Predicting herbicide activity to minimise uncertainty

Todd S. Andrews1,2, Richard W. Medd1,2, Remy J. Van de Ven2 and David I. Pickering1,2
1 CRC for Australian Weed Management
2 New South Wales Department of Primary Industries, Orange Agricultural Institute, Forest Road, Orange, New South Wales 2800, Australia

Summary To develop a predictive model based on factors affecting clodinafop we collated industry data sets and generated independent experimental data for efficacy on wild oat (Avena spp.). Dose rate, maximum temperature on the day of spraying, the sum of minimum temperatures for the seven days prior to spraying, spray water volume, a spray water volume by maximum temperature interaction, and available soil moisture at spraying were generally consistently correlated with clodinafop efficacy. Those data sets were combined with a previous set and analysed using a cross-validation technique to derive an applied predictive model for wild oat control with clodinafop. The factors mentioned above were included in that model and used to produce herbicide response surfaces under a range of different environmental conditions.

The results of this research demonstrate that it is possible to elucidate the effects of environmental, agronomic and spray factors on herbicide efficacy from large industry data sets. In addition, models that predict herbicide efficacy can be derived from such sets. Such a development may allow growers and agronomists to tailor herbicide rates according to prevailing conditions.

Keywords Wild oat, environment, multi-site.

INTRODUCTION

The potential to predict herbicide efficacy, and therefore to tailor herbicide rates according to prevailing environmental conditions, offers growers advantages in flexibility, efficiency and risk management when controlling weeds. Innovative analyses of herbicide efficacy data sets may provide opportunities for more prescriptive recommendations for weed control with herbicides.

To this end, Medd et al. (2001) analysed a multi-site (location and season) industry data set using linear mixed model statistical methods. They found that wild oat control with clodinafop was influenced by clodinafop dose (dose), maximum temperature on the day of spraying (Tmax), spray water volume (Vol), maximum temperature by spray volume interaction, the sum of minimum temperatures seven days prior to application (TminPRE7), and the soil moisture status 10 days prior to application (SMPRE10). Those authors suggested that, provided the influence of those factors was confirmed, a predictive model of clodinafop efficacy could be developed. This paper summarises the processes in pursuing the dual objectives of:

1. Validating the relationships between clodinafop efficacy and the variables described above, by collating and analysing an additional industry data set as well as experimental (field) data; and
2. Combining the original data with the two additional data sets in order to develop a predictive model.

MATERIALS AND METHODS

Efficacy data The original industry data set, collated and described by Medd et al. (2001), was modified to make the measurement and units of some environmental parameters consistent with the two more recent data sets. The second industry data set was collated from experiments conducted across Australia from 1995 to 2003 by Bayer CropScience Pty Ltd, Dow AgroSciences Australasia and Syngenta Crop Protection Pty Ltd. Field experiments were conducted throughout the cropping regions of NSW using a range of treatments, as described by Andrews et al. (in press). The clodinafop doses (dose) applied in field experiments were similar to those used in the industry datasets although spray water volumes (vol) were lower, according to label recommendations (Figure 1).

Clodinafop treatments in the field experiments targeted adverse conditions, including low soil moisture and cool temperatures. Accordingly, SMPRE10 and on the day of clodinafop application (SM) as well as Tmax, TminPRE7, three days prior to application (TminPRE3) or on the day of application (Tmin) were lower in the field experiments (Figure 1).

Linear mixed model analyses of the three independent data sets showed that the factors affecting clodinafop efficacy in Australia are fairly consistent (Table 1) and that it was possible to construct a robust predictive model for that weed/herbicide combination. The final, combined data set included 163 separate experiments with 985 discrete data entries and included data collected in all of the major grain growing
regions in Australia, spanning seasons from 1986 to 2005.

**Weather data** Weather data for the industry data sets were sourced from Data Drill on the Queensland Department of Natural Resources and Mines (NRM) website (www.nrm.qld.gov.au/silo/). Those data were based on information supplied by the Australian Bureau of Meteorology. When combined with map coordinates of the experimental sites, the website provided a range of interpolated information including maximum and minimum temperatures, rainfall and solar radiation. They in turn were used to estimate available soil moisture. The weather data collated with the field results were mostly recorded at on-site, fully automated weather stations.

<table>
<thead>
<tr>
<th>Table 1.</th>
<th>The spray and environmental variables correlated with clodinafop efficacy on wild oat in a range of data sets. Refer to the text for abbreviations. Where two terms are listed in the left hand column, the underlined term was correlated with clodinafop efficacy in the first industry data set. Underlined ticks refer to the underlined term only.</th>
</tr>
</thead>
<tbody>
<tr>
<td>1st industry data set (Medd et al. 2001)</td>
<td>2nd industry data set</td>
</tr>
<tr>
<td>Dose</td>
<td>✅</td>
</tr>
<tr>
<td>Tmax/Tmax²</td>
<td>✅</td>
</tr>
<tr>
<td>TminPRE7</td>
<td>✅</td>
</tr>
<tr>
<td>SMPRE10/SM</td>
<td>✅</td>
</tr>
<tr>
<td>Vol</td>
<td>✗</td>
</tr>
<tr>
<td>Tmax/Tmax² × Vol</td>
<td>✗</td>
</tr>
</tbody>
</table>

**Figure 1.** Some parameters of environmental and spray variables from independent industry and field data sets that were used to develop a predictive model for wild oat control with clodinafop. The solid line across the centre of the box represents the median value; the box contains the middle half of the data (i.e. from the first to the third quartile); the whiskers from the box extend to the extreme ‘non outlying’ results while the points beyond the whiskers are represent outlying results. Refer to text for abbreviations.
Statistical methods A cross validation approach was used to develop the prediction model (Efron and Tibshirani 1993). A k-fold cross validation divided the combined dataset into k subsets (k = 10 in this case), predicting the response in each of the k subsets based on the model fitted to the data excluding the subset being predicted, and determined the mean Predicted Square Error (PSE) for that model. The procedure was repeated for all possible models and the model with the minimum mean PSE was selected. The current approach included the ‘one standard error’ rule, where the most parsimonious model was selected, provided that its mean PSE was within one standard error of the model having minimum mean PSE.

RESULTS
Linear mixed model analyses of the additional industry data and the field data sets indicated that the factors affecting clodinafop were fairly consistent (Table 1). Cross validation of the combined data set confirmed the correlation of spray and environmental factors with clodinafop efficacy identified by Medd et al. (2001), with some modifications (Table 1). For example, whereas Tmax was positively correlated with clodinafop efficacy in the original analyses, the field data and the cross validation model showed that Tmax was correlated as a quadratic effect. This means that there is an optimum temperature for clodinafop activity, beyond which wild oat control declines. In addition, soil moisture on the day of clodinafop application was found to be a better predictor of efficacy, rather than 10 days prior to application.

Response surfaces developed from the final model illustrate the interaction between clodinafop dose and water volume under a range of environmental conditions (Figure 2). Under ‘average’ spraying conditions for cereal crops in New South Wales (Tmax = 14, SM = 80, TminPRE7 = 20, Figure 2a), there is little effect of increasing water volume for higher clodinafop doses. As dose is reduced however, water volume can be increased to maintain efficacy.

The Tmax × Vol interaction varies under adverse conditions. For example, increasing water volume in moist, but cool, conditions increases efficacy, particularly as clodinafop dose is reduced (Figure 2b). Under warm and dry conditions however, increasing Vol does not greatly enhance efficacy, regardless of clodinafop dose (Figure 2c).

DISCUSSION
Analyses of the additional industry data and the field data, in addition to the cross validation of the combined data, have confirmed the predictive value of dose, Tmax, TminPRE7, SM, Vol, and the Tmax × Vol interaction, on clodinafop efficacy. In addition, those analyses confirmed that wild oat growth stage and density are not correlated with clodinafop efficacy (data not shown). The incorporation of these factors into a predictive model means that growers and agronomists can use a knowledge of prevailing weather conditions on the day of application to tailor clodinafop dose and water volume accordingly.

The response surfaces illustrate the function of the Tmax × Vol interaction, whereby water volume can be

Figure 2. Dose response surfaces for wild oat control with clodinafop. The responses were calculated by cross validating a data set collated from 163 experiments conducted throughout Australia. Response surfaces are calculated for clodinafop applied in central west New South Wales under ‘average’ ((a) Tmax = 14, SM = 80, TminPRE7 = 20); cool ((b) Tmax = 11, SM = 100, TminPRE7 = 13); and dry conditions ((c) Tmax = 20, SM = 40, TminPRE7 = 37). Refer to text for abbreviations.
increased to maintain clodinafop efficacy at low Tmax. The potential for increased spray water volume to maintain wild oat control when Tmax is low is important for growers since it means that growers using low water volumes are more likely to experience reduced efficacy when applying clodinafop under cool conditions. This finding may be worthy of further research to determine if it may be more broadly applied. For example, Tmax has also been shown to influence the efficacy of broadleaf herbicides on wild radish (Raphanus raphanistrum; Madafiglio et al. 2006) while the Tmax × Vol interaction has also been correlated with the efficacy of mesosulfuron and iodosulfuron on wild oat (unpublished data).

Finally, this research confirms that more comprehensive analyses of industry data sets can be used to elucidate the effects of environmental, agronomic and spray factors on herbicide efficacy. Whereas herbicide labels may currently recommend rate variations according to ‘ideal’ or ‘adverse’ conditions, the analyses used in this research show that recommendations can specify such conditions. Modelling the effects of environment on herbicide efficacy will thus enable advisors/users to define specific conditions that result in reduced weed control. Such information could provide growers with the options of avoiding application under adverse conditions or using highest recommended rates unnecessarily; thereby ultimately increasing the efficiency of herbicide use.

The model has further potential for population management where low weed densities could be targeted under ideal spray conditions using reduced doses. An important feature of the model is the calculation of confidence intervals, which show the risk associated with given environmental conditions. In addition, the potential for predictive models to be utilised commercially is enhanced by the fact that on site weather data may not be required. Andrews et al. (in press) showed that there was no impact on the correlation of environmental variables with clodinafop efficacy when site weather data was substituted with generic, readily available information.

ACKNOWLEDGMENTS
The financial and technical input of Syngenta Crop Protection, Australia is gratefully acknowledged. Dow AgroSciences and Bayer CropScience generously provided industry data. Pat Farrelly, John Fiegert, Peter Lockley, Brad Palmer, Barry Riley and their staff at the NSW DPI Agricultural Research facilities at Orange, Temora, Wagga Wagga, Cowra and Condobolin respectively provided sites, equipment, technical assistance and advice for the establishment of experimental sites at these locations.

REFERENCES