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A new approach to characterising and predicting crop rotations using national-scale annual crop maps

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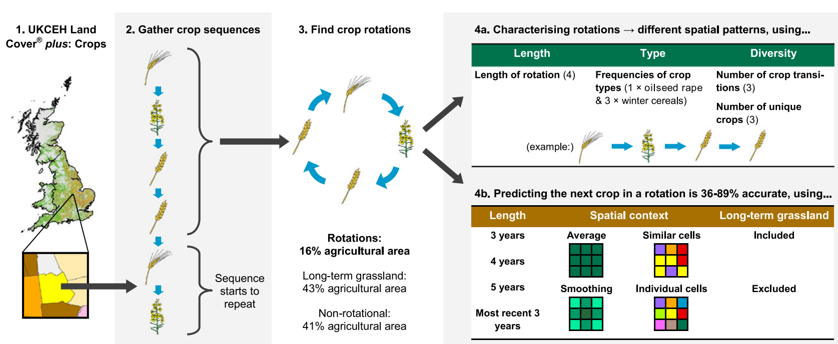
HIGHLIGHTS

- Crop choice is a key driver of agricultural impact on the environment.
- We explore apparent 1–5 year rotations in UKCEH Land Cover® *plus*: Crops 2015–2020.
- Rotations fill less area than long-term grassland and complex-rotational sequences.
- Three rotation classification systems display a range of distinct spatial patterns.
- Predictions more accurate with long-term grassland, local scale and long rotations

GRAPHICAL ABSTRACT



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ABSTRACT

Cropping decisions affect the nature, timing and intensity of agricultural management strategies. Specific crop rotations are associated with different environmental impacts, which can be beneficial or detrimental. The ability to map, characterise and accurately predict rotations enables targeting of mitigation measures where most needed and forecasting of potential environmental risks. Using six years of the national UKCEH Land Cover® *plus*: Crops maps (2015–2020), we extracted crop sequences for every agricultural field parcel in Great Britain (GB). Our aims were to first characterise spatial patterns in rotation properties over a national scale based on their length, type and structural diversity values, second, to test an approach to predicting the next crop in a rotation, using transition probability matrices, and third, to test these predictions at a range of spatial scales. Strict cyclical rotations only occupy 16 % of all agricultural land, whereas long-term grassland and complex-rotational agriculture each occupy over 40 %. Our rotation classifications display a variety of distinctive spatial patterns among rotation lengths, types and diversity values. Rotations are mostly 5 years in length, short mixed crops are the most abundant rotation type, and high structural diversity is concentrated in east Scotland. Predictions were most accurate when using the most local spatial approach (spatial scaling), 5-year rotations, and including long-term grassland. The prediction framework we built demonstrates that our crop predictions have an accuracy of 36–89 %, equivalent to classification accuracy of national crop and land cover mapping using earth observation, and we suggest this could be improved with additional contextual data. Our results emphasise that rotation complexity is multi-faceted, yet it can be mapped in different ways and forms the basis for further exploration in and beyond agronomy, ecology, and other disciplines.

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1. Introduction

Farmland is the dominant land use in the UK, covering 71 % land (Defra, 2020), with farming therefore being of great value to the economy. Agricultural systems currently face a wide range of challenges. These include feeding a growing global population with limited space while simultaneously alleviating environmental pressures of intensive agriculture, the rise of extreme weather events, which are likely to become more frequent and severe on agriculture with climate change (Trnka et al., 2014; Ummenhofer and Meehl, 2017), and increasing pesticide resistance of pest species (Varah et al., 2020). Crops, and crop rotations, are important determinants of the impact of agriculture on the environment. Some degree of crop rotation is traditionally used to maintain soil fertility and decrease the risk of disease build-up through host or habitat persistence. For these reasons, historical crop rotations were often long and included a wide range of crop types (Crop Protection Association, 1996). However, in intensive agricultural systems, these traditional crop rotations have, to some extent, been replaced by the use of intensive tillage, pesticide and fertiliser regimes. With these inputs, high-yield profitable crops, such as winter wheat, can be grown more frequently, shortening rotations and increasing financial return. However, these changes to crops and cropping patterns in the last 50 years is the main driver of change to UK nature (Boatman et al., 2007; Hayhow et al., 2019). Management regimes associated with intensive farming can cause harm beyond the intended time period and to non-target species and habitats (Botías et al., 2016; Dubey et al., 2020; Patterson et al., 2019; Squire et al., 2015; Wintermantel et al., 2020; Woodcock et al., 2016). As cropping decisions vary spatially and temporally, so the risk of environmental impact is likely to be non-uniform in type, distribution and magnitude.

Fundamental to understanding and explaining the impacts of agriculture on the environment and developing effective mitigation polices is accurate and consistent crop mapping. A combination of remote sensing and spatial reference data (such as Land Parcel Identification Systems) is most often used to build these crop maps, sometimes with the additional input of field or environmental data. These maps include multi-year annual data products, such as CropWatch in China (Wu et al., 2014), the US Cropland Data Layer (Boryan et al., 2011), and the Crop Map of England (Rural Payments Agency, 2021). Large-scale crop maps which are not data products have also been created, which often aim to produce maps where not yet publicly available or refine mapping methods (e.g. Blickensdörfer et al., 2022; Qiu et al., 2022). Annual crop maps enable the generation of spatio-temporal data describing cropping patterns and crop rotations. If we are to explore the potential contributions that diversifying crop rotations can make towards meeting such challenges, it is essential to have access to accurate spatio-temporal data concerning crops and crop rotations. Such data should ideally be available at fine resolution (i.e. individual field parcels) and at full coverage, allowing exploration of environmental risks or benefits across spatial scales relevant to agricultural policy or ecological interest (e.g. field, farm, landscape or country). Detailed spatio-temporal crop datasets can also enable prediction of following crops in a sequence or rotation, allowing forecasting of environmental impacts associated with certain rotations and finely targeting potential mitigation strategies. This could be useful in detecting impacts of increasing extreme weather, for example the presence of specific rotations or a lack of strict rotations where crop decisions are changed, measuring the impacts of agri-environment schemes, and tracking impacts of changes in inputs and commodity prices.

Existing and derived crop rotation data have been used in and beyond agronomy to understand or simulate, for example, crop yields, flood financial losses, drought monitoring and ecological outcomes (e.g. Busch et al., 2020; Kollas et al., 2015; Marja et al., 2018; Tapia-Silva et al., 2011; Wu et al., 2014; Yin et al., 2017). However, crop rotation data are generally limited in their spatial coverage, resolution, or are not spatially explicit. Existing approaches to crop prediction modelling have often focused on predicting a single crop type depending on the crop in the previous year or two (Castellazzi et al., 2008; Detlefsen and Jensen, 2007), via a range of methods including transition probability matrices (TPMs; Castellazzi et al., 2008; Detlefsen and Jensen, 2007; Kim et al., 2020; Mignolet et al., 2007; Osman et al., 2015; Zhang et al., 2019; Sharp et al., 2021), rule-based methods (Bachinger and Zander, 2007; Detlefsen and Jensen, 2007; Dogliotti et al., 2003; Schönhart et al., 2011), machine learning (Osman et al., 2015; Zhang et al., 2019), and spatial learning (Yaramasu et al., 2020). However, few studies have tested the relative accuracy of different spatial approaches to refine predictions, or assessed patterns at a national scale. In many cases, approaches to crop predictions focus on linear crop 'sequences' rather than cyclical 'rotations'.

In this paper, we use a series of 6 years of earth-observation-derived cropping data for GB at the field parcel scale – UKCEH Land Cover® plus: Crops, 2015–2020 (LC+ crops), the first national-scale vector crop map for GB – to investigate spatial rotational patterns and rotation predictions. Our aims were threefold:

1) Firstly, to create the first national-extent crop rotation map at the field parcel scale, and characterise these rotations by length, type and diversity.
2) Secondly, to create a framework to predict the next crop in a rotation at the field parcel scale with estimates of accuracy.
3) To explore the effect of including additional spatial elements (scaling, smoothing and classification) within the prediction framework on reliability and accuracy of forecasting crops.

2. Methods

2.1. Crop map data to crop sequences

The UKCEH Land Cover® *plus*: Crops maps (LC+ crops) (https://www.ceh.ac.uk/data/ceh-land-cover-plus-crops-2015) were produced jointly between UKCEH and Remote Sensing Applications Consultants Ltd. (RSAC). These maps have not yet been published in peer-review outlets, but are available upon request through the URL above, or are available for academic research purposes to many institutions via Edina Digimap (https://digimap.edina.ac.uk). At the time of implementation, we used all years available (2015, 2016, 2017, 2018, 2019 and 2020), providing 6 years of crop information for every agricultural field parcel larger than 2 ha across GB ($n = 1.65$ to 1.91 million). We share validation datasets for 2020 and 2021 in Supplementary Table 1. These maps are derived from Sentinel-1 Synthetic Aperture Radar (SAR) data and Sentinel-2 optical data, by matching time-series curves of Sentinel-1 SAR backscatter to those obtained from reference crops, with subsequent correction using Sentinel-2 data to account for anomalies caused by non-standard management (e.g. fields split between two crops). Field parcels are currently classified into 15 distinct crop categories, with some categories diverging in more recent years (Table 1): improved grass, winter wheat, winter barley, winter oats, spring wheat, spring barley, spring oats, OSR, field beans, peas, maize, main crop potatoes, sugar beet, other field and root crops, and solar panels. For rotation analyses, we prepared the data as follows. We excluded sequences with any year containing "NA" values, where a crop had not been identified, as these were incomplete sequences or misclassified as agricultural land. Any parcel classified as solar panels in 2020 was assumed to have been the same in previous years, and as such was not a crop rotation, so these parcels were also excluded. Apart from spring wheat, recently-diverged crop types in more recent datasets were incorporated back into the crop types they were derived from, giving 11 main crop types (Table 1). We joined these 6 maps together, using unique parcel identification numbers and spatial matching, to give a 6-year consecutive cropping sequence for each field parcel across GB.

2.2. Definitions and notation

In this paper, we refer to a crop sequence as a sequence of crops occupying a field parcel through consecutive annual growing seasons. Conversely, we define a crop rotation as a crop sequence of any length that repeats

Table 1
Crop types and how they differ between years of UKCEH Land Cover® *plus*: crops (LC+ crops). We use "main crop type" and "broad crop type" in our analysis. In this paper, we refer mostly to crop codes, main crop types and broad crop types, which are in bold for easier reference.

<table>
<tr><th>Crop code</th><th>LC+ crops crop type 2020</th><th>LC+ crops crop type 2016-2019</th><th>LC+ crops crop type 2015</th><th>Main crop type</th><th>Broad crop type</th></tr>
<tr><td>be</td><td>Sugar beet</td><td>Sugar beet</td><td>Sugar beet</td><td>Sugar beet</td><td rowspan="2">Root</td></tr>
<tr><td>po</td><td>Potato</td><td>Potato</td><td>Potato</td><td>Potato</td></tr>
<tr><td>fb</td><td>Field beans</td><td rowspan="2">Field beans</td><td rowspan="2">Field beans</td><td rowspan="2">Field beans</td><td rowspan="2">Field beans</td></tr>
<tr><td>pe</td><td>Pea</td></tr>
<tr><td>gr</td><td>Grass</td><td>Grass</td><td>Grass</td><td>Grass</td><td>Grass</td></tr>
<tr><td>ma</td><td>Maize</td><td>Maize</td><td>Maize</td><td>Maize</td><td>Maize</td></tr>
<tr><td>or</td><td>Oilseed rape</td><td>Oilseed rape</td><td>Oilseed rape</td><td>Oilseed rape</td><td>Oilseed rape</td></tr>
<tr><td>sb</td><td>Spring barley</td><td>Spring barley</td><td rowspan="3">Spring barley</td><td>Spring barley</td><td rowspan="3">Spring cereals</td></tr>
<tr><td>sw</td><td>Spring wheat</td><td rowspan="2">Spring wheat</td><td rowspan="2">Spring wheat</td></tr>
<tr><td>so</td><td>Spring oat</td></tr>
<tr><td>wb</td><td>Winter barley</td><td>Winter barley</td><td>Winter barley</td><td>Winter barley</td><td rowspan="3">Winter cereals</td></tr>
<tr><td>ww</td><td>Winter wheat</td><td rowspan="2">Winter wheat</td><td rowspan="2">Winter wheat</td><td rowspan="2">Winter wheat</td></tr>
<tr><td>wo</td><td>Winter oat</td></tr>
<tr><td>ot</td><td>Other</td><td>Other</td><td>Other</td><td>Other</td><td>Other</td></tr>
<tr><td>sl</td><td>Solar panels</td><td>Other</td><td>Other</td><td>Omitted all fields in all years where 2020 = "sl"</td><td>Omitted all fields in all years where 2020 = "sl"</td></tr>
</table>

within a given period of time, including continuous cropping of the same crop type. A "Unique rotation name" is a single name given to all possible sequences that give rise to the same unique rotation. We name crop sequences that do not rotate or begin to rotate within 6 years "complex-rotational sequences", as they may still be part of longer rotations than we can detect. We abbreviate LC+ Crops' crop types according to Table 1, using "main crop type" for all rotation characterisation and prediction work, and "broad crop type" in most prevalent crop rotations (characterising) only. We use underscores between crop abbreviations to denote a sequence or rotation, e.g. "or_ww_ww_wb". Where all 6 years are grass, we call this "long-term grassland" as it is likely to be continuous grassland rather than temporary ley beyond this (Defra, 2022). We also refer to a crop rotation type "grass-dominated" where grass appears in 5 or 6 years, in continuity with other rotation types' classification, and allowing for potential misclassification of long-term grassland (e.g. sequences with one cereal among all other grass appeared in large quantities when we initially looked at most prevalent crop rotations).

2.3. Characterising cropping data

2.3.1. Sequences to rotations

In characterising cropping data, we used the 6-year crop sequences to identify rotations of 1–5 years' length. 1- (continuous cropping), 2- and 3-year rotations were where sequences of these lengths fully repeated within 6 years, whereas 4- and 5-year rotations were where sequences began to repeat in part, as in Table 2. Though we do not see 4- and 5-year rotations repeating in full, evidence suggests that this is more commonly applied in practise (AHDB Cereals & Oilseeds, 2018) and therefore we may be seeing an early reflection of real-life rotations. All variations of the same rotation were combined to the same unique rotation name, irrespective of starting point (Table 2). We called the remaining 6-year sequences that did not show any evidence of a rotation "complex-rotational sequences". We calculated the total area and number of parcels per rotation or complex-rotational sequence, for the 11 main crop types and the 7 broader crop types (Table 1). This was to buffer possible misclassifications in LC+ Crops that might mean we detect fewer rotations than actually exist. We used a spatial join to connect every field's rotation data to Ordnance Survey 10 km grid cells, according to field centre, as this would summarise rotation patterns for several neighbouring farms. We removed long-term grassland from exploratory rotation analyses, and grass-dominated from the 20 most prevalent rotations and rotation type analysis as their dominance in the landscape obscured other spatial patterns in these particular analyses. As we were investigating patterns in rotations rather than sequences, we also removed complex-rotational sequences from further analysis.

2.3.2. Exploring crop rotations

We characterised rotations by length, types, and structural diversity to explore current spatial patterns of rotations using main crop types. To classify rotation length, we used the length of the unique rotation name (Table 2). To classify rotation types (Table 3), we followed similar rule-based cropping classifications to Peltonen-Sainio et al. (2017) and ASSET (Redhead et al., 2020; UK Centre for Ecology & Hydrology, 2019), identifying cropping combinations with contrasting agronomic and environmental importance. Every crop sequence in rotation fell into one of these rotation types. Because these types were determined using all 6 years of data (e.g. "fb_wb_ww_or_fb_wb") rather than unique rotation name (e.g. "fb_wb_ww_or"), there is a slight overlap of unique rotation names between rotation types. This was done to simplify the rule system, otherwise different rotation lengths would have required separate sets of frequency- and uniqueness-based rules per length, increasing subjectivity and the

Table 2
Rotation variations collated to unique crop rotation names, and whether they were used in characterising or predicting crop rotations. Matching letters refer to matching crop types, and different letters can refer to either a different or the same crop (e.g. “A_B_C” could represent “winter barley, winter wheat, oilseed rape” or “winter barley, winter wheat, winter wheat”). Cell shading follows crop letters used for easier reference.

Rotation length	Unique rotation name	Rotates fully?	Application	Year 1 2015	Year 2 2016	Year 3 2017	Year 4 2018	Year 5 2019	Year 6 2020
1-year	A	6 cycles	Characterising	A	A	A	A	A	A
2-year	A_B	3 cycles	Characterising	A	B	A	B	A	B
				B	A	B	A	B	A
3-year	A_B_C	2 cycles	Characterising and predicting	A	B	C	A	B	C
				B	C	A	B	C	A
				C	A	B	C	A	B
4-year	A_B_C_D	2 year overlap	Characterising and predicting	A	B	C	D	A	B
				B	C	D	A	B	C
				C	D	A	B	C	D
				D	A	B	C	D	A
5-year	A_B_C_D_E	1 year overlap	Characterising and predicting	A	B	C	D	E	A
				B	C	D	E	A	B
				C	D	E	A	B	C
				D	E	A	B	C	D
				E	A	B	C	D	E
Recent 3-year	A_B_C	1 year overlap	Predicting			A	B	C	A
						B	C	A	B
						C	A	B	C

similarity between different rotation types. We trust this has little effect on our results because of the distinctive patterns that emerged between rotation types. For each class of rotation length and type, in each 10 km cell, we summed the number of fields and total area occupied by each class, and divided the result by the total number of agricultural fields and area, respectively. The resulting maps of rotation length and type use percentile distributions for values above 0, rounded to two significant figures, to better read the spatial patterns of lower values.

Finally, we also analysed rotation structural diversity, following Stein and Steinmann (2018). For each field, we calculated the number of transitions between crops in the rotation name, and the number of unique crop types. These values were aggregated up to 10 km and summarised to mean values. We then used the R package “biscale” (Prener et al., 2022) to create bivariate classes of mean number of transitions and mean number of unique crop types, using quantile breaks at 33 % and 66 % to create three classes for each. We mapped the results using a bivariate colour scheme. While it would be useful to take the analysis further and analyse rotation functional diversity (Stein and Steinmann, 2018), field and cereal crops need to be distinct; unfortunately, the crop category “other” combines these.

2.4. Predicting crop rotations

There has been previous work investigating crop sequences where the main point of interest is in defining the likelihood of which crop is likely to follow another in GB (Sharp et al., 2021). However, existing approaches do not take into account further history of the site or field so that the probability of crop classification at time t is conditionally independent of the crop classification at time t-2, t-3, …,t-n, given the crop at time t-1. We considered crop rotations in the manner of Table 2, for 3-, 4- and 5-year rotations, focusing on the predictive outcome of a crop in year 6 (2020) based on the 5 preceding years. While 6 years of data does not capture all possible rotational patterns irrespective of starting point (Table 2), evidence suggests that longer rotations are more common than shorter (AHDB Cereals & Oilseeds, 2018) and therefore may produce more accurate predictions. In addition to these three rotation lengths, we introduced another rotation category, “recent 3 years”, where year 6 (2020) is contingent upon only the 3 preceding years (2017, 2018 and 2019), but no complete repetition is assumed. This enabled us to look for differences in prediction accuracy between most recent and overall 3-year rotations, as a result of short-term cropping changes. We also made separate predictions including and excluding long-term grassland, due to its dominance across GB, to see how this affected overall prediction accuracy.

We used transition probability matrices (TPMs) to define the probability of moving from one state to another, to quantify the patterns of crop rotation and to enable prediction of the most likely crop at the next time step. In this case the rows of the TPM, previous states, are defined as the unique series of t-1 previous crops in the t-year rotation. The columns of the TPM, future states, are simply the 11 unique crop classifications. The t-year rotations were identified as all continuous series of crops, of length t, across the observed 6 years' of data. Only data from the first 5 years was used to identify sequences so that independent prediction of year 6 crops could be made. The circularity of rotations, rather than just considering sequences, was then acknowledged to merge sequences that reflected the same rotation as shown in Table 2. No filtering of the data was conducted prior to this step. Therefore in an observed series of A_B_C_D_A_B, the 4-year sequences are {A_B_C_D, B_C_D_A, C_D_A_B}, which because of the circularity reduces to the same A_B_C_D rotation (Table 2). The 3-year sequences,

Table 3
Rotation type classification based on 6-year crop sequences. "Winter cereals" includes winter wheat, winter oats and winter barley while "spring cereals" includes spring wheat, spring oats and spring barley. "Roots" includes sugar beet and main crop potatoes. The shaded rotation types "grass-dominated" and "unclassified" were excluded from mapping, because "grass-dominated" masked patterns in other rotation types, and "unclassified" contained rotations with a higher proportion of the crop type "other".

Rotation type	Rules
Grass-dominated	Grass in 5 or 6 years
Short winter cereals	Winter cereals in 5 or 6 years OSR excluded
Short spring cereals	Spring cereals in 5 or 6 years
Short winter cereals & oilseed rape (OSR)	Winter cereals + OSR in 5 or 6 years OSR in at least 1 year
Mixed cereals & OSR	Any winter or spring cereals + OSR in 5 or 6 years OSR in at least 1 year Excludes sequences in Short winter cereals & OSR
Short roots	Roots in at least 2 years Maize in up to 2 years
Short maize	Maize in at least 3 years Roots in up to 1 year
Long mixed crops	4 or more unique crops Excludes sequences in above rotation types
Short mixed crops	3 unique crops Excludes sequences in above rotation types
Unclassified	Remaining rotations after above rotation types excluded

however, are {A_B_C, B_C_D, C_D_A, D_A_B} for which there is no circularity and are therefore all included as distinct rows in the TPM. This ensured that we were looking at all possible 3-, 4-, and 5- year crop rotations and predicting the most likely subsequent crop. Entries in the TPM were calculated based on observed frequency counts and the relative proportions of field parcels moving between the relative states. All observed sequences were fed into each of the 3-, 4- and 5-year TPMs in turn and the corresponding column with the highest associated probability was selected as the most likely subsequent crop. We compared the accuracy of four different TPM based approaches to assess the impact of spatial context on the accuracy of crop rotation predictions.

2.4.1. Spatial scaling approach

Firstly, separate TPMs were calculated for distinct 10 km by 10 km grid cells across GB, aligned with the OS GB National Grid. Cells of size 10 km by 10 km were chosen as they were considered small enough to capture the local rotations specific to a particular area, while at the same time being large enough to ensure that a suitable number of field parcels across multiple farms was contained within each 10 km cell used to calculate the TPMs. This is our first spatial approach (hereafter "spatial scaling").

Entries of the TPMs for each of the 2046 10 km grid cells were calculated as follows:

$$TPM_{\mathrm{i,j}} = N_{(\text{class i that transitioned to class j})} / N_{(\text{class i})}$$

where for 3 year rotations the set of classes {i} is given by the 121 unique combinations of the 11 crop classes across 2 years, for 4 year rotations is given by the 1331 unique combinations of the 11 crop classes across 3 years, and for 5 year rotations is given by the 14,641 unique combinations of the 11 crop classes across 4 years. In both cases the set of classes {j} is given by the 11 unique crop types. Therefore each entry $\mathrm{TPM}_{\mathrm{i,j}}$ gives the probability of a crop field parcel belonging to crop type j conditional on the previous 2, 3 or 4 years of crops observed. For the case of 3 year rotations this therefore resulted in 2046 121 × 11 TPMs, 4 year rotations 2046 1331 × 11 TPMs, and 5 year rotations 2046 14,641 × 11 TPMs, one for each 10 km grid.

2.4.2. National average approach

Secondly, we averaged the full set of 10 km × 10 km TPMs to produce a single national TPM from which to predict crop rotations. Averages were calculated across corresponding i,j entries and, following this, rows of the final TPM were rescaled to sum to 1 to ensure appropriate probability based transitions. This approach (hereafter "national average") is considered as the null case from which to compare spatially explicit approaches and the interpretation of this case is that rotations are consistent across GB and there are no differences either by region or environmental covariates. Of course, a single TPM could have been calculated based on the full dataset rather than averaging 10 km TPMs, however, this approach was used for consistency with the alternative approaches which are all based on different ways of averaging the 10 km TPMs.

2.4.3. Spatial smoothing approach

The third approach incorporated spatial context based on kernel smoothing techniques into crop rotation predictions (hereafter "spatial smoothing"). In this case we assume that rotation patterns vary spatially but that any change across space is smoothly variable, hence avoiding arbitrary step changes that would occur under the first approach that considers 10 km grid cells separately. This approach further implies that fields geographically close to each other are more likely to undergo similar rotations. The distance between the centroids of each of the 2046 10 km grid cells was calculated and, using a Gaussian kernel, a set of weights was determined between each 10 km grid cell and the 2045 others. For a given 10 km grid cell x, the weight corresponding to another cell x_i is given by:

$$w(x_{\mathrm{i}}) = K\left(\frac{\|x_{\mathrm{i}} - x\|}{h}\right)$$

where $K(u) = \frac{1}{\sqrt{2\pi}}\exp\left(-\frac{1}{2}u^2\right)$, h is defined as the bandwidth controlling the degree of smoothness and $\|x_i - x\|$ denotes the Euclidean distance between cells x_i and x. In this case the bandwidth, h, was chosen to be equal to 25 km meaning that approximately 95 % of the weight was within a 100 km area centred on the 10 km cell in question, x. 100 km was chosen because it represents an intermediate between the spatial scaling and national average approaches. We would expect that values larger than 100 km would result in greater convergence of values towards the national average and less spatial differentiation of biophysical, socio-economic and political characteristics. Values smaller than 100 km would become more similar to the spatial scaling approach. Having obtained these weights for each of the 10 km grid cells, the observed TPM was replaced by a weighted average across all of them. For each of the 10 km cells, the $\mathrm{k^{th}}$ entry in the TPM is therefore given by:

$$TPM_k = \frac{1}{\sum_{i=1}^{N} w(x_i)} \sum_{i=1}^{N} w(x_i) \cdot T_{i,k}$$

where $T_{i,\,k}$ represents the kth entry in the $\mathrm{i^{th}}$ observed 10 km grid cell that has a corresponding weight of $w(x_i)$ to the cell in question. A total of 2046 TPMs, one for each 10 km cell, were calculated via kernel smoothing in this way and used for spatially explicit prediction of crop rotations.

2.4.4. Spatial classification approach

The fourth and final approach averaged rotational patterns from 10 km grid cells with similar environmental characteristics (hereafter "spatial classification"). In doing so, we assume that rotational patterns are more similar within regions with similar environmental characteristics than between such regions. We used the ITE Land Classification (Bunce et al., 2007) to define areas with similar environmental and topographical characteristics and classified each of the 10 km grid cells into the one of the 32 land classes based on the dominant coverage. The TPMs of grid cells with the same land class were then averaged to give a single, consistent TPM for the entire land class across GB.

Having established TPMs under each of the four approaches presented, they were used to derive predictions. Information from the 2015–2019 crop maps were used as inputs to match to the defined rows in the TPMs and a random draw, with probabilities proportional to the values in the corresponding columns, made to determine the predicted crop type for 2020. This was then compared, using a confusion matrix approach, to the observed crop data in 2020 to quantify the overall accuracy.

Data analyses were carried out using R (Bivand, 2020; Kuhn, 2020; Oksanen et al., 2019; Pebesma, 2018; R Core Team, 2020; Stabler, 2013; Warnes et al., 2017; Wickham et al., 2020; Wickham, 2007, 2016, 2019; Wickham and Henry, 2020; Wilke, 2020) and ESRI ArcMap 10.6.1.

3. Results

3.1. The first national map of crop rotations in GB

3.1.1. Rotation distribution and prevalence

Crop data for all 6 years occupied 1,616,306 fields covering 9,486,109 ha. Long-term grassland occupied 57 % of these fields and 43 % of this area. There were 11,310 unique rotation names, excluding long-term grassland, with rotations occupying 12 % fields and 16 % area. There were 69,553 unique complex-rotational sequences, taking up 31 % fields and 41 % area. When broad crop types were used (spring cereals, winter cereals, roots), rotations occupied more fields (14 %) and greater area (19 %), whereas unique complex-rotational sequences occupied fewer fields (29 %) and less area (38 %). Further details of field and area numbers and proportions are in Supplementary Table 2. The remainder of the results focuses on land where there is evidence of crop rotation.

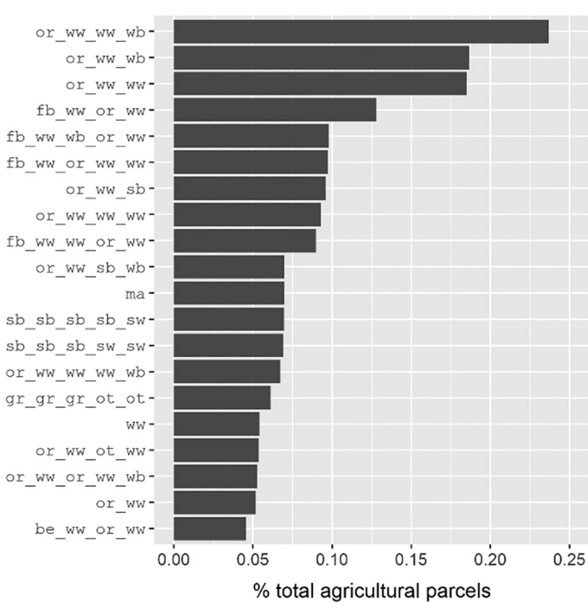
Details of the top 20 most prevalent rotations by % total agricultural fields and area are identified in Fig. 1. Many rotations are 4 or 5 years in length but the top few rotations are 3- and 4-years long. Dominant in these rotations are winter cereals with break crops of OSR and field beans, combinations of spring barley and spring wheat, and some mono-cropping of winter wheat and maize. There is some difference between the rotation order and composition between the two graphs, suggesting there is some association of particular rotations and field sizes. Noticeably, these rotations occupy a very small proportion of total agriculture. Supplementary Fig. 1 shows broader rotations still occupy very small proportions of national agriculture, and that continuous spring cereals are more prevalent than continuous winter cereals, which are commonly in rotation with OSR and break crops.

3.1.2. Rotation length

The spatial distribution of different rotation lengths can be seen in Fig. 2. We see spatial variation in extent and clustering across all rotation lengths. 1-year rotations are fairly scattered but with some geographic clustering, 2-years around central England, 3-years spreads more with larger concentrations in parts of southern England, 4-years shows higher densities in East Anglia and northeast than 3-years, while 5-years occupies much of the east and south of GB, making it the most dominant rotation length in GB (Supplementary Fig. 2 shows this spatial distribution, and Supplementary Table 3 details the break-down of total number of fields and area per rotation length). Longer rotations occupy greater proportions of agricultural area, with 1–4-year rotations mostly occupying <11 % agricultural area at any given 10 km cell. The percentages of area occupied by rotations are always greater than percentages of fields, suggesting that rotations occupy larger field sizes compared to long-rotational sequences and long-term grassland.

3.1.3. Rotation type

Classifying rotations by type gives unique and distinctive spatial clustering patterns for each type, with short mixed crops being the most abundant rotation type (Fig. 3). There is some overlap between distributions of higher values, such as short winter cereals, winter cereals & OSR, short roots and short mixed crops in the East of England, or short spring cereals and short mixed crops in eastern Scotland. In Wales, the most prominent rotation type is short mixed crops. As with rotation length, apart from short maize, all other rotation types occupy a greater percentage of area than fields, suggesting that these types tend to occupy larger field sizes than average. Supplementary Fig. 3 shows the distribution of dominant crop types according to our classifications, and Supplementary Table 5 details the break-down of total number of fields and area per rotation type.



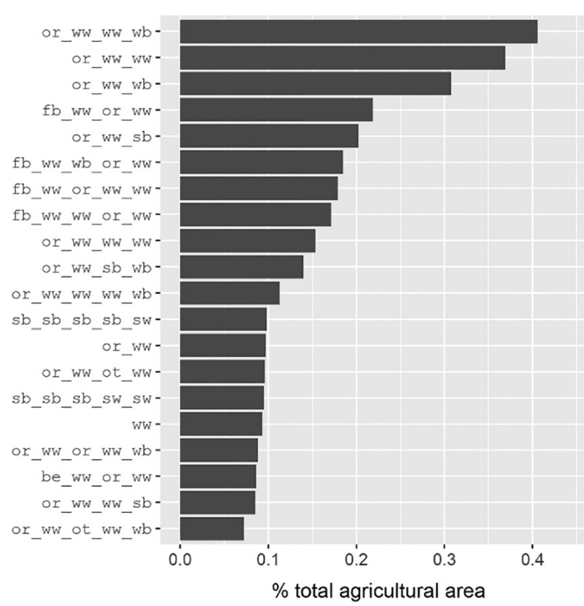


Fig. 1. 20 most prevalent rotations in GB using main crop types, according to % total number of agricultural fields and % total agricultural area, excluding grass-dominated rotations (grass in 5 or 6 years). See Table 1 for crop abbreviations and rotation notation.

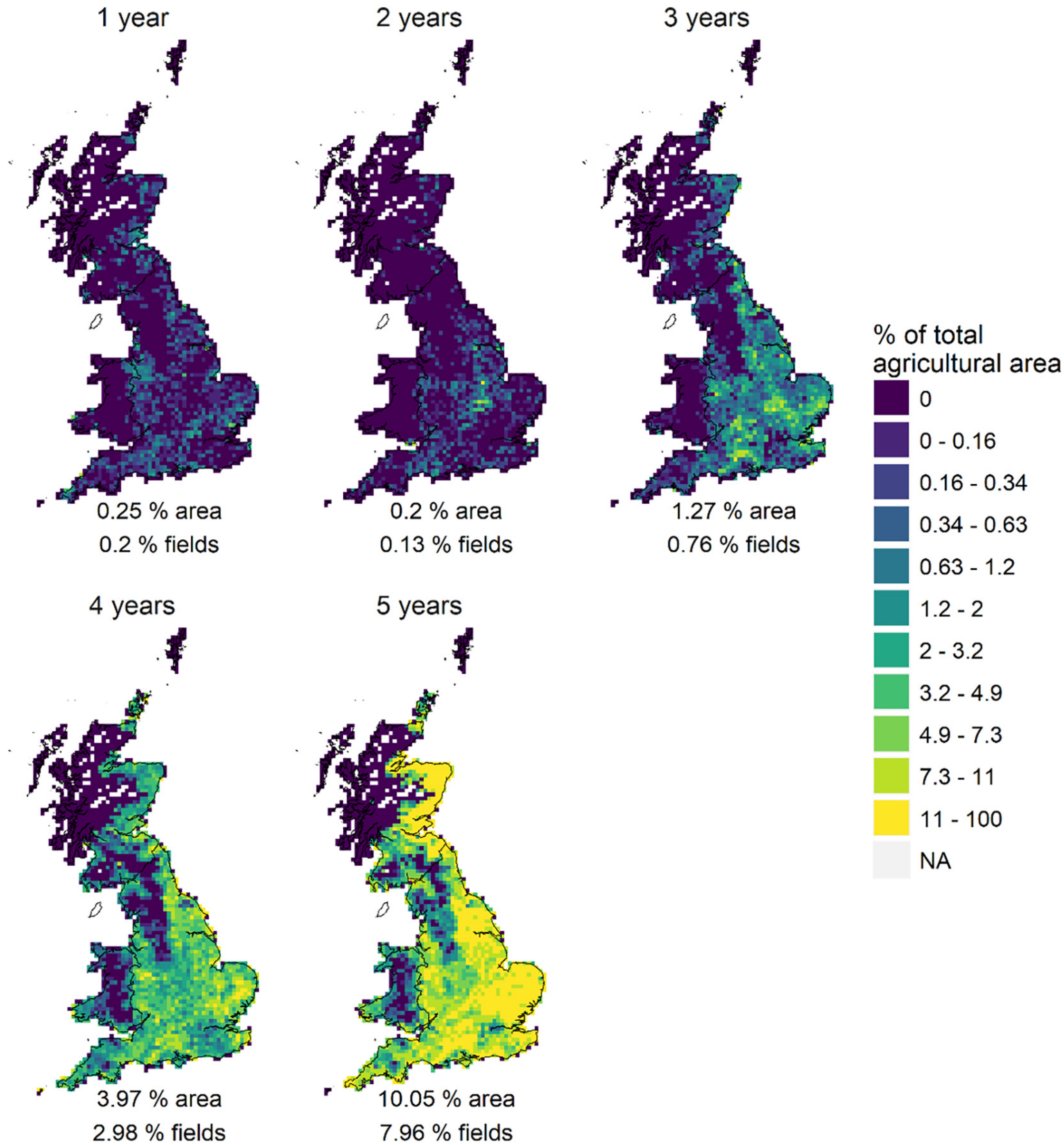


Fig. 2. Spatial distribution of rotation lengths of 1–5 years (excluding long-term grassland) as a percentage of total agricultural area. % area and fields refer to GB-wide occupancy of agricultural land per rotation length. Data were classified as 0 (no rotations), NA (no agricultural area), while values >0 were classified into percentiles of 10 % increments and rounded to nearest 2 significant figures. Frequencies of 10 km cells within each class are in Supplementary Table 4.

3.1.4. Rotation structural diversity

Following Stein and Steinmann (2018), Fig. 4 shows rotation structural diversity across GB. Light grey cells (bottom-left on the scale) show where rotations are generally closer to a single crop rotation, red cells (bottom-right) show where rotations are usually longer but consist of a relatively low variety of crops, blue cells (top-left) show where rotations tend to be shorter but with more variety of crop types, and brown cells (top-right) show where rotations are often longer and have more variety of crop types. As with crop length and type, we see clustering of similar values and blending between them. Generally, areas with a higher number of unique crops are further to the east and south, whereas higher numbers of crop transitions tend to be north and west, with a small concentration in the southeast. The overlap of these higher values is particularly pronounced in east Scotland and parts of east England.

3.2. Predicting crop rotations

The outcomes of prediction accuracies of each spatial context approach are in Table 4, from 36 % to 89 %. Consistently, including long-term grassland improves overall prediction accuracy. The spatial scaling approach is the most accurate spatial context, decreasing across spatial smoothing and spatial classification to national average. Five-year rotations, that is predicting crop types based on the previous 5 years where years 1 and 5 are the same crop, are the most accurate rotation length, and using the most recent 3 years is more accurate than 3-year rotations across the whole time period (2015–2020).

4. Discussion

4.1. Crop maps

Accurate, national-scale annual crop maps of over 1.6 million field parcels derived from satellite data enabled us to classify crop rotations. We identified crop sequences in a similar way to previous research: using crop maps derived from remote sensing image time series, for fields over a series of consecutive years, e.g. US Cropland Data Layer (Merlos and Hijmans, 2020; Socolar et al., 2021; Yaramasu et al., 2020; Zhang et al., 2019) and others (Osman et al., 2015; Waldhoff et al., 2017). However, within the six years of data available, we look for crop rotations – evidence of 1–5-year sequences cycling within the six years – rather than for crop

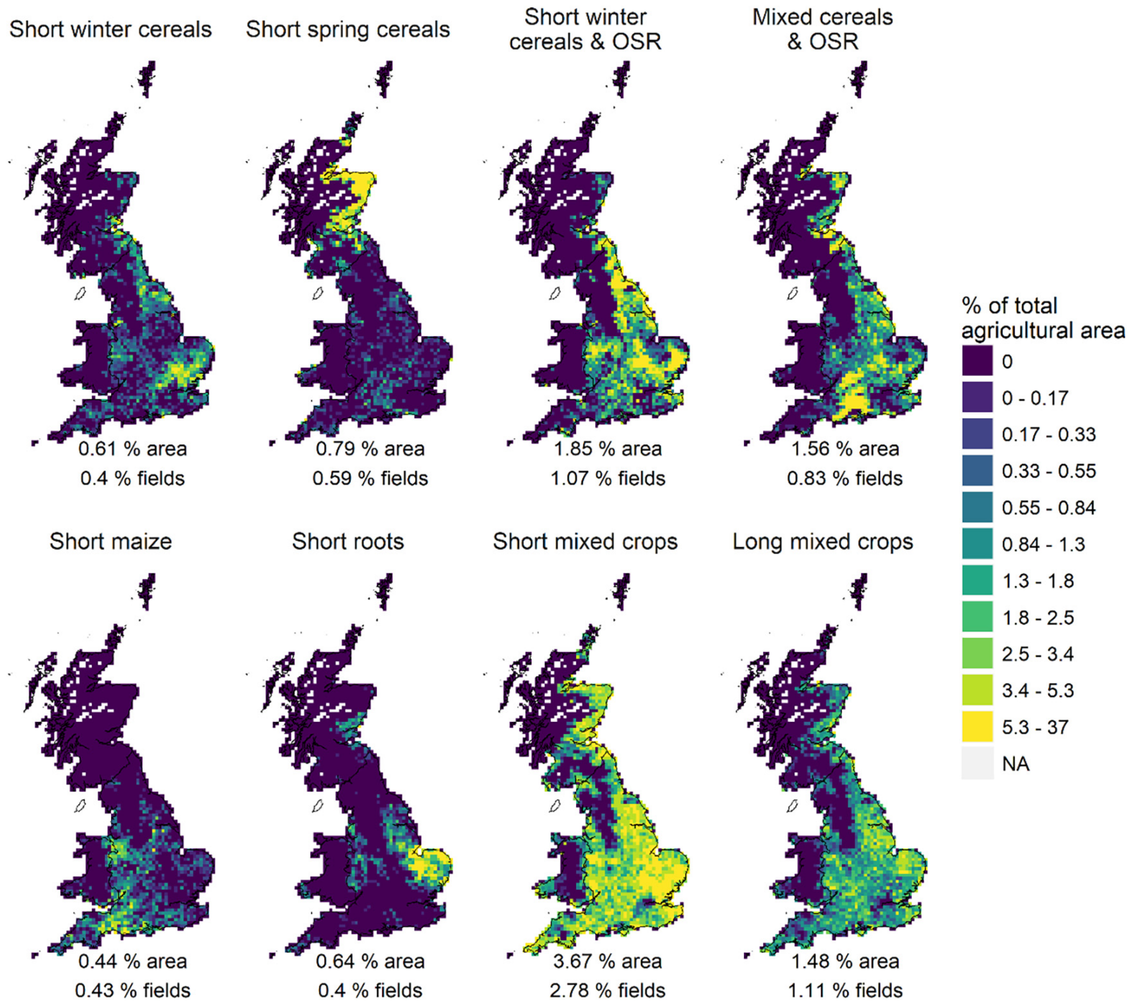


Fig. 3. Spatial distribution of rotation types as a percentage of total agricultural area, excluding "grass-dominated" and "unclassified" (Table 3). % area and fields refer to GB-wide occupancy of agricultural land per rotation type. Data were classified as 0 (no rotations), NA (no agricultural area), while values >0 were classified into percentiles of 10 % increments and rounded to nearest 2 significant figures. Frequencies of 10 km cells within each class are in Supplementary Table 4.

sequences regardless of whether there is evidence of rotation. Similarly to previous research, we chose to classify rotations using length (Osman et al., 2015), cropping composition (Xiao et al., 2014), and diversity (Conrad et al., 2017; Merlos and Hijmans, 2020; Scheiner and Martin, 2020; Socolar et al., 2021; Stein and Steinmann, 2018; Tiemann et al., 2015). We evaluated all three classification systems in the same investigation, so we could evaluate the findings together.

Our approach to rotation predictions is similar to Sharp et al., who used fewer years of LC+ Crops and simulated realistic crop sequences (2021). However, with more years of data, we do not necessarily need to generate longer sequences to investigate current rotations. For instance, we see one of the more prevalent (although only occupying a small proportional area) is OSR and winter wheat in a 2-year rotation, despite OSR grown in short rotation being at greater risk of yield loss from various pests and diseases (Hegewald et al., 2018). This is likely due to economic pressures to grow higher-profit crops in shorter rotations, despite lower yields (Hegewald et al., 2018). If we restricted outcomes using agronomic expertise (as Sharp et al., 2021), we might not have seen this or other patterns emerging from the data. In comparison to our work, we found existing studies characterising or predicting crop rotations have been more limited in at least one way: coarser spatial resolution (e.g. Socolar et al., 2021), smaller geographical coverage (e.g. Osman et al., 2015), shorter timeframes (e.g. Sharp et al., 2021), using crop sequences in lieu of recognised rotations (e.g. Stein and Steinmann, 2018), or restricted by agronomic rules (e.g. Dogliotti et al., 2003) which, though removing unlikely sequences, might hide true farmer decisions (Chongtham et al., 2017). In areas such as the US Corn Belt where fields are often larger and agricultural system broadly less diverse than in GB, coarser imagery may still provide sufficient information, and the same years of data might result in a greater percentage of rotations within agricultural land than we find here in GB.

4.2. Long-term grassland and complex rotational sequences

According to our results, long-term grassland and complex-rotational sequences each fill nearly three times as much land as strict cyclical rotations do. Even the most prevalent rotations only occur infrequently when expressed as proportion of the total area or number of fields, as found by Sharp et al. (2021) using fewer years of this dataset. Omitting long-term grassland from our rotation predictions causes a considerable reduction in overall prediction accuracy, emphasising that the large number of unique rotation names and complex-rotational sequences in our dataset led to this uncertainty. This is in accordance with modern agriculture in GB using rotations that are often longer than we currently have enough data to detect (Crop Protection Association, 1996).

The difference in amounts of rotational and complex-rotational land could also be reflecting that strict cyclical rotations are truly not that common, and that rotations are longer or more flexible. Flexible crop rotations are those that have alternative crop choices in at least one year, variable length, or varied cyclical or linear nature (Castellazzi et al., 2008). Farmers may sometimes choose (or be forced) to change a crop in a rotation, such as

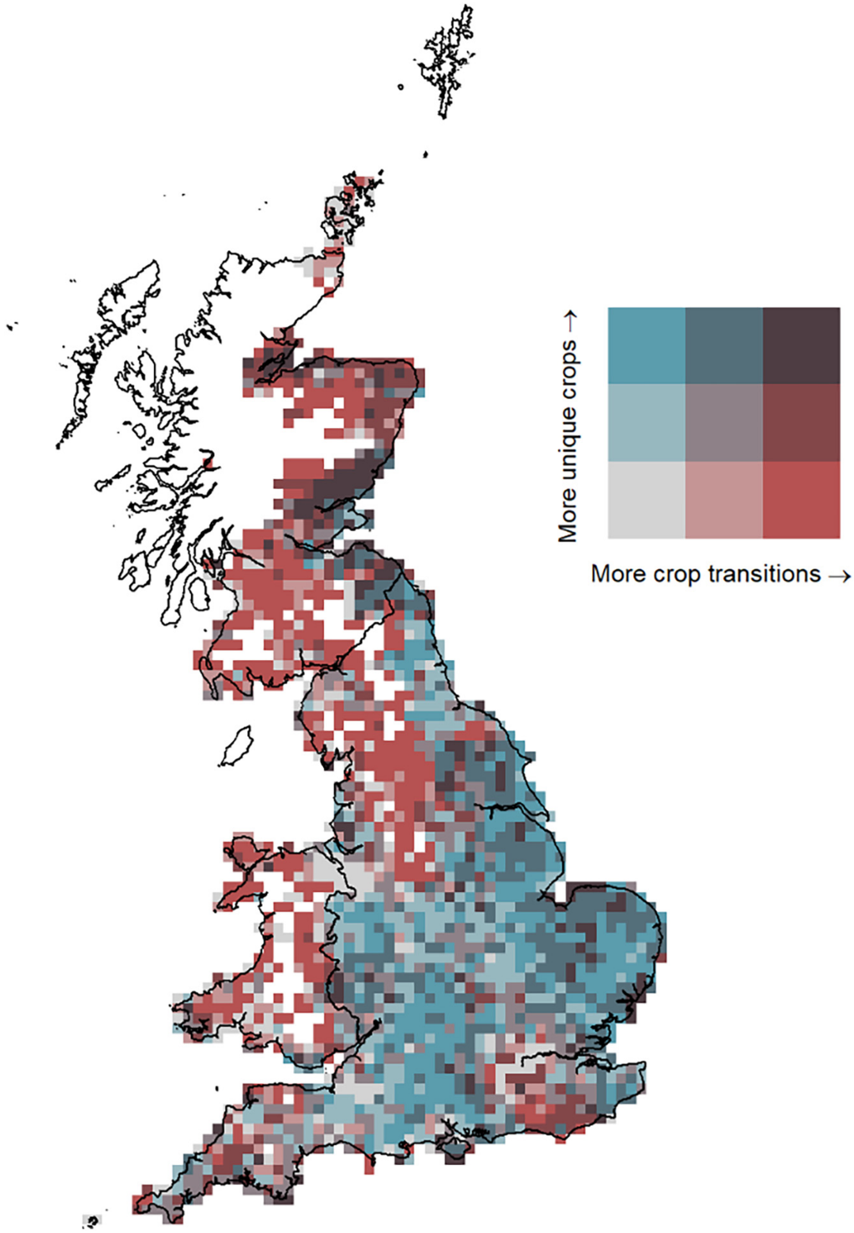


Fig. 4. Spatial distribution of rotation structural diversity (excluding long-term grassland) displayed in a bivariate choropleth map using quantile breaks. Quantile breaks and values of a) mean number of unique crops: 0–33 % = 1.2–2.42, 33–66 % = 2.42–2.86, 66–100 % = 2.86–5; b) mean number of crop transitions: 0–33 % = 0.8–3.45, 33–66 % = 3.45–3.66, 66–100 % = 3.66–4. Cells with no crop rotations are white. Frequencies of 10 km cells within each class are in Supplementary Table 6.

Table 4
Overall within-sample prediction accuracy (%) of different spatial context approaches to predict the 6th year given the sequence of preceding crops (Table 2).

Long-term grassland	Rotation period	Spatial scaling	Spatial smoothing	Spatial classification	National average
Included	3 Years	77.1	74.6	73.9	73.0
	Recent 3 years	80.7	76.4	75.3	74.8
	4 Years	77.7	76.2	68.7	67.1
	5 Years	88.7	80.2	77.6	75.4
Excluded	3 Years	46.3	40.1	38.2	36.1
	Recent 3 years	55.5	44.6	41.8	40.4
	4 Years	59.5	59.5	40.7	39.0
	5 Years	75.7	67.4	47.6	42.1

in response to poor weather conditions at critical times in the farming calendar, pest or disease pressure or to changes in demand of a crop (Bane et al., 2021; Defra, 2020). Longer, more flexible rotations often appear in organic agriculture (European Commission, 2010), where farmers use a rotational approach for pest management and nutrient cycling in place of pesticides and fertilisers, but include certain crops based on fluid market prices (Chongtham et al., 2017). However, as organic farming only accounts for around 2.8 % of all agriculture in the UK (2020; Defra, 2021) and complex-rotational sequences occupy 41 % in GB, our results suggest that these patterns are not unique to organic systems. At the farm scale, there may be transitions between crop rotations, which may also be contributing to the complex-rotational land we see in our results. This could happen, for instance, in response to a changing landscape (Castellazzi et al., 2008). However, there is minimal literature that explains farmer motivations behind crop choice, let alone outside the context of rotational cropping, so we are unable to state the extent of this influence.

4.3. Rotation characteristics

Within crop sequences, we find both shorter rotations that fully repeat and longer sequences that appear to start rotating. Using these rotations, we have identified spatial clusters of different rotation groupings. Linking hotspots of certain crop rotation groupings with associated agronomic or environmental risks could allow us to locate areas of concern and target mitigation. For example, the arable herbicide-resistant weed black-grass (*Alopecurus myosuroides* Huds.), associated with intensive winter cropping Hicks et al. (2021), is becoming increasingly problematic across Europe (Varah et al., 2020). Introducing spring cropping, break crops and lengthening gaps between winter crops can provide effective cultural control of the weed (Chauvel et al., 2001, 2009; Gerhards et al., 2016; Zeller et al., 2021). Our maps of shorter winter dominated rotations could thus be used to identify areas at greatest risk of blackgrass pressure, as well as alternative rotations already used within the same region that may provide better cultural control. Additionally, we see clustering of short maize and roots rotations. Soil loss due to crop harvesting (SLCH) is more of a threat where root or tuber crops are grown more frequently, as harvesting requires heavy soil disturbance. There is net soil loss, reduced soil fertility, and a reduction of water holding capacity (Kuhwald et al., 2022). Conventional maize cropping is associated with higher risk of soil erosion (Vogel et al., 2016), with soil exposed for much of the growing season, and harvest later in the year. Coincidence of these critical periods with heavy rain and erodible soils can cause soil degradation and runoff (Palmer and Smith, 2013), leading to sedimentation of waterways and flooding. The areas where short roots and maize are more abundant in our maps could be used to prioritise preventative erosion and flood measures.

Shorter and less diverse rotations often involve management techniques that are damaging to biodiversity and the wider environment. We demonstrate that we can map rotational diversity based on its structural components of the number of unique crops and transitions within a rotation. Our results highlight areas to target where this diversity could be increased, by introducing additional unique crops to rotations, or lengthening them by changing the existing crop arrangement, adding crops or combining with another rotation. Reverting from intensive to diverse rotational systems has the potential to benefit at scales of field, farm and landscape, increasing system sustainability and resilience, arising from increasing non-provisioning ecosystem services (Landis, 2017). Soil microbial communities and functions can be enhanced with rotational diversity (McDaniel and Grandy, 2016; Peralta et al., 2018; Tiemann et al., 2015), and including nitrogen-fixing leguminous break crops reduces the need for nitrate fertilisers (Nemecek et al., 2015). At a larger scale, a mosaic of different crop types in the arable landscape provides a diversity of habitats year-round for various organisms (Benton et al., 2003). Diverse rotations can also bring benefits for agriculture, including increased natural pest control (Bosem Baillod et al., 2017; Redlich et al., 2018; Rusch et al., 2013; Scheiner and Martin, 2020), pollinator abundance and diversity (Raderschall et al., 2021; Stiles et al., 2021), greater yield (Degani et al., 2019; Gan et al., 2003; Kirkegaard et al., 2008; Macholdt et al., 2020; Matus et al., 1997), lower yield risk and loss (Macholdt et al., 2020; Marini et al., 2020), and greater system resilience (Macholdt et al., 2020).

4.4. Crop predictions

Using the most local spatial approach, spatial scaling, consistently gave the most accurate predictions. Our results echo research showing strengthened prediction accuracy through including spatial elements (Osman et al., 2015; Yaramasu et al., 2020), underlining the importance of using appropriate spatial context in large-scale crop prediction modelling, and comparing the effectiveness of different approaches. This outcome makes agronomic sense, as reduced variation in environmental characteristics in the local area, such as soil properties and climate, would mean crop choice is under similar constraints in the 10 km cell. Additionally, a smaller geographic area has a reduced subset of crop rotations associated with it compared to the full set at the national scale, which increases the chance of correct predictions. Our predictions were more accurate for longer rotations than shorter: the opposite findings of Osman et al. (2015). As 5-year rotations far outweigh 1-year rotations (excluding long-term grassland), 2-, 3- and 4-year rotations combined, so our framework predictions using the LC+ crops datasets favour a longer rotation length. If our framework was applied to systems with typically shorter rotation lengths and fewer crop types contributing to the majority of arable land cover, such as the Corn Belt in the US Midwest (Green et al., 2018), we might expect prediction accuracy to be higher than the results we present here. The prevalence of long-term grassland in GB clearly influences overall prediction outcomes, even doubling the accuracy of 3-year rotation predictions between national average and spatial scaling approaches. In areas with high proportions of permanent grass such as GB, identified long-term grassland could be assumed to be permanent grassland, and so be masked out of rotation predictions. However, this would reduce prediction accuracy and emphasise the apparent diversity of present GB crop rotations.

Our prediction framework has been designed to be extendible: to include additional years of cropping data. LC+ crops maps are produced annually, with a full dataset available in the winter following the corresponding year's crop. With more years of data, we could look for evidence of rotations longer than 5 years. However, additional data creates larger TPMs due to additional rotation combinations, which in turn require substantially greater computing power to calculate prediction outcomes. The framework could be augmented to investigate rotational complexity, such as crop or rotation flexibility (Castellazzi et al., 2008) or transitions between rotations. Rotation mapping and predictions could also be refined by introducing crop classification certainty (Serra and Pons, 2016), agronomic rules or expertise (Bachinger and Zander, 2007; Detlefsen and Jensen, 2007; Dogliotti et al., 2003; Schönhart et al., 2011; Sharp et al., 2021; Xiao et al., 2014), or a metric for agricultural land capability and other biophysical covariates (e.g. Goodwin et al., n.d.; Socolar et al., 2021). As this framework has plasticity for adjustments, the method is also transferable to other regions with annual cropping data, to assess their own rotation predictions in light of their geography-specific cropping concerns.

Introducing additional contextual data to the prediction framework would enable us to address more specific agronomic and ecological risks and opportunities. Given the high resolution of LC+ crops, prediction work could be investigated at different scales. Combining estimates of chemical application loads, such as pesticides and fertilisers (Jarvis et al., 2020; Osório et al., 2019), and their frequency in a rotation, would enable planning of mitigation for the local environment, ensuring mechanisms are readily in place to reduce risk to water quality and non-target organisms. Knowing where and when mass-flowering crops such as OSR and field beans will appear in rotation, along with semi-natural land cover, gives us an idea of temporal and spatial variation in floral resource availability for pollinators. Different pollinator guilds tend to show diet preference of certain types of floral resource (Rollin et al., 2013), with mass-flowering crops providing a "pulse" of resource during relatively short periods. This information could be used to pinpoint pollinator-specific agri-environment schemes to fill anticipated spatial and temporal gaps of mass-flowering crops, providing more continuous floral resources for a variety of pollinators. Due to the influence of the economic market on crop choice, adding an element of the market may further refine prediction outcomes. The market is influenced by quantifiable factors including weather, resource prices, population and demand, which could feed into the framework. In turn, due to the cyclical influence of market, crop choice, harvested crop, resource price and market, we expect that our research would be useful in economics as well as agronomy.

4.5. Limitations

Our findings were based on three key assumptions, the first being that all crop classifications are correct. Each year, LC+ crops data are verified against ground-truthed data, with each crop having a calculated uncertainty value. While these vary between crop types, it is unlikely that systematic bias exists against detecting particular rotations, although misclassifications will add to the 'noise' reducing the detection of genuine cyclical rotations. The second assumption is the crop rotations we detected are complete rotations. Our 4- and 5-year rotations may not reflect true rotations, as they do not repeat fully in the short time period covered in this study and so instead may simply be part repeats within longer, more complex sequences. This provokes the question of how long a sequence can be before it is declared a rotation or not. The third assumption is that crop rotations are strict and there is no flexibility. We know there are short-term cropping changes likely to have impacts within our time-series. For example, particularly wet weather at winter planting in autumn 2019 resulted in the lowest area of winter wheat since the 1970s and resulted in replacement with spring cereals (Defra, 2020). Therefore, there is cropping flexibility in practise, but we cannot unravel where and when this is happening without additional data.

We recognise that we have merged some of the LC+ crops crop types in our analysis (i.e. we classify winter oats as "winter wheat") to increase continuity across years of data, and that the LC+ crops' categories group similar crop types (sugar beet may include some fodder beet; field beans, peas and OSR include both spring and winter variants; grass may be long-term, temporary, or include herb-rich leys, orchards and fallows). Therefore the number of true rotations and sequences will be larger than we account for here, presumably with different prediction accuracy results. This also reinforces the importance of consistent rotation classification systems in order to make generalised but relevant conclusions. Another consideration is that rotation structural diversity assumes equal dissimilarity between crop types, when we know that some crop types are more similar in purpose and requirements than others, such as cereals. An improved metric accounting for this could give us a different picture of cropping diversity across GB.

5. Conclusions

With 6 years of crop data, we are already building an impression of current crop rotations in GB. As strict, cyclical rotations occupied nearly a third of the land that complex-rotational sequences did, it is misleading to assume that strict rotations are practised across the majority of GB. Instead, they appear to be more of a framework with room for crop choice driven by external pressures, such as market forces or extreme weather events. However, that we do see distinctive spatial patterns in length, type and diversity of strict rotations, means that rotations' impacts on the environment are likely to also vary spatially. Our crop prediction framework produces more accurate results when including more local spatial context, and where rotations are longer. Greater accuracy when predicting more recent rather than all rotations indicates a degree of short-term cropping non-stationarity. Our prediction framework is designed to be extended to include further years of cropping data, or to incorporate external data to address specific research questions.

CRediT authorship contribution statement

Emily V. Upcott: Methodology, Validation, Formal analysis, Data curation, Writing – original draft, Project administration. **Peter A. Henrys:** Methodology, Validation, Formal analysis, Writing – review & editing. **John W. Redhead:** Conceptualization, Writing – review & editing, Supervision. **Susan G. Jarvis:** Writing – review & editing. **Richard F. Pywell:** Conceptualization, Writing – review & editing, Supervision.

Data availability

The authors do not have permission to share data.

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.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2022.160471.

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