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Wheat yield is resilient to weed pressure under preventive and herbicide-free integrated weed management

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Introduction: The Swiss PestiRed project aims to reduce pesticide use while maintaining crop productivity by promoting integrated pest management. Despite growing interest in integrated weed management (IWM), its performance under long-term, farmer managed conditions remains insufficiently documented.

Methods: This study assessed how IWM using herbicides (IWM-H) and herbicide-free (IWM-0H) strategies influenced weed biomass and grain yield in 94 on-farm winter wheat fields monitored from 2020 to 2023. Farmers implemented a range of practices (e.g., adapted tillage intensity, delayed sowing, mechanical weeding, false seedbeds, and targeted herbicide applications), resulting in high variability under real farming conditions.

Results: Pre-harvest dry matter weed biomass remained below 50 g m^{-2} in 89% of fields, and grain yield did not differ between IWM-H and IWM-0H. Only a few fields exceeded weed biomass levels associated with yield loss, indicating that low weed pressure resulted from combined management practices rather than a low initial weed pressure. The Cousens model described a clear weed-yield relationship in fewer than one-third of fields, reflecting high response variability. Using variance inflation factor filtering, random forest classification, and linear mixed-effects models, key drivers of weed biomass and grain yield were identified, including false seedbed preparation, well-chosen sowing date and density, tillage intensity, herbicide application, favourable rainfall conditions, soil typology and crop yield potential.

Discussion: Tillage intensity consistently reduced weed biomass, while higher mechanical weeding intensity in herbicide-free systems was associated with yield penalties. Herbicide-free IWM maintained wheat yield when weed biomass was effectively controlled. Higher operational costs of herbicide-free IWM may be offset by price premiums and direct payments, resulting in comparable profitability as herbicide-based IWM. However, findings primarily reflect systems with moderate weed pressure and should be interpreted cautiously when extrapolating to contrasting agroecological contexts.

KEYWORDS

agroecology, crop rotation, harrowing, multivariate analysis, soil tillage intensity rating (STIR), treatment frequency index (TFI), variable selection

1 Introduction

Agriculture is the primary food production source for sustaining a projected population of 10 billion people by 2050 (van Dijk et al., 2021). Reliance on pesticides for crop protection is still enormous. However, farms with an initially high reliance on pesticides showed the greatest potential for reduction by more than 60% (Nandillon et al., 2024). Integrated strategies to manage pests and weeds offer agroecological advantages, while maintaining crop productivity and promoting sustainable food production. Integrated production (IP) is a Swiss intermediate strategy between high input agriculture and organic farming, using integrated pest management (IPM) principles and reducing considerably chemical plant protection products (Wirth et al., 2020; Finger and El Benni, 2013).

Switzerland demonstrates its strong commitment to sustainable agriculture through the "Programme for the Sustainable Use of Resources in Agriculture" (FOAG, 2025). This initiative is based on the Articles 77a and 77b of the Federal Agriculture Act (LAGR, SR 910.1) and supports innovative projects designed to protect natural resources such as soil, water, air, and biodiversity while optimizing the use of inputs. The program encourages technical, organizational, and structural innovations which promote environmental efficiency and practical learning. PestiRed is a sector-specific project funded by FOAG2025 that aims to reduce the use of chemical plant protection products. It is supported by IP-Suisse and the state agricultural offices of the cantons of Solothurn, Geneva and Vaud. Established in 2019, this project planned a 6-year cropping system. It relies on agroecological crop protection, IP, IPM and leveraging ecological processes, such as natural predation, competition and soil health (Deguine et al., 2023).

In Switzerland, about 30% of arable land is dedicated to bread-making cereals, with wheat being among the main cultivated crops (Brugger, 2026) due to its economic importance and role in crop rotations. Winter wheat production in Switzerland, averaged between 2020 and 2023, was 68,675.3 ha cultivated, with a production of 344.3 tonnes and a yield of 5.7 t ha^{-1} (Swissgranum, 2026). Wheat is the most widely grown crop under the Extenso program, accounting for ≈ 60% (in 2022) of the cereal surface area cultivated using reduced chemical inputs. Extenso involves prohibiting the use of synthetic fungicides, insecticides and growth regulators in order to increase sustainability (FOAG, 2025). Comprehensive research on reduction of phytosanitary products, including herbicide-free and low-input farming systems has been done on wheat (Möhring and Finger, 2022; Böcker et al., 2019). Consequently, wheat serves as a model crop for sustainable agriculture, innovative farming, and the transition towards a reduced reliance on synthetic pesticides.

The yield reduction effects of weeds are well-known and weed management is one of the most challenging activities in arable cropping systems. Yield losses in cereals, including wheat, caused by weeds are estimated to range between 18–19% globally (Gaba et al., 2016) and approximately 30% in the absence of weed control (Adeux et al., 2019b). However, yield responses in wheat can vary widely depending on weed pressure, management practices, and environmental conditions. Competition between wheat and weeds is primarily driven by the capture and use of limited resources such as light, water, nutrients, and space for plant growth and root development (Colbach et al., 2020; Kaur et al., 2018). Early access to these resources allows weeds to reduce crop growth and yield by limiting resource availability to wheat. The outcome of these interactions is shaped by weed pressure, relative timing of emergence, environmental conditions, and management practices that influence wheat density and canopy closure (De Vita et al., 2017; Masson et al., 2024). A coherent combination and diversification of chemical, physical, and cultural weed management practices can alter weed population dynamics and interference (Cordeau et al., 2022). Under Swiss experimental conditions, Masson et al. (2024) reported contrasting wheat yield responses under different IWM strategies, ranging from 16–19% yield loss under no-plough + no-herbicide and occasional shallow tillage + harrowing, to around 4% yield gain under ploughing + harrowing combined with reduced herbicide use. PestiRed promotes and implements preventive and alternative practices to synthetic-chemical pesticides. Particularly for weed management, it follows the Integrated Weed Management (IWM) framework described by Riemens et al. (2022) and considering crop rotation effects. Wheat and other crops used in rotations, such as sunflower or ryegrass have strong competitive capabilities against weeds, with fast growth at early stages, extensive rooting systems and allelopathic properties (Jabran et al., 2015). In Switzerland, a high proportion of grasslands within cropping systems is required (Lüscher et al., 2019). Dominschek et al. (2021) reported a more intense suppression effect from a grassland-cropping rotation than from a crop-based rotation. In this case, three years of grassland prevented the selection of weeds causing a significant grain yield reduction in maize, resulting in an economically viable and herbicide-free weed management strategy.

Environmental and soil conditions, as well as farming practices and other abiotic conditions play a critical role in shaping weed dynamics and the effectiveness of weed control using herbicide-reduced and agroecological crop protection (Minhas et al., 2023). Weed pressure tends to increase with precipitation and temperature (Soulé et al., 2024). Under favourable environmental conditions, stronger competition from weeds and greater weed suppression by crops are anticipated (Stefan et al., 2021). Shulner et al. (2025) determined that not only environment and soil conditions, but access to technology and regulations influence significantly the efficiency and environmental consequences of fertilization and weeding activities. Since the effects of weeds depend on factors beyond just weed management, a significant level of uncertainty regarding crop productivity can be expected. Therefore, classifying yield in high, medium and low productivity levels and analysing the sources of variation within each group could provide farmers and advisers additional information to improve weed management strategies (Casagrande et al., 2010; O'Donovan et al., 2005).

Robust statistical approaches are needed to properly identify and rank the most influential predictors of weed presence and yield loss. Random Forests (Breiman et al., 1984; Rothacher and Strobl, 2024) and mixed-effect models (Zuur et al., 2009) are particularly appropriate for capturing complex interactions and hierarchical data structures. Random forests have been used in field studies to predict herbicide resistance, herbicide management, agronomic practices, environmental variables, and to identify the most influential predictors of weed occurrence (Richter et al., 2025). This is the most convenient classification tool for partly correlated and small sample sizes (Lepke et al., 2024). Linear mixed-effect models consider the variability of fixed effects (the average across all observations) and random effects (differences of lesser interest among clusters but affecting fixed effects) (Zuur et al., 2009). These models capture the variance contribution of treatments applied across diverse agroecological conditions, years, and replication in multi-location on-farm trials (Kumar et al., 2025).

Despite the importance of and growing interest in IWM, important knowledge gaps remain regarding its performance under complex and multi-year conditions (*i.e.*, beyond three years). While ecological and IWM practices have demonstrated proof-of-concept in experimental settings, there is still a lack of empirical evidence and practical recommendations under real farming conditions, particularly concerning their temporal dynamics (MacLaren et al., 2020). Although a limited number of long-term experiments provide valuable insights into how individual practices influence weed dynamics and productivity, the multi-year effects of combined IWM strategies remain poorly understood (Adeux et al., 2019a; Petit et al., 2018). Moreover, relatively few studies have integrated multiple analytical approaches (*e.g.*, multi-year field measurements, modelling, and economic or environmental indicators) to disentangle the relative importance of agronomic, environmental, and management factors driving yield outcomes under IWM (Colbach et al., 2025; Cordeau et al., 2022). Addressing these gaps is essential for assessing the robustness and practical applicability of IWM under on-farm conditions. In this context, the present study evaluates IWM performance in winter wheat across 94 on-farm fields within the PestiRed project (2020-2023). Specifically, it examines (i) the influence of IWM strategies, with and without herbicides, on dry matter (DM) weed biomass and grain yield; (ii) the relationship between weed biomass and yield loss; and (iii) the main predictors of weed biomass and grain yield responses. The study further explores the hypothesis that IWM strategies may perform comparably with and without herbicides in maintaining low weed biomass and sustaining yield, while acknowledging that yield variation may also be driven by environmental and management factors.

2 Materials and methods

2.1 Experimental setup

This study is based on the on-farm trials established in the PestiRed project that started in 2019. The trials were monitored by Agroscope and distributed across the properties of 68 farmers. The aim was to reduce the use of plant protection products by 75%, while accepting a maximum of 10% crop yield loss. Five regional groups corresponding to specific pedoclimatic contexts and production types were built in the initial phase. Farmers in these groups jointly decided using five different 6-year crop rotations, accounting for integrated production principles and minimizing the occurrence of noxious organisms. Each crop was cultivated only once per farm during the project duration. Two agricultural management setups were implemented at each farm: a *control* and an *innovative* field. The *control* setup refers to fields where farmers applied their usual agricultural practices (including the use of pesticides). In contrast, *innovative* fields were managed within an agroecological production context that limited pesticide usage and combined it with alternative measures for plant protection. Measures targeting weed management included cover crops, mechanical stubble cultivation, ploughing, delayed sowing, adapted sowing density and spacing, false seedbed, adapted fertiliser application to reduce grass weeds, species mixing, undersowing and manual and mechanical weeding. Each farmer was free to choose their own combination of measures. This study focusses on winter wheat – the most common crop across all rotations – cultivated on 94 fields (47 farms, with *control* and *innovative* fields). Wheat was cultivated during the growing seasons 2019-2020 (34 fields), 2020-2021 (18 fields), 2021-2022 (20 fields), or 2022-2023 (22 fields). *Control* and *innovative* fields applied integrated weed management (IWM) with an herbicide-based strategy for the former and herbicides applied in urgent cases only for the latter. This study grouped fields using IWM with herbicides (hereafter IWM-H) and without herbicides (hereafter IWM-0H), regardless of being *control* or *innovative*.

2.2 Studied variables

Agronomic data were assessed throughout the project at both, field and farm levels. The variables analysed in the present study are listed in Table 1. The variables are grouped according to the PestiRed experimental setup (*ID*s 1, 2), agronomic indicators (*ID*s 3-23), crop and weed assessments (*ID*s 24-27), climate and soil-linked information (*ID*s 28-30), and grain yield variables (*ID*s 31-33). Farmers filled in an *electronic field calendar* online information about the implemented agricultural practices from after harvesting the crop preceding wheat until the harvest of wheat. Inputs of N total (*ID* 9), P mineral (*ID* 10), and K mineral (*ID* 11) were calculated based on the total amount of fertiliser applied (kgha^{-1}) and the number of products used multiplied by the corresponding nutrient content of N, P, and K. Treatment Frequency Index (TFI) was used to measure the intensity of pesticide use (Lechenet et al., 2016; Guinet et al., 2023). It accounts for all applications on a single field, considering the applied dose relatively to the maximal authorised dose for a specific crop and target, as well as the ratio of surface treated. The TFI summarised the pesticide use frequency, without considering their ecotoxicological impact on non-target species. This index is computed according to Equation 1,

$$TFI = \sum_{1}^{n} P_i \frac{applied\ \ dose}{maximal\ \ dose} \times \frac{applied\ \ surface}{total\ \ field\ \ surface} \quad (1)$$

where n is the number of pesticides applied, and P_i the pesticide. The TFI value increases with the dose, number of pesticides, and the sprayed surface. A product applied at maximal dose over the whole field has an TFI of 1. The total TFI (*ID* 14) was calculated for all wheat PestiRed fields, as well as the total Herbicide TFI (*ID* 15), and Glyphosate TFI (*ID* 16). Additionally, the number of herbicide applications in spring (*ID* 12) and in winter (*ID* 13) were assessed.

The soil disturbance intensity due to ploughing, shallow tillage and mechanical weeding was quantified with the Soil Tillage Intensity

TABLE 1 Assessed climatic-, soil-, and management-linked variables influencing weed biomass and wheat grain yield in the PestiRed project.

ID	Label	Description	Units	ExKn	VIF	RFC	LME_W	LME_Y
		PestiRed set-up						
1	PR_ID	PestiRed field ID: 1. Control; 2. Innovative	1; 2				✓	✓
2	Year_w	Year when wheat was sown		✓			✓	✓
		Agronomic indicators						
3	Ploughing	Ploughing / no ploughing from previous harvest to sowing	1 / 0	✓	✓	✓		
4	Tillage.freq	Soil tillage: passes before sowing, excluding ploughing	number	✓				
5	False.seedbed	False seeding: two tillage passes at least 7 days before sowing	number		✓	✓	✓	✓
6	Varieties.association	Sowing of different wheat varieties: presence/absence	1 / 0		✓	✓		
7	Wheat.sow.dens.	Wheat sowing density	seeds m^{-2}	✓	✓	✓	✓	✓
8	Sowing.interval	Sowing date on a 10-day interval		✓	✓	✓	✓	✓
9	Nmin.input	Total N input from previous harvest to wheat harvest	kg ha^{-1}	✓	✓	✓	✓	✓
10	Pmin.input	Total P2O5 input from previous harvest to wheat harvest	kg ha^{-1}	✓		✓		
11	Kmin.input	Total K2O input from previous harvest to wheat harvest	kg ha^{-1}	✓		✓		
12	Nr.spr.herb.app.	Applications of herbicides: 1 Feb.-31 Jul.		✓	✓	✓	✓	
13	Nr.win.herb.app.	Applications of herbicides: 1 Aug.-31 Jan.	number		✓	✓		
14	TFI_wht	Total Treatment Frequency Index, all pesticides			✓			
15	Herbicide TFI	TFI from applied herbicides		✓	✓	✓	✓	✓
16	Glyph.TFI	TFI glyphosate (pre-sowing)			✓	✓		
17	Nr.mech.weed.spr.	Mechanical weeding passes: 1 Feb.-31 Jul.	number		✓			
18	Nr.mech.weed.win.	Mechanical weeding passes: 1 Aug.-31 Jan.	number		✓			
19	STIR.tillage	Pre-sowing Soil Tillage Intensity Rating		✓	✓	✓	✓	✓
20	STIR.mech.weed.	STIR from mechanical weeding		✓	✓	✓	✓	✓
21	Manual.weeding	Manual weeding: presence/absence	1 / 0	✓	✓	✓	✓	✓
22	Grassland	Grassland presence/absence in the preceding year	1 / 0	✓	✓	✓	✓	✓
23	Comp.pl.s.dens	Sowing density: companion plant	seeds m^{-2}		✓	✓		
		Crop and weed assessments						
24	Crop.biom	Total crop biomass pre-harvest	g DM m^{-2}	✓	✓		✓	
25	Biom.companion	Biomass (DM) of companion plant pre-harvest	g DM m^{-2}	✓	✓	✓		
26	Wbiom_ratio	Weed biomass/total biomass		✓	✓			
27	Weed.biomass	Weed biomass pre-harvest	g DM m^{-2}	✓*	✓	✓*	✓*	✓

(Continued)

TABLE 1 Continued

ID	Label	Description	Units	ExKn	VIF	RFC	LME_W	LME_Y
		Climate & soil-linked information						
28	GDD	Growing degree days		✓	✓	✓	✓	✓
29	Rainfall	Cumulative rainfall	mm	✓	✓	✓	✓	✓
30	Soil.typology	Soil suitability score	score	✓	✓	✓		✓
		Grain yield & grouping						
31	Yield.potential	Wheat growing potential	score	✓	✓	✓		✓
32	Grain.yield	DM grain yield	t ha^{-1}	✓*	✓			✓*
33	Cousens.group	Cousens-groups: inside/upper/lower				✓*		✓

*Response variable. Variables were selected via ExKn (expert knowledge), VIF (variance inflation factor), and RFC (random forest classifier). Linear mixed-effects (LME) models (REML approach) were applied to weed biomass (LME W) and grain yield (LME Y). ID: variable ID; Label: label of assessed variable.

Rating (STIR). To determine the STIR, the lapse between the previous harvest to the wheat harvest was considered. The RUSLE2 framework method (USDA, 2008; FiBL, 2022) was employed to calculate the STIR. Numeric values were assigned to the applied driving speed of the machine, the soil disturbance type caused (*e.g.*, inversion with some mixing, turn-over and fracturing, or mixing only), the average working depth and the superficial soil disturbance. The higher the STIR value is, the more disturbed the soil. For instance, in PestiRed the STIR for one ploughing pass was 51, and 6 for one harrowing pass. The STIR due to tillage occurring between the previous harvest and wheat sowing was assessed as *STIR tillage* (*ID* 19). Ploughing and seedbed preparation were considered to calculate the *STIR tillage* value. The STIR value for mechanical weeding operations perfomed after sowing and before harvest was the *STIR mechanical weeding* (*ID* 20).

The sowing interval date (*ID* 8) was categorised into 8 classes of 10-day intervals, 1: 1–10 October, 2: 11–20 October, 3: 21–31 October, 4: 1–10 November, 5: 11–20 November, 6: 21–30 November, 7: February (3 fields), 8: March (2 fields). Wheat quality refers to the yield potential (ranging from – to ++++) of the wheat varieties registered in the field calendar. This potential scale was converted to a numeric score from 1 to 11 and grouped into four numeric classes (1-4), where values 1-2, 3-5, 6–8 and 9–11 were assigned to yield potential (*ID* 31) classes 1, 2, 3 and 4, respectively. The higher the class score, the higher the yield potential. For each field, a class was assigned to the variety sown, assuming seeds were purchased and sown in the same year. In cases where mixtures were used, the yield potential was averaged for all varieties and rounded up.

Crop biomass (*ID* 24), companion plant biomass (*ID* 25) and weed biomass (*ID* 27) were assessed at crop maturity during each growing season, between mid-June and mid-July, before harvesting. Eight frames were placed randomly across the field by walking on a W-shape path. Wheat, companion plants and weeds were cut and collected separately within each frame. All samples of a single field were later pooled, oven-dried during 48 hours at 80 °C, weighed and data recorded separately. The weed biomass ratio (*ID* 26) was estimated by dividing the DM weed biomass by the sum of DM biomass of crop, weeds, companion plants.

Climatic data were obtained from the closest meteorological station to each farm (https://www.agrometeo.ch). Daily rainfall (*ID* 29) and temperature were measured from wheat sowing to harvest date and summed up. Growing degree-days (GDD, *ID* 28) were computed for that same lapse with Equation 2, using a T base of 0 °C and temperatures measured at 2 m above soil surface.

$$GDD = \sum \left(\frac{T_{max} + T_{min}}{2} - T_{base} \right) \quad (2)$$

Soil typology (*ID* 30) describes soil suitability for cultivation of wheat. It is based on inherent soil and site properties, primarily effective soil depth, available water capacity, texture, natural drainage, stoniness, and natural soil pH, all combined using a limiting-factor approach. The cropping typology map (https://map.geo.admin.ch) grades land areas (ranging from +/– to ++), according to their suitability to shelter different crop types. This information was extracted using geo-location of each experimental field and its soil typology scored in three steps. (i) Attributing scores 3, 2 or 1, correspondingly for fields graded ++, + or +/– for cereals; score 1 for fields graded + for field crops and score 0 to fields without quotation for neither cereals, nor field crops. (ii) Assigning score 2 to fields graded ++, + or +/– for cereal crops, score 1 to fields with + for field crops and score 0 to fields without quotation for either cereals or field crops. (iii) The final score was computed as *soil typology* = 1 + (i) + (ii), ranging in values from 1 to 6.

2.3 Statistical analysis

Initially, weed management practices used on IWM-0H and IWM-H strategies were analysed excluding all other environmental factors and management activities. The aim was to identify differences due to measures implementation and highlight them comparing between herbicide-free and herbicide-based practices. For this purpose, the Wilcoxon-Mann-Whitney test (McKnight and Najab, 2010) and Chi-squared test of independence (Cochran, 1952; McHugh, 2013) for continuous and categorical variables were applied, respectively. The weed control operations applied in autumn, namely number of herbicide applications (*ID* 13, Table 1), number of mechanical weeding passes (*ID* 18), glyphosate use (*ID* 16), manual weeding (*ID* 21) and companion plants (*ID* 25) were not evaluated because they were implemented only on a few fields, correspondingly 40%, 20%, 4%, 13%, and 3% out of the total field number. The fertiliser input variables, N (*ID* 9), P (*ID* 10), and K (*ID* 11) were excluded, as well. These variables were rather more closely linked to the specific fertility conditions of each field than to the weed management. Moreover, association of varieties (*ID* 6) was primarily associated with disease management rather than weed control, thus it was not considered. Secondly, several statistical methods were employed to evaluate weed biomass and wheat grain yield responses to weed management strategies with herbicides (IWM-H) and without them (IWM-0H) on the 94 studied fields. Finally, it was evaluated the agronomic indicators, crop and weed assessments, environmental information or yield covariables that influenced the weed biomass and grain yield responses and to which extent.

Given the relatively complexity of on-farm data and the limited sample size, the number of potential explanatory variables was high. Therefore, a multi-step analytical workflow with the following steps was used: nonlinear regression, variance inflation factor (VIF), Random Forest classifier (RFC), and linear mixed-effects (LME). This workflow was explicitly designed to promote a parsimonious modelling approach, rather than increase complexity (*i.e.*, reduced risk of overfitting). Collinear predictors and data dimensionality were reduced with VIF. The RFC was applied using repeated cross-validation and averaging across 100 random data splits to reduce sensitivity to individual partitions; RFC contributed to rank predictors by importance. Finally, only variables consistently identified as influential and retained based on expert knowledge, were subject of analyses by LME, fitting separate models by IWM strategy with a limited number of fixed effects and a simple random-effects structure.

2.3.1 Testing weed biomass effect on yield

Weed-related yield loss under on-farm conditions was tested using the asymptotic function (Cousens, 1985), independently of the IWM-0H and IWM-H strategies. Dry matter grain yield and weed biomass were fitted via nonlinear least squares with the package nlstools (Baty et al., 2015), following the procedure described in Masson et al. (2024). The parameters weed-free yield (*Ywf*), yield loss when weed biomass approached zero (*i*) and asymptotic maximum yield loss (*A*) were computed and accompanied by their 95%-confidence limits (95%-CL). The response curve was displayed with its 98%-CL to group as many fields fitting the function, and group separately those above and below the limits *i.e.*, variable *Cousens.group*, *ID* 33, Table 1). Fields showing a yield reduction due to increased weed biomass and within the 98%-CL were grouped as *Cousens-inside*. Fields with yield responses below or above the 98%-CL boundaries were assigned to *Cousens-lower* and *Cousens-upper* groups, respectively. Fields in *Cousens-lower* and *Cousens-upper* showed a marked deviation from the asymptote but gathered a large yield variation. Here, it was assumed that pedoclimatic conditions and crop management influenced these discrepancies, while weed management remained satisfactory.

2.3.2 Identification of variables influencing weed biomass and grain yield

To identify the variables influencing weed biomass and grain yield, based on their importance, expert knowledge selection (column ExKn; Table 1) and three statistical procedures were applied. Particularly at close-to-zero DM weed biomass, other variables were evaluated to explain the yield variability. The statistical processes applied to variables in Table 1 were VIF, column VIF; RFC, column RFC, and linear mixed-effects (LME) models fitted by the restricted maximum likelihood approach, column LME_W for weed biomass, and LME_Y for grain yield. All analyses were done with the statistical software R, version 4.5.2 [Not] Part in a Rumble (R Core Team, 2025).

Variables 3–32 in Table 1 were analysed and gradually selected via VIF and RFC at each procedure to determine the most influential variable(s) on weed competition and grain yield in VIF and RFC. For LME_W and LME_Y, variables 1–2 were required to correctly adjust the random effects and errors. To test for multicollinearity and detect inflation of the regression coefficients variance, VIF was computed on the explanatory variables influencing grain yield using the package car (Fox and Weisberg, 2019). When a variable had a VIF > 50, then VIF > 10, and finally VIF > 4, it was assigned as highly collinear and removed after each of those sequential steps. At each sequence, variables exceeding the mentioned thresholds were excluded and VIF was computed again, building a new linear model with the remaining explanatory variables. Variables with a VIF ≤ 4 (*i.e.*, without multicollinearity) were subject of analysis in the second step, RFC (Table 1; column RFC). The three groups *Cousens-inside, Cousens-upper* and *Cousens-lower* defined were used as the response categorical variable. When a variable had a VIF > 4 but was selected via expert knowledge, it was kept for RFC.

The RFC procedure requires splitting the data pull into training and testing sets, for model evaluation purposes (Lepke et al., 2024). Observed data were split into training (73.4%) and testing (26.6%) sets, keeping a balanced distribution among the three Cousens groups. The following variables were treated as binomial for RFC: *Glyph.TFI, Grassland, Herbicide TFI, Manual.weeding, Varieties.mixture, Ploughing, Soil.typology, Sowing.date, Wheat.quality*, while the others were treated as numeric. To implement RFC, three hyperparameters required pre-definition (da Silva Chagas et al., 2016), the number of trees in each forest (n_tree), the number of variables to be used on each tree (mtry) and the minimal number of observations in a node allowed to be divided (min_n). The hyperparameter n_tree was set to 1000 trees. A 10-fold cross-validation procedure over 1000 trees was applied to the training set to optimise the other two hyperparameters. Cross-validation allowed maximizing the area under the curve (AUC) on each iteration; AUC is an evaluation metric for classification algorithms. Packages randomForest (Liaw and Wiener, 2002), ranger (Wright and

Ziegler, 2017), vip (Greenwell and Boehmke, 2020), tidymodels (Kuhn and Wickham, 2020), and tidyverse (Wickham et al., 2019) were used for RFC implementation.

Traditional feature selection in classification models could be biased when the number of categories differ (Breiman et al., 1984; White and Liu, 1994; Kim and Loh, 2001; Strobl et al., 2009). Therefore, the best hyperparameters computed during cross-validation served as input in the function cforest for an unbiased feature selection (Hapfelmeier and Ulm, 2013). The feature selection algorithm was repeated 10 times to increase model robustness, and values of importance were averaged for each feature. This whole procedure was repeated over 100 random splits of the data, each time separating into training and testing sets. Evaluation of feature importance on a single run is not reliable especially when predictors are correlated (Richter et al., 2025). Therefore, variable importance in this study was averaged over the results run over the 100 splits. Variables whose averages were greater than the absolute value of the least important variable were estimated as potentially interesting (Rothacher and Strobl, 2024). However, if some variables were positioned below this importance limit and still considered as valuable via expert knowledge, they were integrated into LME analyses.

Finally, LME was applied to variables selected as important after RFC and expert knowledge for verifying their influence on weed biomass and grain yield, Table 1 (columns LME_W and LME_Y, respectively). Data were analysed fitting two linear mixed-effect models for each response variable, one for IWM-H and another for IWM-0H data, with the package nlme (Pinheiro and Bates, 2000; Pinheiro et al., 2025). The weed biomass response to IWM-H and IWM-0H strategies was analysed separately, using the base model (Equation 3). Management and environmental predictors were treated as fixed effects, indexed according to the variable *ID* (Table 1).

$$\begin{aligned} \ln\ (WB + 0.1) = \beta_0 + ID2 + ID8 + \beta_a \cdot ID_{22} + \beta_b \cdot ID_5 \\ + \beta_1 \cdot ID_{24} + \beta_2 \cdot ID_{28} + \beta_3 \cdot ID_{29} \\ + \beta_4 \cdot ID_{20} + \beta_5 \cdot ID_{19} + \beta_6 \cdot ID_7 + \beta_7 \cdot ID_9 + \beta_8 \cdot ID_{15} \\ + \beta_9 \cdot ID_{12} + \mu_{ID1} + \varepsilon \end{aligned} \tag{3}$$

Here, $ln(WB + 0.1)$ is the natural log transformed weed biomass response (added with a constant of 0.1 to accommodate zero values); β_0 is the overall intercept; Year (*ID* 2) and sowing interval date (*ID* 8) are categorical factors; false seedbed (*ID* 5) and grassland (*ID* 22) are binary (0 = absence, 1 = presence) indicators with their corresponding coefficients $\beta_{a,b}$; all other covariates are continuous predictors with coefficients $\beta_{1,\ldots,9}$. The term μ_{ID1} defines the PestiRed field identifier's random effect; ε is the residual error. A fixed variance structure was fitted with the function varFixed of the package *nlme*, which modelled the larger residual error spread as rainfall (*ID* 29) increased without extra parameters involved. Model (3) for IWM-H was applied as shown, while for IWM-0H without the number of herbicide applications in spring (*ID* 12) and herbicide TFI (*ID* 15).

Similarly, grain yield response to both strategies was analysed separately by IWM-H and IWM-0H with the base model (Equation 4),

$$\begin{aligned} Y = \beta_0 + ID2 + ID8 + ID30 + ID31 + ID33 + \beta_a \cdot ID_{22} \\ + \beta_b \cdot ID_5 + \beta_1 \cdot ID_{19} + \beta_2 \cdot ID_{20} \\ + \beta_3 \cdot ID_{15} + \beta_4 \cdot ID_{12} + \beta_5 \cdot ID_{28} + \beta_6 \cdot ID_{29} + \beta_7 \cdot ID_7 \\ + \beta_8 \cdot ID_{27} + \beta_9 \cdot ID_9 + \mu_{ID1} + \varepsilon \end{aligned} \tag{4}$$

where (Y is the wheat grain yield response; β_0 is the overall intercept; Year (*ID* 2), sowing interval date (*ID* 8), soil typology (*ID* 30), yield potential (*ID* 31) and Cousens groups (*ID* 33) are categorical factors; false seedbed (*ID* 5) and grassland (*ID* 22) are binary indicators with coefficients $\beta_{a,b}$; all other covariates are continuous predictors with coefficients $\beta_{1,\ldots,9}$. The terms μ_{ID1} and ε are correspondingly random effects and the residual error with variance allowed to increase proportionally with rainfall. Model (4) for IWM-H was applied as shown, while for IWM-0H without the variables related with herbicides. Throughout the mixed-effect modelling processes, model selection was achieved using the lowest Akaike information criteria. Non-significant factors were excluded, and factor interactions were checked when individual factors were significant ($P< 0.05$). Marginal means adjusted with the Tukey HSD (α = 0.05) method were calculated to explore differences among factors and interactions; predicted effects on weed biomass and grain yield were plotted with the packages cowplot (Wilke, 2024) and ggplot2 (Wickham, 2016).

3 Results

3.1 Weed biomass and grain yield responses to IWM strategies

The two strategies tested, IWM-H and IWM-0H, differed in the weed management practices implemented. These differences were significant for the agronomic indicators *STIR mechanical weeding*, Herbicide TFI, number of herbicide applications in spring and sowing date (Table 2). No significant differences were detected for the remaining agronomic and climatic indicators and for crop yield potential. In the PestiRed fields, false seedbed was used infrequently, and sowing occurred later in most IWM-0H fields (false seedbed class 3: 21–31 October) compared with IWM-H fields (false seedbed class 2: 11–20 October).

Mechanical weeding intensity differed substantially between strategies. On average, the *STIR mechanical weeding* value was 12.53, corresponding to approximately two passes with a harrow (*i.e.*, STIR = 6 per pass). The averaged number of passes with the harrow was 1.85 for IWM-0H and 0.43 for IWM-H.

Herbicide TFI and the number of spring herbicide applications were important in IWM-H fields. PestiRed focused on growing most of the arable crops typically used in Switzerland during the six-year project duration. Inclusion of grassland in the rotation prior the establishment of wheat was low for both strategies and limited to farms already having leys.

TABLE 2 Comparison of agronomic, climatic and crop yield variables between fields with (IWM-H) and without herbicides (IWM-0H).

Indicator	Herbicide [n = 37]	Without herbicide [n = 57]	Significance
Agronomic			
STIR.tillage☆	52.35 (34.64)	64.46 (38.96)	ns
STIR.mech.weed.☆	2.59 (4.59)	12.53 (12.02)	***
Herbicide TFI☆	1.13 (0.61)	0 (0)	***
Nr.spr.herb.app.☆	1.19 (0.66)	0 (0)	***
Wheat.sow.dens.☆	202.12 (53.34)	197.02 (23.5)	ns
Sowing.date‡	2 (2-3)	3 (2-5)	**
Grassland‡	3/37 (0-0)	9/57 (0-0)	ns
False.seedbed‡	0 (0-0)	0 (0-0)	ns
Climatic			
Rainfall☆	985.78 (133.74)	992.2 (169.7)	ns
Crop yield			
Yield.potential‡	2.5 (2-3)	2 (2-2.5)	ns

Statistical significance: > 0.05 = *ns*; <0.05, <0.01 = (**) significant; <0.001 = (***) highly significant. ☆ continuous variable; ‡ categorical variable.
Values for continuous variables represent the population mean (standard deviation in parenthesis) and for categorical variables the median (interquartile range in parenthesis). Mann-Whitney U tests applied to continuous and Chi-squared tests of independence to categorical variables. Variables are defined according to Table 1. STIR: Soil Tillage Intensity Rating; TFI: Treatment Frequency Index.

Weed biomass and grain yield were assessed at crop maturity (mid-June to mid-July). Weed management was efficient in most PestiRed fields (Figure 1), and weed control was similar throughout the study period (2020-2023). A simple linear model indicated significantly different weed biomass levels between strategies ($P < 0.05$; Figure 1). Grain yield did not differ between IWM-H and IWM-0H (Figure 2), whereas differences across years within strategies were observed. Across all farms, a pre-harvest DM weed biomass below 50 g m^{-2} (Figures 1, 3) was observed in 84 of 94 fields. In IWM-H, 35 out of 37 fields showed biomass levels below 33 g m^{-2}, and the remaining two fields were below 55 g m^{-2}. In IWM-0H, 3 fields exceeded 100 g m^{-2} and 1 exceeded 200 g m^{-2}. A gradual increase in weed biomass over project years was observed within IWM-0H fields (Figure 1), however, not statistically significant.

3.2 Weed biomass–grain yield relationship

The nonlinear asymptotic function (Cousens, 1985) depicted the relationship between DM wheat yield and DM weed biomass (Figure 3). Weed biomass adequately fit the function (Masson et al., 2024), allowing classification of fields relative to the curve. Based on their position within the 98%-CL, 25 fields were categorised in the group *Cousens-inside*, 34 in *Cousens-upper*, and 35 in *Cousens-lower*. Grain yield ranged from approximately 6.6 to 8.6 t ha^{-1} in the *Cousens-upper* group and 2.6 to 5.6 t ha^{-1} in the *Cousens-lower* group. The estimated weed-free yield (parameter Y_{wf}) was 5.82 t ha^{-1} (CL: 5.43 to 6.21). Among fields with < 0.5 g m^{-2} weed biomass

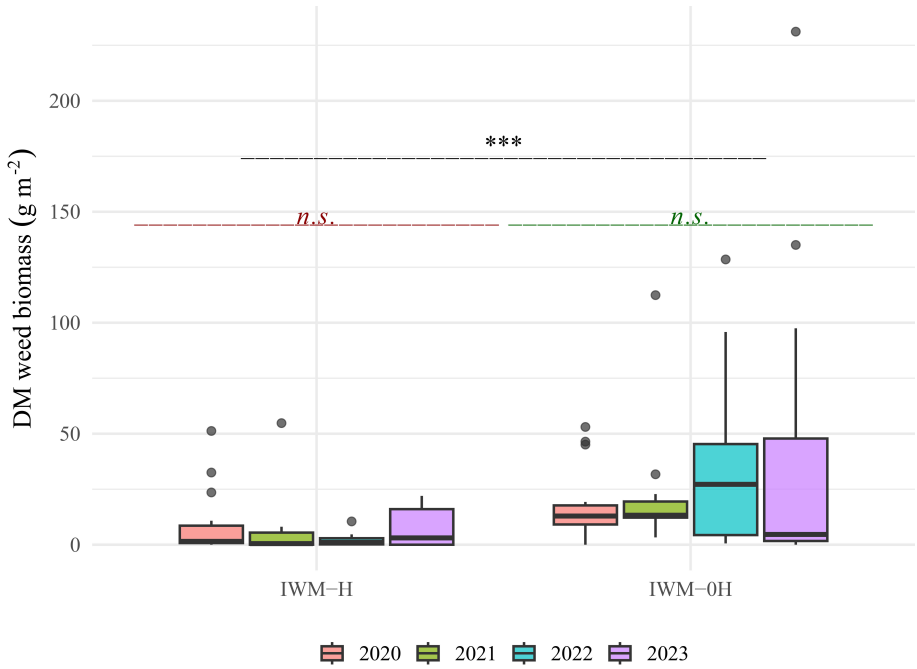

FIGURE 1
Boxplots of pre-harvest dry matter (DM) weed biomass over the first four years weed management in PestiRed fields with (IWM-H) and without herbicides (IWM-0H). Statistical significance: > 0.05 = *ns*; <0.001 = (***) highly significant.

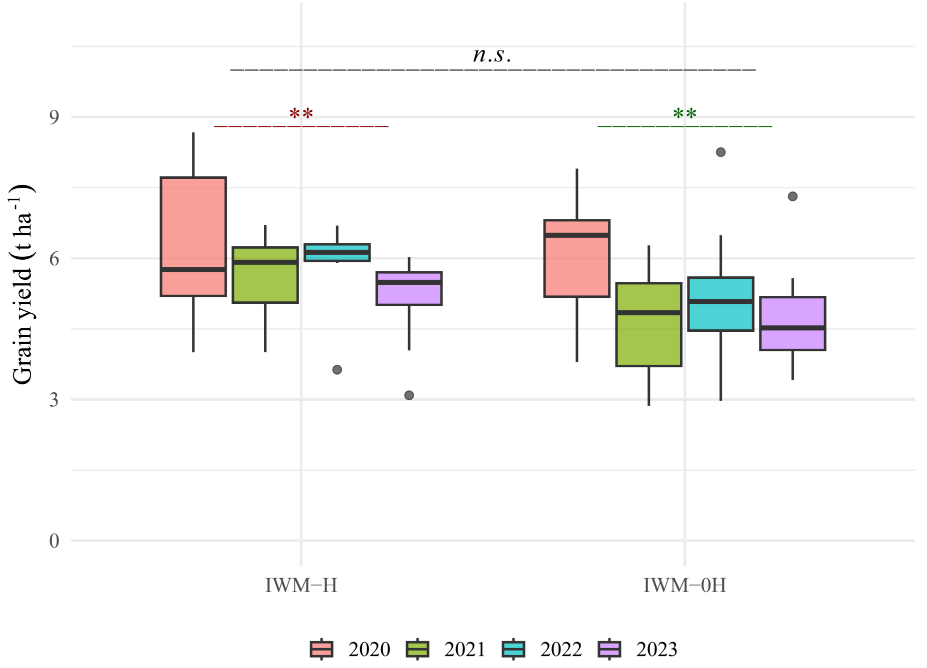

FIGURE 2
Boxplots of observed wheat grain yield over the first four years weed management in PestiRed fields with (IWM-H) and without herbicides (IWM-0H). Statistical significance: > 0.05 = *ns*; <0.05 = (**) significant.

(24% of PestiRed fields, practically weed-free) yields ranged between 4 and 8.5 t ha^{-1}. The initial yield reduction parameter (*i*) at 1 g m^{-2} weed biomass was estimated as 0.4% (CL: –0.2 to 1.1). The maximum yield loss parameter (*A*) was estimated at 58% (CL: 57.1 to 173) after > 200 g m^{-2} weed biomass. Across all fields and years, grain yield remained above 2.5 t ha^{-1}, including years characterised by markedly low rainfall (2022 and 2023). Weed biomass levels exceeding 150 – 200 g m^{-2} were rare, limiting the precision of yield-loss predictions at

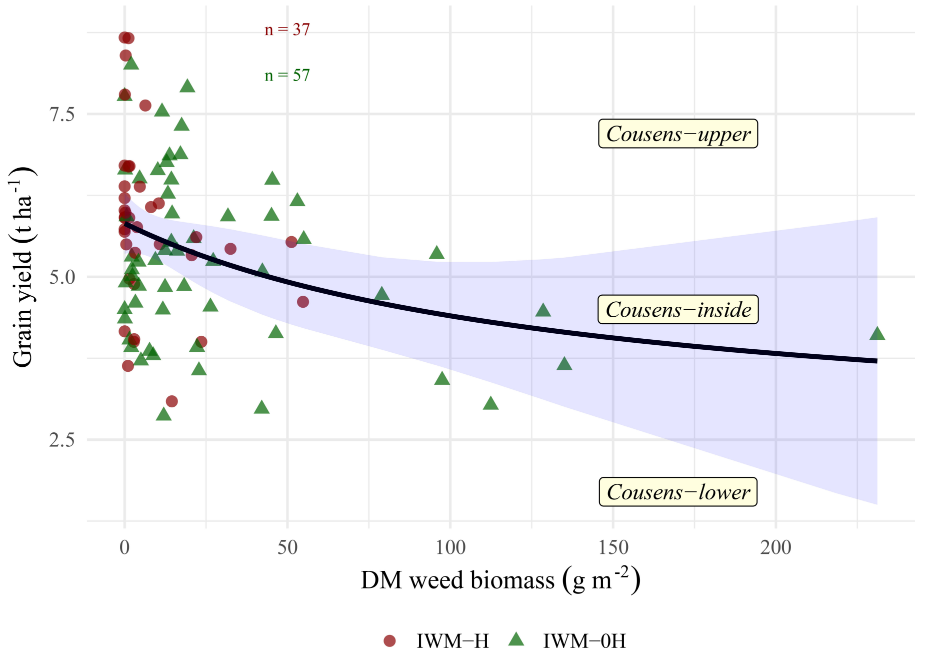

FIGURE 3
Wheat yield response to increasing dry matter (DM) weed biomass from pre-harvest assessments in the PestiRed on-farm trials between 2020 and 2023. Symbols represent observed values; the modeled curve is represented by a solid black line and its associated 98%-confidence limits (98%-CL) are depicted as shaded areas. *Cousens-upper*: fields above the curve and 98%-CL; *Cousens-inside*: fields fitting the curve and inside the 98%-CL; *Cousens-lower*: fields under the curve and 98%-CL. IWM-H: integrated weed management with herbicides; IWM-0H: integrated weed management without herbicides. Estimated parameters: weed-free yield, Y_{wf} = 5.82 t ha^{-1}; initial yield reduction, *i* = 0.4%; maximum yield loss, *A* = 58%.

high weed pressure. The weed communities identified consisted grass and broadleaf species, with an average of 23 species per field (range: 5 – 55). Grass weeds included *Alopecurus myosuroides*, *Lolium multiflorum* and *Poa annua*. Common broadleaf species included *Capsella bursa-pastoris*, *Chenopodium album*, *Lamium purpureum*, *Solanum nigrum*, *Stellaria media*, *Myosotis arvensis*, *Viola arvensis*, *Persicaria maculosa*, *Helianthus annuus*, *Trifolium repens* and *Veronica persica* (Wirth et al., 2024).

3.3 Variables influencing weed biomass and grain yield

The present analyses focus on identifying the most influential predictors of weed biomass and yield variation, without aiming model predictive performance. Of the 26 explanatory variables evaluated through VIF (Table 1; column VIF), 23 remained for RFC analysis (column RF), using *Cousens.group* as response. Ten variables exceeded the importance threshold (Figure 4; vertical red dashed line) to influence yield grouping and were selected for LME modelling. For weed biomass, the RFC-selected variables were analyzed using LME, supplemented by expert-selected variables including *Crop.biom*, *STIR.mech.weed*, and *N.input* (Table 1; column LME_W). The variables *Soil.typology*, *Grain yield*, *Yield.potential*, and *Cousens.group* were excluded as they relate to yield rather than to weed biomass response. *Year_w* and *PR_ID* supported the PestiRed experimental approach, and were included as fixed and random effects, respectively. Separate models were applied for each IWM strategy.

The only significant predictor of weed biomass in both IWM-H and IWM-0H fields was *STIR tillage* ($P< 0.05$), showing comparable negative effects across strategies. The corresponding effect sizes are provided in Table 3 and illustrated in Figures 5a, b. For grain yield in IWM-H, *Soil.typology* and *STIR tillage* were the only significant predictors, with no significant interactions detected (Figure 6). In IWM-0H, LME indicated a consistent negative association between weed biomass and grain yield across all Cousens groups ($P< 0.001$, Table 3; Figure 7a), with stronger responses observed in *Cousens-upper* and *Cousens-lower* compared with *Cousens-inside* (Figure 7a). Mechanical weeding intensity (*STIR mechanical weeding*) also affected yield in *Cousens-upper* and *Cousens-lower* groups (Table 3; Figure 7b), whereas no significant effect was detected for *Cousens-inside*.

4 Discussion

4.1 Differences in IWM practice intensity across strategies

The two contrasting strategies, IWM-H and IWM-0H, differed in weed management intensity, as reflected in several agronomic variables. Mechanical weeding intensity was considerably higher in IWM-0H, while herbicide TFI and spring herbicide applications were employed only in IWM-H. Büchi et al. (2019) reported similar contrasts when comparing conventional, no-till, and organic systems in Switzerland. In that study, conventional and no-till systems relied fully on herbicides, whereas mechanical weeding was more frequent in organic systems, with overall averages of 0 mechanical weeding passes in the former two and 2.35 passes in the latter. The corresponding average STIR values were 94, 24 and 139 for conventional, no-till and organic systems, respectively, with mean HTFI values of 1.18, 2.32 and 0. In the IWM-0H PestiRed fields, *STIR mechanical weeding* values were lower than those reported for Swiss organic systems, whereas Herbicide TFI in IWM-H fields was comparable to Swiss conventional systems, though combined with

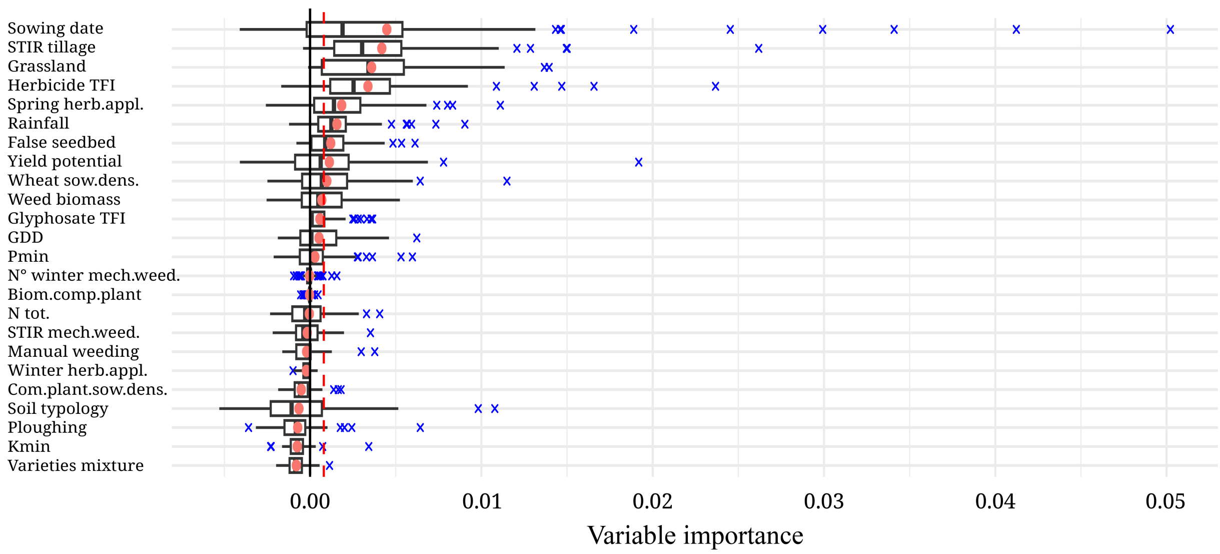

FIGURE 4
Variables influencing Cousens groups of yield after Figure 3, ordered according to average importance calculated over 100 random data splits. Boxplots indicate the proportion of importance variation, red dots are the averages, blue symbols are outliers. Vertical black line: zero importance; vertical red line: threshold defining the most important variables. Variables are defined according to Table 1. STIR, soil tillage intensity rating; TFI, treatment frequency index; GDD, growing degree days.

TABLE 3 Summary of significant weed biomass and grain yield predictor variables from linear mixed-effects (LME) models.

Response	Strategy	Predictor	Effect size	Significance
Weed biomass	IWM-H	STIR tillage	−0.88 g m^{-2} (0.87–0.90)	P< 0.05
Weed biomass	IWM-0H	STIR tillage	−0.90 g m^{-2} (0.89–0.90)	P< 0.05
Grain yield	IWM-H	STIR tillage	0.013 t ha^{-1} (0.001–0.025)	P = 0.03
Grain yield	IWM-H	Soil typology	Significant effect (categorical)	P< 0.001
Grain yield	IWM-0H	Weed biomass (*Cousens-upper*, Figure 7a)	−0.020 t ha^{-1} (−0.029 to −0.010)	P< 0.001
Grain yield	IWM-0H	Weed biomass (*Cousens-lower*, Figure 7a)	−0.017 t ha^{-1} (−0.024 to −0.010)	P< 0.001
Grain yield	IWM-0H	Weed biomass (*Cousens-inside*, Figure 7a)	−0.008 t ha^{-1} (−0.013 to −0.004)	P< 0.001
Grain yield	IWM-0H	STIR mechanical weeding (upper/lower)	Negative effect (see Figure 7b)	P< 0.001

Effect sizes are expressed as predicted changes per unit increase of each predictor. Values in parentheses represent 95% confidence limits. STIR, soil tillage intensity rating.

slightly higher mechanical weeding. Despite this less frequent mechanical weeding relative to national organic averages, seeding density was not increased to compensate for potential crop plant losses, allowing a direct comparison with IWM-H results.

Soil tillage and seedbed preparation are highly effective preventive practices for weed management, as they create a uniform and firm seedbed (regardless of herbicide usage) and support homogeneous seedling emergence (Travlos et al., 2020). In PestiRed, *STIR tillage* and false seedbed practices showed no meaningful differences between the two strategies. Values of *STIR tillage* consisted of those from ploughing combined with seedbed preparation (*i.e.*, ploughing followed by a rotary harrow, or two passes with a deep non-inversion cultivator). False seedbed implementation was limited in both strategies, likely due to autumn rainfall constraints and narrow operational windows. Delayed sowing, was somewhat more common in IWM-0H but also occurred in IWM-H fields, aligning with previous evidence that delayed sowing can improve control of autumn grass weeds such as *Alopecurus myosuroides* when combined with other IWM tactics (Andrew and Storkey, 2017). While delayed sowing can reduce autumn weed emergence, and even slightly increase winter wheat yield when combined with a pre-emergence herbicide application (Gerhards et al., 2022), it may also involve yield penalties (almost 50% yield loss) when used up to mid-November (Copeland et al., 2023). Fields with grassland preceding wheat tended to show reduced weed infestation (Dominschek et al., 2021). However, grassland was relatively scarce across the 94 wheat fields, reflecting rotational constraints linked to the planned rotation within the six-year PestiRed framework rather than differences between strategies.

4.2 Weed biomass-yield relationships and drivers of variability

The relationship between grain yield and weed biomass is complex, showing in some cases a linear behaviour, or a nonlinear yield relationship (Cousens, 1985). For instance, in heavily infested fields a 60% yield reduction has been observed (Liu et al., 2024). In other cases, diverse weed communities mitigate yield losses by suppressing dominant competitive species (Adeux et al., 2019b), which complicate interpretation of the relationship. In the PestiRed

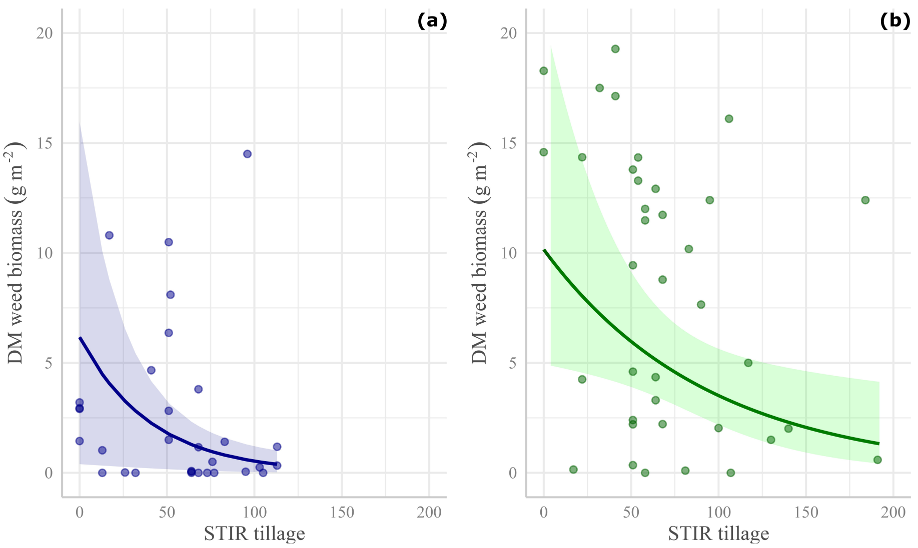

FIGURE 5
Predicted dry matter (DM) weed biomass response (and 95%-CLs) to increasing *STIR tillage* for PestiRed fields using IWM-H **(a)** and for fields using IWM-0H **(b)**. Dots show field observations. STIR, soil tillage intensity rating.

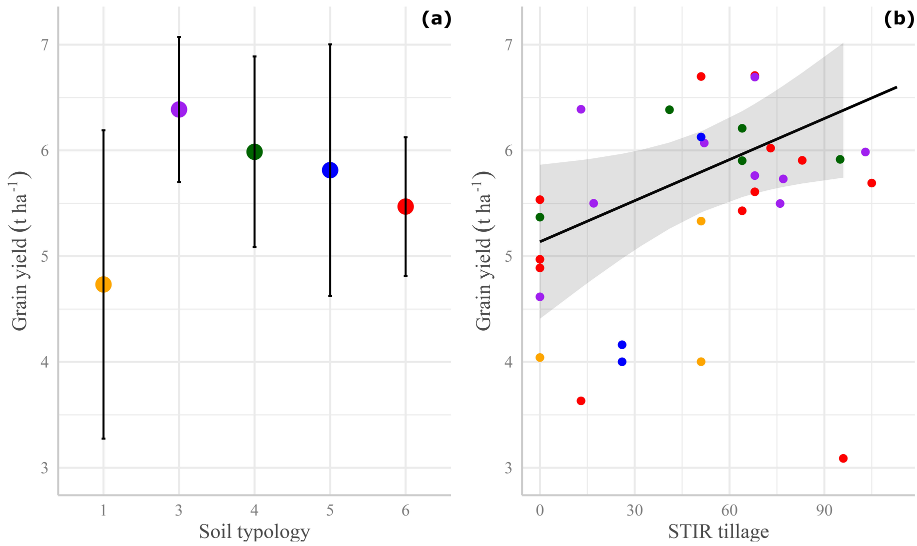

FIGURE 6
(a) Adjusted means (dots) of grain yield on IWM-H fields by Soil typology and 95%-CL (vertical lines). **(b)** Predicted yield response (black line) as a function of increasing STIR tillage for all Soil typology scores and corresponding 95%-CL (gray filled area); soil typology scores are the same as in panel **(a)** and Table 1. STIR, soil tillage intensity rating.

wheat dataset, the nonlinear Cousens model characterised the negative effect of increasing weed biomass on grain yield, across< 30% of fields with diverse on-farm conditions (Figure 3; *Cousens-inside* group). Many fields deviated above (*Cousens-upper*) or below (*Cousens-lower*) the predicted yield loss relationship. Such divergence is common in heterogeneous on-farm datasets, where multiple interacting drivers beyond weed biomass can influence yield (Adeux et al., 2019b, 2022; Majidi et al., 2025).

Grain yield ranged widely, from around 2 to 9 t ha^{-1} across Cousens groups, however, remaining above 2.5 t ha^{-1} even during the drought-affected seasons of 2022 and 2023. The Cousens model estimated parameters showed low yield losses at modest weed biomass levels (50 g m^{-2}). These results are consistent with other European studies, where low (25 g m^{-2} in wheat) to moderate (67 g m^{-2} in soybean) weed biomass levels occurring in diversified systems did not necessarily lead to yield reduction (Adeux et al., 2022; Majidi et al., 2025). Other Swiss study reported low DM weed biomass and no wheat grain yield loss for five diversified IWM strategies in wheat over a 3-year period (Masson et al., 2024). The PestiRed dataset limits the predictive accuracy at high weed pressure, as only 4 fields exceeded a relatively high weed biomass (*i.e.*, > 100 g m^{-2}). Similar limitations were noted in Mediterranean no-till systems, in which weed biomass was high but not resulting large yield losses under drought stress (Gandía et al., 2021). Moreover, these authors highlighted the importance of crop rotation on weed emergence dynamics.

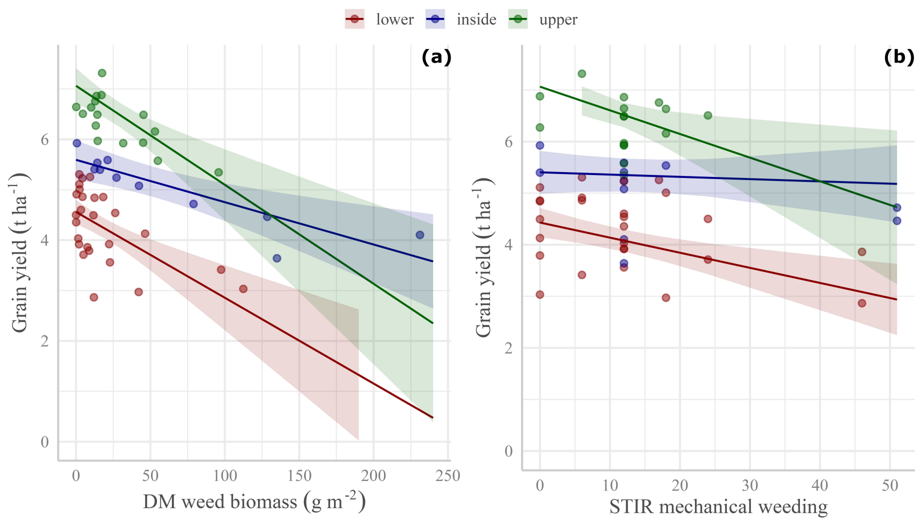

FIGURE 7
(a) Predicted grain yield on fields using IWM-0H in response to increasing dry matter (DM) weed biomass, and **(b)** in response to increasing STIR mechanical weeding value. The response lines are plotted by Cousens groups and shaded with their corresponding 95%-CL. STIR, soil tillage intensity rating.

Weed-induced yield reduction has been found to depend on weed species composition. Aggressive species can produce substantial yield losses at modest biomass levels (tens of g m^{-2}), while in other cases higher weed biomass has not caused proportional yield loss (Minhas et al., 2023). For instance, the Department of Primary Industries and Regional Development of Australia indicated around 70 g dry weight m^2 of great brome (*Bromus diandrus*) diminished grain yield by 43% (Dhammu et al., 2020). In central Greece, 150 to > 300 g m^{-2} DM biomasses of 2 important broad-leaved weeds (*Sinapis arvensis* and *Veronica hederifolia*, respectively) produced correspondingly significantly low grain yields of 2.5 and 1.8 t ha^{-1}, while lower biomasses of other weeds were related with > 3 t ha^{-1} grain yield (Kanatas et al., 2025). Therefore, crop management has been specifically targeted to control the most competitive species (*e.g.*, *Galium aparine*, *Alopecurus myosuroides*, *Cirsium arvense*) to favour late-emerging species with lower competitive ability (Adeux et al., 2022). Weed communities across PestiRed fields were diverse, with an average of more than 20 species (varying from 5 to 55) per field (Wirth et al., 2024). Species composition did not differ systematically between strategies, although this was not the focus of the current analysis. The weed community diversity in PestiRed confirms that weed communities reduce the dominance of highly competitive species and weaken overall competitive pressure (Andrew and Storkey, 2017; Travlos et al., 2020).

The applied multistep statistical workflow, VIF → RFC → LME, were particularly useful to optimise model performance and interpretation of on-farm and experimental data (Kumar et al., 2025; Liu and Zhao, 2017; Nthebere et al., 2025; Richter et al., 2025). In PestiRed, yield effects were not only caused by weed biomass but mainly by various agroecological processes (*e.g.*, nutrient cycling, water management, biodiversity enhancement), varying environmental and soil conditions, as well as agricultural practices (Stefan et al., 2021). Previous studies have reported an important influence on weed-crop competition of delayed sowing date (Andrew and Storkey, 2017), *STIR tillage* (Masson et al., 2024), presence of grassland (Dominschek et al., 2021), herbicide use (Nazarko et al., 2005), rainfall (Gandía et al., 2021), false seedbed (Travlos et al., 2020), soil yield potential (Smith et al., 2010), and wheat sowing density (Olsen et al., 2005). These agricultural tasks might have contributed to the yield responses, summarised in the three Cousens groups. The *STIR tillage* was a consistently significant predictor of weed biomass across both IWM strategies. Comparable results were found in earlier studies on soil disturbance effects on seedbank dynamics (Adeux et al., 2019b; Büchi et al., 2019). Because soil typology represented structural and wheat-cropping suitability differences among fields, other management effects might have been overshadowed when weed biomass remained low, particularly under IWM-H strategies. Under IWM-0H, higher weed biomass levels required more mechanical weeding passes, *STIR mechanical weeding* was significantly associated with yield decreases across *Cousens-upper* and *Cousens-lower* groups, owing to crop plant losses caused by repeated harrowing operations (Rueda-Ayala et al., 2011). Consequently, yield variability under IWM-0H was driven largely by weed biomass and mechanical disturbance, whereas under IWM-H was primarily shaped by soil typology and tillage intensity. Nevertheless, the rare cases of high weed biomass values in both strategies suggests most farmers successfully managed weeds during the four-year period, despite not using herbicides in IWM-0H fields.

4.3 Limitations and future research

This study is based on four years of on-farm data, reflecting substantial environmental and management variability. While this information enhances practical relevance of the analysis, it limits the ability to isolate causal effects of individual IWM components. The dataset included relatively few cases with high weed biomass (> 150 – 200 g m^{-2}), restricting the accuracy of yield loss predictions at severe infestation levels. Additionally, mechanical and chemical interventions were unevenly distributed across farms, making it difficult to fully quantify their standalone effects. Soil characteristics and climatic extremes were considered, but their interactions with weed dynamics may require more detailed temporal measurements. Other biotic factors contributing to yield loss were not analysed in depth. Further analyses of PestiRed data between 2020 and 2022 concentrate on disease and pest pressure, and the preliminary results do not show substantial impact on yield (unpublished).

The combined multi-step analytical approach may appear complex relative to the limited sample size (94 fields and no repetitions). Each step was used to progressively reduce dimensionality and avoid over-parameterization. Nevertheless, the modest number of fields limits the detection of predictors producing weak effects, which may increase uncertainty around variable ranking. Consequently, findings in this study could be employed for identifying dominant drivers of weed biomass and yield variation, without providing exhaustive inference on all potential management factors.

Analysis of the full dataset at the end of the project will improve the model robustness and assess the shifts in weed populations over the six-year term, under the tested IWM strategies. Controlled experiments complementing on-farm trials could help to identify the impact of specific management practices, such as adjustments to seeding density, timing of mechanical weeding or grassland rotation. Further work should also explore species-specific competition effects and integrate precision agriculture tools to optimise non-chemical interventions within herbicide-limited systems.

Findings from this study should be considered in the context of the relatively low weed biomass levels observed, which limits their generalizability beyond the studied conditions. Although other long-term diversified grain systems with very low weed biomass (0 – 5 g m^{-2}) at flowering have also reported crop biomass reductions of ≈ 7% (Adeux et al., 2019b), yield loss thresholds are known to depend strongly on weed species composition, climatic conditions, and management practices (Storkey et al., 2021; Milberg and Hallgren, 2004). In PestiRed, only a small number of cases exceeded weed biomass levels associated with substantial yield loss (> 150 – 200 g m^{-2}), which constrains extrapolation to systems experiencing higher weed pressure. In more intensive cropping systems characterised by simplified rotations and dominance of highly competitive weed species, yield reductions may occur at lower biomass levels (Weisberger et al., 2019). Furthermore, both on-farm and experimental studies indicate that higher weed pressure is generally associated with stronger yield losses, although remaining highly dependent on weed species composition and environmental conditions (Adeux et al., 2022; Travlos et al., 2020). Therefore, the present findings are most representative of diversified temperate cropping systems with moderate weed pressure, and extrapolation to contrasting agroecological contexts should be undertaken with caution.

This study focuses primarily on the agronomic performance but economic considerations are highly relevant for the adoption of IWM practices. Mechanical weeding in winter wheat, such as false seedbed, repeated harrowing or delaying sowing, may increase operational costs (*i.e.*, higher labour, fuel, and machinery requirements compared with herbicide-based strategies). However, an initial complementary analyses within the PestiRed project between 2020 and 2021 showed that these additional costs can be offset by reductions in plant protection products use and improved revenues (Zorn et al., 2023). In that report, the reduced reliance on herbicides led to decreases in costs of plant protection products up to 90%, while labour and machinery costs increased by approximately 17%. At the same time, slightly lower yields (around −7%) were compensated by higher wheat prices (approximately +8%), driven by quality premiums and direct payments for pesticide-free production. Consequently, overall economic performance was maintained or slightly improved, with net returns (direct- and labour-cost-free output) averaging around +90 CHF ha^{-1} in innovative IWM systems. These findings indicate that herbicide-free IWM can be economically viable under Swiss conditions, although outcomes of PestiRed are still under evaluation and a comprehensive cost-benefit analysis is under preparation. Future work integrating detailed economic and agronomic indicators will be essential to fully assess the feasibility and adoption potential of herbicide-free IWM systems.

5 Conclusion

This study demonstrates that diversified integrated weed management (IWM) systems, as implemented in the PestiRed project, can sustain wheat yield under real on-farm conditions in Switzerland, both with and without the use of herbicides. Across four growing seasons and multiple locations, weed biomass was maintained at levels that rarely affected grain yield. Slightly higher weed biomass was observed in herbicide-free IWM fields, and only four fields exceeded weed biomass levels associated with meaningful yield loss. Importantly, these low weed biomass levels reflect the outcome of combined management practices implemented by farmers, rather than necessarily low initial weed pressure. Well-designed and consistently applied IWM strategies, combining preventive, mechanical, and, where strictly needed, chemical measures, can effectively control weeds and maintain crop productivity under practical farming conditions. Herbicide use improved the reliability of weed control but did not translate into higher average yields. Herbicide-free IWM can therefore perform comparably to herbicide-based management when practices are optimised and local environmental conditions are favourable. Based on a preliminary economic analyses, it could be established that increased operational costs in herbicide-free IWM systems can be offset by reduced input costs, provided there are price premiums and direct payments to farmers, resulting in comparable profitability as herbicide-based IWM systems. This study identified false seedbed preparation, well-chosen sowing date and density, tillage intensity, and herbicide application, together with rainfall conditions, soil typology and crop yield potential as key drivers of yield stability and weed suppression, highlighting the importance of context-specific management decisions under real on-farm conditions. However, the observational nature of the dataset and the limited representation of high weed pressure situations constrain the extrapolation of these findings. The results are most applicable to systems where effective weed management maintains weed biomass at moderate or low levels, whether achieved through herbicide-based or herbicide-free IWM. Further evaluations under higher weed pressure or during transitions from less controlled systems would provide a more comprehensive assessment across contrasting agroecological contexts. Ultimately, these findings underscore that well-designed preventive strategies, rather than reactive inputs contribute to maintain resilient, high-performing and productive wheat systems.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

VR-A: Conceptualization, Writing – original draft, Formal analysis, Methodology, Writing – review & editing, Data curation. JéW: Conceptualization, Writing – review & editing, Methodology, Data curation, Formal analysis. SM: Methodology, Investigation, Data curation, Supervision, Writing – review & editing, Conceptualization, Visualization, Resources. SC: Validation, Data curation, Writing – review & editing. PJ: Funding acquisition, Investigation, Writing – review & editing, Supervision, Validation, Project administration, Methodology, Visualization. JiW: Conceptualization, Visualization, Supervision, Validation, Writing – review & editing.

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Conflict of interest

The author(s) declared that this work was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

The author PJ declared that they were an editorial board member of Frontiers, at the time of submission. This had no impact on the peer review process and the final decision.

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