Chapter 6

Predicting yield loss with relative cover measurements

6.1 Introduction

Integrated weed management (IWM) is a systems approach to the management of weeds, combining chemical and non-chemical weed control methods (Sindel 1995). At the core of this management process is the need to decide which control methods to apply, and how and when to implement them. Such decisions are made to conserve the growth of the selected crop plant and impede the growth of undesirable weed plants. Without sound decisions, the process of IWM fails. Thus, there is a need for guidance in IWM decisions to ensure that the best options are implemented, but for wise decisions to be made an indication of the expected outcomes must be known.

Environmental concerns, the aims of sustainable agriculture, and the increasing cost of weed control have shifted the focus of weed management from an indiscriminate broad-scale approach to a more controlled, precise system. The decision to use a weed control method and the timing of its application should be made with an understanding of what will happen if the control is, or is not, applied. In this examination, the economic cost of the control, the ecological cost, and the sociological cost must be addressed (Bhan & Singh 1993).

To aid this decision process, predictive models have been developed. Mechanistic models describe the whole system over time; however, these require too many inputs to be useful for decision-making (Kropff & Lotz 1992a). Descriptive models are characterised by a limited number of inputs that can be relatively easily determined in the field (Lotz *et al.* 1995). In two species competition experiments, regression models have been used to show how variation of the measurable independent variable (weed characters e.g. leaf area, density, and biomass) will change the dependent variable (usually potential yield or yield loss of the crop) (Kropff & Lotz 1993, Lotz *et al.* 1995, Cousens 1996).

Identifying the independent variable is difficult, because it must be easily measured in the field (Lotz *et al.* 1995). Also, the independent variable must also relate to the dependent variable in a predictable manner. Several independent variables have been used to predict yield loss in grain crops: density of weeds m^{-2} (Cousens 1985a, b); relative leaf-area of weeds m^{-2} (Kropff & Spitters 1991, Lotz *et al.* 1992); relative cover of weeds m^{-2} (Lutman 1992); spectral reflectance of weeds m^{-2} (Lotz *et al.* 1994, Lotz *et al.* 1995); and dry matter of weeds m^{-2} (Lutman *et al.* 1996). Different statistical equations have been created for using an independent variable to predict yield loss. It is recommended that the fitting of equations to data for the purposes of description and prediction follow acceptable biological theory (Cousens 1985a). Plant density is one independent variable that can be measured easily, and the rectangular hyperbolic model (Equation 5.1) adequately describes the relationship between yield loss and weed density (Cousens 1985 a,1985b).

Despite the good relationship between weed density and crop yield loss, this model is not recommended for early season prediction purposes (Kropff & Spitters 1991). The use of density deals with each occurrence of a weed equally. As well as suggesting that newly emerged weeds will have as great a competitive effect as established weeds, there is also no consideration of late-establishing weeds or premature weed death. To account for secondary weed emergence, Cousens *et al.* (1987) introduced an additional variable into the hyperbolic density model; this helped to account for the difference in time between crop and weed emergence (Kropff 1988), but not for the natural variability in the weed population that results in some plants being more competitive than others.

The variable nature of weed densities has resulted in the hyperbolic density model being described as a descriptive not a predictive model (Kropff & Spitters 1991). For a model to be successfully used for early prediction, it must account for the variations in size, competitive ability and variable emergence of the weed (Kropff & Spitters 1991).

The 1-parameter leaf-area model was first described by Kropff & Spitters (1991). This model uses the same rectangular hyperbolic curve as the density model, in which the densities of the two plants were replaced by their LAIs (Leaf-area Index is $m^2_{Leaf}m^{-2}_{Ground}$) recorded early in the season (Kropff & Spitters 1991). It was found that the share in total leaf-area of the weed species was more easily measured than the ratio of LAIs so this was used and the model took the form:

Equation 6.1 The 1-parameter leaf-area model (Kropff & Spitters, 1991)

$$Y_L = \frac{qL_w}{1+(q-1)L_w}$$

where: Y_L *is the yield loss due to weeds divided by the yield in the absence of weeds;* L_w *is the leaf-area index of the weeds divided by the leaf-area index of crop and weeds (* $L_w = \frac{LAI_W}{LAI_W + LAI_C}$ *where* LAI_W *is the leaf-area index of the weeds and* LAI_c *is the leaf-area index of the crop); and q is the relative damage coefficient*

Predictions from this model were reliable, and more accurate than from the density model (Lutman *et al.* 1996) for *Chenopodium album* L. in sugar beet (Kropff & Spitters 1991) and for *Sinapis alba* L. in sugar beet and spring wheat (Lotz *et al.* 1996).

The difficulty with the leaf-area model is the measurement of the leaf areas (Lotz *et al.* 1994). The different morphological features of different crops and weeds determine the ease and accuracy with which leaf-area can be measured. In many cases, the leaf-area is measured destructively with calibrated leaf-area measuring equipment (Lotz *et al.* 1994, 1996). This form of prediction is suited to experimental research, but is not suitable for farm field-based situations. The 1-parameter model was also limited by not having a second parameter to describe the maximum yield loss. The absence of a second parameter impeded the predictive capability of the equation when the weed had a procumbent growth form, or flowered early (Lotz *et al.* 1995). A two-parameter leaf-area model has been described by Lotz *et al.* (1992), Kropff and Lotz (1992a), Lotz *et al.* (1995), and Lotz *et al.* (1996).

Equation 6.2 The 2-parameter leaf-area model

$$Y_L = \frac{qL_w}{1+(\frac{q}{m}-1)L_w}$$

where m determines the maximum relative yield loss of the crop.

The inclusion of an additional parameter improved the robustness of the equation when dealing with early flowering or procumbent weeds (Lotz *et al.* 1995). In many situations, however, the additional parameter did not improve the description of the crop/weed relationship (Van Acker *et al.* 1997).

Despite the fact that the 1- and 2- parameter models have been shown to describe relationships between crops and single weed species well, weeds rarely occur as single species (Van Acker *et* *al.* 1997). To use the leaf-area model with multiple weeds, it has been recommended that the q values for each weed be combined in an additive fashion (Kropff & Spitters 1991, Van Acker *et al.* 1997). The model has the following form

Equation 6.3 Leaf-area model for multiple weeds

$$Y_L = \frac{\sum q_i L_{w,i}}{1+(q_i - 1)L_{w,i}}$$

where i represents each added individual species.

This additive system assumes that the weeds are growing independently of each other and that no interaction between the weeds occurs (Van Acker *et al.* 1997). This situation is unlikely, and reports from several authors indicate that interference from multiple weed species could not always be simply added (Haizel & Harper 1973, Blackshaw *et al.* 1987, Hume 1989). The assumption, that inter-weed species competition was negligible, over-estimates the effects of the weeds, so any predictions would err on the side of caution.

Using relative cover instead of leaf-area results in the following equation:

Equation 6.4 Relative cover model

$$Y_L = \frac{qL_w}{1+(q-1)L_w}$$

where $L_w = \frac{RC_W}{RC_W + RC_C}$ *(RC_W = Relative Cover weeds and RC_c = Relative Cover crop).*

The measuring involved to obtain a leaf-area index can be a difficult and time-consuming procedure (Lotz *et al.* 1994). The relative cover of a plant (that is the proportion of the soil surface covered by the plant canopy) is highly correlated with leaf-area (Lutman 1992, Lotz *et al.* 1994). Lutman (1992) suggested that the correlation between relative cover and leaf-area index enabled relative cover to be a substitute for leaf-area index in the leaf-area models.

The advantage of using relative cover instead of leaf-area index relates to ease of measurement. Lutman (1992) suggested that the relative cover of weeds and crop could be estimated visually by a trained observer, which if successful, would provide a cost-efficient means of collecting the independent variable (Lutman 1992, Lotz *et al.* 1994). To confirm the success of the trained observer, surface photographs were taken of the crop and the proportions of weed and crop calculated (Lutman 1992). During experiments by Lutman (1992) and Lutman *et al.* (1996), the correlation between the trained observer and the photographic method was high; however, Lotz *et al.* (1994) did not report the same level of trained-observer accuracy.

The leaf-area models have adequately described the variation in data collected from many experiments. Each assessment by the predictive leaf-area models relates to a snapshot in time, so the removal or emergence of weeds or crop after the assessment will weaken the prediction (Lotz *et al.* 1996). The timing of when to make the prediction is important and is linked to the critical period of weed control.

The critical time of weed removal is an important consideration for the use of prediction modelling. As stated in the introduction, predictive modelling is a tool to help make decisions about the need for weed control. Predictive models must be able to achieve an accurate prediction from the plant resources present before the critical time of weed removal expires. In many cases, the ideal time to use the predictive model is close to the critical time of weed removal, because at this time, the greatest amount of weed and crop information is present.

Chickpea have a slow initial growth rate (Amor & Francisco 1987, Knights 1991), which is similar to many of the weeds competing with them in eastern Australia. The delayed winter growth of some weeds like wild oat (Cousens *et al.* 1991) and pulses like chickpea may suggest that active competition between northern chickpea crops and winter weeds occurs late in the season. This implies a long period between sowing and the time of critical weed control (discussed in Chapter 7). To use accurate predictive modelling to help in the weed control decisions of chickpea crops, the time most suited to prediction and the most suitable form of the model must be identified.

In this chapter, the results from Chapter 5 are re-examined using photographic assessments of cover taken during the season. The objective was to compare the 1- and 2-parameter leaf-area models with a generalised additive model, with the view to identifying the best model for early season prediction. An integral part of this objective was to identify the time for making the most accurate predictions.

6.2 Materials and methods

The experimental design and agronomic methods used in this experiment are described in Chapter 5. During the 1996 and 1997 growing seasons, non-destructive measurements of the plant canopy were made using photographs of the ground surface taken at a set distance above the crop. The method used was a combination of the techniques described by Siddique *et al.* (1989) and Lutman (1992). Canopy cover was measured by taking one photograph per plot at 70 and 129 days after sowing (DAS) in 1996 at Tamworth, and at 51 and 106 DAS in 1996 at Warialda. In 1997, photographic assessments were made at 68, 89, 131 and 160 DAS at Tamworth and 46, 75, 111 and 139 DAS at Warialda. The photographs were taken from a custom-made tripod (David Creed, Rural Science Workshop, UNE) that held the camera parallel to the ground at a height of 1.5 m in 1996 and 2.85 m in 1997. A 50-mm Olympus® lens was used with Kodak® 35 mm print film, ISO 100. The field of vision covered a ground area of 84 by 58 cm in 1996 and 170 by 114 cm in 1997. The photographs were interpreted by placing a sheet of glass, etched with a 6 mm square grid (425 grid points per 150 x 100-mm print in 1996, 609 grid points per 177 x 126-mm print in 1997), over the photograph and counting the number of intersection points covering the crop or weed.

The relative counts recorded for each photograph were expressed on a per metre basis and related to yield loss by fitting the 1- and 2-parameter leaf-area models (Equations 6.1, 6.2). The models were fitted to data from both sites in the presence of turnip weed and wild oat using the non-linear regression and maximum likelihood function of the statistical software package Splus-4 (Mathsoft 1997). In addition, non-parametric regression using the generalised additive models (GAM) function of the statistical software package Splus-4 (Mathsoft 1997) was employed. Curves were fitted using β spline smoothing with 4 degrees of freedom. Spatial variation between plots was accounted for by the use of a single mean yield from which all yield losses were calculated.

The 1-parameter leaf-area model (Equation 6.1) has one parameter (q), which represents the damage coefficient of the weeds. The 2-parameter model (Equation 6.2) has this parameter (q) and a second parameter (m) used to define a maximum, which causes the curve to form the classical hyperbolic shape and, in so doing, increases the values of (q). To determine which model provided the best description of the data, the standard errors of the estimated parameters were compared, as well as the predicted yield losses from a range of cover measurements.

In an attempt to further understand the predictions of these models, non-parametric models were also fitted to the data. The parametric models could not be compared using a test such as Hotelling's T^2 test (Anderson 1958) because of the differing numbers of parameters in each model.

The experiments in 1997 examined the effects of turnip weed only, and attempted to identify the best time to collect information for yield loss predictions. The sequence of collection times began at a similar time to 1996 (about 8 weeks after sowing) and continued at about 4 weekly intervals for 16 weeks. The 1-parameter, 2-parameter and, non-parametric GAM models were fitted to the data of each assessment time at each site. Comparisons were made between the models by assessing the size of the standard errors from predicted values of common cover measurements.

6.3 Results

In 1996, the first photographic assessment of cover was recorded 51 days after sowing (DAS) at Warialda and 70 DAS at Tamworth. Despite this difference in age, the plants at Warialda were more advanced than the Tamworth plants (Plates 6.1 to 6.4). The more advanced state (larger plants) of the Warialda plants improved the results of the photographic assessment because the increased size provided more accurate canopy measurements, which reduced the spread and variation of the data (Fig. 6.1). For the first assessment time at both sites, the 1-parameter model produced smaller damage coefficients (q) values compared with the 2-parameter model, and the standard errors were also smaller (Table 6.1). The Tamworth Time 2 cover estimations showed no difference between the estimated q values for either the 1-or 2-parameter models. The Warialda Time 2 q values showed large differences and the standard error estimations for the 2-parameter model are extremely large (Table 6.1).

Observations of chickpea growth in the presence of turnip weed and wild oat indicate that the weeds are highly competitive, but that the competitive nature of the weeds is displayed late in the season (Plates 6.1-6.4). The 1-parameter model produced curves of little inflection and q values between 2 and 4; however, the data recorded in 1996 were variable and a range of curve trajectories was possible.

Plate 6.1. Example of a Time 1 photograph of chickpea and turnip weed plants at Tamworth 1996 taken 70 days after sowing from a 1.5 m height. White ruler is 30 cm long.

Plate 6.2. Example of a Time 2 photograph of chickpea and turnip weed plants at Tamworth 1996 taken 129 days after sowing from a 1.5 m height. White ruler is 30 cm long.

Plate 6.3. Example of Time 1 photograph of chickpea and turnip weed plants at Warialda in 1996 taken 51 days after sowing from a 1.5 m height. White ruler is 30 cm long.

Plate 6.4. Example of Time 2 photograph of chickpea and turnip weed plants at Warialda in 1996 taken 106 days after sowing from a 1.5 m height. White ruler is 30 cm long. NB. Shadows were less severe in original photographs and did not influence the accuracy of this technique.

Table 6.1 Estimated values for parametric models used for the prediction of 1996 chickpea yield loss due to infestations of turnip weed and wild oat. Standard errors are given in brackets.

Treatment		Time 1		Time 2	
1996	Y_{wf}	q	m	q	m
Tamworth turnip weed 1-parameter model	284.1 (±27.4)	3.0 (±0.8)	-	1.17 (±0.2)	-
Tamworth turnip weed 2-parameter model	284.1 (±27.4)	9.9 (±6.5)	0.57 (±0.1)	1.32 (±0.4)	0.92. (±0.1)
Tamworth wild oat 1-parameter model	300 (±76.0)	2.7 (±0.7)	-	0.89 (±0.2)	-
Tamworth wild oat 2-parameter model	300 (±76.0)	4.9 (±2.8)	0.66 (±0.2)	1.1 (±0.4)	0.85 (±0.2)
Warialda turnip weed 1-parameter model	334.2 (±38.9)	1.6 (±0.3)	-	2.83 (±0.5)	-
Warialda turnip weed 2-parameter model	334.2 (±38.9)	3.4 (±1.5)	0.67 (±0.1)	68.9 (±59.5)	0.56 (±0.03)
Warialda wild oat 1-parameter model	381.1 (±9.7)	2.5 (±0.5)	-	3.19 (±0.7)	-
Warialda wild oat 2-parameter model	381.1 (±9.7)	7.6 (±4.3)	0.63 (±0.1)	106.0 (±170.1)	0.61 (±0.04)

Ywf *: the weed-free yield in g* m^{-2}

q *: the damage coefficient for wild oat or turnip weed*

m*: the asymptotic yield loss parameter.*

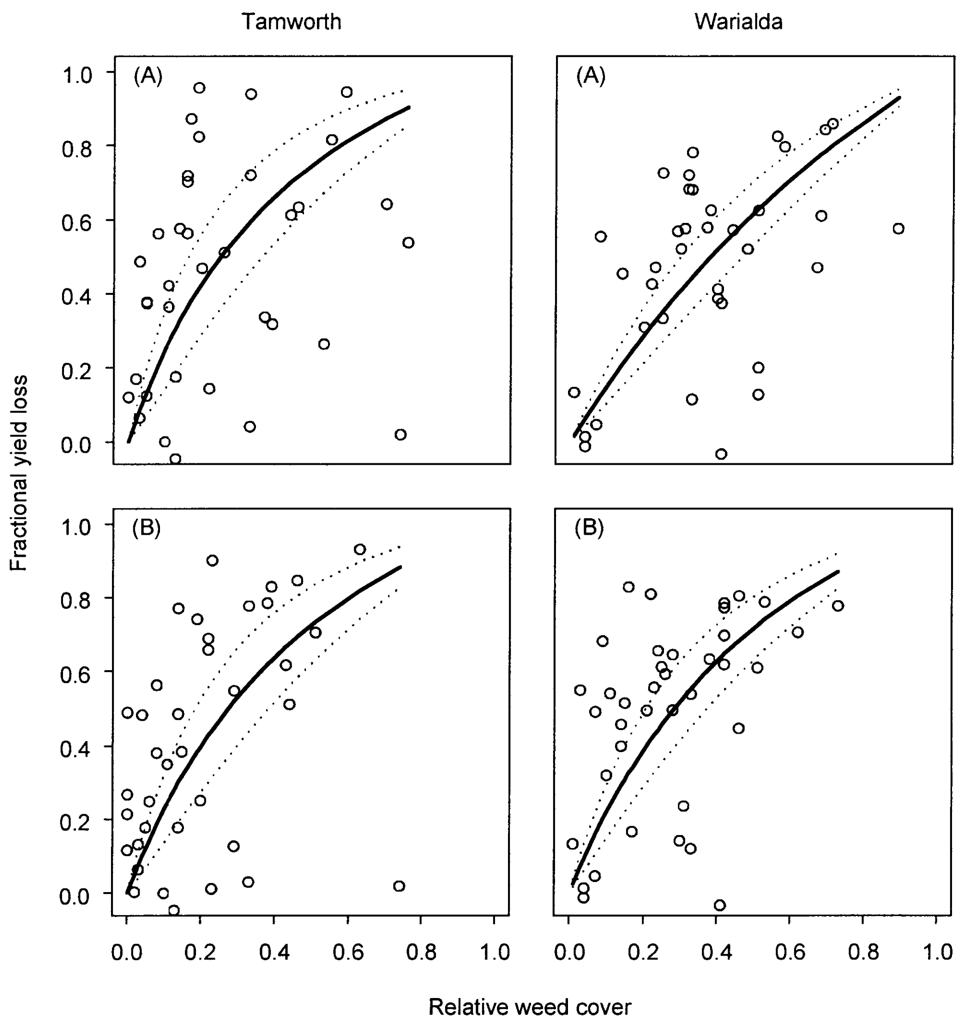

Fig. 6.1 Kropff and Spitters' 1-parameter model fitted to the Time 1 (Tamworth 70 DAS, Warialda 51 DAS) relative cover data for 1996. Columns of graphs refer to the two experimental sites. Letters denote treatments: (A) turnip weed; and (B) wild oat. Broken lines indicate the 95% confidence interval.

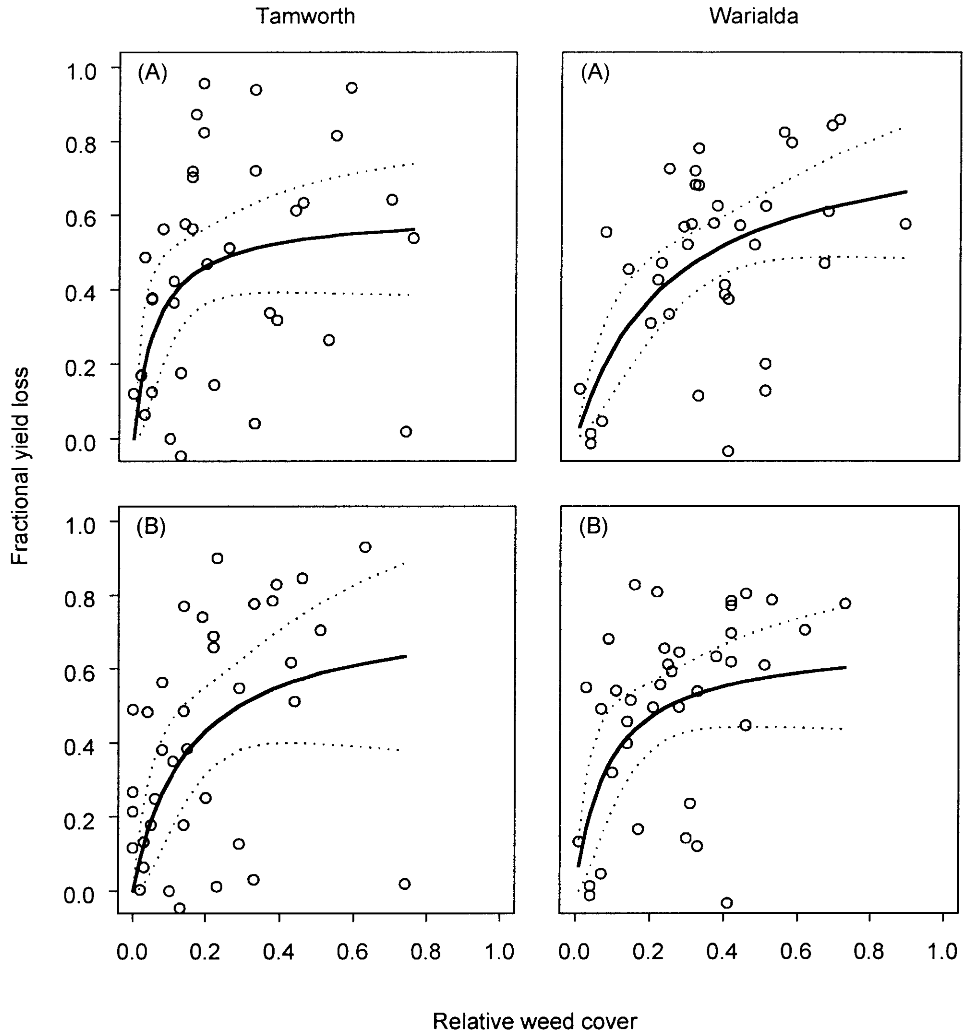

Fig. 6.2 Lotz *et al.* 2-parameter model fitted to the Time 1 (Tamworth 70 DAS, Warialda 51 DAS) relative cover data for 1996. Columns of graphs refer to the two experimental sites. Letters denote treatments: (A) turnip weed; and (B) wild oat. Broken lines indicate the 95% confidence interval.

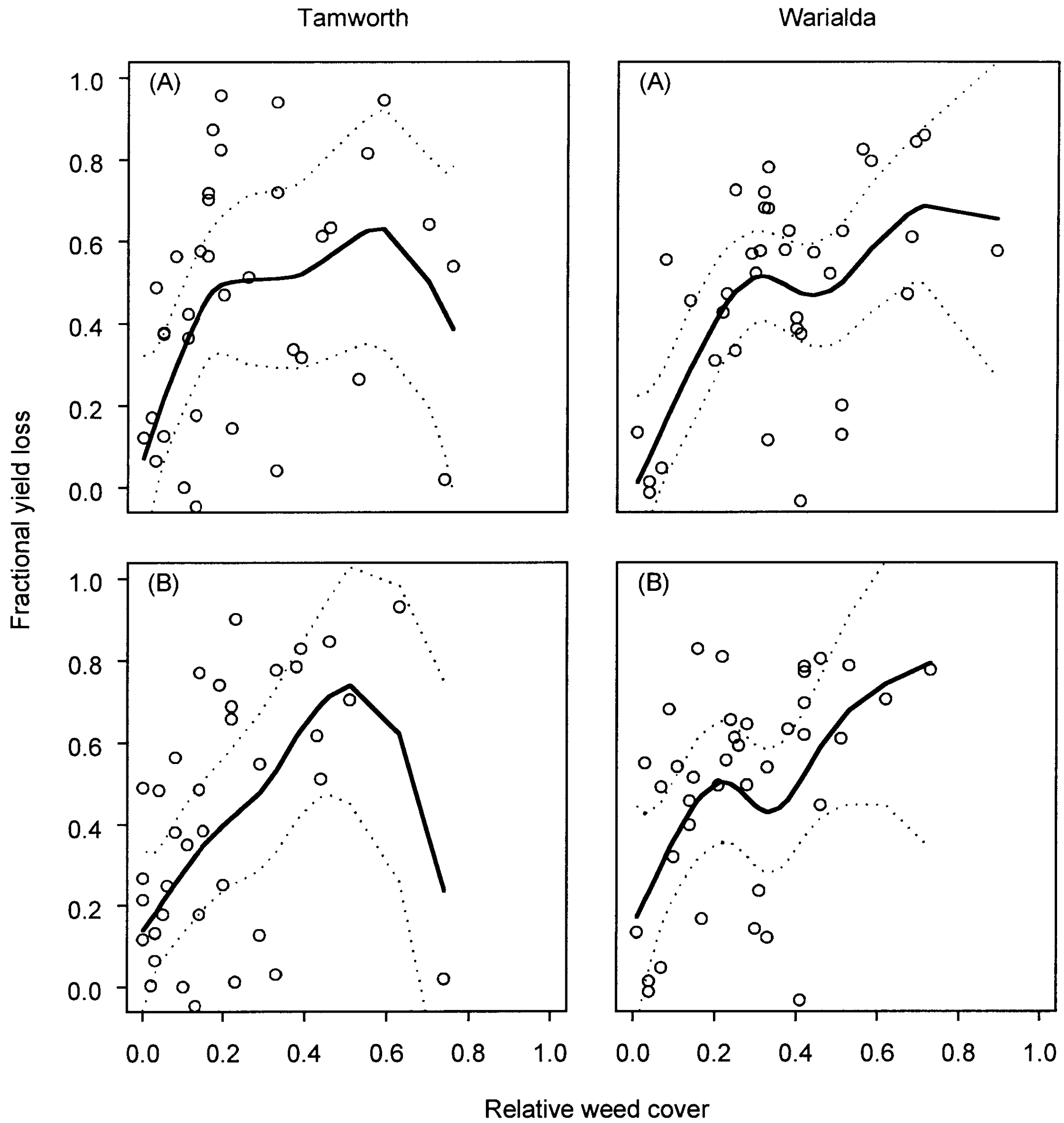

Fig. 6.3 Non-parametric GAM curve fitted to the Time 1 (Tamworth 70 DAS, Warialda 51 DAS) relative cover data for 1996. Columns of graphs refer to the two experimental sites. Letters denote treatments: (A) turnip weed; and (B) wild oat. Broken lines indicate the 95% confidence interval.

Yield loss predictions from simulated cover data showed little difference between the three models for the Tamworth turnip weed data (a relative cover of 0.4 produced fractional yield loss measurements of 0.66 (±0.1), 0.52 (±0.7), 0.48 (±0.1) for the 1-parameter, 2-parameter, and GAM models respectively), but the wild oat and Warialda data were best described by the 1-parameter model. This produced the lowest standard errors for the predicted fractional yield loss values for common relative cover measures (Appendix A, Table A.1). Comparing confidence intervals for Figs 6.1, 6.2, and 6.3 shows that the 1-parameter model also had the narrowest 95% confidence intervals. The estimated values of q for the 1-parameter model had the lowest standard errors (Table 6.1).

The Time 2 results (106 and 129 DAS Warialda and Tamworth) were recorded when full canopy cover was being approached, and in the case of the Warialda results, full cover had been reached. The parameter estimations for the models at Time 2 show no difference between the 1- and 2-parameter models at Tamworth (Table 6.1), but indicate a clear difference at Warialda. The introduction of the second parameter (m) in the 2-parameter model and the full canopy cover of the plots caused very large errors in the estimation of the q parameter for the Warialda data. Comparisons of the confidence intervals of the two parameterised curves and the GAM curve show that the 1-parameter model provided the narrowest range (Figs 6.4 to 6.6). The ability of the three curves to predict yield loss from set cover measurements showed little difference (a relative cover of 0.4 produced fractional yield loss measurements of 0.44 (±0.05), 0.45 (±0.05), 0.43 (±0.03) for the 1-parameter, 2-parameter, and GAM models, respectively) (Appendix A, Table A.1). Generally, for the two sites and the two weeds, the fitted values from the 1-parameter model and the non-parametric GAM curve were similar. Some differences do exist between individual curves and at specific values of cover, but overall, little difference could be seen between the two models. (The predicted values used to compare the three models are in Appendix A).

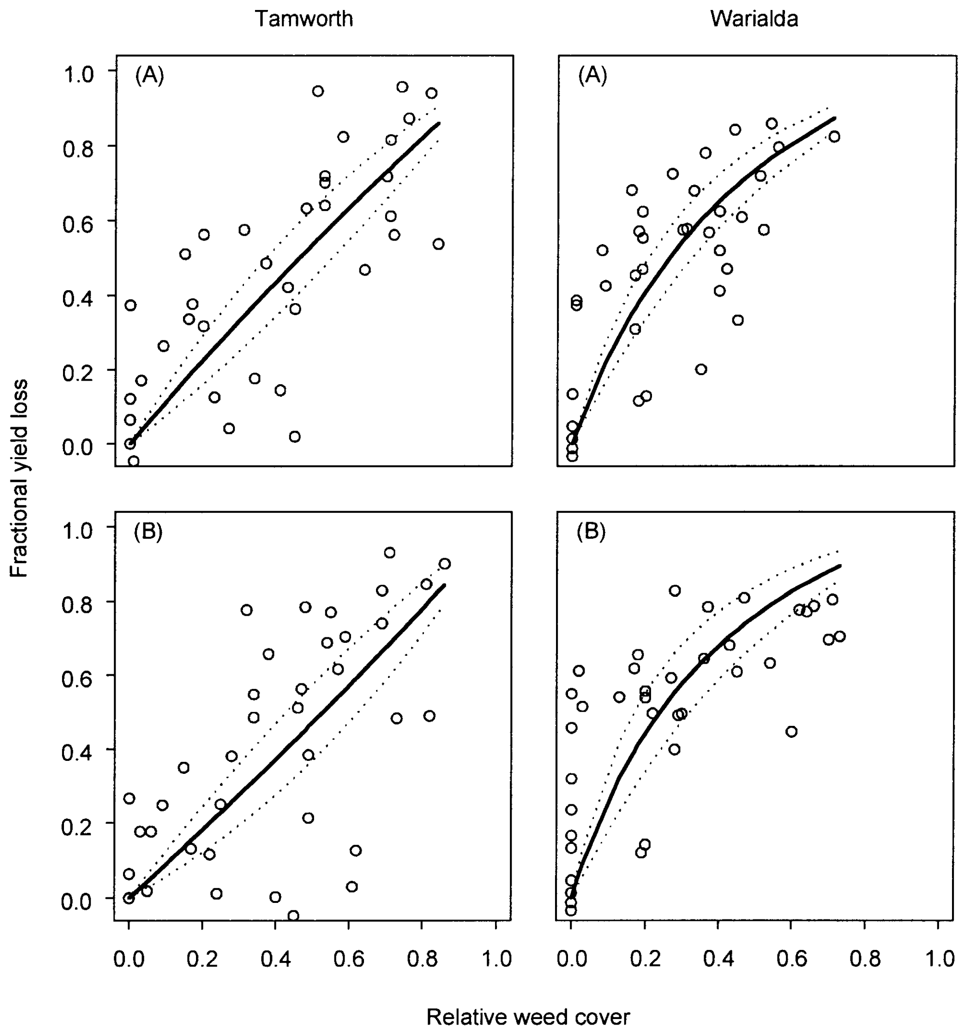

Fig. 6.4 Kropff and Spitters' 1-parameter model fitted to the Time 2 (Tamworth 129 DAS, Warialda 106 DAS) relative cover data for 1996. Columns of graphs refer to the two experimental sites. Letters denote treatments: (A) turnip weed; (B) wild oat. Broken lines indicate the 95% confidence interval.

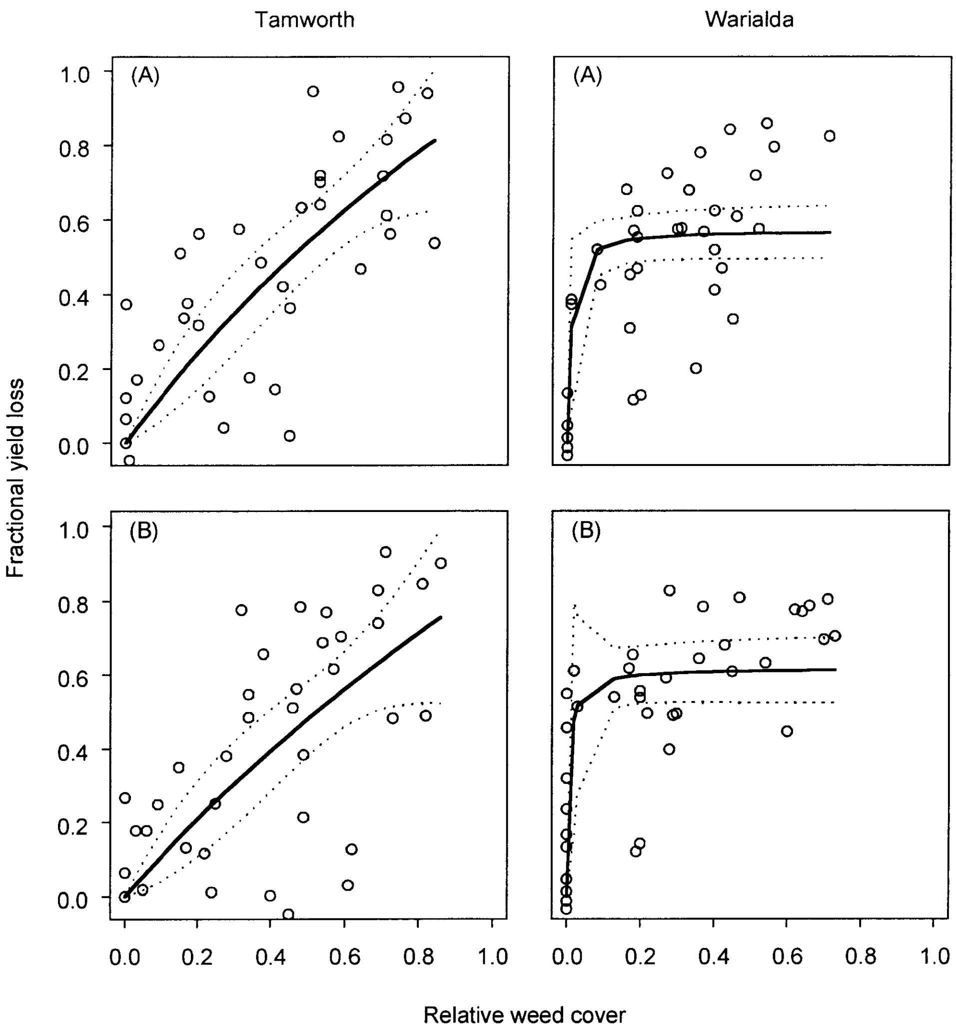

Fig. 6.5 Lotz *et al.* 2-parameter model fitted to the Time 2 (Tamworth 129 DAS, Warialda 106 DAS) relative cover data for 1996. Columns of graphs refer to the two experimental sites. Letters denote treatments: (A) turnip weed; (B) wild oat. Broken lines indicate the 95% confidence interval.

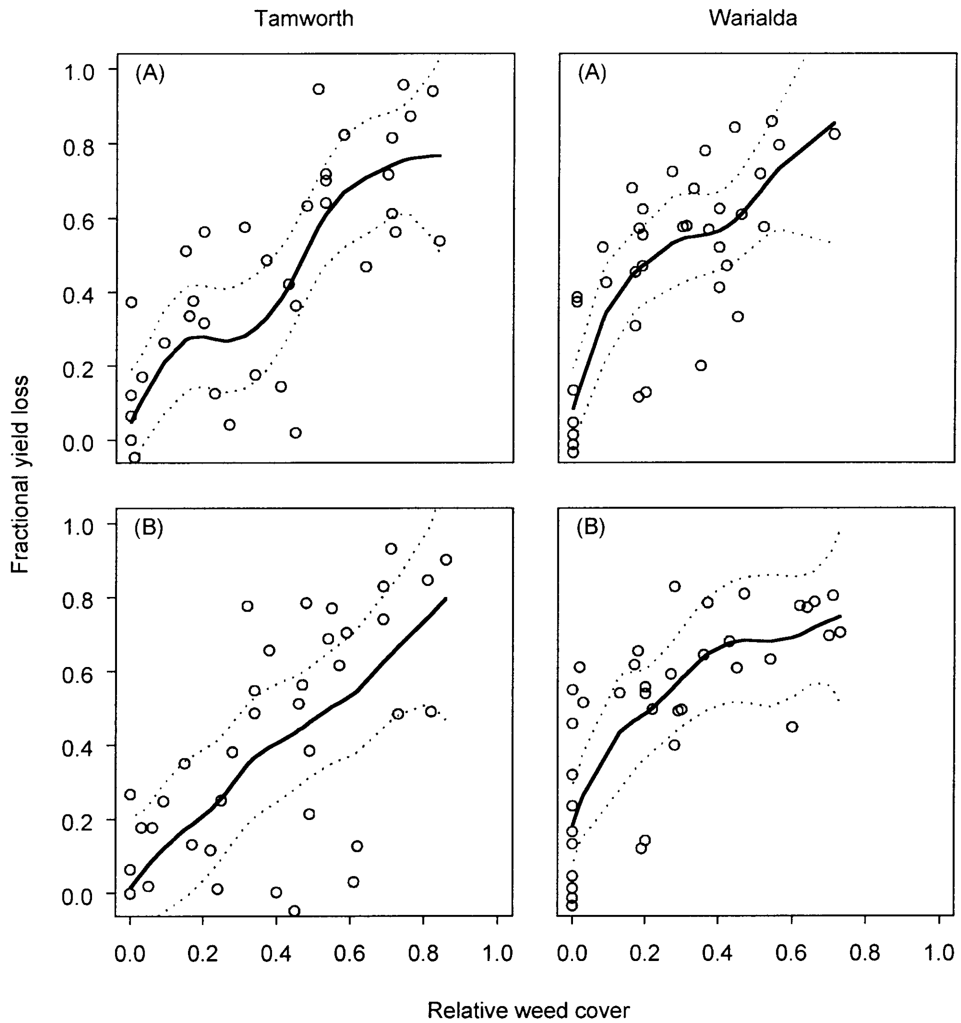

Fig. 6.6 Non-parametric GAM curve fitted to the Time 2 (Tamworth 129 DAS, Warialda 106 DAS) relative cover data for 1996. Columns of graphs refer to the two experimental sites. Letters denote treatments (A) turnip weed, (B) wild oat. Broken lines show the 95% confidence interval.

The experiments in 1997 examined the response of chickpea to weeds over time. Plates 6.5 to 6.8 show the change over time of one plot at Tamworth, while Plates 6.9 to 6.12 show the same time changes at Warialda. Examination of the plates displays how the rapid growth phase of the chickpea crop and turnip weed occurs in the latter half of the season. Phonological data could not be used to describe this point owing to the indeterminate nature of chickpea. Chickpea and turnip weed development from the time of sowing until day 89 at Tamworth and day 75 at Warialda is minimal, and the relative cover counts emphasise this (Fig. 6.7 A, B and Fig. 6.11 A, B, respectively).

The rapid growth phase of chickpea and turnip weed occurred between the 10^{th} and 12^{th} week for Tamworth (Plate 6.7) and between the 16^{th} and 19^{th} week for Warialda (Plate 6.11). During this period, the chickpea approached canopy closure and had begun flowering. The turnip weed plants had increased their size, but their relative height was either less than or equal to the chickpea. From this point onward, turnip weed displayed a competitive advantage by increasing its height well above the chickpea and flowering. At this point, relative weed cover in the high-density turnip weed plots approached 1 (Plates 6.8 and 6.12).

Plate 6.5. Time 1 photograph (68 DAS) of chickpea and turnip weed plants at Tamworth, 1997.

Plate 6.6. Time 2 photograph (89 DAS) of chickpea and turnip weed plants at Tamworth, 1997.

Plate 6.7. Time 3 photograph (131 DAS) of chickpea and turnip weed plants at Tamworth, 1997.

Plate 6.8. Time 4 photograph (140 DAS) of chickpea and turnip weed plants at Tamworth, 1997.

Plate 6.9. Time 1 photograph (46 DAS) of chickpea and turnip weed plants at Warialda, 1997.

Plate 6.10. Time 2 photograph (75 DAS) of chickpea and turnip weed plants at Warialda, 1997.

Plate 6.11. Time 3 photograph (111 DAS) of chickpea and turnip weed plants at Warialda, 1997.

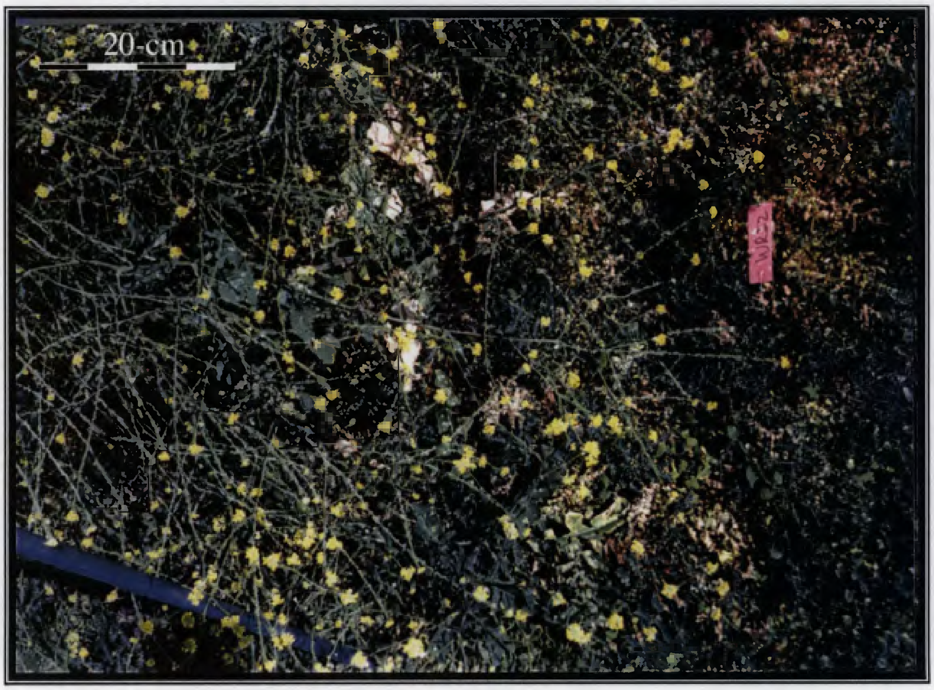

Plate 6.12. Time 4 photograph (139 DAS) of chickpea and turnip weed plants at Warialda, 1997.

The results of the 1- and 2-parameter models (Equations 6.1, 6.2) for 1997 at Time 1 for Tamworth and Warialda showed large variation in the data. The 2-parameter model (Equation

6.2) was unable to adequately account for the variation in the Tamworth data (Fig. 6.8A) so no model is fitted. At Time 2, the difference in relative plant growth between sites is evident. There was little weed cover at the Tamworth site (Fig. 6.7B), while Warialda recorded weed cover measurements of 50% (Fig. 6.9B). The confidence intervals at Tamworth for Time 2 are broad; however, the narrow cover range improved both the 1- and 2-parameter models' curve shape. At Warialda, the increased range of cover measurements expanded the curves (Fig. 6.9). The 1-parameter model fitted the data with the narrowest confidence intervals at both sites (Figs. 6.7 and 6.9). Plates 6.7 and 6.11 show the turnip weed and chickpea canopies competing for light, and it is at this time that the greatest amount of relative cover information was available. The parametric curves produced at this time (Time 3) make use of the additional information and provide a good description of the results (Figs. 6.9C and 6.10C). Again, however, the 1-parameter model provided the best fit with the narrowest confidence intervals (Fig. 6.9C). The results from Warialda have less variation, but both Tamworth and Warialda produced reliable curves. By the final assessment time (Time 4), turnip weed dominated, recording 100% cover measurements in the higher density plots (Plates 6.8 and 6.12).

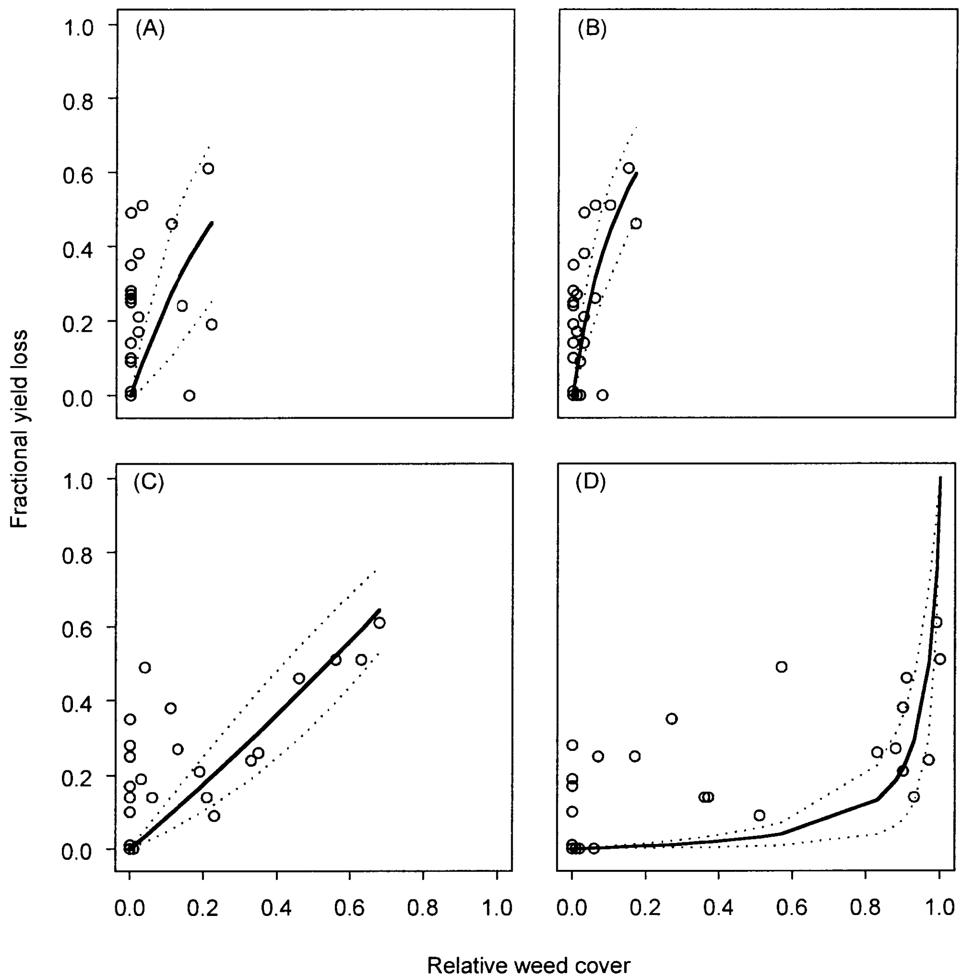

Fig. 6.7 Kropff and Spitters1-parameter model fitted to the Tamworth relative cover data for 1997. Letters denote assessment times: (A) Time 1, 68 DAS; (B) Time 2, 89 DAS; (C) Time 3, 131 DAS; and (D) Time 4, 160 DAS. Broken lines indicate the 95% confidence interval.

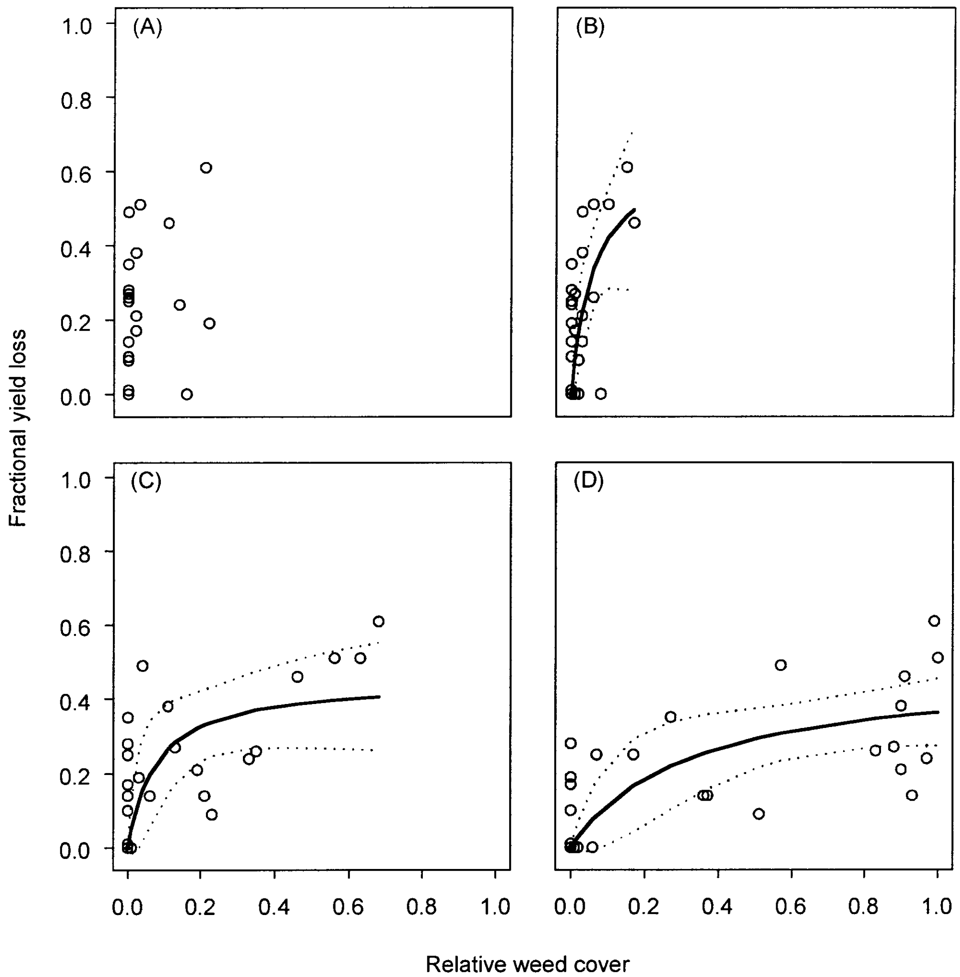

Fig. 6.8 Lotz *et al.* 2-parameter model fitted to the Tamworth relative cover data for 1997. Letters denote assessment times: (A) Time 1, 68 DAS; (B) Time 2, 89 DAS; (C) Time 3, 131 DAS; and (D) time 4, 160 DAS. Broken lines indicate the 95% confidence interval.

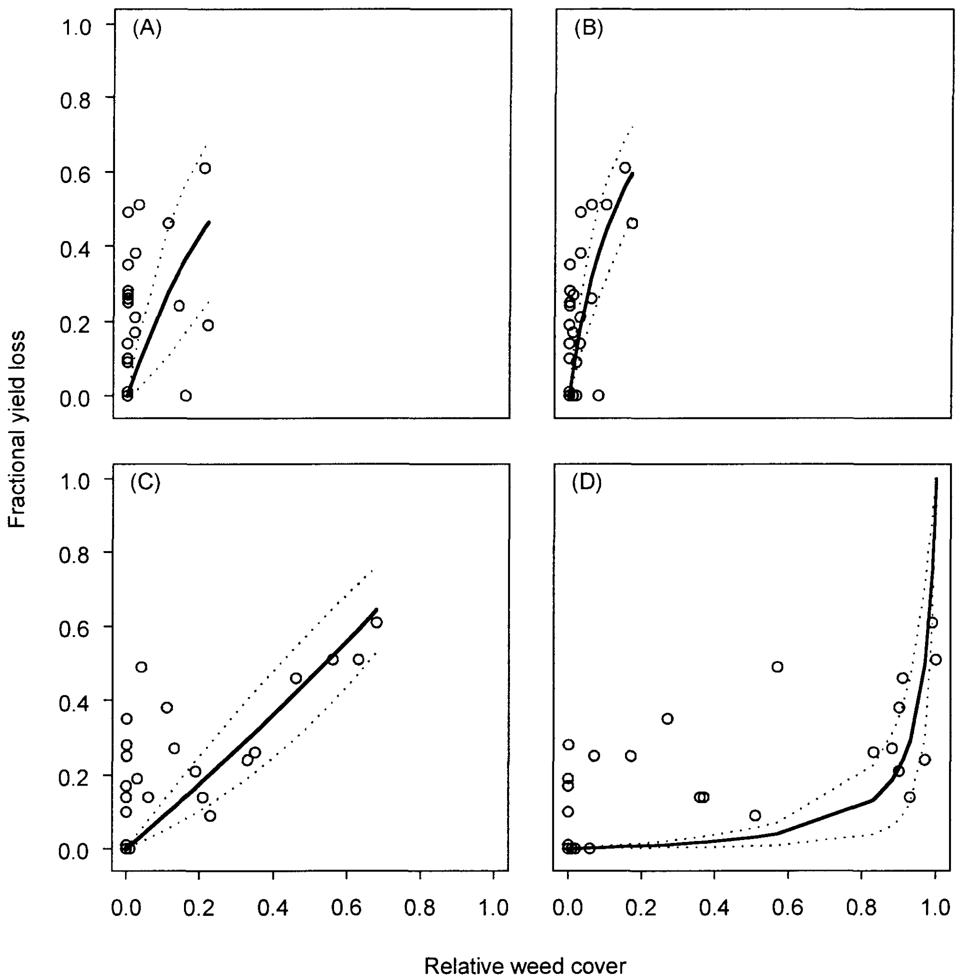

Fig. 6.7 Kropff and Spitters1-parameter model fitted to the Tamworth relative cover data for 1997. Letters denote assessment times: (A) Time 1, 68 DAS; (B) Time 2, 89 DAS; (C) Time 3, 131 DAS; and (D) Time 4, 160 DAS. Broken lines indicate the 95% confidence interval.

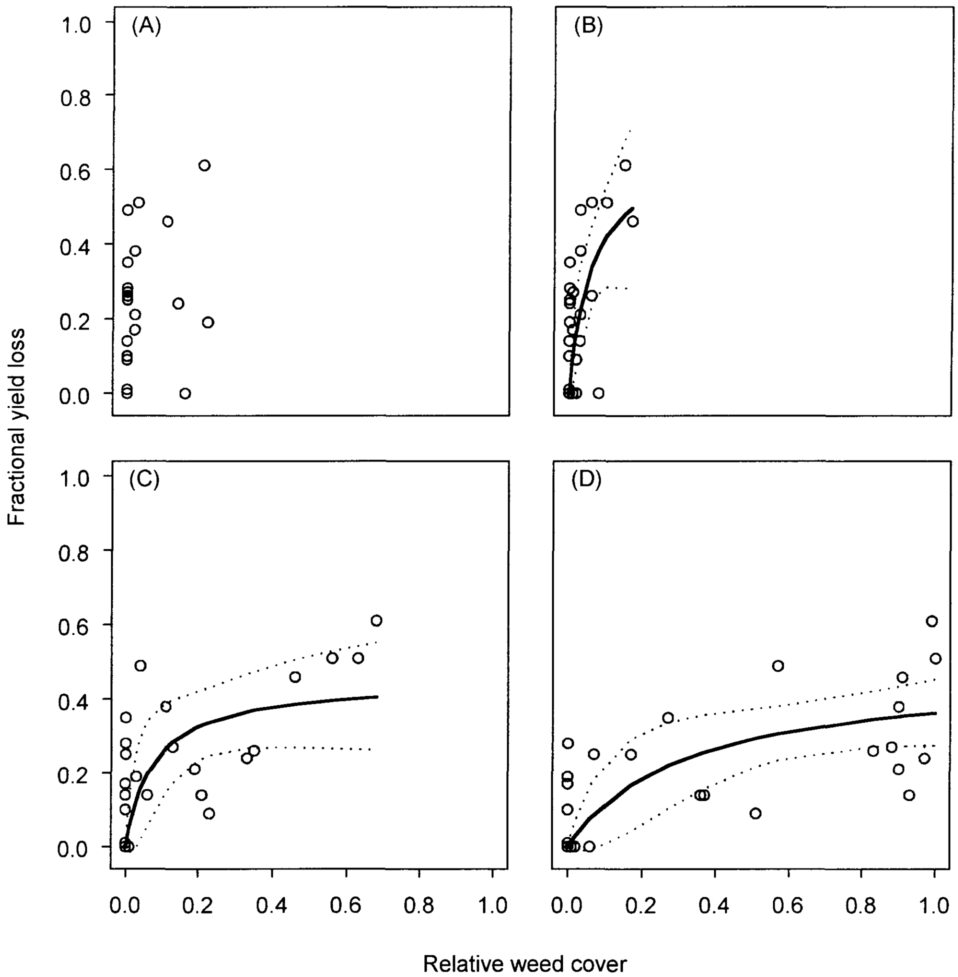

Fig. 6.8 Lotz *et al.* 2-parameter model fitted to the Tamworth relative cover data for 1997. Letters denote assessment times: (A) Time 1, 68 DAS; (B) Time 2, 89 DAS; (C) Time 3, 131 DAS; and (D) time 4, 160 DAS. Broken lines indicate the 95% confidence interval.

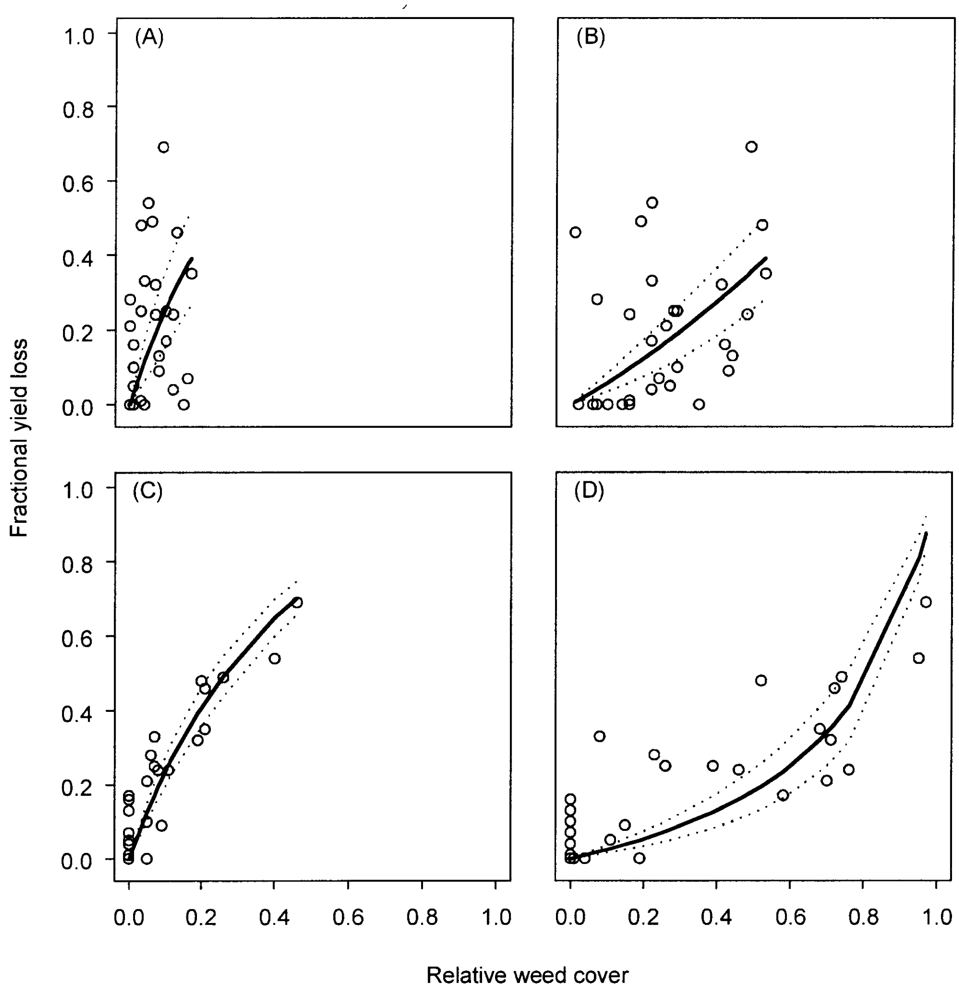

Fig. 6.9 Kropff and Spitters' 1-parameter model fitted to the Warialda relative cover data for 1997. Letters denote assessment times: (A) Time 1, 46 DAS; (B) Time 2, 75 DAS; (C) Time 3, 111 DAS; and (D) Time 4, 139 DAS. Broken lines indicate the 95% confidence interval.

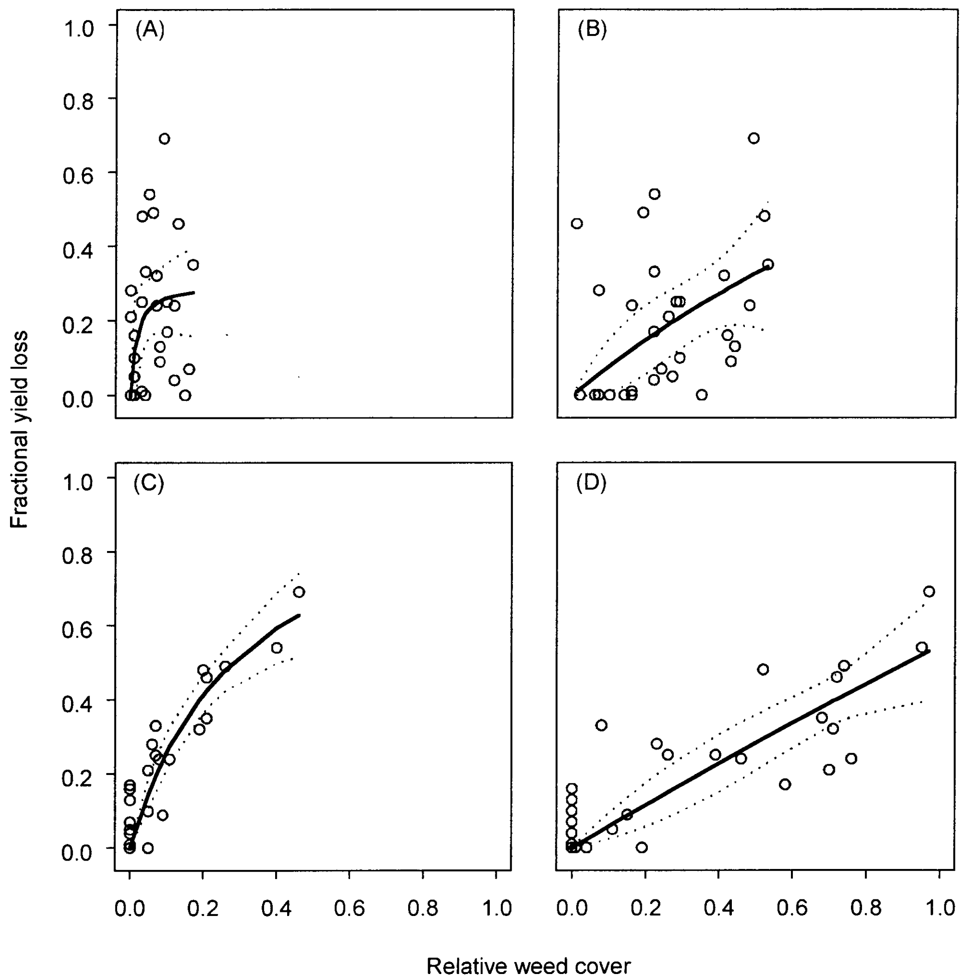

Fig. 6.10 Lotz *et al.* 2-parameter model fitted to the Warialda relative cover data for 1997. Letters denote assessment times: (A) Time 1, 46 DAS; (B) Time 2, 75 DAS; (C) Time 3, 111 DAS; and (D) Time 4, 139 DAS. Broken lines indicate the 95% confidence interval.

Table 6.2 Estimated values for parametric models used to predict 1997 chickpea yield loss due to infestations of turnip weed. Y_{wf} is weed-free yield g m^{-2}; q is damage coefficient for wild oat or turnip weed; m is asymptotic yield loss parameter. Standard errors are given in brackets.

Treatment		Time 1		Time 2		Time 3		Time 4	
1997	Y_{wf}	q	m	q	m	q	m	q	m
Tamworth	215.5	3.08	-	7.20	-	0.85	-	0.03	
1-parameter	(±25.8)	(±1.3)		(±1.9)		(±0.2)		(±0.01)	
Tamworth	215.5	-	-	11.4	0.62	6.9	0.41	1.5	0.36
2-parameter	(±25.8)			(±6.1)	(±0.3)	(±5.7)	(±0.08)	(±1.1)	(±0.05)
Warialda	304.7	3.2	-	0.57	-	2.76	-	0.22	0.54
1-parameter	(±19.8)	(±0.84)		(±0.13)		(±0.3)		(±0.04)	(±0.07)
Warialda	304.7	20.7	0.3	0.83	0.54	3.4	0.80	0.58	0.54
2-parameter	(±19.8)	(±22.1)	(±0.08)	(±0.52)	(±0.36)	(±0.64)	(±0.11)	(±0.20)	(±0.07)

The estimation of the relative damage coefficient q in 1997 showed a similar pattern to 1996 with the q values from the 2-parameter model (Equation 6.2) being larger than from the 1-parameter model (Equation 6.1). The parameter estimation of q in the 1-parameter model (Equation 6.1) had a smaller standard error (Table 6.2) and the confidence intervals around each of the curves were the narrowest (Figs. 6.7 and 6.9).

The non-parametric GAM curves were able to describe all eight sets of data (Figs 6.11 and 6.12), but a comparison of the predicted results for a series of cover measurements between the parametric and the non-parametric models, showed very little difference between the 1-parameter model and the GAM model for Times 1 and 2 (a relative cover of 0.3 produced fractional yield loss measurements of 0.76 (±0.05), 0.55 (±0.16), 0.88 (±0.17) for the 1- parameter, 2-parameter and GAM models, respectively, at Tamworth at Time 2 in 1997). The GAM and the 2-parameter models best described the later assessment times. (The predicted fractional yield losses for set relative cover values from each of the three models are listed in Appendix A).

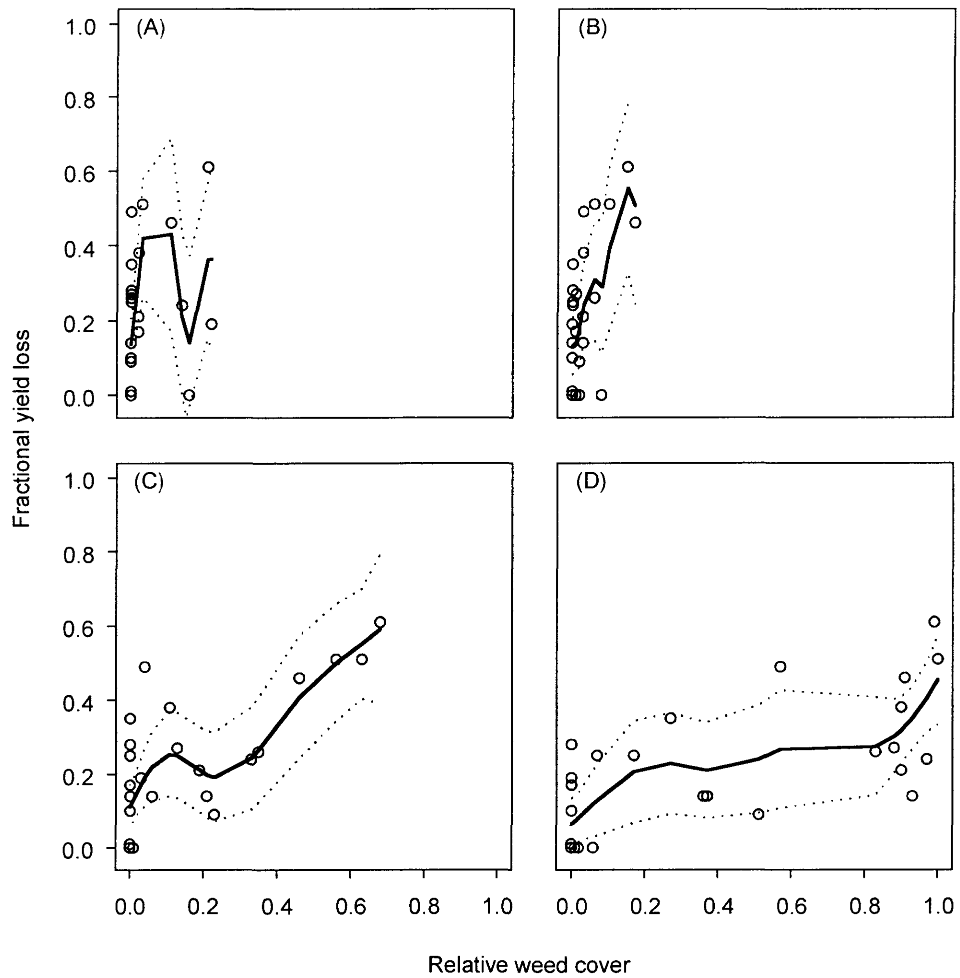

Fig. 6.11 Non-parametric generalised additive model (GAM) fitted to the Tamworth relative cover data for 1997. Letters denote assessment times: (A) 68 DAS; (B) 89 DAS; (C) 131 DAS; and (D) 160 DAS. Broken lines indicate the 95% confidence interval.

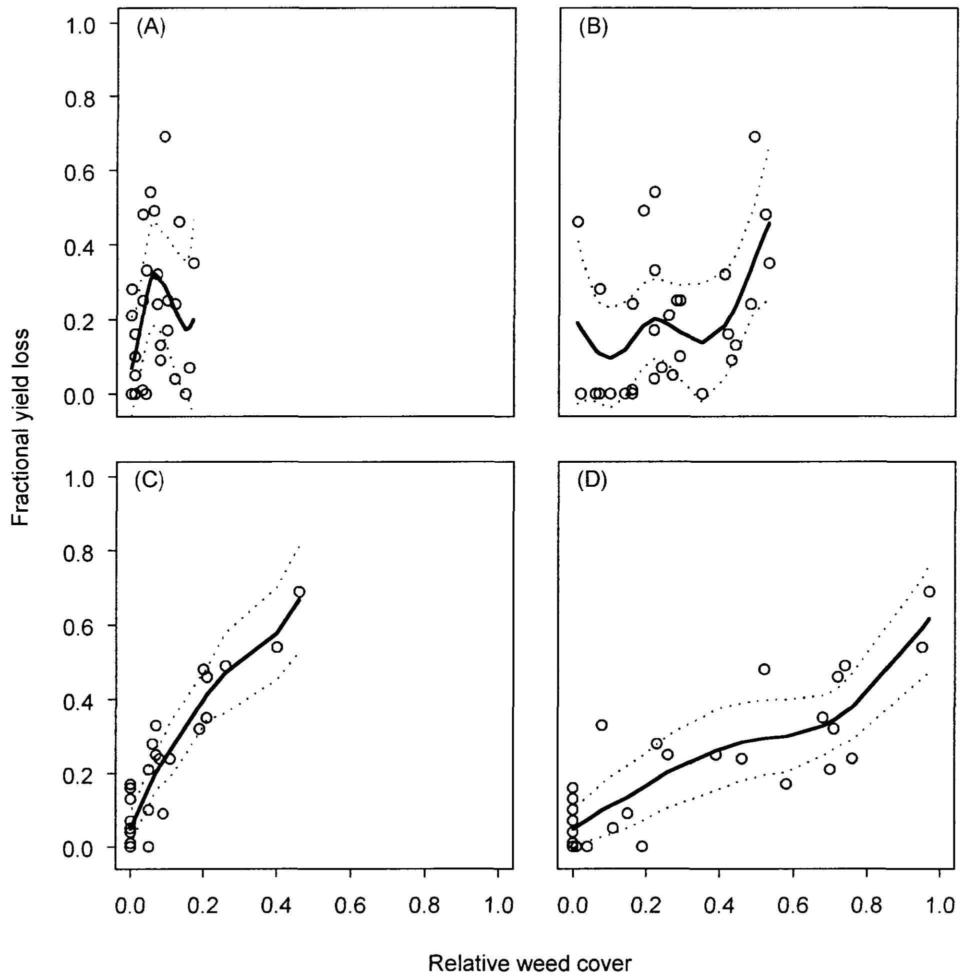

Fig. 6.12 Non-parametric generalised additive model (GAM) fitted to the Warialda relative cover data for 1997. Letters denote assessment times (A) 46 DAS, (B) 75 DAS, (C) 111 DAS and (D) 139 DAS. Broken lines show the 95% confidence interval.

6.4 Discussion

Kropff and Spitters' (1991) 1-parameter model (Equation 6.1) best accounted for the variation within the data collected during the early part of the season. This result is supported by the work of Van Acker *et al.* (1997) who found that the addition of the second parameter (m) for the prediction of yield loss in single weed situations was generally not warranted. The 1-parameter model adequately described the later season results, but as canopy cover approached 100%, the 2-parameter model or the GAM model best accounted for the variation.

The Time 1 data recorded in 1997 showed wide variation and a large standard error for all models. The slow initial growth rate of both the wild oat and turnip weed makes early predictions using relative cover difficult. The small size of the weeds (Plates 6.1, 6.3, 6.5, 6.6, 6.9 and 6.10) and the length of time these weeds remained small may reduce the accuracy of the early cover measurements. Turnip weed and wild oat had a growth phase in which they rapidly elongated, penetrated the chickpea canopy and flowered. Indications of this rapid development can be seen in Plates 6.5 to 6.12. In 1997, rapid weed growth occurred after 131 days at Tamworth and 111 days at Warialda. Similar development occurred in 1996 although insufficient observations were made to pinpoint the actual time.

The measurement of cover prior to, and during, this development phase gave the most accurate prediction of relative yield loss (Figs 6.7B and 6.9C); however, basing decisions on information collected later in the season than this has risk, since in many cases the damage to the crop will have already occurred. The 100% cover results increased the variability of the data. The 1-parameter model (Equation 6.1) was not suited to prediction at this time and the resulting curve was concave (Fig. 6.9D) The 2-parameter model (Equation 6.2) maintained a convex shape, but the fact that full canopy cover had been reached meant that these curves were unsuitable and the data was collected too late in the season for accurate forecasting of yield loss (Fig. 6.10D).

During the season, the leaf-area of the weeds and crop increased, and this improved the yield loss prediction. Examination of the model parameters (q) and (m) show that their standard errors improved (declined) over the four prediction times (Table 6.2). To determine when the onset of competition occurs and the critical time of weed control, specific experiments were completed and reported in Chapter 7.

In an attempt to reduce the time required for an accurate prediction, non-parametric regression was investigated. Parametric regression is used to describe many weed/crop interactions, because it is felt that the parameters can be described biologically and therefore ensure correct predictions based on simple biological theory (Cousens, 1985a, b). This approach can be questioned, because it imposes the model on the data, and does not let the data determine the shape of the model. It also assumes that an array of biological interactions can be summarised by one or two parameters.

Lutman (1992) found that in three experiments examining the weed density/yield loss relationship, linear regression, not the hyperbolic model gave the best fit for four crops. These results support the idea that, provided the biological principles of plant growth and competition are addressed, the curve that best describes the data should be selected. During this experiment generalised additive models were fitted to the data in an attempt to improve prediction from data collected early in the season. The data at Time 1 in both years were variable; however, the 1-parameter model (Equation 6.1) offered the best fit. At Time 2 (1996 and 1997) and Times 3 and 4 (1997), both the 1-parameter and the GAM models produced curves which gave similar predictions (Appendix A). The GAM curve responded to the variation in the data and did not create a smooth curve; however, even with these variations, the predictions of the curve were similar to the 1-parameter model, and the general trajectories of the curves were the same. This result showed that either curve could be used to describe and predict yield loss from cover measurements. Ideally, the best approach is to let the data derive the curve, but as suggested by Cousens (1985 a, 1985 b), this can lead to a lack of biological awareness, and biologically impossible assumptions being made. The 1-parameter model (Equation 6.1) described in this chapter fits the data as well as, and on occasions better than, the GAM model. However, the approach of fitting data to parametric curves has dangers. Non-parametric and parametric curves should be investigated and the curve that best describes the data and the biology of the system should be used. In this case the 1 parameter model was the most appropriate.

The results produced in this experiment using the relative cover measurements were variable, especially when compared with the density results of Chapter 5. The small initial size and the slow growth of the weeds during the early part of the season, followed by the rapid elongation and exponential growth later in the season, may explain this variation. This distinctive growing pattern may enable density measurements to be used also in the forecasting of yield loss. The long slow growth phase would allow the later growth flushes to catch up resulting in the plants from different flushes expanding at the same time. This limited growth followed by a synchronised expansion would cause crop and weed competition to occur at the same time for both early and later emerging weeds. If a suitable assessment time could be identified, the delayed onset of crop and weed competition, combined with the synchronised expansion of the plants, may improve the accuracy of density counts for the purpose of yield loss prediction. Density was not examined as a method of forecasting yield loss in this experiment, but future work may be enhanced by the inclusion of density for yield loss prediction.

The use of predictive modelling relies on the crop having a suitable predictive window (the time when accurate predictions can be made prior to the critical time of weed removal or onset of crop/weed competition). If predictions cannot be made during this time then there is little point in attempting to predict potential yield loss. In Chapter 7, the critical time of weed removal and the observed point of crop and weed competition for chickpea with wild oat and turnip weed will be identified. The combined knowledge of Chapter 7 and the work described in this Chapter will determine the value of predictive modelling for yield loss of chickpea crops competing with turnip weed or wild oat.