Variation across scales indicates that best progress in crop yields should come from farmer-centric research

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Abstract:

Four multi-site datasets with 188 to 14,155 wheat yields from the UK showed two- to five-fold variation. This was partitioned using REML into predictable and unpredictable effects, with the latter being ostensibly associated with season (year), and exceeding predictable variation. Of the predictable factors, 'farm' accounted for most variation in each case. Effects of variety choice and other husbandry factors were small. Some of the farm x season variation must have arisen from inter- and intra-field variation as well as from interactions with season; however, the extent of farm-scale variation suggests that progress in yield enhancement must come through research at farm-scale, to understand farmers' attitudes and designs, as well as their soils, environments and husbandry.

Keywords: Yield variation; spatial scale; farmer-centric research; on-farm experiments.

Introduction:

Progress in crop productivity at national (UK), regional (Europe) and indeed global scales falls far short of the rate required to sustain the global population trajectory (>2%/year; Ray *et al*., 2013). Yet estimates of potential crop yields (Foulkes *et al*., 2009) and farmers' best yields (Kindred & Sylvester-Bradley, 2019) both indicate ample scope for yield enhancement. Much store is placed by electorates, governments and crop technologists in digitally-facilitated 'precision agriculture' to effect crop yield enhancement, hence food security (NASEM, 2018; Gove, 2018). However, the precision of husbandry decisions is not, of itself, an obvious precursor of higher yields; evidence that fine variations in husbandry elicit significant yield enhancements is unconvincing (e.g. Kindred *et al*., 2018). So how could precision agriculture bring a resumption of crop yield enhancement in the many global regions where yields have stagnated? The hypothesis explored here is that most controllable yield variation occurs at farm- and field-scale. If this is shown to be true, the main value in precision technologies might be in using them to analyse, understand and prove farm-specific differences; it would seem that digitally-enabled field-scale experiments (Sylvester-Bradley *et al*., 2018) could reveal to each farm its bespoke best practices and system designs.

Several initiatives to enable and develop 'farmer-centric research' are now emerging (Cook *et al*., 2013; EU, 2017; Macmillan & Benton, 2014; Sylvester-Bradley *et al*., 2018), driven by the assumption that development of crop husbandry to increase crop yields must make fastest progress if research is 'up-scaled' such that the scale of yield comparisons becomes similar to that at which most variation arises, particularly anthropogenic variation. Perhaps inevitably, farmers themselves appear to be responsible for making the most influential decisions on crop yields. However, in designing their individual farming systems and imposing their design decisions across whole farms, most farmers confound multiple husbandry choices. So simple analyses of associations between husbandry and crop performance at the farm scale can prove problematic and inconclusive; experimentation is needed. It is thus important to assess the scale at which agronomic research and experimentation should focus. This paper reports an initial attempt at estimating how the evidently large variability in crop yields is partitioned between husbandry factors and across spatial scales. For this initial exercise, the data used were those that describe yields of wheat in the UK and were easily available to the authors. Analyses embrace temporal variation, but this is largely used to provide replication of spatial effects; temporal trends are not considered here.

Data Sources

Four separate datasets were collated describing annual yields of winter wheat in the UK during the past 17 growing seasons (identified by their harvest years). Spatial scales of individual yield values in these four datasets ranged from 50 m^2 to whole tramlines, whole fields or many farms (Table 1).

Table 1. Structure of multi-site datasets describing field yields of wheat in the UK. Note some yield values had missing explanatory data.

Dataset:	**RL**	**LearN**	**YEN**	**Defra census**
Spatial unit	>45 m^2	> 0.2 ha	>2 ha	multi-farm
Harvest years, AD	2002-2018	2014-2017	2013-2018	1999-2017
Regions[1]	7	6	10[2]	11[3]
Counties	28	12	40	NA
Farms	168	17	123[3]	NA
Varieties	118[4]	17[5]	52[5]	NA
No. yield values	14,155	575	587	209

[1] AHDB, 2015 [2] as AHDB but incl. 3 non-UK [3] Defra, 2017
[4] with >60 yield values [5] with >1 yield value

None of the datasets was originally created to study spatial variation; all datasets included missing information and combinations of spatial units and levels of husbandry factors were often incompletely represented. The datasets, with their strengths and weaknesses, were as follows:

(i) **RL** (Recommended List; AHDB, 2018): Approximately 17,500 yields, each being an average of three replicate plots totalling ~50 m^2 of a common variety from each of 477 trials conducted in all harvest years between 2002 and 2018. The trials were sited on ~28 well-managed farms per year in wheat-growing regions throughout the UK. Trials were managed by the AHDB or their agents according to a common protocol each comparing 26-54 (mean 37) varieties to inform variety recommendations and choice. The standard protocol for and data from these trials are publically available via the AHDB website (2015; 2018). The main strengths of this dataset were in its size, hence likely capacity to show multiple effects, its full representation of all UK regions, its standard methodology, and the extent of genetic variation that it addressed. Shortcomings of this dataset were that some soil and husbandry details were not recorded in the early years, varieties changed gradually over seasons, and some farms differed between seasons. To meet the capacity of the analytical software, varieties with less than 60 yield values were omitted from the analysis, reducing the dataset size to 14,155 yields.

(ii) **LearN:** ~580 yields were obtained from farmers' tramline trials, set up to compare effects of different rates of fertiliser nitrogen (N) (Kindred *et al.*, 2018). Yields here were from each of four tramlines per field (~0.2 ha), two treated with the farmer's standard rate of N (ranging from 174 to 352 kg ha^{-1}), one treated with 60 kg ha^{-1} less and the other treated with 60 kg ha^{-1} more. Three tramline trials were conducted on each of about 16 farms in each year over the four harvest years from 2014 to 2017. Farms were selected from 55 candidates, avoiding those with much organic manure use, to provide groups representing land of different soil types across England. The main strengths of this dataset were its inclusion of the same farms over seasons, inclusion of more than one field per farm and season, hence the ability to test for farm and field effects, and intra-field variation, and effects of N fertiliser. Shortcomings of this dataset were the omission of the AHDB's West region, partial confounding of variety choice and manure use with farm, and determination of yields using monitors on harvesters (which may not have been well calibrated).

(iii) **YEN:** 587 yields were collated from farmers' entries in the Yield Enhancement Network's competitions in harvests 2013 through to 2018 (Sylvester-Bradley & Kindred, 2014). Each yield was from an area exceeding 2 ha and often from a whole field; mean area per entry was 15 ha. Fields and husbandry treatments were chosen by the farmers, according to their own experience and advice, usually to represent the best yields from their farm, but sometimes to represent typical yields. Strengths of this dataset were its wide geographical range, representation of real farming conditions, and trustworthy yields (all were from a weigh-bridge and witnessed). Shortcomings of this dataset were in the proportion of husbandry data missing, and the limited number of fields and seasons per farm (Table 1).

(iv) **Defra:** 188 average regional yields were derived from the government census of UK agriculture (Defra, 2018) for harvests between 1999 and 2017; data are routinely collated from ~30,000 farms according to a standard methodology (Defra, 2017) but the smallest production unit of published data is a region; individual farm yields are not published. The majority (>98% by area) of wheat grown in the UK is sown in the autumn but these national and regional yields include small areas of spring-sown wheat. This dataset described all UK farms, whereas the other datasets were restricted to farms and farmers engaged with the research community. This dataset was included to compare regional with seasonal variation; clearly it lacks any fine-scale information, so could only be used for this one purpose.

These datasets were analysed using the REML directive in Genstat (Payne *et al.*, 2017) to assess the predominant factors contributing to the variation in yield. Each factor in the analysis was included as a random, rather than a fixed term. The term 'region' was consistent between RL, LearN and YEN datasets, except that YEN data included three additional non-UK regions (Ireland; the Netherlands, and Other); regions in the Defra dataset employed similar sized but slightly different divisions to AHDB regions (Defra, 2017).

Results

All seasons represented in these datasets post-dated the commencement of 'yield stagnation' in the UK (Knight *et al*., 2012) so, although significant seasonal variation was evident, with lowest yields in 2012 and highest yields in 2015, Defra and RL data showed no significant linear trends through successive seasons (Fig. 1), and the other datasets were too short to detect linear trends. Mean yield in the Defra dataset was 7.6 t ha^{-1}, compared to 10.4 to 11.4 t ha^{-1} in datasets which arose from trials and research-centric farms (Table 2).

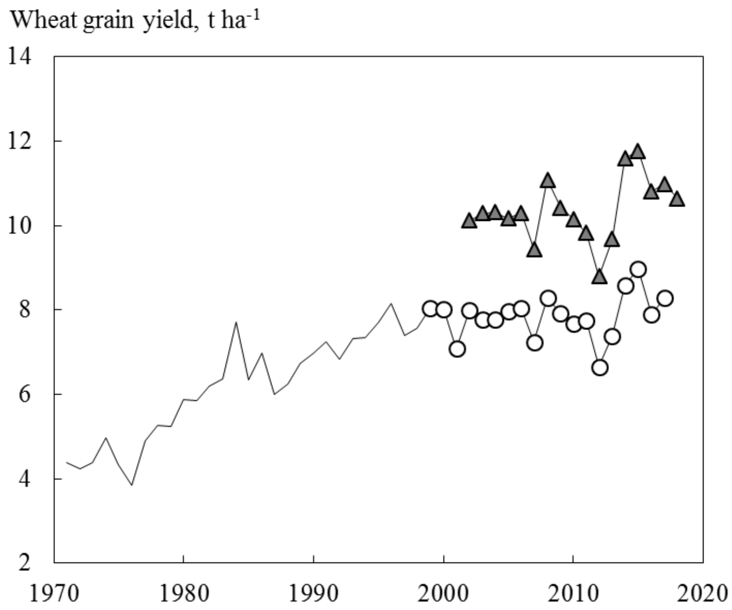

Figure 1. Seasonal yield variation in the Defra (open circles) and RL (closed triangles) datasets. The phase of increasing yields from 1971 is shown for the Defra dataset (no symbol) but was not included in the analyses here.

Table 2. Summary of variation in wheat yields within UK multi-site datasets.

	RL	**LearN**	**YEN**	**Defra census**
Mean yield, t ha^{-1}	10.40	11.43	10.74	7.57
SD, t ha^{-1}	1.82	1.77	1.88	0.84
Max. yield, t ha^{-1}	18.62	16.07	16.50	9.33
Min. yield, t ha^{-1}	3.45	6.56	5.01	4.97

Yield variation in the Defra dataset was significantly less than in the other datasets (Table 2) because of the much larger crop area represented by each value, and the much more numerous source data from which these values were derived. Variation in the other datasets was larger and similar; the range was largest in the RL dataset probably due to the much greater quantity of data. At least a 3-fold range in yield occurred within each of these datasets, with maxima being more than double the national average of 7.6 t ha^{-1} and similar to the world record wheat yield of 16.8 t ha^{-1} harvested in New Zealand in 2017 (Guinness World Records, 2017). This degree of variation appeared to offer ample scope for analysis and attribution to different scales and causes.

Inclusion of the Defra dataset, whilst adding nothing on farm and husbandry effects, allowed a precise assessment of regional effects, with yields in the east and north (8.0 t ha^{-1}) exceeding those in the west and south by 0.9 t ha^{-1}; regional effects were not so clear in the more detailed datasets (Table 3) and although county-level effects may have masked regional effects, county comparisons were not included in analyses here because there were insufficient farms within counties to support separate assessments.

Variation in the three detailed datasets was initially partitioned between factors considered to be unpredictable (i.e. variation involving season, plus residual variation) and factors that are explicable and predictable, or might become so through further research (Table 3). In all datasets, and particularly in the RL, unpredictable variation exceeded predictable variation. Given that there was no systematic replication within any dataset, residual variation was generally small, being comprised of interactions other than those explicitly identified, so season and its interactions with farm and region were largely responsible for the unpredictable yield variation. The origin of this must be not only real interactions with season but also intra-farm spatial variation at field and sub-field scales, especially in the RL where yield values arose from only ~50 m^2 land.

Table 3. Proportions (*V*) of total variance attributed by REML analysis to a range of predictable spatial, agronomic and genetic factors, and to unpredictable (seasonal and residual) effects in four datasets describing UK wheat yields. SE: standard error. NA: factors not included in the analysis.

Dataset	**AHDB RL**		**LearN**		**YEN**		**Defra**	
	V	SE	*V*	SE	*V*	SE	*V*	SE
Predictable								
Region	0.01	0.02	0.00		0.01	0.04	0.49	0.22
Farm (= site)	0.11	0.04	0.22	0.13	0.24	0.07	NA	
Field	NA		0.12	0.06	NA		NA	
Soil type	0.00	0.01	0.00		0.11	0.08	NA	
Previous crop	0.09	0.05	0.02	0.03	0.06	0.04	NA	
Manure use	NA		0.04	0.05	0.01	0.01	NA	
Variety	0.04	0.01	0.03	0.04	0.00		NA	
Variety x Region	0.00	0.00	NA		NA		NA	
Variety x Farm	0.01	0.00	NA		NA		NA	
Fertiliser N[1]	NA		0.02	0.02	0.00		NA	
Unpredictable								
Season (= year)	0.11	0.05	0.22	0.20	0.19	0.13	0.33	0.11
Season x Region	0.05	0.03	0.00		0.00		0.18	0.02
Season x Farm	0.56	0.05	0.17	0.07	0.09	0.06	NA	
Season x Other	0.01	0.00	0.10	0.05	0.01	0.01	NA	
Residual	0.01	0.00	0.06	0.01	0.28	0.13	NA	
Total	1.00		1.00		1.00		1.00	

[1] N policy for LearN (low, normal, high); 50 kg/ha N groups for YEN

The RL dataset was much the largest and so offered most scope to assess the importance of explanatory factors, but in all three datasets ‘farm’ contributed most to the predictable variation (Table 3). In the RL dataset, farm differences contributed 11% of the total variance. Of the farms represented in four or more seasons within the RL dataset, the range of mean yields was from 8.5 to 12.5 t ha^{-1}, and the average SD for these sites was 1.48 t ha^{-1}. Thus, whilst the farm effect was not immediately evident when comparing yields from small parts of individual fields, it nevertheless proved to account for the largest proportion of predictable variance.

Previous crop was significant in the RL dataset, and more important than soil type whereas soil type was more important in the YEN dataset. Variety was a significant factor in the RL & LearN datasets but accounted for only ~4% of total yield variance. Variety was not significant in YEN. The LearN dataset provided replication across tramlines within fields and fields within farms and hence enabled a more precise assessment of effects at farm and sub-farm spatial scales. Both proved important, with the field effect being more certain. Surprisingly, in the LearN dataset, although there were effects of fertiliser N in all tramline trials (Kindred *et al*., 2018), the contribution of N fertiliser treatments to total variance was very small compared to the effects of farm and the large but uncertain effects of season.

As with the RL and the LearN datasets, the effect of farm in the YEN dataset proved as large and relatively more consistent than any other factor examined. There were 123 farms with repeat entries; only 19 of these were responsible for more than 3 entries, and the definition of a farm in the YEN database was more uncertain than in the other datasets. Husbandry factors did not account for significant proportions of the variance in this analysis although analysing factors as fixed effects did show significant associations of yield with soil type, previous crop, fertiliser P, fertiliser N, fungicide use, frequency of plant growth regulator use, use of slurry and form of fertiliser N (Kindred & Sylvester-Bradley, 2019).

Discussion

There is no need for an exhaustive study to reveal how much crop yields vary; farmers, all those that supply them, and all those that they supply, are eminently aware of the extreme variation in crop yields, even in the UK where serious droughts are infrequent. It is an indictment of the farming and crop science industries that much of this variation still remains unrecorded, unanalysed and unexplained. The apparent dependence of yields on seasonal weather, and the focus of research at finer scales, have contrived to thwart the clear assessment, analysis and attribution of yield variation between predictable and unpredictable factors and between different spatial scales, as well as between wide ranging husbandry practices.

All datasets examined here included good representation across regions, and husbandry effects were well represented, yet it is evident that a farm effect was very influential. This was despite farming factors such as soil type, rotation, manure use, varietal choice and fertiliser N use being extracted separately. Of course, intra-field yield variation is also often large, and it is a moot point which of farm-scale or field-scale variation is likely to be the more tractable through research investment. Research into farm effects tends to be problematic because experimentation is difficult, whilst research into variable rates of nutrients or seeds has shown how difficult it is to counteract inherent intra-field variation with single inputs (e.g. Kindred *et al*., 2017). Since yield is a multi-faceted variable, it is likely that future research must go beyond simple conventional considerations of crop genetics, establishment, nutrition and protection. The findings here indicate that farmers' systems, designs and attitudes must be examined for their influences on yield, as well as research at different spatial scales, so that the combinations of factors that account for most of the variation can be identified. Precision Farming technologies are developing apace and, with networks of researchers and farmers working to a common cause, many of these can now be harnessed to facilitate research across scales (Sylvester-Bradley *et al*., 2018; Marchant *et al*., 2018).

Much of the yield variation in all datasets examined in this exploratory study originated at scales of a field or larger. Much larger datasets are now available from farm harvesters so, if calibration and analytical issues can be overcome (e.g. Muhammed *et al*., 2016) and allow robust inter-farm comparisons, further data analyses are justified to validate the primary scales and patterns of yield variation. Clearly, in further analyses, it will be important to recognise that farm differences may be as much due to differences between farmers, their skills, attitudes, motivations and behaviours, as they are due to physical farm differences (e.g. machinery, soils & weather). If the findings here are confirmed, great potential for yield progress should arise through better understanding of farm or farmer-mediated effects on crop productivity.

Conclusions

Given the urgency of increasing food production and the apparent extent of field, farm and farmer effects on crop productivity, compared to say genetic variation, there is a strong case for transferring substantial investments into farmer-centric research. It should be noted that research using conventional small plots is inherently unable to test hypotheses that might explain inter-farm, inter-field and inter-management zone yield effects. It will therefore be important to continue with development of organisations, methodologies and technologies that enable and facilitate research and experimentation at larger scales. The strong influence of 'farm' indicates that these should include analysis and testing of social and behavioural issues as well as physical contrasts. Farmer-centric research has great potential and is required urgently.

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