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Development and Validation of Avena Integrated Management (AIM): A Bioeconomic Decision Support Tool for Wild Oat Management in Australian Grain Production Systems

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Short Title: AIM: wild oat model

Nomenclature: Wild oat, *Avena fatua* L., *A. sterilis* ssp *ludoviciana* (Durieu) Gillet and Magne; sorghum, *Sorghum bicolor* (L.) Moench.; wheat, *Triticum aestivum* L.

Abstract

Wild oat is a long-standing weed problem in Australian grain cropping systems, potentially reducing the yield and quality of winter grain crops significantly. The effective management of wild oat requires an integrated approach of diverse control techniques that suit specific crops and cropping situations. This research aimed to construct and validate a bioeconomic model that enables the simulation and integration of weed control technologies for wild oat in grain production systems. The *Avena* spp. integrated management (AIM) model was developed with a simple interface to provide outputs of biological and economic data (crop yields, weed control costs, emerged weeds, weed seedbank, gross margins) on wild oat management data in a cropping rotation. Uniquely, the AIM was validated against real-world data on wild oat management in a wheat and sorghum cropping rotation, where the model was able to reproduce the patterns of wild oat population changes as influenced by weed control and agronomic practices. Correlation coefficients for 12 comparison scenarios ranged between 0.55 and 0.96. With accurate parameterization, AIM is thus able to make useful predictions on the effectiveness of individual and integrated weed management tactics for wild oat control in grain cropping systems.

Keywords: decision support systems, weed management, modeling

Introduction

The multiple *Avena* genotypes that occur as weeds of Australian cropping systems are collectively referred to as wild oat. The most prevalent species, *A. fatua* L. and *A. sterilis* ssp *ludoviciana* (Durieu) Gillet and Magne, are found throughout Australian grain production regions (Thurston and Phillipson 1976). There are differences in regional distributions, with *A. sterilis* ssp *ludoviciana* the dominant species in northern New South Wales and southern Queensland and *A. fatua* dominant across south-eastern and western Australian grains regions (Broster et al. 2022; Paterson 1976; Whalley and Burfitt 1972). These species, due to their morphological and biological similarities, are treated similarly in terms of predicted competition effects on crop yield and control methods (Bajwa et al. 2017; Mahajan and Chauhan 2021).

Locally adapted wild oat populations are found throughout Australian grain production systems, where they persist to interfere with planted crops annually. Endemic wild oat populations have similar life cycles and growth patterns to grain crops, particularly cereals, which ensures a high capacity for crop interference (Gunton et al. 2011). When established alongside crop plants, wild oat are highly competitive and, in the absence of effective control methods, can cause substantial yield reductions (Mahajan and Chauhan 2021; Martin et al. 1987). Wild oat seed is also a common contaminant in harvested grain, leading to potential downgrading and dockage at receiving points (Cousens and Mortimer 1995; Medd 1996b).

The challenge of managing wild oat populations in grain (cereal focussed) cropping systems is exacerbated by the lack of effective in-crop herbicides and compounded by the widespread occurrence of resistance to these herbicides. Over the last 20 years, the frequency of herbicide resistance in wild oat populations in Australian grain production systems has risen markedly (Broster et al. 2013; Owen and Powles 2016). Wild oat biotypes have been confirmed resistant to many of the herbicides registered for control of this weed, particularly the acetyl-coenzyme A carboxylase and acetolactate synthase inhibitors as well as flamprop-methyl (Ahmad-Hamdani et al. 2012). There has also been a recently confirmed case of glyphosate resistance in a wild oat population collected from a cropping field in SE Queensland (Chauhan 2022). The widespread evolution of resistance to these key herbicides has restricted the ability of growers to control this weed. With the low likelihood of new herbicide options, (Duke 2012; Peters and Strek 2018) the remaining effective herbicides must be carefully managed as part of a management program that includes a range of control tactics.

Integrated weed management (IWM) is the use of diverse weed control tactics that target multiple parts of weed life cycles and is not limited to recurrent use of a single technique (Zimdahl 2018). The need for IWM of wild oat has increased with the widespread occurrence of herbicide resistance (Broster et al. 2011), but the first calls for integrative approaches towards wild oat management in Australian cereal cropping pre-date the discovery of herbicide resistance in local biotypes and even the widespread use of herbicides (Paterson 1969; Selleck 1961). The focus on IMW then, as it is now, was on deposits to and outputs from the weed seedbank, and crop competitiveness. Integrating seed-specific tactics and other potential lifecycle interventions into a system of weed management requires skilled and knowledgeable decision-makers and the capacity to analyze which interventions are most useful and when they are best used in cropping rotations. Land managers seeking to integrate different herbicide and non-herbicide tactics need information, in biological and economic terms, that covers this broad range of choices effectively (Swanton et al. 2008).

With multiple control options and agronomic decisions, and complex interactions between all choices, there are numerous ways in which the crop-weed agroecological system can respond. Static, pre-determined rotations of tactics may not be sufficiently adjustable or applicable in such a complex system, regardless of how well-researched the individual tactics or rotations might be. Instead, growers and weed researchers have increasingly turned to computer-based decision support tools to assess specific scenarios through models that include and can reproduce some of the real system's complexity (González-Andújar 2020; Martin et al. 1997), i.e. IWM requires 'predictive' tools (Swanton et al. 2008). Early computational approaches were limited to attempts to model the economics of weed control either very generally, or in specific situations with little flexibility to predict effects in different situations (Cousens 1985; Pannell and Gill 1994).

Later computational models were designed to be more adjustable; to apply generic rules to a problem space of an increasing number of possible permutations and scenarios. Efforts are often also made to include more approachable user interfaces. Complex, highly adaptable models of crop and weed growth are now available—notably, the Agricultural Production Systems Simulator (APSIM) and the Weed Seed Wizard. However, these highly adaptable models are also complicated to use accurately and generally are restricted to biological predictions such as seed bank density or standing weed population size (Holzworth et al. 2014; Pannell et al. 2004; Peltzer et al. 2012). The Ryegrass Integrated Management (RIM) tool is a long-standing and successful model for both the biological and economic management of a single dominant weed problem: annual ryegrass (*Lolium rigidum*) in Australian grain cropping (Lacoste and Powles 2015). Arguably, one of the reasons RIM is successful is that although it relies on generic ecological functions, scenario modeling is restricted to a single cropping system and a single weed problem. It models a wide range of possible scenarios within Australian winter cereal crops with an annual ryegrass weed problem. To adapt its successful approach, teams of weed researchers have used RIM as a basis for the construction of new models (with varying levels of alteration) that deal with other weeds, different crops, and in alternate environments (Lindsay et al. 2017; Torra and Monjardino 2020). Rather than seeking to add interface complexity to the original RIM, these new versions retain the strength inherent in restricting the modeled problem to a manageable size while dealing with different problem spaces. The programming burden through RIM's Excel- and VBA-based construction is relatively low, and the established interface requires (depending on the cropping system and the approach taken) modest adjustment from RIM to other versions. Additionally, commonly available field data focus on single weed species in specific systems. Models (such as AIM and others derived from RIM) built for a specific problem space can readily use this focussed field trial data for verification and validation. Therefore, the aims of this study were I) development of a bioeconomic model for the IWM of wild oat in grain production systems and 2) validation of the developed model against a wild oat management dataset collected from a long-term rotation field trial.

Materials and Methods

Model Description and Specifications

To provide the capacity to test and model IWM strategies for wild oat, the bioeconomic model Avena Integrated Management (AIM) was developed and validated against a previously published dataset. Using the framework of RIM (Lacoste and Powles 2014, 2015), AIM was developed based on published data on the biological attributes (parameters) of wild oats as occurring in cropping systems. The developed model contains the capacity for simple simulations of wild oat populations and production economics for individual crop and pasture phases, as well as the more detailed in-crop weed management scenarios in 10-year rotations. A diagrammatic view of information types and flows inside

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AIM shows user-defined and fixed parameters for the farming environment, contributing to the development of a scenario (Figure 1).

The AIM model allows the creation of a crop production scenario with user-defined yields, prices, and weed control efficacies. The interface allows the user a high level of freedom in defining which tactics are available and what they cost but restricts how often and when these tactics can be applied in ways that fit with wild oat biology and cropping system parameters. AIM can be used to test the effects of changes in crop prices or input costs, the introduction of new herbicides or other tactics, crop rotation adjustments, planting timing, and density, or combinations of these factors. It is also particularly suited to testing the biological and economic results of changes in herbicide (or other tactic) efficacy and, in this way, can be used to develop and test strategies for dealing with the onset of herbicide resistance at some point in the simulation. However, there is no mechanism in AIM for tracking the evolution of herbicide resistance. Rather, resistant populations can be simulated by changing from a standard efficacy version to a low efficacy version of the same herbicide, at some point in the simulation.

Having defined the cropping system, the user can then develop one or more scenarios, in which decisions are made about which crops appear when in the rotation (of up to ten years), and which control tactics appear in each growing season. As users make changes to the active scenario, biological and economic outcomes are estimated in real time and displayed in numerical and graphical formats. More detailed outputs and comparisons between pairs of scenarios can then be viewed as a third step in the simulation process.

The developed AIM model has predictive capability according to a predefined scenario context:

1. Available crops are wheat, chickpea, canola, faba bean, another legume, sorghum, winter fallow, and pasture (sheep grazing). Each year, the simulated field must be either in crop, fallow, or pasture.
2. Environmental parameters fit an average-to-good year in the northern Australian grain region, with fixed weed-free maximum yield potentials for each crop.

3. The model produces predictions for 10 years, although a simulation may be shorter if desired.
4. Weed control treatments are applied in cohorts (weed control timings, see Table 1). The numbers of different types of control tactics in each cohort are fixed due to the interface layout, though the names, efficacies, and costs of each entry in the list are user-defined.
5. Up to one application of each timing per year is available, except for postemergence (POST) applications, of which there can be up to three.

The user assigns each weed control tactic an efficacy from 0 to 1, where 0 = no effect and 1 = complete weed population control, with separate values allowed in each crop type, fallow, or pasture. Accordingly, weed seedling reduction in each period is a cumulative factor of all weed control efficacies applied in that period. Efficacy due to planting machinery and harvest methods are defined on the ‘More Options’ page. Allowing user-defined efficacies ensures accurate model inputs for specific weed populations based on past experience or specific information.

The user interface allows up to four different environments to be saved, plus a conserved default (at the DEFINE step) and up to six different strategies based on any saved environments (at the BUILD step). Two different scenarios at a time can be compared graphically and as numerical outputs (Figure 2).

Wild oat lifecycle

AIM’s functioning as a predictive decision-support tool relies on concurrent simulation of the weed lifecycle and a yield effect competition model. The lifecycle of wild oat is modeled as a set of equations converted into Excel IF statements. Excel’s automatic user interface behavior causes every change of parameter values or other choices to be reflected immediately in all other cells in the model.

The annual lifecycle of wild oat is separated into seven periods of unequal length. The length of each period is determined agronomically—i.e., a new period begins when a new type or phase of weed management is available or appropriate. The model may test germination, or seedling survival or both in each period except for the summer period, depending on the parameters entered.

The periods are:

1. End of summer (i.e., prior to growing season)
2. First chance for planting (beginning of growing season)
3. 10 days after beginning of growing season (early seasonal rains)
4. 20 days after beginning of growing season
5. Post-emergence in-crop spraying opportunity
6. Onset of spring (pre-harvest)
7. Over summer

By default, germination of cohorts occurs in the first four periods, but this can be adjusted for specific use cases. While effects on seedbank input at harvest (harvest weed seed control) are available, this is treated as a discrete event rather than a seasonal period and does not affect germination or existing plants.

Germination is calculated as:

$$G_i = p_i(r_i.S_{i-1})\#(1)$$

where G_i is the size of the germinating cohort in period I, p is the total effect of pre-emergent herbicides applied in period I ($0 \leq p \leq 1$), r_i is a germination factor for period I, and S_{i-1} is the seedbank density at the end of the previous period. (The derivation of parameters in Equations 1-6 is described in various references in Table 1.)

Total herbicide effects h on the population of plants T_i are calculated together:

$$h_i = h_{i1}.h_{i2} \ldots h_{in}\#(2)$$

where $h_{i1,2 \ldots n}$ are individual knockdown herbicide effects (with user-defined values for each herbicide) applied to seedlings during period i.

Accordingly, cohorts of plants T at the end of each period are calculated as:

$$T_i = h_i.T_{i-1} + G_i\#(3)$$

Wild oat seed set is calculated in a single event in spring.

$$SS = \frac{SS_{max}}{c_w.T + c_c.D} * \frac{E.s}{T} \#(4)$$

where SS is the number of seeds produced m^{-2}, SS_{max} is the estimated maximum seed production m^{-2} in a pure stand of wild oat, *cw* and *cc* are intra- and inter-specific competition factors, *D* is the number of crop plants m^{-2}, *s* is a discounting factor for seed reduction due to non-lethal but damaging herbicide applications, and *E* represents healthy weed equivalents, wherein seed production of each cohort is affected by emergence timing of the cohort relative to the crop. *E* is calculated dynamically in the model per cohort, and can be generalised as:

$$E = \frac{1}{n}\sum_{i=1}^{n} k_i T_i$$

where the discounting factor *k* for each cohort is returned from a set of simple tables, with values ranging from 0 (early emerging weeds) to 98% (weeds emerging after POST herbicide timing in early-sown crops).

At maturity, seeds enter the seedbank, reduced by any harvest weed seed control factors (*HW*) chosen by the user, and the total seedbank is then reduced by a factor for mortality over summer (*MS*):

$$S_i = \big(S_{i-1} + (SS.HW)\big)MS \qquad (5)$$

AIM alters germination percentages early in the season when pre-planting preparation includes tillage (either full or shallow disturbance). The effect of deep burial of weed seeds by cultivation (e.g. plowing) is modeled simply by killing a proportion of the current seedbank, with the proportion dependent on the number of years since burial. The proportion can be altered in the underlying code if specific situations (such as net exhumation of buried seeds) need to be simulated.

Yield calculation

Wild oat effect on crop yield is determined with a rectangular hyperbolic function adjusted from the standard model described by Cousens (1985) and used in many weed-crop interaction models since. Variables in Equation 6 are as described by Pannell et al. (2004), with parameters either unchanged (for crops described by Pannell et al. (2004)) or estimated (for other crops that appear in AIM). Adjustments by Pannell et al. (2004) allow for the relationship between the actual crop density and a standard crop density (for which competition factors are valid):

$$YL = \left(\frac{D_s + c_b}{D_s}\right) * \left(\frac{D}{c_b + D + c_w T}\right) * YL_{max} + (1 - YL_{max})\#(6)$$

where YL is percent yield reduction, YL_{max} is an estimated maximum percentage yield loss from wild oat in the given environment, c_b is a background intraspecific competition factor, D_s is a standard crop density, and other factors are as described above.

Economic estimates for net present value in each year are determined from the post-weed yield multiplied by the crop value per tonne, minus all cost factors included in the model: weed control treatment and application costs are treated individually, and the model responds according to the decisions included in each scenario. Conversely, fertilizer and other input costs are generalized as simple estimates for each crop type. Each of these economic variables is user-defined and is static throughout the simulation.

Biological parameter values

Key wild oat biological parameters are included in the model (Table 2) and these can be changed by the user, but only by going beyond the user interface into the underlying model spreadsheets. The model’s Start page briefly describes the effects and risks of unlocking the user interface to edit biological parameters.

There are over 700 individual parameters included in AIM, relating to effects and characteristics such as crop stand densities, seed weights, and establishment rates; small yield benefits and penalties from various actions; germination differences in crop vs pasture; and progeny reductions for late emergence. As wild oats are a very widespread weed in

Australian cropping, they are subject to substantial variation in growing conditions and intrinsic biotype variations. A high degree of parameterization allows AIM to respond to this variability in detailed ways, provided data are available to guide the process. Interested users can access a set of standard parameters on the model's Profile, Strategy, Prices, and Options pages. The large number of hidden parameters can be viewed and adjusted by unlocking the user interface and viewing the 15 tables of related parameter sets on the Calcs page and the right-hand side of the Options page.

Validation and testing

To test AIM's capacity to produce relevant outputs from region-specific farming system inputs, we reproduced a range of scenarios from a published study (Martin and Felton 1993). This study assessed wild oat infestation dynamics over four years (1983-1986) in continuous wheat and wheat-sorghum rotations with reduced tillage operations in summer fallows and optional use of in-crop selective wild oat herbicides, either PRE (triallate) or POST, applied at tillering (flamprop-methyl). There is sufficient published detail on the timing of operations to reconstruct each experimental treatment (with some assumptions, adjustments, and additions) in AIM (Table 3).

A full set of permutations of the experimental parameters (Table 3) by Martin and Felton (1993) were reproduced in AIM. Thus, 'WW CF Nil H' refers to plots (in the experiment) or a scenario (in AIM) with wheat each winter and no summer cropping, cultivation for weed management in summer fallows, and no in-crop herbicides. Each scenario runs for four years, as was the case for the field evaluation. Continuous wheat scenarios allow harvesting of four crops. The wheat-sorghum rotation allows harvesting of three crops: two wheat crops in years one and four, and one sorghum crop that is grown in the summer between winter fallows in years two and three, reported in the year three column.

The experimental data were produced under field conditions, and there were several events and anomalies that reportedly impacted the field experiments. Summer of the third year was unusually dry, resulting in the failure of sorghum crops in that year and presumably also affected wild oat germination, growth, and seed production. Dry conditions during winter in the third and fourth years resulted in reduced efficacy of in-crop herbicides. Martin and Felton (1993) noted that there was zero seed production of wild oat in winter fallows in the WS rotation, due to a briefly outlined glyphosate-centric winter fallow weed management strategy. Wheat planting was exceptionally late in the second year (24 August, 79 days later than the average wheat planting date in the other three years), potentially affecting weed management.

No weed control efficacy estimates were given for either the herbicide or soil disturbance tactics, so estimates were made in the process of setting up the scenario environment. A screenshot of the DEFINE stage illustrates the environment (Figure 3. Note, however, that many of the tactics and crops referenced in the DEFINE screen were not used in the scenarios detailed here).

Scenarios were built in AIM's BUILD page. Each consisted of a four-year rotation of either continuous wheat, or wheat-winter fallow-sorghum-winter fallow-wheat (Figure 4). The scenarios were as close as possible to the operations described in Martin and Felton (1993).

Based on the weed control treatments used in Martin and Felton (1993) 12 scenarios were constructed in AIM's BUILD user interface, using consistent entries for each of the three variable factors – crop rotation, fallow type, and in-crop herbicide (Table 3).

Data analysis

To validate AIM effectively, a robust quantitative comparison between predicted and observed data is required. As the model results from AIM are non-linear and highly multivariate, a distance correlation method was used to compare AIM outputs and Martin and Felton (1993) observations, within each scenario. The distance correlation (*dCor*) metric was developed (Székely et al. 2007) to solve the problem of comparing between observations and predictions for non-linear models—since familiar R^2 methods based on Pearson's coefficient of correlation account only for linear comparisons (Kvalseth 1985).

The implementation of Székely's *dCor* in the R package *energy* was used in the present work. In *energy*, *dCor* is defined as:

$$dCor = \sqrt{\frac{V^2(X,Y)}{\sqrt{V^2(X)V^2(Y)}}} \#(7)$$

where (X,Y) denotes the scalar product of the values in X and Y, and X and Y are two vectors being compared; that is, a set of observed values and a corresponding set of predicted values from a model. *V* (the distance covariance) is defined as:

$$dCov = \sqrt{\frac{1}{n^2}\sum\nolimits_{k,l=1}^{n} A_{kl}B_{kl}} \ \#(8)$$

where A_{kl} and B_{kl} are functions summing distances between values in the vectors *X* and *Y*:

$$A_{kl} = a_{kl-\ \bar{a}_{k.} - \bar{a}_{.l} + \bar{a}_{..}} \#(9)$$

B_{kl} is similarly defined for values in b. Here,

$$a_{kl= \|x_k - x_l\|} \#(10)$$

that is, a function describing the distances between the values in the vector X, and b_{kl} is similarly defined for Y-vector values.

The resulting value for *dCor* lies between 0 and 1, where *dCor=0* indicates complete independence between X and Y.

Results and Discussion

Validation – weed density

AIM was largely able to reproduce the annual wild oat population patterns as influenced by various crop production conditions, including different rotations (continuous wheat and wheat-sorghum) and herbicide strategies. Across all crop rotations AIM outputs of wild oat population densities at maturity (seed production) were consistent with the results from the comparative field study of Martin and Felton (1993) (Figure 5). In most cases, there were high (> 0.8) distance correlation values (dCor) for weed count comparisons between the field collected data and AIM's predictions. Qualitative patterns of change in weed numbers were similar between the field, and the model-predicted data and the greater efficacy of both in-crop herbicide treatments compared to nil herbicide were also reproduced.

Some scenarios were less closely reproduced than others; in particular, plant density values were most widely divergent between the model and the field data for some cultivated fallow/continuous wheat scenarios (Figure 5). AIM overestimated the combined effectiveness of in-crop herbicide and fallow cultivation in those scenarios, particularly in the final year, compared to the results of Martin and Felton (1993). In other cases where the model less closely reproduced year 4 results, such as WW NT Tri and WW NT NilH, variation between treatments in the Martin and Felton (1993) data for that year is substantial, and they refer to reduced or poor weed control in both unseasonably dry years 3 and 4. Apart from these variable years, population trends and general annual population sizes were well reproduced.

Long-term field studies typically do not collect or publish sufficiently detailed and comprehensive data to enable the complete validation of all control strategies included in a weed population dynamics model. With no specific weed emergence data collected through the growing season by Martin and Felton (1993) it is possible that the AIM predicted effects of tillage on both weed emergence and direct weed control at either end of the summer fallow period may have differed from the real situation in any given year. Also, tactic timings described in the paper were, in some cases, difficult to reproduce exactly in AIM, especially in the third year of continuous wheat, where planting was 80 days later than usual. The relative timings of crop emergence, weed cohort emergence, and weed control application are critically important in AIM's end-of-season results (as in real situations). Without estimates of cohort emergence timings and sizes in the real data, some years may be poorly matched between the model and the experiment. Fitting exercises with efficacy values and/or tactic timings could be undertaken to simulate this situation better. Low- and high-efficacy versions of the same herbicide tactics could be developed to attempt to fit the effects of poor years, which could be manipulated to more closely match years 3 and 4 of the triallate and flamprop-methyl data in Martin and Felton (1993). This approach has been used in attempts to model herbicide resistance evolution in a similar bioeconomic model (Thornby and Werth 2015).

Many of the most important biological parameters of a weed population dynamics model are also quite mutable in real situations, depending on environmental factors and differences in crop and weed biotypes from the default assumptions (Lacoste and Powles

2015). Maximum crop yield reductions due to wild oat competition, for example, vary substantially between studies (Cudney et al. 1991; Mahajan and Chauhan 2021). Similarly, maximum wild oat seed production estimates vary from 10,000 to almost 30,000 m^{-2} (Medd 1996a; Xue and Stougaard 2002). These differences presumably stem from differences in biotype crop parameters and environmental factors, as well as artifacts of measurement. Consequently, AIM and similar bioeconomic models (Lacoste and Powles 2014, 2015) develop parameter estimates based on data from published and unpublished sources, which can then be weighted according to local data and expert advice for specific location scenarios. As a result, some variation between AIM’s predictions and the real results of Martin and Felton (1993) or any other dataset is to be expected.

Despite variations in the level of correlation between AIM and the data of Martin and Felton (1993), there are good reasons to accept AIM's outputs as valid even where they differ in magnitude from variable real data. AIM is a deterministic model, so a single set of input values will always return the same output. In scenario terms, the background biotic and abiotic conditions for plant growth (weather, pest, disease pressure, etc.) are identical. As demonstrated in our validation exercise, real-world data often does not agree precisely with model outputs due to the inherent variability of real agronomic situations, increasing the challenge of demonstrating model veracity. The data of Martin and Felton (1993), for example, included a loss of herbicide efficacy (and possibly other, more random effects) that may help explain increases in weed counts in that year (Figure 5), but AIM applies the same weed tactic efficacies each time a tactic is used. Accordingly, the model provides a stable estimate of the ongoing effect of those tactics, which is not entirely analogous to the real situation but is nevertheless useful. In particular, for use in learning to control wild oats in northern Australia (or similar locations), generalized, deterministic outcomes such as AIMs are arguably more useful than more variable and stochastic ones.

Model outputs – weed seedbank dynamics

Estimates of the weed seedbank at the beginning, during, and end of the wild oat growing season allow AIM users to track the influences of cropping systems and weed management practices on seedbank dynamics within and across seasons. The importance of the soil seedbank in the persistence and problematic nature of annual weed populations infesting cropping systems is well-known (Buhler et al. 1997; Forcella 1984; Warr et al. 1993). Thus, the size of a viable weed seedbank is a predictor of potential in-crop weed infestations; however, accurate seedbank measurement is difficult and time-consuming. A substantial amount of research has explored wild oat seedbanks (Banting 1962; Hsiao and Quick 1983; Medd 1996), providing ample data supporting robust predictions of seedbank responses. Weed managers will highly value the ability to accurately simulate the impact of individual weed control treatments and weed management programs on the wild oat seedbank.

Poor seedbank control is seen in all scenarios where no in-crop herbicide is used in wheat years (Figure 6: Nil H curves, years 1 and 4 in WS CF and WS NT, and all years in WW CF and WW NT). Notably, the reversion to wheat after two years of sorghum led to immediate increases in seedbank density in nil-herbicide treatments (Fig 6: Nil H curves, WS CF and WS NT, year 4). The magnitude of change in the post-sorghum year was much greater under no-till fallow conditions, but even a moderate, consistent increase in seedbank density is of concern for long-term cropping sustainability. Where in-crop herbicides and summer cultivations were included (leading to a level of seed burial below germination depth), there was a decline in seedbank size over the four years of the simulation (Figure 6, all remaining curves). In some scenarios, however, seedbanks in years 3-4 were still large enough to lead to rapid loss of control of the population if the strategy or effectiveness of a tactic were to change: in continuous wheat with cultivated fallows and triallate in-crop (Fig 6: WW CF, triallate curve), for example, there were 25 seeds m^{-2} remaining after three years. In wheat-sorghum with triallate used in wheat and no cultivation in summer (Fig 6: WS NT, triallate curve), seedbank density was 28 seed m^{-2} in year 4. In continuous wheat without summer cultivation, seedbank density never dropped below 40 seed m^{-2} with the best-performing in-crop herbicide (Fig 6: WW NT, flamprop-methyl). In the same rotation with triallate, seedbanks were around 200-300 seed m^{-2} in years 3-4. These figures are large enough to lead to rapid increases in weed population in the absence of continued good control of emerged weeds—for comparison, the seedbank density before weed emergence in year 1 was 97 seed m^{-2} in all scenarios. These predictions warn users that although weed seedbank densities remained manageable with consistently targeted herbicide strategies (Figure 6, triallate and flamprop-methyl curves), future success could be jeopardised quickly by reductions in in-crop weed control.

Model outputs - gross margins

One of the key intentions behind AIM is to supply users with economic return data along with biological predictions. It does this in the form of gross receipts, weed control and other costs, and gross margins. As costs are merely a report of the cumulative value of the user's own inputs, gross margins are the most appropriate measure for comparing economic performance between scenarios. In the continuous wheat scenarios (Figure 7, WW-CF, WW-NT, bottom row), the no-till fallow gross margins were reduced in each successive year, most notably in the nil herbicide treatment. The triallate treatment's gross margin is predicted to reduce most slowly. Where cultivation was used in summer fallows, AIM predicts a stable gross margin after the first year, with differences in final value attributable to differences in weed management cost and phytotoxicity-associated yield penalties.

In the wheat-sorghum scenarios, the high-value sorghum crop is largely unaffected by herbicide tactics, although there is a notable (\$72 ha^{-1}) difference between the economic loss incurred in cultivation versus herbicide-centric summer fallows due to estimated environmental costs of cultivation and additional machinery costs. Wheat gross margins in the final year of the wheat-sorghum rotation were higher in 1986 than in 1983, at over \$400 ha^{-1}, in contrast to the consistent reduction in wheat values from 1983 to 1986 in the continuous wheat scenarios, which in 1986 varied from less than \$100 ha^{-1} to around \$350 ha^{-1}.

Gross margin estimates are useful for growers and advisers to see directly the accumulated effect of the trade-off between weed pressure and control tactic costs, plus other minor cost effects. While weed seed bank density and emerging plant numbers are important outputs and are the key drivers of long-term sustainability, economic margins provide another dimension of decision support. In the case of the scenarios reproduced from Martin and Felton (1993), gross margins varied relatively little between treatments where weed control was robust, and decisions could then be made effectively on differences in herbicide input costs. Where weed control was inadequate, such as in the no-till, nil herbicide treatment, the declining gross margin value year-on-year underscores the need to seek a different strategy, especially when extrapolating beyond these short four-year simulations. The economic estimates in this paper were based on 2019 costs and prices. Gross margin values reflect and respond to changes in both cropping and economic conditions, and in years where input costs and crop prices vary disproportionately, the cost and value of killing each weed may produce qualitatively different results from the ones shown here (Figure 7).

Practical Implications

AIM has been developed as a decision support tool to assist in the development of weed management programs for wild oats in grain production systems. It is a user-friendly decision support tool capable of predicting with reasonable accuracy the biological and economic effects of implementing weed control strategies on wild oat populations in grains cropping-based rotations. AIM has the potential to provide useful biological and economic feedback to growers, agronomists, and the weed control industry wanting to test potential control strategies for long term effects on wild oat populations in prescribed cropping systems. Users gain substantial benefit from being able to simultaneously compare differences in biological and economic model feedback on specific or combined strategies, and with a wide degree of choice over simulation parameters such as tactic efficacy, crop frequency, and input costs.

The validation process undertaken here demonstrates the practical applicability of models to weed management questions. It also illustrates the challenges of performing accurate validations using previously published datasets, which often do not consider all the key variables of a specific model. One alternative is to collect new datasets specifically for validation, which requires a certain amount of resourcing and planning, but is a potentially valuable approach for future model development efforts.

AIM has been developed using parameter data from Australian cropping systems; however, the opportunity to use similar data from other systems ensures that this model can be relevant in all cropping systems where wild oats are problematic. The use of AIM in other regions/production areas may require collecting relevant data through specific research activities. This highlights an additional role of AIM in identifying research needs that lead to the effective management of wild oat populations in diverse production systems. Conversion to suit other weeds and/or production systems is feasible but would be a larger task requiring substantial reprogramming and parameterization.

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Competing interests

The authors declare none.

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Table 1. Types and frequencies of weed control tactics available for use in an AIM-developed scenario for the management of wild oat in an Australian cropping scenario.

Weed control tactic type	Tactic choices	Max applications per year
Pre-planting knockdown	2	1
Pre-planting double knock†	1	1
Pre-emergence herbicide	5	1
Post-emergence	5	3
Pre-harvest crop-topping*	2	1
Harvest weed seed control	2	1

†The double knock is a common Australian weed management tactic in which two different knockdown/burndown herbicides are used approximately 3-10 days apart on the same cohort of weeds, to reduce resistance evolution and increase efficacy. Planting operations (pre-planting soil preparation and planting method) may also have seedling kill effects occurring between double knock and PRE applications, if seedlings are present. These cannot be modified in the user interface, but can be changed in the model's back end

*Several default harvest alternative operations with effects on weed numbers are also predefined and available pre-harvest, such as green/brown manuring, hay, and silage.

Table 2. Biological parameters for wild oat populations, default values, and reference sources used in AIM model development.

Parameter	Crop/Period	Value	Origin of estimate
Maximum seed production (SS_{max})	All	20,000 seeds m^{-2}	(Medd, 1996a; Xue and Stougaard, 2002); unpublished data
Seed mortality mid-season	All	20%	Adjusted from RIM
Seed mortality between seasons	All	50%	(Banting, 1962; Hsiao and Quick, 1983; Mickelson and Grey, 2006)
Maximum yield penalty	Wheat	70%	(Cudney et al., 1991; Felton et al., 2004; Mahajan and Chauhan, 2021; O’Donovan et al., 1985)
	Fabas	70%	(Felton et al., 2004)
	Canola	80%	(Felton et al., 2004; Zand and Beckie, 2002)
	Chickpeas	80%	(Whish et al., 2002)
	Other legume	95%	(Manuchehri et al., 2020)
Wild oat competitiveness vs crop (*cc*)	Wheat	0.38	(Cousens et al., 1991; O’Donovan et al., 1985)
	Fabas	0.40	Adjusted estimate from RIM
	Canola	0.33	(Daugovish et al., 2003)
	Chickpeas	0.40	Adjusted estimate from RIM
	Other legume	0.40	Adjusted estimate from RIM
Crop competitiveness vs wild oat (*cw*) (Adapted from Pannell et al. 2004)	Wheat	25	Adjusted estimate from RIM; (O’Donovan et al., 1985)
	Fabas	20	Adjusted from RIM
	Canola	23	(Daugovish et al., 2003; Zand and Beckie, 2002)
	Chickpeas	19	Adjusted estimate from RIM
	Other legume	19	Adjusted estimate from RIM
In-crop emergence (*r*)*	First chance for planting	3%	(Banting, 1962; Mickelson and Grey, 2006)
	10 days after beginning of season	30%	
	20 days after beginning of season	23%	
	Prior to in-crop spraying	18%	
	After in-crop spray opportunities	6%	
Estimated maximum germination	All	60%	(Cousens et al., 1991)

*Sample values for minimum-tillage planting, representing percent of current seedbank at beginning of each period. Other versions for various levels of cultivation are present in the model, but not shown.

Table 3. Twelve wild oat management scenarios comprising crop rotation, fallow treatments, and in-crop herbicides used in the field trial conducted at Tamworth New South Wales (1983 to 1986) by Martin and Felton (1993). Wild oat data from this study was used for AIM validation analysis.

Rotation	Treatment name	Pre-plant weed control	Fallow weed control treatments	In-crop herbicides in wheat
Conventional: continuous wheat[1]	WW CF Flam	Tillage	Tillage + glyphosate	Flamprop-methyl POST
"	WW CF Tri	"	"	Triallate PRE
"	WW CF Nil	"	"	Nil
No-till: continuous wheat	WW NT Flam	Glyphosate	Glyphosate	Flamprop-methyl POST
"	WW NT Tri	"	"	Triallate PRE
"	WW NT Nil	"	"	Nil
Conventional: Wheat, Winter fallow[2], Sorghum[3], Winter fallow[4], wheat	WS CF Flam	Tillage	Tillage + glyphosate	Flamprop-methyl POST
"	WS CF Tri	"	"	Triallate PRE
"	WS CF Nil	"	"	Nil
No-till: Wheat, Winter fallow, Sorghum, Winter fallow, wheat	WS NT Flam	Glyphosate	Glyphosate	Flamprop-methyl POST
"	WS NT Tri	"	"	Triallate PRE
"	WS NT Nil	"	"	Nil

Typical crop and winter fallow phase timings and durations in Martin and Felton (1993) [1] Wheat: May to December; [2] Winter fallow: after wheat, January to October; [3]Sorghum: November to May; [4] Winter fallow after sorghum, June to April.

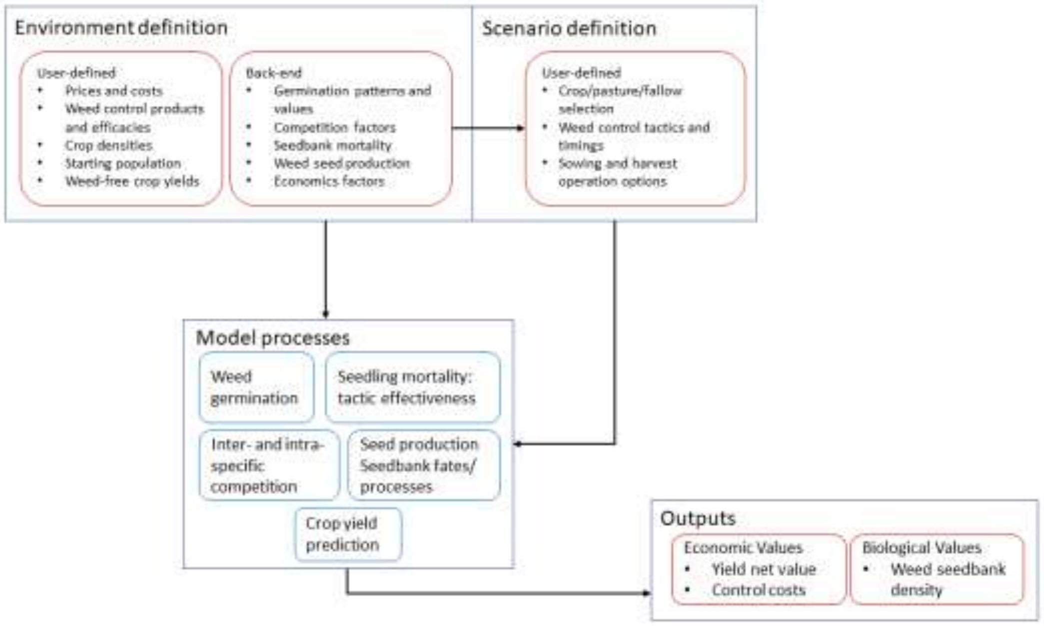
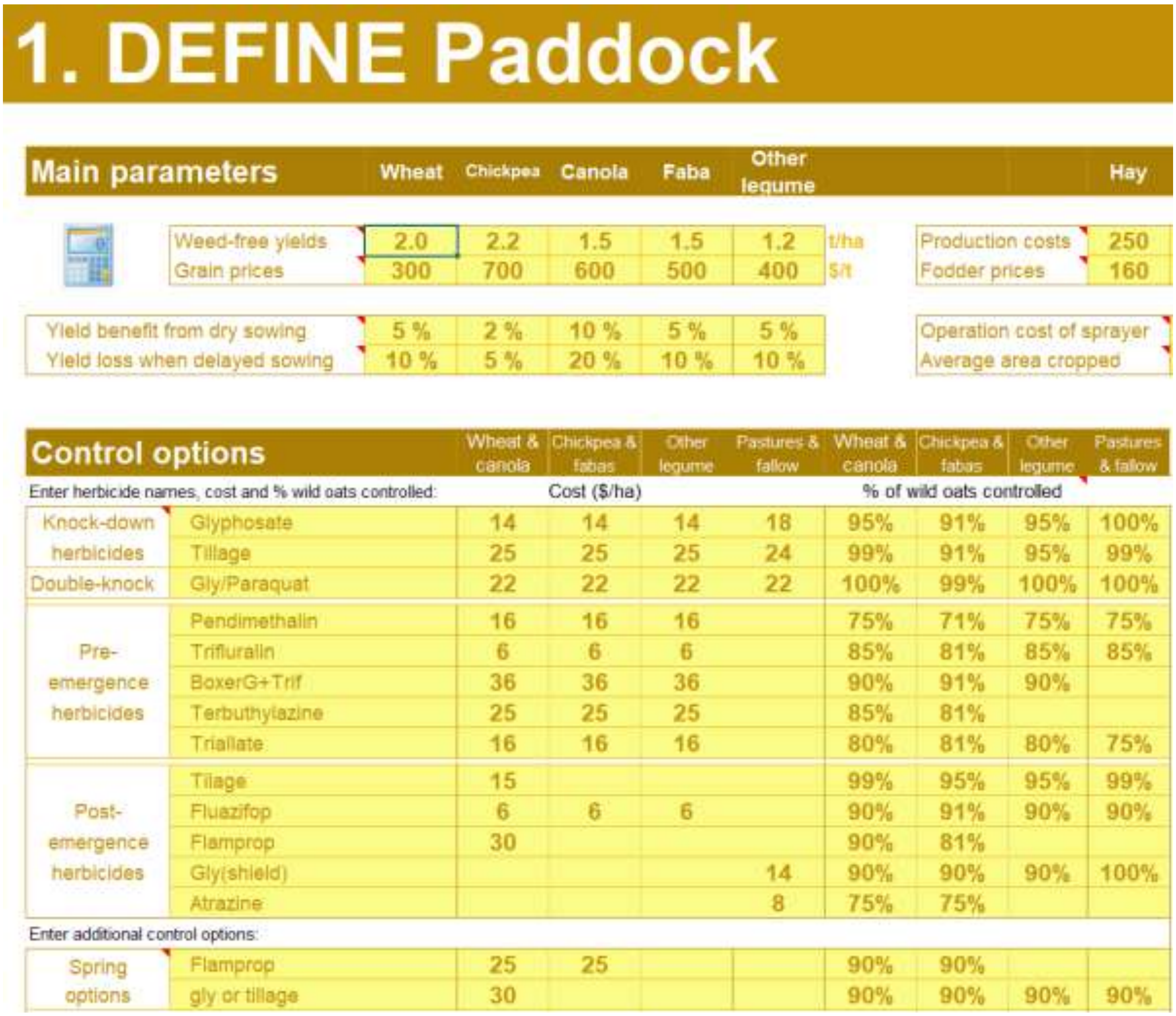


Figure 1. AIM model structure with red boxes representing data values (parameters or levels) and blue boxes identifying arithmetic models receiving inputs and delivering predicted outputs. Arrows represent information flows between model compartments.

Figure 2. The DEFINE (top panel) BUILD (middle panel) COMPARE (bottom panel) structure for the user interface of the AIM bioeconomic model developed for the evaluation of wild oat control strategies in grain production systems.

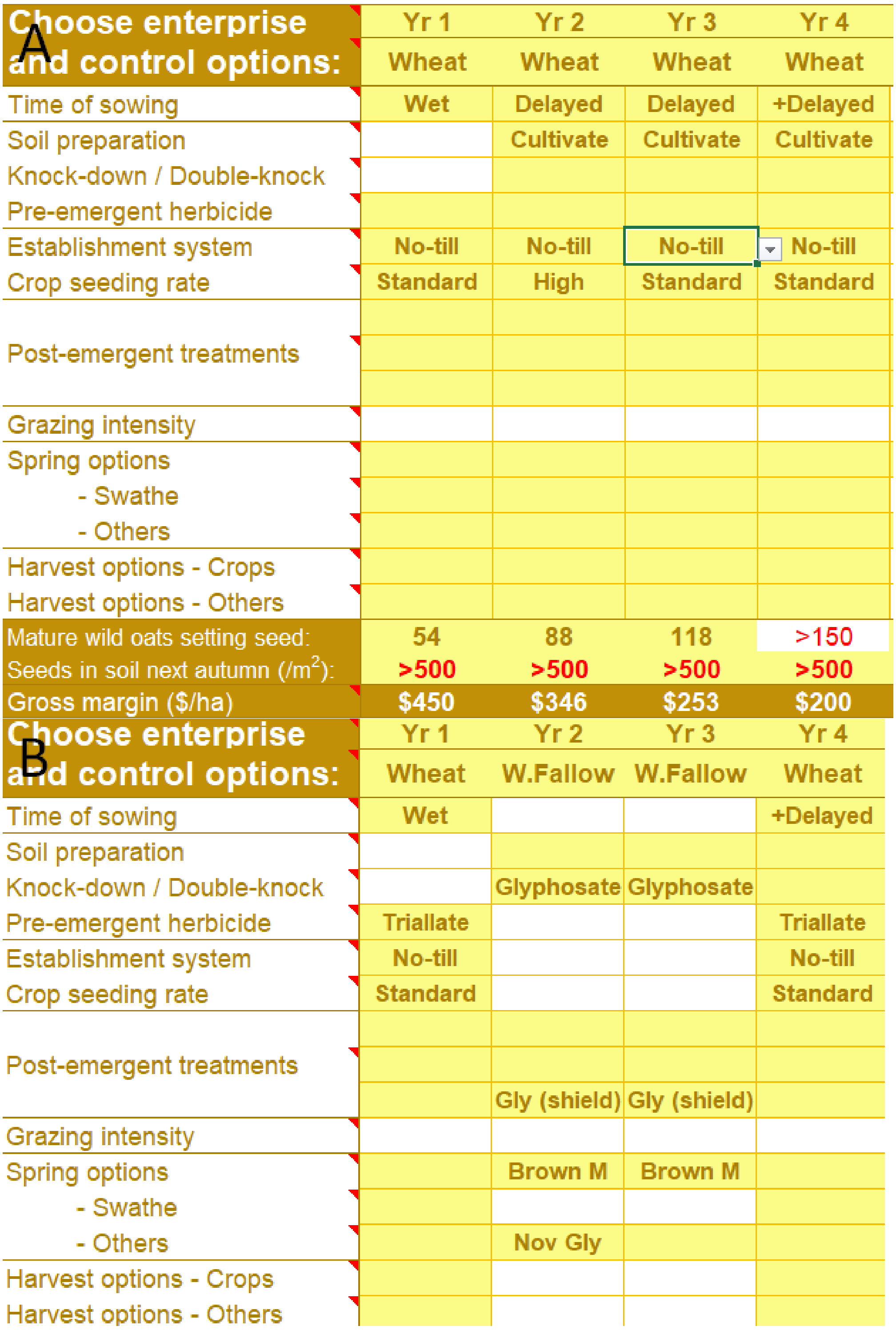


1. DEFINE Paddock

Main parameters	Wheat	Chickpea	Canola	Faba	Other legume			Hay
Weed-free yields	2.0	2.2	1.5	1.5	1.2	t/ha	Production costs	250
Grain prices	300	700	600	500	400	$/t	Fodder prices	160
Yield benefit from dry sowing	5 %	2 %	10 %	5 %	5 %		Operation cost of sprayer	
Yield loss when delayed sowing	10 %	5 %	20 %	10 %	10 %		Average area cropped	

Control options		Wheat & canola	Chickpea & fabas	Other legume	Pastures & fallow	Wheat & canola	Chickpea & fabas	Other legume	Pastures & fallow
Enter herbicide names, cost and % wild oats controlled:		Cost ($/ha)				% of wild oats controlled			
Knock-down herbicides	Glyphosate	14	14	14	18	95%	91%	95%	100%
	Tillage	25	25	25	24	99%	91%	95%	99%
Double-knock	Gly/Paraquat	22	22	22	22	100%	99%	100%	100%
Pre-emergence herbicides	Pendimethalin	16	16	16		75%	71%	75%	75%
	Trifluralin	6	6	6		85%	81%	85%	85%
	BoxerG+Trif	36	36	36		90%	91%	90%	
	Terbuthylazine	25	25	25		85%	81%		
	Triallate	16	16	16		80%	81%	80%	75%
Post-emergence herbicides	Tilage	15				99%	95%	95%	99%
	Fluazifop	6	6	6		90%	91%	90%	90%
	Flamprop	30				90%	81%		
	Gly(shield)				14	90%	90%	90%	100%
	Atrazine				8	75%	75%		
Enter additional control options:									
Spring options	Flamprop	25	25			90%	90%		
	gly or tillage	30				90%	90%	90%	90%

Figure 3. Agroeconomic environment for continuous wheat and wheat-sorghum rotations from Martin and Felton (1993), as replicated in AIM



Choose enterprise and control options:	Yr 1	Yr 2	Yr 3	Yr 4
	Wheat	Wheat	Wheat	Wheat
Time of sowing	Wet	Delayed	Delayed	+Delayed
Soil preparation		Cultivate	Cultivate	Cultivate
Knock-down / Double-knock				
Pre-emergent herbicide				
Establishment system	No-till	No-till	No-till	No-till
Crop seeding rate	Standard	High	Standard	Standard
Post-emergent treatments				
Grazing intensity				
Spring options				
- Swathe				
- Others				
Harvest options - Crops				
Harvest options - Others				
Mature wild oats setting seed:	54	88	118	>150
Seeds in soil next autumn (/m^2):	>500	>500	>500	>500
Gross margin ($/ha)	$450	$346	$253	$200

Choose enterprise and control options:	Yr 1	Yr 2	Yr 3	Yr 4
	Wheat	W.Fallow	W.Fallow	Wheat
Time of sowing	Wet			+Delayed
Soil preparation				
Knock-down / Double-knock		Glyphosate	Glyphosate	
Pre-emergent herbicide	Triallate			Triallate
Establishment system	No-till			No-till
Crop seeding rate	Standard			Standard
Post-emergent treatments				
		Gly (shield)	Gly (shield)	
Grazing intensity				
Spring options		Brown M	Brown M	
- Swathe				
- Others		Nov Gly		
Harvest options - Crops				
Harvest options - Others				

Figure 4. Example scenario settings for (A, top) continuous wheat/cultivated fallow/nil herbicide (designated WW-CF NilH hereunder) and (B, bottom) wheat-sorghum/no-till fallow/triallate (designated WS-NT Tri hereunder), for simulating wild oat management treatments (Martin and Felton 1993)

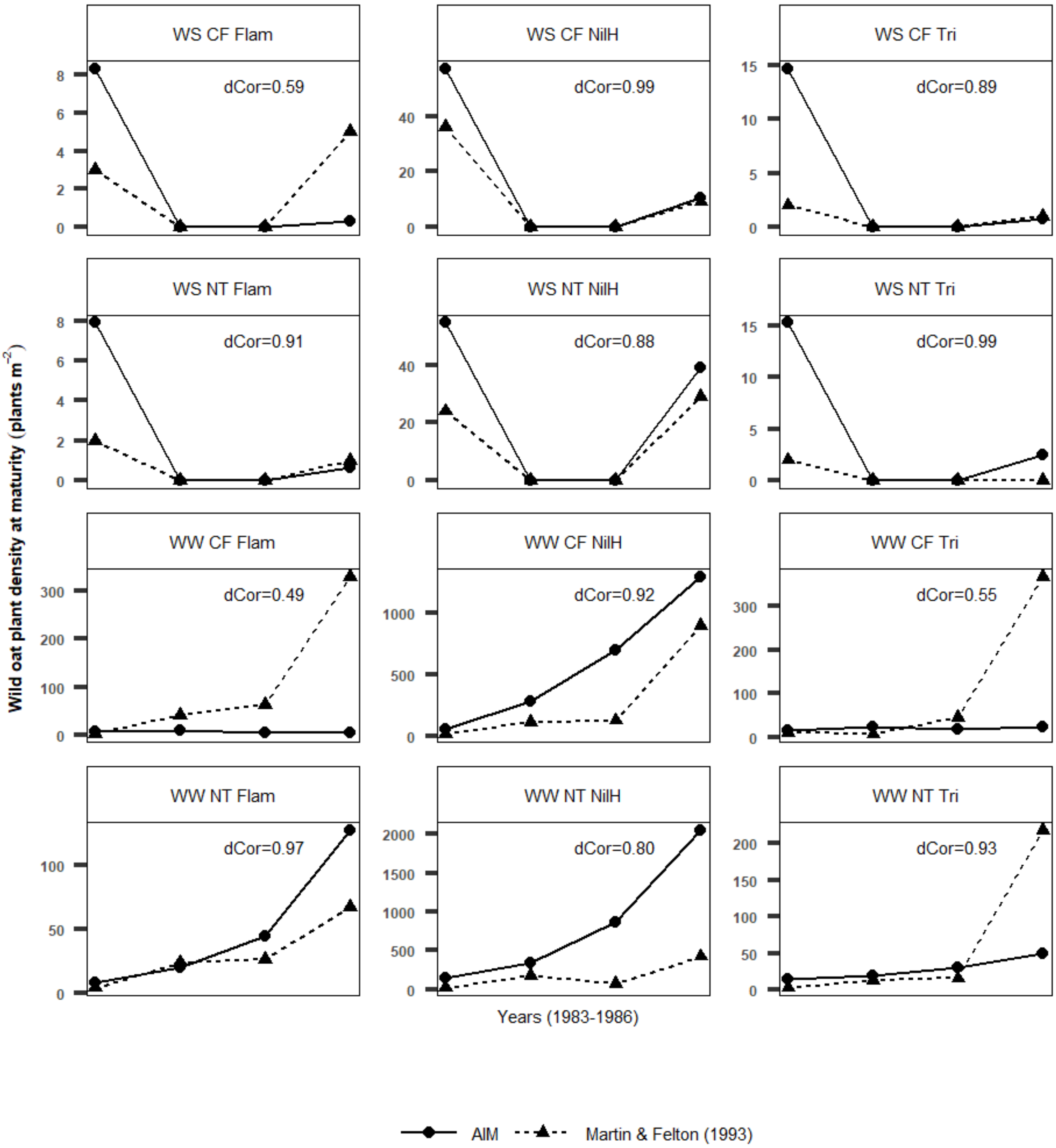


Figure 5. Comparisons between AIM model predictions and experiment data from Martin and Felton (1993) for wild oat plant density at maturity. Scenarios were wheat-sorghum rotations (labelled WS, top two rows) or continuous wheat (WW, bottom two rows), with either cultivation in summer fallows (CF, rows 1 and 3) or no-till summer fallows (NT, rows 2 and 4) and three different in-crop herbicide choices (flamprop-methyl/Flam; no herbicide/NilH; triallate/Tri, left to right).

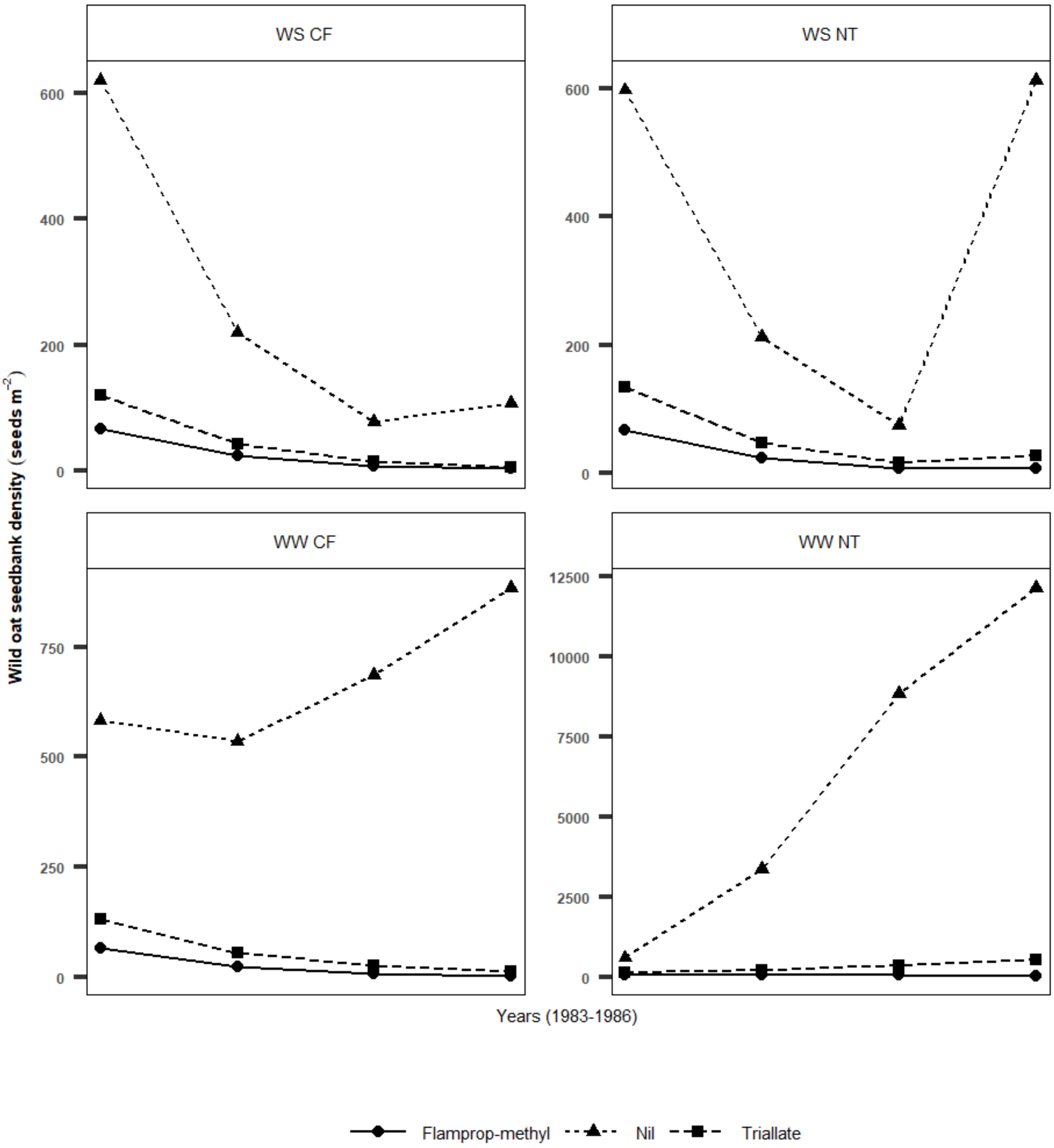


Figure 6. Wild oat seedbank density prior to first seasonal emergence in wheat-sorghum (labelled WS, top panels) or continuous wheat (WW, bottom panels), with cultivated summer fallows (CF, left panels) or no-till fallows (NT, right panels), responding to the use of three in-crop weed control options.

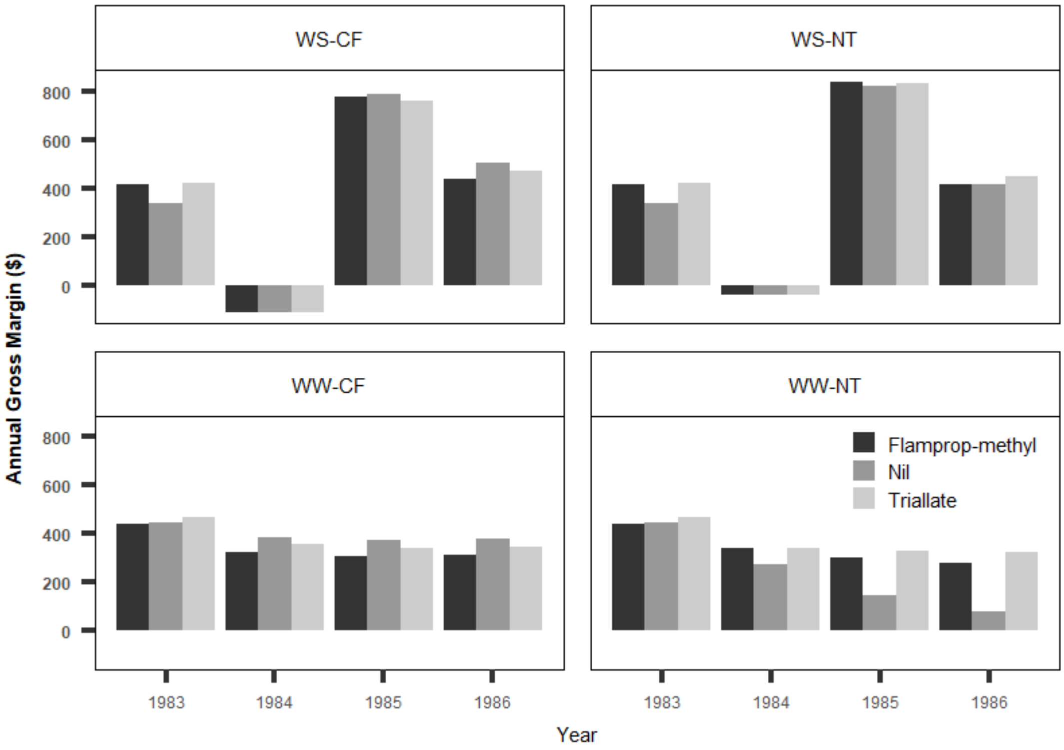


Figure 7. Gross margin outputs from AIM for wheat-sorghum (WS, top row) and continuous wheat rotations (WW, bottom row), with cultivated summer fallows (CF, left) or no-till fallows (NT, right) and a range of in-crop herbicide tactics (see legend)