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Stop wasting time on mechanical weed control research that lacks a theoretical foundation

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Abstract

In mechanical weed control research, there is a tendency to prioritise practical application over the establishment of a solid theoretical foundation. This emphasis can lead to a fragmented knowledge base and relatively modest research progress. The widespread use of ANOVA exacerbates this issue by primarily focusing on the differences between treatments, neglecting an exploration of the mechanisms behind the observed results. In response to these limitations and in line with rapid advances in sensor and robotics technology, this paper presents a proposal to establish a theoretical framework for mechanical weed control. The framework aims to emphasise understanding of the underlying mechanisms of mechanical weed control, rather than solely focusing on their observable outcomes. As part of this proposal, a simulation model known as HarrowSim based on regression parameters is presented. Simulation runs show the importance of factors such as treatment intensity, selectivity, crop tolerance and weed pressure in relation to crop yield response to post-emergence weed harrowing. While currently parameterised for post-emergence weed harrowing, it is argued that HarrowSim is relevant for all post-emergence mechanical weed control methods, and is useful for teaching purposes and for inspiring future research. While the theoretical framework and HarrowSim have their weaknesses, these can also be perceived as opportunities since they can help focus attention on key issues for future research.

KEYWORDS

ANOVA, experimental designs, models, physial weed control, regression, scientific quality

1 | INTRODUCTION

There have been multiple peer evaluations of weed research and its readiness for meeting future challenges, with some openly criticising the quality of research in this field. Cousens (1999) criticised the predominance of empirical studies without explicit theoretical foundations, labelling them repetitive and superficial. His critique focused on an overreliance on the inductive research approach, which starts with the collection of empirical data and then seeks to derive general principles or theories from that evidence. In contrast, the deductive approach starts with a theory or hypothesis, and seeks to test it against empirical evidence in order to confirm, refine or refute it.

Moss (2008) and Ward et al. (2014) later supported Cousens' critique (1999), stating that many weed research papers merely describe factual results without striving for a deeper understanding of the mechanisms behind those results. They called for a more scientific approach aimed at improving understanding of why things happen, rather than merely documenting what occurs.

Inductive and deductive approaches are both important in science (Guthery, 2007). Inductive reasoning allows researchers to explore new phenomena and generate new theories and research hypotheses, while deductive reasoning enables these hypotheses to be tested and refined. However, a pertinent question arises of how long phenomena should be regarded as new and how long inductive reasoning should continue to be employed? For instance, is the inductive research approach still relevant in mechanical weed control research?

Any debate on this issue is missing from the literature. Discussions rarely explore which research avenues will improve understanding and advance weed management, and which will not. This may hinder progress and limit the ability to address future challenges. Debate and disagreements are essential in science for a field to emerge stronger and more focused.

The overall purpose of this article is to challenge the prevailing inductive research approach that dominates studies of mechanical weed control. This approach is exemplified in studies that compare practice-oriented treatments, such as different tools for mechanical weed control, which frequently lack hypotheses and expectations about results or relevant information about treatment intensity (aggressiveness). It is implicitly assumed that the tools are used according to best practice, whatever that may be. While results from such experiments offer insights into 'what happens', they often fail to provide explanations for 'why things happen'. Such studies do not address the question of causality, and the reproducibility of results is limited. Consequently, their contribution to a deeper understanding and progress in weed management is minimal.

Instead, this article advocates for a shift towards a deductive approach, emphasising that research begins with hypotheses deduced from established theories and utilises methods that promote reproducibility. This can help explain results, deepen understanding and facilitate knowledge accumulation.

The potential for a shift in approach holds promise for accelerating research progress to keep up with the rapid advances in machinery and software technologies, such as sensor-guided tools and robotic weeding (Machleb et al., 2020; Melander et al., 2015). In contrast to these technologies, progress in weed research has been relatively modest. This disparity becomes evident when comparing earlier reviews of mechanical weed control (Bond & Grundy, 2001; Parish, 1990) with more recent ones (Gallandt et al., 2018; Machleb et al., 2020). Enduring questions persist about how aggressive treatments should be applied, the optimal frequency and timing of treatments, and how various factors such as growth stages, weed populations and soil conditions should be taken into account in order to optimise weed control.

The underlying rationale for this article is that new sensor-based technologies could accelerate a breakthrough in mechanical weed control in the near future provided there is adequate support from weed research. However, this requires attention to be paid to theory and appropriate methodologies.

The objective here is to introduce a simple yet coherent theoretical framework for mechanical control of weed seedlings in growing crops that has the potential to inspire future research. It represents a deductive research approach and involves mathematical modelling aimed at elucidating knowledge and filling gaps in our understanding of mechanical weed control. To illustrate the important causalities involved in mechanical weed control, simulations were performed using HarrowSim, an Excel-based tool developed for teaching and hypothesis generation.

2 | THE THEORETICAL BACKGROUND

The theoretical framework behind HarrowSim (see Supporting Information) serves to elucidate central mechanisms that are essential for comprehending mechanical weed control. It holds relevance for various mechanical weed control methods, including intra-row hoeing, due to similar constraints involving trade-offs between weed control and crop damage (Melander, 1997; Zhang et al., 2022). However, parameter estimates for weed control methods other than post-emergence weed harrowing are currently lacking. Therefore, HarrowSim is parameterised based on experiments with this specific method.

2.1 | Experimental designs—ANOVA versus regression analysis

HarrowSim builds on concepts such as resistance, selectivity, tolerance and competition. While resistance and selectivity can be evaluated at the time of treatment, crop tolerance and weed competition must be based on historical data to estimate the optimum treatment intensity at the time of treatment. All concepts are quantified as regression parameters, emphasising the significant role of regression analysis within the theoretical framework. This differs from the prevailing research trend, which predominantly relies on experimental designs for analysis of variance (ANOVA).

As explained by Ritz et al. (2015), ANOVA should be restricted to distinguishing between non-quantifiable treatments, such as various weed management methods, but should not be utilised to enhance understanding of individual weed control methods, particularly those reliant on application levels, such as most chemical and physical weed control methods. For instance, in mechanical weed control, the intensity of treatment is just as important as dosage in chemical weed control (Streibig, 1998), propane dosage in flame weeding (Knezevic et al., 2014), and soil temperature in soil steaming (Melander & Jørgensen, 2005) and soil solarization (Miles et al., 2002).

2.2 | Selectivity

Selectivity is a crucial factor in all mechanical weed control methods that cannot control weeds without also causing crop damage. While theoretically capable of achieving total weed control, it often results in such significant crop damage that it is not a feasible option in real-world scenarios.

Thus, information about weed control without corresponding data on crop damage is of limited value. Selectivity is crucial in determining the potential for achieving effective weed control while minimising crop damage, thereby preventing subsequent yield reduction. Selectivity refers to the difference between crop and weed resistance to harrowing (Rasmussen et al., 2008). A high level of selectivity indicates that the crop is significantly more resistant to harrowing than weeds.

Crop and weed resistance is estimated by the decline rate in crop leaf cover and weed density, respectively, when the intensity of harrowing is increased (Table 1). Crop leaf cover is the percentage of the ground covered by leaves when viewed from above. The parameter that describes the decline in crop leaf cover is the crop resistance parameter (b), and the parameter that describes the decline in weed density is the weed control parameter (d). Equations and procedures for this estimation are given in Table 1. Uprooting of crop plants is ignored because this is considered to be negligible for strongly anchored crops such as cereals and seed legumes, despite the acknowledgement that uprooting plays a role with weakly anchored plants on sandy soils (Kurstjens & Kropff, 2001).

The selectivity parameter is the weed control parameter (d) (Table 1) divided by the crop resistance parameter (b), and describes the percentage of weed control (WC) as a function of the percentage of crop soil cover (CSC) according to Equation (1):

$$\mathrm{WC} = 100\left(1 - \exp\left(\frac{d}{b}\cdot\ln\left(1 - \frac{\mathrm{CSC}}{100}\right)\right)\right). \tag{1}$$

CSC is the percentage of crop leaf cover that has been covered by soil due to harrowing when viewed from above.

The selectivity parameter is fundamentally distinct from the crop resistance (b) and weed control (d) parameters, as it is assumed to be independent of implement configuration and utilisation (Gerhards et al., 2021; Rasmussen, 1990, 1991). Primarily, it reflects biological differences in crop and weed resistance to harrowing, which are largely related to differences in size. This suggests that independent research teams would determine the same selectivity parameter in the same field on the same day, irrespective of the configuration and utilisation of the implement. In contrast, the crop resistance (b) and weed control (d) parameters are highly influenced by the methods used for creating varying treatment intensities. For example, a variation in driving speed yields different parameters compared with a variation in the number of consecutive passes. This should be self-evident due to different units of intensity, such as km h^{-1} and number. The key point is that the proportion between parameters, known as selectivity, remains unaffected by the method used to adjust intensity.

Therefore, the introduction of selectivity has addressed a significant problem in mechanical weed control research: the lack of reproducibility. Learning from experiments is extremely difficult when results cannot be reproduced. This issue will persist while mechanical treatments are described solely in technical terms, such as implement configuration and utilisation. This is analogous to describing a herbicidal treatment solely by the active ingredient without specifying the dosage and targeted weed species. A specific configuration and utilisation of a harrow generates unpredictable outcomes across different environments (Pardo et al., 2008; Rasmussen, 1990; Rasmussen et al., 2008). This is because the primary mechanism of harrowing is soil disturbance; it is not the implement itself that kills weeds. Forecasting crop and weed impacts based solely on technical descriptions of treatments is therefore exceedingly challenging because even small

TABLE 1 Regression parameters in HarrowSim required to calculate the selectivity and crop tolerance parameters, as outlined in the text.

	Crop resistance parameter	Weed control parameter	Crop response parameter
Definition	The decline in crop leaf cover immediately after cultivation relative to cultivation intensity. The ability of the crop to resist cultivation. Assessment shortly after cultivation before recovery takes place.	The decline in weed density immediately after cultivation relative to cultivation intensity. The ability of the weed to resist cultivation. Assessment shortly after cultivation before recovery takes place.	The decline in crop yield relative to the intensity of cultivation under weed-free conditions.
Equation	Parameter b in $L = L_0 \cdot \exp(-b \cdot I)$ The resistance parameter (b) expresses the relative decline rate of L relative to I. L is leaf cover, L_0 is leaf cover in untreated plots and I is the cultivation intensity, which could be the number of passes.	Parameter d in $W = W_0 \cdot \exp(-d \cdot \ln(I+1))$[a] The weed control parameter (d) expresses the relative decline rate in weed density (W) relative to I. W_0 is weed density in untreated plots and I is cultivation intensity, which could be the number of passes.	Parameter c in $Y = Y_0 \cdot \exp(-c \cdot I)$ The crop response parameter (c) expresses the relative decline rate of yield relative to I. Y is crop yield in the absence of weeds, Y_0 is crop yield in untreated plots in the absence of weeds and I is the cultivation intensity, which could be the number of passes.
Relative estimates	Percentage crop soil cover (CSC) is calculated as $\mathrm{CSC} = 100 \cdot (1 - \exp(-b \cdot I))$	Percentage weed control (WC) is calculated as $\mathrm{WC} = 100 \cdot (1 - \exp(-d \cdot \ln(I+1)))$[a]	
Protocol for experiments and statistics	Rasmussen et al. (2008)	Rasmussen et al. (2008)	Rasmussen et al. (2009)

[a]There are two further equations that describe the weed response, providing a progression in terms of curve curvature (Rasmussen et al., 2008), but for the sake of simplicity only one equation is included in HarrowSim.

differences in soil conditions may produce different outcomes (Duerinckx et al., 2005; Rasmussen, 1990). This explains why Naruhn et al. (2021) could not find an optimum setting and utilisation of a harrow across different environments. No such optimum exists; each field and timing of treatment calls for a field-specific setting or, more precisely, site-specific settings because soil conditions may vary within fields (Gerhards et al., 2021).

However, if there is no optimal setting and utilisation in technical terms, the pertinent question is how to describe and choose an optimal treatment resulting in high weed control and low crop damage. When reviewing the literature, it becomes evident that little information is available with regard to how researchers decide on the treatment intensity in their experiments. Typically, information about the implement configuration and setting is provided, but with no justification for their selection. There is often an implicit assumption that implements are used according to best practice.

This is untenable in a scientific context because 'best practice' is heavily biased. Instead of relying solely on technical descriptions to characterise treatments, it is advisable to use the induced impacts on crops and weeds as metrics for describing treatment intensity, as suggested by Gerhards et al. (2021), Rasmussen et al. (2008, 2009) and Spaeth et al. (2020). Hence, weed control and crop damage should no longer be considered primary outcomes in mechanical weed control experiments. Assessment of induced crop and weed impacts may be conducted manually or on the move using sensors on automated harrows (Esposito et al., 2021; Gerhards et al., 2021) or on tool carriers (Berge et al., 2023; Laursen et al., 2017).

However, this raises a seldom-addressed question in weed research: what level of weed and crop impacts should serve as prerequisites for treatments with optimal intensity? To answer this question, crop tolerance and weed competition must also be taken into consideration.

2.3 | Crop tolerance and weed competition

Crop yield response to harrowing is a trade-off between reduced weed competition and crop damage. The immediate impact on the crop after harrowing, CSC, is related to a decline in crop yield at harvest in weed-free scenarios. This relationship defines crop tolerance (Rasmussen et al., 2009). Therefore, two mechanisms are important for yield losses due to crop damage: crop resistance to soil covering and the ability to recover from it.

As with selectivity, crop tolerance is a user-independent parameter unaffected by implement configuration and utilisation. The crop tolerance parameter is the crop response parameter (*c*) (Table 1) divided by *b*, and it describes the percentage of crop yield loss (Y_L) as a function of the percentage of CSC according to Equation (2):

$$Y_L = 100\left(1 - \exp\left(\frac{c}{b}\cdot\ln\left(1-\frac{\mathrm{CSC}}{100}\right)\right)\right). \quad (2)$$

The decreased weed competition following harrowing is estimated by evaluating the weed density just before and after harrowing. The rectangular hyperbola model proposed by Cousens (1985) is employed to quantify the relationship between crop yield and weed density. By comparing the yield calculated before the treatment with that calculated after the treatment, the impact of reduced weed competition is determined.

3 | HarrowSim

3.1 | Procedure

HarrowSim integrates all the components mentioned above to estimate the optimal treatment intensity, expressed in terms of CSC, with the objective of optimising yield. HarrowSim requires inputs on six parameters to generate curves, as shown in Figures 1–4. Table 1 outlines the definitions and procedures for estimating the crop resistance parameter (*b*) (Figure 1), the weed control parameter (*d*) (Figure 1) and the crop response parameter (*c*). Two further parameters, selectivity and crop tolerance, are derived from the regression parameters in Table 1 according to Equations (1) and (2). In order to make yield estimations, three weed competition parameters are approximated according to Cousens' (1985) rectangular hyperbola model. HarrowSim functions as a tool for predicting the optimal intensity in relation to yield or can be employed to examine how parameters influence the potential for achieving effective weed control while maximising yield gains.

The selectivity curve (Figure 2) constitutes a key component in the calculation of the optimal treatment intensity. CSC represented on the X-axis is converted into crop yield loss in weed-free scenarios using the crop tolerance curve (Figure 3). Weed control, represented on the Y-axis, is converted into weed densities, which are used to calculate the crop yield gain resulting from reduced weed competition due to harrowing. Finally, the positive yield contribution from weed control is added to the negative yield contribution from CSC to obtain the overall yield response to harrowing (Figure 4).

3.2 | Simulations

Figure 1 shows curves generated in HarrowSim using parameters from an experiment involving post-emergence harrowing in spring barley using narrow (5.3 cm) and wide (24 cm) row spacings. The crop displays increased resistance to soil covering with the wider row spacing, leading to greater selectivity (Figure 2). At 5.3 cm spacing, achievement of 80% weed control results in 40% CSC, whereas at 24 cm spacing there is only 15% CSC.

In Figure 3, a crop tolerance parameter from Rasmussen et al. (2009) is applied without considering the impacts of row spacing because the significance of this factor is uncertain and its expected effect is deemed negligible. Additionally, crop yield impacts from two weed populations with low and high competitive ability are shown.

In Figure 4, crop yields are calculated based on Figures 1–3. It appears that yield gains from harrowing are very small and almost completely absent with the 5.3 cm row spacing. The potential yield

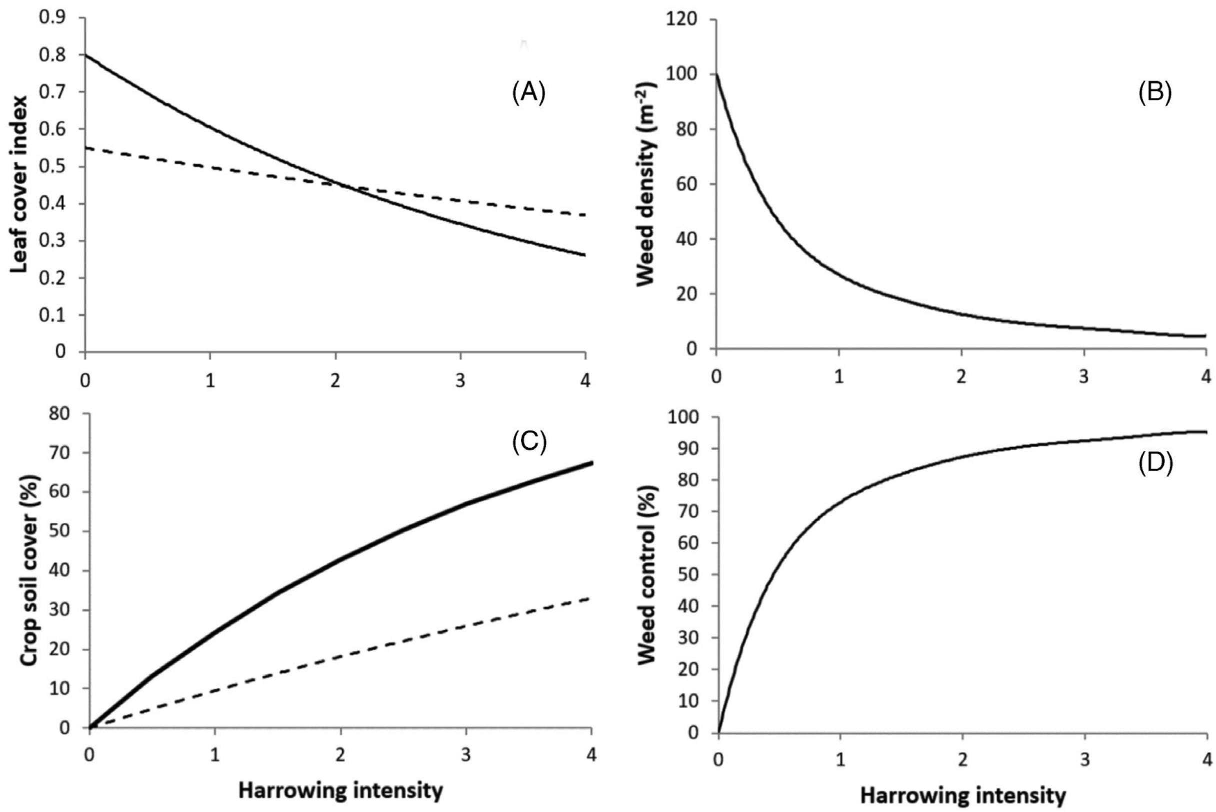

FIGURE 1 Crop resistance (A and C) and weed control (B and D) at two row spacings: 5.3 and 24 cm. The intensity of harrowing corresponds to the number of consecutive passes on the same day. For crop resistance (A and C), the solid lines represent 5.3 cm row spacing, while the dotted lines represent 24 cm row spacing. For weed control (B and D), the solid lines denote both row spacings. Parameters are from Rasmussen et al. (2008).

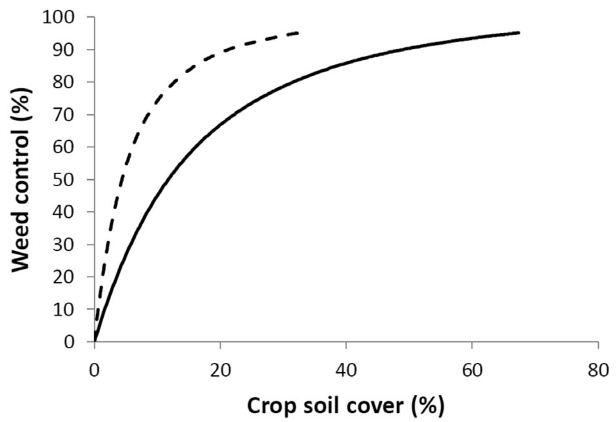

FIGURE 2 Selectivity curves based on the crop resistance and weed control presented in Figure 1. The solid line denotes 5.3 cm row spacing and the dotted line 24 cm row spacing.

gain is much larger when weeds are more competitive (H). The optimum treatment intensity for the highly competitive weed population is 18% CSC at the 24 cm row spacing and 35% at the 5.3 cm row spacing (Figure 4), which corresponds to 82% and 72% weed control respectively (Figure 2). The potential yield gains were 9% in the low selectivity scenario and 12% in the high selectivity scenario. In the low competition scenario, potential yield gains were less than 2%, and the risk of yield reduction was high if the applied intensity of harrowing was not optimal.

4 | DISCUSSION AND CONCLUDING REMARKS

The outputs from HarrowSim prompt several areas of consideration: the learning outcomes from the simulations, the reliability of the models and parameters, and the practical and scientific applicability of HarrowSim.

4.1 | The learning outcome

The results in Figure 4 indicate that the optimal intensity of harrowing in terms of yield depends on both the selectivity and weed pressure. In instances of low weed pressure, the potential yield gain is minimal, while the risk of yield depression is high. Likely conclusions from experiments designed for ANOVA in the same range of weed pressure would be that harrowing has no impact on crop yield. This is because numerical yield differences in the order of 10%–20% are typically not

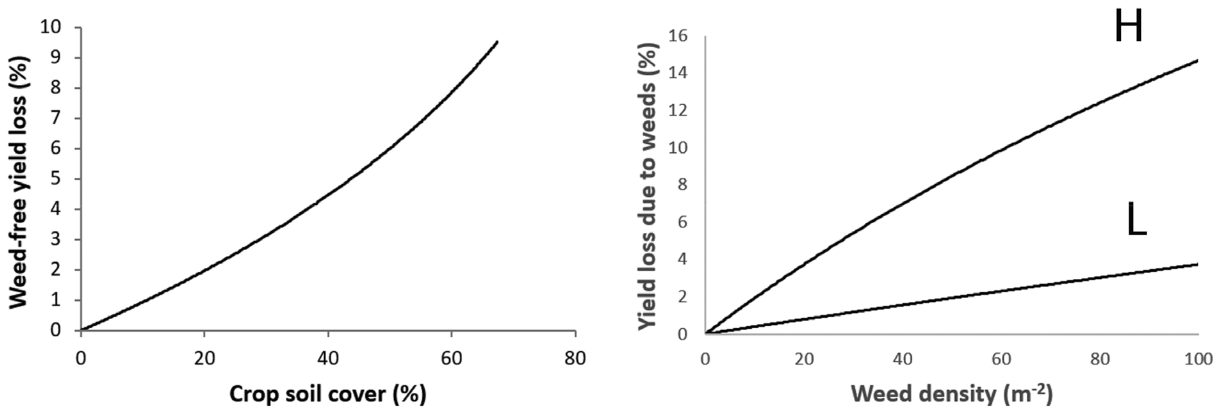

FIGURE 3 Crop tolerance (left) and weed competition (right) from high (H) and low (L) competitive weed populations. Curves generated in HarrowSim. Additional details in the text.

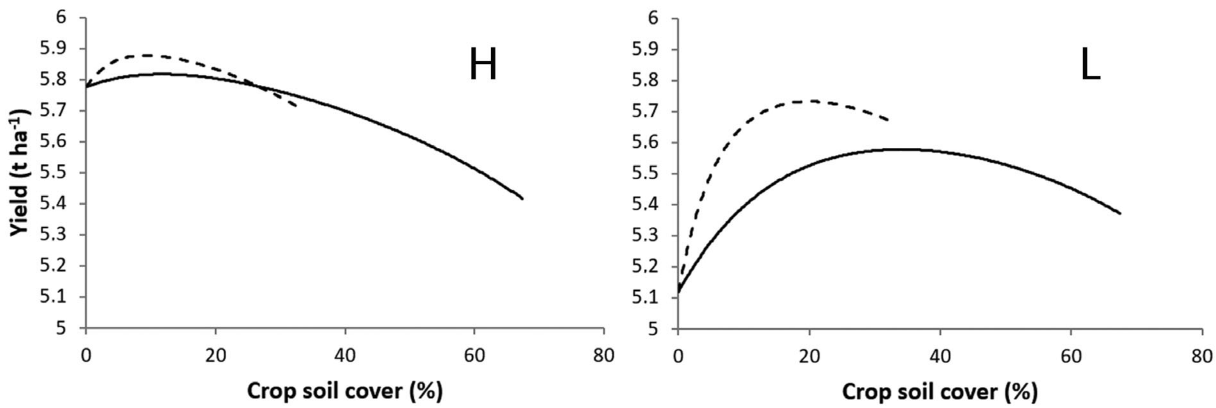

FIGURE 4 Crop yield response to post-emergence harrowing under the conditions given in Figures 2 and 3. Solid lines denote the low selective scenario (5.3 cm row spacing) and dotted lines denote the high selective scenario (24 cm row spacing) in Figure 2. H and L denote two weed competition scenarios according to Figure 3.

statistically significant in experiments designed for ANOVA (Gerhards et al., 2021; Saile et al., 2022; Sobkowicz & Tendziagolska, 2022). Alternatively, conclusions could be drawn that harrowing reduces crop yield if the applied treatment intensity deviates significantly from its optimal intensity. One thing is certain: experiments designed for ANOVA would never be able to infer the patterns and understanding provided by HarrowSim.

Therefore, if yield response to harrowing is considered relevant, as it should be, experiments designed for ANOVA provide limited insight into harrowing, as yield responses below 10% are generally not measurable. Experiments based on regression analysis have much stronger statistical power and may reveal small, but important yield impacts.

4.2 | Reliability of models and parameters

There is no doubt that the reliability of models and parameters is open to debate. While there is substantial experimental evidence supporting the ability of the model behind Figure 4 to describe experimental data through non-linear regression (Rasmussen, 1991, 1993; Rueda-Ayala et al., 2011), transitioning from there to predicting yield at the time of treatment is a different matter. If the selectivity parameter is determined on site, there is little uncertainty about this parameter. However, for predictive purposes, the crop tolerance and weed competition parameters have to rely on historical data. Currently, only a limited amount of such data is available on crop tolerance (Hansen et al., 2007; Rasmussen et al., 2009). The estimation of crop yield impacts from weed competition poses another challenge because robust models for prediction of weed competition are still scarce (Ali et al., 2013). However, Gerhards et al. (2012) suggested a promising approach based on models that categorise weed populations into a few, but distinct, species groups according to their competitive abilities.

Many questions can be raised about HarrowSim but, for the most part, such inquiries may motivate reflections and structured discussions that can stimulate learning—including the type of learning that weed research represents. Everything perceived as lacking or inadequately described in HarrowSim presents an opportunity for exploration in future research. This may include questions regarding the timing of treatments and the combination of treatments at different growth stages. Furthermore, the relevance of HarrowSim in relation to mechanical weed control methods other than post-emergence weed harrowing may be open to debate. Some have argued that it is difficult to create and evaluate graded levels of treatment intensities and the associated crop damage for some intra-row weed control methods, but the author of this article is sceptical about this. Nevertheless, this issue must be clarified in further research.

In conclusion, the weaknesses of the theoretical framework can simultaneously be perceived as opportunities since they can help focus attention on key issues for future research.

4.3 | Application and barriers

Although the theoretical framework as a whole has never been implemented in decision support systems for sensor-based harrowing, a first step has been taken by Gerhards et al. (2021). They tested a harrow equipped with a sensor system designed to automatically adjust the angle of the harrow tines in order to modify the intensity of harrowing. This system included two cameras: a front camera used to assess crop leaf cover before harrowing, and a rear camera for evaluating crop leaf cover after harrowing. These measurements were then used to estimate CSC, which served as a metric for the treatment intensity. Based on selectivity curves similar to Figure 2, Gerhards et al. (2021) approximated the optimal treatment intensity expressed as CSC. Weed competition and crop tolerance were not considered. Nevertheless, this represents a significant advancement compared with studies that lack explicit considerations about applied treatment intensities.

Future research needs to validate simulations from HarrowSim and figure out how the model can be improved.

The theoretical framework presented in this article, like all other mathematical frameworks, involves simplifications of the real world. These simplifications are made to distinguish important aspects from unimportant ones, aiding comprehension of complex phenomena such as post-emergence weed harrowing. The overarching goal here is to advocate for a more scientific approach in future research endeavours, emphasising the importance of understanding why phenomena occur rather than solely focusing on what happens. Scientific understanding arises when ideas about how methods work are formalised, tested, refined, and then tested again.

This involves deductive reasoning and quantitative research methods formalised in mathematical models, which has proven to be an obvious barrier in mechanical weed control research. None of the models underlying HarrowSim are new; in fact, the theoretical foundation was first presented over 30 years ago (Rasmussen, 1991), but has scarcely been used in weed research. There may be many reasons for this, but as documented in Rasmussen (2023), it is not because it has been challenged or criticised in the literature. It has largely just been ignored, even in articles that use Rasmussen (1991) as a reference. It is tempting to attribute the main reason for this to a communication barrier similar to that identified in other biological fields that encompass both theoretical and practical-oriented research: the mathematical language barrier (Grainger et al., 2022). Theoretical research often utilises mathematics that may not be accessible to an audience who are unfamiliar with it. The more equations an article contains, the fewer citations it receives within research fields that are more practically oriented, such as biology (Fawcett & Higginson, 2012). It imposes a requirement on authors of theoretical articles to explain themselves in such a way that their ideas can be understood without necessarily deciphering all the mathematics.

Adopting mathematical models in research typically involves designing experiments suited to regression analysis rather than ANOVA. A practical argument against this could be increased experimental costs. For instance, in field experiments it is common to use block experiments with four replications. If experiments require the application of four or five graded levels of intensity for each factor investigated, the experiments could become quite large and consequently expensive. However, when shifting from experiments designed for ANOVA to regression analysis, considerations regarding the requirement for replications should be taken into account. There is a need for innovation regarding the need of replicates in experiments designed for regression analysis. In variety testing, non-replicated experimental designs adapted to regression analysis showed comparable statistical accuracies to ANOVA designs with block replications in terms of yield (Jensen et al., 2023).

There is little doubt that the traditional experimental approach to mechanical weed control requires in-depth examination in future. It is likely that block experiments with four replications designed for ANOVA, lacking a clear basis in an explicit theoretical framework, will appear outdated and dubious following such an examination.

4.4 | Concluding remarks

The prevailing inductive approach in mechanical weed control research must cease. Research lacking theoretical foundation or explicit hypotheses rooted in prior research still contributes to the body of scientific literature but offers little advancement in knowledge and weed management. Theoretical considerations and simulations conducted with HarrowSim reveal that experiments emphasising practical application of implements, employing ANOVA approaches, lack the necessary analytical power to provide new insights into post-emergence weed harrowing. Future research in mechanical weed control demands quantitative research methods, employing mathematical modelling, or at the very least, clear justifications for their absence. While HarrowSim is specifically parameterised for post-emergence weed harrowing, the conclusions drawn are presumed to be applicable to all post-emergence mechanical weed control methods in growing crops, including intra-row weeding.

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DATA AVAILABILITY STATEMENT

Data is available in "supporting information".

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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