'Farms like Mine': A Big Data Method in Peer Matching for Agricultural Benchmarking

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Abstract

To find opportunities to improve, in efficiency or performance, farms are often compared on the basis of standard typologies (i.e. categorisations). For example the EU "specialist-cereals-oilseeds-pulses" farm type, known in Britain as "cereals" farms. These categories, being aggregates, contain significant numbers of atypical enterprises. For example, in 2017 there were 30 cattle and 69 sheep on the average "general-cropping" farm in England. This means that comparators are averages across farms with widely divergent scales of different enterprises (and hence farm characteristics), that are not relevant for the comparison. Furthermore, farmers may not necessarily even know their own farm "type" when undertaking benchmarking or comparative analysis. We therefore present a novel method that matches a specific farm against all farms in a survey (drawing upon the Farm Business Survey (FBS) sample), and then selects the nearest "bespoke farm group" of matches based on distance (Z-score) away. Across 34 dimensions, including almost all the enterprises characteristic of English farms, as well as tenure and geographic proximity. Means and other statistics are calculated specifically for that bespoke farm comparator group, or "peer set" of 25 farms or more if less than 1 Z-score away. This generates a uniquely defined comparator, for each individual farm and gives a substantially improved key-performance-indicators for benchmarking purposes. This methodology has potential to be applied across the full range of FBS farm types and across a wider range of contexts.

INTRODUCTION:

Individual farmers face considerable problems when attempting to compare their individual performance with the performance of other farms: every farm is different, with a number of different enterprises, generating a variety of different income streams. However, it is clearly helpful for individual farmers to be able to have some standard against which to judge their performance, in order to identify areas in which they may be underperforming, and thus which aspects of the business that could be improved. Benchmarking (also "Decision Support", Rose and Bruce 2017) is an increasingly popular approach in efforts to enable farmers to increase their incomes and levels of productivity (e.g. Camp 1989, Jack 2009, Vitale et al. 2019, Wilson et al. 2005) or to reduce their ecological footprint (e.g. de Olde et al. 2016, de Snoo 2006, Halberg et al. 2005, Mu et al., 2017). Currently farms are often categorised and compared on the basis of typologies. For example, in the European FADN/RICA classification (European Commission 2013), "Specialist COP" (cereals-oilseeds-pulses, also called "cereals" in Britain) or "Specialist other field crops" (also called "mixed-cropping", or in Britain "general-cropping"). These categories, being aggregates, contain significant quantities of atypical enterprises. Meaning that comparators are aggregates (usually averages), of a number of farms with widely divergent characteristics (in scales of different enterprises), that are often not relevant for the comparison being sought for an individual farm business. For example, there are 30 cattle and 69 sheep on the mean "general-cropping" farm in England. Which will be atypical of most farms - as most (general-

cropping) will have nil livestock and a few may have substantial numbers of livestock. In addition, many farmers may not even know their "type" - or are close to the cut-off point between types. Meaning that the comparator group based on standard typologies may be less appropriate than an alternative grouping of comparator data from within a dataset, but which lacks a typology that closely matches that of the individual farm business. Furthermore, there is a tendency to assume that a farm is "mixed", where there are small numbers within a particular enterprise (to take an extreme example, a farm with cereal crops and a single sheep is not a mixed farm). To address these issues, this paper introduces the innovation of matching to "farms like mine", where matching is primarily on land use areas and livestock numbers contained in farm survey datasets. We thus demonstrate a novel method for the identification of benchmark standards, that can provide more relevant and useful standards for farm management decision-making.

METHODOLOGY:

In the UK, the Farm Business Survey (FBS) has ten "robust" farm types, where type is determined by an enterprise or combination of enterprises that exceed a threshold of two thirds of total farm output. Outputs are standardised to reflect a "normal farm in average conditions" (Defra 2018). For example, Dairy Farms are "holdings on which dairy cows account for more than two thirds of their total Standardised Output (SO)"; Cereal Farms are "holdings on which cereals and combinable crops […] account for more than two thirds of the total SO". A Mixed Farm is effectively a farm that does not fit into any of the other FBS categories, as no single or defined combination of enterprises meets the two thirds threshold (Defra *ibid*). As noted in the introduction, the problem for an individual farm manager is that these farm types may have different characteristics to the farm being managed. For example, Mixed Farms in the FBS can be "mixed" in different ways: the "mean" farm may include a wider range of livestock enterprises, whereas the benchmark farm may only contain a subset of these enterprises. In contrast, we present results here from an alternative methodology, normally used with a small number of dimensions in "clustering" (Piegorsch 2015). That matches farms to all farms in the comparator group (survey sample) and then selects the nearest neighbours (on Z-score) in 34 dimensions. The matching procedure includes almost all characteristic enterprises for farms in England, including additionally tenure and geographic proximity. Means and other statistics are then calculated immediately following the user entering their own farm business characteristic data, which then generates the bespoke "peer set", along with the average data for that peer set. That the user can then compare their own performance to. Peer sets are a minimum of 25 farms in our case (as we have a large sample), or more if the total summed distance is less than one Z-score across the 34D. Euclidean, Mahalanobis, and other distance metrics (incl. Manhattan Block) (Piegorsch 2015) were also tested in the methodological development stage. The Euclidean method was deemed to be optimal, as described below.

Euclidean distances are:

$$d_i = SQRT(SUM(\mathbf{X}_{ij}-x_j)^2)$$

$$x_j = (MyFarm_j-SampleMean_j)/SampleSD_j$$

$$\mathbf{X}_{ij} = (\mathbf{Y}_{ij} - SampleMean_j)/SampleSD_j$$

Where d_i is a vector of 1-to-n sums of normalised distances, away from each farm in the sample of n farms. $\mathbf{X}_{ij}$ is a matrix of j standardised variables (the 34D) by i, the 1-to-n, farms (the sample n). x_j is a vector of the j standardised variables (the 34D) for "my farm" (x). And $\mathbf{Y}_{ij}$ is the matrix of un-standardised 1-to-n sample, i, values (for each j variables). SD is standard deviation. The peer set is then chosen by selecting 25 farms that are the smallest distance away, or within one Z-score (across the 34D).

RESULTS:

The "farms like mine" methodology outlined above generates a bespoke peer comparator data set and hence results from the approach are bespoke to the individual farm business data that users enter into the system. In this section we detail the dimensions of the methodology to demonstrate the breadth of variables that the system draws upon in the generation of a bespoke peer set of comparator data. Specifically, 34 dimensions are chosen (that characterise British farms). Namely: *winter wheat area; winter barley area; spring barley area; other cereals area; oilseeds area; peas beans area; potatoes area; sugar beet area; other arable crops area; fodder crops area; fallow area; uncropped area; temporary grass area; permanent grass area; sole rough grazing principle area; top fruit area; outdoor vegetable area; other male cattle 1 to 2years; other female cattle 1 to 2years; other male cattle over2years; heifers; dairy cows; beef cows; ewes; other sheep; breeding sows*; store pigs*; broilers*; laying flock*; growing pullets*; organic area fully*; EASTING†; NORTHING†; TENANTED_Percentage*

Note that * represents double (2x) weighting within the Euclidean-based optimisation approach, while † refers to weighting at 0.6. These alternative weightings were adopted following extensive testing of the approach in order to appropriately capture and represent enterprises that occur less frequently within the dataset for England that the approach was tested on. The corollary to this is the lower weighting attributed to geographical dimensions. Farms that are geographically far away will be matched very closely on all other dimensions; farms which are in close proximity may diverge more in other dimensions. However, note that the closest matches will be chosen in all cases, ensuring that, where farms match on both enterprise mix and geographical proximity, these will be chosen with the bespoke peer set, in preference to farms with close enterprise mix matches, that are geographically more removed from the individual farm business as entered by the user of the system. The results generated will draw upon a dataset of a minimum of 25 farm businesses. The simplest distance metric (namely Euclidean), on Z-scores (of farms with the enterprise only), was found to be superior to others, in terms of closer peer sets (by inspection). The method has the capacity to provide farmers with better guidance as to how the management and organisation of their business might be improved.

DISCUSSION AND CONCLUSIONS:

This paper has demonstrated a new approach to benchmarking. While this has been applied to farms, there is no reason in principle why it should not be applied in benchmarking in other sectors (like that discussed by: Camp 1989, and ten Raa 2009), from survey or administrative datasets. However, the need for benchmarking in agriculture is clear for a range of reasons.

The rate of productivity increase in the UK is low (Baráth and Fertő 2017). Allowing for uncontrollable farm diversity due to environmental factors - such as altitude, soil type and weather - it is clear from the Farm Business Survey that performance varies considerably between similar farms. BREXIT (Ward 2019) and a potentially more stringent financial environment gives an added urgency to the need to increase farm productivity and incomes, through techniques such as Benchmarking. "Farms like mine" (i.e. matched to closest-peers) gives a better idea in experience here and in principle - because the "peer set" is closer, in scale of type-enterprises, tenure, and proximity, to "my farm" - than industry aggregates, to a farm manager. For example of key-performance-indicators such as cost per unit weight produced - because the comparison is made to a more relevant set than is the case for comparisons with standard farm type groupings. It is thus expected that this method should reduce dispersion in values, and ameliorate systematic bias, (in benchmarking values). From, for example in the presence of farms: in other regions (which differ in climate/ soil/ and market); of other sizes (scales of operation); and in the presence of other enterprises. Which differences will manifest themselves in management effects, too.

In the case of General Cropping farms in particular, average figures, from farms with a large range of enterprises, will compromise the usefulness of benchmark comparisons with farmers' own farm. By contrast, with "farms like mine", these peer sets of more similar farms, as outlined using the approach described here, provide more relevant comparisons.

Options for future development may be: i) selection of different variables for matching, ii) doing more to understand farmers' objectives and developing matching around those objectives (be they climate, farm-income, or economic - e.g. Total Factor Productivity), iii) systematic analysis of the weighting criteria for different variables; iv) more extensive and systematic testing of comparisons, from "peer-sets" with "industry-aggregates"; and v) finding new technologies or enterprises that might be added in particular circumstances - and then extending matching to encompass these alongside the 34 dimensions already included in the approach.

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