Precision Agriculture in Citrus: A Probit Model Analysis for Technology Adoption

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Abstract. The objective of this study is to identify the likelihood of Florida citrus producers adopting precision agriculture technologies. This is the second stage of a multi-part study on precision agriculture in Florida citrus production. Stage one involved the use of a mail questionnaire to collect growers’ information regarding production management practices in citrus. The results of the citrus producer survey regarding adoption trends and attitudes towards precision agriculture were used to analyze the likelihood of adoption for precision agriculture technologies in Florida citrus production. The objective was to identify demographic characteristics of adopters versus non-adopters, and determine from questionnaire responses if there were other factors that influenced the decision to adopt precision agriculture technologies. The indicators that were measured included the growers’ demographic characteristics, a self-perceived technology adoption attitude and the grower's self-perceived in-grove level of variability. A random selection of citrus growers from the top 10 counties (in production area) in Florida was questioned regarding current and future practices. Multinomial probit models were developed to estimate the probability of adoption of 10 different precision agriculture technologies based on the indicators measured in the survey.

Early results from the probit models have shown a statistically significant correlation to the independent variables related to in-grove spatial variability, age and land ownership influencing the decision to adopt precision farming technologies in citrus production.

Keywords. Precision agriculture, Technology adoption, Citrus, Probit model theory.
Introduction

The State of Citrus in Florida

Citrus was introduced to Florida between 1513 and 1565. Citrus originated in the Orient, specifically China, and it was introduced into the New World by Christopher Columbus via the Mediterranean. The first planting of citrus in the Americas by Columbus was on the island of Hispaniola. Juan de Grijalva first recorded mainland plantings in 1518 when he landed in Central America (FASS, 2003). By the year 1563, many groves had already been established around the St. Augustine and Orange Lake areas of northeastern Florida. Although these groves had been established for a number of years, commercial production did not begin until 1763. By 1890, commercial production in Florida consumed 46,458 hectares (Jackson and Davies, 1999).

The citrus industry began to boom and fruit was being transported across the Atlantic back to Great Britain and other European countries. In the winter of 1894-1895, the citrus industry in northern Florida experienced its first true disaster. A major freeze killed 90-95 percent of the states plantings. The freeze brought the total area of citrus plantings down to 19,506 hectares in a single winter. Of this area, 97 percent were immature nonbearing trees. Six more catastrophic freezes occurred between 1899 and 1962. This forced many growers to relocate groves farther south, out of the reach of winter freezes. Much of this relocation and expansion occurred in the 1960’s. By 1971 there were approximately 354,910 ha of citrus in Florida (Jackson and Davies, 1999).

In 2002, there were 322,658 ha of citrus in commercial groves in Florida, down 4.2 percent from 2000. Bearing production area in Florida is represented in Figure 1. This figure illustrates the area in production by state, which has matured to an age that is producing fruit for commercial sales. Of that total production area, 81.4 percent was dedicated to orange production, second was grapefruit production (13.2 percent) and lastly, specialty fruit (e.g. tangerines, tangelos, lemons, limes, etc.) made up the final 5.4 percent (FASS, 2002). Figure 2 illustrates the total citrus production in metric tones by state for all citrus varieties. These varieties include oranges, grapefruit, tangerines, and lemons. As both figures reveal, Florida is the primary citrus producing state in both area and total production in the United States.

Florida agriculture consists of what most agriculturists consider specialty or non-traditional crops. This categorization is mostly as a result of the predominance of citrus in the agriculture landscape. In the panhandle and northern end of the state, the production area is composed primarily of soybean, peanuts, tobacco and cotton. The area from just north of Orlando, FL spanning southward is dedicated to winter vegetables and fruit, nursery and horticultural crops; sugarcane and citrus account for the majority of that production area.

Precision Agriculture in Florida

The purpose of precision agriculture is multifold. First growers are always seeking ways to increase profits by maximizing yield while simultaneously decreasing production costs by limiting input applications. Secondly, producers are becoming more environmentally aware, and as a result of limiting inputs more environmentally friendly practices are implemented. Potentially growers can realize economic benefits by reducing their overall cost of production, likewise the environment benefits, and what appears to be a win-win situation is as a result of simply being able to limit inputs to production.
Prior to the study by Sevier and Lee (2003), there was no available literature on the topic of precision farming technology adoption by citrus producers in Florida. Their research set out to determine the current adoption rate of the citrus industry with regard to precision agriculture technologies. The most commonly used technologies were the sensor-based variable rate applicators and the soil variability mapping. The least commonly used technology was remote sensing data.

The most prevalent reason for not adopting new technologies was quite simply that the respondents were satisfied with their current production practices. Anecdotally, “why change it if it already works”. Respondents did indicate that additional information and technology support...
from the Cooperative Extension Service, would be influential in making the decision to adopt precision farming technologies.

**Objectives**

This research set out to establish a measure for predicting the adoption level of precision farming technologies for citrus producers in the state of Florida. This is the second stage of a precision farming study that began in 2003. Survey data collected last year and presented by Sevier and Lee (2003), was used as the base dataset for this study. The objectives of the first stage of the study were to determine characteristics and decision criteria that influenced the technology adoption. Results reported by Sevier and Lee (2003), indicated that citrus growers in Florida, were currently using or planning to use precision farming technology. These results reported adoption on a per technology basis, not as an aggregate adoption level for citrus producers. The specific objectives of this stage of the study are to:

- Identify grower’s characteristics that influence the adoption of precision farming technology.
- Analyze technology adoption as an aggregate, not on a per technology basis. The justification being that an adopter of GIS technologies and a second adopter of remote sensing imagery, still represent collectively two adopters of precision farming technology.
- Develop a probit model to measure the significance and correlation of the independent variables that influence technology adoption.
- Investigate the reliability of the probit model by measuring the frequency of actual and predicted outcomes from the model.

**Methodology**

**Survey Data Collection**

In previous research (D’Souza et al., 1993; Daberkow and McBride, 1998; Khanna, 2001), it was determined that one of the primary barriers to the adoption of alternative production practices was the scale of the operation. In identifying a sample, Sevier and Lee (2003) selected the top 10 citrus producing counties in the state, based on the area in citrus production. They used a sampling technique referred to as a systematic random sample. This allowed for the use of a predefined characteristic, which influenced the selection for sampling, for example geographic location or a demographic characteristic (Fowler, 2002). In this case, Sevier and Lee (2003) systematically chose all members who had reported or were known to own/operate citrus in excess of 40.5 ha. It was hypothesized that 40.5 ha was the lower bound of scale needed to adopt precision farming technologies, and that scale was a primary barrier to adoption.

In identifying the sample frame, 2,391 growers were identified in the 10 county sample. Of the 2,391 growers, 84 were identified as growers with greater than 40.5 hectares based on membership records provided by the State’s growers’ organization. The 84 identified growers each received a questionnaire. Among the remaining 2,307 growers, half were chosen to receive the questionnaire. Those chosen were randomly selected by a coin flip. Each of the 2,307 growers were given a unique numeric identifier, a “head” on the coin flip meant the selection of odd-numbered growers, and vice versa “tale” on the coin flip meant even-numbered. The coin flip resulted in a “tale” so all even-numbered growers were selected to receive the questionnaire. This resulted in a final sample of the 84 “large” growers and the remaining even-numbered growers, or a total sample size of 1,238 growers. The use of
production area as a segregation tool, and then following with a coin flip to randomize the remaining sample resulted in what is referred to as a “systematic random sample” (Fowler, 2002). The sample frame resulted in selecting more than 50% of the member growers in the 10 county sample.

The primary research question in the survey was to identify the adoption rate of precision farming technology in Florida citrus production. In order to determine this adoption rate, a response matrix was provided to the participants. Respondents were asked to answer yes or not questions as to whether the technology was currently in use, and, if so, what total area was the technology used for. The matrix collected information about future plans for adoption, or whether or not current usage was to be increased onto additional hectares.

The technologies investigated in this matrix were:

- Sensor-based variable rate applicators (e.g. – “Tree See”)
- Prescription map based variable rate applicators
- Pest scouting and mapping (e.g. – “EntoNet”)
- Weed scouting and mapping
- Remote sensing (e.g. – aerial or satellite imagery)
- GPS receiver (e.g. – boundary mapping)
- Soil variability mapping
- Water table monitoring (e.g. – automated irrigation scheduling)
- Harvesting logistics (e.g. – mapping brix, acid and sugar levels to determine peak harvest time)
- Yield monitoring (e.g. – GOAT yield monitoring system)

Additional information was collected for the purpose of establishing demographic profiles for adopters versus non-adopters. These questions will also provide information pertaining to the cost of production estimates for these growers for future research in connection with the profile that is built.

These questions included the following:

- Grower demographic information (age, highest education level achieved, and grove management experience)
- Size and type of operation (hectares of: fresh oranges or grapefruit, processed oranges or grapefruit, or “other” citrus)
- Personal willingness to adopt technology
- Current use of computer applications (email, internet, financial record keeping, weather networks, GIS, expert decision systems for production management, or none)
- Could they identify the current level of in-grove variability

**Probit Model Theory**

Linear regression assumes that the dependent variable being tested is both continuous and measured for all of the observations within the sample. In this survey, the dependent variable is
not continuous; instead it is a dichotomous binary variable. The dependent variables were the 10 respective technologies, and each had 2 choices. The choices were designed to measure current adoption and then planned adoption of the 10 technologies. Data was collected from surveys and recorded using a binary 0/1 response. The respondent was scored a one (1) for a “yes” response to either “currently using” or “planning to use” a technology. Alternatively, a negative response was assigned a zero (0). Additionally, some survey respondents did not indicate a positive or negative response; hence there is an incomplete measurement for that case. This scenario has broken both initial assumptions of linear regression. This is the primary reason for using an alternative means of running a regression analysis on the survey data.

Linear regression models have other assumptions that are violated by the data in this survey. \textit{Linearity} is assumed, in that the dependent variable is linearly related to the independent variables through the beta parameters. A theoretical illustration of a linear regression model is shown below.

\begin{equation}
 y_i = \beta_0 + \beta_1 x_{i1} + \ldots + \beta_k x_{ik} + \varepsilon_i
\end{equation}

In equation 1, where $x_{i1}$ through $x_{ik}$ are explanatory variables thought to influence the dependent variable, denoted by $y_i$; $\beta_0$ through $\beta_k$ are parameters to be estimated, and $\varepsilon_i$ is the error term.

The matrix formed by the observations on the $x$’s is assumed to be of full rank so that the inverse of $x^x$ exists. This assumption means there is no collinearity among the explanatory variables. \textit{Homoscedastic and uncorrelated errors} also require the errors to have a constant variance and a randomly distributed error term (Greene, 1990).

In working with data that represents binary outcomes, there are several methods to perform regression analysis. The linear probability model (LPM) is the first of such methods, but it also has shortcomings in dealing with heteroscedasticity and normality. An LPM illustration can be seen below in equation 2, where $x_i$ is an explanatory variable thought to influence the dependent variable, denoted by $y_i$; the parameters to be estimated $\beta$, and $\varepsilon_i$ is the error term.

\begin{equation}
 y_i = x_i \beta + \varepsilon_i
\end{equation}

Since the expected value of the dependent variable $y$ given the independent variable $x$ is $x\beta$, the variance of $y$ depends on $x_i$, which implies that the variance of the errors depends on $x$ and is not constant therefore not homoscedastic. In addition, binary values (0/1) result in errors not being normally distributed, hence breaking the normality assumption as well. This results in the LPM not being appropriate for the analysis of this study.

The next option is the binary response model (BRM) that is the basis for both the probit and logit models. The BRM is represented below in equation 3:

\begin{equation}
 y_i = \begin{cases} 
 1 & \text{if } y_i^* > \tau \\
 0 & \text{if } y_i^* \leq \tau 
\end{cases}
\end{equation}

where $\tau$ = a threshold generally assumed to be 0

\begin{equation}
 y_i^* = x_i \beta + \varepsilon_i
\end{equation}

In equation 3, $y_i^*$ is continuous and can avoid problems that are generally encountered when using the LPM. The only shortcoming now is that we cannot observe the dependent variable so the model cannot be estimated using ordinary least squares (OLS). We have to use maximum
likelihood estimates (MLE) and assume a normal distribution of the errors. When considering a normal distribution of errors it is referred to as a normit model or more commonly as a probit model. You can also choose to assume a logistic error function, and this would be known as the logit model.

The probit model, as derived from the linear probability model, estimates the probability of observing an event \( y \) given \( x \). This can be illustrated as follows:

\[
\begin{align*}
\Pr(y = 1 \mid x) &= \Pr(y^* > 0 \mid x) \\
\Pr(y = 1 \mid x) &= \Pr(x\beta + \varepsilon > 0 \mid x) \\
\Pr(y = 1 \mid x) &= \Pr(\varepsilon > -x\beta \mid x) \\
\Pr(y = 1 \mid x) &= \Pr(\varepsilon \leq x\beta \mid x) \\
\Pr(y = 1 \mid x) &= F(x\beta) \\
\Pr(y = 1 \mid x) &= F(\alpha + x\beta)
\end{align*}
\] (4)

In equation 4, where \( F \) represents the normal cumulative density function (CDF) also illustrated as \( \Phi \) in equation 6, and \( \alpha \) is the dispersion parameter in the nonlinear BRM.

The BRM can predict values of \( \Pr(y = 1 \mid x) \) that are larger than 1 or smaller than 0. To remove this issue of \( y > 1 \) or \( y < 0 \), \( \Pr(y = 1 \mid x) \) must be transformed into a function that ranges from negative to positive infinity \((-\infty \text{ to } \infty)\).

The first step of the transformation is to change the probability into two odds can be seen in equation 5:

\[
\frac{\Pr(y = 1 \mid x)}{\Pr(y = 0 \mid x)} = \frac{\Pr(y = 1 \mid x)}{1 - \Pr(y = 1 \mid x)} \] (5)

The explanation for transforming this into odds is that the odds illustrate how frequent a positive response \( y = 1 \) occurs relative to a negative response \( y = 0 \). This happens within the range from 0 when \( \Pr(y = 1 \mid x) = 0 \) to 1 when \( \Pr(y = 1 \mid x) = 1 \). The probit model can then be constructed by choosing functions of \( \beta x \) that range from 0 to 1, and finally looks like equation 6:

\[
\Pr(y = 1 \mid x) = \int_{-\infty}^{x\beta} \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{t^2}{2}\right) dt = \Phi(x\beta) \] (6)

Scientific literature, especially within the area of econometrics, commonly illustrates the probit model in the following form, shown in equation 7:

\[
\Pr(y = 1 \mid x) = \beta_0 + \beta_n x + \varepsilon \] (7)

Equation 8 represents the final probit model used in this study. Variable’s definitions are shown in table 1. The dependent variable is USETECH. USETECH is the variable name that represents the aggregation of all responses from the survey questioning current use of precision farming technology in Florida citrus production.

\[
\begin{align*}
\Pr(y = 1 \mid x) &= \beta_0 + \beta_1 x_{own} + \beta_2 x_{age} + \beta_3 x_{exp} + \beta_4 x_{adt1} + \beta_5 x_{adt2} + \\
&\quad \beta_6 x_{ed2} + \beta_7 x_{ed3} + \beta_8 x_{ed4} + \beta_9 x_{modvar} + \beta_{10} x_{maxvar} + \varepsilon
\end{align*}
\] (8)

In table 1, there are several multi-level variables that were present in the probit model. The variables for the respondent’s self-perceived adoption attitude, their maximum education achieved, and the in-grove variability are each multi-level variables.
Table 1. Independent variables used in the probit model analysis.

<table>
<thead>
<tr>
<th>Probit Variables</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>OWN</td>
<td>Total citrus land owned by respondent</td>
</tr>
<tr>
<td>AGE</td>
<td>Age of the respondent</td>
</tr>
<tr>
<td>EXP</td>
<td>Respondent's years of experience</td>
</tr>
<tr>
<td>ADT1</td>
<td>Respondent is likely to adopt</td>
</tr>
<tr>
<td>ADT2</td>
<td>Respondent will wait to adopt</td>
</tr>
<tr>
<td>ED2</td>
<td>Some college education received</td>
</tr>
<tr>
<td>ED3</td>
<td>A college degree achieved</td>
</tr>
<tr>
<td>ED4</td>
<td>A graduate or professional degree achieved</td>
</tr>
<tr>
<td>MODVAR</td>
<td>Moderate in-grove variability</td>
</tr>
<tr>
<td>MAXVAR</td>
<td>Maximum in-grove variability</td>
</tr>
</tbody>
</table>

When multi-level variables are used as independent variables in a probit analysis, one level of the variable is excluded. Results are then interpreted by using the omitted level as the point of comparison for the other levels. The omitted variables are shown in table 2. Also shown in table 2 is a variable named DKVAR. This was collected to allow respondents to indicate that they were uncertain of their in-grove variability. This variable was omitted entirely from the analysis, since less than one percent (<1%) of the respondents chose this option.

Table 2. Omitted variables from the probit model analysis.

<table>
<thead>
<tr>
<th>Variable Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>ADT3</td>
<td>Respondent never adopts</td>
</tr>
<tr>
<td>ED1</td>
<td>A high school education or less</td>
</tr>
<tr>
<td>MINVAR</td>
<td>Minimal in-grove variability</td>
</tr>
<tr>
<td>DKVAR</td>
<td>Don’t know in-grove variability</td>
</tr>
</tbody>
</table>

Lastly, the probit model analysis was performed using a statistical software package named LIMDEP, version 7.0 (Greene, 1995). The significance level for this analysis was 90% (α=0.9).

Results and Discussion

The binomial probit model in equation 8 was estimated using 135 observations. Recall 1,238 surveys were distributed by mail. Respondents returned more than 300 surveys, 212 were considered to be completed and contain usable data. The probit model can only make estimates for responses in which every variable measured contained a response. This being the case, the probit model could only be used for 135 observations. Results (provided in the appendix in full detail) indicated that three of the independent variables were statistically significant in influencing the decision to adopt precision farming technologies.

The variable for the grower’s age was significant and negatively correlated to USETECH, indicating that as the grower’s age increases, the likelihood of adopting precision farming...
technologies decreased. The variables associated with the in-grove variability resulted in two significant independent variables. The variables representing maximum variability and moderate variability were significant and positively related to likelihood to adopt. The positive correlation indicates that either level of variability higher than minimum in-grove variability would influence the decision to adopt precision farming technologies. Marginal probabilities indicate that farmers with maximum and moderate variability are more likely to adopt the technology compared to those in the minimum variability group.

Table 3 below illustrates the predicted outcomes versus the actual outcomes measured in the survey results. Recall, respondents were asked to identify from a list of ten technologies if they were currently using or planning to use any of the technologies. For the sake of the probit model in this study, current usage was only taken into consideration (referred to as USETECH above). Those survey responses were measured against the predicted outcomes of the binary probit model.

Table 3. Frequencies of actual and predicted outcomes matrix.

<table>
<thead>
<tr>
<th>Actual</th>
<th>Predicted</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>64</td>
<td>12</td>
</tr>
<tr>
<td>1</td>
<td>24</td>
<td>35</td>
</tr>
<tr>
<td>Total</td>
<td>88</td>
<td>47</td>
</tr>
</tbody>
</table>

The benefit of the predicted outcomes matrix is in identifying the percentage of correct guesses versus naïve predictions by the probit model. In table 3, you can tabulate that 99, or 73%, correct predictions were made (64 “no” responses and 35 “yes” responses). A correct prediction is when the model guesses a “no” (0) and it actually was, and likewise when it predicts a “yes” (1). If one were to make a naïve prediction, the correct prediction rate would be 76, or 56%. The naïve prediction is calculated by always guessing either “no” (0) or “yes” (1). In this case, we would always guess “no” (0), as we would be correct more frequently. Therefore, the probit model is better at predicting the dependent variable (73% correct prediction) compared to the naïve prediction (56%).

There are two types of incorrect predictions in a probit model – type I errors and type II errors. With a Type I error, the model incorrectly predicts a “no” when it should have predicted “yes” (in our sample, this occurred 24 times). A Type II error occurs when the model predicts a “yes” when it should predict a “no” (in our sample, this occurred 12 times). Type I error is not a major concern because if this model was established to assist growers in deciding whether or not to adopt based on their own demographic characteristics as inputs, an incorrect “no” prediction would simply result in the farmer not investing when they should have. The only measurable loss would be the opportunity cost of not adopting early and missing the opportunity to reap a major payback from the investment in the technology. However, with a Type II error, the model would recommend the farmer make rather large investment in technology that would not be appropriate. The results from Table 3 indicate that there are only 12 Type II error predictions (approximately 8.89% of the sample) that would result in a mistaken investment.
Conclusion

The goal of this study was to identify certain key demographic characteristics of citrus growers that could influence the decision to adopt precision farming technologies. Results from a probit analysis with decision to adopt as the dependent variable indicated that variables associated with age, and moderate and maximum variability, were significant influences on the decision to adopt. Age influenced likelihood to adopt negatively influenced adoption, while moderate and maximum in-grove variability compared to minimum in-grove variability were positive influences on the decision to adopt.

The probit model accurately predicted outcomes 73.33% of the time. In addition, Type II error predictions resulting in a mistaken decision to invest only occurred 8.89% of the time. Overall, the success of the probit model is at best average. If this model were to be used as a grower decision tool, more data would need to be collected in order to validate the predictions. Although 8.89% is relatively low, that represents approximately 1 in 10 incorrect predictions about whether a grower should adopt precision farming technologies. That is an extremely expensive error when considering the cost of the technologies involved in precision farming in citrus.

Acknowledgements

The authors would like to acknowledge efforts made by Dr. Lisa House and Dr. Ron Ward of the Food & Resource Economics Department, University of Florida for their assistance in the development of the CLDV probit models.

References


Statistical and Probit Model Results

+-----------------------------------------------------------------------+
| Dependent variable is binary, y=0 or y not equal 0                      |
| Ordinary least squares regression Weighting variable = none           |
| Dep. var. = USETECH Mean= .4370370370 , S.D. = .4978672035           |
| Model size: Observations = 135, Parameters = 10, Deg.Fr.= 125         |
| Residuals: Sum of squares= 26.19664518 , Std.Dev.= .45779           |
| Fit: R-squared= .211296, Adjusted R-squared = .15451                 |
| Model test: F[  9,    125] = 3.72, Prob value = .00036               |
| Diagnostic: Log-L = -80.8808, Restricted(b=0) Log-L = -96.9029       |
|             LogAmemiyaPrCrt.= -1.491, Akaike Info. Crt.= 1.346         |
+-----------------------------------------------------------------------+

|Variable | Coefficient  | Standard Error |b/St.Er.|P[|Z|>z] | Mean of X|
+---------+--------------+----------------+--------+---------+----------+
|TC_OWN  | .1611888556E-04  | .11095516E-04    |1.453   | .1463     | 837.61296 |
|AGE     | .2975581064E-03  | .24367421E-02     |.122    | .9028      | 58.696296 |
|YRS_EXP | -.3942252586E-02 | .36000163E-02    |-1.095  | .2735      | 29.733333 |
|LIKEADT | .3048825378      | .13132816        | 2.322   | .0203       | 1.185185  |
|WAITADT | .2893071501E-01  | .10880994        | .266    | .7903       | .651851   |
|SOMEED  | .3212441544      | .12816781        | 2.506   | .0122       | .237037   |
|BSED    | .3302916708      | .11808518        | 2.797   | .0052       | .414814   |
|GRADED  | .3544126782      | .14818655        | 2.392   | .0168       | .148148   |
|MODVAR  | .2004367428      | .85718669E-01    | 2.338   | .0194       | .414814   |
|MAXVAR  | .3588914937      | .12008715        | 2.989   | .0028       | .170370   |


Appendices
| Variable     | Coefficient  | Standard Error | b/St.Er. | P[|Z|>z] | Mean of X |
|--------------|--------------|----------------|----------|---------|-----------|
| TC_OWN       | .4390390174E-03 | .26705878E-03 | 1.644    | .1002   | 837.61296 |
| AGE          | -.1642453096E-01 | .79138701E-02 | -2.075   | .0379   | 58.696296 |
| YRS_EXP      | -.7439444811E-02 | .11309781E-01 | -.658    | .5107   | 29.733333 |
| LIKEADT      | .5686880888    | .41653625     | 1.365    | .1722   | .185185   |
| WAITADT      | -.1338363165   | .34040528     | -.393    | .6942   | .651851   |
| SOMEED       | .6193040949    | .39873538     | 1.553    | .1204   | .237037   |
| BSED         | .5153843892    | .37667667     | 1.368    | .1712   | .481481   |
| GRADED       | .7517915387    | .47205160     | 1.593    | .1112   | .148148   |
| MODVAR       | .4308330425    | .25950603     | 1.660    | .0969   | .414814   |
| MAXVAR       | .8486323138    | .39455804     | 2.151    | .0315   | .170370   |
Frequencies of actual & predicted outcomes
Predicted outcome has maximum probability.

<table>
<thead>
<tr>
<th>Predicted</th>
<th></th>
<th></th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>64</td>
<td>12</td>
<td>76</td>
</tr>
<tr>
<td>1</td>
<td>24</td>
<td>35</td>
<td>59</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>88</strong></td>
<td><strong>47</strong></td>
<td><strong>135</strong></td>
</tr>
</tbody>
</table>