Using choice experiments to improve the design of weed decision support tools

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Abstract

The potential for computer-based decision support tools (DSTs) to better inform farm management decisions is well-recognised. However, despite considerable investment in a wide range of tools, the uptake by advisers and farmers remains low. Greater understanding of the demand and the most valued features of decision support tools has been proposed as an important step in improving the impact of DSTs. Using a choice experiment, we estimated the values that Australian farm advisers attach to specific attributes of decision support tools, in this case relating to weed and herbicide resistance management. The surveys were administered during dedicated workshops with participants who give weed management advice to grain growers. Results from various discrete choice models showed that advisers' preferences differ between private fee-charging consultants, those attached to retail outlets for cropping inputs, and advisers from the public sector. Reliably accurate results were valued, but advisers placed a consistently high value on models with an initial input time of three hours or less, compared to models that are more time demanding. Results from latent class models revealed a large degree of personal preference heterogeneity across advisers. Although the majority of advisers attributed some value to the capacity for DST output that is specific to individual paddocks, approximately one quarter of respondents preferred generic predictions for the district rather than greater specificity. The use of a novel non-market valuation approach can help to inform development of decision support tools with attributes valued by potential users.

Keywords: Decision support; Weed management; Herbicide resistance; Adoption; Agriculture; Choice Modelling;

JEL codes: Q19; Q51;

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1. Introduction

Many agricultural management problems such as weed and herbicide resistance involve complex interactions, multiple year time frames, major environmental influences, and high levels of uncertainty. Because of these complexities, the impacts of possible management interventions are often evaluated using computer-based simulation models. While such models are commonly used as research tools, the uptake and use of computer-based decision support models by advisers and farmers has generally been low with a widely recognised 'implementation problem' (Hochman and Carberry 2011).

Decision support tools (DSTs) can be defined as computer-based, interactive models that provide "what-if" analyses to help evaluate the impacts of alternative management decisions (McCown 2002). Despite increasing use of on-farm computer technology, the role for using DSTs in routine farm decision making has remained limited (Hayman 2004; Hochman and Carberry 2011). A reason for this is that typical farm-level decision-making usually involves processes very different from the detailed quantitative analyses and calculation of optimal solutions in DSTs (Hayman and Easdown 2002; McCown 2002). Nevertheless, potential for successful impact for DSTs has been identified. This potential includes roles where DSTs are designed as a tool to help farmers' tactical decisions for simpler component issues, and/or as a consultant's tool where advisers help place the DST output in a farm-specific context, particularly if underlying scientific principles can be more readily understood by both farmers and advisers (McCown 2002).

Given the often limited use of DSTs, more pre-development effort needs to be made to identify the needs and preferences of likely users (Hochman and Carberry 2011). It has been recognised that while farmers have usually been the target audience for DST development, the actual users have been their advisers (Carberry et al. 2002). Although advisers are increasingly well-placed to make use of DSTs and achieve impact with farmers, relatively little attention has been paid to designing DSTs for their needs.

In the case of weed management, and strategies to deal with weed resistance to herbicides, there is increasing use of models in research (Holst, Rasmusssen, and Bastiaans 2006) and increasing interest from researchers to develop DSTs for advisers and farmers based on these research models (Parsons et al. 2009). Dealing with increasingly complex weed and herbicide resistance management scenarios is often a core role for farm advisers, so it may be expected that use of weed-related DSTs would be relatively high. While there are examples of successful DSTs that have found ongoing application in research and workshop settings (e.g. Pannell et al. 2004), or in the generation of information with extension impact (e.g. Llewellyn et al. 2006; Neve 2008; Renton et al. 2011), there is no evidence to suggest that the use of DSTs for weed and herbicide management is higher than for other aspects of agricultural systems (Wilkerson, Wiles, and Bennett 2002).

The challenge of offering sufficient return on investment of time and effort to users of a DSS remains paramount. This will typically involve dealing with trade-offs involving a number of non-pecuniary characteristics such as simplicity, completeness, robustness, and capacity to educate and engage users (Hochman and Carberry 2011). The study described in this paper uses a choice experiment method to inform DST development for weed and herbicide resistance management by assessing farm advisers' preferences for different characteristics of weed DSTs. Choice experiments are widely used to estimate preferences for consumer products or for environmental management scenarios. To the authors' best of knowledge, this is the first time this economic valuation technique is used to determine the value placed on features of computer-based decision support tools.

In the next section, there is a description of the choice experiment study followed by the results of a socio-demographic analysis and discrete choice models. The paper concludes with implications for decision support tool design and development.

2. The choice experiment study

Economic valuation methods that could be used to estimate the value of separate DST characteristics include direct market pricing methods, revealed preference methods, and stated preference methods (Hanley and Barbier 2009). Market pricing methods are used when goods and services are traded in markets. In the context of DSTs for farmers and advisers, direct market prices would be useful if there were many different tools commercially available to farmers and their advisers. By observing which DSTs (and how many) are bought and sold at different prices, one could infer directly how users value the different types of DSTs. However, there is no perfect market for weed DSTs to allow the use of a direct market pricing valuation approach. Furthermore, pro-active development of a DST that incorporates the features desired by users will require the use of valuation methods that do not rely on preference behaviour that is already *revealed* through users' decisions. In this study, we therefore use a *stated* preference choice experiment (CE) survey to estimate farm advisers' preferences for different features of weed DSTs.

2.1 The choice experiment method

People's preferences are estimated by means of a 'stated preference' survey in which respondents are asked to make choices between different (hypothetical) alternatives presented to them. A CE survey typically describes several hypothetical management scenarios that will lead to different outcomes. These outcomes are described by different levels of attributes, including a monetary attribute (costs), which together describe the good under valuation. Respondents to a CE survey are presented with a series of questions (choice sets-see Figure 1), where each question includes two or more alternatives, from which respondents are asked to choose their preferred option. Preferences are inferred from the hypothetical choices or trade-offs that people make between the different combinations of attributes (Bennett and Blamey 2001). The CE method is particularly useful in cases where product developers or policy makers are interested in the trade-offs between the multiple characteristics of a good. The method has been used in many different contexts, including consumer research (e.g. Swait and Adamowicz 2001), transport choices (e.g. Hensher and Rose 2007), health economics (e.g. McIntosh and Ryan 2002) and environmental management (e.g. Kragt and Bennett 2011).

Consider the following four options for a **Herbicide Resistance Prediction** Tool

Suppose that Options A, B, C and D are the only ones available. Which **one** would you choose?

	Option A	Option B	Option C	Option D
One-off costs	$50	$500	$0	$200
Specificity	Representative for district	Representative for district	Specific to paddock	Representative for district
Input time	3 hrs	0.5 hr	1 hrs	1 hr
Accuracy	40-60%	61-80%	40-60%	81–100%
My preferred option	☐	☐	☐	☐

Figure 1 Example choice set in the weed DST choice experiment questionnaire

The CE method originates from the marketing literature where it has been used to analyse consumers' choices of products (Louviere, Hensher, and Swait 2000). Choice experiments have their theoretical foundation in random utility theory (McFadden 1986) and Lancaster's 'characteristics theory of value' (Lancaster 1966). The random utility model describes utility U_{ijt} that individual *i* derives from possible choice *j* in situation *t* as a latent variable that is observed indirectly through the choices people make. Utility consists of an observed 'systematic' utility component V_{ijt} and a random unobserved error term ε_{ijt} (Louviere, Hensher, and Swait 2000). Lancaster's theory of value is based on the premise that any good can be described in terms of its attributes or characteristics, which contribute to utility as components of $\boldsymbol{x}_{ijt}$:

$$U_{ijt} = V_{ijt} + \varepsilon_{ijt} = \beta_i' \mathbf{x}_{ijt} + \varepsilon_{ijt} \qquad i=0,1,\ldots,N;\ j=0,1,\ldots,J;\ t=1,2,\ldots,T \quad (1)$$

The systematic component of utility V_{ijt} is assumed to be a linear, additive function of a vector of explanatory variables $\boldsymbol{x}_{ijt}$, which includes the attributes of the choice options, but can also include individual *i*'s socioeconomic and behavioural characteristics and features of the choice task itself (Hensher and Greene 2003).

Choice alternative *j* will be preferred if and only if the utility derived from that alternative is greater than the utility derived from any other alternative *z* (Equation 2). It is expected that if the quantity or quality of a 'good' attribute in an alternative rises, the probability of choosing that alternative increases, *ceteris paribus*:

$$\Pr(j \mid \mathbf{x}_{ijt}, \varepsilon_{ijt}) = \Pr\{(\beta'_i \mathbf{x}_{ijt} + \varepsilon_{ijt}) > (\beta'_i \mathbf{x}_{izt} + \varepsilon_{izt})\} \quad (2)$$

2.2 Choice experiment questionnaire development

A CE study was implemented to assess advisers' preferences towards different features of a weed DST. The CE questionnaire was developed following guidelines provided by (for example) Louviere et al. (2000), Bennett and Adamowicz (2001), and Hensher et al. (2005). The questionnaire was developed by a team of agricultural scientists, agronomists and environmental valuation experts. Initial survey versions were pre-tested with farm advisers from the low rainfall cropping regions of South Australia and Victoria. The draft surveys described two types of hypothetical DSTs that would predict the effects of different management scenarios: (1) a tool that would predict the likely rate of herbicide resistance evolution; and (2) a tool that would predict likely crop yield losses. From the pre-tests, it became clear that the two types of DSTs were not sufficiently different to respondents. The final CE therefore only used the example of a DST for predicting the likelihood of herbicide resistance evolving under different weed management options. Example research models on which such adviser-targeted DSTs could be based are described in, for example, Neve (2008) or Renton *et al.* (2011).

Expert opinion and literature reviews provided information about the attributes that could be used to describe the DST. Five attributes were considered to be relevant to most DSTs used by farm advisers: (1) Costs; (2) Specificity of results; (3) Time input demands; (4) Platform in which the tool would be delivered; and (5) Accuracy of model predictions. The levels of each attribute were designed to cover the range of levels currently observed in DSTs. To reduce design dimensionality (Caussade et al. 2005), the final CE included four attributes: costs, accuracy, time requirements, and ability to make results specific to individual paddocks (Table 1).

Table 1 Attributes and levels used in the weed DST choice experiment

Attribute	**Attribute description in questionnaire**	**Attribute levels[a]**
Costs	One off payment you will have to make to gain ongoing access to the tool.	\$0, **\$50**, \$200, \$500
Accuracy of results	The frequency that the tool generates predictions that are accurate within *reasonable* margins[b]	**40-60%**, 61-80%, 81-100% of the time
Input time	The time it will cost you to collect the information required and run the tool for the first time (including time spent learning how to use the tool). This may vary because some tools require more detailed data inputs and set-up than others.	0.5hr, 1hr, **3hr**, 6hrs
Specificity	The degree to which the tool produces customised paddock results: (i) Results for the actual specific paddock; ii) Results for a representative paddock in that district.	-1 = Representative for district; **1 = Paddock-specific**

[a] Bold levels represent the 'base option' A against which trade-offs were made. [b] The questionnaire explained that accurate input data would be used, and specified 'reasonable' as a +/- 2 year margin around the predicted number of applications until resistance. The mid-points of each accuracy range (50%, 705, 90%) were used in the model analysis.

The final questionnaire consisted of four sections: (1) introductory questions about farm management advice; (2) a set of Likert scale questions aimed to identifying the type of model-derived weed management information valued by advisers; (3) an explanation of the choice task followed by five choice questions; and (4) socio-demographic questions. The CE was designed using a factional orthogonal design, which provides a balanced set of alternatives where each attribute level is presented the same number of times to respondents, and where attributes level are fully independent from each other. Each choice set consisted of four alternatives. Respondents were presented with five choice sets and were asked to select their preferred alternative in each set. An example choice set is shown in Figure 1.

2.3 Econometric model specification

The utility U_{ijt} that individual *i* derives from choice alternative *j* in choice situation *t* (Equation 1) is inferred indirectly through the choices people make. Different econometric models can be used to estimate parametersβ for each explanatory variable included in the utility specification. The choice of model follows from assumptions about the error distribution and heterogeneity in preferences across respondents. The specific focus of this paper is to assess:

a) Whether advisers' preferences toward DST characteristics systematically vary with observable advisers' characteristics. If they do, then model developers can target their DSTs to the envisaged market.
b) Whether advisers have non-linear preferences for the attribute levels. If they do, then (for example) the marginal benefits from improving a DST to provide 61–80% accuracy may be larger than the marginal benefits from improving predictions to 81–100% accuracy.

Multinomial logit model

It is often assumed that the error terms ε_{ij} are independently and identically distributed (IID) Gumbel distributed over alternatives and individuals, in which case the choice probabilities can be estimated by a multinomial logit (MNL) model (Cameron and Trivedi 2005, 490-503: 490-503):

$$\Pr(j_{it} \mid \mathbf{x}_{ijt}, \beta) = \frac{\exp(V_{ijt})}{\sum_{q=1}^{J} \exp(V_{iqt})} \tag{3}$$

The MNL model has become known as the 'workhorse' of discrete choice analysis. The model is estimated by maximum likelihood (Hensher, Rose, and Greene 2005).

The analysis can account for observed (systematic) heterogeneity in tastes through an *a priori* selection of variables (such as socioeconomic characteristics). In this study, we explore how socioeconomic characteristics affect advisers' preferences for weed DST features by interacting socioeconomic variables with the attributes that describe the DSTs (Section 4.1).

Latent Class model

Although the MNL model provides a computationally convenient choice model, the IID assumption on the error term implies that-in the model estimation-β_i does not vary across individuals (that is, β_i

= β). This means that the MNL model does not account for any unobserved heterogeneity in preferences (i.e. heterogeneity that is not observed in socio-economic characteristics of the respondent). We use an alternative model known as the Latent Class (LC) model that can represent unobserved preference heterogeneity.

In the LC model, the population is assumed to consist of a discrete number of classes, where preferences β_c are homogeneous within class *c* but may vary between classes. The model thus allows for a discrete distribution of unobserved preference heterogeneity between classes. The utility that individual *i* derives from choice alternative *j* in choice situation *t* is now:

$$U_{ijt} = \beta_c' \mathbf{x}_{ijt} + \varepsilon_{ijt} \tag{4}$$

The probability of choosing alternative *j* is conditional on belonging to a certain class: $\Pr(j_{it}|c)$. Class membership is modelled as a logistic probability function of respondents' characteristics $\boldsymbol{z}_i$ (Birol, Karousakis, and Koundouri 2006):

$$\Pr(c_i) = \frac{\exp(\gamma_c' \mathbf{z}_i)}{\sum_{s=1}^{C} \exp(\gamma_s' \mathbf{z}_i)} \tag{5}$$

Where γ_c is a vector of parameters to be estimated in the model[1]; and C is the total number of classes specified by the analyst. One of the parameter vectors γ_c must be restricted to zero to enable model estimation (Boxall and Adamowicz 2002). For a given individual, the choice probability is the expected value of the class specific probabilities:

$$\Pr(j_{it}) = E_c \left[\frac{\exp(\beta_c' \mathbf{x}_{ijt})}{\sum_{q=1}^{J} \exp(\beta_c' \mathbf{x}_{iqt})} \right] = \sum_{s=1}^{C} \Pr(c_i) \left[\frac{\exp(\beta_c' \mathbf{x}_{ijt})}{\sum_{q=1}^{J} \exp(\beta_c' \mathbf{x}_{iqt})} \right] \tag{6}$$

In the MNL model, it is implicitly assumed that the errors across choices made by the same respondent are independent. An added advantage of the LC model is that the analyst can take account of the panel nature of discrete choice data by controlling for systematic, but unobserved, correlations in an individual's repeated choices (Revelt and Train 1998). This is done by including an individual specific error term that is correlated across the sequence of choices made by individual *i*.

Implicit prices

[1] Technically, the parameters that are estimated are scaled by a scaling factor. This scaling factor is normalised to one to allow estimation of the model.

CE survey respondents are assumed to make a trade-off between the levels of the attributes included in the choice sets. The expressed trade-offs between attributes can be used to estimate the relative marginal utility of each attribute (Bateman et al. 2006). If money is the unit of measurement for one of the attributes, it is possible to estimate the marginal attribute *values* in terms of the marginal 'willingness to pay' (WTP) for each individual attribute. The marginal WTP is expressed as the part-worth (or 'implicit price') for a unit change in an attribute:

$$Marginal\ WTP = \frac{\beta_{attribute}}{\beta_{cost}} \tag{7}$$

Where $\beta_{attribute}$ is the estimated attribute coefficient; and β_{cost} is the estimated coefficient of the monetary attribute. The implicit price for an attribute is based on the *ceteris paribus* assumption that the levels of all other attributes are held constant.

2.4 Survey administration

The CE surveys were administered during workshops conducted across Australia with 134 participating advisers who give weed management advice to farmers. These included private fee-charging consultants, advisers attached to retail outlets for cropping inputs, and advisers from the public sector. Those from the public sector included advisers who also have some involvement in applied research.

A total of eight workshops were organised in October and November 2011; in Western Australia, South Australia, Victoria, New South Wales and Queensland. These day-long workshops were marketed and targeted at experienced (senior) advisers seeking an update on weed and herbicide resistance management information. The workshops were promoted through the coordinating communications company and through regional weed research and extension networks. The workshops provided information on weed management for farm advisers, with a range of expert weed management speakers, and included a session dedicated to weed management DSTs. During this session, respondents were given an introduction to a range of existing and potential DSTs, after which they were asked to complete the CE questionnaire.

3. Results

The weed advisers' workshops yielded a total of 109 questionnaires that were used to estimate the values for different weed DST features (not all advisers answered all choice questions). In this section, we describe the survey sample and econometric model results.

3.1 Sample demographics

Respondents were asked about their type of employment; the region where they mostly work; the proportion of their time spent on giving advice to farmers and providing weed management advice; the proportion of 'their' farmers with herbicide resistance problems; their age and highest level of completed education.

The majority of advisers were commercial consultants (employed by an agricultural retailer or herbicide manufacturer), working in the southern States of Victoria and South Australia (Table 2). They spent, on average, a third of their work time giving weed advice to farmers. On average, an estimated 74% of the farmers they advise have herbicide resistant weeds on their farm. The average age was 37.8 years, and 81% of advisers had a (undergraduate or postgraduate) university education.

Table 2 Socio-demographic results of the weed DST CE survey

Type of adviser	*Commercial (e.g. agricultural retailer)* 58 (53.4%)	*Public (e.g. State or local government)* 18 (17.5%)	*Private (e.g. agricultural consultancy firm)* 30 (29.1%)
Region*	*North* 12 (11.7%)	*South* 73 (70.9%)	*West* 18 (17.5)

State	*Queensland*	*New South Wales*	*Victoria*	*South Australia*	*Western Australia*
	8 (7.8%)	6 (5.8%)	46 (44.7%)	25 (24.3%)	18 (17.5)

	Average	*(st.dev.)*	*Range*	*# of answers*
Time spent giving farm management advice (% of total work time)	62.6%	(29.7)	0–100	100
Time spent giving weed management advice (% of total work time = *weed_time*)	36.3%	(22.2)	0–80	99
Farmers with herbicide resistance problems (% of all clients = *resist*)	74.4%	(31.9)	0–100	100

Age (years)	37.8	(10.5)	24–64	103
Education (years)	15.0	(1.46)	12–17	104

[*] Based on GRDC regions: http://www.grdc.com.au/director/about/panels

Advisers were asked to rank-order the usefulness different software platforms that can be used to deliver weed advice. In Table 3, rank 1 indicates that the adviser found that platform 'most useful', and rank 5 indicates 'least useful'. The results show that the majority of advisers prefer a weed management tool to be a stand-alone model in, for example, Excel. There is also a large proportion of advisers who would like to have weed DSTs delivered in an 'App' format for Tablets.

Table 3 Advisers' preferences for delivery platforms of weed DSTs

	Rank 1	*Rank 2*	*Rank 3*	*Rank 4 or 5*
Stand-alone Excel-based tool	43 (42%)	22 (21%)	20 (19%)	18 (17%)
App (e.g. for smartphone or Tablet)	30 (29%)	33 (32%)	23 (22%)	18 (17%)
On-line only tool	13 (13%)	28 (27%)	37 (36%)	25 (24%)
Integrated into commonly used paddock management software	17 (16.5%)	16 (15.5%)	23 (22%)	47 (45%)

3.2 Multinomial model results

Data from the choice experiments were tested in several different model specifications.Ee estimated a range of MNL models without and with socio-demographic indicators. Results are presented in Table 4.

MNL1 is a simple, attribute-only model in which utility is specified as a linear function of the DST attributes (cost, time, accuracy, and specificity). An alternative specific constant (ASC) is included in all models to capture any systematic, but unobserved, preferences towards the choice option A (the 'status quo' alternative), over options B, C or D.

In MNL2, socio-demographic indicators were interacted with the DST attributes to show how advisers' characteristics affect their preferences towards cost, time, accuracy, and specificity. Only interactions between "time spent giving weed management advice" (*weed_time*) and "input time", "weed_time" and "specificity", and between "specificity" and "employment type" (*private, commercial, public*) were significant in our data-set. Interactions with other advisers' characteristics such as proportion of resistance problems, work region, age, or education were not significant predictors of preferences.[2]

The third model (MNL3) allows for the possibility of non-linear preferences towards input time and accuracy through forward difference-coding of the attribute levels. This coding allows us to estimate the marginal change in choice probability for each discrete change in the attribute levels rather than for per unit changes (for example, a reduction in input time from the presented 6hrs to 3hrs).

Table 4 Multinomial logit model results

	MNL1		**MNL2§**		**MNL3**	
Variable	*Parameter*	*S.E.*	*Parameter*	*S.E.*	*Parameter*	*S.E.*
ASC (status quo = 1)	-0.532	0.317	-0.474	0.321	-0.769**	0.345
Attributes of weed DSTs						
One-off costs ($)	-0.003***	0.000	-0.003***	0.000	-0.003***	0.000
Input time (hr)	-0.310***	0.049	-0.586***	0.129		
Accuracy (%)	0.073***	0.006	0.075***	0.007		
Specificity (paddock-specific = 1)	0.197***	0.077	0.887***	0.320	0.133*	0.077
Advisers' characteristics						
Time x weed_time			0.006**	0.003		
Spec x weed_time			0.009**	0.004		
Spec x private			-0.946**	0.387		
Spec x commercial			-1.196***	0.385		
Non-linear preferences						
Input time_1 to 0.5					-0.132	0.208
Input time_3 to 1					0.271	0.200
Input time_6 to 3					2.049***	0.366
Accuracy_50 to 70					2.141***	0.295
Accuracy_70 to 90					1.135***	0.190
Log-likelihood	-307.9		-278.1		-297.6	
Adjusted - ρ^2 ‡	0.294		0.310		0.317	
AIC/n	1.710		1.709		1.670	
BIC/n	1.763		1.811		1.755	

Notes: ***, **, * = significance at 1%, 5% and 10% level; n=366; § n = 336 because not all respondents answered the socio-demographic questions; ‡ Adjusted to the number of parameters, against a constant only model with LL=-443.36 for MNL1 and MNL3, and LL=-410.38 for MNL2

[2] All models referred to in this paper are available upon request from the authors.

In the MNL1 and MNL2 models, the estimated parameters on the DST attributes are all highly significant and have the *a priori* expected signs. The negative sign on the cost and time attributes means that respondents were less likely to choose an option with higher costs or higher input times. The positive sign on accuracy and specificity means that respondents were more likely to choose DSTs that are more accurate in their predictions, or provide paddock-specific (compared to district-representative) predictions.

The interpretation of the interaction variables in the MNL2 model is as follows: the proportion of time that an adviser spends on giving weed management advice affects his attitude towards the input time and specificity of a DST (but not attitude towards cost and accuracy, since those interactions were not found to be significant). The significant and positive parameter estimates suggests that advisers who spend more time on giving weed management advice (higher levels of *weed–time*) are less likely to prefer shorter input times then adviser who spend less time on giving weed management advice. The positive sign on (*spec* x *weed_time*) means that advisers who spend more time giving weed management advice are also more likely to prefer paddock-specific DSTs, compared to advisers who spend less time on weed management advice.. Attitudes towards specificity also varied with the type of advisers' employment. The negative parameter estimates mean that private and commercial advisers were less likely to choose paddock-specific over district-representative models, *compared to* public advisers.

In the MNL3 model, the costs parameter is negative, and specificity is positive—similarly to the MNL1 and MNL2 models. The attribute levels for input time and accuracy were forward-difference coded, allowing us to assert whether preferences are linear or non-linear towards the attribute levels.. The significance and positive parameter on 'Input time_6 to 3' means that respondents had a strong preference to reduce the input time from six hours to three hours. The insignificant parameter estimates on the other two 'input time' variables show that advisers' have no strong preferences to reduce input time from three hours to one hour, or from one hour to half an hour. The significant, and positive, estimates on 'Accuracy_50 to 70' and 'Accuracy_70 to 90' reveal non-linear preferences towards the accuracy attribute. Advisers have a preference for more accurate model predictions, with a decreasing marginal utility as accuracy increases.

The adjusted-ρ^2 of MNL2 and MNL3 higher than MNL1, indicating an improvement in model fit when interaction variables or non-linear effects are included. Judged by the Akaike or Bayesian

Information Criteria (AIC or BIC), the non-linear MNL model explains the probability of choice best on this data-set.

3.3 Latent class model results

A major drawback in the MNL models described in the previous section is their inability to account for: (i) *unobserved* preference heterogeneity, and (ii) *repeated choices* made by the same respondent. Alternative models were estimated that incorporate unobserved heterogeneity and the panel nature of the choice data. Estimates of mixed logit (ML) models (Hensher and Greene 2003; Train 2003), revealed significant individual preference heterogeneity towards the DST attributes. However, the interest in the current study was not unobserved heterogeneity between individuals, but rather preference heterogeneity between types of advisers.

To understand more about how preferences may vary across the advisers' 'population', several latent class (LC) models were estimated. The models were specified with varying number of classes, and with different advisers' characteristics as determinants in the class membership probability function.

First, the optimal number of classes was determined. Since log-likelihoods will always increase when the number of classes C (equation 5) increases, researchers cannot use regular likelihood ratio tests to compare models. Instead, the Aikaike and Bayesian Information Criteria (AIC and BIC) are used to guide the choice of C.

The results of models with varying numbers of classes are shown in Table 5. A two-class model had the lowest BIC in a model with, and a model without, non-linear attribute specifications. Models with more latent classes resulted in classes with comparatively small improvements in log-likelihood, insignificant parameter estimates, and larger AIC and BIC. The exceedingly small estimates of class probabilities, and large estimated standard errors in models with more latent classes led us to a preferred model where advisers are grouped into two 'preference classes'.

Table 5 Model performance of linear latent class models with varying numbers of classes

Number of classes	***2***	***3***	***4***
Log-likelihood	-281.97	-272.92	-269.38

AIC/n	1.601	1.584	1.598
BIC/n	1.718	1.766	1.843

We also estimated LC models in which class probabilities were a function of advisers' characteristics (such as employment type, region of work, time spent on weed advice etc.). However, none of the variables collected in our study were found to be significant predictors of class probability. That means that we cannot explain preference heterogeneity between classes based on the socio-demographics collected in the questionnaire. Although, in the MNL models, time spent on weed management determined advisers' preferences for input time and specificity, weed_time did not explain the class membership probability.

The results of our two-class models are presented in Table 6. Preferences are heterogeneous between the two latent classes. Approximately 72% to 81% of respondents are predicted to belong to class 1, and 28% to 19% of respondents are predicted to fall into class 2. One can think of these classes as two 'categories' of advisers. The LC1 model results show that respondents have a consistent negative utility for higher costs and longer input times, and positive utility for higher accuracy. The LC1 model shows that there is a difference in preferences for the specificity attribute between the two classes of advisers. The majority of respondents (those in class 1) have a preference for paddock-specific predictions. Respondents in class 2, on the other hand, prefer district-representative decision support tools.

The LC2 model defines the input time and accuracy attributes as non-linear parameters (compare MNL3). The signs of the cost and specificity coefficients are the same as in the LC1 model. Respondents in class 1 have a preference for paddock-specific outcomes, while class 2 prefers district-representative predictions. The non-linear estimates show that class 1 respondents have a strong preference to reduce input time from six to three hours, but derive little utility from further reductions in input time. The majority of respondents (class 1) have preferences for increased accuracy, although the marginal benefits of increased accuracy decreases as accuracy increases. Respondents in class 2 put more emphasis on reducing input time than on improved accuracy. These respondents have a significant and positive preference to reduce input time from six hours to three hours, and a smaller but significant positive preference to reduce input time further from three hours to one hour.

Table 6 **Latent class model results**

	LC1		*LC2*	
Variable	*Parameter*	*S.E.*	*Parameter*	*S.E.*
Latent class 1	*72.08%* ***		*80.58%* ***	
ASC_1	-1.231	0.883	-1.369**	0.661
One-off costs	-0.003***	0.001	-0.003***	0.001
Input time	-0.287***	0.077		
Accuracy	0.108***	0.017		
Specificity	0.652***	0.224	0.427***	0.104
Input time_1 to 0.5			0.030	0.253
Input time_3 to 1			0.282	0.244
Input time_6 to 3			1.542***	0.429
Accuracy_50 to 70			2.587***	0.386
Accuracy_70 to 90			1.471***	0.249
Latent class 2	*27.92%* **		*19.42%* ***	
ASC_2	-0.864*	0.481	-1.791*	0.941
One-off costs	-0.004**	0.002	-0.006***	0.002
Input time	-0.595***	0.150		
Accuracy	0.053***	0.017		
Specificity	-0.863**	0.353	-1.267***	0.384
Input time_1 to 0.5			-1.189	0.818
Input time_3 to 1			1.535**	0.738
Input time_6 to 3			4.347***	1.267
Accuracy_50 to 70			0.893	0.755
Accuracy_70 to 90			1.480*	0.861
Log-likelihood	-281.97		-273.44	
Adjusted - ρ^2 ǂ	0.353		0.372	
AIC/n	1.601		1.587	
BIC/n	1.718		1.768	

Notes: Estimated class probabilities in parentheses; ***, **, * = significance at 1%, 5% and 10% level; n=366; ǂ Adjusted to the number of parameters, against a constant only model with LL=-443.36

3.4 Implicit prices

Of interest from a valuation perspective is advisers' willingness to pay (WTP) for the different features of a DST. Based on the model results from our CE study, one can estimate the implicit prices for input time, accuracy and specificity using equation 7. These results are summarised in Table 7 for the linear models, and in Table 8 for the non-linear models.

Table 7 Linear models - Implicit price estimates‡

	Time ($/hour)	Accuracy ($/%)	Specificity ($)
MNL1 model			
Average WTP	100.42*** (56.8–144.0)	23.76*** (15.7–31.8)	63.78** (11.3–116.3)
*MNL2 model*ᶜ			
Public advisers	159.34*** (80.7–266.6)	22.76*** (16.4–32.8)	298.1*** (104–542)
Private advisers	124.61*** (48.6–225.3)	22.76*** (16.4–32.8)	66.04 (-128–266)
Commercial advisers	100.65*** (24.7–195.2)	22.76*** (16.4–32.8)	26.60 (-174–228)
LC model			
Average WTP§	$ 109.28	$ 30.66	$ 111.09
Class 1	100.52*** (45.1–215)	37.91*** (21.8–75.9)	228.21*** (69.4–525)
Class 2	131.91** (46.2–719)	11.92** (2.9–68.7)	-191.34** (-1153–-19.5)

Notes: ‡ 95% confidence intervals in parentheses; ***, **, * = significance at 1%, 5% and 10% level; ᶜCalculated using average weed management time for each type of adviser; §Calculated using the class probabilities of 0.7208 for class 1, and 0.2792 for class 2.

The implicit price estimates from the MNL1 model are all significant at the 1% level. The price estimates for the MNL2 model were based on average weed management times for public, private and commercial advisers, which were 10.9%, 31.2%, and 44.9% respectively. The results suggest that all types of advisers would be willing to pay to reduce model input time (between $100 and $160 for every hour less). Advisers would be willing to pay around $23 for every percentage improvement in predictive accuracy of a DST, *ceteris paribus*. Implicit price estimates for specificity varies with adviser type, with only public advisers being willing to pay for paddock-specific models (nearly \$300). It should be noted that the wide confidence intervals around the implicit prices estimates indicate uncertainty in the mean WTP estimates.

The implicit price estimates from the linear LC1 model (which accounts for non-observed preference heterogeneity) are in line with the MNL model estimates. The results suggest that advisers are willing to pay around \$109 for every hour reduction in model input time; \$31 for every per cent improvement in predictive accuracy; and \$111 for a paddock-specific DST compared to a representative-district DST. The implicit price estimates for the different classes confirms the varying preferences of advisers towards specificity, with respondents in class 1 willing to pay for a paddock-specific model, and respondents in class 2 willing to pay for a representative district-model. The class-specific estimates further show that class 2 (28% of the sample) have a higher WTP for reducing input time, and a smaller WTP for accuracy, than respondents in class 1 (72% of the sample).

Table 8 Non-linear models - Implicit price estimates (\$)

Model	**WTP to reduce input time**			**WTP to increase accuracy**		**Specificity**
MNL3	*1hr→0.5hr*	*3hr→1hr*	*6hr→3hr*	*50%→70%*	*70%→90%*	
Average WTP	NS	NS	\$640.6***	\$669.6***	\$354.8***	\$41.6*
LC2	*1hr→0.5hr*	*3hr→1hr*	*6hr→3hr*	*50%→70%*	*70%→90%*	
Average WTP§	NS	\$137.6	\$613.3	\$789.8	\$487.1	\$78.2
Class 1	NS	103.2	563.0***	940.0***	534.2***	154.8***
Class 2	NS	280.2**	821.8***	166.4*	291.6**	-239.5***

Notes: NS = not significant; ***, **, * = significance at 1%, 5% and 10% level; § Calculated using the class probabilities of 0.8058 and 0.1942.

Table 8 displays the implicit price results for the non-linear models. The MNL3 and LC2 estimates show that the majority of advisers does not significantly value reductions in model input time to less than one hour. The LC model results show that advisers have an average WTP of about \$613 to reduce model input time from six hours to three hours, but that further reductions in input time from three to one hour are valued much lower at around \$138. The non-linear model results indicate that DSTs will be more attractive when input time is reduced, but that reducing input time to less than three hours may not yield much additional benefit for the majority of advisers.

The WTP estimates for accuracy are significant, but reveal a decreasing marginal utility from increased accuracy. In both models, advisers are shown to value increasing accuracy from 50% to

70% higher ($670-%790) than increasing accuracy from 70% to 90% ($355-$487). Finally, the implicit price estimates for specificity show significant heterogeneity in preferences, with class 1 respondents willing to pay about $155 more for a paddock-specific DST, while class 2 respondents are willing to pay about $240 more for a regional DST.

4. Discussion and conclusion

Reflections on the role and future of agricultural decision support systems have highlighted the need for greater understanding of the characteristics of demand from DST users, who are increasingly likely to be farm advisers (Hochman and Carberry 2011). There has also been suggestions that developers of DSTs have focused excessively on achieving accuracy and generating specific recommendations, and not enough on the ability to engage with broader principles (Hayman and Easdown 2002; McCown 2002). Underlying this is the suggestion that not enough attention has been paid by—typically research-oriented—DST developers to the return on investment proposition for intended users of DSTs. In this study we have applied a novel use of a choice experiment (CE) non-market valuation approach to assess preferences of farm advisers relating to several of these aspects.

The CE survey described a hypothetical decision support tool that could potentially be used by advisers to evaluate the likely risks and rates of herbicide resistance under different weed management scenarios. The advisers who responded to the survey were highly engaged with giving weed management advice and generally very familiar with herbicide resistance, with a majority of their clients dealing with the problem. Four attributes were used to describe a generic herbicide resistance prediction DST: cost, time demands, predictive accuracy, and the ability to produce outputs specific to particular paddocks versus 'indicative' regional outputs. The choice models produced strong predictive power and the DST attributes were significant in in all model specifications. The survey results indicated that stand-alone formats (such as Excel-based programs) are most favoured as a delivery platform for weed DSTs, although we expect preferences for 'App'-type formats for smartphones or Tablets to increase as data networks improve in regional areas.

Based on linear multinomial and latent class model specifications, the CE results suggest that respondents are willing to pay between $100–$160 for every hour reduction in the input time required before the DST can be used. This figure is similar to the typical earning capacity from farm consulting. However, respondents were shown to have strong nonlinear preferences to reduce the time required to initiate model usability (input time). A high value was attributed to reducing input time from six hours to three hours ($204-$214 per hour), but only a small proportion of respondents (<20% in LC model class 2) valued reducing input time from three hours to one hour (at about $140 per hour). A MNL model with interactions showed that a higher proportion of time spent on giving weed management advice will reduce preference for shorter input time.

Overall, the value attributed to increasing frequency of a reasonably accurate model result was between $12–$38 for every percentage point improvement, although further analysis also showed non-linear preferences towards this attribute. Increasing accuracy from 50% to 70% was valued higher (at $670-$790) than increasing the frequency of accurate results from 70%-90% (at $355-$487). Attitudes towards accuracy were not affected by the proportion of time spent giving weed management advice.

Willingness to pay for a tool that can produce results customised to a specific individual paddocks varied with adviser type. Respondents from the public sector strongly preferred paddock-specific predictions, while private or commercial advisers did not place a significant value on specificity. A MNL model with interactions showed that a higher proportion of time spent on giving weed management advice will increase preferences for paddock-specific model outputs.

Latent class models allowed for greater insights into unobserved preference heterogeneity across respondents. A two-class model performed best on our data-set, with approximately three quarters of respondents predicted to belong to class one, and one quarter to class two. These two classes of advisers can be summarised as:

Class 1: Those in this largest category of advisers have a stronger preference for increasing model accuracy above 50%, and favour a tool that generates paddock-specific outcomes. Preferences towards input time are highly non-linear. Respondents significantly valued reducing input times from six hours to three hours, but further reductions generated no positive utility. Class 1 respondents could be described as advisers who have an interest in accurate, paddock-specific, model predictions, and who are willing to invest input time and money to achieve this outcome.

Class 2: This smaller second category of advisers has a significant preference for district-representative, rather than paddock-specific DSTs. They place less value on improving accuracy than respondents in class 1, and place more importance on avoiding input times of six hours. Class 2 respondents may be advisers who are looking for fast, generic, models that can give indicative results – and who don’t need the level of predictive accuracy required by class 1 type advisers.

The class results demonstrate that characterising and understanding sub-populations of potential DST users is not as simple as categorisations based on retail agronomist versus private consultant versus public government employees. None of the variables measured in our study, including adviser type, region, time spent giving weed advice etc. were significantly associated with the two model classes. As demonstrated by Jakku and Thorburn (2010), it is possible that advisers’ characteristics related to personal attitudes, learning styles, and information needs are more important in determining the value placed on DST attributes than the observable socio-demographic characteristics collected in our questionnaire.

In summary, the ability to consistently generate a reasonably accurate result is valued highly by weed advisers, but there is evidence that the marginal benefits of model accuracy decrease with an increasing frequency of accurate predictions. A consistent result from our study is the greatly diminished value placed on DSTs that require a ‘set-up time’ of more than three hours. Further, there appear to be two groups of adviser types, with one group preferring customised paddock-specific DSTs, and a second (smaller) group preferring a tool that delivers only regionally representative output. Developers of decision support systems should thus be aware of the likelihood that one DST will not ‘fit all’. Sub-groups among target users can have very different personal preferences and/or attitudes to the value of decision support tools. An encouraging result for weed management DST developers is the large sub-group of advisers in this study, who value a tool with more highly developed simulation capacity and are prepared to invest time and money to achieve more accurate, paddock-specific, results.

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Appendix 1 Stages in developing a choice experiment questionnaire

1. Problem identification	Describing the issue at stake. What is the resource that will be considered in the CE study? What is the current state of knowledge? What are the relevant stakeholders? Etc.
2. Management scenarios	Identifying what actions could be undertaken to address the issue at stake (e.g. new product development or alternative resource management policies).
3. Selecting attributes	Decide on the attributes relevant to the resource under consideration. What are the characteristics that best describe the resource? Expert opinion, focus groups and literature reviews can provide information on the attributes that are likely to be influenced by the management scenarios and that are valued by stakeholders.
4. Assigning levels to attributes	The likely levels of the attributes need to be determined. Existing model results, expert opinion and literature can provide the necessary information to determine realistic attribute levels.
5. Choice set design	Experimental design techniques are used to allocate the levels of the attributes to each alternative within the choice sets.
6. Choice set presentation	A decision needs to be made on how to describe the levels of the attributes, how many choice sets to include in the questionnaire and how to present the choice sets to respondents.
7. Pre-testing	Focus groups are useful to test whether chosen attributes and their levels are understood by respondents. Pre-testing also shows whether the quantity and quality of information provided about the resource and the management scenarios is appropriate.
8. Survey delivery	Choosing the sample size, sample locations and survey procedure (mail-out, drop-off, in-person etc.).