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Proven Science versus Farmer Perception

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Abstract.

Resource use efficiency is at the core of sustainable farming practices for the future of agriculture. Given the abolition of quotas in the EU and the increasing demands for food globally food producers are faced with a challenge to increase production in an environmentally sustainable manner. This paper examines the adoption of a suite of grassland management practices by Irish dairy farmers which are proven to improved grass utilisation. The Technology Acceptance Model is applied to a nationally representative sample of specialist Irish dairy farmers to investigate the use of belief based variables and traditional socio-economic and demographic variables in predicting intention to use six grassland management practices.

Keywords: technology acceptance model, adoption, grassland management practice

JEL codes: O330, Q160, Q240, Q550

1. Introduction

The Technology Acceptance Model (TAM) is a powerful tool in identifying perceptions towards using a practice for the prediction of intention to use. This paper examines the perceptions of dairy farmers toward the use of six grassland management practices using the TAM. The diversity which exists within the population is controlled for in the models using farmers' self-reported objectives. Two sets of latent factor variables are incorporated into models using more traditional economic variables to explore the power of prediction. Farm perceptions of the land management practices are derived using TAM and farm objectives are based on statements using existing literature. In comparing the use of the traditional economic and latent factor variables, in estimating intention to use a practice, the results support the superior predictive power of farmer objectives and the TAM perceptions beyond traditional economic variables. This indicates the importance of farmers own personal beliefs in having a positive intention to use practice. It is widely accepted in the social psychology literature that perceptions or attitudes are extremely influential in decision making. Traditional economics literature largely ignores this. Finding in this paper highlight the relative importance of such in decision making.

Irish research on grassland practices has focused on the scientific benefits (Patton et al. 2012; Läpple Hennessy and O'Donovan 2012) rather than the perceptions of users. This represents an imbalance in the current Irish research in the area. The herbage mass measurement practices developed in the 2000s (O'Donovan et al. 2002) have shown a low uptake of grassland management practices (Creighton et al. 2011; NFS 2009[1]). This paper shows adoption rates have more than doubled over the period 2009-2013. The introduction of financial incentives for farmers in 2010 as part of the Dairy Efficiency Programme (DEP[2]) may have influenced

[1] Adoption of GMP's by Irish dairy farmers: Creighton et al. (2011) average adoption rate 18%. Grass budgeting and grass covers 15% and 20% respectively (NFS 2009). This study shows an increased to 44% and 40% (2013) respectively, see Table 2.1.

[2] The DEP was designed to promote farmer participation in discussion groups. It was funded through Article 68(1) of Council Regulation (EC) 73/2009 which makes the provision for the use of unused Single Payment Scheme funds to address disadvantages and economic vulnerability affecting dairy farmers. These funds were used to support the DEP. A total of €6m was made available in each of the following years 2010,2011 and 2012. For details on criteria and provisions see Teagasc or the DAFM website [Online] available from

this significant increase. However farmers with a more conservative orientation are still not likely to use such practices.

2. Literature Review

Social scientists have studied farmers in terms of their attitudes and behaviours since the 1920s (Garforth 2010). To explore the perceptions of Irish dairy farmers toward the use of grassland management technologies this paper uses the TAM, in predicting intention to use. The TAM is the most widely used model in the information systems field (Lee, Kozar and Larsen 2003) in examining information technology usage. Individual intention to use is determined by two beliefs: perceived usefulness (PU) and perceived ease of use (PEOU). These beliefs are defined as the extent to which using an IT will enhance job performance and the degree to which the use of the IT will be free from effort respectively (Davis 1989; Davis, Bagozzi and Warshaw 1989; Venkatesh and Bala 2008).

Flett et al. (2004) were the first to apply the model to agriculture. There have been five applications in total to the broad agricultural literature. Two in the dairy sector (Flett et al. 2004; McDonald et al. 2013), two applications to use of precision agriculture tool (Adrian, Norwood and Mask 2005; Reichardt et al. 2009) and one agricultural study focused on agricultural students (Hooker et al. 2009). This is the only Irish application of TAM to a nationally representative population and is the only application examining Grassland Management Practices (GMPs). Descriptions of each practice are available from the Farmers Grazing Notebook[3]. Studies examining adoption of agricultural technologies tend to focus on the scientific and economic benefits without alluding to the role of attitudinal factors, by contrast, this the strength of using a beliefs based model. TAM is criticised for failing to account for policy (Bagozzi 2007) and social

http://www.teagasc.ie/advisory/dairy_efficiency/ or http://www.agriculture.gov.ie/farmingsectors/dairy/dairyefficiencyprogramme/dairyefficiencyprogramme-anoverview/ [Accessed on 27/12/2013].

[3] Available at http://www.agresearch.teagasc.ie/moorepark/Publications/pdfs/Open%20Day%20Moorepark%202009%20Grazing%20Manual.pdf accessed on the 08/09/2013.

influence. This paper addresses the impact of policy using variables measuring participation in past and current policy interventions.

2.1 Social Psychology Models

Understanding and predicting behaviour at an individual level is the focus of social psychology models. They are used in a wide range of research areas including health (Humphreys Thompson and Miner 1998) consumer behaviour (Thompson and Thompson 1996) education (Greenfield and Rohde 2009) and more recently in the agricultural literature in the UK (Garforth et al. 2006; Rehman et al. 2007) and Ireland (Läpple and Kelley 2010).

The major constructs of all such models are attitude, intention and behaviour. They are most severely critiqued for failing to account for the intention-behaviour "gap" which exists. The relationship between these constructs is complex and earlier models[4], use summative product terms to identify global measures for these constructs. They have been viewed as difficult to interpret given the relative importance of these attitudes and beliefs are unaccounted for in the models[5].

The TAM was developed to evaluate the market potential of emerging Personal Computer based applications and guide investments in new product development for IBM Canada (Davis and Vanketesh 1996). The power of TAM can be seen in its large number of empirical applications in varied disciplines and contexts (Venkatesh, Davis and Morris 2007) and its structure, with strong evidence to support the main constructs (PU and PEOU) as determinants of intention (Venkatesh and Davis 2000). Its strength as a model is its parsimony however it is also its weakness (Bagozzi 2007). One of the biggest criticisms of TAM is the lack of usable knowledge for managers (Lee, Kozar and Larsen 2003) with the focus in the literature now at the level of beliefs.

The main constructs of TAM are the belief variables, PU and PEOU. Literatures which support PU and PEOU are self-efficacy, contingent decision behaviour and

[4] The Theory of Reasoned Action (TRA) and The Theory of Planned Behaviour (TPB)

[5] Bagozzi (2007) summarises the issues placing an emphasis on beliefs. Bagozzi (2007) proposes a shift towards goal setting in identifying predictors of such constructs also highlighting the lack of group, cultural and social effects in decision making.

adoption of innovations as the three main theoretical frameworks from which these constructs emerged Davis (1989). PU is defined as the prospective user's subjective probability that using a specific application system will increase his or her job performance. It has been identified as the most critical belief given its direct effect, (Davis 1989). PEOU is defined as the degree to which the prospective user expects the target system to be free of effort (Davis, Bagozzi and Warshaw 1989). The TAM belief constructs are chosen a priori and are designed to be applied across populations to determine intention to use.

The TRA and the TPB are intention-based models which dominated the social psychology field emerge from the same expectancy value genre as expected utility theory (Lynne 1995). Criticisms of such models have led to a realisation that shortcomings of the neo-classical theory and the expectancy-value formulation may not describe the process of combining individual beliefs to produce global measures (Ajzen 1991).

The TRA and TPB models are based upon the summation of product terms in explaining and understanding the intention-behaviour relationship. The use of product terms summed to form one condensed term is difficult to understand in terms of analysis. Bagozzi (2007) called for the abandonment of such summated multiplicative models on the basis that they treat pairs of beliefs as equal, they fail to allow for underlying structure and relationships among salient beliefs existing in memory, they will not reveal how specific components of knowledge affect the decision making process, and the terms are not ratio scaled.

In choosing a model for examining the adoption of technology it must be noted that all of the models assess a global issue at an individual level. The problem most cited in the works which have been explored in this literature review has been that of self-reporting of beliefs, generally using bipolar/unipolar scales. The issue being the arbitrariness of the decision made. TAM was chosen based on its extensive use in the literature its well defined scales and its powerful results beyond the other competing models.

3. Research Question

- What are the influential factors in determining intention to use grassland management practices?
    - Are latent factor variables based on farmer beliefs and objectives more appropriate in predicting intentions to use practice than more traditional measurable variables?

Despite evidence to suggest their use increases grass utilisation (Shalloo et al. 2004) and improve overall efficiency (Kennedy et al. 2005, Shalloo 2009), grassland management practices exhibit low rates of adoption (NFS 2009; Creighton et al. 2011). This paper investigates the strength of perceptions and faming objectives of a nationally representative Irish dairy sample in predicting intention to use grassland management practices.

4. Methodology

The sample of 389 is nationally representative of Irish specialist dairy farmers, interviewed face to face in the autumn of 2013. The sampling strategy was based on herd size[6] and region fulfilling a nationally representative criteria designed by the National Farm Surveys Department Teagasc. The instrument, based on the Technology Acceptance Model, farming objectives literature and traditional economic theory, was administered by an independent survey company.

The socio-economic and demographic variables focused on farm and farmer characteristics. Farmers were then asked to respond to 21 statements regarding their farming objectives adapted from the Willock et al. (1999) and Flett et al. (2004) studies. This provided the identification and analysis e identification of farmer objectives allows the analysis to investigate the differences which exist between like-minded farmer groups. Farmers attributed a level of importance to 21 statements (Table 3) using a five point Likert scale ranging from: Not very important to me-extremely important to me. These statements are grouped using

[6] Number of dairy cows required to be greater than 50% of all other animals, populated across eight regions and five categories based on numbers of dairy cow ranging from <=24 to 70+.

data reduction methods: Principle Component Analysis (PCA). PCA groups statements together based on similar responses.

Logit analysis is used to identify the probability of a farmer to: have a positive intention to use the practice in the next twelve months or not. Success is indicated by having a positive intention to use the practice. The binomial distribution is based upon the success or failure of an event occurring. Bernoulli trials estimate the probability of success (s) is one minus the probability of a failure (p), denoted $s = 1 - p$. The probabilities are based on a number of independent variables controlled for in the model.

Six logit models are carried out for each management practice. The variables used are consistent across all models. The first model uses traditional and latent factor variables (Table 9). The chosen variables are well established based on existing literature. The latent factor variables are far superior predictors. The six models are then re-run using traditional variables only (Table 10) and then using latent variables only (Table 11). These models are then examined in terms of strength of prediction using comparative model analysis (Table 12 and Figures 1-6).

Goodness-of-fit post-estimation tests determine whether variation in the model residuals are small, follow the model specification and are not systematically clustered. Pearson's chi-squared examines the sum of square differences between observed and expected cases per covariate pattern, divided by the standard error (Archer and Lemeshow 2006). The statistic is dependent on the number of covariate patterns and the number of independent covariates in the model. When continuous variables are used in the model, this test is not effective since the number of distinct covariate patterns can be equivalent to the sample size (*ibid*). The distribution of the covariate pattern is a function of the controlled variables.

Hosmer and Lemeshow (1980) developed a test to overcome this issue through grouping on deciles of risk. This is the percentiles of the estimated probabilities in the model: the differences between observed and estimated frequencies in cells. This is estimated using the Pearson chi-squared statistic which displays contingency tables displaying expected frequencies less than one (Hosmer et al. 1997). The Hosmer and Lemeshow test groups participants. A chi-squared test is then estimated using the amalgated cells (Archer and Lemeshow 2006). The major concern with this test is the procedure in choosing numbers of groups.

The results of the goodness of fit test should not be evaluated in isolation. Rather it is an indicator of fit which may prompt the researcher to search for more appropriate models (Evans and Hosmer 2004) particularly in relation to the test assumptions (Hosmer et al. 1997). In this paper the observed and estimates predicted values are compared for each model. They are estimated by STATA using the *estat* command. The observed and predicted values are compared using classification of the probabilities as stated below which indicates how well the model correctly predicts the outcome (Long and Freese 2006).

Predicted probabilities range from 0-1. Each model predicts individual probabilities based on the controlled variables in the model. These predicted probabilities are visually and statistically compared for each practice, in Figures 1-6. A binary variable is generated to compare the number of predicted cases compared to the number of actual outcomes. By defining the predicted probabilities as:

$$\hat{y}_i = \begin{Bmatrix} 0 \ if \ \ \pi_i \ \leq \ .5 \\ 1 \ if \ \ \pi_i \ \geq \ .5 \end{Bmatrix}$$

Where π_i is the predicted probability of the *i* the individual. This permits the comparison of predicted probabilities from each model with the actual outcome. This gives an indication of the overall model fit of the predicted probability accurately predicting outcome.

5. Model Variables

Descriptives of the population are first examined using socio-demographic variables. The main findings are split into four sections first looking at farmer objectives and second an assessment of farmers intention to use practices and perceptions toward using each of the six grassland management practices. Thirdly six logit models identify the likelihood of predicting intention to adopt practice using traditional and latent factor variables. These model are then ran as separate models and the last section compare the predictive power of latent factor variables over the use of traditional variables.

5.1 Independent variables

Five socio-economic and demographic variables are used in the logit analysis including total livestock units, farmer age, having agricultural education, membership of a discussion group and their future expectations of dairy farming. These are discussed in the next section. Four latent factors are used including three objective variables, experimental, conservative and productive orientated farmer and the TAM perception factor.

5.1.1 Socio-Demographic variables

All participants are owner operators of specialist dairy farms, with the number of dairy cows greater than 50% of all other animals on the holding, 92% are male. Almost 60% of households have no person under 18 years of age with 52% of houses having 3 persons in the house and 30% of farmers had identified a successor (Table 1). These findings are in line with NFS findings. As regards the future, 13% plan to exit or an unsure about dairy in the future and 48% of farmers intending to increase milk output post quota removal in 2015. For those not intending to expand reasons included satisfaction with current output (18%) or no access to land (15%). A further 10% refer to the required increase in labour with increased output as a reason for not expanding. The next section compares most recent NFS rates of adoption of GMP with adoption rates from this study.

Rotational grazing and reseeding are the most widely adopted practices (Table 2). The adoption of measurement practices: grass covers and grass budgets from the NFS are in line with Creighton et al. (2011) however, adoption rates from this paper shows considerable increase in adoption.

There appears to be a significant increase in the adoption of the measurement of herbage mass (grass budgeting and grass covers) from these two separate surveys carried out in the years examined (Table 2). The apparent increasing trend in the usage of GMP as seen in the two sets of survey results could be attributed to the increased numbers of farmers participating in discussion groups. This has increased by 10% (NFS 2009) to 42% according to finding in this study (TAM 2013). This is also based on the introduction of the Dairy Efficiency Programme in 2009; this requires farmers to conduct a specific work package relating to management of grass through discussion groups, consequently having an impact on usage.

5.1.2. Latent factor variables: Farming objectives

In examining farmer objectives preventing pollution had the highest mean ranking (Table 3). The top five objectives all relate to land maintenance and structure. To identify farmers' objectives in terms of grouped variables PCA is applied and individual objective scores are grouped together reflecting the factors. These factors compromise of objectives which load together for the sample. Each participant is attributed a factor score based on his scoring of individual objectives.

PCA assumes a common variance and does not discriminate between shared and unique variance (Costello and Obsourne 2005). The 21 farming objectives are rotated using an oblique rotation allowing factors to correlate. The Kaiser-Meyer-Olkin (KMO) (.890) and Bartlett's test of Sphericity (x^2 =3069 p=.000) both indicate the data is suitable for factor analysis. When factors are rotated using these 21 objectives, three factors emerge. The factors or linear components in the data set called eigenvectors represent the weights of each variable and they provide loading for each vector on a factor. The factors loadings for each objective are then compared. The eigenvalues determine the importance of each eigenvector.[7]

The model reveals the shared variance between factors. The three factors in this model using Kaiser criterion, were retained. The factors explain 51% of total variance. The first factor accounts for 31% of variance, after rotation the factor structured are optimized; this equalisation addresses the relative importance of factors (Field 2009). The communalities indicate an accurate variance for each item. All items were retained. These factors scores were saved for use in further analysis. Table 4 is the rotated component matrix which identifies the items and respective factor loadings.

[7] The Kaiser criterion retains factors with a value greater than 1.

Three factors represent objective of Irish dairy farmers. The factor names were chosen by the authors, reflecting statement items. The factors are identified as: experimental, conservative and productive which relate to their farming objectives. This is a self-selection process where farmers rank a number of statements on the relative level of importance of each statement.

Each individual is then is given a score weighting for each statement. The high factor loadings are highlighted in bold (Table 5). Having identified the objective factors the TAM latent factor perception variables are derived, this is discussed in the next section.

5.1.3 Latent Factor variable: TAM Perception (PU and PEOU)

Each scale is checked to indicate the reliability of items in terms of internal consistency, corrected item-total correlation (Table 5) and reliability given by Cronbach's alpha also indicates strong scale measure.

The item total correlation (ITC) matrix indicates items are measuring the same characteristic to the overall perception factor. The item total statistic gives an indication of how much each item correlates with the overall score for that practice. The lowest correlated item is saving time; this is as expected and is consistent across all six practices. The item saving time if removed from reseeding and rotational grazing scale would improve the Cronbach's alpha marginally; however, it was left in as it did not impact on reliability of the scale.

The high Cronbach's alpha suggests good internal consistency for each scale in the sample. Reliability of scores indicates item suitability for summation in attaining the overall TAM perception. These variables are used in predicting intention to adopt with the objective factor variables.

The mean total score of each scale ranged from 25-30 for the six practices. Given the differences in scores of individual items of the TAM constructs t-tests were carried out to compare users and non-users. Perceptions of the farmers using GMPs were significantly higher than non-users (Table 7). This was as expected as users will have experienced the benefits of using the practice on their farm.

Findings indicate significant agreement with statements from users and large neutral responses [8] generally from non-users. Most widely used practices (rotational grazing and reseeding) have an average neutral rating of 9%-11%, while all other practices have between 31%-48%[9] neutral responses. These high levels are a concern.

The factor analysis suggests the theorised two factor TAM model are measuring one construct not two. Based on the exploratory factor analysis the seven items[10] are measuring one factor. This latent factor is called the TAM perception factor, and is used in the regression analysis to identify the probability of adopting GMPs.

5.2 Dependent variable: Intention

The distribution of the intention variable as measured from the survey is positively skewed. Table 8 identifies the number of users and non-users who have a positive intention to use. Users have statistically significant higher average TAM intention to use than non-users. The Eta indicates the strength of this difference.

The responses to the TAM intention measured using Likert scales were collapsed to negative, neutral and positive categories and into the binary response[11]. This measures the farmers positive intention to use the practice. Farmers who agree or strongly agree they will use the practice in the next 12 months as opposed to those who do not. This was used as the dependent variable in a logit analysis.

6. Findings: Logit analysis

The logistical regression estimates the probability of having a positive intention to use a technology. The rationale for using intention to adopt is based on the

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[8] Tables 2.9 item responses.

[9] Grass budgeting 32%, grass covers 37%, grass wedge 48% and spring rotational planner 31%.

[10] Important to your farming needs, increase profits, better than what it replaces, increase production, saves time, easy to understand, easy to use.

[11] For information on the seven TAM perceptions in terms of negative neutral and positive categories see Table 6.

TAM. It is theorised that intention to adopt in the next 12 months is used rather than actual use, as it reflects future intentions.

The regression analysis predicts the intentions of dairy farmers to use six GMPs. For all practices TAM is a positive and significant explanatory variable. Traditional variables and latent factor variables are combined in one model (Table 9) to predict intention to use practice and then these set of variables (traditional and latent factors) are modelled independently (Table 10 and 11 respectively). The independent analysis uses a comparative model (Table 12) to compare the strength of traditional variables with latent factor variables in predicting intention to use GMPs. Results indicate the TAM and objective, latent factor variables, are stronger predictors of intention to use.

The findings support the large body of TAM literature which suggests perceptions towards usage significantly impacts intention to use. Through identifying perceptions of individuals the probability of intention is strongly predicted for all models. Those models including TAM have a much lower log-likelihood than models without. In modelling the traditional variables, the hypothesized relationships are validated (Table 10). The results of models using TAM perception variable and the three objective factors (Table 11) indicate the significance of TAM in the prediction of intention to use.

The last section compares both models using traditional variables only (Table 10) and models using latent factor variables only (Table 11) to identify the variables which more accurately predict intention to use. Two variables exhibited levels of collinearity, income and intensity. Statistically it was not problematic, but the model fit suggested they were collinear. Therefore income was dropped from the regressions. The rationale is based on the theoretical significance of intensity for the use of management practices over income. The Log-Likelihood chi2 p-value is statistically significant for all models (<0.001) indicating model significance.

Prior to main analysis an initial run of the model using socio-economic and demographic and social psychology variables findings (Table 10) identify the TAM perception variable dominated the predictive probability of all other variables in the model. When trials were carried out removal of the TAM perception resulted in many changes. It was decided to investigate this further through running two separate models, splitting variables used into socio-economic and perception variables discussed in the next section. Models are run separately and then their predictive probabilities compared against the outcome which is the intention variable.

The inclusion of all variables into a logistical regression analysis (Table 2.9) shows the relative strength of the latent factor variables as predictors of probability of intention to use a practice. For all six models the TAM perception is the only consistent predictor of intention to use practice. TAM perception is statistically significant for all practices at the 1% level. Other variables which are influential at the 5% level include education (grass wedge). The grass wedge is the most technology intensive practice. The generation of the wedge involves the inputting data on grass measures to create a predictive chart which is informed by grass growth conditions in the region, although it had the highest neutral rating in terms of perceptions of usefulness and ease of use. The membership of discussion group or dairy efficiency programme and productive oriented farmers are also significant at the 5% level (reseeding). Reseeding (81% adoption) is a well-established grass management practice it is not surprising farmers more oriented at increasing production, utilising resources and maximising profit are more likely to be reseeding.

At the 10% level intensity measured by total livestock unit per hectare is significant (rotational grazing) this reflects a less formal measuring practice this is most widely used (85% adoption). Membership of discussion groups or the dairy efficiency programme is significant (rotational grazing, grass budgets and grass wedge) this is reflective of the programmes agenda to promote use of practices which improve herbage utilisation, in particular budgets and wedges. The experimental orientated farmers are more likely to use grass budgeting, reseeding and are less likely to use grass wedge. Productive oriented farmers are more likely to use grass budgets and spring rotational planner.

Results Overview

- TAM perception variable predicted strongly the intention to use all six grassland management practices.

- The farmers with conservative objectives are less likely to have a positive intention to use any of the grassland management practices.
- Members of discussion groups or the DEP scheme are significantly more likely to have a positive intention to use four of the six practices.
- Having a third level agricultural education is positive and significant (5%) factor in predicting the probability of intention to use grass wedges. This is expected given the technical computer skills required to generate a digital wedge for the farm.
- Level of intensity is significant only for use of rotational grazing. This may be an indicator of a farm led need for increased planning with greater demand for grass in highly stocked farms.
- Experimental oriented farmers are more likely to have a positive intention to use grass budgets and reseeding in the future but less likely to have a positive intention to use grass wedges. The negative relationship could again be reflective of the technical nature of the practice.
- Similarly the productive oriented farmers are more likely to have a positive intention to use reseeding, grass budgets and also the spring rotational planner.

This section indicates the relative importance of the latent factor variables in modelling intention to use six grassland management practices. The findings suggest farmer perceptions based on TAM more accurately predict a positive intention to use practice in the next 12 months. This is given by the relative strength of the model fit and specifications in the traditional models (Table 10) and the latent models (Table 11). To expand on these findings further, examining sets of variables used (traditional versus latent), the next section discusses the formal comparisons, visually using predictive power and more specific classification model analysis.

7. Findings: Comparative analysis

This section visually and statistically compares the predicted probabilities of each model specified. The models are compared in terms of their predictive power to accurately identify farmer's positive intention. The goodness of fit using the Hosmer and Lemeshow test is one post estimation test. As indicated previously this may not always be the best estimate as it is based on the number of covariate patterns in the data. When using continuous variables this is can be problematic as the chi-squared[12] approximation is dependent on the number of clustered covariate values comparing observed and fitted frequencies. Due to the unreliability of the tests when using continuous variables, a comparison using predicted probabilities and outcomes was first visually inspected and compared (Figures 1-6). Then predictive power is formally tested.

The visual graphics give an indication they do not show if the strength of prediction matches outcome. The correct classification statistics (Table 12) formally test this. Results suggest the graphics are good indicators of strength of prediction. For all six models the TAM perception factor and objective factors outperform the socio-economic and demographic variables in terms of their prediction of individuals' intention to use practice. This is consistent across all six practices.

The classification of predicted probabilities and outcome is based on first defining individual probabilities into a binary variable. As stated a predicted positive outcome is based on the probability is 0.5 or more. This is then compared to the outcome intention variable. Table 12 displays the percentage of correctly classified predictions for each model specified in bold.

The classification (Table 12) indicate the models using the TAM and farming objective factors more accurately predict intention outcome than the models using socio-economic and demographic models. On average they correctly predict 19% more correctly classified cases over the six comparative models. The correctly classified cases are given by the figures in bold. The sensitivity results identify the percentage of farmers who have a positive intention to use. The specificity figures indicate the prediction of non-use among non-users. The specificity statistics for the more established practices, rotational grazing and reseeding are low for both models using traditional variables and models using latent variables. This indicates the relative difficulty the model has in identifying non-users within the population. This is also reflected in Figures 3 and 4 which identify the predicted probabilities. The rate of adoption is high, 81% and 85% respectively.

[12] Chi squared is a non-parametric statistic used for goodness of fit or as a test for independence.

8. Discussion

The adoption of formal practices such as those discussed in this paper is relatively low given the proven scientific benefits. However the management of grass exists at some level for almost all Irish farmers as they operate mainly a grass based system. Such practices may be part of a process based on experience or tacit knowledge and so formally may not be captured by this the survey instrument. The adoption rate of innovations also may be attributed to regional characteristics and variations in socio-economic conditions as well as localised application of technology-specific information (D'Emden, Lelwellyn and Burton 2006). This research highlights the comparative strength in using attitudinal variables to predict adoption as farmers perceptions are an integral part of decision to adopt. The rationale for using intention to use practice is based on the theory of the Technology Acceptance Model. The intention to use variable is more informative than the more tradition binary adoption variable (1=yes, 0= no) as it is based on future use. There are also issues with this variable as stated most adopters display a post-positive adoption bias and the intention may not always reflect the action (Intention-behaviour). The intention represents the probability dimension of the relationship between the person and the behaviour, placing the farmer as the key decision maker.

Agricultural studies support this, farmers revealed their own knowledge and expertise, supplemented by the expert advice is preferred to view of an institution with a mandate to advise and inform (Garforth et al. 2006). While individual demographics remain important part of the discussion intention to adopt practice is highly dependent on individual perceptions and it is at this level it is possible to influence attitude. More specifically this research suggests the Technology Acceptance Model as one that exhibits potential for further use for future agricultural adoption studies examining recently introduced technologies. This model highlights the importance of the characteristics of the technology relative to what the technology is useful for on their farms.

Farmer's decision making is viewed as being dynamic and specific to farm (Vanclay 2004). The issue is often not to merely predict attitudes but also to realise the problem may not always be farmers having the wrong attitude, but rather to understand it. Conflicting views may exist for example Vanclay (2004) expands on “good farm management” not as a singular absolute, but rather a process with many different beginnings. In light of the findings in this paper conservative farmers are not likely to use any of the potentially efficiency improving practices. This questions if these technologies are only suited to the more productive and experimental orientated farmers. There may be an issue in terms of supporting their existing means of managing grass based systems. This suggests further research is necessary to understand the existing perceptions towards the use of grassland management practices.

9. Conclusion

Findings recognise the importance of the inclusion of farmer perceptions and farm objectives in researching use of farm management practices. The strength of the Technology Acceptance Model (TAM) perception variable on the intention to use grassland practices supports the substantial body of literature which exists using TAM in the prediction of intention. The findings of this study are not directly comparable to findings from other TAM applications as the hypothesized factors of PU and PEOU were not found. However, the study strongly supports the relevant importance of perceptions towards using a practice in predicting intention. Based on the broader social-psychology literature that suggests intention to adopt is closely linked to behaviour and given the findings of this study the relative importance of individual goals and objectives in decision making are reemphasized by the findings from this research. The decision to use new practice or to have a positive intention to use a practice is largely based on perceptions on individuals rather than socio-economic or demographic variables.

This study has looked beyond the use of socio-economic and demographic variables. Through exploring the use of latent factor variables, it has found perceptions of farmers to have much greater influence on to use practice than the more traditional variables used in the wider literature. The limitations of focusing on characteristics of a population for informing policy have been identified (Geroski 2000). This research highlights the issues and recognises the importance of farmers’ beliefs about a practice. This places the emphasis on the farmer.

Tables and Figures

Table 1 Descriptive Characteristics

Variable	Mean	Range	Frequency (%)
Farm Size	52 (32)	9-283	
Dairy Platform	30 (19)	.4-182	
Age	52 (11)	22-79	
Num. Cows	58 (48)	10-450	
Yrs. Farming (main holder)	27 (13)	1-60	
Agri-Education			68
Teagasc Client			58
Discussion Group			42
Dairy New Entrant			8
Received Derogation			73
Successor identified			30
Employment (off-farm)			18
(N 389)			

Table 2 Usage: Specialist Dairy Farmers

Practice	Using (%) NFS 2009	Using (%) TAM Survey 2013
Rotational Grazing	93[a]	85 (n= 386)
Reseeding	54[b]	81 (n= 383)
Spring Rotational Planner	-	51 (n= 381)
Grass Budgeting	15	44 (n= 387)
Grass Cover	20	41 (n= 384)
Grass Wedge	-	35 (n= 382)

[a] NFS question: How do you allocate grass to cows controlled grazing? Controlled grazing included the use of paddocks (30%), 12-48 hour grazing (23%) or 12 hour strip grazing (40%).

[b] NFS question: Have you reseeded 10% or more of the holding in the last three years?

Table 3 Objectives

Farming Objectives	Mean	Std. Deviation
Preventing pollution	4.61	0.65
Leaving land in as good a condition as you received it	4.55	0.68
Producing high quality products	4.54	0.60
Minimising risk in farming	4.53	0.75
Keeping debt as low as possible	4.46	0.81
Maximising profit	4.43	0.77
Utilising your resources fully	4.37	0.77
Having the best livestock/pastures	4.29	0.70
Being environmentally friendly	4.26	0.85
Spending time with the family	4.25	0.85
Maximising production	4.25	0.88
Using chemicals sparingly	4.17	0.96
Meeting challenges	4.06	0.86
Having the respect of other farmers	3.97	1.06
Reinvesting in the farm	3.86	1.08
Being innovative by using new technologies/practices	3.85	1.09
Having up-to-date equipment and machinery	3.72	1.18
Having a successfully diversified farm	3.36	1.32
Expanding the business	3.35	1.26
Trying new varieties of livestock/crops	3.05	1.28
Entering and winning competitions/shows	2.12	1.31
Valid N (389)		

Table 4 Factor Component Matrix

Farming Objectives	Factor 1 Experimental	Factor 2 Conservative	Factor 3 Productive
Q43_29 Having a successfully diversified farm	**.731**	.029	.098
Q43_17 Trying new varieties of livestock'/'crops	**.699**	-.009	.021
Q43_35 Expanding the business	**.690**	-.090	.341
Q43_34 Entering and winning competitions'/'shows	**.651**	-.115	-.253
Q43_15 Having up-to-date equipment and machinery	**.602**	.257	.226
Q43_26 Being innovative by using new technologies/practices	**.602**	.130	.437
Q43_19 Reinvesting in the farm	**.596**	.205	.404
Q43_30 Meeting challenges	**.584**	.171	.378
Q43_20 Having the respect of other farmers in the community	**.506**	*.484*	.025
Q43_9 Keeping debt as low as possible	-.018	**.706**	.052
Q43_21 Using chemicals sparingly	.224	**.703**	.063
Q43_23 Leaving land in as good a condition as you received	-.019	**.673**	.342
Q43_10 Being environmentally friendly	.201	**.647**	.118
Q43_13 Minimising risk in farming	.008	**.632**	.300
Q43_25 Preventing pollution	-.110	**.605**	.223
Q43_12 Spending time with the family	.086	**.430**	*.418*
Q43_5 Maximising profit	.226	.075	**.734**
Q43_6 Producing high quality products	-.003	.371	**.649**
Q43_1 Utilising your resources fully	.060	.188	**.632**
Q43_32 Maximising production	*.442*	.102	**.620**
Q43_3 Having the best livestock'/'pastures	.157	.280	**.539**
Valid N (389)			

Table 5 TAM: Item Total Correlation

Practices / TAM items	Grass Budget		Reseeding		Rotational Grazing		Grass Wedge		Spring RP		Grass Covers	
	Mean	ITC	Mean	ITC	Mean	ITC	Mean	ITC	Mean	ITC	Mean	ITC
Farming needs	3.7	.823	4.34	.864	4.37	.872	3.44	.904	3.87	.909	3.65	.888
Production	3.8	.855	4.34	.891	4.37	.908	3.47	.936	3.87	.932	3.68	.917
What it replaces	3.72	.887	4.32	.857	4.31	.884	3.47	.913	3.82	.918	3.67	.923
Profits	3.77	.890	4.35	.858	4.35	.877	3.49	.927	3.84	.922	3.65	.886
Saves time	3.54	.764	3.97	.605	4.16	.710	3.40	.880	3.76	.876	3.50	.804
Understand	3.66	.854	4.34	.849	4.35	.876	3.51	.929	3.84	.917	3.65	.887
Use	3.70	.875	4.26	.835	4.30	.874	3.45	.900	3.82	.922	3.63	.922
Cronbach $\propto$	.940		.943		.957		.976		.977		.969	
Mean (SD)	25.9 (5.9)		29.9 (5.1)		30.2 (4.8)		24.2 (6.1)		26.8 (5.9)		25.4 (6.1)	
N389												

ITC: Item Total Correlation

Table 6 TAM Items: Frequencies

Practice	Grass Budget			Grass Cover			Rotational Grazing			Reseeding			Grass Wedge			Spring Rotational Planner		
Adoption Rate	**44**			**40**			**84**			**80**			**34**			**50**		
Likert / **Items**	DA	N	A	DA	N	A	DA	N	A	DA	N	A	DA	N	A	DA	N	A
Farming needs	11.6	27.8	60.7	11.1	34.2	54.7	2.1	9	88.9	4.6	8.2	87.1	12.1	46	41.9	6.4	28.3	65.3
Production	6.7	30.3	63	8.7	34.4	56.9	2.8	9.5	87.7	3.1	9.5	87.4	11.1	46.5	42.4	6.4	30.6	63
What it replaces	6.2	36.2	57.6	7.2	39.3	53.5	1.8	12.6	85.6	2.6	11	86.4	9	50.6	40.4	4.9	34.2	60.9
Profits	7.5	29.8	62.7	8	37	55	1.5	9.8	88.7	4.6	7	88.4	10.5	46.8	42.7	4.6	31.9	63.5
Time	12.3	37.3	50.4	12.9	38	49.1	5.1	14.9	80	9	20.6	70.4	12.1	49.6	38.3	8.7	30.8	60.4
Understand	10.3	33.4	56.3	9.3	36	54.8	1.3	10.5	88.2	2.6	8.5	88.9	7.5	49.4	43.2	4.9	32.4	62.7
Use	8.7	33.2	58.1	9.5	35.5	55	2.6	11.3	86.1	4.9	9.8	85.3	10.5	48.8	40.6	6.2	31.9	62
Intention	14.9	29.6	55.5	15.7	31.1	53.2	4.9	9.5	85.6	7.5	12.9	79.7	19	39.3	41.6	13.6	27.5	58.9
N 389																		

DA: Disagree or Strongly Disagree

N: Neutral

A: Agree or Strongly Agree

Table 7 Mean TAM Perception for users and non users.

Practice (n=using, not using)	Using	Not	t-Test (df)
Mean TAM perception		**Using**	
Rotational Grazing (n=328,58)	31.1	24.9	t (384)= 10.1, p<<0.001
Reseeding (n=310,73)	31.3	24.8	t (381)= 11.4, p<<0.001
Spring Planner (n=193,188)	30.3	23.3	t (379)=13.9, p<<0.001
Grass Budgeting (n=171, 216)	30	22.6	t (385)= 15.5, p<<0.001
Grass Cover (n=156, 228)	30	22.3	t (382)= 15.6, p<<0.001
Grass Wedge (n=134,248)	29.7	21.2	t (254)=16.7, p<0.001
Average TAM perception			

Table 8 Positive Intention to use.

Practice (n=using, not using)	Using	Not Using	Overall	Eta sq (%)
	%	**%**	**intention**	
Grass Budgeting (n=215)	73	27	56%	12 (t= 5.47, p=<0.001)
Grass Cover (n=205)	72	28	53%	7 (t= 4.04, p=<0.001)
Rotational Grazing (n=330)	91	9	85%	15 (t= 6.43, p=<0.001)
Reseeding (n=309)	91	9	81%	7 (t= 4.90, p=<0.001)
Grass Wedge (n=157)	77	23	41%	4 (t= 2.72, p=0.007)
Spring Planner (n=224)	76	24	59%	5 (t= 3.63, p=<0.001)
TAM positive intention (mean)	**80**	**20**	**63%**	

Table 9 Traditional & Latent (TAM and Objectives)

Technology	GB	OR	GC	OR	R	OR	RG	OR	GW	OR	SRP	OR
Variables												
TAM	+ ***	1.9	+ ***	2.3	+ ***	1.4	+ ***	2.3	+ ***	2.3	+***	1.9
Total lu/ha							+*	2.2				
Age												
Agri Edu.									+ **	8.9		
D.G/DEP			+ *	2.4	+ **	2.2	+ *	2.8	+ *	4		
Future exp.												
Experimental	+ *	1.6			+*	1.3			- *	0.6		
Conservative												
Productive	+ *	1.5			+ **	1.5					+*	1.4
Log-L	93.74		60.36		115.1		48.93		62.01		88.85	
Pseudo R2	0.649		0.776		0.414		0.695		0.765		0.663	
Hosmer-L	8.24		3.25		16.47		1.48		18.66		67.01	
Prob > chi2	0.41		0.917		0.033		0.993		0.016		0.00	
N 389												

Table 10 Traditional Variables only

Technology	GB	OR	GC	OR	R	OR	RG	OR	GW	OR	SRP	OR
Variables												
Total lu/ha	**	1.5	*	1.4	**	1.9	*	1.7	*	1.3		
Age			- **	0.9	- **	0.9	- **	0.9	- **	0.9	- **	0.9
Agri Edu.	**	2.1	**	2.2					**	2.5		
D.G/DEP	***	3.3	***	4.1	**	2.4			***	3.4	***	2.5
Future exp.	**	1.9			***	2.9						
Log-L	228.0		221.8		167.4		143.3		223.9		210.7	

Pseudo R2	0.147	0.175	0.147	0.106	0.152	0.082
Hosmer-L	4.47	3.03	29.88	11.95	7	2.20
Prob > chi2	(0.81)	(0.93)	(0.00)	(0.15)	(0.54)	(0.9)
N 389						

Table 11 Latent (TAM and Objectives) Variables only

Technology	GB	OR	GC	OR	R	OR	RG	OR	GW	OR	SRP	OR
Variables												
TAM	***	1.9	***	2.3	***	1.4	***	2.2	***	2.2	***	1.9
Experimental	*	1.5	*	1.6	**	1.5					*	1.5
Conservative												
Productive	*	1.5			**	1.7					**	1.5
Log-L	95.69		63.61		118.9		52.02		69.24		91.05	
Pseudo R2	0.642		0.763		0.394		0.676		0.738		0.654	
Hosmer-L	5.48		3.72		14.69		5.54		23.18		67.55	
Prob > chi2	(0.70)		(0.88)		(0.06)		(0.69)		(0.00)		(0.00)	
N 389												

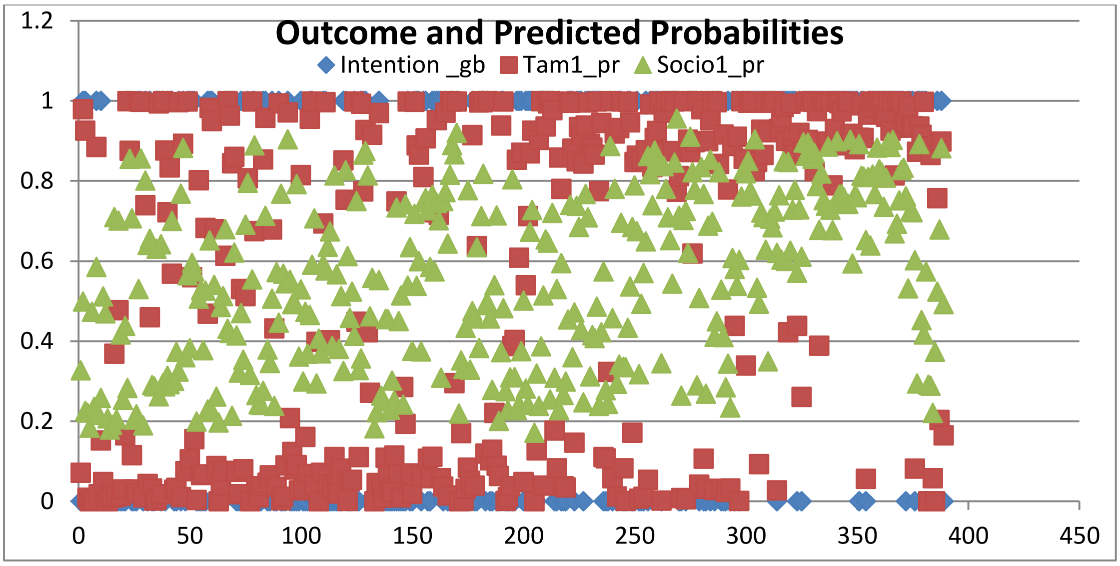

Figure 1 Predicted probabilities: Grass Budgeting

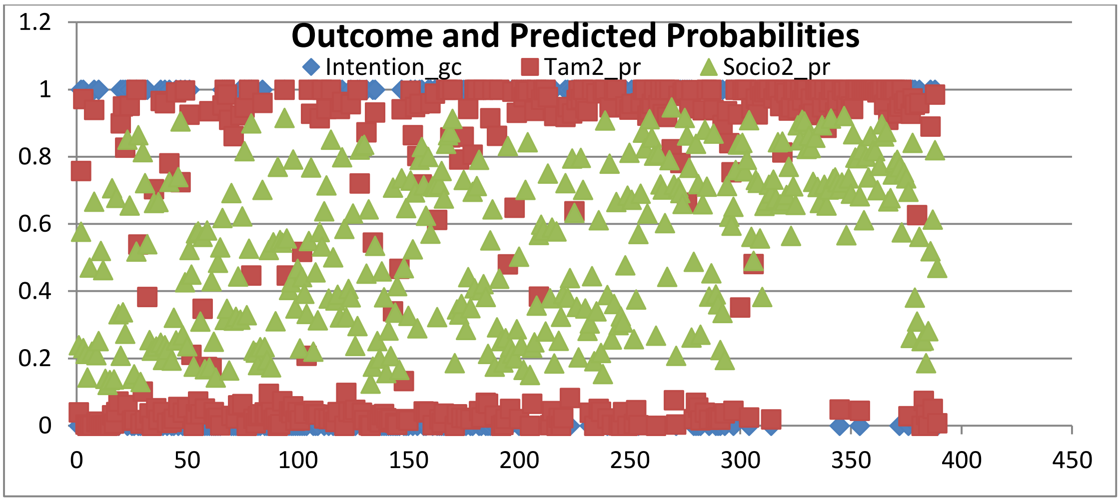

Figure 2 Predicted probabilities: Grass Covers

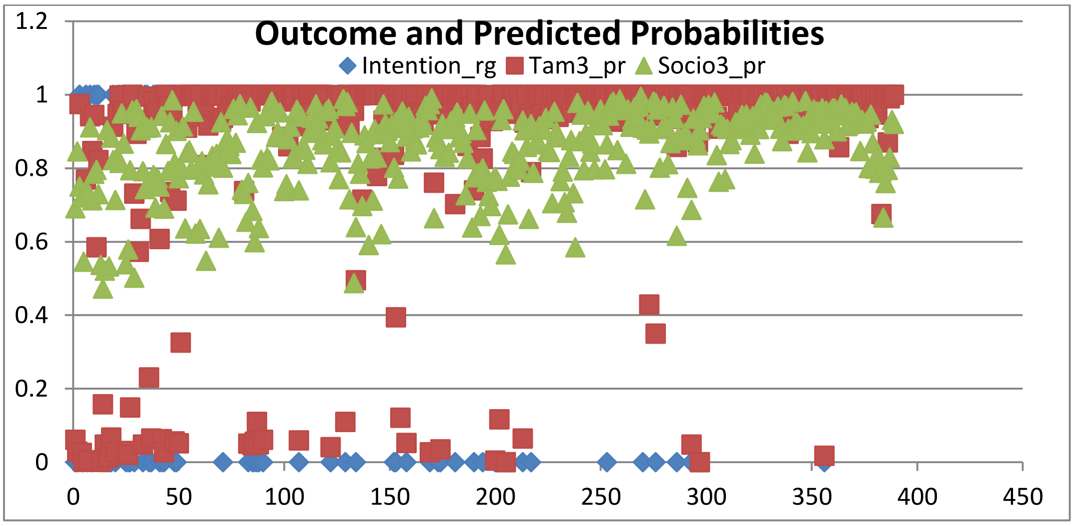

Figure 3 Predicted probabilities: Rotational Grazing

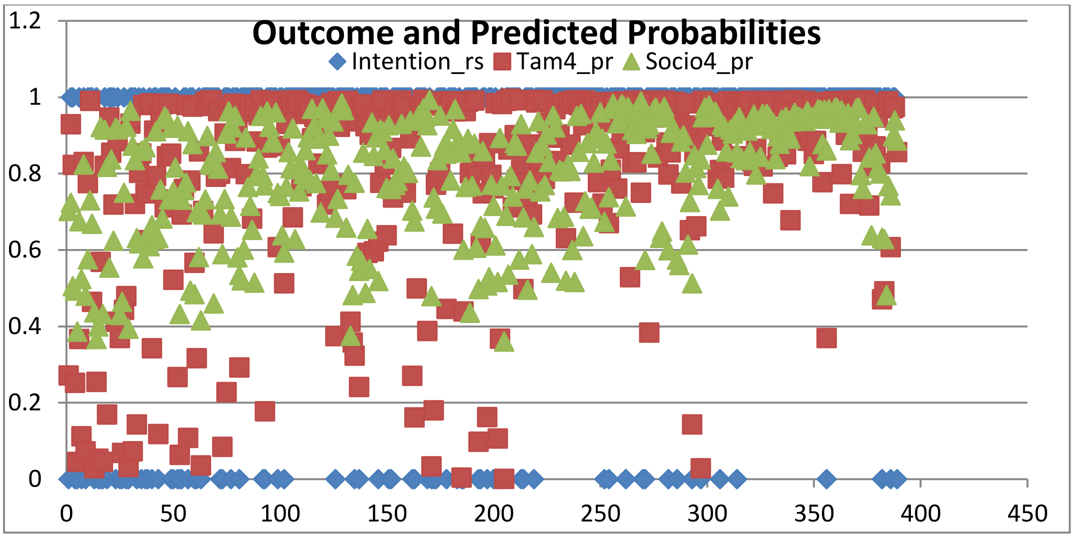

Figure 4 Predicted probabilities: Reseeding

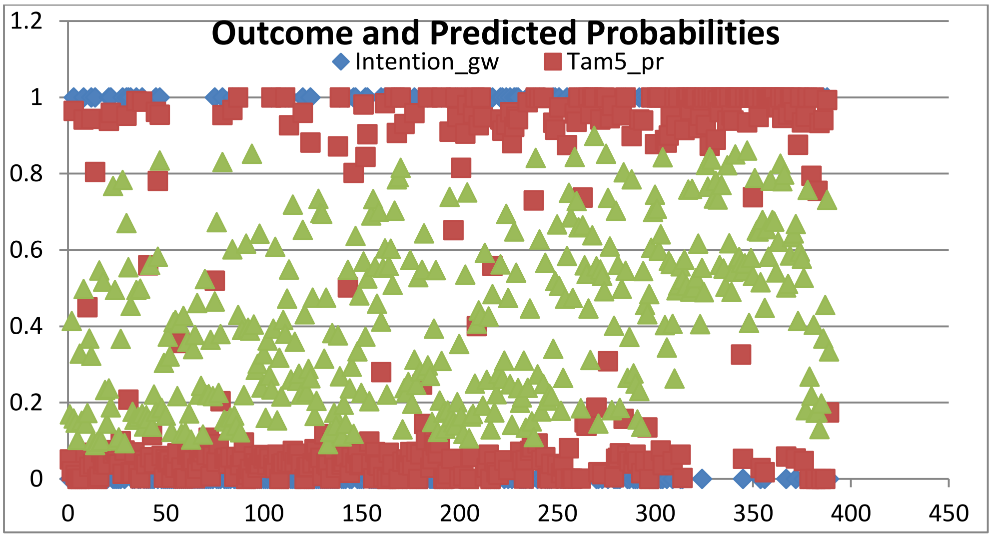

Figure 5 Predicted probabilities: Grass Wedge

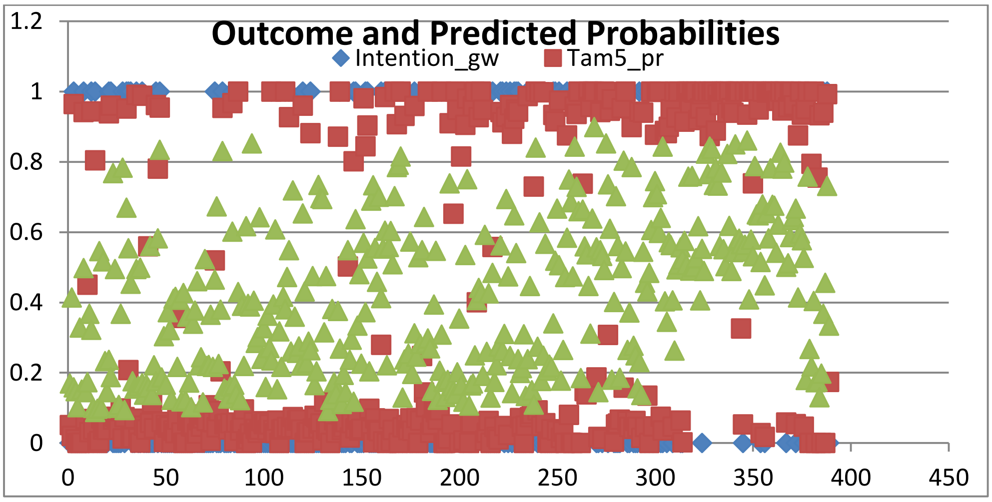

Figure 6 Predicted probabilities: Spring Rotational Planning

Table 12 Comparative Model Analysis

Classification Table	Grass Budget	Grass Cover	Reseeding	Rotational Grazing	Grass Wedge	Spring Planner
TAM & Objective	**92**	**94**	**89**	**95**	**95**	**92**
Sensitivity	94	95	96	99	93	95
Specificity	90	92	58	75	96	88
Socio & Demographic	**68**	**71**	**81**	**86**	**72**	**65**
Sensitivity	74	75	97	99.7	62	77
Specificity	61	67	19	2	78	48
N389						

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