultural cropping systems (Lu, Watkins, Teasdale) and using soybean oil in horticultural crops (Pendergrass et al.). These studies demonstrated that the higher the CV, the more risky the situation.

Break-even analysis literature demonstrates its usefulness as a farm management tool.
The foundation for break-even analysis is presented in many basic farm management textbooks (e.g. Kay and Edwards). The most basic form of break-even analysis calculates either the yield or commodity price to be received, given selected costs, to generate a return above those selected costs of zero dollars. Examples include the calculation of the maximum level of an input price (diesel fuel) one would pay to break even (Dillon and Roberts), calculation of break-even points among enterprises (Dillon 1992), and break-even planting and harvesting decisions (Dillon 1994). Other studies have demonstrated break-even analysis as a decision rule in studying the economics of Roundup Ready® (RR) soybeans (Pearce et al., Roberts, Pendergrass and Hayes).

While break-even analysis can be used to measure risk, farmers also want tools to help manage risk. One such option available to farmers is crop insurance. Current yield-based insurance, commonly referred to as actual production history, or APH, available to farmers include the Multiple Peril Crop Insurance (MPCI), Group Risk Plan (GRP) and Dollar Plan, as well as several pilot programs across the States (RMA online). The lack of precise yield data has been identified as one of the most limiting factors in predicting accurate insurance premiums (Goodwin and Ker). With the introduction of PA technologies, more accurate ways of making such measurements have been established.

While the literature regarding PA is quite diverse, a majority of the studies have focused on agricultural production and profitability. Studies include adoption of technologies (Shearer et al.1999; Swinton, Harsh, and Ahmad; English et al.), variable rate technologies (Engebretson; Clark and McGuckin), and profitability (Engebretson; Schnitkey, Hopkins, and Tweeten). The most comprehensive review of PA profitability studies came in 2000, by Lambert and Lowenberg-DeBoer. Of the 108 studies they collected reporting economic results, 63% reported positive economic benefits, 26% reported mixed results, and 11% reported no economic benefits.

PA practitioners are not only affected by the typical risks faced by farmers, but must also deal with a unique set of risk factors because of the technologies. Lowenberg-DeBoer (1999)
outlined a number of risk factors faced by PA adopters, such as the following: up-front payments for services could make the bad years worse (production risk); profitability of the technologies depends on people’s ability to correctly use the technologies (human risk); obsolescence of technologies (technological risk); and investment in the technologies (financial risk). In addition, he claimed that PA may also reduce risk through providing early yield estimates with remote sensing, make contracting easier, and “‘as-applied maps’ can provide an important trace back mechanism that could reduce insurance premiums and liability claims for input suppliers, producers, and processors” (p. 278).

The role of PA in the area of decision making has been more limited. While there has been general discussion on decision making and information needs in PA (Watermeier; Atherton et al., Fleming et al.), the availability of decision-making tools has been identified as a weakness in the literature (Gibbons; Atherton et al.; Lowenberg-DeBoer 1996). Adding to the general break-even studies listed above, break-even analysis has recently begun to appear in PA literature. Studies include spatial break-even analysis for VRT (English, Roberts and Mahajanashetti), ownership of precision equipment (Gandonou et al.) and enrolling buffer strips into the Conservation Reserve Program (CRP) (Stull et al.). Using yield maps for decision making has been introduced in the literature, but again, the number of studies is limited (Larscheid, Blackmore and Moore).

Precision agriculture’s usefulness as a risk management tool extends beyond its capabilities to record accurate yields for crop insurance. Any statistic can be calculated for individual grids within a field using yield monitor data. The field can then be mapped according to these particular statistics. This section has discussed the use of an E-V framework, the CV and break-even analysis as risk management tools. The next section will outline the procedures for developing risk maps from yield monitor data using these statistics.

**Model Development and Data**
Risk maps were created beginning with three years of yield monitor data collected from a cooperating producer in western Kentucky. Before yield monitor data can be analyzed, any potentially erroneous points must be removed. Yield monitor data were first adjusted to actual yield averages reported by weigh scale tickets. Standards for speed, crop moisture and harvester throughput used to determine potentially erroneous data points, according to expert opinion, were as follows: between 25 and 140 inches traveled per second; moisture between 10% and 35%; or mass flow less than 75 pounds per second. Any point not meeting all three conditions was removed. Although it is common to see misleading information in yield monitor data, properly calibrated equipment can minimize its occurrence (Shearer et al. 1999).

The yield monitor data were averaged into 1,076 ft$^2$ grids to permit comparisons across years. Production decisions are more reliable when data are available for several years to capture more variability in production. The problem created by the current lack of historic yield monitor data was resolved by developing a procedure to predict yields for the unavailable years based on average farm yields for twenty years and the three years of spatial yield data. However, before implementing this prediction procedure, the historic farm yield averages were detrended for consistency with this study’s use of current input and output prices in calculating net returns, as well as technological developments and other factors having positive effect on yields. The data were detrended according to the process used in many crop insurance programs, as well as that suggested in Goodwin and Ker. Equation 3 was used for regressing yields,

\[
y = \beta_0 + \beta_1 x + \epsilon,
\]

where $y$ is the annual yield average and $x$ is the year. Each year’s adjusted yield, $Yield_y$, was then calculated using Equation 4,

\[
Yield_y = \frac{\text{Actual Yield in Year } x}{\text{Trend Yield in Year } x} \times \text{Trend Yield for 2000}
\]
The prediction procedure was developed assuming a linear relationship between yield per grid and the farm average yield within the same year, as in Equation 5,

Equation 5.  \[ y_g = m_g x + b_g \]

where \( y_g \) is the percent of total yield for a given grid, \( g \) in a year to be calculated and \( x \) is that year’s average yield. The highest and lowest averaging years were chosen among the three years of yield monitor data collected to establish this linear relationship. The spatial variability captured in the yield maps of these two years was used to calculate the percentage of average yield in each grid, allowing the spatial variability in the field to change across time. Based on these indices, a slope and intercept (\( m \) and \( b \)) were found between the maximum and minimum average years. The linear relationship was completed by solving Equation 5 for each grid cell. Thus, the spatial variability captured in the yield maps and the temporal variability from historical yield averages were combined to create yield maps for seventeen years, resulting in a total of twenty years of yield maps. Finally, because the prediction procedure required there be no missing data points within the field, a “nearest neighbor” method within Surfer® was used to estimate missing grid data within the field boundary. The “nearest neighbor” approach assigned the value of the nearest data point to each grid.

Data for this research were obtained from a large, privately owned grain farm in western Kentucky. This producer’s involvement with PA began with yield monitoring in 1996. The following data were collected to perform this analysis: 1) yield monitor data from corn fields, 2) field level average corn yields for the yield monitored fields, 3) farm level average corn yields for twenty years (1981 - 2000), 4) estimated production expenses, 5) relevant Loan Deficiency Payments (LDPs) for the county, and 6) crop insurance producer paid premiums, indemnity payments, and insurance trigger yield levels.

Yield monitor data were collected from a 39 acre corn field for three production years (1996, 1998, and 2000). After employing the filtering process previously discussed, there were
1,588 grids of 1,076 ft². Descriptive statistics of yield data are presented in Table 1. Included in the table are both temporal and spatial yield statistics for the estimated yield monitored data. All statistics are expressed on a per acre basis.

The series of risk maps begins with a twenty year average net returns map. Net returns per grid, \( NR_g \), were calculated according to Equation 6:

\[
NR_g = \frac{\sum (Yield_g * P_N) - TVC}{n},
\]

where \( Yield_g \) is the yield per grid \( g \), \( P_N \) is the net sales price, \( TVC \) are the total variable costs, and \( n \) is the number of years in the study. The net sales price was calculated as follows:

\[
P_N = P_G - Fuel - DS + LDP,
\]

where \( P_G \) is the gross sales price, \( Fuel \) is the harvest and transport costs, \( DS \) is drying and storage, and \( LDP \) is the relevant Loan Deficiency Payment. All amounts are given in dollars per bushel.

The remaining maps are based on average net returns per grid. The break-even probabilities map calculates the percent chance that an individual grid will break-even, based on its twenty year average of net returns. The CV map reflects the CV of average net returns for each grid over the twenty year history.

Finally, the E-V risk map of net returns is based on the break-even point of net returns from Equation 1. Those break-even points are outlined in Equation 8:

\[
BE_{NR} = \frac{VC + \Phi \cdot VAR_{NR}}{P_N \cdot Yield},
\]

where \( \Phi \cdot VAR_{NR} \) is the risk component of net returns. The \( Z \) value for calculating the RAC was generated using \( \alpha \) levels from 50% to 95% in 5% increments, where 50% represented a risk neutral producer and 95% represented the highest level of risk aversion. Given that producers
would not know their exact risk aversion level, four general levels were used to calculate the E-V net returns map, neutral ($\alpha=50\%$), low ($\alpha=60\%$), medium ($\alpha=70\%$), and high ($\alpha=80\%$).

Although chosen subjectively, each $\alpha$ was determined based on its relative effect on net returns.

Production expenses were based on the most recent data available from the Kentucky Farm Business Management (KFBM) Program (Moss, Ibendahl, Riggins). Total variable costs (TVC) were $178.84 per acre, or $4.42 per grid. This does not include the yield related expenses, drying, storage and fuel, which were included in the net sales price. The total fuel expense reported by KFBM included more than harvest and transport costs, which are the only necessary fuel expenses. However, because the reported expense was a modest amount ($6.74 per acre, or $0.04 per bushel), it was not unreasonable to include the entire amount as yield dependent with the net sales price. The corn commodity price, $2.35 per bushel, came from 2001 University of Kentucky enterprise budgets. The net sales price outlined by Equation 4 was $2.588 per bushel. The LDP payment, $0.33 per bushel was the study’s local average LDP payment received, as reported by the Farm Service Agency. KFBM’s total fixed costs (TFC) were used to identify grids whose net returns cover all costs in the net returns map. Machinery interest, unavailable from KFBM, was found in the 2002 University of Tennessee No-till Corn Field Crop Budget. TFC were $36.79 per acre, or $0.91 per grid.

As previously discussed, a standard APH insurance option, MPCI, was added to create a second series of risk maps to observe how insurance might affect risk in net returns. Based on expert opinion for a reasonable coverage level, a 75% coverage level was applied. A target yield (105 bushels per acre), indemnity payment ($2.00 per bushel) and premium ($9.68 per acre) were calculated for the current year, 2002 for consistency in using the most recent data available. The insurance data were incorporated into each year in the data set to evaluate the impact crop insurance could have on risk.

Results
Results from this study, provided in Figures 1 through 4 and Tables 1 through 3, show that yield monitor data can be combined with expenses to create a series of risk maps to help the producer identify changes in temporal risk, spatially. This section will provide interpretation and insight into the meanings of these maps, beginning with a short discussion of the yield prediction procedure tests, followed by a discussion on the risk maps, with and without crop insurance.

Tests for the yield prediction procedure indicate that yields were not perfectly predicted. Two of the three years of available yield monitor data were required to estimate yields, leaving the third year available to test the prediction procedure. The adjusted $R^2$ between the estimated and the actual yield data for the third year was .3005, suggesting a poor capture of the actual yields. Using measures for bias and precision outlined in Mueller et al., the procedure was also shown to be somewhat biased, with a less than desired prediction efficiency. However, it was concluded that yields were not unreasonably predicted for the purposes of this study.

These results offer two suggestions. First, the prediction procedure poorly estimated yields for the one out of sample year available. Thus, conclusions for prediction efficiency cannot be drawn for every year in the study. Secondly, the overall objective of this study was to develop economic decision aids for risk management for users of PA. This objective was achieved through the creation of the various maps. While the prediction procedure directly impacts the results of this study, they are not invalidated. Accounting for spatial variation has not been easily accomplished. According to Sadler et al. (2000), classical statistics were found not well suited for spatial problems in their corn yield prediction study. “The multitude of causes and effects operating to create spatial variation within a field poses a challenge to even the most advanced experts or simulation models” (p. 395). In their results, “little correlation was found among any simple combination of crop characteristics” (p. 401). Thus, while the information provided by these maps to the decision maker will improve with a better prediction estimator, finding this estimator is beyond the scope of this study.
The net returns map, not presented here, showed that this is a profitable field. There are only 63 grids (1.56 acres) that did not cover variable costs and 24 grids (0.59 acres) that covered variable costs, but not fixed costs (shown by the yellow grids). The average net returns above variable costs across the entire field was $7,760. With the exception of a small number of interior grids, grids not covering variable or total costs are located at the field borders.

However, the remaining maps illustrate that positive net returns does not imply a lack of risk. Figure 1 is the break-even probabilities map, showing the percent chance that each grid will break even, given the twenty year history. The lighter the color, the higher the break-even probability. While most of the field displays a 100% chance of breaking even, the entire field is not represented as such. The net returns map showed problems with field borders and the break-even map confirms this. Black areas had a 25% or less likelihood of breaking even. This map also illustrates some riskiness in interior portions of the field. However, there is still a high likelihood (80-95%) that most of the areas will break even. Additional information on this map is presented in Table 2, providing the percent of the field in each of the break-even categories.

Figure 2 represents the spatial array of the coefficients of variation for net returns. Although the categorizations were chosen independently, results for the CV map and break-even probabilities map showed similar patterns. Those areas with a less than 100% chance of breaking even have a higher CV. Also, by definition of CV, grids with a negative average net returns will have a negative CV. Again, field borders are revealed as the main problem areas, with interiors portions causing minor concerns.

The E-V map of net returns is Figure 3. This map displays the areas that a producer of a certain risk aversion level may choose not to produce, given their break-even requirements. The “produce” areas would always remain in production and the “risk neutral” areas would never be in production, regardless of risk preferences. These areas show consistent results with the previous maps. Intuitively, as the producer becomes more risk averse, more land would be
removed from production, assuming that there is some risk in agricultural production. Table 3 can be reviewed for further information about this map. Statistics are calculated for the four risk aversion levels based on the producer’s decision to remove grids with negative average net returns from production. There is a trade-off between net returns and risk. As Table 3 illustrates, as a producer’s risk aversion level increases, of the land left in production, riskiness decreased, but so does average net returns.

Including crop insurance changed the results very little. The target yield to trigger an insurance payment was 105 bushels per acre. Only one year out of twenty averaged a yield less than the trigger. Thus, for nineteen years, the only change in net returns resulted from the producer’s loss of the premium. The most noticeable change can be found in Table 2, showing the percent chance of breaking even. Receiving the indemnity payment for that one year slightly increased the percent of the field with 100% chance to break even. The net insurance benefit that year was only $0.40 per grid., showing how close some grids were originally to breaking even.

Adding crop insurance had some impact on the decision to remove land from production among the various risk aversion levels, presented in Figure 4. For most of the field (90.17%), the decision did not change. However, in 5.23% of the field, where originally only a highly risk averse producer would chose to produce on those areas, adding crop insurance reduced risk enough to encourage production regardless of risk aversion levels, the “produce” areas. In another 4.47% of the field, the decision not to produce was delayed one higher risk aversion level. For example, in Figure 4, a risk neutral producer would not produce on grid number 196. With the insurance option, a risk neutral producer would produce on that grid, however a low risk averse producer, being more risk averse than the risk neutral producer, would not.

Results from the crop insurance maps showed that this particular field would not effectively demonstrate the role crop insurance could have for risk management, because of its
productivity. Surprisingly, there were only two grids in the average net returns map that were affected by crop insurance. The difference in average net returns was only $0.60 per grid. The negligible impact was a direct result of using a highly productive field in this research. There will be little effect when only one year out of twenty triggers an insurance payment. Given its production history, this field would likely not be enrolled in a crop insurance program.

Overall, these maps show that the chosen statistics can be used to identify risky areas of a field. The net returns map established that this is a profitable field. However, this map is just “the cover” of the field. As the remainder of the maps showed, there is more to the story. Managers do not manage according to net returns alone. Risk must also be managed, as it directly impacts net returns. After reviewing the risk maps, problem areas not identified by the net returns map appeared. If the producer went no further than the net returns map, many risky areas would be missed and net returns could potentially suffer. Consequently, the manager would not have the best information to make sound decisions. By including risk maps into the decision-making process, more problem areas can be identified and managed accordingly. The producer can then find economically feasible remedies that could lower the riskiness of the field.

These maps can also be used to compare production strategies. For example, would variable rate applications have an effect on risk? Would chemical resistant seed varieties reduce risk? By developing maps before and after implementing different production strategies, these maps can further improve farm management decisions.

Conclusions

For several years, many farmers have been collecting a large amount of yield monitor data with PA technologies. However, relatively few economic decision aids have been available to help these producers make economic decisions with this data. This study has shown that with the combination of yield maps and production expenses, a series of risk maps can be created to identify temporal risk spatially across a field. Using these maps, producers can now begin to
address the underlying issues creating this spatial risk.

Risk maps benefit producers through decisions made based on that knowledge. In this field, for example, some of the field borders were both highly risky and unprofitable. This producer may be better off not planting these areas and leave them as field access strips. If eligible, these areas could be enrolled in the Conservation Reserve Program (CRP). While the objective of this research was not to give producers the solutions to the problem areas identified in the field, identifying problem areas is a necessary first step in the decision-making process. The producer must then decide on the most feasible and economical course of action.

This study raised important issues in using yield monitor data for research. In most PA studies, the data were collected with the specific study in mind, paying special attention to the quality of that data. This study was completed with data collected by a farmer, as a farmer would collect it. If decisions are going to be made using PA data, this is the type of data that will be used in the decision-making process. It will not be a perfect data set. Some producers may pay closer attention to the calibration and maintenance of their yield monitors than other farmers. Hopefully, the sooner farmers begin using yield monitor data for decision-making, the sooner they will discover any errors and can take corrective actions to improve future decisions.

One of the concerns in this study was the derivation of the unavailable yield maps. Tests of the prediction procedure showed less than desirable results, leaving two options: developing a better yield prediction procedure or determine if a prediction procedure is needed. Would using three years of actual yield monitor data have been good enough to make long-term decisions? For this study, maps using only the three years of data showed similar patterns to the twenty year average maps. Considering that more than three years are generally desired for long term planning and waiting the ten to twenty years it would take to collect actual data, some type of prediction process will have to be used. Although the prediction procedure used in this study may not be perfect, it is an important first step.
Table 1. Descriptive statistics of farm level average yields and estimated yield monitor data from 1981-2000 (bushels per acre).

<table>
<thead>
<tr>
<th>Statistics</th>
<th>Farm Level Average Yields&lt;sup&gt;1&lt;/sup&gt;</th>
<th>Estimated Yield Monitor Data</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Actual</td>
<td>Detrended</td>
</tr>
<tr>
<td>Mean</td>
<td>128.5</td>
<td>143.6</td>
</tr>
<tr>
<td>Maximum</td>
<td>168.0</td>
<td>184.4</td>
</tr>
<tr>
<td>Minimum</td>
<td>79.0</td>
<td>97.5</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>19.31</td>
<td>19.1</td>
</tr>
<tr>
<td>Coefficient of Variation</td>
<td>15.0%</td>
<td>13.3%</td>
</tr>
</tbody>
</table>

1. Farm level average yields are temporal averages, based on the twenty years of historical yields.
2. Temporal yield data are based on the annual field averages for 20 years.
3. Spatial yield data are based on the yield averages per grid for 20 years.

Table 2. Percent of field in break-even probability categories, with and without insurance.

<table>
<thead>
<tr>
<th>Percent chance for net returns above breakeven</th>
<th>Percent of Field (No Insurance)</th>
<th>Percent of Field (With Insurance)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0 - 25%</td>
<td>2.77%</td>
<td>2.90%</td>
</tr>
<tr>
<td>30 - 50%</td>
<td>2.08%</td>
<td>2.08%</td>
</tr>
<tr>
<td>55 - 75%</td>
<td>2.14%</td>
<td>2.08%</td>
</tr>
<tr>
<td>80 - 95%</td>
<td>12.98%</td>
<td>10.65%</td>
</tr>
<tr>
<td>100%</td>
<td>80.03%</td>
<td>82.29%</td>
</tr>
</tbody>
</table>

Table 3. Descriptive statistics for E-V map.

<table>
<thead>
<tr>
<th>Risk Aversion Level</th>
<th>Percent of Land in Production</th>
<th>Mean Net Returns</th>
<th>Net Returns Coefficient of Variation (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Full Production</td>
<td>100%</td>
<td>$7,760</td>
<td>38.8%</td>
</tr>
<tr>
<td>Risk Neutral</td>
<td>96.03%</td>
<td>$7,852</td>
<td>25.5%</td>
</tr>
<tr>
<td>Low Risk Averse</td>
<td>92.25%</td>
<td>$7,769</td>
<td>23.8%</td>
</tr>
<tr>
<td>Medium Risk Averse</td>
<td>87.65%</td>
<td>$7,502</td>
<td>22.5%</td>
</tr>
</tbody>
</table>
High Risk Averse | 79.33% | $6,876 | 20.6%

Figure 1. Break-even Probabilities Map

Figure 2. Coefficient of Variation Map
Figure 3. EV Risk Map without Insurance

Figure 4. EV Risk Map with Insurance
Bibliography

2002 Field Crop Budgets. Department of Agri. Econ. Univ. of Tennessee.  
http://economics.ag.utk.edu/budgets.html.

Atherton, B.C., M.T. Morgan, S.A. Shearer, T.S. Stombaugh, and A.D. Ward.  “Site-Specific  
Farming: A Perspective on Information Needs, Benefits and Limitations.” J. Soil and  
Water Conservation.  54 (Spring 1999):455-461.


Boisvert, R.N. and B.A. McCarl. Agricultural Risk Modeling Using Mathematical  
Station, July 1990.

Clark, R.L. and R.L. McGuckin. “Variable Rate Application Equipment for Precision Farming.”  

(Eds). Univ. of Minnesota Press, Minneapolis, 1981.

Dillon, C.R. “Advanced Breakeven Analysis of Agricultural Enterprise Budgets.” Amer. J. of  

Dillon, C.R. “Breakeven Analysis As An Aid To Planting and Harvesting Decisions.” J. Amer.  

Rental Arrangements From the Tenant’s and Landlord’s Perspective.” Dept. Agr. Econ.  
and Rural Soc. SP0598, Univ. of Arkansas, 1998.

Dillon, C.R. and T.A. Roberts. “Breakeven Analysis for Interrelated Input Prices.” The  

Engebretson, A. “Is Site Specific Profitable?” Ag Consultant, September 1999. Summary of  

Variable Rate Technology Adoption.” Proceedings of the 4th Intnl Conf. on Precision  

“Precision Farming: From Technology to Decisions, A Case Study.” Proceedings of the  


