Adoption of herbicide resistance management practices by Australian grain growers

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Abstract

Extension programs in Australia are encouraging farmers to adopt integrated weed management (IWM) practices, in order to delay the development of herbicide resistance in weeds infesting cropping land. Logistic and Tobit regression models were developed and used to analyse, survey data from Western Australian grain growers. Factors shown to influence IWM adoption included perceptions of IWM practices and expectations about the future of the herbicide resource. The results were consistent with the prior that farmers regard IWM as an information-intensive package of techniques, and that extension may have the potential to increase the rate of adoption.

Introduction

Over large areas of the Australian wheatbelt, important weed species can no longer be controlled by some selective herbicides on which farmers once relied (Llewellyn and Powles, 2001; Nietschke *et al*., 1996; Pratley *et al*., 1993; Walsh *et al*., 2001). The stock of effective selective herbicides used to control such weeds can be considered a potentially exhaustible resource (Llewellyn *et al*., 2001; Pannell and Zilberman, 2001), with farmers' management of resistance requiring consideration of both short and longer-term costs (Orson, 1999).

Extension programs in Australia are encouraging farmers to adopt integrated weed management (IWM) practices in order to delay the development of herbicide resistance in weeds infesting cropping land. A necessary condition for such programs to be effective is that some or all of the primary determinants of adoption of IWM must be susceptible to influence by extension activities. Obvious examples of potential variables are farmers' perceptions of the seriousness of herbicide resistance, farmers' perceptions of the value of IWM in controlling it, and farmers' perceptions of the possibility of alternative solutions.

In this paper, hypotheses derived from a conceptual framework detailed in Llewellyn et. al. (2001) about the relationships between specific variables and the adoption of IWM practices are tested using regression analysis. Of primary interest is the hypothesis that grower perceptions of herbicide-resistance-related factors and perceptions of IWM practices are significant in explaining the adoption of IWM practices. This may demonstrate the potential for information provided through extension activities to contribute for better-informed decisions about adoption of IWM. Also tested is the applicability of a resource conservation model in explaining growers' adoption behaviour, the objective being to identify an appropriate framework for considering herbicide resistance management.

The resource management approach to considering farmers' resistance problem has largely been developed through economic studies of insect pest management problems (Hueth and Regev, 1974; Miranowski and Carlson, 1986) where rapid resistance development to a very limited range of pesticides has led to the complete exhaustion of pesticide efficacy in some situations. In such scenarios, farmers essentially face an optimal resource use problem, balancing exploitation of the pesticide or an investment in its conservation, usually through the use of more costly alternative practices. For weed control, the alternatives to selective herbicide use are referred to here as integrated weed management (IWM) practices comprising a range of cultural, mechanical and biological methods (Gill, 1997; Matthews, 1994)

Key objectives of the larger study from which this paper is derived are: a) to identify an appropriate framework for considering the IWM adoption behaviour of growers; b) to identify perceptions important in the decision to adopt IWM; and c) to measure the importance of informational variables in the decision, and d) to inform further research into the impact of targeted information/extension on perceptions influencing IWM adoption.

Presented in this paper are analytical and empirical models of the adoption of IWM practices and the extent of IWM use. Methods used to generate appropriate explanatory and dependent variables are detailed, along with descriptions of the logit and tobit regression models used, and the results obtained.

Decision framework for IWM adoption

A framework for considering IWM adoption under the presence or risk of herbicide resistance development (Llewellyn *et al*., 2001) is expressed in reduced form below. This includes an integral role for herbicide-related factors in the IWM decision framework. For the purposes of this study, herbicidal weed control refers to post-emergent selective herbicides for ryegrass control. Alternative weed control practices are represented by the IWM practices, some of which are physical or biological, and some of which involve the use of non-selective herbicides. Essentially, the decision problem for the grower is assumed to be the maximisation of present value of annual returns (NPV) by selecting optimal levels of IWM use, IWM*, and herbicide use, H*, for each year, t.

$$NPV = \Sigma_{t=1..n} (P.Y_t – C_w - C_F) \beta_t \qquad (1)$$

$$C_w = C_H .H_t^* + C_{IWM} .IWM_t^* \qquad (2)$$

P = price per unit yield
Y = crop yield
C_w = cost of weed control
C_F = costs associated with growing the crop excluding weed control. These costs include seeding, fertiliser and harvesting costs and are considered fixed

C_H = cost of herbicide treatment

C_{IWM} = cost of IWM practice

H_t = level of herbicide use in year t

IWM_t = level of IWM use in year t

β = discount factor

The dependent variables in this study are all measures of the level of IWM use. In terms of utility, it is assumed that when IWM_t is greater, the utility of IWM use, U_{IWM} , is greater. A grower's utility function, ranking the preference for IWM use, is expected to include a range of factors and can be expressed as:

$$U_{IWM} = f(G, F, R, I) \quad (3)$$

G = A vector of grower factors, including informational variables

F = A vector of farm factors

R = A vector of herbicide factors

I = A vector of IWM factors

IWM factors include perceptions of efficacy and economic value relative to herbicides. Perceptions of the attributes of an innovation have been shown to be major factors in determining its adoption (Adesina and Zinnah, 1993; Cary and Wilkinson, 1997). Perceptions of a problem also have a role in the adoption of related conservation innovations (Ervin and Ervin, 1982; Sinden and King, 1990; Traore *et al*., 1998). Herbicide factors in this study generally relate to a problem, in this case herbicide resistance. The adoption of IWM has been hypothesised to be consistent with a resource management framework in which the resource, a stock of effective selective herbicides, is potentially exhaustible due to the development of herbicide resistance. Perceptions of the existing level of herbicide resistance and perceptions relating to future exhaustibility are hypothesised to contribute to the expected utility of IWM practices and, consequently, the likelihood of IWM use.

Grower factors of primary interest relate are those relating to information and learning. By definition, IWM adoption is complex and is therefore expected to have high information requirements. For this reason, higher exposure to, or seeking of, extension and other information sources is expected to be positively associated with IWM adoption. These informational variables can also be described as policy variables given that extension is a common policy instrument used by government and industry in affecting change. Greater human capital can result in more cost-effective information acquisition and learning (Feder *et al*., 1985; Feder and Slade, 1984; Lindner, 1987) and is therefore expected to be positively associated with adoption. Grower factors also include the rate at which future returns are discounted. Consistent with studies of conservation innovations involving short-term cost and longer-term returns (Baidu-Forson, 1999; Pannell, 1999), growers placing a greater relative value on short-term returns (i.e. a high discount rate) are expected to be less likely to adopt IWM practices.

Data Source

The data for this study is derived from a survey of 132 randomly selected grain growers from within the Dalwallinu (DAL) shire (64 growers) and Katanning-Woodanilling (KAT) shires (68 growers) of Western Australia. Properties managed by growers in the DAL region were larger on average (3864 ha), had a greater proportion of land cropped (70%), and received a lower average annual rainfall (approx. 325mm) compared to properties in the KAT region (1812ha, 55%, 450mm). Farm visits were conducted prior to crop seeding in February-March 2000 and interviews conducted with the primary cropping decision-maker(s) on each farm based on a fully-specified questionnaire. Most questions on herbicide resistance and weed management focused on the most important cropping weed annual ryegrass (*Lolium rigidum*) (Alemseged *et al*., 2001) and resistance to herbicides in the Group A (ACCase–inhibitors) and B (ALS-inhibitors) herbicide groups. These represent the most common forms of herbicide resistance in Western Australia (Llewellyn and Powles, 2001). The two regions represent an area of the Western Australian wheatbelt where more intensive cropping and herbicide resistance is well-established (DAL) and an area where cropping has only relatively recently become more intensive and weed populations with serious levels of resistance are not yet widespread (KAT).

Dependent Variables

Measuring IWM adoption

The difficulties involved with measuring the adoption of IPM have generated considerable discussion (McDonald and Glynn, 1994; Shennan *et al*., 2001; Wearing, 1988). It is recognised in most studies that growers adopt specific practices rather than a total system (e.g. de Buck *et al*., 2001; Dorfman, 1996). Consistent with this approach, some studies (e.g. Harper *et al*., 1990) analyse the adoption of individual practices specifically, whilst others (e.g. Fernandez-Cornejo *et al*., 1994) consider the adoption of just one of a suite of possible practices to represent adoption. This approach has allowed binary dependent variables to be used. By definition, however, IPM involves the integration of more than one practice into a pest control system. Growers in this study generally use more than one IWM practice selected from a relatively wide range of available practices. IWM adoption is therefore assumed to involve multiple practices. Growers have a range of practices available to them and elect to use the combination of practices that offers the greatest utility.

IWM practices

Six IWM practices for which detailed perceptions were elicited are described below.

Delayed seeding: a deliberate delay of crop seeding for two weeks or more to facilitate the control of a greater proportion of weeds prior to seeding.

Doubleknock: the use of the non-selective herbicide glyphosate followed by a later application of the non-selective, low-resistance risk, herbicide paraquat prior to seeding.

High seeding rate: an average wheat seeding rate of greater than 65 kg/ha.

Catching: the use of specialised machinery to capture weed seeds in the harvest process.

Croptopping: the use of a non-selective herbicide to prevent weed seed set usually applied to non-cereal crops at or near crop maturity.

Manuring: the sacrifice of a sown crop to achieve weed control.

Two of these six practices are non-herbicide practices (catch and high seeding rate), two are herbicide-based practices (doubleknock and croptopping), and two are practices that may or may not involve the use of additional herbicides (delayed seeding and manuring). Based on use in 2000, there are no notably high correlations between farmers' usage of these practices (Table 1).

Table 1 Correlation coefficients for the use of IWM practices in 2000

	Delay seeding	Doubleknock	Manuring	Croptopping	Catching
Doubleknock	.12				
Manuring	.08	.10			
Croptopping	.23	.34	.24		
Catching	.18	.11	.04	.21	
High seeding rate	.10	.15	-.10	.19	.06

For the purposes of this study, these six practices are considered to be independent IWM options as there are no technological grounds for assuming that the use of one practice strongly favours the use or non-use of another practice. Specifically, use of one or more of the six practices contributes to two dependent IWM variables. These variables aim to represent two important aspects of IWM use; namely the use of several IWM practices and the proportion of land on which IWM practices are used.

The use of multiple IWM practices

The use of just one of the six practices does not satisfy the definition of IWM. An alternative approach would be to use an interval variable where it is assumed that the more of these practices used the 'more IWM' is being used. Poisson regression models, using count data for IPM practices used have had very limited use for this purpose (Maumbe and Swinton, 2000). However, the use of all, or almost all, of the practices does not necessarily represent rational IWM use. As it is a restricted list, growers may be using several other IWM practices that would make the use of all of the six listed practices unnecessary, and in some cases, counterproductive. In this study, a grower is classified as an IWM user if he or she uses several of the six practices.

A binary dependent variable is defined, with growers who use three or more practices being classified as IWM users. This allows for the conditions that more than one of the practice should be used to satisfy the 'integrated' definition of IWM, but also accepts that the use of a large number of these particular practices may not necessarily be appropriate. This binary classification was applied to use in the year 2000 (USE), as stated by growers just prior to crop seeding for that season. Of the six practices, the mean number to be used by growers in 2000 was 2.1. No grower used more than five practices.

The extent of IWM practice use on a property

Most IPM adoption studies examine the use (or non-use) of IPM practices on a property. Here, the extent of IWM use, or the proportion of land treated with an IWM practice is also considered. This is intended to account for the possibility that several individual practices may be being used, but only on a small proportion of cropping land. For the same reasons as those described above, the extent of use of one particular practice is not of major interest as substitute practices may be in use. Therefore a score has been developed that measures the cumulative proportion of cropped land treated with the six IWM practices. The extent variable (EXTENT) is measured using:

$$\text{EXTENT} = \sum \text{IWM\%}_{i=1\ldots6} \tag{4}$$

where the IWM% is the percentage of land being cropped in 2000 that was expected to be treated with the i^{th} IWM practice. No grower planned to use all practices on all crop land (i.e. EXTENT = 600), with the maximum score being 318 (see Table 2).

Explanatory variables

Using innovation-specific and problem-specific variables presents challenges when a dependent variable comprises several substitutable components. Perceptions of one particular component are not necessarily relevant to the grower's adoption of several of the practices. For example, a grower may perceive the value of a practice to be high but have no need to use it as a large number of IWM practices are already being used. In addition, a limited number of observations (and degrees of freedom) make multiple perceptions of multiple individual practices difficult to accommodate. Potential problems related to multicollinearity amongst the perceptions also need to be addressed. A high level of positive correlation between perceptions of different practices (data not shown) is demonstrated by the analyses in the next section. Composite variables can help to overcome these problems. Principal component analysis has been used to produce single variables that capture general perceptions of the six IWM practices whilst still explaining a high proportion of the variation in the data.

Indices for multiple practices

First described by Pearson (1901) and Hotelling (1933), the objective of principal component analysis is to take a set of variables and find combinations of these that produce a lesser number of indices that account for much of the variance in the original data. The use of these indices, or principal components, has been suggested as an approach to addressing multicollinearity in estimating econometric regression models (Greene, 1997). The method has had some use in evaluation of IPM (Douce *et al*., 1983; Hubbell *et al*., 1997; Thomas *et al*., 1990) and other agricultural innovations (Cioffi and Goritano, 1998). Principal component analysis is only useful when variables are correlated. The procedure is based on a covariance matrix, or usually a correlation matrix (Manly, 1986). The correlation matrix involves normalisation of all variables to have mean 0, standard deviation 1, so that the scale of the response to particular variables does not significantly weight the analysis.

For the purposes of this study, the objective is to identify from the sets of explanatory variables relating to the six IWM practices, I_1, I_2, …, I_6, components Z_p based on linear combinations of the variables. The usual aim is that a small number of components ($p < 6$) will account for a large proportion of the variance. The first component always accounts for the most variance, with the other components being uncorrelated with the first (and with each other) and accounting for decreasing amounts of variance. For the first principal component, Z_1, to be useful in this study it needs to account for a relatively large proportion of the variance and represent general positive perceptions towards the six IWM practices. This would be the case if the coefficients, or elements of the eigenvector, a_{11}…, a_{16}, are all positive

$$Z_1 = a_{11}I_1 + a_{12}I_2 + a_{13}I_3 + a_{14}I_4 + a_{15}I_5 + a_{16}I_6 \qquad (5)$$

Principal components with some positive and some negative coefficients are most probably measuring the degree of preference for particular practices over others. These dimensions in the data are unlikely to be of value in explaining what are general measures of IWM adoption being used as dependent variables in this study.

Perceptions relating to the six IWM practices were subjected to principal component analysis (Stata: factor, pc: analysing the default correlation matrix) with the objective of finding an appropriate component, or index, to act as an explanatory variable for each of perceived mean control, reliability of control, and economic value. The use of these single indices means that the influence of the original practice-specific perceptions on adoption cannot be directly identified as the index is a function of all of the original practice-specific perceptions. While this is a disadvantage of this approach (Greene, 1997), the relative weighting of each original practice-specific perception's influence on the index value can be seen in the first eigenvector in the principal component analysis output. For the purposes of this study, where general IWM adoption measures are being explained comprising multiple practices, perceptions of individual practices are of lesser interest in the regression analyses.

The other possible disadvantage of using a principal component-derived index value as an explanatory variable is that the weightings are calculated independently of consideration of the dependent variable that is being explained. This could be a particular problem when there is strongly positive and negative weightings that cannot be related to what is being explained. For the components used here (see eigenvector 1 in Boxes 8.1- 8.5) the perceptions of each practice are generally weighted strongly and positively. To allow for any inconsistencies resulting from the use of these index values to be observed, regression analyses were also conducted with perceptions of each practice included individually.

Perceptions of IWM practices

Perceived value

Grower's perceived value for each of the six practices was subjected to principal component analysis (Box 1). The eigenvalues indicate the proportion of variance explained by each of the components generated. Component 1, with an eigenvalue of 2.91, explains 48 per cent of the variance in the data, several times more variance than any other component. This confirms that there is a reasonably high level of correlation amongst the variables. Other components have eigenvalues below 1.0, indicating that they explain less variance than any one of the original six variables. Looking at the eigenvector corresponding to component 1, all coefficients are positive. It appears that an index of positive attitudes towards the value of IWM practices has been extracted. Other components appear to measure preferences for some practices over others .For example, component 2 has a strong loading for catching, component 3 has strong loadings for manuring and delayed seeding above all other practices. These minor dimensions in the data are not relevant to the dependent variable being tested in this study, and in any case, explain relatively little variance. The value of the first principal component for each grower was then calculated (Stata: score) based on the coefficients for eigenvector 1. This measure (IWM Value) was used in the regressions as the variable for perceived value of the IWM practices (described in Table 2).

Box 1 Principal component analysis output for perceived value of IWM practices (Stata output).

```
(obs=123)

            (principal components; 6 components retained)
Component    Eigenvalue     Difference    Proportion    Cumulative
------------------------------------------------------------------
     1        2.90945         2.12636      0.4849         0.4849
     2        0.78309         0.02602      0.1305         0.6154
     3        0.75707         0.11889      0.1262         0.7416
     4        0.63818         0.10640      0.1064         0.8480
     5        0.53178         0.15136      0.0886         0.9366
     6        0.38043               .      0.0634         1.0000

            Eigenvectors
 Variable |      1          2          3          4          5          6
----------+-----------------------------------------------------------------
 D-KNOCK  |   0.42163   -0.48350   -0.25370    0.02099   -0.58325    0.42833
 DELAY    |   0.39664   -0.07467    0.50997   -0.64779    0.29683    0.26325
 SEEDRATE |   0.40844   -0.42061   -0.32193    0.27986    0.66641   -0.17380
 CROPTOP  |   0.47367    0.18062   -0.11756   -0.27064   -0.31413   -0.74650
 CATCH    |   0.36899    0.72981   -0.39093    0.05441    0.12688    0.39916
 MANURING |   0.37089    0.13594    0.63662    0.65223   -0.11330   -0.02081
```

Expected percentage control

As previously described, subjective probability distributions were elicited from growers based on triangular distributions of the percentage ryegrass control that can be expected from the practices. For each practice, the mean of the distribution (expected value, EV) is used as a measure of expected control, and the coefficient of variation (CV) for the distribution is used as a measure of reliability. The principal component analysis for expected percentage control (Box 2) was conducted with the objective of extracting a multi-practice index for expected percentage control from IWM practices.

The first principal component is again positive for all variables and accounts for substantially more variance than other components (Box 2). The second principal component, the only other component with an eigenvalue above 1, weighs negatively on the two early-season practices, delayed seeding and doubleknock. This is likely to represent the degree to which growers perceived pre-seeding practices to be effective relative to other practices. It may also capture some observed inconsistencies in growers' interpretation of the questions or practices. For the pre-seeding practices, they were required to consider later emerging weeds and state the percentage control offered by pre-seeding treatments in terms of in-crop weed numbers. The component has a high positive weighting for manuring. Some growers, consistent with research opinion, believed that, if practiced, manuring would always be done in a manner that achieved at least 95 per cent ryegrass kill. Others would have accepted a range of control levels and responded accordingly. The second component may therefore represent an 'interpretive' dimension to the data. Only the first principal component appears relevant to the objectives of this study, with the corresponding scores for each grower being used as a variable explaining expected percentage control from IWM practices (IWM Efficacy).

Box 2 Principal component analysis output for mean expected percentage control (EV) of IWM practices (Stata output).

```
(obs=112)
            (principal components; 6 components retained)
Component    Eigenvalue     Difference    Proportion    Cumulative
------------------------------------------------------------------
     1        2.03800         0.87066      0.3397         0.3397
     2        1.16734         0.26338      0.1946         0.5342
     3        0.90396         0.12076      0.1507         0.6849
     4        0.78320         0.13166      0.1305         0.8154
     5        0.65154         0.19559      0.1086         0.9240
     6        0.45595               .      0.0760         1.0000

            Eigenvectors
 Variable |      1          2          3          4          5          6
----------+------------------------------------------------------------------
 CROPTOP |     0.48329    0.30369   -0.19051   -0.40282   -0.44974   -0.52285
MANURING |     0.23107    0.50307    0.78607   -0.08742    0.03260    0.25867
   CATCH |     0.45067    0.27338   -0.48654   -0.16277    0.52953    0.42255
SEEDRATE |     0.41984    0.11439   -0.04104    0.88217   -0.04843   -0.16853
 D-KNOCK |     0.38503   -0.53235    0.32356   -0.14832    0.52451   -0.40811
   DELAY |     0.43062   -0.53242    0.05191   -0.05811   -0.48868    0.53499
```

Coefficient of variation for expected percentage control

The coefficient of variation of percentage control represents the confidence that growers have in achieving the expected control percentage. This may be due to uncertainty regarding the efficacy of the practice and/or the known variation in efficacy that results from factors such as environmental conditions. Principal component analysis extracted a single principal component that explains a relatively large proportion of the variance in the data and acts as an index of certainty for the IWM practices (Box 3). The second principal component has an eigenvalue only slightly higher than 1 and appears to be consistent with the second component for expected value of control. Scores using the first principal component have been used as an index of the coefficient of variation for expected IWM control (IWM Uncertainty).

Box 3 Principal component analysis output for coefficient of variation (CV) for percentage control (reliability) of IWM practices (Stata output).

```
 (obs=112)
            (principal components; 6 components retained)
Component    Eigenvalue     Difference    Proportion    Cumulative
------------------------------------------------------------------
     1        2.35315         1.33245      0.3922         0.3922
     2        1.02070         0.20767      0.1701         0.5623
     3        0.81303         0.08261      0.1355         0.6978
     4        0.73042         0.11339      0.1217         0.8195
     5        0.61703         0.15135      0.1028         0.9224
     6        0.46568               .      0.0776         1.0000

            Eigenvectors
 Variable |      1          2          3          4          5          6
----------+------------------------------------------------------------------
 CROPTOP  |   0.42882    0.02159    0.59146   -0.11321   -0.64041   -0.20708
MANURING  |   0.30859    0.77252    0.18051   -0.06837    0.26709    0.44653
   CATCH  |   0.40631   -0.01860   -0.26333    0.85845   -0.14884    0.07831
SEEDRATE  |   0.43363    0.25294   -0.57741   -0.32573    0.00280   -0.55541
  DKNOCK  |   0.42535   -0.35051    0.38109    0.05165    0.69683   -0.25049
   DELAY  |   0.43224   -0.46428   -0.26387   -0.36987   -0.10396    0.61674
```

Farm factors

Resistance status

A herbicide resistance problem on a farm can have a number of dimensions. A single measure of a resistance problem needs to incorporate the extent of the problem across a property, the peak intensity of the problem in any one area and the level of intensity typical for the property (modal). Both the intensity and the extent of an agricultural problem have been shown to play a role in the adoption process (Sinden and King, 1990). The scoring system developed for measuring the 'seriousness' of a resistance problem integrates these dimensions using principal component analysis (Box 4). The scores for the 'most serious' and 'typical' paddock (intensity) are incorporated here, as has information on the percentage of land affected (extent). The high level of correlation between these three measures produces a first principal component that explains 82 per cent of variation (Box 4). The resulting scores have been used as an index of a property's resistance problem.

Box 4 Principal component analysis output for resistance status variables relating to percentage of farm affected, status of most seriously affected paddock and status of typical cropping paddock.

```
(obs=131)

            (principal components; 3 components retained)
Component    Eigenvalue     Difference    Proportion    Cumulative
------------------------------------------------------------------
     1        2.45942         2.16685      0.8198         0.8198
     2        0.29257         0.04455      0.0975         0.9173
     3        0.24801               .      0.0827         1.0000

            Eigenvectors
 Variable |      1          2          3
----------+-------------------------------
%FARMHR   |   0.57823   -0.53180    0.61874
SERIOUSHR |   0.57183    0.80510    0.15757
TYPICALHR |   0.58194   -0.26270   -0.76963
```

Region

A binary variable identifying growers from the KAT region (1) or the DAL region (0) was used.

Proportion of land cropped

The percentage of the property to be cropped in the 2000 season was used as a measure of cropping intensity. As all of the IWM practices included in the regression analyses are for use in the cropping phase of rotations, this variable is included to allow for the likelihood that growers with a high cropping percentage are more likely to use these crop-based practices.

Grower factors

Management horizon

Although it is common in adoption studies to include the age of the grower as an explanatory variable, in this study the number of years before the grower intended to cease working on the farm has been included. A high level of collinearity (-0.76 correlation coefficient) exists between the measure of growers' age and this variable. The variable has been included as a proxy for the planning horizon of growers. It is possible that growers who intend to be managing the property for a longer period are more likely to consider any longer-term costs of future resistance development than growers who plan to cease managing the property in the near future. This is based on an assumption that the herbicide resistance status beyond this time is of diminished concern to the current grower as, for example, the resistance status may not be reflected in the sale price of the farm. Possible reasons for this include information asymmetry regarding past herbicide use and/or unobservable levels of resistance development at the time of sale.

Discount rate

To gain some measure of growers' future discount rate, growers were posed a hypothetical question where they were asked to choose a lump sum amount to be received in five years time that would result in a switch from preferring a present day payment of $10000. The five-year time frame was used to make the scenario consistent with a time frame of resistance development and management. Based on the resource management framework, growers with a higher discount rate are expected to use less IWM. The variable (Future Discount) uses the growers' five-year dollar value; therefore the hypothesised sign for this variable is negative.

Education

A higher level of education, by increasing human capital, can result in reduced costs of information gathering and processing (Feder *et al.*, 1985; Feder and Slade, 1984; Lindner, 1987; Rahm and Huffmam, 1984) or perhaps an increased ability to process otherwise intractably complex information. Given the expected high information requirements for IWM adoption (see below), a positive association is expected. A binary variable indicating whether a farm (co)manager has completed a university degree or diploma has been used.

Information exposure

IPM is widely considered to be information intensive (Wearing, 1988). Accordingly, exposure to extension and higher levels of information has been found to be positively associated with IPM adoption (Harper *et al*., 1990; Maumbe and Swinton, 2000; Napit *et al*., 1988; Thomas *et al*., 1990). As there are numerous sources of information from which growers can attain information, and learning styles that favour some sources of information over others (Kolb, 1984), the measurement of information exposure needs to account for this diversity. As defined and measured here, information exposure is best considered as an 'active' process of information seeking rather than exposure through passive means, although there may be limits to the availability of some information sources in some areas.

Collinearity between some information sources meant that each source could not suitably be included as explanatory variables. Principal component analysis was used to produce a single index of information exposure based on farm-specific information [commercial agronomist visits per year (COAGRON) and consultant use (CONSULT)] and non-farm-specific information [subscriptions to publications that often contain weed management information (PRINT) and the number of field days or cropping-related meetings attended (GROUPS)]. The first principal component, the only component with an eigenvalue greater than 1, explains 50 per cent of the variance and weighs positively on all information sources (Box 5). The second component appears to capture the substitution of a commercial agronomist for a paid agronomist/consultant (or vice versa). The third component represents the use of farm-specific information (agronomists) over non-specific information sources (group events and publications). The final, least important, component appears to represent a preference for group events over publications. The first principal component was used as an index of general information exposure.

Box 5 Principal component analysis output for information exposure variables relating to farm specific information [commercial agronomist visits per year (COAGRON) and consultant use (CONSULT)] and non-farm-specific information [subscriptions to

publications that often contain weed management information (PRINT) and the number of field days or cropping-related meetings attended (GROUPS)].

```
(obs=131)
            (principal components; 4 components retained)
Component    Eigenvalue     Difference    Proportion    Cumulative
------------------------------------------------------------------
     1        1.99885         1.13040      0.4997         0.4997
     2        0.86845         0.22621      0.2171         0.7168
     3        0.64224         0.15178      0.1606         0.8774
     4        0.49046               .      0.1226         1.0000

            Eigenvectors
 Variable |      1          2          3          4
----------+-------------------------------------------
     PRINT|   0.56816   -0.01591   -0.38520   -0.72702
    GROUPS|   0.56106   -0.08510   -0.45906    0.68355
   CONSULT|   0.45689   -0.57419    0.67931    0.00971
   COAGRON|   0.39199    0.81413    0.42359    0.06409
```

Perceptions of the herbicide resource/resistance

Expected years until new herbicide

The expected number of years until a new mode of action herbicide becomes available is represented by the expected value of the subjective probability distribution elicited from each grower. Growers believing that the existing stock of selective ryegrass herbicides will be renewed soon are expected to be less likely to adopt IWM practices.

Certainty of a new herbicide

The coefficient of variation for the number of years until a new mode of action herbicide becomes available is used to represent growers' certainty of new herbicides replenishing the herbicide resource. Growers with greater uncertainty are expected to be more likely to adopt IWM practices.

Probability of resistance reversion

Also a measure of perceived renewal, this measures a growers' subjective probability that herbicide resistance is not permanent but that a population may revert to susceptibility within five years. Growers with greater certainty that this will happen, that is, that a herbicide will return to being effective, are expected to be less likely to adopt IWM practices.

Remaining herbicide resource

The expected number of applications of a Group A herbicide (clethodim) remaining before herbicide resistance development on the typical paddock was calculated from the subjective probability distribution elicited from each grower. Growers expecting fewer remaining applications are considered to be more likely to adopt IWM practices.

Certainty of remaining herbicide resource

This variable is the coefficient of variation for the expected number of applications of a Group A herbicide remaining before herbicide resistance develops on the typical paddock.

Cost of herbicide resistance (resource value)

The reduction in willingness to pay for cropping land that is known to have a ryegrass population that cannot be controlled using any Group A and B selective herbicides is used as a measure of the perceived cost of herbicide resistance. The reduction is represented as a percentage of the willingness to pay for land that has no herbicide resistance.

Mobility of resistance

Relating to the private versus common property nature of the stock of susceptibility, this variable measures the subjective probability (chance out of 10) that a paddock may gain resistant plants (or genes) from external sources. Growers who perceive a higher probability of this occurring are expected to behave in a manner consistent with a common property resource and be less likely to invest in conserving herbicide susceptibility through the use of IWM practices (Carlson, 1977).

Descriptive statistics

Several explanatory variables are derived from survey questions that required growers to be aware of a range of IWM practices and herbicides. A non-response to one of these questions resulted in the omission of all responses by that grower from the analysis. The use of composite variables such as those described above using principal components resulted in a grower's observations being unusable if they failed to provide a value for any one of the components of one of the variables. These growers may be growers who do not have sufficient knowledge of particular IWM practices to provide the required probability distributions. Twenty growers provided a non-response for at least one IWM practice. These growers may be in stages of adoption that precede non-trial evaluation (Lindner *et al*., 1982; Rogers, 1995) for a particular practice. This includes growers who were not aware of the practice. Missing values also resulted from unfamiliarity with the relevant herbicides (11) and unwillingness to respond to the discount rate question (6). Descriptive statistics for the omitted growers indicate no notable differences for any of the variables that form part of the regression analyses. Descriptive statistics for the 100 observations included in the analyses are shown in Table 2.

Table 2 Descriptive statistics for variables used in regression analyses (n=100).

Variable	units	Mean	Std. Dev.	Min.	Max.
USE	Binary	.40	.49	0	1
EXTENT	Index (%)	82.9	66.1	0	318
IWM Value	Index (pc)	-.059	1.73	-3.98	3.29
IWM Efficacy	Index (pc)	.017	1.45	-3.68	3.82
IWM Certainty	Index (pc)	.034	1.54	-3.60	4.61
Resistance status	Index (pc)	-.012	1.52	-1.43	4.28
Region	Binary	.52	.50	0	1
Crop proportion	%	62.3	17.7	25	100
Management horizon	Years	18.2	9.2	2	40
Discount rate	Index	18935	7317	12000	50000
Education	Binary	.23	.42	0	1
Information exposure	Index (pc)	-.011	.70	-1.25	1.65
New herbicide EV	Years	6.0	2.8	1	14
New herbicide CV	%	23.2	10.7	0	71
Regression	Prob./10	3.2	3.0	0	10
Herb. remaining EV	Apps.	6.6	5.2	.3	25
Herb. remaining CV	%	20.2	10.2	8	71
Cost of resistance	%	25.6	18.7	0	100
Mobility	Prob./10	4.6	2.7	0	10

pc : index extracted from principal component analysis

Testing for multicollinearity

The use of composite principal component-derived variables appears to have avoided most multicollinearity problems. The correlation analysis indicates no notable multicollinearity between explanatory variables, with the exception of the measures of expected value of percentage control (IWM Efficacy) and the related coefficient of variation (IWM Uncertainty) with a correlation coefficient of -0.699. That is, when the mean percentage control of practices is expected to be high, the size of the variance of the distribution, relative to the mean tends to be low (and vice versa). This is most likely due to the upper limit of the distribution being limited at 100 per cent. Because of this relationship, IWM Uncertainty was dropped from the analyses, with IWM Efficacy remaining as the measure of perceived efficacy of IWM.

Analytical models of IWM adoption and extent of use

Two dimensions of the decision to adopt IWM are considered. One is the dichotomous (binary) decision to adopt or not adopt several IWM practices. The other is the decision involving the extent of use of IWM on the property. These are considered to be separate; the former acting as a measure of the diversity of practices used for weed control, the latter acting as a measure of the amount of land treated with the practices. It is therefore possible that a grower using only one of the IWM practices on all cropping land would score relatively highly on extent of use, despite not having adopted a diverse range of IWM practices. For this reason, the study does not employ the widely used Tobit procedure (Tobin, 1958) in which the determinants of adoption and extent of use of a particular innovation can be estimated simultaneously (Adesina and Zinnah, 1993; Baidu-Forson, 1999; Featherstone and Goodwin, 1993; McDonald and Moffitt, 1980; Smale and Heisey, 1993). The decision to adopt several IWM practices has been modelled independently from extent of use.

Adoption model

Probit and logit model have been commonly used in binary choice econometric applications (Cary and Wilkinson, 1997; Goodwin and Schroeder, 1994; Greene, 1997; Nkamleu and Adesina, 2000; Sinden and King, 1990). For each grower, the probability of IWM adoption can be described as

$$P_{IWM} = f(\beta X) = f(Z) \qquad (6)$$

Where β is the set of coefficients relating to the set of explanatory variables X. In this study X includes individual's farm, IWM, herbicide and grower factors. In the probit model, a normal distribution is used to give,

$P_{IWM} = \Phi(Z)$ (7)

Alternatively, a logistic distribution can be assumed to give the logit model,

$P_{IWM} = e^Z/(1+ e^Z)$ (8)

There is no strict theoretical basis for using one model over the other and for most applications similar results can be expected (Greene, 1997). Differences in predictions can be expected when there are relatively very few adopters or very few non-adopters. This is not the case for the data set used in this study (Table 2). The logit model is used in this study.

For the logit model, the change in P_{IWM} relative to a change in X, is

$\partial P_{IWM}/\partial X_k = e^Z/ (1+ e^Z)^2 \beta_k$ (9)

where β_k is the coefficient estimate relating to the explanatory variable of interest, X_k.

Extent of use model

Growers may be using three or more of the IWM practices but only treating a small percentage of their cropping land with any IWM practice. To determine if the factors associated with IWM adoption are also significant in determining the extent of use, linear regression techniques were used. To account for any lower censoring (Greene, 1997), a censored regression, tobit, model was used (Tobin, 1958). The tobit censored regression model estimates:

$y^* = X\beta + \varepsilon$ (10)

y^* = a latent continuous variable indexing adoption

ε = an independently distributed error term assumed to be normally distributed.

In this study y^* corresponds to the extent of use score (EXTENT) when greater than zero ($y^* = y$ if $y^* > 0$). Below zero y^* can be viewed as an index of ‘desire’ to adopt, which only becomes observed when adoption takes place. The tobit model can therefore also be used to predict the probability that growers have adopted at least one of the six IWM practices. In the data used here 90 per cent of growers had used at least one of the six practices so a change in the probability of adoption was not of major interest. There was no evident upper censoring, with the maximum score being 318 per cent out of a possible 600 per cent so the only censoring is at zero.

In this case the marginal effects for an individual's change in the predicted extent of use score, y, resulting from a change in an explanatory variable X_k can be described as

$$\partial y/\partial X_k = \beta_k \ \text{x} \ \text{Prob}(y^* > 0) = \beta_k \Phi (X\beta/\sigma) \tag{11}$$

where Φ is the cumulative normal distribution function at $X\beta/\sigma$, σ being the standard deviation of the error (Greene, 1997).

The McDonald and Moffitt (1980) decomposition of the marginal effects can be used to identify the change in the probability that $y^* > 0$ and the change in the predicted extent of use, y. However, as only 10 out of 100 growers did not use one or more of the practices in 2000 (i.e. 0 per cent of land treated with any of the six practices in 2000), a consistently high expected probability for $y^* > 0$ was recorded, making any changes in probability insubstantial. In addition, marginal effects on the probability of one practice being used are not of primary interest in this particular analysis.

A useful measure of the responsiveness of the extent of use to changes in the variables is achieved by incorporating the level of variability in the population for individual variables. This measure is based on the change in the expected extent of use (y) resulting from an interquartile shift in one variable, when all other variables remain at their mean. To allow for censoring, the expected extent of IWM use E[y] is calculated by multiplying the probability of adoption by the sum of the latent variable, y^*, ($X\beta$, see equation 10) and a term including the inverse Mills ratio, $\sigma\lambda$;

$$E[y] = \Phi (X\beta/\sigma) (X\beta + \sigma\lambda) \tag{12}$$

where,

λ is the inverse Mills ratio calculated as the standard normal probability density function over the standard normal cumulative distribution function, $(\text{Ø} (X\beta/\sigma)) / (\Phi (X\beta/\sigma))$ (Greene, 1997).

Results

Factors influencing IWM adoption

Logit model estimations were calculated for the use of several IWM practices (three or more) in the 2000 season. Results are shown in Table 3. The models predicting expected use in 2000 and over the next four years correctly classify 89 per cent. The model performs well in classifying both users and non-users and have a high predictive power relative to comparable IPM adoption models in the literature (e.g. Fernandez-Cornejo *et al*., 1994; Harper *et al*., 1990).

Herbicide resistance, perceptions and information are all shown to influence IWM adoption. Perceptions of IWM Value and IWM Efficacy are all significant ($P < 0.05$) in explaining IWM use. So too are resistance status and information exposure. All have a positive association with IWM adoption. The education level of growers is a significant predictor of adoption in model 1 (Table 3). This is consistent information-intensive innovations where greater education can lower information-gathering costs and result in more rapid adoption (Feder *et al*., 1985; Feder and Slade, 1984). Grower factors other than education and information exposure are not significant at the five per cent level.

In the presence of the other explanatory variables, such as resistance status and crop proportion, the region in which growers are located is not significant in explaining adoption. This indicates that the models are successful in identifying factors that influence IWM adoption across regions with an emerging herbicide resistance problem (KAT) and regions with an established and more serious resistance problem (DAL).

Growers who expect a longer period before a new herbicide becomes available (higher EV) were significantly more likely to use IWM practices in 2000. There was also a positive relationship with use in the past four years ($P = 0.07$). Similarly, growers who are more uncertain of how many years it may be until a new herbicide becomes available (higher CV) appeared more likely to be users of IWM over the past four years ($P = 0.05$) and in 2000 ($P = 0.07$). The perceived probability of herbicide resistance regression did not significantly influence IWM adoption.

Growers who perceive it to be more probable that a hypothetical susceptible paddock on their property will gain resistance from external sources (mobility) are more likely to be IWM users (Table 3). It was hypothesised that growers who perceived resistance to have the common property characteristic of high mobility would be more likely to exploit the herbicide resource and be less likely to invest in IWM practices. As previously discussed, the mobility question did not specify inter-property mobility and therefore may not be measuring perceptions of common versus private property. In addition to mobility, the variable may be capturing another dimension to growers' awareness of the local resistance problem. Possibly, those who expect cross-boundary movement are more aware of resistance and/or have higher levels of local resistance. A moderate positive correlation (Pearson correlation coefficient = 0.18) between resistance status and the expected probability that resistance-free land on that farm will gain resistance genes was found. Growers with more resistance are more likely to be IWM users (Table 3).

Other herbicide resistance factors are generally statistically insignificant. A possible explanation for this is that some of the variables are based on perceptions of resistance to specific herbicides and in specific (typical) paddocks (e.g. cost of resistance, herbicide remaining EV and CV) while the dependent variable relates to the whole property. The mobility variable also suffers from this specificity weakness. It is also likely that resistance status captures some of the variance associated with the amount of herbicide resource remaining.

Table 3 Logit regression results for the extended model of the use of IWM practices.

Explanatory variables	Coef.	s.e.	P > |z|
IWM Value	1.12	.324	.001
IWM EFFICACY	0.913	.386	.018
Resistance status	0.920	.344	.007
Region	0.047	.895	.958
Crop proportion	0.060	.027	.029
Management horizon	-0.031	.049	.523
Discount rate	-0.00018	.00011	.106
Education	2.18	1.17	.062
Information exposure	1.88	.816	.021
New herbicide EV	0.324	.148	.028
New herbicide CV	0.081	.045	.072
Regression	-0.074	.132	.573
Herb. Remaining EV	0.133	.103	.197
Herb. Remaining CV	-0.022	.037	.561
Cost of resistance	0.021	.022	.339
Mobility	0.355	.158	.025
Constant	-7.83	3.06	.010
Log likelihood	-29.46		
Pseudo R^{2a}	.56		
Model Chi^2	75.69		
Level of significance	0.0000		
% predicted correctly [b]	89 (83/93)		

P-values (P > |z|) are for tests of H_0 that the coefficient is zero

[a] Pseudo R^2 is based on the log-likelihood ratio, with 1 being perfect prediction

[b] Percentage of growers classified correctly (sensitivity/specificity). Sensitivity is the percentage of users classified correctly, specificity is the percentage of non-users classified correctly.

A refined model of IWM use in 2000 was also constructed using a reduced set of explanatory variables. Explanatory variables that were insignificant or lacking specificity to the dependent variable were omitted (Table 4). All explanatory variables in the refined model are statistically significant predictors of current IWM use ($P < 0.05$, with the exception of information exposure $P = 0.051$), with all signs in the hypothesised direction. In addition to perceptions of IWM, resistance status and information exposure/education (all of which were significant in the full model), perceptions relating to resource management are also significant in this refined model. Expectations of the availability of a new herbicide are significant, with the expected number of years (EV) and the uncertainty about it (CV) both significant predictors of IWM use. Growers who expect the herbicide resource to be replenished with new modes of action soon, and are more certain of when they will become available, are less likely to be IWM users. Growers' discount rate for future returns is also significant. Those with a high discount rate (i.e. those placing a relatively higher value on short-term returns over long-term returns) are less likely invest in IWM practices. The direction of influence of the discount rate variable is consistent in all models.

Table 4 Logit regression results for the refined model of the use of IWM practices

Explanatory variables	Coefficient	Std. Error	P > |z|[a]
IWM Value	0.956	.271	.000
IWM EFFICACY	0.919	.313	.003
Resistance status	0.789	.260	.002
Crop proportion	0.048	.023	.036
Discount rate	-0.00015	.00007	.046
Education	2.05	.913	.024
Information exposure	1.18	.605	.051
New herbicide EV	0.320	.136	.019
New herbicide CV	0.084	.038	.028
Constant	5.53	2.18	.011
Log likelihood	-33.11		
Pseudo R^{2}[b]	.51		
Model Chi^2	68.39, P <.00001		
% predicted correctly[c]	86 (80/90)		

[a] P-values are for tests of H_0 that the coefficient is zero.

[b] Pseudo R^2 (McFadden's) is based on the log-likelihood value, on a scale where 0 corresponds to the 'constant only' model and 1 is perfect prediction.

[c] Percentage of growers classified correctly (sensitivity/specificity). Sensitivity is the percentage of users classified correctly, specificity is the percentage of non-users classified correctly.

Models produced by replacing the composite indices IWM Efficacy and Value with each of the components from which they are derived (i.e. perceptions of each of the six IWM practices) produced generally consistent results (see Appendix). In these expanded models, the discount rate variable remained consistently in the hypothesised direction although it was not significant at the one per cent level. All significant perceptions of IWM were in the hypothesised direction, however, several perceptions of efficacy and value for individual IWM practices were not significant. The results indicate that not all perceptions of practices contribute equally to the adoption of three or more IWM practices. Also contributing to this result may be collinearity between perceptions of individual practices that leads to some practices capturing a high proportion of the variation in the data. The result that growers' with generally positive perceptions of IWM efficacy and value are more likely to be IWM users is common to all models.

Changes in the probability of adoption that result from shifts in a variable are shown in Table 5. These are provided as indicators of the importance of variables in explaining changes in the dependent variable (as distinct from their statistical significance). McCloskey and Ziliak (1996) have highlighted the need to consider indicators of the importance and strength of influence of each variable, beyond their statistical significance. The indicators shown in Table 5 are calculated with all other variables set at their sample means. The results for a one unit change in the variable show that increasing the expected number of years until a new herbicide becomes available by one year results in the probability of IWM adoption being 6 percentage points higher. A highly influential variable is education. Properties with a manager with a university degree have a probability of IWM adoption that is 45 percentage points higher than those without a degree.

Of major interest to this study is the potential influence of changes in grower perceptions. However, given the different, and often arbitrary, scales used in this study, some of the marginal changes, or elasticities, are difficult to interpret. As an indicative measure of the importance of variables given a discrete change within the data range, the probability changes for interquartile shifts are presented (Table 5). These are calculated for a shift in the variable from the 25th percentile to the 75th percentile, with all other variables remaining at their means. The variable that results in the greatest change in the probability of adoption is the perceived value of IWM. *Ceteris paribus*, a shift from the 25th percentile of growers to the 75th percentile in the perceived value of IWM practices results in the probability of IWM adoption being higher by 50 percentage points. A grower at the 75th percentile for the perceived percentage control provided by IWM practices has a probability of IWM adoption 29 percentage points higher than a grower at the 25th percentile. The equivalent shift in herbicide resistance status results in a similar difference (31 percentage points) in the probability of adoption. From this, it is concluded that herbicide resistance development is clearly an important influence, but does not appear to dominate the probability of IWM adoption.

Table 5 Implied probability changes for model of the use of IWM practices in 2000.

	Variable Statistics		**Changes in Probability**	
Explanatory variables	**Mean**	**Std. Dev.**	**One unit change[a]**	**Interquartile change[b]**
IWM Value	-0.06	1.73	.181	.503
IWM EFFICACY	0.02	1.45	.174	.290
Resistance status	-0.012	1.52	.150	.307
Crop proportion (%)	62.3	17.7	.009	.184
Discount rate	18935	7317	-2.8E-05	-.156
Education[c]	0.23	0.42	(.449)	(.449)
Information exposure	-0.011	0.70	.222	.235
New herbicide EV (years)	6.02	2.77	.061	.182
New herbicide CV (%)	23.2	10.7	.016	.199

[a] Change in probability resulting from a marginal variable change, with other variables at sample means.

[b] Change in probability resulting from a shift from the 25th to 75th percentile, with other variables at sample means.

[c] Probability changes shown for change in Education from 0 to 1.

Factors influencing extent of IWM use

Results from the censored regression (tobit) model of the percentage of crop land treated in 2000 with any of the six IWM practices (EXTENT) are shown in Table 6. Of interest is whether the same variables that significantly predict the adoption of IWM practices can also predict the extent of use of IWM practices. Explanatory variables are the same as for the binary adoption model, with the exception of crop proportion, which was omitted because the dependent variable in this regression is based on the proportion of 2000 crop land treated.

Table 6 Tobit regression model for extent of IWM practice use (EXTENT) and implied changes in expected extent of IWM practice use (EXTENT) given interquartile variable shifts.

	Tobit Censored Regression				Changes in expected use	
Explanatory variables	**Coef.**	**s.e.**	**t**	**P > |t|**	**One unit change[a]**	**Interquartile change[b]**
IWM Value	22.46	3.23	6.97	.000	21.54	63.17
IWM Efficacy	9.33	3.71	2.52	.014	8.95	15.49
Resistance status	16.72	3.48	4.80	.000	16.03	35.19
Discount rate	-0.0011	0.0007	-1.50	.137	-0.00107	-5.38
Education[c]	23.91	12.2	1.97	.052	22.93	23.16
Information exposure	13.60	7.45	1.83	.071	13.04	14.40
New herbicide EV	4.80	1.85	2.59	.011	4.60	14.45
New herbicide CV	0.64	0.48	1.34	.183	0.62	8.02
Constant	52.1	21.7	2.40	.018		
Regression s.e.	47.8	3.61				
Log likelihood	-483.8					
Squared correlation between observed and expected values 0.52						
Model Chi^2	79.2 P < 0.0001					

[a] Change in extent of IWM practice use resulting from a marginal variable change, with other variables at sample means.

[b] Change in extent of IWM practice use resulting from a shift from the 25th to 75th percentile, with other variables at sample means.

[c] Probability changes shown for change in Education from 0 to 1.

The model of the extent of IWM use (Table 6) shows that the variables significant in predicting the use of three or more IWM practices (Table 4) are significant (P < 0.1) in determining the extent of IWM use, with the exception of the certainty of a new herbicide becoming available (P = 0.183) and discount rate (P = 0.137). All signs in the extent of IWM use regression models are in the predicted direction. The tobit model correctly classified 90 per cent of growers as users (i.e. y* > 0) or non-users of at least one of the six practices. This comprised 96 per cent of users and four of the 10 non-users.

Also shown in Table 6 is an indicative measure of the importance of variables in influencing the extent of IWM use given changes in individual variables. The marginal effect based on a one unit change in each variable is shown. Given the high expected probability (0.959) of at least one practice being used (i.e. an EXTENT score greater than zero) the marginal effect differs little from the coefficient values.

A shift in the perceived value of IWM practices from the 25th percentile to the 75th percentile resulted in an increase in the measure of extent of IWM use (EXTENT) of 63.2 percentage points, clearly the highest level of change (Table 6). The equivalent shift in the resistance status variable resulted in the second highest increase (35.2), indicating that if a grower went from being ranked 75th out of 100 growers in terms of resistance status to having the 25th highest level of resistance, 35 per cent of the grower's crop land will receive additional treatment with an IWM practice. Discount rate was the least influential variable by this measure (-5.4). As with the indicators of change in the probability of IWM practice adoption (Table 5), increases in herbicide resistance status are associated with substantial increases in the extent of IWM use, however, information-related variables such as farmer perceptions of IWM and herbicide resistance factors, education and information/extension exposure are also shown to have important roles in growers' use of IWM.

Discussion

Understanding the decision of Western Australian grain growers to adopt a range of IWM practices involves understanding herbicide resistance. As expected, adoption of the IWM practices is strongly associated with the observed level of herbicide resistance development on a property. However, the study confirms an important role for factors associated with information provision. Information exposure (e.g. as a result of extension practices) and human capital (e.g. education) have influential roles in determining IWM adoption. Perceptions of both IWM and resistance are also important. Information that increases growers' perceptions of the economic value and efficacy of IWM practices is likely to result in increased adoption.

Perceptions relating to the exhaustibility of the herbicide resource were important. Growers who were more certain of the time that replacement post-emergent selective herbicides for ryegrass control will become available, and those who expected replacements to be available sooner, were less likely to be IWM adopters. Therefore appropriate information that reduced the confidence that replacement herbicides will become available in the short-term may be influential.

Also related to exhaustibility are expectations of herbicide-resistant weed populations returning to susceptibility, and perceptions of high resistance mobility (common property characteristics). These were not shown to reduce the likelihood of IWM adoption in this study. This is despite a high proportion of growers perceiving resistance reversion and mobility to be probable. Further research into the influence of these perceptions on IWM resistance management behaviour using variables with greater specificity may yield more conclusive results.

Consistent with the hypothesised longer-term resource management framework, growers' future discounting rate is shown to be an influence in determining adoption of IWM practices. Although not shown to be the most important of the variables in influencing IWM use, the results showed consistently that growers with higher discount rates, who placed a higher relative value on short-term returns, were likely to use less IWM practices. An investment in the delay or prevention of herbicide resistance is likely to involve shorter-term costs and longer-term returns. Given this, the negative influence of higher discount rates on IWM adoption should be expected. Those with the objective of increasing investment in IWM adoption need to recognise the role of the discounting of future returns and will need to accept the negative influence this is likely to have on preventative IWM adoption by growers.

Growers' adoption of IWM appears consistent with the framework for management of a potentially exhaustible herbicide resource. This does not imply, however, that most growers perceive that the herbicide resource will be exhausted in the short to medium term. The results do suggest that the herbicide resource management framework is applicable to understanding IWM adoption in regions with both emerging and established herbicide resistance problems. A potentially influential role for information and extension was found. Along with confirming the information-intensive nature of IPM systems, the study demonstrates the potential for targeted extension to increase the rate of adoption of IWM practices.

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Appendix: - Expanded regressions with no composite IWM variables

Table 7 Logit regression results for the model of IWM practice use with all perceptions of IWM practices included rather than composite variables (n=100).

	1. Use in Past 4 Years			2. Use in 2000		
Explanatory variables	**Coef.**	**s.e**	**P > |z|[a]**	**Coef.**	**s.e**	**P > |z|[a]**
Resistance status	2.130	0.655	0.001	1.146	0.347	0.001
Crop proportion	0.063	0.035	0.071	0.045	0.028	0.110
Discount rate	-.00014	0.00010	0.178	-.000099	0.00082	0.230
Education	3.274	1.512	0.030	2.306	1.093	0.035
Information exposure	3.985	1.667	0.017	2.038	0.943	0.031
New herbicide EV	0.647	0.332	0.051	0.454	0.189	0.016
New herbicide CV	0.120	0.053	0.023	0.079	0.040	0.046
Doubleknock Value	-0.229	0.360	0.523	0.117	0.261	0.654
Delay Value	1.032	0.492	0.036	0.577	0.309	0.062
High rate Value	1.045	0.514	0.042	0.634	0.324	0.050
Croptop Value	0.339	0.520	0.515	0.093	0.411	0.821
Catch Value	-0.412	0.544	0.449	-0.217	0.316	0.492
Manure Value	0.518	0.358	0.148	0.152	0.248	0.538
Doubleknock Efficacy	0.026	0.029	0.363	0.016	0.023	0.487
Delay Efficacy	-0.014	0.026	0.593	0.014	0.020	0.494
High rate Efficacy	0.030	0.038	0.427	-0.010	0.027	0.713
Croptop Efficacy	0.099	0.050	0.048	0.099	0.039	0.012
Catch Efficacy	0.157	0.071	0.027	0.047	0.042	0.259
Manure Efficacy	-0.031	0.037	0.401	-0.031	0.029	0.294
Doubleknock Efficacy	0.026	0.029	0.363	0.016	0.023	0.487
Constant	-35.185	11.008	0.001	-21.541	5.771	0.000
Log likelihood	-21.2			-27.8		
Pseudo R^{2a}	0.688			0.59		
Model Chi^2	93.56			79.0		
Level of significance	0.000			0.000		
% predicted correctly [b]	92 (90/93)			92 (88/95)		

P-values (P > |z|) are for tests of H_0 that the coefficient is zero

[a] Pseudo R^2 is based on the log-likelihood ratio, with 1 being perfect prediction

[b] Percentage of growers classified correctly (sensitivity/specificity). Sensitivity is the percentage of users classified correctly, specificity is the percentage of non-users classified correctly.

Table 8 Tobit and OLS regression models for extent of IWM practice use with all perceptions of IWM practices included rather than composite variables.

	Tobit Censored Regression			OLS Regression (n = 90)		
Explanatory variables	**Coef.**	**s.e.**	**P > |t|**	**Coef.**	**s.e.**	**P > |t|**
Resistance status	15.65	3.511	0.000	13.46	3.648	0.000
Discount rate	-0.0009	0.00071	0.185	-0.0011	0.00073	0.148
Education	26.412	12.133	0.032	21.700	12.697	0.092
Information exposure	19.97	7.741	0.012	22.186	8.096	0.008
New herbicide EV	5.413	1.795	0.003	7.151	2.039	0.001
New herbicide CV	0.792	0.475	0.099	0.918	0.499	0.070
Doubleknock Value	3.435	3.469	0.325	2.314	3.630	0.526
Delay Value	7.793	3.130	0.015	6.752	3.227	0.040
High rate Value	12.257	3.415	0.001	12.121	3.518	0.001
Croptop Value	-1.463	3.932	0.711	-5.689	4.205	0.180
Catch Value	5.778	3.093	0.065	5.901	3.180	0.068
Manure Value	2.374	2.857	0.408	2.737	3.043	0.371
Doubleknock Efficacy	0.173	0.268	0.520	0.230	0.814	0.419
Delay Efficacy	0.160	0.253	0.530	0.150	0.560	0.577
High rate Efficacy	-0.037	0.306	0.904	-0.081	0.320	0.801
Croptop Efficacy	0.655	0.408	0.112	1.071	0.441	0.018
Catch Efficacy	0.493	0.430	0.255	0.147	0.322	0.748
Manure Efficacy	-0.199	0.320	0.536	-0.187	0.338	0.582
Constant	-164.04	40.965	0.000	-147.9	44.577	0.001
Regression s.e.	44.996			**Root MSE**	45.57	
Log likelihood	-478.67			**Adj. R^2**	0.48	
Pseudo R^2	0.086			**F (18,71)**	5.59, P<0.000	
Model Chi^2	89.46, P<0.000					

n=100, 10 left-censored observations at 0.