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Identifying pathways to more sustainable farming using archetypes and multi-objective optimisation

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ABSTRACT

The benchmarking of farm environmental sustainability and the monitoring of progress towards more sustainable farming systems is made difficult by the need to aggregate multiple indicators at the relevant spatial scales. We present a novel framework for identifying alternative pathways to improve environmental sustainability in farming systems that addresses this challenge by analysing the co-variance of indicators within a landscape context. A set of sustainability indicators was analysed within the framework of a published set of Farm Management Archetypes (FMAs) that maps the distribution of farming systems in England based on combinations of environmental and management variables. The archetype approach acknowledges that sustainability indicators do not vary independently and that there are regional constraints to potential trajectories of change. Using Pareto Optimisation, we identified optimal combinations of sustainability indicators ("Pareto nodes") for each FMA independently, and across all FMAs. The relative sustainability of the archetypes with respect to one another was compared based on the proportion of Pareto nodes in each FMA. Potential for improvement in sustainability was derived from distances to the nearest Pareto node (either within or across FMAs), incorporating the cost of transitioning to another archetype based on the similarity of its environmental variables. The indicators with the greatest potential to improve sustainability within archetypes (and, therefore, should have a greater emphasis in guiding management decisions) varied between FMAs. Relatively unsustainable FMAs were identified that also had limited potential to increase within archetype sustainability, indicating regions where more fundamental system changes may be required. The FMA representing the most intensive system of arable production, although relatively unsustainable when compared to all other archetypes, had the greatest internal potential for improvement without transitioning to a different farming system. In contrast, the intensive horticulture FMA had limited internal potential to improve sustainability. The FMAs with the greatest potential for system change as a viable pathway to improved sustainability were dairy, beef and sheep, and rough grazing, moving towards more mixed systems incorporating arable. Geographically, these transitions were concentrated in the west of England, introducing diversity into otherwise homogenous landscapes. Our method allows for an assessment of the potential to improve sustainability across spatial scales, is flexible relative to the choice of sustainability indicators, and—being data-driven—avoids the subjectivity of indicator weightings. The results allow decision makers to explore the opportunity space for beneficial change in a target landscape based on the indicators with most potential to improve sustainability.

1. Introduction

Agriculture is a major driver of negative global environmental change, contributing to biodiversity loss, water pollution and climate change (Balmford et al., 2012; Foley et al., 2011; Keys and McConnell, 2005; Ramankutty et al., 2008). These unintended consequences of the

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expansion and intensification of agriculture associated with the Green Revolution (Pingali, 2012) mean that the benefits to society from farming in terms of provisioning ecosystem services (ES, *sensu* the Millennium Ecosystem Assessment (Carpenter et al., 2009)) now need to be balanced against its impact on associated regulating, supporting and cultural ES. Achieving this balance will require alternative, sustainable approaches to managing farming systems variously described as 'sustainable intensification' (Rockstrom et al., 2017), 'agroecological' (Wezel et al., 2020) or 'regenerative' (Giller et al., 2021). These terms generally capture guiding principles for change but lack strict definitions and a set of universally agreed criteria (that may also depend on local context) for classifying a farm as, for example, 'regenerative'. It is difficult, therefore, to quantify progress towards more sustainable agriculture based purely on the level of transition to these alternative systems. Rather, benchmarking farms and agricultural landscapes, and monitoring progress towards a more sustainable future, will require an assessment based on multiple environmental criteria (in addition to productivity and profitability) that will vary continuously in space and / or time. For the purposes of our argument, 'sustainability' is, here, defined as "meeting the needs of the present without compromising the ability of future generations to meet their own needs" (Brundtland, 1987) and is, hereafter, used to mean *environmental* sustainability narrowly as opposed to general sustainability that includes social and economic aspects.

While the development of more environmentally sustainable farming systems has received a considerable amount of public attention and research effort, conceptual frameworks for quantitatively benchmarking farming systems and identifying beneficial trajectories of change are less well developed. Research effort in this area has tended to focus on identifying suites of indicators for monitoring multiple environmental outcomes. There are now a number of reviews of these potential environmental sustainability indicators and frameworks (Bockstaller et al., 2008; Bonisoli et al., 2018; Gharsallah et al., 2021; Mahon et al., 2018; Smith et al., 2017), which reflect the complex and multi-functional nature of agricultural landscapes. These indicators of sustainability range from single variables, such as the rate of fertiliser application per unit of time and area, to complex composite indicators (e.g. the farmland bird index (Gregory et al., 2005)) or outputs from process-based models (e.g. carbon storage and nutrient runoff; (Latruffe et al., 2016; Mander et al., 2000)). However, significant additional challenges remain before these suites of indicators can be practically implemented to benchmark farms, monitor progress and identify trajectories of change. These include: 1) how to aggregate multiple indicators into an overall measure of sustainability, 2) how to critically compare alternative trajectories of change, and 3) how to account for regional variation in environmental constraints. Addressing these challenges is the focus of this paper.

The most common approach to aggregating indicators is to apply weights in summing the indicators' relative importance (Gan et al., 2017). This, however, ignores the potential complexity of interactions (trade-offs and synergies between indicators) and is subjective due to its reliance on expert or stakeholder opinion (Gan et al., 2017; Morse et al., 2001). Additionally, indicators are often converted to the same unit of measure – typically monetary cost – raising the issue of how to evaluate non-market goods such as supporting ES (Gomez-Baggethun and Ruiz-Perez, 2011). Here, we explore the alternative, data driven approach of Pareto Optimisation (PO) to aggregate multiple, potentially conflicting, indicators of farm environmental sustainability. PO does not require the user to quantify the preference for the objectives (in this case, between sustainability indicators), therefore avoiding the subjective assignment of relative weights. Rather, once a set of objectives is defined, based on an empirical, multidimensional dataset, PO algorithms look for "Pareto-optimal" data points, for which none of the objectives can be further improved without degrading some of the other objectives. In the absence of a preference among the objectives, all Pareto-optimal points represent equally well optimised combinations of objectives, or in this case indicators. Relative sustainability of a farm or landscape parcel can then be assessed in terms of distance from a Pareto-optimal point within the reference dataset of which it is part.

The use of PO in landscape allocation problems and the optimisation of farming practices is an established methodology in the literature. Concerning the former, PO is typically used in conjunction with mathematical optimisation methods (e.g. evolutionary algorithms and simulated annealing) to find the optimal distribution of land-cover classes or farm management classes in a landscape; a comprehensive review of allocation methodologies is provided by Kaim et al. (2018). While at the farm scale, PO is used to optimise farming practices internally, based on inputs from farmers and mechanistic models of farm management (eg. Groot et al., 2012). Here, we take the novel approach of applying PO to national scale datasets of landscape and farm management metrics for England, within the context of an archetype framework, described below.

Most analyses of agricultural sustainability have been carried out either at the national or at the farm scale (Graymore et al., 2008; Mili and Martinez-Vega, 2019). However, many ecological, social, and economic processes interact and are regulated at intermediate "regional" scales. Analytical tools aimed at this intermediate scale remain underdeveloped (Graymore et al., 2010; Orenstein and Shach-Pinsley, 2017) but are important in providing the context for benchmarking current practice and identifying constraints on possible trajectories of change. As a 'farm system' is a combination of fixed elements of the regional landscape (for example, soil type and climate) and more flexible elements of management practices (for example, crop choice or fertilizer inputs), management choices and opportunities for change will be constrained to a greater or lesser degree by regional landscape factors. Any assessment of sustainability needs to take account of this regional context. One promising avenue to provide this contextualization is to take an archetype approach that captures variation in both environmental context and farm management.

Archetypes are recurring patterns of an intermediate level of abstraction (Oberlack et al., 2019) and their utility lies in simplifying and describing complex systems typically characterised by variability across many dimensions. Recently, archetype analysis has been successfully applied to sustainability research (Eisenack et al., 2021), showing the potential to upscale and generalise sets of sustainability indicators (Sietz et al., 2017). Here, we use pre-determined archetypes, that have recently been published for the agricultural landscapes of England and Wales (Goodwin et al., 2022), to interpret co-variation in a suite of sustainability indicators and to analyse trajectories of change within and between archetypes using England as a case study. The archetype framework of Goodwin et al. (2022) is based on Self-Organising Maps (SOMs) (Kohonen, 1990) and derived three tiers of archetypes: Tier 1 characterised different landscapes at the coarse scale, Tier 2 further differentiate between farmed landscapes where agriculture is the dominant land use and Tier 3 between farm management strategies – all at the spatial resolution of 1 km^2.

Our assumption is that that it will be easier to implement beneficial change within, as opposed to across, archetypes and that the Tiers identified in Goodwin et al. (2022) represent a gradient of opportunity for adaptation and intervention. The social, economic and environmental barriers to change are assumed to become increasingly prohibitive in the following order: changes within the same Tier 3 archetype; changes between Tier 3 archetypes but within the same Tier 2 archetype; changes to a different Tier 2 or Tier 1 archetype. The focus of our analysis is on Tier 3, hereafter Farm Management Archetypes (FMAs), that has the greatest potential for system change impacting environmental sustainability. FMAs are also analysed in the context of Tier 2 to capture regional constraints on trajectories of change.

In developing the framework, our focus was not on the selection of sustainability indicators *per se* – a plausible set related to regulating ecosystem services was chosen based on the literature and expert knowledge to illustrate our approach – but on their implementation with regards to aggregation, benchmarking and analysis of potential trajectories of change in a landscape context. The framework was intended to (1) develop the capacity to handle multiple sustainability indicators without using subjective weights, (2) have the flexibility to use any set of sustainability indicators, and (3) be applicable across multiple geographical locations and scales.

2. Material and methods

There were five steps in the development of our framework (Fig. 1):

1) To explore sustainability indicator variability and potential trajectories of change *within*, as well as *between* FMAs, the supervised training of a *large* SOM (i.e. a SOM with many more nodes than the number of FMAs) was completed using the same input variables used to characterise the archetypes in Goodwin et al (2022). This maintained the published archetype framework while identifying multiple nodes within each FMA that could be explored using PO.
2) A subset of archetype variables that were predicted to impact environmental sustainability (hereafter, sustainability indicators) was selected to use as the objectives by which to define Pareto-optimal SOM nodes within a PO algorithm.
3) Pareto-optimal SOM nodes (hereafter, Pareto nodes) based on the sustainability indicators were identified either on an individual FMA basis ('Within Archetype (WA)') or across the whole large SOM. The analysis of Pareto nodes optimized using the whole SOM is hereafter termed 'Across Archetype Unrestricted (AAU)' analysis.
4) To analyse the relative cost of transitioning to a different FMA to improve sustainability, a similarity matrix of FMAs in terms of their landscape setting was derived based on the relationship of FMAs to the Tier 2 Farmed Landscape archetypes; the assumption being it is easier to transition to an archetype that is more similar in terms of its landscape context (as defined by Tier 2 archetypes).
5) The mean distance of each node to the nearest Pareto node (trajectories of change) was then calculated based on the PO performed within each individual FMA. Two separate analyses were done: firstly, trajectories of change were only allowed within an archetype (WA). Secondly, archetype transitions were permitted but *restricted* by dissimilarity in landscape variables (hereafter, 'Across Archetype Restricted' (AAR) analysis).

These steps are described below, all data analysis was carried out in R (R Core Team, 2022) and the annotated code is made available in the Appendices.

2.1. Large SOM training

The framework of Goodwin et al. (2022) identified data-driven, spatially-explicit archetypes by clustering multiple descriptor variables within an SOM – a simple neural network (the map), the neurones of which (the SOM nodes) are programmed to migrate towards the regions of the data space with the highest densities of points (Kohonen, 1990). To facilitate a comparison of within vs. across archetype trajectories of change, we greatly increased the number of nodes in a *large* SOM while maintaining the FMA structure. The benefits and constraints of increasing the size of the SOM are discussed in Supplementary Materials. We reproduced the 12 Tier 3 FMAs for England from Goodwin et al (2022) on a large SOM by supervised training on a rectangular grid using R package "kohonen" (V3.0.10, (Wehrens and Kruisselbrink, 2018)). Supervised training was achieved by providing the archetype membership of each 1 km^2 cell from Goodwin et al (2022) to the "xyf" function together with the same set of input variables. The size and conformation

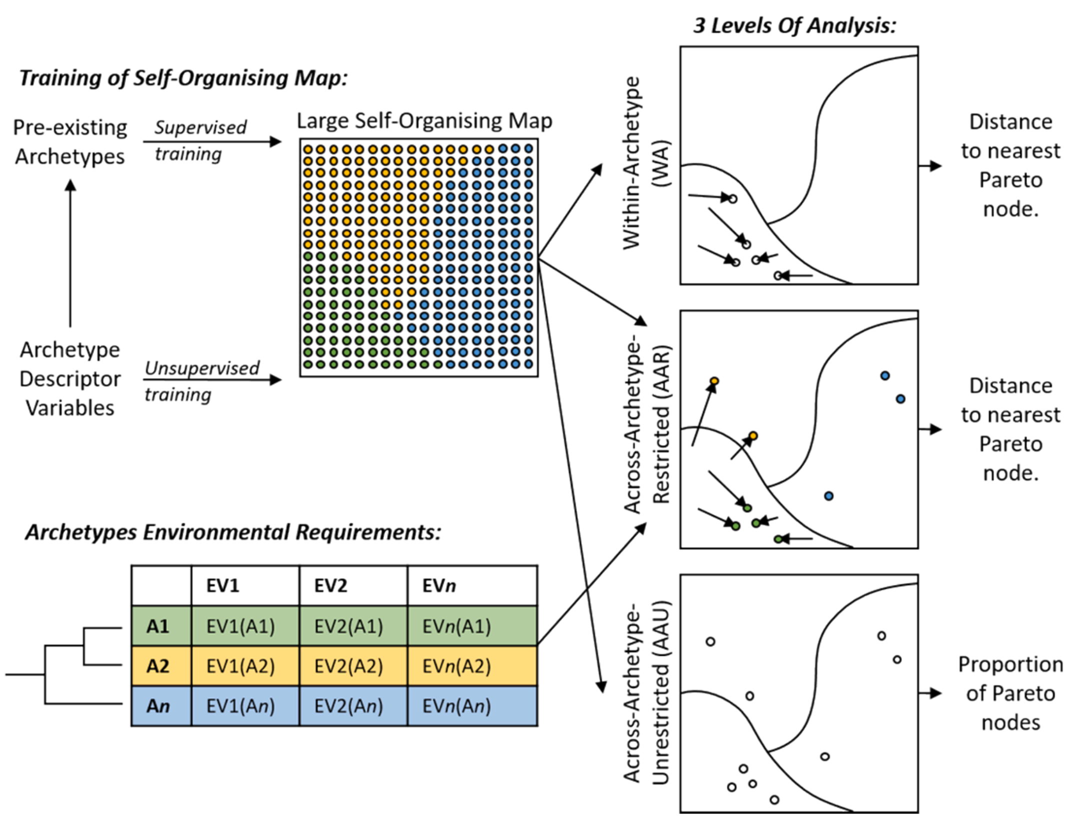

Fig. 1. Flow-chart of our framework integrating Self-organising Maps (SOM) with a three-level Pareto Optimization (PO). In the Archetypes Environmental Requirements table EV stands for Environmental Variable and A stands for Archetype. Dots in the "Large Self-Organising Map" are the nodes, and colours represent the archetypes. In "3 Levels of Analysis", the SOM is simplified by showing only the Pareto nodes; arrows represent example distances to the nearest Pareto nodes (in reality, each node would have an arrow to the nearest Pareto nodes, only a sample was shown for clarity).

of the SOM grid were selected by an iterative process aimed at minimising the mean distance of 1 km^2 cell data values mapped to each SOM node, maximising the spread across the grid of the number of cells mapped to each node, and minimising the number of nodes with no cells mapped to them (Wehrens and Buydens, 2007). In so doing, we created a data structure for exploring within-archetype variability as well as between-archetype variability. The batch SOM algorithm was used, and the training dataset was re-presented to the algorithm 300 times. To account for the stochasticity of random initialisation of the grid coordinates we trained 50 replicates of the large SOM and proceeded with the following steps of the analysis in parallel on these 50 replicate threads.

2.2. Choice of sustainability indicators

Starting with the list of variables used to define the FMAs we selected a subset that ~~are~~ we expected, based on the literature, to relate to environmental sustainability as PO objectives (Table 1). These variables are predicted to enhance sustainability mostly by increasing agro-ecosystem resilience (Hooper et al., 2005; Loreau and de Mazancourt, 2013; Mori et al., 2013) through landscape diversity (Dauber et al., 2003; Duelli, 1997; Tamburini et al., 2020; Weibull et al., 2000) and supporting biodiversity (Benton, Vickery & Wilson, 2003; Tscharntke et al., 2005; Storkey et al., 2024). Several are landscape metrics, which have been shown to relate to landscape functions and ecosystem services (ES), and biodiversity (Schindler et al., 2008; Schindler et al., 2013; Walz and Syrbe, 2013), especially in the context of land use change (Uuemaa et al., 2013). Although our set of input variables contains several that are likely colinear, note that – unlike statistical models – PO algorithms do not return results biased towards groups of correlated variables. On the contrary, very highly correlated objectives become equivalent to a single objective. The indicator Pesticide ("CEH land cover plus: pesticides") was found to be highly correlated with fertiliser usage in England as expressed by the "CEH land cover plus: pesticides" spatial layer (https://www.ceh.ac.uk/data/ukceh-land-cover-plus-fertilisers-and-pesticides). Because of this correlation and the fact that the fertilisers layer was omitted from the FMA characterisation (that also included Wales for which fertiliser data were not available) we omitted fertiliser data from our analysis. However, note that indicator Pesticide can be assumed to also indicate fertiliser usage and is therefore an indicator of farming intensity.

Table 1
Variables on which Pareto Optimisation was performed (predicted to be indicators of environmental sustainability). Direction of optimisation indicates whether the Pareto Optimisation process attempted to maximise or minimise the variable.

Name	Description	Aspect of environmental sustainability	Direction of optimisation
Field Shape	Standardised field edge to area ratio	Field-margin vegetation, edge effects, landscape diversity	Maximised
Diversity	Crop diversity index	Landscape diversity and configurartion	Maximised
Evenness	Crop evenness index		Maximised
Isolation	Mean nearest-neighbour distance between same-crop patches (see A3)		Maximised
Edge Contrast	Neighbouring crop patches diversity proxy		Maximised
Subdivision	Probability that any two points in a 1 km^2 cell do not fall within the same patch		Maximised
Farm Size	Mean farm area for each 1 km^2 cell		Minimised
Field Size	Mean field size for each 1 km^2 cell		Minimised
Patch Area	Mean area of same-crop patches		Minimised
Pesticide	Pesticide application rates	Farming intensity	Minimised
AES	Income from agri-environmental schemes	Represents several practices that "supports biodiversity, enhances the landscape, and improves the quality of water, air and soil"	Maximised
Hedge	Total hedge length	Prevalence of natural habitat, landscape diversity	Maximised
Woodland	Proportion of woodland within farm boundaries		Maximised

2.3. Pareto Optimisation

PO was used to identify the SOM nodes that optimised the chosen sustainability indicators. It was carried out with the R package "rPref" (V1.3, (Roocks, 2016)). Each node on the trained SOM was characterised by a so-called "codebook vector", which contains the coordinates of the node in ~~the~~ multidimensional variable~~s~~ space. PO was carried out on a so-called "codebook matrix" where each row is the codebook vector of a SOM node (N x V matrix where N=number of nodes, and V=number of variables). To reduce the number of Pareto nodes returned by the PO, we prevented SOM nodes with values worse than an empirically selected threshold from being considered Pareto nodes (further details and the justification for reducing the number of Pareto nodes can be found in supplementary materials, Threshold selection). A threshold at the 95th percentile was selected as it was the highest one that still resulted in no archetype being devoid of Pareto nodes.

The PO was repeated at two levels.

The "Within-Archetype" (WA) level optimised within the same FMA. Here, Pareto nodes were found by constraining the search to the nodes allocated to each FMA. This resulted in a set of Pareto nodes representing the most sustainable "sub-archetypes" within each archetype. Note that this measure is not a measure of archetype "broadness", where more varied FMAs necessarily have higher sustainability values; instead, this is a true representation of the net margin for sustainability improvement. This is because broader FMAs may have improvements to some variables that are counteracted by coupled degradation in other variables resulting in a lack of net change in sustainability.

The Across-Archetype, Unrestricted (AAU) level analysed the distribution of Pareto nodes throughout the SOM (across all FMAs), thus resulting in their uneven distribution among FMAs. The archetype hosting the highest proportion of Pareto nodes relative to the total number of nodes allocated to that archetype~~,~~ is assumed to be the most optimised for sustainability.

2.4. Estimating the cost of transitioning between FMAs

For the Across Archetype Restricted (AAR) pathway analysis that allowed transitions between FMAs (see "2.5. Pathways to Pareto nodes") we estimated the relative cost of transitioning to a neighbouring (i.e., neighbouring in terms of multi-dimensional variable space, not geographically) FMA by calculating landscape similarity, so capturing the resistance to management change associated with differences in contextual landscape elements like soil type and climate. This involved retrieving information on the similarity of landscapes for each archetype pair. We obtained this measure from the spatial overlay analysis between the Tier 3 (FMAs) and Tier 2 archetypes carried out in Goodwin et al. (2022), which returned the proportion of 1 km^2 cells of each Tier 3 archetype that overlap with each Tier 2 archetype. A Euclidean distance matrix for each pair of Tier 3 FMAs was then computed from the Tier 2 overlay values. These distance values were rescaled from zero to one, relative to the observed maximum, and inverted to obtain a value of similarity between all pairs of FMA landscapes. Here, the pairs that differed the most were given a similarity value of zero, while identical pairs were represented by the value one (i.e., the similarity of each FMA to itself).

2.5. Pathways to Pareto nodes

At the WA and AAR levels, the mean distance from each SOM node to its nearest Pareto node was computed for each FMA as a measure of its sustainability potential (with and without permitting archetype transitions for AAR and WA respectively). To compute distances on the SOM, we first transformed it into a four-neighbours graph (i.e. a graph where each vertex is connected to four other ones, since that was the topology of the SOM) with the nodes as vertices and edges representing conductance—the reciprocal of the inter-node distance. Distance values were then obtained by computing least-cost path lengths on this graph with the R package "gdistance" (V1.3–6, (van Etten, 2017)). Since SOMs are not identical in all directions with respect to inter-node distances and some regions are more stretched out than others, we corrected the mean distance to the nearest Pareto node by the mean inter-node distance within the archetype. The distance of each node to its nearest Pareto node was also re-projected onto a map of England by attributing the same value to all 1 km^2 cells mapped to the same node.

The AAR level allows archetype changes, but restricts change by a proxy for the transition difficulty or "cost". Here, the optimisation process was also carried out separately for each archetype, but the search was expanded to all the nodes in the SOM. We quantified the relative cost of transitioning to another FMA using information on the degree of environmental similarity for each pair of FMAs (see 2.4). The more dissimilar the environmental characteristics of the FMA pair, the higher the cost of transition. Since similarity values reduced conductance (the graph's edge values) proportionately to the difference in environmental characteristics, transitions between the two most divergent FMAs were excluded (the result of multiplying conductance for similarity equal to zero). In addition to the distance to the nearest Pareto node, at the AAR level we also recorded whether the nearest node was in the same or a different FMA. This allowed us to compute the number of transitions that occur for each FMA and the new geographical distribution of FMAs after the transitions. As expected, raising the threshold for the minimum acceptable values for each objective (see supplementary materials, 'Threshold selection') increased the number of archetype transitions (Figure S1).

2.6. Synergies, trade-offs, and opportunity space

We explored synergies and trade-offs among sustainability indicators by analysing their covariance at the Pareto front (i.e. the set of Pareto nodes produced by PO). When considering the values of the Pareto nodes for each pair of sustainability indicators, synergies are characterized by a positive correlation among indicators, and trade-offs by a negative correlation. We looked for synergies and trade-offs for each FMA independently and for the study area as a whole. The former was done by using the Pareto nodes obtained at the WA level; the latter using the Pareto nodes obtained at the AA levels (both AAU and AAR share the same PO analysis). For each FMA, we also computed the opportunity space for improving each of the indicators as the average distance difference in the indicator value between all nodes and their nearest Pareto node. This computation was carried out only at the WA level as it is meant to provide insight over which indicators can be improved the most for each FMA without fundamental changes to the farm system (i.e. without changing FMA).

3. Results

3.1. Optimisation of the large SOM

The iterative process for establishing the grid conformation in the large SOM resulted in a 70x70 nodes grid, which satisfied all criteria that we attempted to optimise (Figure S2, see "2.1 Large SOM training" for the criteria). A 95th percentile threshold was set for nodes to be included in the PO process at the WA and AAU levels. This is the most conservative value we tested, rejecting only 5 % of the 4900 nodes (Figure S3).

3.2. Comparison of environmental sustainability of archetypes and potential for improvement without system change

At the WA level, the most marked difference in terms of the mean distance to the nearest Pareto node, a measure of the internal potential for improvement, was between two archetypes characterised by broad acre cropping – "Broad acre arable with pigs and poultry" and "Broad acre arable" – and all other FMAs (Fig. 2A). In contrast, at the AAU level, the broad acre archetypes have a lower proportion of optimised nodes, while the "mixed" archetypes have a higher proportion, and therefore higher overall sustainability (Fig. 2B). This is likely due to the inherent internal diversity of the mixed archetypes, which tend to be associated with a diverse agricultural landscape.

When distances to the nearest Pareto nodes (mean across the 50 replicates) were mapped in geographical space (Fig. 3A) and compared to the distribution of FMAs (Fig. 3B), FMAs with low to moderate mean within-archetype distances to Pareto nodes (calculated using data from across the entire study area) could still show large distances in local~~ised~~ areas (e.g. northern "Beef and sheep" and "Beef and sheep with arable"). Therefore, areas with high internal sustainability potential can also be identified outside of the best performing archetypes (e.g. inside poorly performing "Broad acre arable with pigs and poultry" and "Broad acre arable").

3.3. Landscape similarity of FMAs and potential for transitions

The results of the FMA landscape similarity analysis are presented in the form of a hierarchical clustering dendrogram (Fig. 4A). The archetype pairs with the highest proportion of transitions across the 50 SOM replicates were all close in the dendrogram of environmental requirements (Fig. 4A). Those with the highest number of transitions were "Dairy", "Beef and sheep" and "Rough grazing" – all grassland archetypes occurring in the West which ranked poorly at the AAU level. The worst archetypes at the AAU level however, ("Broad acre arable" and "Broad acre arable with pigs and poultry") had high potential for improving improvement (WA level), implying the presence of internal regions with much higher sustainability (and consequently higher number Pareto nodes), which likely allowed them to avoid transitioning.

By assigning the FMA transition results to each 1 km^2 cell, potential trajectories of land use change can be explored for a pre-defined region and scale; this will be particularly relevant for regions dominated by FMAs with a low internal sustainability potential. For example, the proportion of predicted FMA transitions were higher around the large semi-natural areas of the northwest and the east of the country (Fig. 3C). The transition from "Beef and sheep" to "Rough grazing" or "Beef and sheep with arable" accounted for the high values in the former region, while transitions from "Broad acre arable with pigs and poultry" to "Broad acre vegetables" accounted for the latter. Additionally, several transitions occurred from "Dairy" to "Dairy with arable" in the west of the country, representing a viable pathway to improved sustainability for this FMA with an overall low sustainability (Fig. 2B).

3.4. Synergies, trade-offs, and opportunity space

Based on the analysis of Pareto nodes identified in the AAU analysis,

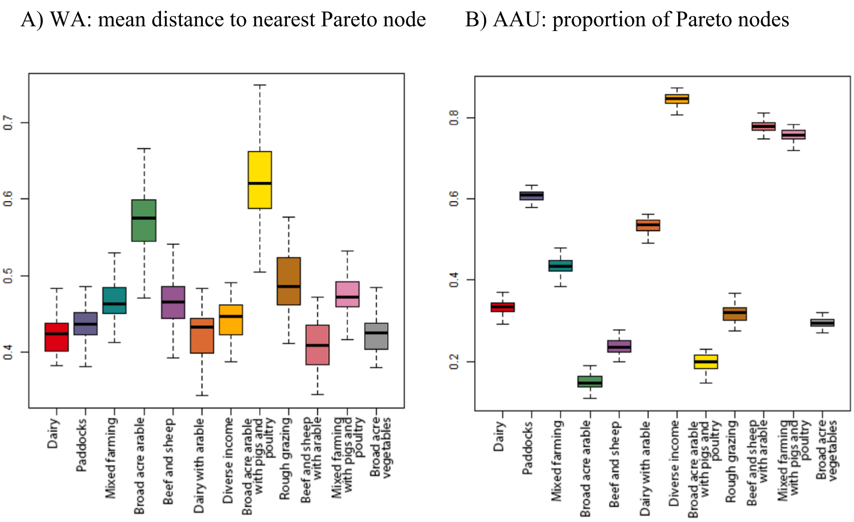

Fig. 2. A) Pareto Optimisation at the archetype level showing the mean distance to nearest Pareto node within archetype (or 'internal sustainability potential) and B) at the country level showing the proportion of Pareto nodes for each archetype. Boxplots represent the variability of the 50 SOM replicates.

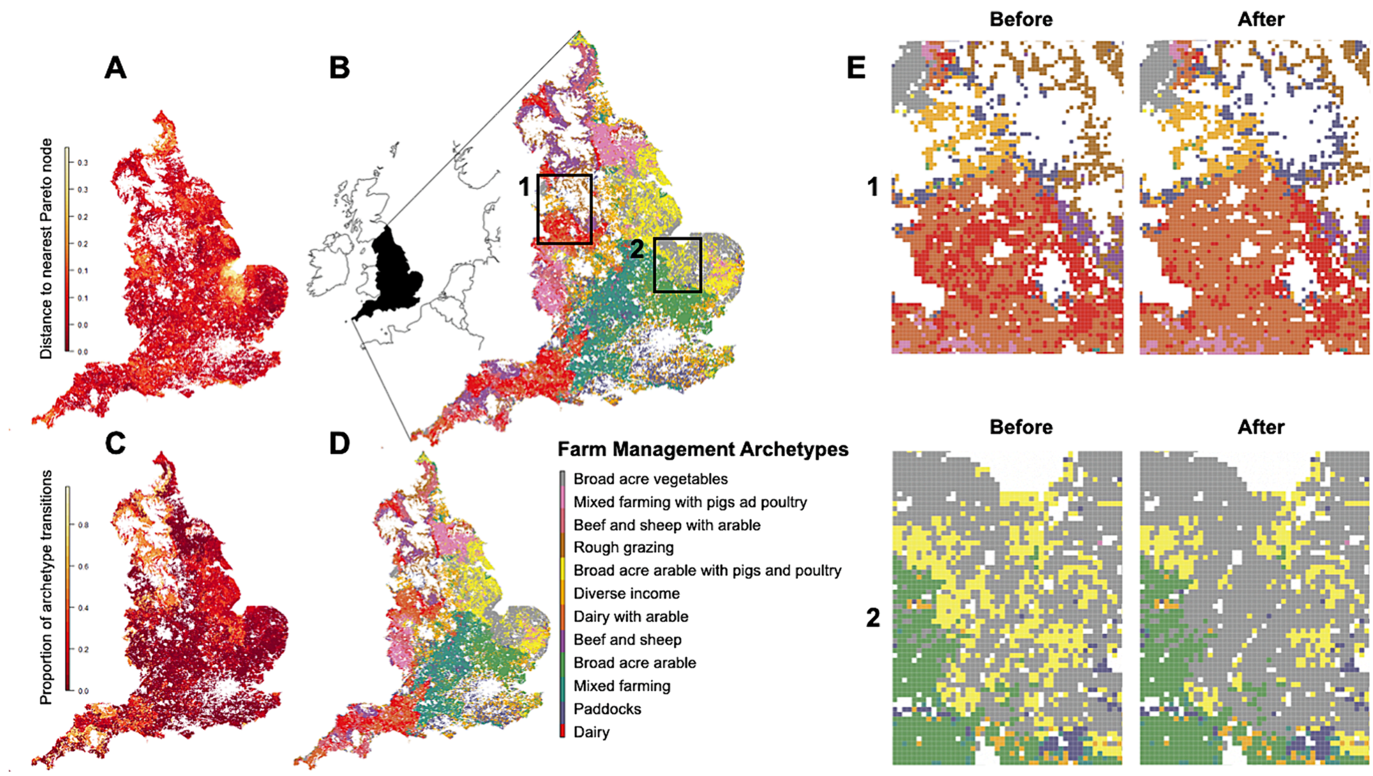

Fig. 3. A) FMA internal sustainability potential (WA) computed as distance to nearest Pareto node (average of 50 SOM replicates) mapped onto geographical space. High values represent high potential for improving environmental sustainability without transitioning to another FMA, B) Spatial distribution of FMAs, C) Proportion of FMA transitions after accounting for similarity of landscape context (AAR) across 50 SOM replicates, D) New distribution of FMAs (AAR, mode of 50 SOM replicates), E) Enlargements of B and D for the two areas marked in panel B, showing details of the FMA transitions.

we found synergies among all landscape-metrics indicators except Isolation, where there was a trade-off with the other landscape metrics (Fig. 5, "Whole SOM). This is a consequence of the nature of these indicators; Diversity, Evenness, Edge Contrast and Subdivision are all indicative of a diverse and interspersed landscape. The indicators characterising intensive agriculture – Field Size and Pesticides, were also positively correlated (i.e. in synergy) with the landscape metrics (except Isolation). This is likely due to the landscape-metrics indicators being based on crop diversity and not land-cover diversity. Crop Diversity, Evenness, Edge Contrast and Subdivision are low in the extensive grassland-dominated regions (grassland is one of the crops used to compute landscape metrics). These regions are also where pesticide usage is low, and fields are smaller. However, the relationship between crop diversity and intensity of pesticide use will also be determined by idiosyncratic effects of specific crops (Metcalfe et al., 2024) (i.e. whether or not additional crops have a higher or lower demand for pesticides).

Constraining the selection of Pareto nodes to within an archetype (WA) resulted in differences between the FMAs in terms of the trade-offs and synergies between the indicators. Although the sign of the

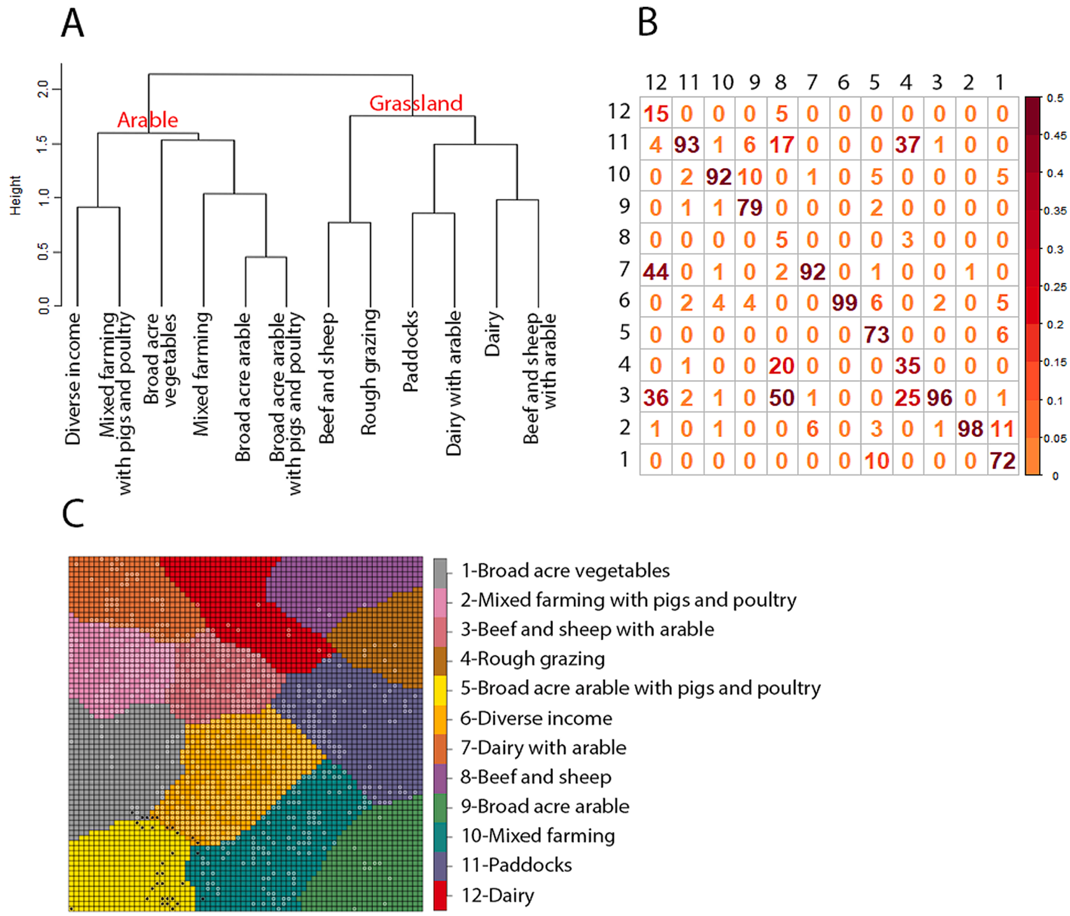

Fig. 4. A: Similarity of the Archetypes' (FMA) environmental characteristics based on their association with Tier 2 archetypes that describe landscape context. The main two groups divide arable (left branch) from grassland (right branch) archetypes. Arable archetypes are further divided in diverse and homogeneous (broad acre) ones, while grassland archetypes divide into more and less intensive ones. B: Numbers of 1 km cells predicted to transition between FMAs to reach the nearest Pareto node when accounting for transition cost (AAR; threshold value set at the 95th percentile), with source archetypes as columns and destination archetypes as rows. C: example SOM (one of 50 replicates) with Pareto nodes calculated using the threshold value at 95th percentile. White circles are all Pareto nodes detected, black circles are the nearest Pareto nodes to all nodes of "Broad acre arable with pigs and poultry".

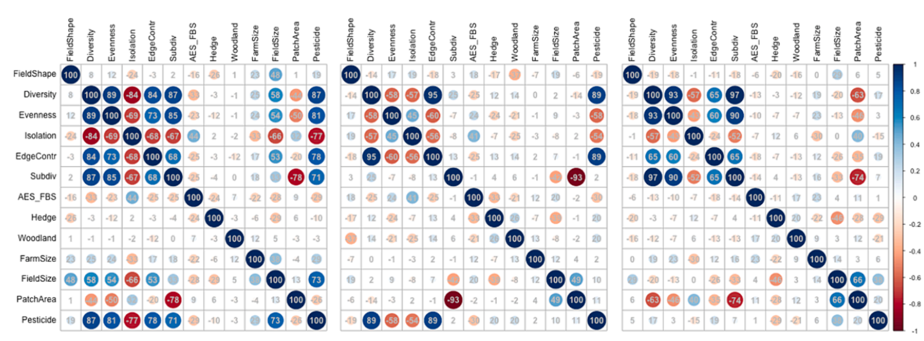

Fig. 5. Correlograms showing synergies (blue) and trade-offs (red) computed as the correlation among pairs of indicators for the Pareto front—numbers are Pearson correlation coefficients. Shown for the whole SOM (i.e. AA level) and for two example FMA illustrating variance in the properties of the data between the FMAs that explain contrasts in available opportunity space and the potential trajectories of change. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

correlations remains mostly unchanged, the strength of the relationships varied between FMAs (Fig. 5, "Broad acre with pigs and poultry" and "Beef and Sheep" shown as examples). As a result of the contrasting data structures of different FMAs, the relative importance of each indicator in explaining internal sustainability potential also varied between FMAs; computations of the opportunity space for each indicator for each FMA are shown in Fig. 6. For example, there was relatively high potential for improving sustainability in Broad acre arable with pigs and poultry by reducing farm size and patch area and increasing habitat subdivision whereas in the Beef and sheep FMA, increasing hedge length and woodland area had more potential. Farm size had a consistently large distance to the nearest Pareto node across most archetypes but is the indicator that is most difficult to change.

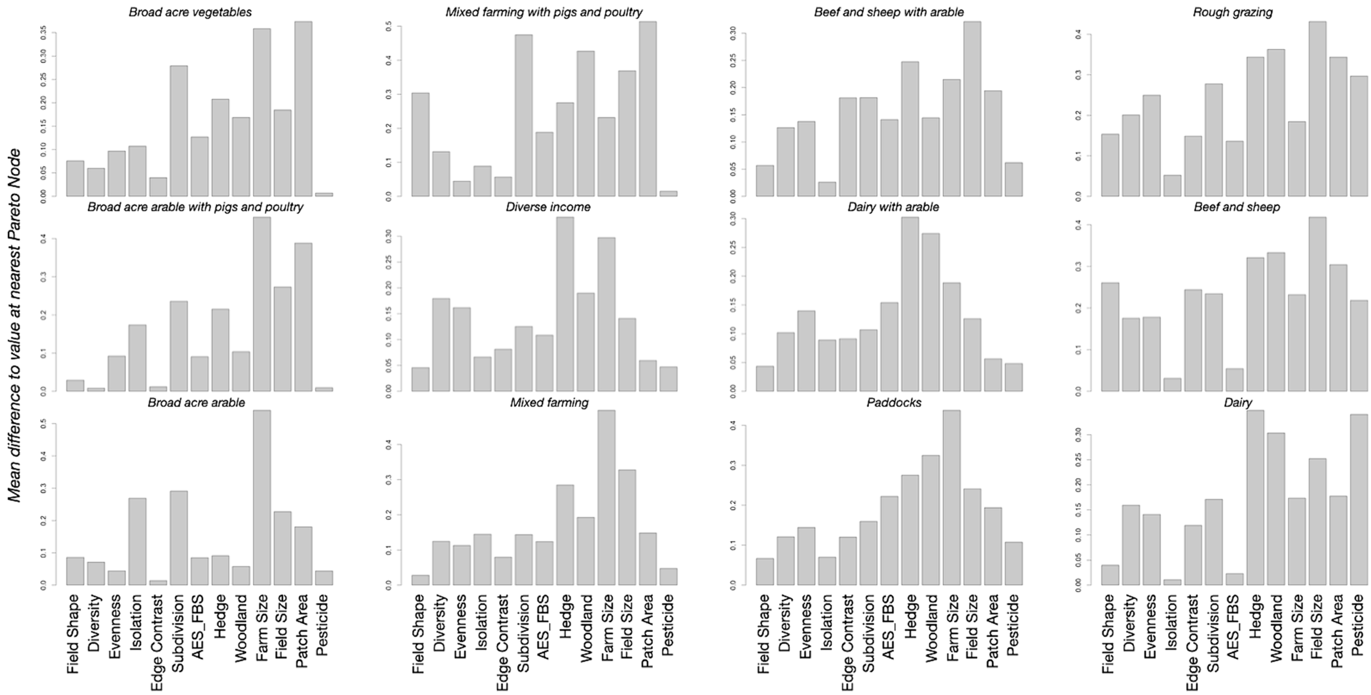

Fig. 6. Opportunity space for each indicator in each FMA as the mean distance to the indicator value at the nearest Pareto node. The overall, combined contribution of all indicators to distance to nearest Pareto node is shown in Fig. 2A.

4. Discussion

Defining a list of sustainability indicators that can be used to benchmark farms is the subject of debate, and further efforts are required to agree on criteria for their selection (de Olde et al., 2017). Regardless of the chosen suite of sustainability indicators, however, robust, generalizable methodologies are also required to equip practitioners and policy makers with the tools to interpret these lists of indicator variables at multiple scales in the context of implementing change (Dittrich et al., 2017; Gan et al., 2017; Graymore et al., 2008). By using a published archetype framework that captures regional variation in environmental constraints as well as variation in farm management systems, our novel framework addressed this problem using the agricultural landscapes of England as a case study. In so doing, we help meet the pressing need to critically assess alternative pathways to a future that better balances productivity with environmental sustainability (Cassman and Grassini, 2020).

Both PO and Archetype analysis are established methodologies for optimising landscapes against multiple sustainability criteria. However, by combining these approaches in a novel analysis of multivariate, national-scale data we realised four additional benefits for identifying potential trajectories of change. (1) While still providing suggestions on the re-allocation of some FMAs in the study landscape, our analysis also quantified the potential for beneficial trajectories of change *internal* to the classes being allocated without fundamental changes to the production system. (2) Many PO-based methodologies typically rely on the exploration of multiple future theoretical scenarios (Kanter et al., 2018) which entails both difficulties in generating the scenarios and uncertainty in their practical implementation. Our approach constrained future scenarios to currently observable farming management strategies, ensuring that proposed solutions are viable (as they are currently in use somewhere in the study area). Using archetypes also constrained the allocation of future scenarios to the local environmental conditions, thus avoiding changes to future scenarios that are not compatible with, e.g., the local pedo-climatic conditions. (3) Methodologies of re-allocation of farming classes typically generate new landscapes with optimal allocation that may involve unrealistically radical change in a study region. In contrast, our analysis started from the current landscape configuration and suggested progressively less conservative changes, thus ensuring the feasibility of the transformation; our analysis focussed on providing suggestions on the most efficient changes rather than providing a single solution involving the re-allocation the whole study landscape. Finally (4) this is the first combination of PO and Archetype analysis, providing a bridge to integrate work done in these two domains of sustainability research. For instance, our example application relies on previously published archetypes generated at the national scale that can be readily used by other researchers, and for which additional information can be published independently. Using the same archetypes in different research projects facilitates the integration of results from multiple authors.

Because every 1 km^2 cell in England can be assigned an FMA, an internal sustainability potential and a potential for archetype transition, our results are useful for exploring alternative trajectories of change in different regions and at multiple scales. In this regard, the potential pathways to more sustainable farming systems we identified are consistent with those proposed in the wider literature on farmland biodiversity. The analysis at the AAU level showed that the “Broad acre” FMAs have lower overall sustainability when compared to all the other archetypes. However, among them “Broad acre arable” and “Broad acre arable with pigs and poultry” have good potential to increase their sustainability without transitioning to another FMA, which may involve significant investment in infrastructure or a change in the business model. The analysis of the opportunity space for these FMAs suggests that, in regions dominated by these FMAs, action to reduce the size of fields and patches of the same crop, as well as the redistribution of patches of the same crop to avoid large monoculture areas (i.e. increase of Subdivision) would be particularly beneficial for improving sustainability. Historically, these are two of the farming systems have suffered the largest post-war declines in farmland biodiversity and the ecosystem services it delivers owing to loss of habitat and inputs of agrochemicals (Firbank et al., 2008; Robinson and Sutherland, 2002). Our results support the view that restoring this function can also be achieved without fundamentally changing the farming system through targeted habitat creation that takes account of the landscape context (Tscharntke et al., 2005) and through integrated pest management (Barzman et al., 2015).

In contrast, in regions dominated by FMAs with a low internal sustainability potential, for example “Broad acre vegetables”, a shift to another archetype may be necessary to improve environmental sustainability. Analysis at the AAR level shows that transitions to “Mixed farming with pigs and poultry” are well suited for this purpose as these systems co-exist in similar landscapes (are closely associated in Tier 2 of the Goodwin et al. (2022) archetype framework). This transition would reduce the proportion of intensive vegetable production and introduce patches of grassland and grain-based farming and reflects the benefits of more mixed farming systems (Baker et al., 2023). Although it should be noted that while this will increase habitat diversity, there may be negative trade-offs with emissions which are not directly accounted for in our example because of the introduction of animals into the system. Clearly, any archetype transition implies some change in the products delivered in the study area. For example, a transition from “Broad acre vegetables” towards “Mixed farming with pigs and poultry” would potentially reduce vegetable production. Since changes in the business model of a study system will likely have social and economic consequences (which remained outside the scope of our case study), we suggest that realising an archetype’s internal sustainability potential should be prioritised over archetype replacements. Nonetheless, weighing the costs and benefits of within-archetype interventions against archetype transitions can offer useful insights not only on which archetypes, but also in which regions, there may be potential for land use change.

By accounting for environmental constraints of change, the analysis at the AAR level detected the most efficient archetype transitions to improve sustainability, and the geographical regions with the greatest potential for these changes. For instance, the transition from “Broad acre arable with pigs and poultry” to “Broad acre vegetables” is moderately beneficial (intermediate number of transitions modelled at the AAR level) and is likely a result of the added crop diversity resulting from the introduction of vegetables. However, since “Broad acre arable with pigs and poultry” also has the highest internal sustainability potential among all archetypes (see above), it would be best to limit the exploration of archetype transitions to the Cambridge area – where most transitions are detected – and focus on internal improvements to this archetype (by leveraging the opportunity space results mentioned above) elsewhere. This illustrates the importance of considering landscape context when exploring alternative pathways for improvement. A second example was archetype transitions away from grassland-only archetypes “Dairy”, “Beef and sheep”, and “Rough grazing” in the west of England. This is likely due to the homogeneity of these landscapes; indeed, “Rough grazing” areas transitioned towards the more diverse archetypes “Paddocks” and “Beef and sheep with arable”, while “Dairy” areas transitioned to “Dairy with arable”. This reflects the fact that the loss of arable habitats in areas dominated by livestock production has been an important driver of the loss of farmland biodiversity in these regions (Chamberlain et al., 2000) and, again, highlights the benefits of more mixed systems (Baker et al., 2023). This notion is also agreement with our interpretation of the synergies and trade-offs found in the study area, whereby crop diversity and pesticide usage are both low in extensive grassland-based areas, and both high in intensive cropland regions, thus producing the unexpected synergy (positive correlation) among pesticide and diversity indicators.

Overall, our analysis showed better sustainability for archetypes that deliver multiple products. This can easily be linked to their inherently high values for crop and landscape diversity-related sustainability indicators. However, these archetypes also come with additional desirable features like less intensive farming practices (e.g. lower pesticide use) and greater occurrences of natural elements (e.g., “hedge”, “woodland” or “AES”), which mattered equally during PO.

The example set of sustainability indicators we used to illustrate our approach was selected from the input data used to derive the archetypes, largely based on their association in the literature with one aspect of environmental sustainability: farmland biodiversity and the regulating and cultural ecosystem services it delivers. These services include pollination and pest control (Pywell et al., 2015) and the support of farmland birds (Henderson et al., 2012). As a consequence, our analysis was weighted towards benchmarking FMAs in terms of landscape metrics, for example habitat diversity (Benton et al., 2003) and configuration (Martin et al., 2019) that are known to relate to the level and resilience of these services. However, the framework has the flexibility to use alternative and additional sets of indicator variables already included in the SOM archetype analysis that could be selected on the basis of additional outcomes—for example, number of livestock units and intensity of fertiliser use as indicators of emissions (de Vries and de Boer, 2010), or proportions of different crops related to their calorific value as a measure of productivity (Driscoll et al., 2022). It is also likely that indicators not included in our analysis are implicitly accounted for by the general nature of archetypes (i.e., by virtue of their possible correlation with some of the many other variables used to define them).

A potential issue related to the combination of indicators and PO used in our framework is that indicators are currently assumed to have a monotonic relationship with sustainability. This is not always true, for instance, while we maximised Isolation (the nearest neighbour distance between patches of the same crop) to promote diverse landscapes, some pollinators may benefit from having multiple patches of the species they depend on within their home range. Although this issue is partly compensated by the maximum nearest neighbour being less that 1.4 km due to the 1 km pixels use in our analysis, similar non-monotonic relationships among indicators and sustainability are neglected. A possible solution to this would be to transform the indicator values according to the expected or modelled relation with sustainability (e.g. polynomial transformation to account for multinomial relationships) before performing PO, but this requires a deeper numerical characterisation of the indicators’ effects on sustainability than we had access to.

Finally, we have focussed solely on environmental sustainability and have deliberately disregarded the socio-economic costs of transitions and the interaction with additional external policy drivers (e.g. maintaining food security). This allowed us to maintain consistency with the Archetypes published in Goodwin et al (2022) but uncoupling socio-economic aspects of sustainability from their environmental counterpart may lead to impracticable and undesirable solutions. Secondly, potential pathways of change are constrained by the data included in the SOMs. An example in our study case is the use of the British Farm Business Survey to derive data on farm management; although this is representative of general trends, it does not capture as well less common, alternative practices (e.g. organic farming) potentially resulting in an underestimation of the opportunity space.

These limitations aside, through using PO, our approach successfully avoids the problem of attributing weights to very different indicators, faced by alternative frameworks that use a combination of sustainability indicators. Additionally, considering multiple levels of analysis (i.e., WA, AAU, AAR) provides multiple optima instead of a single solution, which allows a more flexible exploration of sustainable development and the acknowledgement of the role of policymakers in reconciling conflicting demands on agriculture land. Multiple solutions are also more realistic since complex, multivariate systems like agroecosystems are likely to contain several pathways to maximising their sustainability. Given the difficulty in retrieving sustainability indicators at meaningful resolutions and for large extents, sustainability analyses are likely to rely on incomplete sets of indicators, whereby multiple optima likely confer higher safety levels (e.g. by bet-hedging) than single-solution methods. Finally, since our approach is data-driven, no assumptions about theoretical optima are needed. Although highly sustainable farming system that are not yet implemented or detected in available data are possible, we have no means of telling which ones would be viable in reality. By basing our approach on empirical data, we err towards the side of caution, knowing results are most likely viable.

5. Conclusion

The interpretation of our results has been at the national scale and has highlighted specific case studies to illustrate the value of exploring opportunity space within and between archetypes. However, we anticipate that our framework would most likely be integrated into decision making tools applied at the local level as part of local nature partnerships, catchment management or farm clusters. Defining the archetype composition of a local, target landscape, benchmarking sustainability and identifying indicators with the most potential to improve sustainability could be used as valuable supporting evidence in making land management decisions. In practice, this would be done alongside socio-economic criteria including access to government subsidy schemes or initiatives supported by private finance to identify the most appropriate interventions to target.

CRediT authorship contribution statement

Luca Bütikofer: Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Cecily E.D. Goodwin:** . **Varun Varma:** Writing – review & editing, Methodology, Investigation, Conceptualization. **Paul M. Evans:** . **John W. Redhead:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **James M. Bullock:** Writing – review & editing, Writing – original draft, Methodology, Funding acquisition, Conceptualization. **Richard F. Pywell:** Writing – review & editing, Methodology, Funding acquisition, Data curation, Conceptualization. **Andrew Mead:** Writing – review & editing, Visualization, Methodology, Investigation, Formal analysis, Conceptualization. **Goetz M. Richter:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Formal analysis, Conceptualization. **Jonathan Storkey:** Writing – review & editing, Writing – original draft, Supervision, Project administration, Methodology, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

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