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Economic viability of reduced agricultural inputs in farmer-co-designed large-scale experimental trials in western France

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Reducing agricultural inputs is necessary for sustainable farming, but raises concerns over yields and farmers' income. Here, we used large-scale experimental trials on cereal fields in western France for the period 2022–2023 to assess the effects of input reductions on yields and gross margins under real farming conditions. The trials, co-designed with farmers, involved substantial nitrogen and pesticide reductions in conventional fields, and reductions in soil work or mechanical weeding in organic fields. The results showed that input reductions led to average yield gaps of about 5% in both conventional and organic systems. Cost savings compensated for economic losses and even surpassed these in many conventional field experiments. Simulated price scenarios confirmed the economic viability of input reductions, with heightened advantages during price crises driven by energy or inflation shocks. These findings demonstrate that input-reduction strategies can align environmental and economic goals in real farming conditions, challenging concerns about profitability while supporting the ambitious sustainability targets of policies.

An increase in agricultural inputs has significantly boosted yields and reduced food shortages[1,2]. However, these gains have come at a high environmental damage[3,4], convincing public bodies to pursue policy actions to reduce input use and de-intensify agriculture[5]. There are ambitious public policies, such as the European Union Green Deal, which aim to reduce the use of chemical pesticides by 50% and fertiliser by at least 20%, and halt soil degradation by 2030[6]. However, these targets have raised concerns in the agricultural sector, as seen in the protests and blockades across Europe in early 2024[7,8]. Opponents of policy targets argue that reducing inputs could threaten food sovereignty in Europe and elsewhere, risking major yield gaps while destabilising entire regions[9,10]. Protests by farmers are also driven by uncertainty and a drop in income, with many facing economic difficulties; this has been felt particularly keenly following the sharp rise in energy prices and resulting agricultural input prices in 2022 and 2023 as a result of the COVID-19 pandemic and the war between Russia and Ukraine[11]. Price-scissor effects—rising input prices combined with falling product prices[12]—have recently been observed in several countries. For instance, in France, many organic farmers exited the organic market between 2021 and 2023 due to extremely low product prices combined with high input prices[13]. Since agricultural inputs are costly, it is therefore critical to address the balance between input reduction and yield gaps and their combined impact on farm income. However, these issues have been neglected in the literature or at least poorly investigated.

At the farm scale, a few studies have examined the relationships between inputs, production and income, concluding that reducing inputs may increase profitability[14–20]. However, these have been criticised for relying on questionable modelling choices—such as omitting resistance to change and neighbours, or production function specification. These choices may systematically bias input productivity downward and thus underestimate the real effect of input reduction[21–24]. Hence, robust field-scale experimental studies are required to test such reductions in real field conditions, since this would avoid modelling bias, isolate the effects of input reductions and make it possible to evaluate their implications for income. In particular, there is a need to address the relative effects of input reduction on yield, income or both. In the case of a yield gap resulting from input reduction, the acceptability of impacts on food sovereignty or farmer's income must be ascertained with research designs accounting for actual farmers and field conditions. To the best of our knowledge, there is the only one study that has experimentally measured the impact on income of input reduction, with experiments conducted from 2013 to 2014 on small experimental plots (100–200 m²) within farmer's fields[25]. Given fluctuating and increasing prices as well as changing environmental conditions for agriculture[26,27], it is crucial to assess the impacts of input reductions in the wider economic and environmental context and to take account various possible scenarios.

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Our experimental study explores such issues, in the particular production and price context from 2022 to 2023, to determine whether it is possible to reduce inputs while maintaining or increasing either incomes or yields. We conducted input-reduction experiments in farmers' fields and assessed the consequences in terms of yield and gross margin. Experiments were conducted in 58 winter cereal fields in a study area in western France, involving 31 fields using conventional farming (CF) and 27 fields employing organic farming (OF). Experimental trials were co-designed with farmers, who decided the number of fields, the area of each experimental plot, and the type and magnitude of the reduction. Some fields included several experimental plots, producing in total 76 experimental plots with highly diverse and sometimes complex designs (see Supplementary Information 1 for examples). Conventional farmers opted for reductions in nitrogen (in the 25%–65% range) and/or pesticides (either herbicide and/or fungicide and/or insecticide and from 10% to 100%), with half combining nitrogen and pesticide reductions. For organic farming, reductions in the number and type of soil operations (tillage and mechanical weed control) ranged from 15% to 100%.

The experiments were operated by the farmers and were conducted under real cropping conditions. Experimental plot size averaged 0.87 ha (SD: ±2.1); in most cases, the plots were within field trials (i.e., control and experimental plots in the same field). In a few cases however ($n = 7$), these included entire fields; in such situations, a nearby control field, from the same farmer and with the same crop, was selected for a paired comparison. Crop samples were collected in each experimental and paired control plot just before harvest to measure yields accurately; over 1300 samples (9.55 ± 4.5 per plot) were collected. Farmers were surveyed after the cropping season for an accurate record of agricultural practices and yields across all experimental and control plots. Based on these data, revenues and costs were precisely calculated for each plot based on the prices of each product and operation to closely reflect actual conditions (see Methods below and Supplementary Information 2). Paired difference tests were used to assess the impact of input reductions on yield and income (gross margin/ha) for control and treatment(s) in each field. The results showed input reductions led to average yield gaps of 5% in CF and OF systems, and the economic losses were offset by cost savings and even surpassed in many CF experiments. Finally, we assessed the robustness of our results by conducting simulations over a wider range of economic conditions (e.g., higher energy costs or a deeper price scissors effect), as well as varying yield gaps. This exercise allowed us to assess whether de-intensification is likely to become more or less viable as a strategy during agricultural crises or under varying pedoclimatic conditions. Simulations confirmed the overall economic viability of input reductions, with advantages increasing during price crises. These findings demonstrate that input-reduction strategies can align environmental and economic goals, challenging concerns about profitability while supporting the ambitious sustainability targets of policies like the European Green Deal.

Results

Effect of input reduction on crop yields

An assessment of initial conditions indicated that, in control areas, pesticide use in CF fields and mechanical weeding in OF fields had only a minimal effect on yields whereas nitrogen use had a strong, positive impact—up to a plateau (Supplementary Information 3, $F = 11.39$, $P < 0.001$, $df = 46$, Table S3, Fig. S3). The estimation from the stochastic plateau response model (Eq.3) indicates that the yield plateau differed significantly between 2022 and 2023, with the plateau occurring on average 2.5 $t.ha^{-1}$ lower in 2022 than in 2023 (Table S3). This is consistent with the observed difference in average yields between the two years in CF plots (Table S4) and may be explained by the water deficit conditions in 2022 (Table S5). Ultimately, this may have affected the impact of input reductions: in 2022, the lower nitrogen threshold at which the yield plateau begins (Fig. S3) could have led to smaller effects of nitrogen reductions compared to 2023.

The impact of input reduction on yields was measured using paired differences between control and treatment(s) for each field (within field comparisons) or matched fields (between field trials). No effect of comparison type (within vs. between) nor of crop type was detected in the paired differences (permutation tests were used; see further details in Supplementary Information 5). In CF fields, nitrogen-input reduction decreased the yield by 5.7% ± 18% on average (Fig. 1a; Table S6). A Wilcoxon signed-rank test confirmed that yields were significantly lower in treatment areas compared to control areas, ($P = 0.038$). Similar trends were observed for pesticide reduction with an average decrease of 3.1 ± 17% but the effect was not significant ($P = 0.097$; Fig. 1b; Table S6). When combining all types of reduction in CF fields, the yield gap was an average of 3.9% ± 16% and statistically lower in treatment compared to control ($P = 0.037$; Fig. 1c; Table S6). In OF experiments, reducing soil work and/or mechanical weeding also significantly decreased the yield ($P = 0.042$; Fig. 1d; Table S6), but the average effect was also moderate (−4.9% ± 22%).

The estimation of the relationship between nitrogen input and yield presented above suggested that input reduction effects may depend on two key parameters: (i) weather conditions during the year which may influence the yield plateau, and (ii) the initial nitrogen load in the field (Fig. S3). In our case, these two parameters were not independent, as nitrogen input in the CF-field control situation varied considerably from 196 $kg·ha^{-1}$±34.8 in 2022 to 138 $kg.ha^{-1}$ ± 41.6 in 2023. We then reanalysed the small yield gap caused by input reductions by stratifying the sample according to these two parameters: cropping year (2022 or 2023), and nitrogen by adding a two-level factor describing initial nitrogen input as high or low, with a threshold set at the median value (178 $kg.ha^{-1}$ and 35.1 $kg\ ha^{-1}$ for CF and OF, respectively). Our results showed that CF and OF experiments in 2023 exhibited a significantly negative yield gap (−7.6% to −13.4%), while no significant gap was observed in 2022 (Fig. 1a–d, Table S6). Regarding initial nitrogen levels, we observed a trend where experiments conducted on fields with lower initial nitrogen tended to produce larger yield gaps (Fig. 1a–d, Table S6).

To further investigate how initial nitrogen influenced the effect of input reduction magnitude, we modelled the absolute paired yield differences ($t.ha^{-1}$) in CF fields as a dependent variable, using three separate models where the independent variables were either nitrogen reduction, pesticide reduction, or both, each interacting with the initial nitrogen input. For all CF experiments, the magnitude of nitrogen reduction significantly increased the yield gap in fields with higher initial nitrogen supply, indicating an interaction between initial nitrogen levels and the effect of input reductions (Fig. 1e–g, Table S7). No significant effect of the magnitude of soil operation reduction was observed in OF experiments (Fig. 1h).

Effect of input reduction on economic returns

Paired differences in the gross margins between the experimental and control areas were positive overall for CF fields, with a mean difference of plus €95.4 ha^{-1}, but since differences varied widely across experiments, the effect of treatments was not significant (Wilcoxon signed-rank test, $P = 0.064$; Fig. 2a; Table S8). Over the two years, 55% of the CF experiments resulted in gains for farmers (+€292 ha^{-1} ±213 on average) but 25% showed a margin loss >€100 ha^{-1}. As expected, given the absence of a yield gap in 2022, gross-margin paired differences were significantly positive that year (+€252 ha^{-1}±324; $P = 0.013$), with 70% of CF experimental reductions showing margin increments. The 2023 experiments presented slightly negative but non-significant paired differences in the gross margins (−€13.2 ha^{-1} ± 206; $P = 0.89$; Fig. 2a; Table S8). In the OF field experiments, the average effect was slightly negative, −€16.8 ha^{-1} ± 289, but the effect size was not different from zero ($P = 0.62$), and again there was a positive effect on margins in 2022 (+€65.2 ha^{-1} ± 367) and a loss in 2023 (−€56.1 ha^{-1} ± 242), both of which were non-significant (Fig. 2b; Table S8). Decomposing the effect of input reduction on gross-margin components (yield and cost components) revealed yield-related gains in 2022 (+€60.9.ha^{-1} and +€17.7.ha^{-1} in the CF and OF fields, respectively; Table S8) and yield-related losses in 2023 (−€131.ha^{-1} and −€101.ha^{-1}; Table S6), but cost savings in both years and farming systems (Fig. 2a,b; Table S8). For instance, cost savings in CF averaged €191 ha^{-1} in 2022 and €117 ha^{-1} in 2023, mostly resulting from cost savings on fertilisers (€119 ha^{-1} in 2022 and €40.8 ha^{-1} in

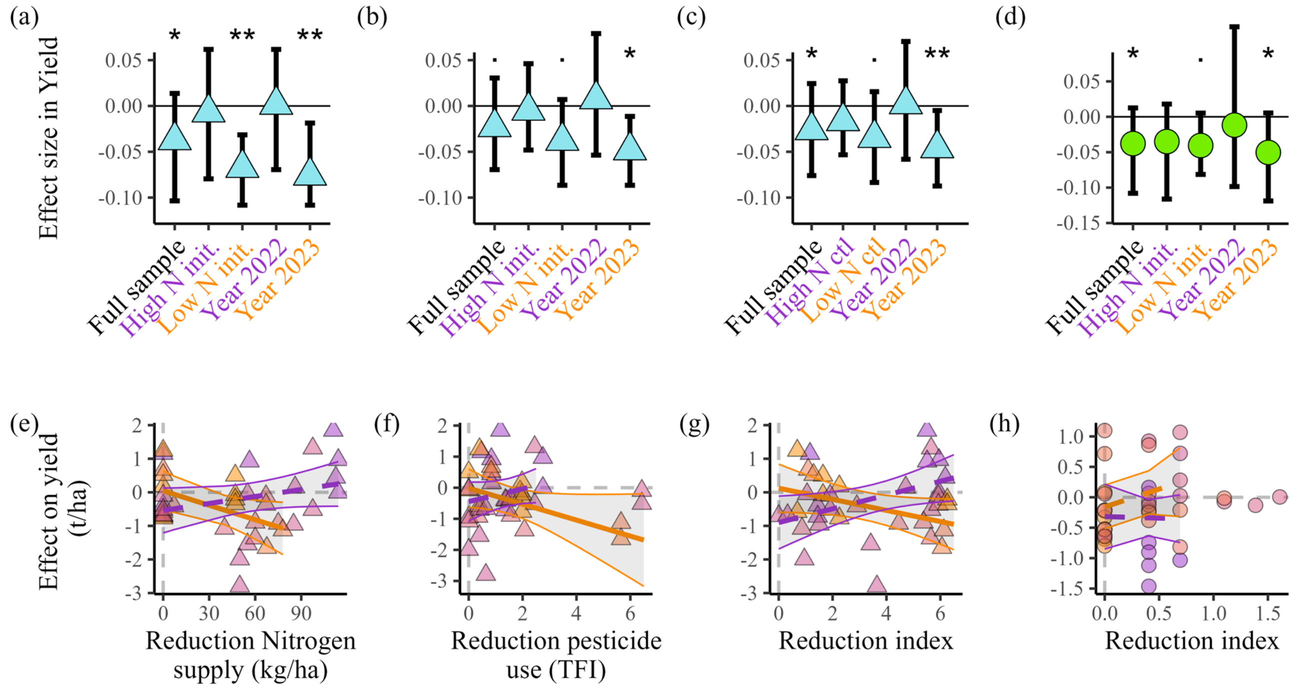

Fig. 1 | Effects of input reductions on yields across experimental plots. Effect size on yield (computed from paired differences) with nitrogen reduction (**a**), pesticide reduction (**b**), all reductions in CF fields (**c**), and all reductions in OF fields (**d**). CF in blue, OF in green (medians and 25% and 75% quantile bars are shown). Significance levels of signed-rank Wilcoxon tests comparing the sample median difference to 0 are shown above. For each graph, effect size is first shown for the full sample, then subdivided by initial nitrogen supply (above the median: purple; below the median: orange) or by year (2022: purple; 2023: orange). Relationship between input reductions and yield impacts (t.ha^{-1}) in plots with nitrogen reduction (kg.ha^{-1}; **e**), pesticide reduction (TFI; **f**), and standardised reduction indices in CF (**g**) and OF fields (**h**). Observed values are shown as triangles (CF) or circles (OF), and coloured from orange to purple according to the plot's initial nitrogen supply. Lines are predictions from the linear models developed in Methods, with initial nitrogen supplies fixed at the 25% quantile (yellow; 110.5 kg.ha^{-1} for CF, 15.1 kg.ha^{-1} for OF) and 75% quantile (purple; 210.9 kg.ha^{-1} for CF, 75.9 kg.ha^{-1} for OF). Predicted regression lines are restricted to the observed range of experimental combinations of reductions and initial nitrogen supplies. Solid regression lines indicate significant relationships, while dashed lines indicate non-significant ones. *p*-value < 0.1:; *p*-value < 0.05: *; *p*-value < 0.01:**; *p*-value < 0.001: ***.

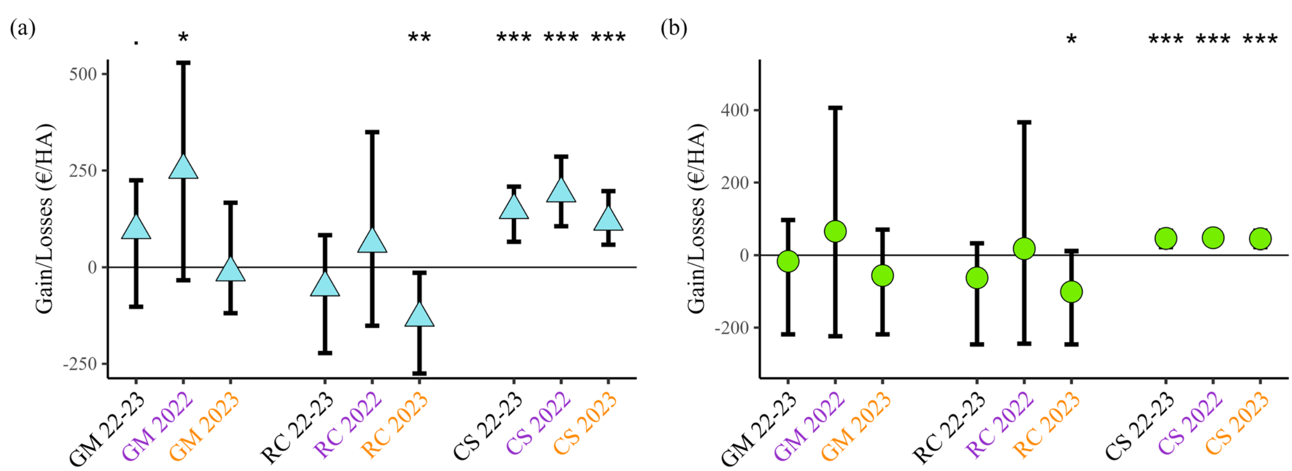

Fig. 2 | Gains and losses. Gains and Losses (in €.ha^{-1}) in gross margin (GM), revenue change (RC) and cost savings (CS; see 'Methods') for all CF (**a**) and OF (**b**) experiments. It shows the paired differences in GM, RC and CS for the two years and per year (2022: purple; 2023: orange); CF in blue, OF in green (median and 25% and 75% quantile bars). Significance levels of signed-rank Wilcoxon tests comparing the median of paired differences to 0 are as follows: *p*-value < 0.1:.; *p*-value < 0.05: *; *p*-value < 0.01: **; *p*-value < 0.001: ***.

2023, Table S8), while pesticide-related cost savings remained stable at approximately €60 ha^{-1} (Table S8). Cost savings in OF fields were €45 ha^{-1} in both years (Table S8).

Simulations of economic scenarios and crop growth conditions

We observed a strong year dependence in our findings on the economic consequences of input-reduction experiments in CF, which could be attributed both to the differences in yield gaps observed between the two years and to price variations, as cereal and nitrogen prices differed substantially between the two years (Table S1). We first evaluated whether the experiments in 2022 (respect, 2023) would have yielded similar results if assessed under the 2023 (or 2022) price conditions, and more generally, in the price contexts of the last decade (2012–2021). We found that the 2022 experiments would have had beneficial effect in the 2023 price context, and

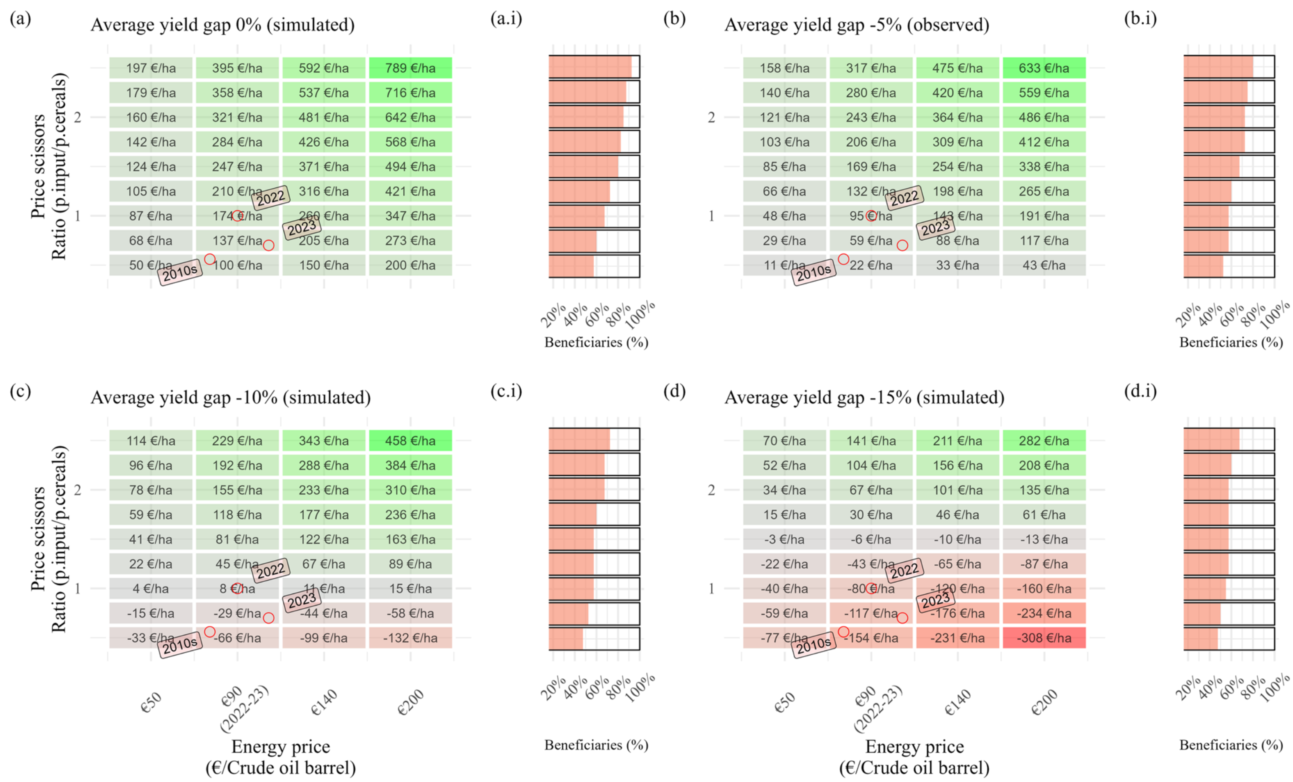

Fig. 3 | Impact of reductions on gross margins in simulated contexts. Heatmaps showing the mean of paired differences in gross margins (€.ha^{-1}) resulting from input reductions (see 'Methods'). Positive values are represented in green, near-zero values in grey, and negative values in red. The margins are simulated for four yield gaps: 0% (**a**), 5% (**b**), 10% (**c**) and 15% (**d**). Margins are simulated along two dimensions: on the x-axis, the average level of prices (both inputs and outputs) guided by energy prices and thus the crude oil prices, representing inflation/deflation scenarios, is shown for €50, €90 (2022–2023 situation), €140 and €200 per barrel. The y-axis represents the price-scissors effect, which is simulated by changing the ratio of input prices to cereal prices (ranging from 0.5 to 2.5). It reflects the average cost of inputs relative to stable cereal prices. The combination of crude oil price and price ratios for 2022, 2023 and the 2010s is represented by red circles. The proportion of farmer's beneficiaries (i.e., paired differences greater than zero) is shown for each price-scissor level (rose bars, in %), for four yield gaps: 0% (**a.i**), 5% (**b.i**), 10% (**c.i**), and 15% (**d.i**).

this would have also been the case for the entire 2012–2021 period (Supplementary Information 9, Fig. S6). Similarly, the marginal loss observed in 2023 would have occurred under 2012–2022 price conditions but would have remained not significantly different from zero (Fig. S6). However, this analysis is based on the observed crop growth conditions and the corresponding yield gaps. While pest pressure remained within the average range during both experimental years, 2022 experienced an abnormal late-season water deficit, which may have influenced the effect of nitrogen reductions on yields (Table S5, Fig. S3).

To assess the robustness of our results, we calculated the mean of paired differences in gross margins across various simulated scenarios. Economic scenarios included oil shocks—defined as a simultaneous increase in all economic prices driven by rising crude oil costs—and price-scissor effects. For each scenario, we also tested four yield gap levels to represent alternative crop growth conditions not observed in the experiments. These ranged from no yield gap to a 15% yield gap—for example, in a year with high fungal disease pressure, reducing fungicide use could result in a larger observed gap—while the 5% gap reflects the conditions observed in our experimental data.

A simulated increase in the yield gap led to a reduction in paired differences in gross margins, regardless of the price configuration (Fig. 3a–d). At yield gaps higher than those observed in this study (i.e., 10% and 15%; Fig. 3c, d), there was a sign reversal in margin outcomes, depending on the presence of scissor effects (especially when cereal prices decreased relative to input prices), where revenue losses would outweigh cost savings. A larger yield gap increased the risk by reducing the proportion of farmers who benefited from input reductions (Fig. 3a.i–d.i). The price scissor positively impacted the economic outcomes from input reductions by increasing the absolute paired differences in gross margins (Fig. 3a–d, bottom to top) and raising the proportion of reductions that would produce positive economic outcomes (Fig. 3a.i–d.i, bottom to top), thereby reducing risk. Finally, an increase in energy prices, which drives overall price levels, amplified the gains and losses from input reductions (Fig. 3a–d, left to right). When reductions resulted in economic gains for farmers, higher price levels increased those gains.

Discussion

Our 2-year experimental study showed a yield gap of less than 5% when farmers reduced (on average, halved) agricultural inputs or workload in OF and CF systems; the economic losses were offset by cost savings, even entirely in many CF experiments. Although the experiments were conducted under real conditions over only two seasons, the results confirm and extend earlier findings from comparable cereal experiments with input reductions of similar magnitude in 2013 and 2014[25], yielding similar outcomes regarding paired differences in yield and income. More broadly, these insights contribute to the ongoing debate on input reduction in the context of the European Green Deal[10]. They indicate that there is significant potential for adjustment, particularly in conventional farming systems, where a substantial portion of the gross margin depends on the inputs targeted by the experimental reductions. Beyond this, the evidence that input reduction can be achieved at no cost implies that policymakers should focus on why such reductions are not implemented in practice. Is this due to beliefs or information gaps? Or rather to more psychological factors, such as perceptions of the risks associated with inputs?

Compared to previous experimental studies, our work goes further by testing whether the possibility of reducing inputs without reducing gross margins holds across a wide range of economic and pedoclimatic contexts. Our simulations demonstrated that reducing management intensity is a winning strategy during agricultural price crises, and neutral otherwise. Input reduction is increasingly advantageous as crises deepen: a higher ratio of input prices to grain prices—the price-scissor effect noted above[12]—generally improves economic outcomes and reduces the risks associated with input reductions. It is widely acknowledged that the use of inputs should be adjusted according to this ratio[28,29] and that an increase in this ratio represents a critical threat for agriculture, often resulting in widespread bankruptcies. Furthermore, price-scissor effects are often driven by inflation, which may further enhance the appeal of input reduction, as shown in this study. Price risks may arise more frequently in the future[30], which may result in greater interest on the part of farmers to de-intensify; this is in accordance with recent results on fertilisers[29] and, more generally, at the farm scale[31]. Nevertheless, all these assertions remain uncertain, particularly because widespread input reductions could also affect global market prices[32].

We showed that the profitability of input reductions in winter cereals depends on both the type of input and the crop growing conditions. This stems from the saturating relationship between inputs and yields—a pattern that has also been observed at the national scale for cereal crops in France[33]. Specifically, we found that the drought in 2022 likely reduced the magnitude of the yield plateau at which nitrogen exhibits a saturating relationship with yield, making nitrogen reduction highly profitable in that year. In contrast, in 2023—a year with higher yield potential—nitrogen reductions led to neutral economic outcomes. Importantly, in both years, since farmers did not experience significant financial losses on average, this suggests that nitrogen was overused, a finding often reported in the literature[14,34,35]. We hypothesise—pending confirmation through further studies of this kind—that the lower the yield potential, the greater the economic advantage of de-intensification. It means that, at the regional level (where yield potential is similar), similar reductions could be beneficial to farmers on average. However, at the national level, particularly in regions with higher yield potential, the generalisation of our results is less certain. From the farmer's perspective, it remains difficult to predict yield potential in advance and, consequently, the impact of input reduction on yields. Although digital tools in agriculture remain costly at present, they represent one of the most promising solutions for improving input use efficiency—particularly by accurately reporting yield potential and actual input requirements[36]. For example, some authors demonstrated that nitrogen use in wheat production could be reduced by 5–40%[37].

Regarding damage-abating inputs—pesticides in CF and soil operations in OF—their effectiveness is also likely to depend on crop growing conditions. However, the time frame of our experiments does not allow us to draw firm conclusions on this aspect. These inputs are often considered as 'facilitator inputs'—complementary to growth inputs such as nitrogen[38]—and frequently raise more complex issues, as they are closely tied to risk and uncertainty, thereby involving a psychological dimension. Our findings align with existing literature showing an overuse relative to their marginal revenue product[17,39], in particular in France where it has been shown on similar crops and farms[18]. However, defining their optimal use must account for farmers' risk aversion[40–43], since farmers themselves often justify their use by referencing risk management[44]. Nevertheless, it has been shown that significant reductions are possible, either through decision support systems that improve prediction capabilities for farmers[45] or through the development of public policies that provide financial support for pesticide-free agriculture[46].

Input overuse has been extensively criticised, primarily due to flaws in model assumptions and the fact that very different systems are compared, which can bias estimations[21,22,24]. We overcame these biases in our experimental study by reducing inputs under strict controlled conditions, keeping all other factors constant since there control and experimental plots were in the same field. This allowed us to isolate the effect of input reduction in a robust way[47]. Moreover, our experiments were conducted under real farming conditions, that is, as experienced by farmers, and on a sufficiently large scale to account for within-field heterogeneity[48] (e.g., soil variability, microclimate). This approach also minimises edge effects and ensures compatibility with actual agricultural practices. It would enhance the robustness and applicability of our findings to conduct similar large-scale experimental studies in other areas, with different climate or pedoclimatic conditions. It is important to note that we tested input reductions on a year-to-year basis and did not conduct a longitudinal experiment. Therefore, our results should be interpreted within this scope. That said, it would be valuable to test the robustness of these findings over longer time horizons. Indeed, one can expect that the residual effects of inputs may persist for several years, meaning that the profitability of input reduction could decrease over time as these residual benefits fade. For instance, some authors found pesticide residues in the soil even after twenty years of organic farming[49], and some showed that the historical use of tillage influences the effectiveness of no-tillage practices[50]. It has also been shown that growth inputs, such as nitrogen, can contribute to yield stability in the long-term and thus influence risk[51], which may partly explain why farmers can be reluctant to reduce nitrogen use.

Beyond increasing the number of field experimental studies, it would be valuable to conduct this type of experiment on other crops, in order to draw conclusions not only at the field scale but also at the whole-farm level—the actual scale at which farmers make decisions. Non-experimental studies suggest that input reduction may also have limited effects on farm income for crops other than the winter cereals studied here—for example, vegetables[19] or potatoes[20]. Such an upscaling of the approach to reducing management intensity is essential, particularly when considering the risks associated with input reductions. Indeed, it remains unclear whether expanding the number of plots where inputs are reduced would amplify risk through cumulative exposure or mitigate it through diversification. In our study, farmers engaged in the experiments with only a few fields: with more fields involved, the variability in margin results could average out, reducing overall risk. Indeed, the risk is higher at the field level than at the farm level if the variation is random across fields. While our variability calculations support this conclusion, this would need to be confirmed by replicating experiments across multiple fields per farmer. Our findings highlight the importance of scaling up de-intensification experiments and, more broadly, implementing agroecological practices on a systemic level[47,52].

Methods

Study area

The study was conducted in the LTSER 'Zone Atelier Plaine & Val de Sèvre,' a long-term social-ecological research site covering 450 km² in central western France, in the Nouvelle-Aquitaine region[53] (46.23°N, 0.41°W; Fig. 4). This agricultural landscape is characterised by intensive cereal crop production, with 40–45% dedicated to winter cereals (mainly winter cereal cultivars), 8–12% to oilseed rape, sunflower, or maize, 15% to meadows and alfalfa, 4% to woods, and 9% to villages. The average field size is approximately 4–5 ha.

Sampling design and farming system description

No statistical methods were used to predetermine the size of the study sample. Farmers were not chosen randomly; the sample was selected based on the willingness of farmers to participate in the experiments. However, the sample was selected along a management intensity gradient, based on historical farming practices collected through surveys conducted in the study area in previous years[47]. This ensured a broad range of input use and management practices, which is reflected both in the initial levels of input use and in the types of reductions implemented.

Experiments were conducted over two cropping seasons: 2021–2022 and 2022–2023. The first season, referred to as 2022, began with autumn sowing (September–October 2021) and ended with harvest in June–July 2022 (26 fields belonging to 14 farmers). The second season, 2023, started with autumn sowing (September–October 2022) and concluded with harvest in June–July 2023 (32 fields belonging to 13 farmers). The experiment was carried out in real field conditions, and the sample comprised a total of 19 farmer participants. In the second cropping season, nine farmers remained in the experiment, and four new farmers joined. We considered two main groups of agricultural farming systems: (i) CF with 13 farms (31

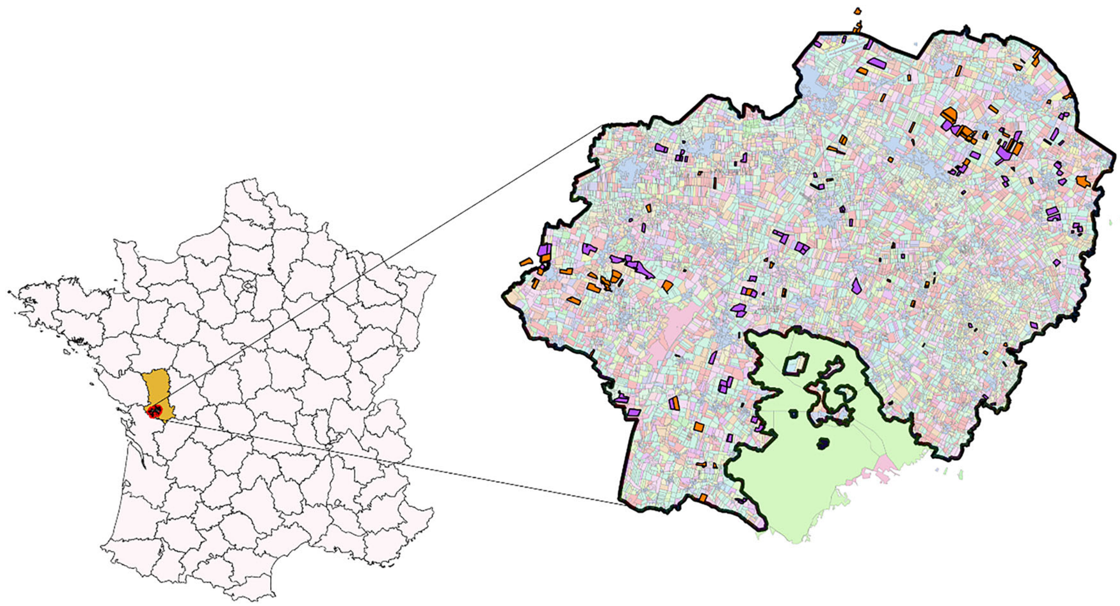

Fig. 4 | Study area in western France. Fields followed are colourised by year (purple: 2022, orange: 2023).

fields) using inorganic crop fertilisation and chemical pest control techniques; ii) OF with 7 farms (27 fields) complying with a set of rules for farming specified in Regulation (EU) 2018/848 on organic production and labelling of organic products, such as the restriction on inorganic fertilisers and chemical pesticides. Six winter cereal types were cultivated: winter wheat (25 CF and 19 OF fields, including 9 OF fields with legumes, such as fava beans), durum wheat (2 CF and 1 OF fields), barley (4 CF and 1 OF fields), spelt (2 OF fields), triticale (3 OF fields), and oats (1 OF field). We checked that there was no effect of crop type on variables of interest (see Supplementary Information 5), and thus we grouped these six species under the broad term 'winter cereal' as their agronomic characteristics are very similar.

Co-designed experiments

The experiments were co-designed with farmers in face-to-face meetings during the winter of each season (November–December 2021 for 2022 and November–December 2022 for 2023). Once the type of reduction and the layout of the experimental zone were decided by the farmer and agreed upon by the research team, the areas were marked with flags as a visual guide for the farmer. The farmers decided on the magnitude of reduction, independently of the researcher. These reductions were deviations from the baseline agricultural practices implemented in the rest of the field. They consisted either of lower doses or skipped operations, and no other management changes were introduced in order to isolate the effect of the reduction. The location and size of the experimental zone were decided by farmers. A total of 39 experimental plots were established in CF fields and 37 in OF fields. In seven cases, the experimental plot encompassed an entire field, which was compared to an adjacent control field. For these cases, the pair of fields was selected to ensure they had the same conditions, as determined by the farmer. We checked that there was no effect of the type of comparison (within-field *vs* between-field comparisons) on variables of interest (see Supplementary Information 5). In all other cases, the experimental plots were designated zones within a field and were compared to the non-experimental portion of the same field, which served as the control plot.

For CF fields, the reductions targeted nitrogen, herbicides, fungicides, and insecticides. Experimental plots included one or multiple types of reductions, with areas ranging from 0.048 ha to 11.5 ha (mean: 0.87 ± 1.9 ha; Table S4). Overlapping zones occasionally resulted in complex reduction combinations. A summary of the experimental plots for each reduction type is provided in Fig. S1. Nitrogen reductions were applied in 25 plots, with six plots implementing nitrogen reduction alone and the remainder combining this with pesticide reductions. Fourteen plots focused exclusively on pesticide reductions, including fungicides only ($n = 7$), herbicides only ($n = 4$), or a combination of pesticides (e.g., fungicides and insecticides). Nitrogen reductions ranged from 40 to 114 kg·ha^{-1} (mean: 71.5 ± 24.2 kg·ha^{-1}), corresponding to reductions of 24.3% to 64.2% (mean: 44.7% ± 11.7%). However, most nitrogen reductions were concentrated at around 25% or 50% (see Fig. S2a,c). Pesticide reductions, by contrast, ranged from 10% to 100%, with a uniform distribution across this range (see distribution in Fig. S2b,d).

For OF fields, 35 mechanical weeding reductions were implemented, of which eight were combined with ploughing being replaced by shallow tillage (Fig. S1). Experimental-plot areas ranged from 0.011 ha to 11.6 ha (mean: 0.87 ± 2.4 ha; see Table S4). Of the mechanical weeding reductions, seven involved a complete cessation of weeding, while the remainder reduced the number of passes from one to four (mean: 1.74 ± 0.78), corresponding to reductions of 16.7% to 75%.

Timing of reductions and crop growth conditions

All reductions of nitrogen, fungicides, herbicides, insecticides (CF) and mechanical weeding (OF) were implemented by the farmers themselves in spring (February to April) and were fully integrated into the farmers' usual crop management practices. Regarding crop growth conditions, overall pest pressure in the region was within the normal range compared to the past decade (2012–2021; see Table S5 for all details on crop growth conditions). Concerning meteorological conditions, while the second experimental campaign was relatively close to the decade's norm, the 2021–2022 season was marked by unusual water stress beginning in May, which may have contributed to lower average yields, particularly in CF systems.

Farmer survey and yield estimations

We collected information about crop yields and farming practices (pesticide and fertiliser use, ploughing and mechanical weed control system) and general information about the farm (number of crops, agricultural equipment) through interviews with all the individual farmers after harvests. The general statistics obtained from the questionnaires are presented in Table S4 for each farming system. Nitrogen input values, pesticide use indicators and yield estimates were derived from the farm surveys. For each input (nitrogen and pesticides), we checked whether the average use of the farmers obtained from the surveys were similar or consistent to those from the region or France for wheat cultivation. Overall, the sample is fairly close to the regional average in terms of input use and yields, except in 2022, when yields for CF were slightly below average (Table S4). Both our sample and the region in which the experiments were conducted show lower yields than the national average, which is consistent with the fact that this region has a lower yield potential for winter cereals. While the use of most inputs (except weed control, whether chemical or mechanical) is close to the regional and national averages, farmers in our sample use slightly less weed control on average, both in organic and conventional systems.

There are two main types of nitrogen used by farmers: inorganic and organic fertilisers. Since inorganic nitrogen is rapidly available to plants, the quantity of nitrogen used was directly calculated according to the fertiliser composition and the respective quantity applied. Conversely, organic nitrogen is a relatively stable compound and must go through mineralisation to be converted into its inorganic form. Thus, the quantity of nitrogen mineralised in the organic fertilisers was calculated using the technical literature[25].

In CF, we used the treatment frequency indicator (TFI) to account for the intensity of pesticide use; this quantifies the total number of pesticide applications applied to a crop, standardised to the recommended dose rate for a single application. TFI per hectare can be computed for each family of pesticides (herbicides, fungicides, insecticides) and summed to evaluate the total pesticide pressure in an area[54]. This includes all the pesticide treatments applied in a given crop area (except for seed treatment). The reference dose is provided for a given commercial pesticide product, and this corresponds to the minimum registered dose for a given crop and a given year. Over our sample of CF fields, the TFI ranged from 0.8 to 9.1 (mean: 3.6 ± 2.3) for all pesticides, from 0 to 2.7 (mean: 1.4 ± 0.6) for herbicides, from 0 to 6.4 (mean: 1.4 ± 1.7) for fungicides and from 0 to 1 (mean: 0.5 ± 0.4) for insecticides.

In OF, we surveyed the number of mechanical weeding operations for each area. Mechanical weed control operations were performed prior to the establishment of the crop through soil tillage, such as ploughing or disking, or after crop establishment in the crop row using specific equipment, such as rotary hoes. Over our sample of OF fields, mechanical weeding operations ranged from 1 to 6 (mean: 3.6 ± 1.6).

Yields. The yields in experimental and control plots (or fields when entire fields are compared) were assessed 1 to 15 days before the farmer's harvest. Two rows of five 1 m² quadrats were evenly spaced from the edge to the centre of the field, and a random 0.25 m² section of each quadrat was harvested in its entirety. A total of 1328 samples were collected, including 768 in CF fields and 560 in OF fields. Cereal grains were separated, weighed after being dried for 48 h at 80 °C, and scaled to a per-hectare yield. The average yield across the ten quadrats provided the yield estimate for each area.

Field-level yields were also obtained through farmer surveys. These values were for the entire field, as reported by the cooperative at harvest. They thus reflect the actual yield across the entire field without distinguishing between control and experimental areas. Yields in control plots were strongly correlated with farmer-reported yields ($R^2 = 0.84$, $F = 206.2$, d.f. = 47, $P < 0.001$). For fields entirely under experimental treatment or control, the surveyed yield replaced the measured yield to ensure maximum accuracy. When there were multiple plots within a single field, the yield measured in the control plot (which was systematically the largest) was replaced with the yield reported by the farmer for the entire field. The difference between the yield in the control plot and that in the other plots, as measured (in t.ha^{-1}), was then applied to each other plots.

Gross margin. Farmers' income at the field scale was assessed using gross margins (GM), which allowed accounting for the economic impact of de-intensification. The gross margin per hectare was calculated accounting for the final grain yield revenue plus revenues related to other crops, when applicable, minus the variable costs (VC; detailed below) associated with the agricultural activity (winter cereal production). GM was calculated as follows:

$$GM = p.Y + AL - VC, \tag{2}$$

where p represents the grain price (expressed in €), Y is the yield of winter cereals (in t.ha^{-1}), AL is the revenue from associated legumes, when applicable (in €.ha^{-1}), and VC refers to variable costs (in €.ha^{-1}). Variable costs included all input costs associated with a single crop production cycle. These included the cost for purchasing seed varieties, soil tillage, fertilisers, pesticides (including their application), mechanical weeding, and irrigation. Grain prices for 2022 and 2023 were set as the average values for the third trimester (July–September), which corresponds to the typical harvest and sales period for most farmers. Specific values and references for prices are provided in Table S1.

Fertiliser costs per hectare were calculated based on the quantities applied and their respective prices. Prices for each product and year were obtained directly (~85% of the applications) or calculated based on the content of nitrogen, phosphorus, potassium, magnesium, and sulfur. When possible, we used the average price from the last trimester of the year preceding the harvest (e.g., October–December 2021 for the 2022 season). For one product, where this data was unavailable, we used the online price from summer 2024. Regarding the cost of organic fertilisers for farmers in OF, these costs can vary depending on potential economies of scope. For instance, manure may be a co-product of the livestock activity, thereby reducing fertiliser expenses. We distinguish three situations within our sample: (a) the farmer is strictly arable and purchases manure on the market (100% of fertiliser costs maintained); (b) the farmer is strictly arable but exchanges part of the straw produced for manure, which reduces fertiliser costs (40% cost reduction); (c) the farmer is both arable and livestock-producing, allowing them to directly use their own manure (90% reduction in fertiliser costs). Estimations were based on technical documentation[55,56]. Pesticide costs per hectare were determined based on market prices (retrieved from cooperative or technical institute price lists), the quantities applied, and the application costs. Different prices were used for the two years if they differed. References for the prices of inputs and machinery are detailed in Table S2.

After calculation, the average revenue in the sample over the 2 years was €1703 ha^{-1} ±526 for CF, and €1768 ha^{-1} ±526 for OF (Table S4). The average costs were €759 ha^{-1} ±142 for CF and €1088 ha^{-1} ±510 for OF. Accordingly, the average gross margin was €824 ha^{-1} ±527 for CF and €270 ha^{-1} ±662 for OF. It is also worth noting that these figures can be put into perspective by considering the average amount of CAP subsidies received per hectare: €121 ha^{-1} for CF and €410 ha^{-1} for OF. When put into perspective with the average subsidies per hectare in France (€121 ha^{-1} for CF and €410 ha^{-1} for OF), which are independent of input use—namely nitrogen and pesticides in CF, and fuel in OF—these subsidies account for only about 12% of revenue in CF, whereas they represent nearly two-thirds of revenue in OF.

Data analyses

Effect of inputs on winter cereal yields. We used farmer survey data to analyse the impact on yields of nitrogen and risk-mitigating inputs (using TFI for CF and the number of times the fields were mechanically weeded for OF). We used only data from control plots to ensure that the observed yield variations were driven by agricultural inputs rather than treatment effects (CF: 31 fields, OF: 27 fields). Following recent recommendations on modelling the effect of inputs on yield, we fitted a linear response plateau function[57]. The rationale behind this type of function is that yield increases with the most limiting input until another input becomes limiting, beyond which further increases no longer affect yield. As illustrated in Fig. S3, Stage I represents the phase where adding input X leads to yield increases, while Stage II represents the phase where additional input no longer improves yield. Weather factors, such as rainfall, can become the limiting factor at this point, which has led researchers to allow year-to-year variation in the model parameters—for example, making the onset of the plateau dependent on the year[58]. We followed this approach, as our data show differences in water availability between 2022 and 2023 (Table S5). This type of function has been used to model the effect of nitrogen use[58] or risk-mitigating inputs[59] on yield. The stochastic plateau function we used is:

$$y_i = \min(\beta_0 + \beta_1 n_i + \beta_2 r_i, \lambda + \delta \cdot \text{Year}) \tag{3}$$

where y_i is the yield of field i, n_i is nitrogen use, and r_i is the use of risk-abating inputs (pesticides for CF and mechanical weeding for OF). λ represents the yield potential (plateau level), and "Year" indicates the cropping year. Finally, β_0, β_1, β_2 and δ are coefficients associated with the respective explanatory variables.

Effect of input reduction on yields and economic returns. We evaluated the effect of input reductions on yields while holding all other conditions constant, by computing paired differences between each treatment plot and its matched control (either within field or between field). The focus on differences between paired observations reduces the impact of between-pair variability. First, the difference in yield was calculated for each pair: $\Delta Y_i = Y_{T,i} - Y_{C,i}$, where $Y_{T,i}$ and $Y_{C,i}$ are the treatment and control yields, respectively. We evaluated the difference in yield by calculating the yield effect size for each matched pair. The effect size ratio in the matched-pair i was defined as $E_i = \Delta Y_i/(Y_{T,i} + Y_{C,i})$. Compared to a percentage, this index has the advantage of ranging between -1 and 1, minimising the influence of large values. We used a paired difference test to determine if the median effect size ratios of the sample were different from zero. A non-parametric Wilcoxon signed-rank test was chosen over a t-test because of the small sample sizes. This test is also a more powerful alternative to the sign test because it considers the magnitude of the differences. A positive (respect. negative) effect size indicates that the yield was higher (resp. lower) in the treatment than in the control plot, showing a positive (resp. negative) impact of input reduction on yields. Standard percentages were reported in the main text to improve the interpretation. Table S6 reports the statistics (mean, standard deviation, and median) of the paired differences: in absolute value ΔY_i (t.ha^{-1}), as a classical percentage $\Delta Y_i/Y_{T,i}$, and as an effect size ratio $\Delta Y_i/(Y_{T,i} + Y_{C,i})$, as well as the Wilcoxon test statistics. We assessed the economic effects of input reductions (holding all other conditions constant) by calculating three economic indicators for each treatment plot: the paired difference in gross margins (ΔGM), revenue changes (RC), and cost savings (CS). The paired difference in gross margins represents the difference in the gross margins (in €.ha^{-1}) of the treatment and control plots: $\Delta GM_i = GM_{T,i} - GM_{C,i}$. Revenue changes (RC) reflect the impact of yield differences between the treatment and control zones in €.ha^{-1}: $RC_i = p * (Y_{T,i} - Y_{C,i})$. Cost savings (CS) capture the reduction in input costs due to input reductions in €.ha^{-1}: $CS_i = -(VC_{T,i} - VC_{C,i})$, with the negative sign indicating a cost reduction. Note that $\Delta GM_i = RC_i + CS_i$. For each sample of matched pairs, we also employed a non-parametric Wilcoxon signed-rank test to determine if the mean of the sample is different from zero. For all Wilcoxon tests, the exact conditional (on the data) p-values and confidence intervals of the test were computed using the R package *exactRankTests* and the function *wilcox.exact* using the Streitberg-Röhmel shift algorithm[60].

Effect of the magnitudes of reduction on yields. We investigated the impact of input reductions on yields (t.ha^{-1}) and how these effects were modulated by initial nitrogen supply (kg.ha^{-1}). We evaluated the effects of reductions using four linear models, focusing on the effects of (1) nitrogen supply reduction (kg.ha^{-1}; CF only; Table S7a), (2) pesticide use reduction (TFI; CF only; Table S7b), (3) combined nitrogen and pesticide reduction using a standardised index (CF only; Table S7c), and (4) combined tillage and mechanical weed control reduction using another standardised index (OF only; Table S7d), in interaction with initial nitrogen supply for all model. Each index was calculated as follows: $Reduction = \log[(1 + Reduction_i) * (1 + Reduction_j)]$ with i and j representing the reduction in nitrogen supply and TFI in CF experiments, and in tillage and mechanical weeding control in OF experiments. The index is then rendered positive by adding its minimum in each case. Each model followed the same structure, including as explanatory variables the magnitude of the input reduction, the initial nitrogen supply, and their interaction (see Supplementary Information 7).

We visualised the effects of input reductions and their interactive effect with initial nitrogen levels by generating prediction plots based on the fitted models using *predict* R function. For each reduction type, predictions were made using two distinct levels of the initial nitrogen supply: one standard deviation below the mean and one standard deviation above the mean. Confidence intervals (95%) were computed for all predictions to provide an estimate of uncertainty. For all models, model assumptions were verified through visual residual diagnostics, and all analyses were performed using R (version 4.2.2.)[61].

Simulations. The experiments were conducted under real farming conditions but only over two growing seasons, which may limit the generalisability of our results—especially since some characteristics were specific to those years. As previously mentioned, 2022 was marked by a drought that may have influenced the impact of input reductions on yields. In addition, both 2022 and 2023 experienced market prices that were markedly different from those of the previous decade (2012–2021). To address this limitation, we proceeded in two steps.

First, we extended our results to other price contexts to test whether the observed experimental outcomes would have held under the price conditions of the previous decade. This analysis isolated the effect of price variation by holding experimental parameters constant, including observed levels of input reduction and yield gaps for 2022 and 2023 separately. Price adjustments were based on national price indices for winter cereals, nitrogen inputs, fuel, pesticides and general input costs for the agricultural years 2012 to 2023[62]. These indices were then applied as scaling factors to the calibrated 2022 and 2023 prices (see Tables S1 and S2), and paired gross-margin differences were re-computed between treatment and control.

In a second step, we assessed the robustness of the economic outcomes by varying both economic and yield gaps—namely, the effects of input reductions, which may differ under other pedoclimatic or crop growing conditions. For example, reducing fungicide use in a year with high fungal disease pressure could have a greater impact on yield gaps. The economic outcomes of input reductions were recalculated by computing paired differences in gross margins using simulated yield differences and/or price variations. Concerning pedoclimatic conditions, we started with the observed yield gaps, which averaged 5% over the 2022 to 2023 period, and then applied the coefficients to simulate alternative yield gap scenarios of 0%, 10%, and 15%, consistent with the range reported in literature[63].

These yield gap scenarios were then considered in different price situations, some reflecting agricultural price crises. First, the mean paired gross-margin differences were calculated under various price-scissor effect scenarios, where input prices increase while crop prices remain stable or decrease[12]. The price-scissor effect was represented by the ratio of agricultural input prices to winter cereal prices. Input prices were scaled using a coefficient, where $\rho_1 = 1$ corresponded to the 2022 baseline; for example, a coefficient of $\rho_1 = 2$ represented a doubling of input prices relative to stable crop prices.

Second, the mean of paired gross-margin differences was calculated under scenarios simulating inflation or deflation (a simultaneous increase or decrease in all prices in the economy[64]). Inflation/deflation was modelled using a scaling coefficient, ρ_2, applied to all prices, including crops, fertilisers, fuel, pesticides. The baseline coefficient ($\rho_2 = 1$) corresponded to 2022 prices, with ρ_2 values of 0.5, 1.5, and 2 representing a 50% decrease, a 50% increase, and a 100% increase in prices, respectively. Given the strong correlation between agricultural and energy prices[65–68], the general price level was represented by crude oil prices (€ per barrel) to facilitate interpretation.

Inclusion and ethics

All collaborators have been acknowledged. The research was conducted within European institutions under established ethical and legal frameworks, involved no human participants or sensitive materials, and entailed no risks to researchers or local communities.

Data availability
The anonymized data are available at: https://doi.org/10.48579/PRO/FSLWPH.

Code availability
The code is available at: https://doi.org/10.5281/zenodo.16937668.

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Author contributions

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Competing interests

The authors declare no competing interests.

Additional information

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