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Research Paper

Whole-farm yield map datasets – Data validation for exploring spatiotemporal yield and economic stability

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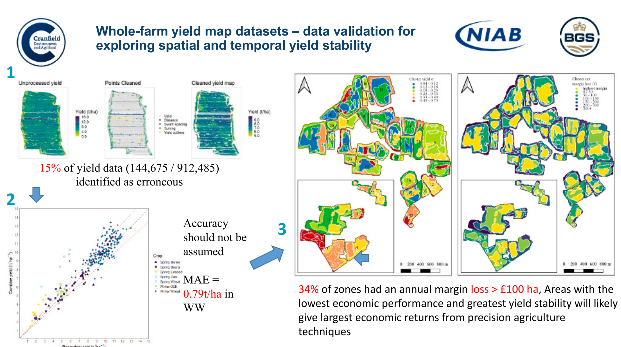
HIGHLIGHTS

- Whole-farm spatial appraisals are rare and often without yield data validation.
- We processed, validated and analysed a ten year whole-farm yield map data set.
- Wheat yield map data had a RMSE of 1.0 t/ha with a mean error of 8.1%.
- 33% of the farm was losing >£100/ha compared to the best performing zone per field.
- Yield data validation is required when developing precision agriculture techniques.

GRAPHICAL ABSTRACT



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ABSTRACT

CONTEXT: Statistical methods used for delineation of field management zones and yield stability are frequently only applied to relatively small areas, with few studies performing rotational, whole-farm economic spatio-temporal appraisals. To enable accurate economic analysis, yield map datasets must contain minimal errors while cleaning procedures are often used to remove errors, it is rare that cleaned data is validated before its application.
OBJECTIVE: The objective of this study was to process, validate and combine spatial statistical approaches for a rotational yield map dataset from a whole-farm across 7 crops in a winter wheat based rotation. Developing a framework for using validated yield map datasets to support precision agriculture techniques that are applicable for farm-level decision making.
METHODS: The rotational completeness of a 10 year combine yield map dataset for a 435 ha farm in Eastern England was assessed. The dataset was cleaned statistically, and its accuracy assessed by comparison with recorded yields from trailer weigh cells. The cleaned, validated, and corrected yield map dataset was used to identify management zones across the whole farm using fuzzy clustering. The temporal stability of management zones and economic performance across the rotation was also assessed.

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RESULTS AND DISSCUSION: Data cleaning methods removed 16% of data points, improving the degree of spatial correlation within the individual yield maps. Independent validation demonstrated varied accuracy of yield maps from combine harvester data and errors in wheat ranged from 0.53 to 1.53 t/ha RMSE. These errors have implications for researchers using combine yield data to develop and validate precision agriculture technologies. This data set required correction before yield data can be applied with confidence for on-farm decision making. Compared to the zones with the highest margin in each field, 34% of zones had an average annual margin loss of >£100 ha. The temporal stability of the resulting management zones also varied. Areas with the lowest economic performance and greatest yield stability across years will potentially see the greatest economic and environmental benefits from precision agriculture techniques.

SIGNIFICANCE: The accuracy of combine yield map data should not be assumed. The application of these datasets, including for the identification of management zones or in developing precision agriculture techniques should attempt to address this through data cleaning and validation procedures. Only then should it be used for on farm decision making, such as identifying areas with the most economic benefit by applying precision agriculture tools such as variable rate nutrient applications.

1. Introduction

The influence of soil properties on agricultural productivity usually shows structured or periodic temporal and spatial variation (Shaddad et al., 2016). It is therefore practical for farmers to divide fields into management zones (MZ) to account for this variation, potentially adjusting fertilizer, pesticide inputs or field operations to better suit the soil or potential yield of the zone (Milne et al., 2012). Identifying MZ can be achieved through measuring spatial variation in soil properties and adjusting inputs based on known crop responses to the quantified properties (Lark et al., 2020). Soil sampling in a random or grid scheme that is subsequently interpolated using geostatistical methods to provide spatial information about soil properties is one way to achieve this (Marchant et al., 2012). 'On the go' sensors such as those recording soil electrical conductivity (James et al., 2003; Moral and Terrón, 2010) and gamma ray spectrometry (Dierke and Werban, 2013; Kassim et al., 2021) offer increased sampling density at relatively low cost and are therefore being increasingly used to delineate MZ. A limitation of these techniques is that it is assumed they sufficiently reflect those soil properties that are responsible for variation in crop yield and that therefore farmers would benefit economically from site specific management through either increased yields or reduced inputs. For MZ to be advantageous there should be a strong and consistent relationship between soil properties and the spatial and temporal patterns in yield (Guastaferro et al., 2010). These patterns in yield may also be impacted by other factors outside soil-climate interactions, for example spatial pattern in agronomic factors such as weed, and pest pressures (Metcalfe et al., 2019).

Yield maps have been used to interpret spatial and temporal yield trends since their early adoption (Blackmore, 1999). More recently, farmers have compiled datasets having sufficient yield observations to allow spatial yield variability and temporal yield stability to be captured across rotations (Maestrini and Basso, 2021). Geostatistical methods for identifying spatially coherent MZ from combine harvester yield data often use non-hierarchical fuzzy clustering and spatial smoothing approaches to ensure that zones are spatially coherent and are of practical use in farm management (Milne et al., 2012). The identification of MZ through clustering identifies homogenous yield zones that are significantly distinct from others. However, this provides little context for variation in the magnitude, scale or stability of yield without further investigation (Maestrini and Basso, 2021); this being a key influence on MZ-specific operations (Khosla et al., 2010; Muhammed et al., 2016). Identifying MZs where yield is consistently temporally higher or lower can allow for strategic soil and/or agronomic management that is proportional to the yield and economic trend (Basso et al., 2011). Management zones with unstable yield trends over time may need more reactionary approaches that consider seasonal influences using remote sensing or crop and soil modeling (Maestrini and Basso, 2018).

Statistical criteria used to assess the yield stability and/or management zone identification using yield maps are frequently applied at a sub-farm spatial scale (Cammarano et al., 2020; Bazzi et al., 2015) and over a large selection of fields across many farms (Maestrini and Basso, 2018). Applying the zoning across whole farms and rotations are less common. Studies of spatial-temporal yield patterns across whole farms commonly only focus on a single crop (Filippi et al., 2019; Kharel et al., 2019; Oliver et al., 2012) offering little context to the overall rotational productivity and stability of an area.

More recently field level economic information such as fixed and variable costs and grain market price has been incorporated to produce multi-field economic appraisals, identifying economically optimal areas for delivering ecosystem services and precision agriculture techniques (Adhikari et al., 2023; Capmourteres et al., 2018). In addition to economic appraisals researchers and farmers are increasingly relying on combine harvester yield data to support more complex processes such as the spatial calibration and validation of crop simulation models at a management zone level (Cammarano et al., 2020; Wallor et al., 2018), conducting on-farm field experiments (Marchant et al., 2019) or validating remote sensing technologies (Maresma et al., 2020).

Systematic and operator error can lead to inaccuracies within combine yield data (Arslan and Colvin, 2002; Blackmore and Marshall, 1996; Robinson and Metternicht, 2005). This can be addressed using a range of methods to remove outliers and erroneous points and has led to the development of data cleaning protocols (Sun et al., 2013; Vega et al., 2019) and software (Sudduth and Drummond, 2007). It is often assumed that after cleaning procedures this represents a true reflection of the yield. However, systematic errors within the data sets can occur (Morgan, 2020; Simbahan et al., 2004)in some cases deviating by 5–10% (Grisso et al., 2002; Morgan, 2020). Validating combine yield data with independent yield data is scarce. In the few cases where validation occurs this has been performed under controlled conditions on small data sets collected under optimum use and calibration (Arslan and Colvin, 2002; Grisso et al., 2002; Morgan, 2020). These conditions are unlikely to represent inaccuracies resulting from commercial combine yield data typically used in research and for decision making on farm. For greater levels of accuracy appropriate calibration using specific manufacturer recommendations is crucial. In most studies using combine yield data it is rare for details of calibration procedures to be described. However, calibration procedures are often skipped or not possible during harvest under time and resource pressures. Previous studies have concentrated on each aspect in isolation such as data cleaning or management zone formation/stability analysis or economic mapping or accuracy validations. Our work integrated all these components into a comprehensive framework. This framework considered these different sources of error so that accurate yield data is used in spatio-economic appraisals or for supporting precision agriculture technology such as validating crop model outcomes. Accounting for all these errors avoids erroneous outputs or misguided management decisions. Specifically, the framework demonstrated how long-term, rotational yield map datasets can effectively underpin the application, development, and monitoring of precision agriculture techniques. The framework used a long-term yield map dataset for an entire farm in Eastern England. The dataset was cleaned statistically and evaluated by comparison with recorded field yields. Management zones were identified across the whole farm using the corrected dataset and their temporal stability was assessed along with the economic margins across rotation.

2. Materials and methods

2.1. Study site and data sets

The study was conducted across 35 fields at Lodge Farm, Westhorpe, Suffolk, UK (Lat: 52.262837, Lon: 1.005092), with a total farm area of 457 ha. The soils range from a clay loam to sandy clay loam (Ashley and Beccles 1 associations, Cranfield University 2022). The farm operates a twelve-year rotation comprised of first and second wheats (*Triticum aestivum*) with spring barley (*Hordeum vulgare*), spring beans (*Phaseolus vulgaris*), winter oilseed rape (*Brassica napus*), and a two-year grass seed crop (*Lolium perenne*) as break crops, in this context these are defined as non-cereal crops. In addition, spring oats (*Avena sativa*), spring linseed (*Linum usitatissimum*) and spring wheat (*Triticum aestivum)* have also been grown intermittently. For each field, operations, fertilizer and pesticide inputs and management costs were recorded by the farm. The mean market value (grain price) that outputs were sold for, by year was also recorded. This enabled the profitability (net margin (£ ha^{-1})) for each location within a yield map to be calculated. Over a ten-year period (2011−2020) 258 yield maps were collected using a combine harvester equipped with yield monitoring capabilities. Two combine harvesters were used, a CLAAS 570+ from 2011 to 2014 and a CLAAS 760tt from 2015 to 2020. The yield monitoring equipment was calibrated at intervals throughout the seasons, primarily when switching between varieties within crops or between different crop types and is likely representative of typical on-farm use. At each yield point the combine harvester records a time stamp and grain moisture content. In addition to yield maps, total grain offtake was recorded for each field using an RDS Liftlog weighing system fitted to the grain trailers. These were calibrated using a public weighbridge and provide an accurate record of total field crop offtake (tonnes) at harvest grain moisture. The spatial and temporal completeness of the dataset was assessed in two ways: i) the number of yield maps were recorded for each crop for the harvestable crops grown, and ii) the proportion of spatially mapped farm margin was recorded from arable operations for the ten-year period.

2.2. Yield data cleaning

Yield data cleaning is required to identify and remove points that are unlikely to hold an accurate representation of yield and will therefore lower the accuracy of the yield map and any subsequent analysis. These points are most easily denoted through identifying points recorded outside optimal combine harvester operation or expected yield values. The time stamp recorded for each field yield point was used to provide the combining sequence for each yield map. The sequence was split at data points recording a change of direction that exceeds 0.6 rad (34.4°) (Kindred et al., 2016). These points are recorded as the combine harvester turns out of, or into, each transect (swath) and were removed. The point preceding and succeeding these points were also removed to exclude points with yield values obtained as the combine harvester fills and empties at the beginning and end of a respective transect (Sudduth and Drummond, 2007). Points recorded at combining speeds in excess of 10 km/h were also deleted as these are considered outside realistic optimal working speeds. Very short swaths (< 3 yield points) were also removed as the combine harvester has likely not reached optimal grain flow operation over a short distance. The distance to the closest parallel swath was further calculated for each point. The mean yield and distance to adjacent swath was also calculated for each swath. Any such transect with a mean distance <5.5 m (2 m less than header width) to the closest adjacent transect was identified as a potential partially filled swath. Then, to avoid the closest full swaths to the partial swaths being also identified, only swaths with a yield 10% below or above the field average swath yield for the field were removed. The final cleaning stage was to remove data outliers. Firstly, all points lying well outside expected yield values (<0.1 or > 18 t/ha) were removed. Secondly, all points that were greater or less than the mean field yield, plus or minus 2.5 standard deviations respectively were also removed. This is threshold is often applied for outlier identification in yield maps data sets (Córdoba et al., 2016; Muhammed et al., 2016; Sun et al., 2013).

The success of the cleaning process was then assessed by comparing the points removed for each step, and the effect that this had on the mean field yield. An experimental semi-variogram was also used to quantify the spatial correlation evident within each yield map, prior to and after the cleaning process. Spherical, exponential and gaussian models were used to fit the semi-variogram, and the model with the best fit selected and recorded for each field year. The relative structural variability has been used to determine the success of data cleaning in other studies (Vega et al., 2019). However, this method fails to include the range of spatial correlation, which might only be a few meters, implying little spatial correlation between nearby yield points regardless of the nugget to sill ratio used in the calculation. Here, we measure the degree of spatial correlation by considering the ratio of the area under the variogram to the area of the pure nugget model with the same sill variance up to 40 m. The 40 m threshold was used for all yield maps as some degree of spatial correlation is expected but is also of adequate distance to feature sufficient yield points. It is also the same threshold that other spatial variation statistics for yield maps have used (Peralta et al., 2013). The values reported are 1 minus the ratio, so a higher value indicates a higher degree of spatial correlation at a distance 40 m.

2.3. Yield data validation

To create co-located yield measurements across years, a 10 m × 10 m grid was imposed over each field area. Cleaned yield and corresponding moisture content in each year were assigned to their nearest grid cell, and if more than one measurement was found within a grid cell the mean of all points within that grid cell was calculated. Applying data to a grid prevents areas having a potentially greater density of yield points, for example if combine speeds were slower in certain areas of the field (e.g. due to lodging), having a disproportionate impact on the mean yield for that combine yield map. A Combine Yield (CY) mean for each field was calculated using the mean of all grid cell yields. Yields were not adjusted for moisture at this stage so they could be compared to yields recorded by the grain trailer weigh cells which recorded weights at the actual moisture content at harvest. Some yield maps displayed areas of fields with gaps (no yield points). Field years were discarded from the analysis if large areas of missing data were found to be due to recording error, for example if the yield monitoring software was not engaged or a field trial had taken up a large area of the field. Also, gaps in the data identified through consultation with the farmer as having been a result of 'failed' or 'unharvestable' crop were treated as zero yields, these gaps often arose as a result of crop destruction prior to harvest to minimize grass weed return. In these maps a field average CY would likely overestimate yield as these zero yields do not feature in the mean. To mitigate this, the CY average for these fields was calculated by dividing the total offtake (the combine yield map average yield, multiplied by the total area of the yield map) by the true field area. Trailer Weigh cell Recorded Yield (RY) was then calculated by dividing total crop offtake (t) by the recorded sown crop area (ha). The accuracy of CY compared to RY was assessed for each crop. For winter wheat, which had the greatest number of fields in each year (>10), the accuracy over time was also assessed. The Root Mean Square Error (RMSE), Mean Bias Error (MBE) and Mean Absolute Error (MAE) were used to evaluate combine yield monitor accuracy compared to recorded yields. These were calculated by:

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}\left(X_{RY,i} - X_{CY,i}\right)^2}{n}} \tag{1}$$

$$\mathrm{MBE} = \frac{1}{n}\sum_{i=1}^{n}\left(X_{RY,i} - X_{CY,i}\right) \tag{2}$$

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}\left|X_{RY,i} - X_{CY,i}\right| \tag{3}$$

where, n is the number of yield maps, X_{RY} is the recorded field average yield (t/ha), and X_{CY} is the combine field average yield (t/ha). The mean percent error was also calculated from the MAE and the RY.

2.4. Yield correction and gridded net margin

To account for large errors in the dataset, gridded yields were adjusted so the mean of the CY equaled the mean of the RY for that field. Corrected points were then adjusted to an industry standard of 15% moisture for cereals and pulses, and 9% moisture for oilseeds. This adjustment used the corresponding gridded moisture content recorded by the combine. For each yield value, moisture adjusted yields were normalized to have a mean unit variance ($\mu = 0$, $\sigma = 1$) to allow for comparison between years and different crops.

Net margin (NM) (£) for each grid cell in each year was calculated using the following formula:

$$\mathrm{NM} = \left(\mathrm{Y_{CY}Gp}\right) - \left(\mathrm{Fc} + \mathrm{Vc}\right) \tag{4}$$

where $\mathrm{Y_{CY}}$ is the grid cell corrected and moisture adjusted yield recorded by the combine yield monitor (t/ha), Gp is the grain price (£) for that crop achieved on farm that year, Fc is the fixed costs (£) (including machinery depreciation, and land rent) and Vc is the variable costs (£) (seed, pesticides, fertilizers and machinery operations). All Fc and Vc are actual costs incurred on the farm for inputs and machinery costs for a given season, not values derived from an industry standard reference material such as the John Nix Farm Management Pocket Book (e.g., Redman, 2015).

2.5. Clustering and yield stability analysis

Spatially coherent zones of homogenous yield performance for each field were identified using the Fuzzy c-means clustering algorithm with optimal completion strategy as outlined by Hassall et al. (2019) was employed. The Fuzzy c-means algorithm was used to identify clusters within the standardized yield dataset, the auto completion strategy of which allows for the algorithm to be run on locations (grid cells) when a complete set of yield observation is not available. In long term datasets such as this study this can be a high proportion. Normalized classification entropy was used to identify the appropriate number of clusters. The number of clusters was restricted to between 2 and 6 to avoid a high number of clusters having only subtle yield variations, with cluster entropy used to distinguish the optimal number clusters. Clusters were then smoothed using a coherence index and variogram.

The temporal yield stability for each grid cell was identified using the methods set out by Maestrini and Basso (2018) and thresholds reported by Maestrini and Basso (2021). The mean and standard deviation of the normalized yields across all available years for every grid cell was calculated. A grid cell was classed as stable if the mean SD of all grid cells within that cluster was <0.8, and unstable if SD >0.8. The stable grid cells were classified as high yielding if the standardized mean yield was >0.2, or low yielding if the standardized mean yield was <-0.2, and those falling between these boundaries classed as medium. These thresholds were identified by Maestrini and Basso (2021) using a simplex search procedure to ensure repeatability regardless of what years yield map data was included in the analysis. No thresholds for categorizing cluster, rather than grid cell, stability have been previously reported. Therefore, to provide context to cluster stability, the standard deviation of the mean standardized yield across seasons for each cluster is reported.

Table 1
Number of field years and number of yield maps for each crop across the 35 fields (2011–2020). Margins are reported as a % of the total farm net margin for each crop (2011–2020). Financial (£) data not presented for data protection. Margin contribution is the total contribution that the crop has made to total farm profits. Margin mapped is the percent of which this has been spatially mapped through yield maps.

Crop	Field years (n)	Yield mapped (n)	Margin contribution (%)	Margin mapped (%)
Winter Wheat	186	172	54	48
Spring Barley	31	30	7	7
Spring Beans	22	19	3	2
Winter OSR	21	19	7	6
Spring Linseed	21	12	3	1
Spring Oats	5	4	1	1
Spring Wheat	2	2	1	1
Herbage Grass	55	0	25	0
Other crops	2	0	1	0
Total	345	258	100	65

3. Results and discussion

3.1. Spatial data availability across rotations

Between 2011 and 2020 harvestable crops were grown in 345 fields, and the yields spatially mapped in 258 (75%) (Table 1). A large proportion of the fields missing yield maps were found to occur when fields were cropped with herbage grass seed. Combine yield monitors do not currently reliably measure yields for this crop as combining takes place at high seed moisture content and lodging is often widespread. The 258 yield maps accounted for 65% of the total farm margin (2011–2020), with over one third of the total farm net margin (2011–2020) unable to be spatially allocated. In this study herbage grass accounted for just 16% of crops grown but 25% of the total farm margin. These data gaps, place limitations on the confidence in spatially mapping productivity for rotational management decisions, particularly if, as is the case in this study, a high value, rotationally valuable crop is not spatially mapped. This will likely be representative of the situation on many UK farms. In 2020, 15% of the total cropped area was in crops not widely spatially mapped (DEFRA, 2021a, 2021b), a large proportion of these where high value potato and vegetable crops (El Chami and Daccache, 2015). The reason for areas having relatively poor economic performance in a combinable crop might not follow the same patterns of spatial variability in crops that are biologically very different, such as root or horticultural crops (Boubou, 2018). The true rotational value of these area/zones could therefore be undervalued.

For precision agriculture the spatial patterns identified in combinable crops is likely to provide sufficient contextual information to enable management decisions for that crop alone. However, land managers are now being incentivized to take areas of land out of production across rotations to support environmental schemes. Under a re-design of the European Union's Common Agricultural Policy, farmers will be encouraged to devote between 3 and 7% of their land to non-productive schemes (European Commission, 2023). In England under the Sustainable Farming Incentive as currently outlined, this area will be between 5 and 10% of land entered (DEFRA, 2021a, 2021b). Yield maps, and the economic productivity maps derived from them, can be used to undertake cost/benefit analysis by growers to identify areas that are

Table 2
Yield map cleaning results including data points removed in each cleaning step, valid points retained, mean yields before and after cleaning (t/ha) and the degree of spatial corelation (DSC) for all raw (unprocessed) and cleaned yield maps by crop.

Crop	Raw points	Swath spacing	Turning	Yield outliers	Distance	Total removed	Valid	Raw yield	Clean yield	Raw DSC	Clean DSC
Winter Wheat	586,742	5788	55,186	23,963	915	85,852	500,890	9.80	10.52	0.07	0.24
Spring Barley	128,631	1617	11,150	5395	150	18,312	110,319	7.92	8.57	0.06	0.25
Winter OSR	62,580	3602	8240	2107	74	14,023	48,557	4.75	5.29	0.07	0.25
Spring Linseed	57,298	2319	7813	2026	267	12,425	44,873	3.35	3.79	0.12	0.26
Spring Beans	49,246	132	4895	2389	31	7447	41,799	3.93	4.26	0.07	0.24
Spring Oats	17,702	992	3318	597	58	4965	12,737	6.94	7.80	0.05	0.22
Spring Wheat	10,286	37	1129	480	5	1651	8635	5.28	5.89	0.17	0.36
All (n258)	912,485	14,487	91,731	36,957	1500	144,675	767,810	–	–	0.09	0.26

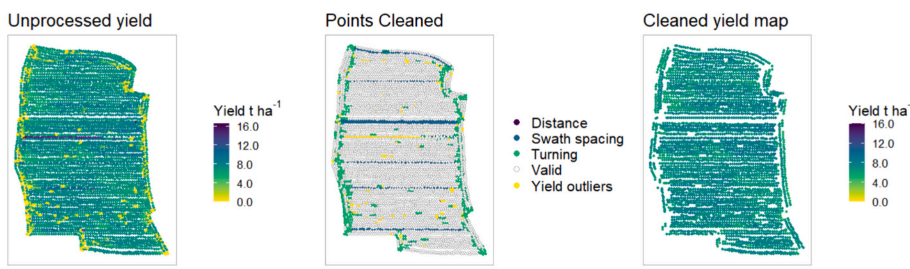

Fig. 1. Yield map cleaning example, Field 4, 2015 winter wheat.

economically likely to obtain the best returns from these schemes (Capmourteres et al., 2018). However, gaps in spatial productivity data as described here will limit the applicability of these "precision conservation" approaches.

An incomplete record of spatial productivity across a rotation also imposes limitations of some precision agriculture techniques. Crop-soil nutrient cycling models developed using experimental plot data could be extrapolated to guide precision management decisions. These models often require a complete across-season record of crop offtake (yield) in order to perform correctly (Shan et al., 2021). Even simpler nutrient removal calculations based on grain analysis or standard figures (Inman et al., 2005) will have significant limitations with large gaps in the data set (Longchamps et al., 2022). The limitations of rotational data sparsity will need to be addressed for complete nutrient budgeting to be achievable, either through yield mapping of all crops across the rotation or using other sources of information to fill in the data gaps, such as remote sensing and crop modeling techniques (Jeffries et al., 2020; Pasquel et al., 2022).

3.2. Data cleaning

Across the 10-year period, the farm collected 912,485 individual yield data points. Across all crops, 16% of points were identified as erroneous through the cleaning procedures and were removed (Table 2), an example field prior to and after cleaning is shown in Fig. 1. Spring linseed, winter oilseed rape and spring oats had a higher proportion of errors (22% and 28% respectively). The cleaning process increased the yields on average in all crops; for winter wheat, field mean yields increased by 0.72 t/ha after cleaning. Across all yield maps the degree of spatial correlation was found to improve following data cleaning, increasing from 0.09 to 0.26 across all crops. Spring wheat presented the greatest degree of spatial correlation after data cleaning (0.36), although from a relatively small sample size ($n = 2$). The degree of spatial correlation at 40 m was found to be relatively consistent across all other crops, ranging from 0.22 to 0.26. Previous studies have shown that large errors in yield maps can occur, and cleaning is advantageous (Blackmore and Marshall, 1996; Sudduth and Drummond, 2007; Vega et al., 2019). The identification of areas of similarity (management zones) relies on the data having a certain level of spatial correlation, the larger degree of spatial correlation achieved through cleaning indicates that

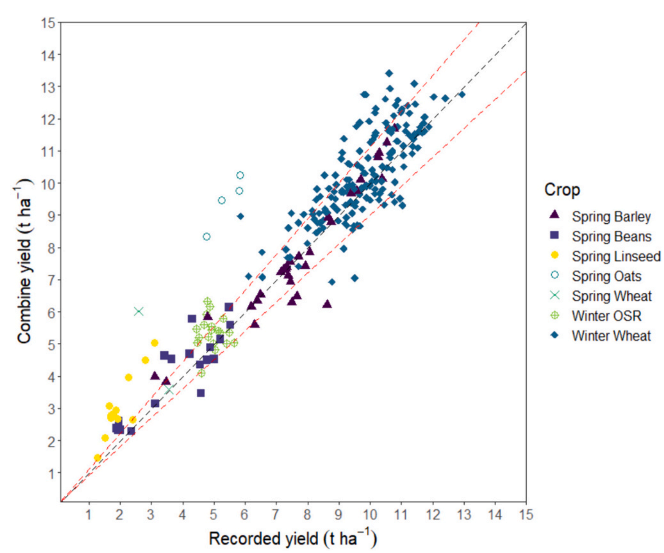

Fig. 2. Average field yield from recorded and. Combine harvester yield monitor (t/ha), grey line is y = x, red line is y = x plus and minus 10% error. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

geostatistical prediction (in this study through clustering) is likely to be more accurate than if performed with raw yield map data (Schabenberger and Pierce, 2001).

3.3. Yield map accuracy

All crops except for spring barley had CY mean yields higher than RY, with an MBE of 0.46 t/ha for all winter wheat crops (Fig. 2 and Table 3). The accuracy of the combine yield maps varied depending on crop. The MAE as a percent of mean recorded yield (%E) was 8.1% for winter wheat and 6.0% for spring barley, representing 63% of crops grown across the rotation. The reported accuracy of yield monitor data by manufacturers has been found to vary between 1% and 6% (Arslan and Colvin, 2002; Blackmore and Marshall, 1996; Blackmore, 1999;

Table 3
Summary statistics for combine harvester mapped yield and recorded yield.

Crop	Year	n	Recorded mean yield	Combine mean yield	r	MBE	MAE	%E	RMSE
Spring Barley	All	30	7.79	7.77	0.94	−0.02	0.47	6.0	0.69
Spring Beans	All	19	3.73	3.98	0.90	0.25	0.48	12.9	0.63
Spring Linseed	All	12	2.01	3.06	0.90	1.05	1.05	52.2	1.18
Spring Oats	All	4	5.42	9.45	0.95	4.03	4.03	74.4	4.04
Spring Wheat	All	2	3.07	4.80	–	1.73	1.73	56.4	2.43
Winter OSR	All	19	4.95	5.36	0.02	0.41	0.61	12.3	0.73
Winter Wheat	All	171	9.78	10.25	0.77	0.46	0.79	8.1	1.03
	2011	20	9.54	10.39	0.54	0.85	1.30	13.6	1.53
	2012	20	9.67	10.44	0.26	0.77	0.96	9.9	1.21
	2013	11	9.74	9.81	0.65	0.08	0.69	7.1	0.93
	2014	13	11.30	11.47	0.64	0.17	0.43	3.8	0.60
	2015	17	11.05	11.81	0.03	0.76	1.20	10.9	1.39
	2016	21	8.68	8.76	0.88	0.08	0.51	5.9	0.64
	2017	18	10.34	10.16	0.84	−0.18	0.37	3.6	0.53
	2018	16	8.40	9.20	0.56	0.80	0.92	11.0	1.16
	2019	20	10.58	11.22	0.91	0.64	0.71	6.7	0.84
	2020	15	8.85	9.28	0.76	0.44	0.66	7.5	0.80

n = number of fields, r = correlation coefficient, MBE = mean bias error, MAE = mean absolute error, %E = mean percent error, RMSE = root mean square error.

Blackmore et al., 2003; Larscheid and Blackmore, 1996). The mean percent errors for winter wheat and spring barley of 8.1% and 6.0% respectively, are comparable to errors reported in previous, smaller validation studies. (Grisso et al., 2002) reported errors of 10%, while (McNaull and Darr, 2020) found mean field yield errors of around 5% for a single cropping season calibration study in corn (maize) and (Morgan, 2020) reported a 5.7% mean error over two seasons for wheat. Accuracy decreased to 12.3% and 12.8% for winter oilseed rape and spring beans respectively. The greater inaccuracies in these two crop types are likely to be a result of larger variations within the field due to agronomic and external (pest damage) pressures experienced in these crops (Ortega-Ramos et al., 2022; Wright, 2008). The accuracy of spring linseed, spring oats and spring wheat was very poor, with differences between RY and CY of 52.2%, 74.4% and 56.4% respectively. These crops are not part of the main rotation, the farmer in this study acknowledged that it is possible that yield monitoring equipment calibration was not as rigorous prior to the harvesting of these crops as they were not considered of long-term importance to the farm, this may explain the much larger errors in these crops. It is not possible to provide evidence of the calibration steps taken for each yield map across the ten-year dataset, nor would it be for most studies using yield map data. It is likely that during harvest, a time-pressured operation, with work rates optimized to maintain efficiency, that occasionally yield monitor calibration procedures can be missed, or operational errors occur. This study presents a real-world data set, that is likely to be comparable to those collected under commercial farms in the UK and globally. Generally, in the main combinable crops (wheat and barley), yield map accuracy was good, however with potential for large errors were present, with 29 out of the 171 wheat fields (17%) presenting errors >15% (Fig. 2). These large errors will have significant limitations for their use on farm, reducing the accuracy and effectiveness of the methods discussed previously including spatial economic analysis and nutrient budgeting.

These reported errors would also have implications for the use of yield map data for implementing PA technologies. It is common to use combine yield data to calibrate and validate modeling and remote sensing techniques. For a model/technique to be appropriately assessed, high quality "observed" data that is free from errors is required (Boote et al., 2016), particularly when identifying the best performing from a selection of models/methods. For remote sensing applications (Zhao et al., 2020) reported an RMSE of 0.88 to 1.44 t/ha when comparing 6 canopy indices derived from Sentinel 2 data with yield monitor data. (Wallor et al., 2018) used yield monitor data to assess the accuracy of 11 crop simulation models for modeling within-field variation in yield, reporting a RMSE ranging from 0.5 to 3.5 t/ha for a field in Germany. There is nothing to suggest that the yield map data in those studies has the same level of errors as the dataset reported in this study. However,

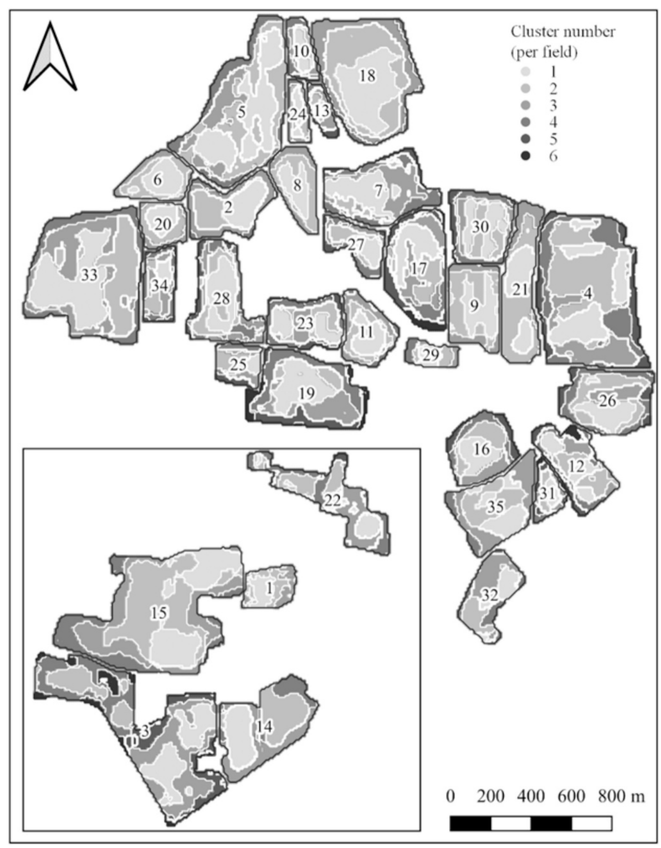

Fig. 3. Clustering results for each field, with field number, grey scale is used as no significance in cluster number between fields.

the errors in modeling techniques reported in these studies are of a similar magnitude to the average errors reported in this study between yield map data and weighed recorded yields for winter wheat across years (0.53 to 1.53 t/ha RMSE). If similar exercises were performed on this data set, there is potential to not identify the best model, but that which is closest to the errors in the validation data set. (Kersebaum et al., 2005) found that when spatially validating the HERMES crop model, results agreed well with hand-harvested yield data, but poorly with combine harvester yield map data, demonstrating the limitations that inaccurate yield map data can pose in modeling exercises.

Researchers and farmers should make use of, and where currently

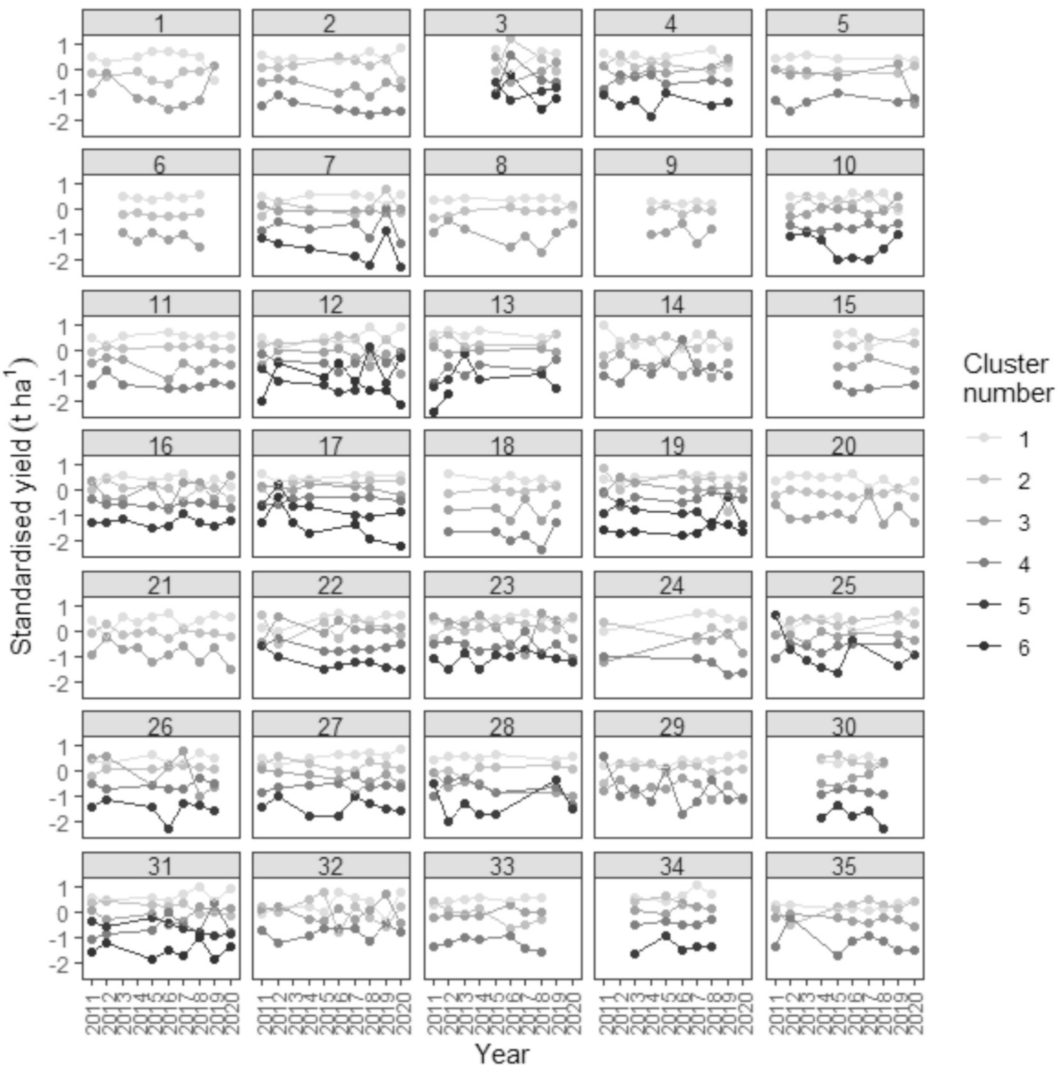

Fig. 4. Standardized (mean unit variance μ = 0, σ = 1) yields for each cluster by field number. Field number can be identified in Fig. 4.

not available commence collecting, data sets to validate combine harvester yield data, including field level yields recorded over weighbridges or grain trailer weigh cells. Studies, using combine yield data would also benefit from reporting the specific calibration methods employed, an exact record of calibration timings would have also strengthened this study. Further development and testing of automatic methods of identifying erroneous yield maps is also required (Blasch et al., 2020). These additional data sources will provide validation of yield map data and where possible allow for some level of correction for large errors, strengthening the applicability of yield maps on farm and in the development of precision agriculture techniques.

To minimize the impact of potential yield map errors in subsequent management zone and yield stability analysis in this study, the field combine yields were adjusted to the mean RY for a given field. This correction assumed that the errors in the yield maps were relative, i.e., consistent across the whole field. The majority (158/258) of CY are within 10% of RY, so adjustments required for these maps were small. The main purpose of this correction is to reduce the influence large errors will have on interpreting temporal trends in yield stability or the accuracy of long-term margin analysis.

3.4. Clustering and yield stability

In this study 159 clusters (MZ) were identified across an entire 35 field, 457 ha arable farm in eastern England using a fuzzy-c means clustering algorithm with an optimal completion strategy (Fig. 3). The optimal number of clusters in each field varied. With limits set between 2 and 6 clusters, no fields had just two clusters, 6 fields had 3 clusters, 12 fields had 4 clusters, 9 fields had 5 clusters, and 8 fields had 6 clusters. The mean cluster area was 2.87 ha. It is recognized that the number of zones and the size of these zones needs to be manageable for a farmer. While its recognized managing 159 individual zones is more complex than 35 individual fields it is by no means infeasible. Recent estimates indicate 31% of UK farms, 36% of farms in the United States and 49% of Australian farms are already using variable rate technology (Lowenberg-deboer and Erickson, 2019). At a fundamental level, yield based management could be employed using the validated and corrected management zone yield performance (Rodriguez et al., 2019), for which there are UK specific nitrogen recommendations (AHDB, 2023). Sampling management zones either at a single composite sample from within each zone (Oliver et al., 2010) or multiple points within each zone to provide some context of homogeneity within the identified zones (Tagarakis et al., 2019). Both methods would also require less samples compared to commercial grid sampling services, typically surveying at one sample per ha (Marchant et al., 2012). In the past, farmers bore the financial burden of adopting PA technologies. However, in the UK, there has been a notable shift, with farmers now having the opportunity to receive payments for implementing PA technologies (DEFRA, 2024). This incentivizes the adoption of these technologies, offering financial support to manage the increased complexity associated with

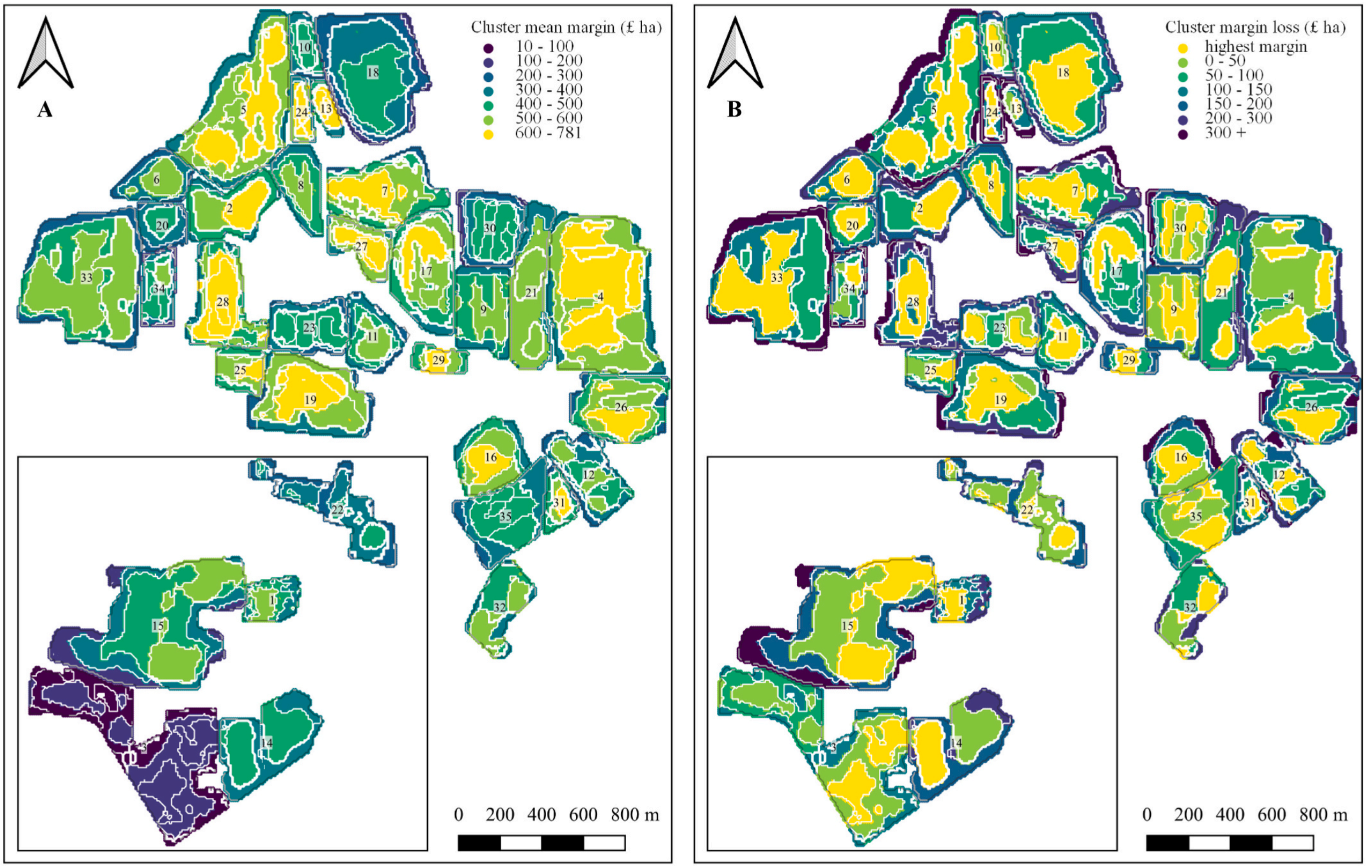

Fig. 5. A: Mean cluster margin across rotation (£ ha, 2011–2020), B: Mean annual cluster net margin loss compared to the cluster with the highest net margin within each field (£ ha, 2011–2020).

transitioning from a whole-field approach to a more nuanced management zone strategy.

Across the rotation, all clusters where profitable, but large variation in cluster performance was recorded with the least profitable cluster recording a mean annual margin of £10 ha, the most profitable with a mean annual margin of £781 ha (Fig. 5). Caution should be exercised when comparing cluster performance across fields. Margins within a field are impacted by the number of data years available for each field, ranging from 4 to 10 years (Fig. 4). Other compounding factors such as different cropping histories, drilling dates, inputs and crop varieties make it difficult to compare cluster margins across fields. Capmourteres et al. (2018) claim to be the first study estimating economic feasibility of set-aside to deliver ecosystem services, using a small sample size of 3 farms across 140 ha in Ontario Canada. More recently Adhikari et al. (2023) produced spatial margin data and stability across 3 fields (56.3 ha) in Texas from 3 years of yield data. In this study a whole farm ten-year rotational margin map across 435 ha in the UK is created, where farmers have the potential to be paid for actions that protect and improve the environment (DEFRA, 2023). There are areas that are clearly underperforming compared to the margin potential for a given field and therefore might be suitable candidates for environmental land management schemes. For example, the most productive zone in field 19 (Fig. 3) has a mean annual margin of £654 (top 5th percentile of all clusters) compared to the worst performing cluster which had a mean margin of £275 (85th percentile of all clusters). This can be compared with the actions that support farmland and wildlife, paying between £590 - £732 ha/per year under the Sustainable Farming Incentive (DEFRA, 2023). Although calculations on the cost of establishment and management of these actions would need to be subtracted and fixed costs accounted for these areas have to potential to be more profitable under agri-environmental schemes. In a high yielding system, with mean wheat yields of 10 t ha (Table 3) however, the profitability appraisal of cropping against environmental schemes is likely to be close and therefore having accurate data that has been under appropriate cleaning and validation to generate such analysis is vital, and to our knowledge this validation applied here is a novel step in the analysis.

As well as identifying areas most suitable for environmental land management schemes whole farm economic assessments such as this provide information to guide more targeted management. All though rotational history make it difficult to compare across zones, it is possible to compare economic performance of zones within the same field (Fig. 5B). Across the farm the highest margin MZ within each field account for 30% of the total farm area (135.0 ha). Over 34% (155.5 ha) of total farm area had a margin loss > £100 ha compared to the most productive (economically) performing MZ within each field, 13% (58.2 ha) had a margin loss > £200 ha and 6% (25.9 ha) had a margin loss >£300 ha.

Across the farm 31% (140.5 ha) of grid cell yields are classified as high yielding and stable, 15% (66.2 ha) as medium yielding and stable, 17% (79.0 ha) as low yielding and stable, and 35% (159.0 ha) of grid cells as unstable Fig. 6. When averaged across clusters mean standardized yield standard deviation is below 0.8 t/ha in all clusters (Fig. 6B). Visually, the rank order of cluster yields tends to be fixed with only a few clusters exhibiting large inter-annual variation in standardized yield performance (Fig. 4). The highest yielding and most stable grid cells are notably concentrated away from field edges (Fig. 6). The lower yields and greater yield instability close the field edges is likely attributed to the presence of headlands where wheeled traffic is more intensive and grater levels of soil compaction is expected (Sunoj et al., 2021), possible shading from trees, and greater weed competition(Robinson et al., 2022). However, yields can sometimes be higher close to field boundaries as a result of helpful ecosystem services (Duelli and Obrist, 2003).

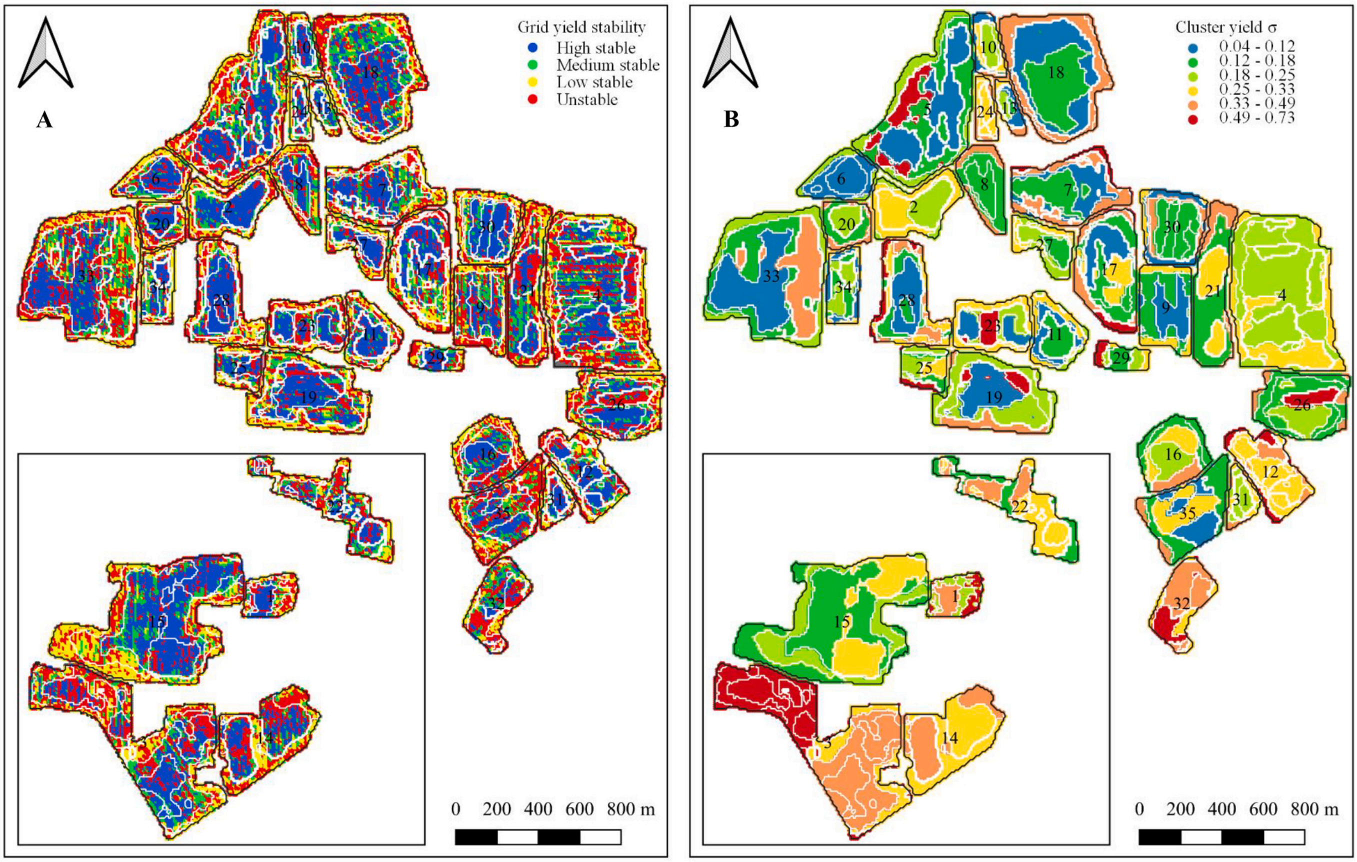

Fig. 6. A: Grid cell yield stability across available years yield data for all fields, B: Standard deviation of cluster mean yields across available years (2011–2021) for each field.

It is recognized that there will always be a certain level of subjectivity to interpreting stability (Maestrini and Basso, 2021). This allows the stability of a MZ performance to be compared with the long-term economic performance. As all management has historically been uniform within a field (no precision agriculture technologies used), net margin maps change proportionally with yield, however it highlights the range of income within fields across the rotation, not just across a single crop or year providing an economic justification for precision agriculture technologies. This rotational validated spatial economic data set is vital for monitoring the success of precision agricultural techniques that might be employed on farm. The benefit of precision agriculture is often inconclusive and further ground truthing is required on many technologies (Ingram et al., 2022; Jin et al., 2019). This need for "validation research" has been recognized in recent perception studies analyzing digital agriculture/smart farming technologies (Ingram et al., 2022; Regan, 2019). Accurate measurements of crop yield is crucial for the science of crop production at the field and farm scale (Sylvester-Bradley et al., 2017). The validated management zone yield performance, stability maps along with spatial economic data provides a framework for the farm to measure the economic success of any precision agriculture or environmental scheme adopted against relative historic economic performance. Precision agriculture techniques might reduce input costs (i.e., fertilizer application) to account for lower yield potential and demand, therefore, yield map patterns will remain unchanged in subsequent years, but the relative economic performance of the zone, in theory will improve.

4. Conclusion

This study has demonstrated how the accuracy of yield map data from a combine harvester after data cleaning steps cannot be assumed, and that any application of yield map datasets, including the identification of management zones in developing and validating precision agriculture techniques should attempt to address this through careful data cleaning and accuracy validation procedures, ideally with the potential to correct for errors. Once the data has been validated and corrected only then the real value can be obtained from geostatistical analysis at the farm level. We advocate for a proactive approach, encouraging farmers to not only conduct proper calibration but also collect data sets for suitable data validation. Allowing for more reliable and robust results in precision agriculture applications and economic assessments. The fuzzy clustering with an autocompletion strategy identified management zones and allowed for yield stability assessed at the farm scale. The data validation and correction allowed for an accurate whole farm, rotational spatial economic appraisal. Such data sets will be key in performing economic cost benefit (compared to continued cropping) analysis of environmental schemes for which farmers will be paid for delivering ecosystem services.

The accurate management zone yield, yield stability, and economic performance data should be used to develop, and access the success of precision agriculture management strategies, particularly those that require the calibration and validation of crop, soil, or nutrient budgeting models.

CRediT authorship contribution statement

David E. Clarke: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Visualization, Writing – original draft, Writing – review & editing. **Elizabeth A. Stockdale:** Funding acquisition, Methodology, Project administration, Supervision, Writing – review & editing. **Jacqueline A. Hannam:** Funding acquisition, Methodology, Project administration, Supervision, Writing –

review & editing. **Benjamin P. Marchant:** Funding acquisition, Methodology, Project administration, Supervision, Writing – review & editing. **Stephen H. Hallett:** Supervision, Writing – review & editing, Funding acquisition, Methodology.

Declaration of competing interest

The authors declare that they have no conflict of interest.

Data availability

Please contact author for data requests. Financial data is business sensitive and will only be shared once permission has been sought from the farm.

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