Journal of Environmental Management 398 (2026) 128389

Contents lists available at ScienceDirect

Journal of Environmental Management

journal homepage: www.elsevier.com/locate/jenvman

Research article

# Rethinking land-use Strategies: A multi-objective analysis of combined sparing and sharing approaches applied across great britain

Imane El Fartassi [a,1,3], Ryan T. Sharp [a,2,3], Victoria A. Bell [b], Andrew P. Whitmore [a], Helen Metcalfe [a], Nathan Missault [b], John Redhead [b], David M. Cooper [c], Jonathan Storkey [a], Helen Davies [b], Theo Jackson [a], Kevin Coleman [a], Alice E. Milne [a,*]

[a] Rothamsted Research, West Common, Harpenden, Hertfordshire, AL5 2JQ, UK
[b] UKCEH, Benson Lane, Crowmarsh Gifford, Wallingford, OX10 8BB, UK
[c] UKCEH, Environment Centre Wales, Deiniol Road, Bangor, Gwynedd, LL57 2UW, UK

ARTICLE INFO

*Keywords:*
Agricultural and seminatural land use
Macronutrients
water quality
Hydrological modelling
Land management change
Pareto-optimal

ABSTRACT

The land-sharing versus land-sparing debate represents a critical juncture in agricultural policy development. However, applying either of these approaches uniformly at a national scale has been challenged suggesting that more effective strategies may require a context-dependent mix of methods. This study evaluates plausible strategies of land sparing and land sharing at regional scale in Great Britain using the Long-Term Large Scale integrated modelling framework. We consider these strategies in various combinations to get national scale outcomes for nutrient losses to freshwater and agricultural productivity. By simulating various land-use configurations across 11 International Territorial Level regions, we generated over 1.79 trillion scenarios with differing regional distributions of arable and semi-natural land. We used multiple objective optimization to find an optimal solution set. Our analysis identified 24,412 Pareto-optimal solutions that also improved on business-as-usual. The Pareto-optimal solutions all favoured combining land-sparing and land-sharing approaches. These optimized scenarios achieved increases of up to 9.7 % in livestock calories and 5.2 % in crop calories, while reducing phosphorus losses by 6.9 % and nitrate losses by 11.9 % in comparison to a business-as-usual scenario. Our findings demonstrate that spatially differentiated land-use strategies tailored to regional characteristics outperform uniform national sharing or sparing approaches. However, these modest improvements suggest that transformative change will require complementary innovations beyond land allocation strategies alone. This approach advances landscape planning from binary sharing-sparing debates towards a multidimensional optimization of food production and environmental quality that acknowledges the inherent complexity of dynamic landscapes while supporting evidence-based agricultural policy development.

## 1. Introduction

The debate surrounding land-sharing versus land-sparing strategies has long been central to agricultural and environmental policy discussions. Land sharing (arable expansion with reduced inputs) refers to integrating biodiversity conservation and agricultural production on the same land, typically through lower-intensity farming practices that maintain some wildlife-friendly features, while land sparing (semi-natural expansion) involves separating intensive, high-yield agriculture from land specifically set aside for conservation (Phalan et al., 2011). Initially conceived as a theoretical framework to balance agricultural productivity with biodiversity conservation, this concept has since evolved to address broader sustainability challenges, including nutrient runoff (Dunn et al., 2022), greenhouse gas emissions (Jovarauskas et al., 2021), and freshwater contamination (Balmford et al., 2012). While numerous studies have demonstrated the benefits of both land-sharing and land-sparing approaches, most of these analyses focus on localised case studies or specific taxa or ecosystem functions. This limitation

* Corresponding author. Rothamsted Research, West Common, Harpenden, Hertfordshire, AL5 2JQ, UK
*E-mail address:* alice.milne@rothamsted.ac.uk (A.E. Milne).
[1] Current address: Cranfield Environment Centre, Cranfield University, College Road, Cranfield, Bedford MK43 0AL, UK.
[2] Current address: The Cool Farm Alliance, Grantham, Lincolnshire, NG31 6LE, UK.
[3] These authors have equal contribution.

https://doi.org/10.1016/j.jenvman.2025.128389
Received 22 June 2025; Received in revised form 10 November 2025; Accepted 17 December 2025
Available online 30 December 2025
0301-4797/© 2025 The Authors. Published by Elsevier Ltd. This is an open access article under the CC BY license (http://creativecommons.org/licenses/by/4.0/).

makes it difficult to assess the broader implications of these strategies at national or regional scales.

Over the next 25 years, global agriculture faces unprecedented challenges as the world's population is projected to exceed 10 billion by 2050 (Godfray et al., 2010). This growth will necessitate increased food production while simultaneously reducing greenhouse gas emissions, minimising nutrient losses, and enhancing ecosystem resilience (Springmann et al., 2018). Great Britain, with its temperate climate and high-level of agricultural investment, has the potential to lead sustainable intensification efforts and reduce reliance on food imports (Pretty, 2018). However, a lack of coherent agricultural policy, coupled with restrictive regulatory frameworks, has hindered the translation of scientific advancements into practical farming innovations (Firbank et al., 2013). Recent policies have taken varied approaches, with some incentivising agricultural extensification through land set-aside and low-intensity farming, while others focus on protecting and restoring natural habitats (Coe and Finlay, 2020; Coe, 2024). However, these policies have often lacked integrated spatial targeting that considers regional variations in landscape characteristics and agricultural potential. While beneficial for biodiversity in specific contexts, a more strategic approach may be needed that optimally combines intensive and extensive practices across different regions to maximize both food security and environmental sustainability at a national scale.

Agricultural intensification is a major driver of nitrogen (N) and phosphorus (P) losses to freshwater systems, contributing to biodiversity loss, and declining water quality (Withers et al., 2014). Both land-sharing and land-sparing approaches have been proposed as potential solutions, yet recent landscape-scale studies have challenged the binary nature of the sharing-sparing framework, suggesting that neither approach applied uniformly is optimal. There is a lack of robust, spatially explicit assessments that quantify how these approaches impact nutrient losses and food production. Finch et al. (2021) evaluated spatially explicit sharing-sparing scenarios across contrasting regions of lowland England, examining multiple environmental outcomes including nutrient pollution, bird populations, and global warming potential. Their analysis revealed that environmental outcomes depended critically on the spatial arrangement of spared land, the types of habitats promoted, and whether strategies combined elements of both sharing and sparing approaches. They found that "mixed scenarios which combine elements of both sharing and sparing" often outperformed pure approaches, and that optimal strategies varied between regions with different landscape characteristics. This work, alongside similar studies (Law and Wilson, 2015; Verhagen et al., 2018), has established that blanket application of either sharing or sparing approaches across diverse landscapes is suboptimal, and that the most effective strategies require spatially differentiated mosaics of land-use approaches. This body of evidence points to a critical gap in our understanding: whilst we know that spatially optimized combinations of sharing and sparing strategies are likely superior to uniform approaches, we lack comprehensive assessments of how such strategies might be implemented to simultaneously optimise multiple objectives.

The British government has set ambitious targets to enhance domestic food self-sufficiency, aiming to increase production by 30 % while halving the environmental impact of farming by 2050 (DEFRA, 2020). The land-sharing versus land-sparing debate is particularly relevant in this context. Recent assessments indicate that land-sparing approaches, which concentrate production on a smaller footprint, can improve food output per unit of land while potentially reducing greenhouse gas emissions and nutrient runoff, provided that intensification is coupled with improved fertilizer management and mitigation strategies. However, empirical data are lacking to support or reject this hypothesis, particularly for large spatial scale, highlighting the need for comprehensive modelling approaches to address this knowledge gap (Balmford et al., 2018). Land-sparing strategies have been shown to be generally better for beneficial insects, with Redhead et al. (2020). However, the benefit of these ecosystem services providers to crop production will, again, be dependent on the spatial integration of seminatural habitat in agricultural landscapes.

Land-sharing strategies, which distribute lower-intensity farming across larger areas, may limit the efficiency of nutrient use, potentially leading to cumulative environmental trade-offs (Koning et al., 2017). However, proponents of land-sharing argue that these approaches can deliver important benefits through ecological intensification, where biodiversity-supporting practices enhance ecosystem services such as pollination, pest control, and soil health, potentially maintaining or even increasing yields (Garibaldi et al., 2019; Tamburini et al., 2020). Land-sharing strategies may also provide greater landscape connectivity for wildlife and more resilient agricultural systems that are less vulnerable to environmental shocks (Kremen and Merenlender, 2018). The key question remains: how can land-sharing and land-sparing approaches be optimally combined and spatially targeted across Great Britain to simultaneously improve agricultural productivity while reducing nutrient pollution at a national scale? Given the variation in landscape and environment, evidence from Finch et al. (2021) support the expectation that the optimal combination of land-use strategies will vary spatially, requiring place-based approaches rather than uniform national policies. While Finch et al. (2021) provided insights using statistical analysis and the InVEST framework at landscape scale, their approach treated spatial units as largely independent and relied on simplified nutrient delivery ratios. To advance our understanding of these complex trade-offs, we need process-based modelling approaches that can capture the dynamic interactions between land-use changes and local management practices, account for hydrological connectivity between regions, and simulate how outcomes in one area depend on the characteristics and changes occurring in surrounding regions.

The Long-Term Large Scale (LTLS) integrated modelling framework provides such a tool (Bell et al., 2021). The model dynamically couples terrestrial (semi-natural and agricultural), hydrological and hydro-chemical process-based models to predict agricultural production and nutrient losses to water across Great Britain. The model is spatially explicit with outcomes from the various land use types aggregated to 5 km $\times$ 5 km scale. Importantly, this means that larger scale implications of regional land use change are predicted as opposed to trade-offs being studied in spatially isolated study regions. The model has been previously used to predict historic nutrient cycling of two centuries (Long-Term) across the whole of Great Britain (Large-Scale) and more recently has been used to predict the impact of climate change (Missault et al., 2025).

In this study, we use the LTLS framework to evaluate the impacts of land-sharing and land-sparing scenarios in terms of nutrient pollution outcomes and agricultural productivity across Great Britain. Our scenarios are built from the national land cover strategies developed by Redhead et al. (2020), which define a series of 12 plausible changes to land use (broadly equating to increases in arable land cover 8 %–59 % compared with current land use or increases in 4 %–29 % in seminatural landscapes compared with current land use). To align these strategies with concepts of land-sharing and land-sparing we simulate more intensive management of arable in scenarios where arable land is diminished and less intensive management where arable land is increased. An important consideration in our analysis is whether such strategies should be applied uniformly across Great Britain or differentially. We therefore considered scenarios with combinations of different strategies applied to each of the 11 regions in Great Britain, in total resulting in over $1.79 \times 10^{12}$ different scenarios.

We present an approach which can be used to compare various land use and management strategies to identify a set of plausible options that reduce environmental nutrient losses whilst also improving farming productivity.

## 2. Methods

### 2.1. Study area

This study focuses on the International Territorial Level (ITL) regions C through M of Great Britain as spatial units of analysis, representing a gradient of agricultural systems, soil types, and climatic conditions across England, Scotland, and Wales (Fig. 1). In so doing we captured the regional scale variation in existing land use and environmental conditions that determine the response to alternative scenarios and the optimization of land sparing/sharing combinations. These regions include the predominantly arable landscapes of Eastern England (ITL E, F and H), characterized by intensive farming practices, with intensive cereal, oilseed, and root crop production on the fertile soils of East Anglia and Lincolnshire (Hurford et al., 2021). Northeast England (ITL C) exhibits a diverse agricultural landscape that integrates both arable farming and livestock systems (Hey, 2014; Williams et al., 2010). Northwest England (ITL D) is characterized by its focus on pastoral agriculture with significant dairy production in Cheshire and Lancashire's lowlands, alongside extensive sheep grazing in the Lake District and Cumbrian uplands (Ryschawy et al., 2017). The West midlands (ITL G) and East of England (H) represent a transition zone between the arable dominated east and the more pastoral west, with mixed farming systems increasingly common (Ilbery and Watts, 2004). Southwest (ITL K) and Southeast (ITL J) are characterized by diverse agricultural patterns, ranging from intensive agriculture, improved grasslands, and protected areas (Broomfield et al., 2025). Wales (region L) and parts of Scotland (region M) are characterized by extensive livestock farming, particularly sheep and cattle grazing on permanent pasture and rough grazing land (Clark and Thompson, 2018; Ross et al., 2016).

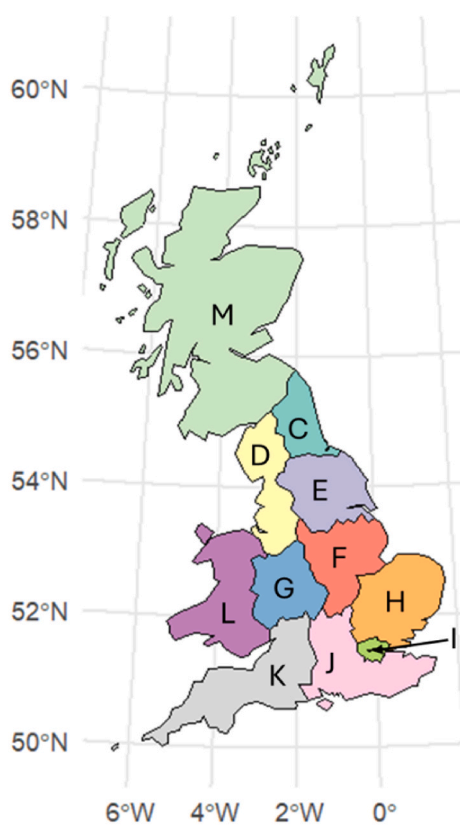


**Fig. 1.** International Territorial Level Regions C to M of Great Britain. The regions are C=Northeast; D = North West; E = Yorkshire and The Humber; F = East Midlands; G = West Midlands; H = East; I = London; J = South East; K=South West; L = Wales; M = Scotland.

### 2.2. Overview of LTLS modelling framework

We used the Long-Term Large Scale (LTLS) integrated modelling framework (Bell et al., 2021) to model terrestrial and freshwater macronutrient loads, and production across GB. The LTLS framework includes terrestrial soil-vegetation sub-models for semi-natural ecosystems (N14CP (Davies et al., 2016):) and agricultural landscapes (Rothamsted Landscape Model, (RLM) (Coleman et al., 2017):). These sub-models provide spatially distributed estimates of soil macronutrient storage and runoff, and in the case of RLM, crop production and yield.

The framework includes a dynamic freshwater hydrological model (LTLS-FM (Bell et al., 2021):), which receives water and nutrient outputs from the terrestrial sub-models as inputs. It then routes water and nutrients through the simulated river network to the sea (Fig. 2).

The framework operates on a 5 km × 5 km grid, resulting in 244 x 144 grid cells that cover the GB landmass. Each grid cell is comprised of one or more land use categories (Arable, Bog Broadleaf, Conifer, Fen/Marsh/Swamp, Freshwater, Heath, Improved grass, Rock, Rough grazing, and/or Urban) defined by the UKCEH Land Cover Map 2015; Rowland et al. (2017). Depending on the defined land uses the semi-natural (N14CP) and/or agriculture (RLM) components are run and the outputs combined and transferred to the freshwater model. The model driven by grid-specific weather variables including temperature, precipitation and potential evapotranspiration (PET). Atmospheric nitrogen deposition input is directly integrated into the terrestrial models. Agricultural management data for the RLM are derived from national estimates (see Section 2.2.2). Population-based nutrients estimates, derived from sewage works and septic tanks (Naden et al., 2016), are input to river grid cells. Missault et al. (2025) validated the LTLS framework estimates of yield against national statistics, and river flow and macronutrient concentrations and loads against measured values from monitoring sites.

#### 2.2.1. The N14CP terrestrial sub-model

The N14CP sub-model is used to estimate macronutrient dynamics in semi-natural landscapes (Davies et al., 2016). The model differentiates heath, rough grazing, coniferous woodland, deciduous woodland, fen/marsh/swamp, and bog. For each land cover class, N14CP has a single conceptual soil layer with three organic pools, with each pool having a different mineralisation rate. Decaying plant material is incorporated into each pool. The key processes influencing the fate of soil nutrients are representations of plant growth; atmospheric deposition; nitrogen fixation; weathering, soil sorption and desorption of phosphorus; decomposition of decaying plant material and incorporation of nutrients into soil organic matter; and mineralisation of soil organic matter with the release of nitrogen and phosphorus. Rate coefficients for these processes are from Bell et al. (2021). Any unbound nutrient in soil water may be released to surface runoff and drainage according to hydrological conditions. The model does not explicitly include soil hydrology but generates amounts of nutrients available for removal by water. Water volumes of surface runoff and drainage are estimated using the (separate) probability distributed model (PDM (Moore, 2007);). N14CP runs at a 3-monthly time step starting January–March with outputs disaggregated to a daily timestep to generate inputs to the river component of LTLS (Section 2.1.4). The 3-monthly nutrient outputs are disaggregated to a daily timestep for association with daily runoff and drainage generated by the PDM.

#### 2.2.2. Rothamsted Landscape Model (RLM) terrestrial sub-model

The RLM simulates soil processes (including soil organic matter, soil nutrients and water dynamics), livestock production, crop growth and crop yields (wheat, barley, oats, oilseed rape, field beans, sugar beet, forage maize, potato, and peas), and improved grass on a daily timestep. The assumes the soil is comprised of three layers. The soil properties including texture (percent clay, silt and sand), soil carbon (%), bulk density (g $cm^{-3}$), soil water (%) and nutrient status (P, kg $ha^{-1}$, $NO^3$-N,

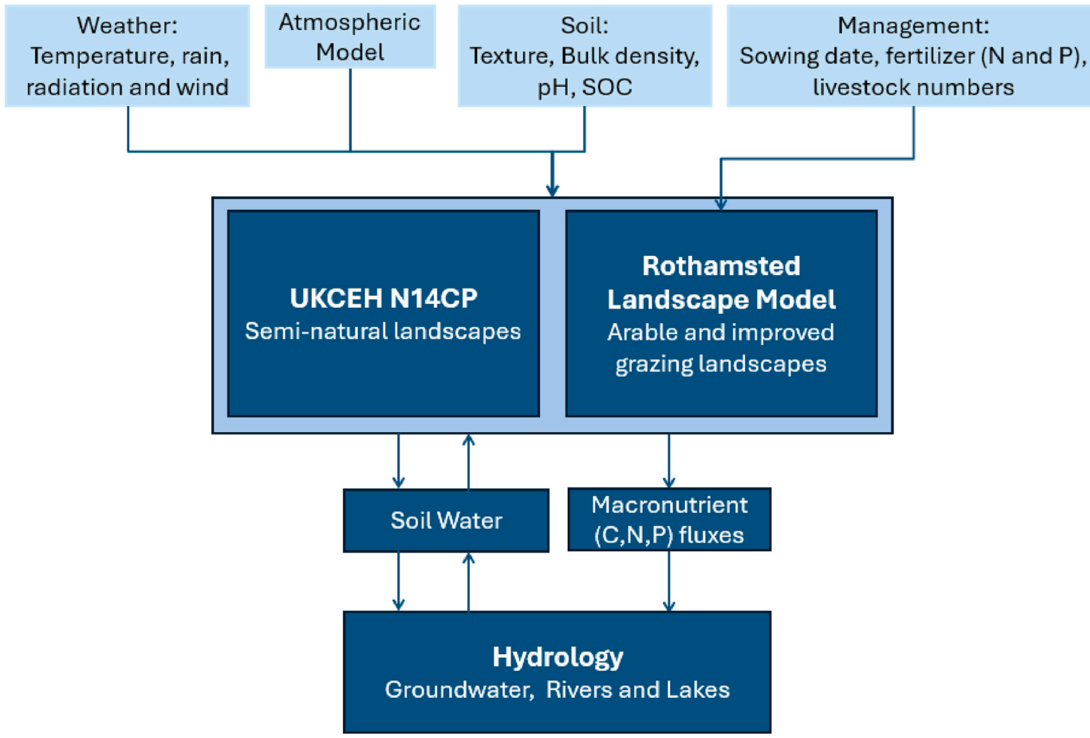


**Fig. 2.** Schematic of the LTLS framework.

kg $ha^{-1}$ and $NH_4$-N, kg $ha^{-1}$) are initialised at the start of the simulation, with dynamic properties (e.g. soil water and nutrient status) updated each day. The crop model component uses daily weather variables (min/max temperature $^{o}$C, precipitation mm, radiation kj $m^{-2}$, vapour pressure kPa, wind m $s^{-1}$) to predict canopy development and resource accumulation. As well as crop yields, nutrient losses through drainage, runoff and emissions are quantified. The model components are based on well-established existing models as described in (Coleman et al., 2017) and previously validated by (Coleman et al., 2017; Hassall et al., 2022; Missault et al., 2025).

Management inputs for areas designated as arable comprise typical crop sequences, sowing dates, and fertilizer application (see supplementary methods). We used the method by Sharp et al. (2021) to generate typical sequences of arable cropping according to ITL and soil texture, and associated these with fertilizer programmes based on the British Survey of Fertilizer Practice. For more details see SI.

No comprehensive data on sowing dates are available and so we consulted with expert agronomists and elicited the earliest, most likely, and latest sowing dates for the range of crops modelled. We fitted simple triangle distributions to these data. Then having determined the crop with the sequence generator, the model samples from these distributions to assign a realistic sowing date to each crop.

For fields designated as permanent grassland management inputs comprise fertilizer applied (N kg $ha^{-1}$ and P kg $ha^{-1}$), animal type and stocking rates (number $ha^{-1}$). The typical values for each of these variables change across the UK. We considered dairy, beef, and sheep livestock systems. The spatial variation in stocking rates was taken from Redhead et al. (2020) and rescaled to update the numbers so that they aligned with the numbers in the 2020 June survey (DEFRA, 2020).

### 2.3. Scenarios

We used a scenario-based approach to investigate the impacts of various combinations of land sparing and land sharing across GB. We based our scenarios on a subset of the national land cover strategies developed by Redhead et al. (2020). These 13 plausible land cover strategies (including business as usual, BAU) describe the potential changes in the area and distribution of farmed land. The BAU strategy is the baseline of current land use patterns. Complex changes in the areas of arable, improved grazing, and semi-natural rough grazing land are incorporated to produce six strategies which broadly equate to increases in arable land of 8, 17, 26, 36, 47, and 59 % compared with BAU (we align these with concepts of land sharing), and six strategies which broadly equate to increases of 4, 8, 13, 18, 23, and 29 % in semi-natural land (we align these with concepts of land sparing) (Fig. 3). From here on, we refer to these land use change strategies are denoted as either AR or SN (for arable or semi-natural land expansion respectively), followed by the % change. Changes in other land use categories (e.g. "Broadleaf", “Conifer", “Fen marsh", “Freshwater", and “Urban") are negligible except for “Heath" which is slightly changed across scenarios in Scotland (ILT M) to allow for the desired changes to arable and semi-natural land (see Fig. 3).

In this study we are not concerned with the application of each strategy as a blanket approach across GB, but instead apply them at the ITL regional scale, systematically combining the strategies within each region to generate 1.79 trillion scenarios (i.e., all combinations of 13 land use strategies and 11 ITL regions). However, that set of scenarios includes combinations where a single strategy is applied uniformly across all ITLs, and these provide an important reference point to determine whether spatially targeted combinations can outperform blanket approaches.

In addition to land use change, land sparing/sharing also encompasses changes in agricultural management. To simulate the more intensive management associated with land-sparing scenarios (the SN scenarios in Fig. 3), we constrained the distribution of crop sowing dates to be earlier and fertilizer rates were constrained to more closely follow recommendations for best practice (AHDB, 2023). Management for land sharing scenarios conversely were associated with a distribution where rates were reduced by 5 %. Livestock stocking rates (number of head/ha) were maintained across all scenarios meaning that absolute numbers of livestock vary with varying grassland area.


**Fig. 3.** Land use (LU) changes across International Territorial Level regions under the 13 different strategies. The bars represent the percentage distribution of LU types for each scenario.

### 2.4. *Multiple objective optimization*

We considered four key metrics: (1) calorie production from livestock, (2) calorie production from crops, (3) terrestrial losses of nitrate nitrogen ($NO_3$-N) to fresh water, and (4) terrestrial losses of total dissolved phosphorus (TDP) to fresh water. We calculated the average annual value for each metric at GB scale for all scenarios. We compared each scenario to BAU and filtered to select only those scenarios that outperform the BAU scenario for all four objectives (higher calorie production from both crops and livestock and lower N and P losses to fresh water). This set of *viable solutions* was further reduced using multiple objective optimizations to determine Pareto optimal fronts between multiple objectives (our four key metrics). A scenario is defined as Pareto optimal solution if no other scenario exists that improves on all four metrics. The optimized Pareto-optimal solutions describe the synergies and trade-offs between production and pollution metrics. In our case the control variables were the land use strategies applied in each of the 11 ITL regions. Therefore, we have 11 control variables each of which can (potentially) take one of the 13 states **(**i.e. the 13 land use strategies described in Section 2.3 and Fig. 3) giving a total of $13^{11}$ possible scenarios. We used a non-dominated sorting algorithm to identify the optimal solutions. A point is said to be dominated by another if it is worse for every single objective (Todman et al., 2019). We refer to the subset of scenarios selected by the non-dominated sorting algorithm as the *optimal solution set*.

### 2.5. *Canonical correlation analysis*

To identify which of the control variables (the strategy applied in each of the 11 ITL regions) were most strongly correlated with the variation in the optimal solution set we undertook a Canonical Correlation Analysis (CCA) using the MATLAB Software version 9.12.0 (The MathWorks Inc, 2022). The dataset consisted of the 11 regional variables (X1–X11) as predictor variables (***X***), and the four key agricultural metrics (Y12–Y15) as response variables (***Y***). The predictor variables were ranked such that the land sharing strategies have low values and land sparing strategies have high values, with AR59 ranked as number 1, and SN29 ranked as 13. Prior to analysis, all response variables were standardized using z-score normalization to address scale differences.

Canonical Correlation Analysis identifies linear combinations (canonical variates) of variables within each set that maximize correlation between the two sets. The canonical correlations (r) were derived, representing the strength of association between the canonical variates.

Canonical loadings were obtained by computing the correlation between the original variables ($X$ and $Y$) and the corresponding canonical variates ($U$, $V$). Canonical loadings were derived to interpret the contribution of each original variable to the canonical variates:

$$R_x = \mathrm{corr}(X_{\mathrm{std}}, U)$$

$$R_y = \mathrm{corr}(Y_{\mathrm{std}}, V)$$

where $R_x$ and $R_y$ represent the correlations between the original variables and their respective canonical variates. The statistical significance of the canonical correlations was assessed using Wilks' Lambda (Krzanowski, 2000).

### 2.6. *Clustering*

To identify common combinations of management strategies in our optimal solution set, the control variables were further analysed using a cluster analysis. The cluster analysis used a minimum variance, hierarchical clustering approach following the Ward (1963) method, with the number of clusters informed from the Dendrogram. This was implemented in MATLAB version: 9.12.0 using the standardized Euclidean distance (The MathWorks Inc, 2022). Hierarchical clustering was selected over alternative approaches such as k-means because it does not require a priori specification of the number of clusters. Instead, the dendrogram allows us to explore the natural grouping structure within our data and make an informed decision about the optimal number of clusters post-hoc. This is particularly valuable for our analysis, where the Pareto-optimal solutions represent a continuum of trade-offs between objectives, and hierarchical clustering preserves the nested structure of these relationships, providing insight into how solutions relate at multiple scales of similarity.

## 3. Results

### 3.1. *Impacts of adopting the Ar59 and SN29 across GB scale*

Figs. 4 and 5 show the spatial distribution of changes in agricultural

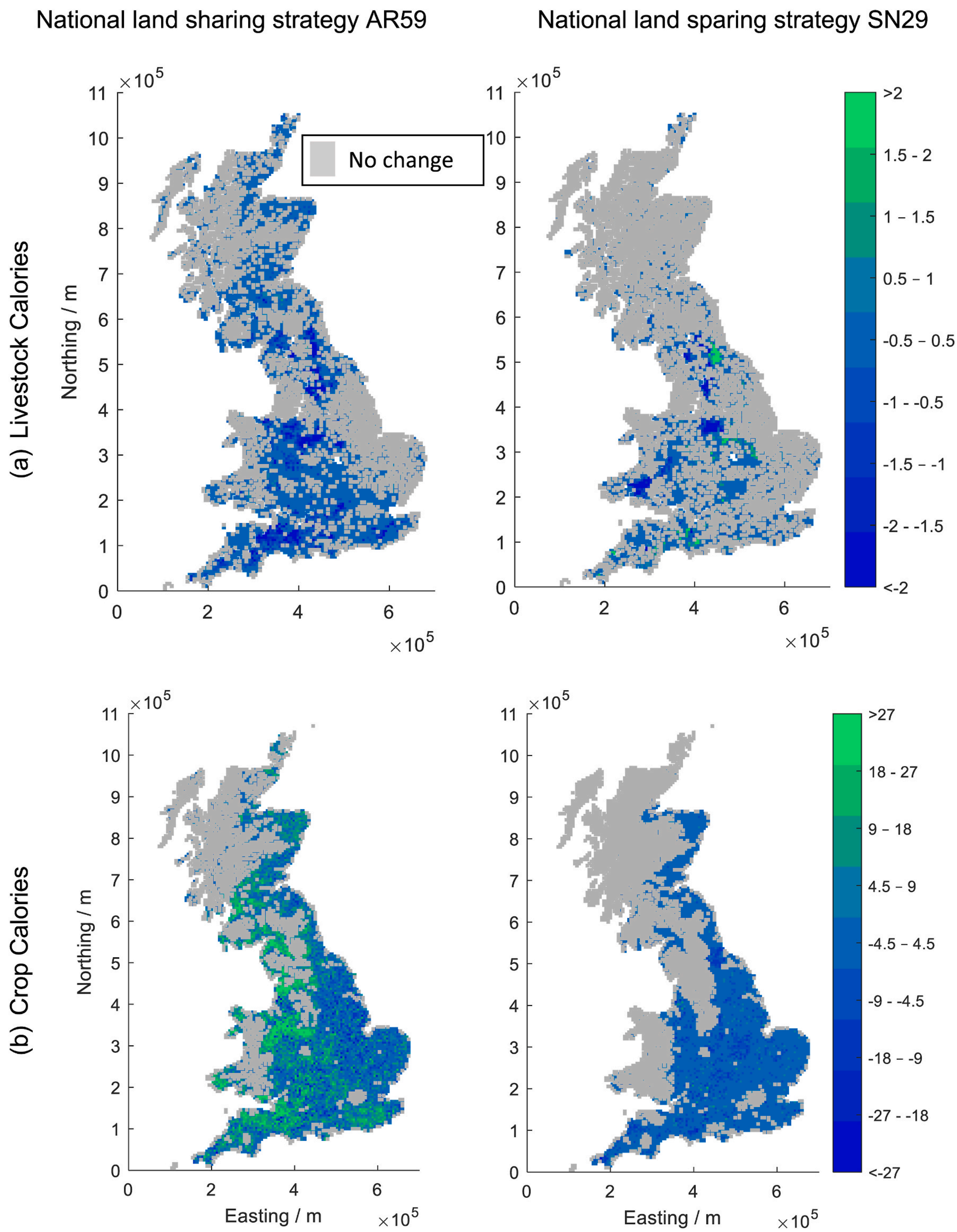


**Fig. 4.** Average annual change in each 5 km × 5 km cell for (a) Livestock Calories, kcal x $10^9$ (b) Crop Calories, kcal x $10^9$ from Business-As-Usual to land sharing strategy AR59 and land sparing strategy SN29.The grey blocking shows where no changes have been observed.

and environmental metrics when transitioning at the national scale from Business-As-Usual (BAU) to either extreme of land sparing (Ar59) or land sharing (SN29) across all ITL regions.

In the Ar59 national land sharing scenario, livestock calorie production decreases, particularly in Southwest England (region K), the West Midlands (region G), Northwest England (region D), and parts of Wales (region L). These regions traditionally support intensive livestock farming. Converting improved grassland to arable land substantially reduces livestock carrying capacity. TDP increases throughout these same regions, reflecting the increase in phosphorus fertilizer use. Overall, this national Ar59 scenario shifts production towards arable systems, improving crop output locally but at the cost of higher nutrient losses and reduced livestock capacity. Changes in crop calories are spatially heterogeneous with some localised coherent increases in crop production where extensive improved grassland is converted to arable (Fig. 4a and b). More spatially variable responses arise where land conversion is patchy or influenced by stochastic variation in cropping between scenarios.

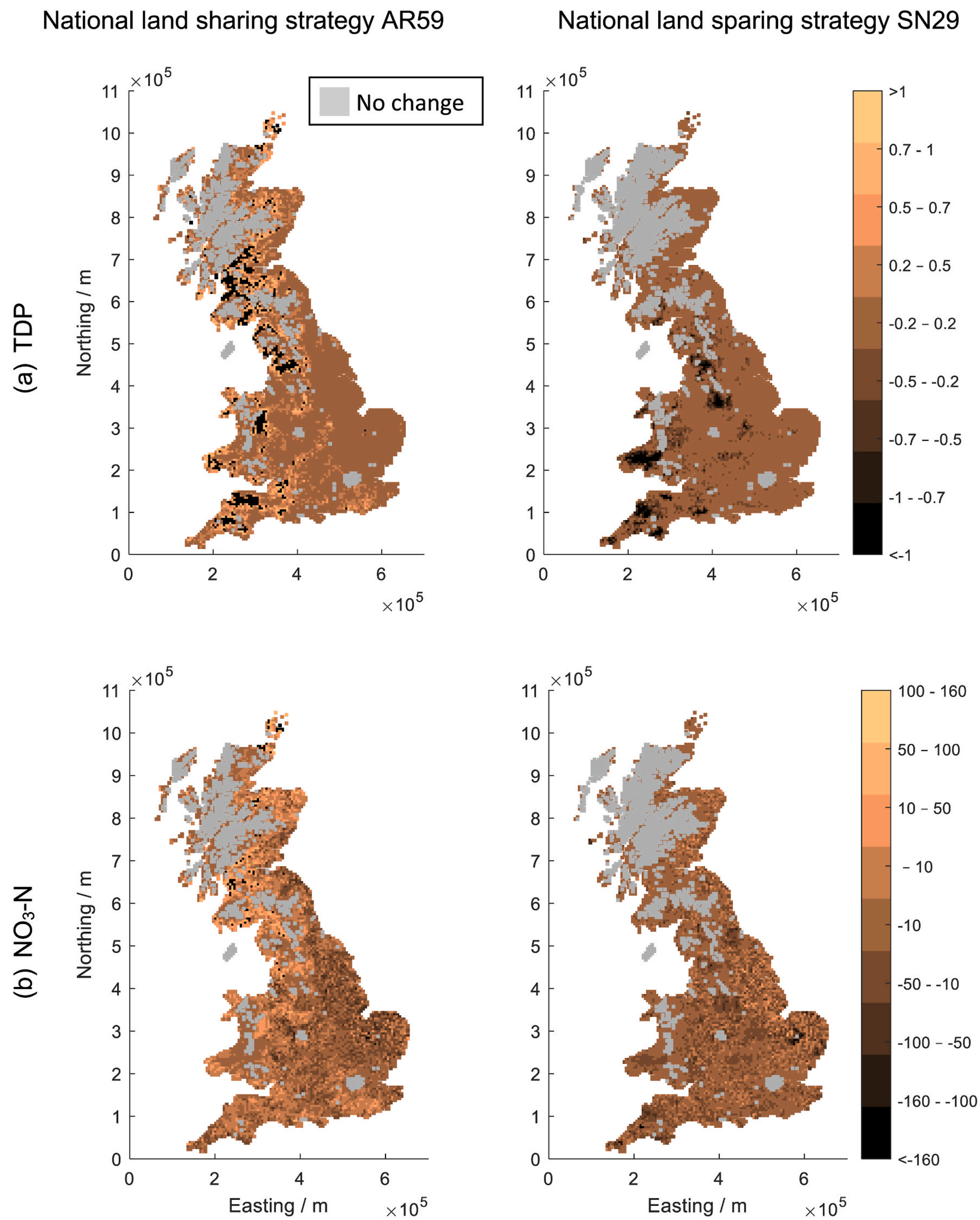


**Fig. 5.** Average annual change in each 5 km × 5 km cell for terrestrial losses of (a) Total Dissolved Phosphorus (TDP) t to fresh water and (b) nitrate ($NO_3$-N) t to fresh water from Business-As-Usual to land sharing strategy AR59 and land sparing strategy SN29.The grey blocking shows where no changes have been observed.

Nitrate losses to fresh water increase most strongly in the Midlands (region G) and Northwest England (region D), corresponding to grassland-to-arable conversion (Fig. 5b). In contrast, reductions in nitrate losses occur in areas already dominated by arable due to the reduced i fertilizer intensity. Together, these patterns indicate that under national-scale land sparing, environmental pressures become spatially concentrated in arable expansion zones.

In the SN29 national land sharing scenario, reductions in livestock calorie production are more pronounced and spatially concentrated in Wales (region L), Northwest England (region D), the West Midlands (region G) and Southwest England (region K). Decreases in phosphorus losses align with reductions in arable and livestock output, reflecting reduced fertilizer use as arable land and improved grassland transition to improved grassland or rough grazing. Crop calorie production declines across England and parts of Scotland and Wales due to land use change, with only localised increases where arable land is more intensively managed or due to stochastic cropping variation between scenarios. Overall, the comprehensive land sharing scenario promotes environmental benefits at the expense of national food production, with particularly strong impacts in livestock-dominated regions.

### 3.2. Pareto-optimal solutions

Out of the $13^{11}$ scenarios tested, 24,412 scenarios improved on all metrics compared with business as usual (BAU) at the scale of Great Britain and formed part of the Pareto-optimal solution set.

Fig. 6 shows how frequently each land use strategy occurs in the Pareto-optimal solutions for each of the ITL regions (Fig. 1). The skew towards the extremes of the horizontal axis reflects the overall weighting towards land sparing (right) or land sharing (left) strategies. In regions C, D and E, the land sharing SN23 strategy is most often selected as the Pareto-optimal solution. In those regions, this strategy entails an increase in seminatural land, primarily rough grazing, by +5.71 % to +9.08 %, at the expense of improved grassland (−4.14 % to −7.56 %) and arable (−1.56 % to −7.56 %)(Fig. 3). These regions therefore favour moderate extensification that enhances seminatural cover while reducing intensive land uses.

For regions F and G, the most prevalent solution is SN4, requiring only marginal increases in seminatural land (+0.11 and + 0.36 %). Conversely, for region H, the most prevalent solution is AR8 representing a small shift towards extensification of arable. Together, these regions tend towards modest adjustments rather than strong directional change.

Regions I and J exhibit a more balanced distribution of Pareto-optimal solutions, with region I showing an even mix across scenarios, suggesting flexibility in how production and environmental goals can be met. In region K, dominant solutions SN8 and SN18 lead to increases in both improved grassland (+1.91 % and +2.02 %) and rough grazing lands (+1.82 % and +3.91 %). This indicates that moderate land sharing can achieve multi-metric improvements without major land reallocation.

Region L is characterized by arable expansion, with Ar26 the most predominant solution, followed by Ar17, leading to increases in arable land (+7.22 %, and +3.33 %)at the expense of grassland(-7.65 and −3.29). Similarly, in region M, arable expansion dominates, with Ar17 increasing by +4.25 % and replacing improved grassland (−1.24 %), rough grazing (−1.48 %) and Heathland (−1.1 %). These regions therefore favour land-sparing trajectories focused on arable expansion.

Overall, the Pareto-optimal set reveals clear regional differentiation: regions in northern England lean towards land sharing and increased seminatural cover, whereas Scotland and Wales favour land sparing and arable intensification. This spatial contrast underscores the influence of existing land use and biophysical conditions on optimal trade-offs between production and environmental outcomes.

### 3.3. Canonical correlation analysis

Canonical correlation analysis identified four significant canonical dimensions ($p < 0.001$), with the first two dimensions explaining 62.5 % of the variance in the response variables given the predictors (Fig. 7, see also Fig. S2).

The first canonical dimension showed a strong correlation ($r = 0.98$). This dimension was characterized by strong negative loadings of predictor variables ITL D (−0.87), ITL E (−0.75), ITL F (−0.75), and ITL G (−0.64), contrasted against strong positive loadings across all response variables (ranging from 0.65 to 0.75). The observed negative correlations stem from the scenario ranking, where land sharing scenarios are assigned lower numbers (e.g., Ar59 is scenario 1) and land sparing scenarios are assigned higher numbers (e.g., SN29 is scenario 13). The negative loadings indicate that solutions associated with land sharing (lower-numbered scenarios) are linked to higher crop calorie production and increased nutrient losses.

The second canonical dimension ($r = 0.91$) revealed a more nuanced

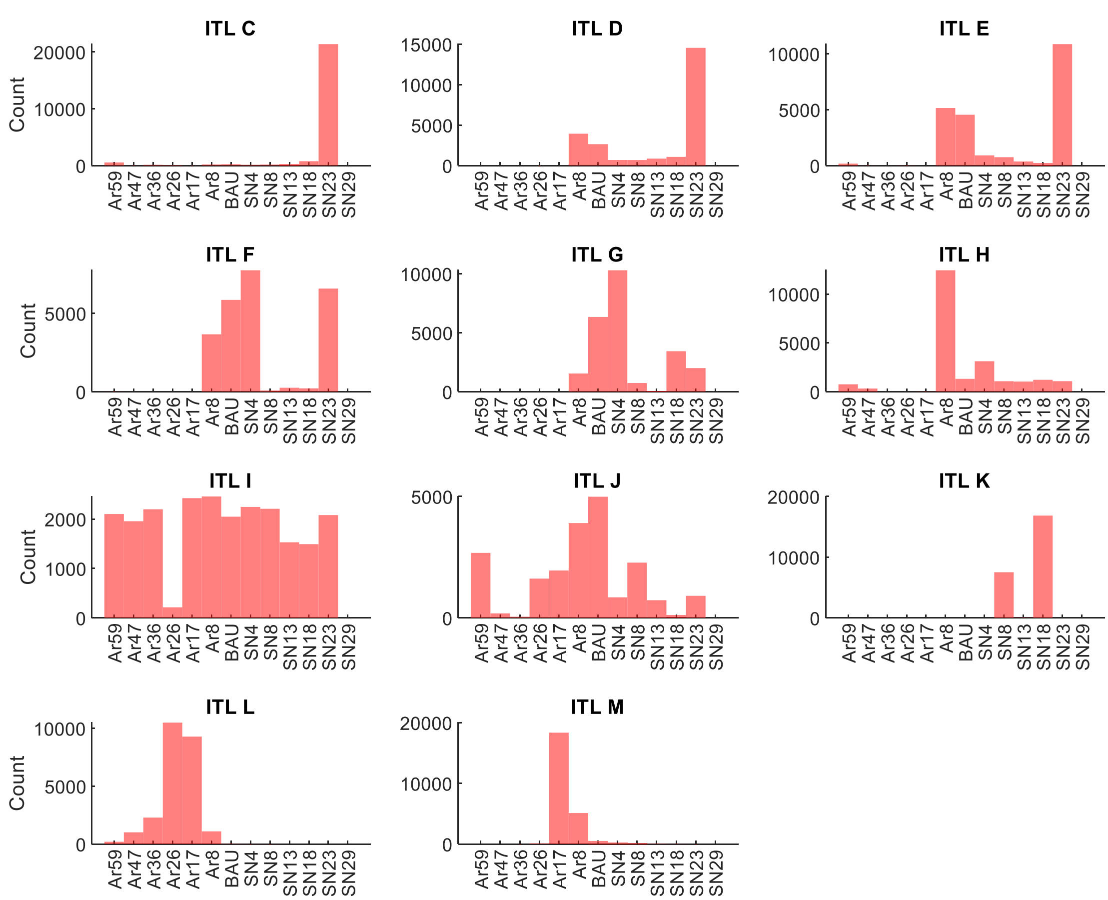


**Fig. 6.** The frequency of Pareto-optimal solutions for different land-use scenarios across multiple ITL regions. See Fig. S1 information for this plot on the log scale.

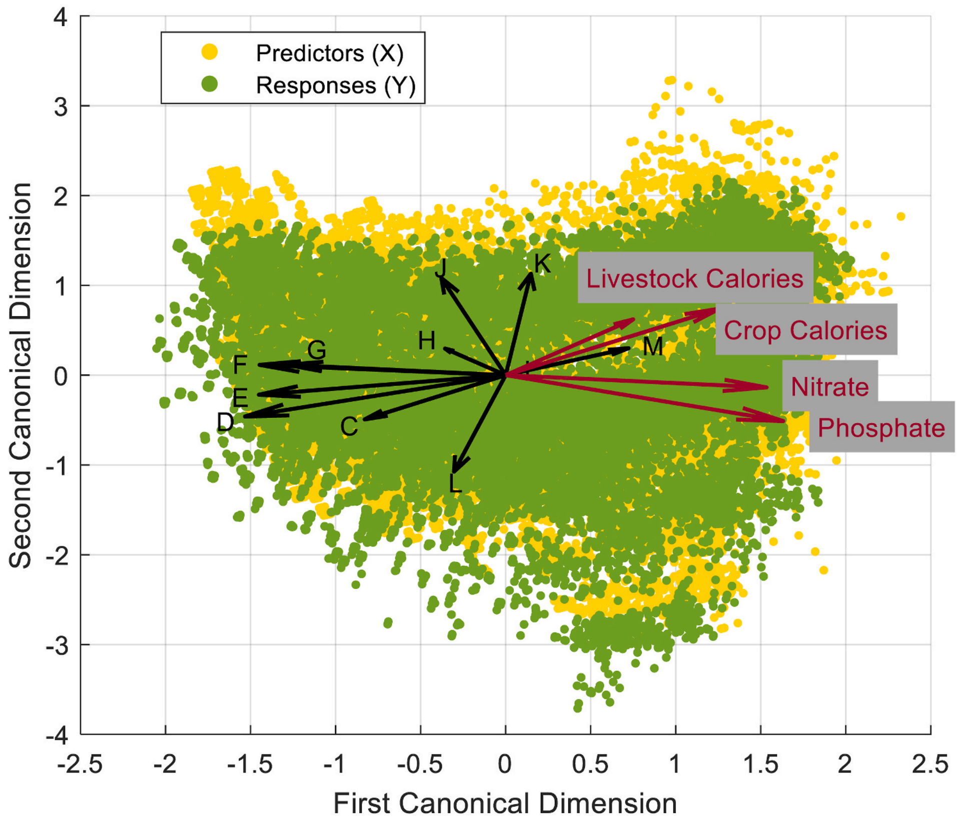


**Fig. 7.** Canonical Correlation Analysis Biplot of Predictors and Responses. The biplot displays the relationships between predictor variables (yellow) and response variables (green) along the first and second canonical dimensions. Black arrows represent ITL regions (C: North East, D: North West; E: Yorkshire and the Humber; F: East Midlands; G: West Midlands; H: East of England; I: London; J: South East; K: South West; L: Wales; M: Scotland), and red arrows denote key response variables, which are Livestock Calories, Crop Calories, Nitrate losses, and Phosphate losses.

relationship structure, primarily influenced by predictors ITL K (0.73) and ITL J (0.53). This dimension, showed positive associations with livestock calories (0.35) and arable calories (0.41) but negative associations with phosphate leaching (−0.29). This pattern suggests that, in these regions, moderate increases in production can coincide with reduced phosphorus losses, indicating scope for synergistic outcomes rather than strict trade-offs.

Together, the first two canonical dimensions highlight distinct spatial patterns in the relationships between regional land use strategies and system outcomes. The first reflects a production–environment trade-off under land sharing, and the second reveals the potential for production gains to be compatible with environmental improvements.

Redundancy analysis confirmed that response variables are better explained by the predictors than vice versa, with the model capturing substantial shared variance between the two sets. This indicates that regional land-use strategies account for a substantial proportion of the variation in system outcomes.

### *3.4. Cluster analysis*

We identified three clusters of scenarios within the Pareto-optimal solution set (Fig. S3). Each cluster represents a collection of scenarios with similar distribution of land use change strategies across the ITL regions.

Fig. 8 shows the trade-off frontiers between food production (crop and livestock calories) and nutrient losses (TDP and $NO_3$-N) across the three clusters. We refer to these as Cluster 1, Cluster 2 and Cluster 3. Cluster 1 maximized food production achieving the highest crop and livestock calorie production, but at the cost of increased nutrient losses relative to other solutions. Cluster 3, in contrast, showed lower TDP and $NO_3$-N values, indicating the best environmental performance (note axis for these variables are presented reversed so that more beneficial outcomes are further from the origin). However, this came at the cost of lower calorie production. Cluster 2 occupied intermediate positions balancing environmental protection and agricultural productivity. Together, these three clusters delineate clear trade-offs between production and nutrient losses.

Fig. 9 displays the frequency of Pareto-optimal solutions across six ITL regions (D, E, F, G, J, and K) within the three hierarchical clusters. We focus on these six regions as the CCA identified them as important in explaining variation in the outcomes.

The high production cluster (Cluster 1) strongly favours the SN23 strategy in region D. Regions D and F have a bimodal distribution with high frequencies of AR8, BAU and SN23 solutions. Notably AR59 dominates in region J within this cluster evidencing a more extreme shift towards arable expansion in this region (Fig. 2). Overall, Cluster 1 reflects a high-intensity land-use pattern prioritizing production gains, particularly in south-east England.

The moderate-production cluster (Cluster 2) favours a mild arable expansion strategy (Ar8) in regions D–F. This suggests small shifts towards land sharing can achieve higher caloric output while still improving environmental metrics. Cluster 2 configurations appear to strike a balance enhancing both food production and environmental performance, though with greater emphasis on productivity (Fig. 8). This cluster therefore represents a transitional, moderate-intensity pathway with relatively efficient trade-offs.

Cluster 3 shows a dominance of SN23 across regions D, E and F, with SN4, SN8 and SN18 also appearing prominently in G and K. Land-sharing approaches are almost absent in this cluster for the ITL regions shown. These patterns indicate a strong preference for land-sparing strategies under environmentally focused solutions.

Overall, the cluster analysis highlights three distinct solution

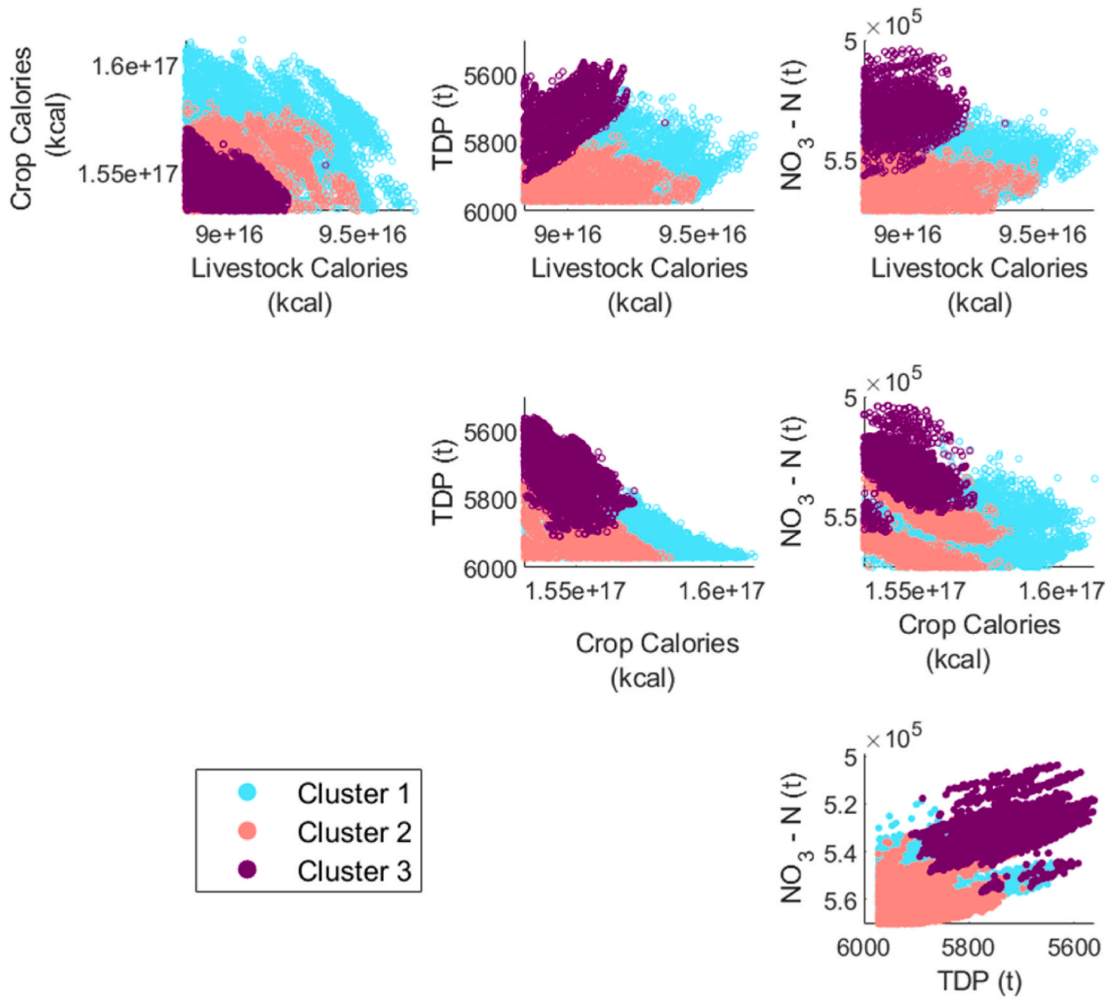


**Fig. 8.** Trade-off frontiers between average annual measures of food production (crop and livestock calories) and nutrient losses (TDP and $NO_3$-N) for Great Britain across the three Pareto-optimal clusters identified in the hierarchical clustering analysis. All solutions retained improve on BAU across all metrics.

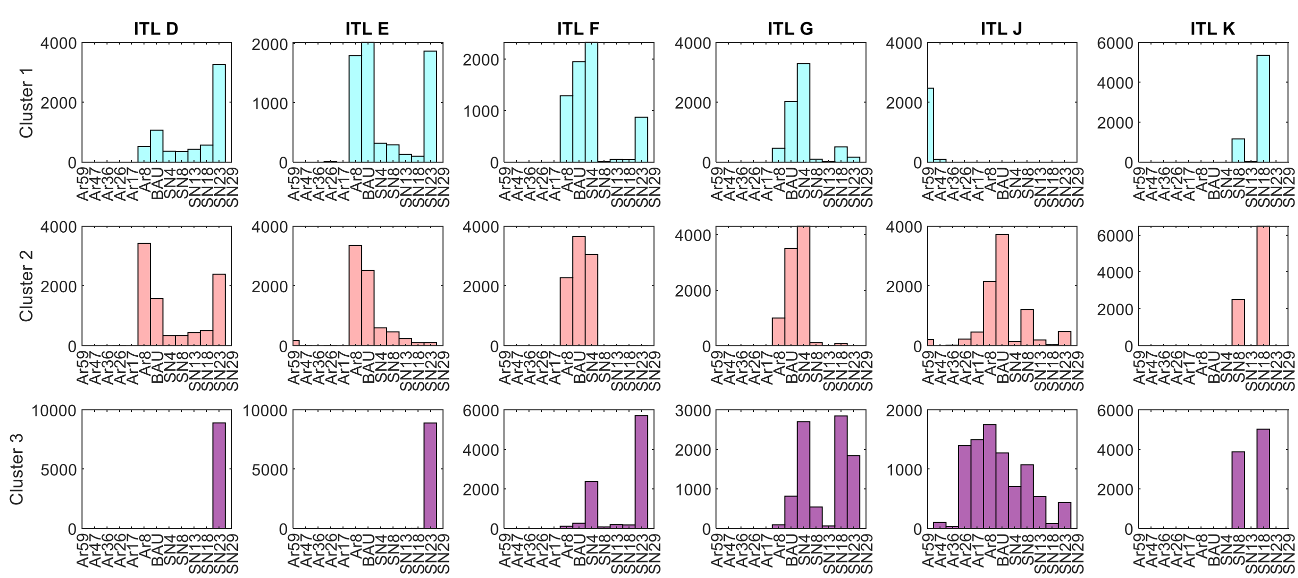


**Fig. 9.** Frequency of Pareto-optimal solutions across six ITL regions (D, E, F, G, J, K) within the three hierarchical clusters. The Pareto-optimal solutions represent land-use scenarios that outperform business-as-usual, achieving higher calorie production from crops and livestock while reducing total dissolved phosphorus (TDP) and nitrate-nitrogen ($NO_3$-N) losses to fresh water.

spaces—high-production, moderate-production, and high- environmental-performance—each associated with specific regional tendencies and land-use strategies. These clusters demonstrate that regional configuration strongly shapes the balance between agricultural output and environmental quality within the Pareto-optimal space.

## 4. Discussion

Our analysis offers a novel, spatially explicit assessment of changes in land use and the intensity of crop production, and the associated trade-offs between food production and nutrient losses to freshwater at a national scale.

The predominance of land-sparing scenarios (SN) in our Pareto-optimal solutions, particularly in the environmentally optimal Cluster 3, suggests that strategic semi-natural habitat expansion has an important role to play in reducing the environmental footprint of agriculture whilst still maintaining or increasing food production. This finding aligns with Balmford et al. (2012) and Lamb et al. (2016) who demonstrated that optimizing agricultural intensity within appropriate landscapes while dedicating others entirely to ecological restoration can advance both conservation and production objectives. However, critically none of our optimal solutions comprised SN strategies alone, all had some component of agricultural extensification (i.e. at least one ITL was allocated an AR strategy in all optimal solutions). This finding aligns with the recent global synthesis by Augustiny et al. (2025), who found that 52 % of cases supported context-specific combinations of both strategies rather than pure approaches, with only 41 % favouring pure land sparing and 7 % favouring pure land sharing exclusively. Recent UK-specific evidence aligns with this. Collas et al. (2022) found that land sparing achieved identical biodiversity and climate outcomes at just 48 % of the cost of land sharing approaches. This stark cost-effectiveness differential reveals a critical policy misalignment, as most of current UK conservation funds are allocated to land sharing strategies. Our results, showing that optimal solutions require spatially targeted combinations of both approaches, suggest that policy reform toward more flexible, regionally differentiated strategies could deliver both greater environmental benefits and better value for public investment.

Our regional analysis reveals distinct optimization patterns across ITL regions that reflect underlying agricultural systems. The dominance of SN23 in Northern England (regions C, D, E) aligns with these regions' mixed farming systems and available marginal land for conversion. In contrast, the prevalence of AR8 in Eastern England (region H) reflects the highly productive arable landscapes where intensification offers greater returns. Wales (region L) showing predominantly arable expansion (Ar26, Ar17) may seem counterintuitive given its traditional pastoral focus, but this reflects optimization opportunities where limited arable land can be highly productive. These regional patterns support Berry et al. (2022)'s quantitative demonstration that between-county variation significantly exceeds within-county variation in English and Welsh agriculture, providing statistical evidence against uniform policy approaches.

The comparison between the BAU scenario and the Pareto-optimal solutions reveals improvements in both agricultural productivity and environmental outcomes, with increases of up to 9.7 % in livestock calories and 5.2 % in crop calories, while simultaneously reducing losses of TDP by up to 6.9 % and $NO_3$-N by 11.9 %. Although our simulations demonstrate measurable improvements in environmental and production outcomes, these gains represent only incremental progress toward the transformative changes envisioned in frameworks such as the Innovation Agenda for UK Agriculture (APPG, 2025).

Our simulation results align with and extend previous studies examining nutrient losses under different land management strategies. The 11.9 % reduction in nitrate losses we observed in Pareto-optimal scenarios is comparable to findings from other European studies. Wynants et al. (2024), working with agricultural catchments in Europe, reported that combinations of management interventions including reduced fertilizer application (20 %) and cover crops could achieve 16–26 % reductions in inorganic nitrogen loads under certain climate scenarios. Similarly, a basin-scale modelling of Baltic Sea catchments found that plausible stakeholder-approved measures could reduce nitrogen loads by up to about 9 % (Capell et al., 2021). Notably, Karner et al. (2021) demonstrated through a multi-objective land-use optimization in Austria that relatively small sacrifices in agricultural output can significantly curb nitrate leaching. In their stochastic optimization, a mere ~1 % reduction in net economic benefit led to an 18–19 % decrease in nitrate leaching. This illustrates the non-linear gains possible with more intensive optimization. Our 11.9 % reduction represents a conservative but achievable target that maintains agricultural productivity gains, positioning our findings within the established range of nutrient reduction potential.

The 6.9 % reduction in TDP we report also corresponds well with regional studies examining phosphorus dynamics. For example, Collins et al. (2016) estimated that ambitious but realistic uptake of on-farm mitigation measures in England and Wales, could yield phosphorus load reductions of up to 15 %, depending on soil characteristics, legacy phosphorus, and management intensity. Our TDP reductions are particularly notable given the tendency of phosphorus to be fixed in soil (Mahdi et al., 2012), which makes phosphorus mobilization highly dependent on soil erosion and surface runoff patterns rather than simple leaching processes.

Regarding agricultural productivity, our findings of 5.2 % increase in crop calories and 9.7 % increase in livestock calories under optimal land allocation strategies compare favourably with meta-analyses of agricultural intensification effects. Wu and Ma (2015) found that integrated nutrient management strategies enhance crop yields by 8–150 % compared with conventional practices, though these figures include more extreme intensification scenarios than we modelled. Our results reflect the gains achievable within the limits of current technologies and management practices, rather than speculative future improvements.

Achieving the ambitious dual targets of expanding agricultural output by 30 % by 2050 whilst halving its environmental footprint will necessitate comprehensive systems-level approaches beyond land allocation strategies alone. Rockström et al. (2017) emphasize that agriculture must integrate dual and interdependent goals of using sustainable practices to meet rising human needs while contributing to resilience and sustainability of landscapes, the biosphere, and the Earth system. Similarly, Pretty (2018) demonstrates that system redesign is essential to deliver optimum outcomes as ecological and economic conditions change, requiring the integration of multiple agricultural processes rather than singular interventions. Our findings echo this assessment, demonstrating that merely shuffling land-use allocations is insufficient to meet these ambitious goals. Instead, we must complement optimized land-use strategies with innovative agricultural solutions that can improve both productivity and environmental performance. Our analysis constrains intensified yields to what can be achieved with existing technologies and current crop varieties. Future advances in crop breeding could substantially raise this ceiling, with developments in nitrogen-use efficiency, drought tolerance, and photosynthetic capacity potentially amplifying the land-sparing benefits observed in our study (Long et al., 2015; Ray et al., 2013; Walsh et al., 2022). Recent advances demonstrate significant potential for improvements in nitrogen management, with studies showing that nitrogen losses can be minimized by 15–30 % through adopting improved agronomic approaches such as optimal nitrogen dosage, precision agriculture, intercropping of legume and non-legume crops, and improved plant populations (Anas et al., 2020; Xu et al., 2012) Further changes to agricultural practices such as the use of non-leguminous cover crops (Macdonald et al., 2005) can also significantly impact nutrient dynamics enabling greater while requiring fewer external inputs. The integration of precision agriculture technologies offers additional pathways for improvement, with studies demonstrating 20–30 % yield increases through optimized input use and resource efficiency (Chen, 2025). However, adoption of these technologies faces significant barriers including high upfront costs, lack of technical literacy, and inadequate infrastructure, particularly for small and medium-sized farms (Paustian and Theuvsen, 2017; Pierpaoli et al., 2013). Overcoming these barriers requires coordinated policy support, including financial incentives, training programs, and improved rural infrastructure (Kernecker et al., 2020). The process-based modelling included in the LTLS framework means that it has the functionality to incorporate these innovations in future scenario testing to assess their potential contribution.

A critical insight from our analysis is that improving production while reducing pollution requires targeted interventions. Our canonical correlation analysis identified regions D, E, F, and G as having the strongest influence on national-scale outcomes, suggesting these regions should be priority targets for policy interventions. Similarly, ITL K and J showed differential associations with production versus pollution metrics, indicating potential for specialized regional strategies. This regional heterogeneity in response to land use change aligns with findings from (Law and Wilson, 2015), who emphasized that the effectiveness of land-sparing versus land-sharing strategies is highly context-dependent and varies with landscape characteristics. This conclusion is also supported by Finch et al. (2021), who demonstrated that environmental outcomes depended on the spatial arrangement of spared land, the types of natural habitat promoted, and regional characteristics. The importance of regional targeting is further supported by Karner et al. (2021) who found climate conditions fundamentally alter trade-off structures, with dry regions prioritizing water-economy trade-offs while wet regions emphasize nutrient-economy relationships. Tscharntke et al. (2012) argue, landscape context strongly mediates the effectiveness of different land-use strategies, suggesting that policies should be tailored to regional conditions rather than applied uniformly. Our analysis provides empirical support for this perspective, demonstrating that strategic land-use changes in specific regions can yield benefits that significantly outweigh their proportional land area contribution.

While our study applies the land-sharing versus land-sparing framework as a foundation for analysis, our spatially targeted optimization approach demonstrates the value of moving beyond binary thinking toward more nuanced, regionally differentiated solutions across the landscape. This evolution reflects broader trends in the literature, with Grass et al. (2019) proposing “connectivity landscapes" that combine both strategies within spatially connected mosaics. Feniuk et al. (2019) proposed a “three-compartment model", which is an advanced approach within the land sparing-sharing framework, that aims to balance agricultural production with biodiversity conservation. This model divides land into three distinct compartments: high-yield agriculture, low-yield agriculture, and natural habitats. Our findings can be interpreted within this framework, but we argue that neither the land-sharing or sparing framework nor the three-compartment model acknowledge the true spectrum of intensities under which our landscapes are managed. Defining discrete compartments creates an artificial landscape that fails to reflect the underlying complexity and continuity of real-world land management.

Our analysis focuses primarily on nutrient pollution and caloric production, without explicitly considering biodiversity outcomes. While land sparing may benefit certain species by preserving habitat patches, Tscharntke et al. (2012) argue that many species depend on heterogeneous agricultural landscapes rather than completely separated natural and agricultural areas. Where agricultural production is dependent on ecosystem services provided by biodiversity (e.g. crop pollination) at least some level of spatial integration of natural and agricultural habitats is essential.

Model validation and accuracy are critical considerations for interpreting our results. The LTLS framework builds on established soil-vegetation models (N14CP for semi-natural systems and RLM for agricultural landscapes), which have been extensively validated in previous studies (Bell et al., 2021; Missault et al., 2025; Coleman et al., 2017; Hassall et al., 2022). Coleman et al. (2017) demonstrated strong model performance for wheat and grass yields over a 44-year period, with RMSE of 22.98 % and 34.35 % for standard fertilizer treatments. Hassall et al. (2022) evaluated the yields of other key crops against regional (spring barley, winter barley and oilseed rape) and national averages (field beans and maize) and found that observed means fell within the modelled interannual variation. Similarly, Missault et al. (2025) used regional and national statistics to validate crops yields. For major crop yields, they reported median percentage errors ranging from 1 % (potato) to 34 % (oilseed rape) (overall average across crops 18 %). For nutrient losses, predicted and measured annual averages of nitrate and TDP over a 30-year period showed strong correspondence ($R^2 = 0.85$ and 0.76, respectively). It is noteworthy that oilseed rape yields tended to be overestimated, likely reflecting increased pest damage following neonicotinoid restrictions, which the model does not account for. Consequently, our predictions may be biased towards over-predicting yields in contexts where disease and pest pressures are high.

Our model does not capture how investing in natural capital through land-sharing approaches might support crop production and potentially allow for reductions in agrochemical inputs. Garibaldi et al. (2019) and Tamburini et al. (2020) show that ecological intensification can maintain or increase yields while reducing environmental impacts, particularly in diverse and biodiversity-enhancing systems. This potential for ecological intensification is further supported by MacLaren et al. (2022), who provided long-term evidence that ecological intensification can serve as a viable pathway to sustainable agriculture, demonstrating that biodiversity-enhancing practices can maintain productivity while reducing environmental impacts over extended time periods. This limitation may account for the paucity of land sharing approaches in our Pareto optimal set.

A key contribution of our work is the identification of 24,412 alternative land-use configurations across Great Britain. While our analysis focused on agricultural productivity and nutrient pollution, this extensive solution space provides a foundation for further multi-objective analyses. For instance, these configurations could be assessed at finer scales for goals such as enhancing habitat connectivity and supporting ecological networks—critical for biodiversity conservation in fragmented landscapes (Rudnick et al., 2012). Importantly, this can be done without the computational cost of generating new solutions, allowing for efficient evaluation of additional priorities such as nature corridors.

The absence of any “blanket" solutions (where the same strategy, including BAU, is applied to all ITL regions) in our Pareto-optimal set underscores that one-size-fits-all approaches fail to capture the inherent heterogeneity of Britain's landscapes and their functional responses to land-use change. This aligns with findings from (Bateman et al., 2024; Verhagen et al., 2018), who demonstrated that spatial targeting of interventions yields substantially greater benefits than homogeneous implementation across diverse landscapes. The regional optimization approach we employed represents a departure from conventional land-use planning paradigms that often prescribe uniform policies across administrative boundaries regardless of landscape characteristics (Bateman et al., 2013). Instead, our work recognizes that the optimal balance between agricultural production and environmental protection varies according to local biophysical conditions, existing land-use configurations, and regional agricultural specializations. The marked improvement in both production and environmental metrics achieved through regional optimization reinforces (Brady et al., 2012) assertion that tailored regional policies can create win-win outcomes that uniform approaches cannot match. This principle of spatial differentiation in land-use policy represents a crucial shift in thinking about agricultural sustainability, moving beyond debates about whether land sparing or sharing is universally “better" toward recognizing that optimal approaches are inherently context-dependent and spatially diverse.

## 5. Conclusion

Our study demonstrates that land-sparing/land-sharing approaches, applied differentially across regions, can deliver modest but meaningful improvements in both agricultural productivity and environmental outcomes. However, realising transformative change will require moving beyond the sharing-sparing debate to embrace more nuanced approaches that recognize the value of landscape heterogeneity, capitalize on ecological intensification opportunities, and explicitly consider biodiversity alongside production and pollution metrics. The extensive solution space of 24,412 land-use alternatives generated in this study provides a valuable foundation for future research exploring additional objectives beyond agricultural productivity and nutrient pollution.

## CRediT authorship contribution statement

**Imane El Fartassi:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis. **Ryan T. Sharp:** Writing – review & editing, Software, Methodology, Investigation, Formal analysis, Conceptualization. **Victoria A. Bell:** Writing – review & editing, Software, Funding acquisition, Conceptualization. **Andrew P. Whitmore:** Writing – review & editing, Software, Methodology, Funding acquisition, Conceptualization. **Helen Metcalfe:** Writing – review & editing, Methodology, Investigation, Formal analysis, Conceptualization. **Nathan Missault:** Writing – review & editing, Software, Methodology. **John Redhead:** Writing – review & editing, Methodology, Data curation. **David M. Cooper:** Writing – review & editing, Software, Formal analysis, Data curation, Conceptualization. **Jonathan Storkey:** Writing – review & editing, Resources, Investigation, Funding acquisition, Conceptualization. **Helen Davies:** Writing – review & editing, Methodology, Data curation. **Theo Jackson:** Writing – review & editing, Methodology, Data curation. **Kevin Coleman:** Writing – review & editing, Software, Methodology, Data curation. **Alice E. Milne:** Writing – review & editing, Writing – original draft, Supervision, Software, Project administration, Methodology, Funding acquisition, Formal analysis, Conceptualization.

## Declaration of competing interest

The authors have nothing to declare.

## Acknowledgements

Rothamsted Research receives strategic funding from the Biotechnological and Biological Sciences Research Council (BBSRC) of the United Kingdom. We acknowledge support from the AgZero+ (NE/W005050/1) Institute Strategic Programme that is jointly funded by the Natural Environment Research Council (NERC) and BBSRC.

## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jenvman.2025.128389.

## Data availability

The data set generated by this research will be made available via zenodo

## References

AHDB, 2023. Nutrient Management Guide (RB209) Section 1 Principles of Nutrient Management and Fertiliser Use.

Anas, M., Liao, F., Verma, K.K., Muhammad, A.S., Mahmood, A., Chen, Z., Li, Q., Zeng, X. P., Li, Y.R., 2020. Fate of nitrogen in agriculture and environment: agronomic, eco-physiological and molecular approaches to improve nitrogen use efficiency. Biol. Res. 53, 47. https://doi.org/10.1186/s40659-020-00312-4APPG (2025). Innovation Agenda For UK Agriculture (Issue January).

APPG, 2025. Innovation Agenda for UK Agriculture. All-Party Parliamentary Group on Science and Technology in Agriculture. https://www.appg-agscience.org.uk/.

Augustiny, E., Frehner, A., Green, A., Mathys, A., Rosa, F., Pfister, S., Muller, A., 2025. Empirical evidence supports neither land sparing nor land sharing as the main strategy to manage agriculture–biodiversity tradeoffs. PNAS Nexus 4 (9). https://doi.org/10.1093/pnasnexus/pgaf251.

Balmford, A., Amano, T., Bartlett, H., Chadwick, D., Collins, A., Edwards, D., Field, R., Garnsworthy, P., Green, R., Smith, P., Waters, H., Whitmore, A., Broom, D.M., Chara, J., Finch, T., Garnett, E., Gathorne-Hardy, A., Hernandez-Medrano, J., Herrero, M., et al., 2018. The environmental costs and benefits of high-yield farming. Nat. Sustain. 1 (9), 477–485. https://doi.org/10.1038/s41893-018-0138-5.

Balmford, A., Green, R., Phalan, B., 2012. What conservationists need to know about farming. Proc. Biol. Sci. 279 (1739), 2714–2724. https://doi.org/10.1098/rspb.2012.0515.

Bateman, I.J., Binner, A., Addicott, E.T., Balmford, B., Cho, F.H.T., Daily, G.C., De-Gol, A., Eisenbarth, S., Faccioli, M., Ferguson-Gow, H., Ferrini, S., Fezzi, C., Gannon, K., Groom, B., Harper, A.B., Harwood, A., Hillier, J., Hulme, M.F., Lee, C.F., et al., 2024. How to make land use policy decisions: integrating science and economics to deliver connected climate, biodiversity, and food objectives. Proc. Natl. Acad. Sci. U. S. A 121 (49). https://doi.org/10.1073/pnas.2407961121.

Bateman, I.J., Harwood, A.R., Mace, G.M., Watson, R.T., Abson, D.J., Andrews, B., Binner, A., Crowe, A., Day, B.H., Dugdale, S., Fezzi, C., Foden, J., Hadley, D., Haines-Young, R., Hulme, M., Kontoleon, A., Lovett, A.A., Munday, P., Pascual, U., et al., 2013. Bringing ecosystem services into economic decision-making: land use in the United Kingdom. Science 341 (6141), 45–50. https://doi.org/10.1126/science.1234379.

Bell, V.A., Naden, P.S., Tipping, E., Davies, H.N., Carnell, E., Davies, J.A.C., Dore, A.J., Dragosits, U., Lapworth, D.J., Muhammed, S.E., Quinton, J.N., Stuart, M., Tomlinson, S., Wang, L., Whitmore, A.P., Wu, L., 2021. Long term simulations of macronutrients (C, N and P) in UK freshwaters. Sci. Total Environ. 776. https://doi.org/10.1016/j.scitotenv.2021.145813.

Berry, R., Vigani, M., Urquhart, J., 2022. Economic resilience of agriculture in England and Wales: a spatial analysis. J. Maps. https://doi.org/10.1080/17445647.2022.2072242.

Brady, M., Sahrbacher, C., Kellermann, K., Happe, K., 2012. An agent-based approach to modeling impacts of agricultural policy on land use, biodiversity and ecosystem services. Landsc. Ecol. 27 (9), 1363–1381. https://doi.org/10.1007/s10980-012-9787-3.

Broomfield, C., Maher, A., Winter, M., 2025. "We can only grow grass here": unsettling the traditionality of grassland narrative. Rural Hist. https://doi.org/10.1017/S0956793324000219.

Capell, R., Bartosova, A., Tonderski, K., Arheimer, B., Pedersen, S.M., Zilans, A., 2021. From local measures to regional impacts: modelling changes in nutrient loads to the Baltic Sea. J. Hydrol.: Reg. Stud. 36, 100867. https://doi.org/10.1016/j.ejrh.2021.100867.

Chen, Y., 2025. The role of modern agricultural technologies in improving agricultural productivity and land use efficiency. Front. Plant Sci. 16, 1675657. https://doi.org/10.3389/fpls.2025.1675657.

Clark, C., Thompson, P., 2018. Balancing the needs of food production, farming and nature in the UK uplands. In: Farming, Food and Nature: respecting Animals, People and the Environment, pp. 116–122. https://doi.org/10.4324/9781351011013-16.

Coe, S., Finlay, J., 2020. The Agriculture Act 2020. BRIEFING PAPER Number CBP 8702. House of Commons Library.

Coe, S., 2024. New approaches to farm funding in England. Insight. House of Commons Library. https://commonslibrary.parliament.uk/new-approaches-to-farm-funding-in-england/.

Coleman, K., Muhammed, S.E., Milne, A.E., Todman, L.C., Dailey, A.G., Glendining, M.J., Whitmore, A.P., 2017. The landscape model: a model for exploring trade-offs between agricultural production and the environment. Sci. Total Environ. 609, 1483–1499. https://doi.org/10.1016/j.scitotenv.2017.07.193.

Collas, L., Crastes dit Sourd, R., Finch, T., Green, R., Hanley, N., Balmford, A., 2022. The costs of delivering environmental outcomes with land sharing and land sparing. People Nat. 5, 228–240. https://doi.org/10.1002/pan3.10422.

Collins, A.L., Zhang, Y.S., Winter, M., Inman, A., Jones, J.I., Johnes, P.J., Cleasby, W., Vrain, E., Lovett, A., Noble, L., 2016. Tackling agricultural diffuse pollution: what might uptake of farmer-preferred measures deliver for emissions to water and air? Sci. Total Environ. 547, 269–281. https://doi.org/10.1016/j.scitotenv.2015.12.130.

Davies, J.A.C., Tipping, E., Rowe, E.C., Boyle, J.F., Graf Pannatier, E., Martinsen, V., 2016. Long-term P weathering and recent N deposition control contemporary plant-soil C, N, and P. Glob. Biogeochem. Cycles 30 (2), 231–249. https://doi.org/10.1002/2015GB005167.

DEFRA, 2020. The Path to Sustainable Farming: an Agricultural Transition Plan 2021 to 2024. Defra, pp. 1–66. https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/954283/agricultural-transition-plan.pdf.

Dunn, R.M., Hawkins, J.M.B., Blackwell, M.S.A., Zhang, Y., Collins, A.L., 2022. Impacts of different vegetation in riparian buffer strips on runoff and sediment loss. Hydrol. Process. 36 (11), 1–13. https://doi.org/10.1002/hyp.14733.

Feniuk, C., Balmford, A., Green, R.E., 2019. Land sparing to make space for species dependent on natural habitats and high nature value farmland. Proc. Biol. Sci. 286. https://doi.org/10.1098/rspb.2019.1483.

Finch, T., Day, B.H., Massimino, D., Redhead, J.W., Field, R.H., Balmford, A., Green, R. E., Peach, W.J., 2021. Evaluating spatially explicit sharing-sparing scenarios for multiple environmental outcomes. J. Appl. Ecol. 58 (3), 655–666. https://doi.org/10.1111/1365-2664.13785.

Firbank, L.G., Elliott, J., Drake, B., Cao, Y., Gooday, R., 2013. Evidence of sustainable intensification among British farms. Agric. Ecosyst. Environ. 173, 58–65. https://doi.org/10.1016/j.agee.2013.04.010.

Garibaldi, L.A., Perez-Mendez, N., Garratt, M.P.D., Gemmill-Herren, B., Miguez, F.E., Dicks, L.V., 2019. Policies for ecological intensification of crop production. Trends Ecol. Evol. 34 (4), 282–286. https://doi.org/10.1016/j.tree.2019.01.003.

Godfray, C., Beddington, J., Crute, I., Haddad, L., Lawrence, D., Muir, J., Pretty, J., Robinson, S., Thomas, S., Toulmin, C., 2010. Food security: the challenge of feeding 9 billion people. Science (New York, N.Y.) 327, 812–818. https://doi.org/10.1126/science.1185383.

Grass, I., Loos, J., Baensch, S., Batáry, P., Librán-Embid, F., Ficiciyan, A., Klaus, F., Riechers, M., Rosa, J., Tscharntke, T., 2019. Land-sharing/sparing connectivity landscapes for ecosystem services and biodiversity conservation. People Nat. 1 (3), 262–272. https://doi.org/10.1002/pan3.21.

Hassall, K.L., Coleman, K., Dixit, P.N., Granger, S.J., Zhang, Y., Sharp, R.T., Wu, L., Whitmore, A.P., Richter, G.M., Collins, A.L., Milne, A.E., 2022. Exploring the effects of land management change on productivity, carbon and nutrient balance: application of an Ensemble modelling approach to the upper River Taw observatory, UK. Sci. Total Environ. 824, 153824. https://doi.org/10.1016/j.scitotenv.2022.153824.

Hey, D., 2014. The medieval origins of south Pennine farms: the case of westmondhalgh bierlow. Agric. Hist. Rev. 62 (1), 23–39.

Hurford, C., Wilson, P., Storkey, J., 2021. The changing status of arable habitats in Europe: a nature conservation review. In: The Changing Status of Arable Habitats in Europe: a Nature Conservation Review. https://doi.org/10.1007/978-3-030-59875-4.

Ilbery, B., Watts, D., 2004. Agricultural Restructuring in the West Midlands Region, 1950-2002, vol. 165. Journal of the Royal Agricultural Society of England. https://www.scopus.com/inward/record.uri?eid=2-s2.0-21644471466&partnerID=40&md5=06a598fb07392ef204ba1016e9056b9e.

Jovarauskas, D., Steponavičius, D., Kemzūraitė, A., Zinkevičius, R., Venslauskas, K., 2021. Comparative analysis of the environmental impact of conventional and precision spring wheat fertilization under various meteorological conditions. J. Environ. Manag. 296 (May). https://doi.org/10.1016/j.jenvman.2021.113150.

Karner, K., Schmid, E., Schneider, U.A., Mitter, H., 2021. Computing stochastic Pareto frontiers between economic and environmental goals for a semi-arid agricultural production region in Austria. Ecol. Econ. 185, 107044. https://doi.org/10.1016/j.ecolecon.2021.107044.

Kernecker, M., Knierim, A., Wurbs, A., Kraus, T., Borges, F., 2020. Experience versus expectation: farmers' perceptions of smart farming technologies. Precis. Agric. 21, 34–50. https://doi.org/10.1007/s11119-019-09651-z.

Koning, A.A., Moore, J., Suttidate, N., Hannigan, R., McIntyre, P.B., 2017. Aquatic ecosystem impacts of land sharing versus sparing: nutrient loading to Southeast Asian Rivers. Ecosystems 20 (2), 393–405. https://doi.org/10.1007/s10021-016-0032-9.

Kremen, C., Merenlender, A.M., 2018. Landscapes that work for biodiversity and people. In science. American Association for the Advancement of Science 362 (Issue 6412). https://doi.org/10.1126/science.aau6020.

Krzanowski, W.J., 2000. Principles of Multivariate Analysis. Oxford University PressOxford. https://doi.org/10.1093/oso/9780198507086.001.0001.

Lamb, A., Green, R., Bateman, I., Broadmeadow, M., Bruce, T., Burney, J., Carey, P., Chadwick, D., Crane, E., Field, R., Goulding, K., Griffiths, H., Hastings, A., Kasoar, T., Kindred, D., Phalan, B., Pickett, J., Smith, P., Wall, E., et al., 2016. The potential for land sparing to offset greenhouse gas emissions from agriculture. Nat. Clim. Change 6 (5), 488–492. https://doi.org/10.1038/nclimate2910.

Law, E.A., Wilson, K.A., 2015. Providing context for the land-sharing and land-sparing debate. Conserv. Lett. 8 (6), 404–413. https://doi.org/10.1111/conl.12168.

Long, S.P., Marshall-Colon, A., Zhu, X.G., 2015. Meeting the global food demand of the future by engineering crop photosynthesis and yield potential. In: Cell, vol. 161. Cell Press, pp. 56–66. https://doi.org/10.1016/j.cell.2015.03.019, 1.

Macdonald, A.J., Poulton, P.R., Howe, M.T., Goulding, K.W.T., Powlson, D.S., 2005. The use of cover crops in cereal-based cropping systems to control nitrate leaching in SE England. Plant Soil 273 (1–2), 355–373. https://doi.org/10.1007/s11104-005-0193-3.

MacLaren, C., Mead, A., van Balen, D., Claessens, L., Etana, A., de Haan, J., Haagsma, W., Jäck, O., Keller, T., Labuschagne, J., Myrbeck, Å., Necpalova, M., Nziguheba, G., Six, J., Strauss, J., Swanepoel, P.A., Thierfelder, C., Topp, C., Tshuma, F., et al., 2022. Long-term evidence for ecological intensification as a pathway to sustainable agriculture. Nat. Sustain. 5 (9), 770–779. https://doi.org/10.1038/s41893-022-00911-x.

Mahdi, S.S., Talat, M.A., Dar, M.A., Hamid, A., Ahmad, L., 2012. Soil phosphorus fixation chemistry and role of phosphate solubilizing bacteria in enhancing its efficiency for sustainable cropping – a review. J. Pure Appl. Microbiol. 6 (4), 1905–1911.

Missault, N., Bell, V.A., Cooper, D., Sharp, R.T., Whitmore, A.P., Milne, A.E., Davies, H. N., Carnell, E., Dragosits, U., Tomlinson, S., 2025. Impact of climate change on freshwater macronutrients and agricultural yields across Britain. J. Clean. Prod. submitted for publication.

Moore, R.J., 2007. The PDM rainfall-runoff model 483 the PDM rainfall-runoff model. Hydrol. Earth Syst. Sci. 11 (1). www.hydrol-earth-syst-sci.net/11/483/2007.

Naden, P., Bell, V., Carnell, E., Tomlinson, S., Dragosits, U., Chaplow, J., May, L., Tipping, E., 2016. Nutrient fluxes from domestic wastewater: a national-scale historical perspective for the UK 1800–2010. Sci. Total Environ. 572, 1471–1484. https://doi.org/10.1016/j.scitotenv.2016.02.037.

Paustian, M., Theuvsen, L., 2017. Adoption of precision agriculture technologies by German crop farmers. Precis. Agric. 18 (5), 701–716. https://doi.org/10.1007/s11119-016-9482-5.

Phalan, B., Onial, M., Balmford, A., Green, R.E., 2011. Reconciling food production and biodiversity conservation: land sharing and land sparing compared. Science 333 (September), 1289–1291.

Pierpaoli, E., Carli, G., Pignatti, E., Canavari, M., 2013. Drivers of precision agriculture technologies adoption: a literature review. Procedia Technol. 8, 61–69. https://doi.org/10.1016/j.protcy.2013.11.010.

Pretty, J., 2018. Intensification for redesigned and sustainable agricultural systems. Science 362 (6417). https://doi.org/10.1126/science.aav0294.

Ray, D.K., Mueller, N.D., West, P.C., Foley, J.A., 2013. Yield trends are insufficient to double global crop production by 2050. PLoS One 8 (6). https://doi.org/10.1371/journal.pone.0066428.

Redhead, J.W., Powney, G.D., Woodcock, B.A., Pywell, R.F., 2020. Effects of future agricultural change scenarios on beneficial insects. J. Environ. Manag. 265, 110550. https://doi.org/10.1016/j.jenvman.2020.110550.

Rockström, J., Williams, J., Daily, G., Noble, A., Matthews, N., Gordon, L., Wetterstrand, H., DeClerck, F., Shah, M., Steduto, P., de Fraiture, C., Hatibu, N., Unver, O., Bird, J., Sibanda, L., Smith, J., 2017. Sustainable intensification of agriculture for human prosperity and global sustainability. Ambio 46, 4–17. https://doi.org/10.1007/s13280-016-0793-6.

Ross, L.C., Austrheim, G., Asheim, L.-J., Bjarnason, G., Feilberg, J., Fosaa, A.M., Hester, A.J., Holand, Ø., Jónsdóttir, I.S., Mortensen, L.E., Mysterud, A., Olsen, E., Skonhoft, A., Speed, J.D.M., Steinheim, G., Thompson, D.B.A., Thórhallsdóttir, A.G., 2016. Sheep grazing in the North Atlantic region: a long-term perspective on environmental sustainability. Ambio 45 (5), 551–566. https://doi.org/10.1007/s13280-016-0771-z.

Rowland, C.S., Morton, R.D., Carrasco, L., McShane, G., O'Neil, A.W., Wood, C.M., 2017. Land Cover Map 2015 (1Km Percentage Target Class, GB).

Rudnick, D.A., Ryan, S.J., Beier, P., Cushman, S.A., Dieffenbach, F., Epps, C.W., Gerber, L.R., Hartter, J., Jenness, J.S., Kintsch, J., Merenlender, A.M., Perkl, R.M., Preziosi, D.V., Trombulak, S.C., 2012. The role of landscape connectivity in planning and implementing conservation and restoration priorities. Issues in Ecology 16, 1–23. https://www.scopus.com/inward/record.uri?eid=2-s2.0-84868160117&partnerID=40&md5=1aeb7d32cfc24db10a506ee2caa82267.

Ryschawy, J., Martin, G., Moraine, M., Duru, M., Therond, O., 2017. Designing crop–livestock integration at different levels: toward new agroecological models? Nutrient Cycl. Agroecosyst. 108 (1), 5–20. https://doi.org/10.1007/s10705-016-9815-9.

Sharp, R.T., Henrys, P.A., Jarvis, S.G., Whitmore, A.P., Milne, A.E., Coleman, K., Mohankumar, S.E.P., Metcalfe, H., 2021. Simulating cropping sequences using earth observation data. Comput. Electron. Agric. 188, 106330. https://doi.org/10.1016/j.compag.2021.106330.

Springmann, M., Clark, M., Mason-D'Croz, D., Wiebe, K., Bodirsky, B.L., Lassaletta, L., de Vries, W., Vermeulen, S.J., Herrero, M., Carlson, K.M., Jonell, M., Troell, M., DeClerck, F., Gordon, L.J., Zurayk, R., Scarborough, P., Rayner, M., Loken, B., Fanzo, J., et al., 2018. Options for keeping the food system within environmental limits. Nature 562 (7728), 519–525. https://doi.org/10.1038/s41586-018-0594-0.

Tamburini, G., Bommarco, R., Wanger, T.C., Kremen, C., van der Heijden, M.G.A., Liebman, M., Hallin, S., 2020. Agricultural diversification promotes multiple ecosystem services without compromising yield. Sci. Adv. 6 (45). https://doi.org/10.1126/SCIADV.ABA1715.

The MathWorks Inc, 2022. MATLAB version: 9.12.0 (R2022a).

Todman, L.C., Coleman, K., Milne, A.E., Gil, J.D.B., Reidsma, P., Schwoob, M.H., Treyer, S., Whitmore, A.P., 2019. Multi-objective optimization as a tool to identify possibilities for future agricultural landscapes. Sci. Total Environ. 687 (June), 535–545. https://doi.org/10.1016/j.scitotenv.2019.06.070.

Tscharntke, T., Clough, Y., Wanger, T.C., Jackson, L., Motzke, I., Perfecto, I., Vandermeer, J., Whitbread, A., 2012. Global food security, biodiversity conservation and the future of agricultural intensification. Biol. Conserv. 151 (1), 53–59. https://doi.org/10.1016/j.biocon.2012.01.068.

Verhagen, W., van der Zanden, E.H., Strauch, M., van Teeffelen, A.J.A., Verburg, P.H., 2018. Optimizing the allocation of agri-environment measures to navigate the trade-offs between ecosystem services, biodiversity and agricultural production. Environ. Sci. Pol. 84, 186–196. https://doi.org/10.1016/j.envsci.2018.03.013.

Walsh, O.S., Marshall, J., Nambi, E., Shafian, S., Jayawardena, D., Jackson, C., Lamichhane, R., Ansah Owusu, E., McClintick-Chess, J., 2022. Spring wheat yield and grain quality response to nitrogen rate. Agron. J. 114 (4), 2562–2572. https://doi.org/10.1002/agj2.21101.

Ward, J.H., 1963. Hierarchical grouping to optimize an objective function. J. Am. Stat. Assoc. 58 (301), 236–244. https://doi.org/10.1080/01621459.1963.10500845.

Williams, A.G., Audsley, E., Sandars, D.L., 2010. Environmental burdens of producing bread wheat, oilseed rape and potatoes in England and Wales using simulation and system modelling. Int. J. Life Cycle Assess. 15 (8), 855–868. https://doi.org/10.1007/s11367-010-0212-3.

Withers, P.J.A., Neal, C., Jarvie, H.P., Doody, D.G., 2014. Agriculture and eutrophication: where do we go from here? Sustainability 6 (9), 5853–5875. https://doi.org/10.3390/su6095853.

Wu, W., Ma, B., 2015. Integrated nutrient management (INM) for sustaining crop productivity and reducing environmental impact: a review: a review. Sci. Total Environ. 512–513, 415–427. https://doi.org/10.1016/j.scitotenv.2014.12.101.

Wynants, M., Strömqvist, J., Hallberg, L., Livsey, J., Lindström, G., Bieroza, M., 2024. How to achieve a 50% reduction in nutrient losses from agricultural catchments under different climate trajectories? Earths Future 12 (7). https://doi.org/10.1029/2023EF004299.

Xu, G., Fan, X., Miller, A.J., 2012. Plant nitrogen assimilation and use efficiency. Annu. Rev. Plant Biol. 63, 153–182. https://doi.org/10.1146/annurev-arplant-042811-105532.