Title

Use of bootstrapped, regularised regression to identify factors associated with lamb-derived revenue on commercial sheep farms

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Abstract

The profitability of UK sheep farms is variable with many farms making a net loss. For economic sustainability, farms have to be profitable, therefore it is important to maximise income whilst controlling costs. The most important source of income in sheep flocks is from lamb production but there is little information on factors that explain variability between farms in revenue from lamb sales. The aim of this research was to identify farm, farmer and management factors likely to have the largest, most reliable associations with lamb-derived revenue.

From a population of 830 sheep farms, 408 farmers completed an online questionnaire comprising over 300 variables. Total lamb-derived revenue was calculated for each farm using abattoir information including carcass classification. The median flock size was 560 ewes, median land size 265 acres, median revenue per acre from lambs sold was £197 (IQR=120-296) and median revenue per ewe £95 (IQR=72-123). A robust analytic approach using regularised (elastic net) regression with bootstrapping was implemented to account for multicollinearity in the data and to reduce the likelihood of model over-fitting. To provide model inference and allow ranking of variables in terms of relevance, covariate stability and coefficient distributions were evaluated.

Factors with high stability and relatively large positive associations with revenue per acre were (median effect size (£); 95% bootstrap probability interval); an increased stocking rate of 0.2 ewe/acre (13; 6-17), fertilizer being used on most of the grazing land (18; 0.1-37), the use of rotational grazing (13; 0.3-34), decreased proportion of ewes with prolapses (4; 0.3-9), separation of lame sheep from the rest of the flock (16; 0.9 – 37), selecting ewes for culling based on prolapses (20; 0.2-55) and infertility (20; 2-46), conducting body condition scoring of ewes at lambing (28; 3-58), early lactation (21; 1-54) or weaning (25; 2-70), increased farmer education (20; 2-54) and farmers with a positive business attitude (15; 0.2-38). Additional

factors with a high stability and relatively large associations with increased revenue per ewe were; never trimming diseased feet of lame ewes (9; 0.8-22) and making use of farm records (5; 0.3-12).

This is the first study in animal health epidemiology to use bootstrapped regularised regression to evaluate a wide dataset to provide a ranking of the importance of explanatory covariates. We conclude that the relatively small set of variables identified, with a potentially large influence on lamb-derived revenue, should be considered prime candidates for future intervention studies.

Keywords

Sheep; production; risk factor; elastic net; regularised regression; bootstrap stability

1. Introduction

Concerns remain regarding the sustainability of red meat production in a world with growing demand for food of animal origin (Delgado et al., 1999; Poore and Nemecek, 2018; Tilman et al., 2002) and it is increasingly recognised that farming systems need to be sustainable. Sustainability is commonly considered to comprise three overarching pillars with environmental, social and economic components (Adams, 2006). Whilst environmental and social sustainability are also of the utmost importance, farms also require economic sustainability, that is, to trade profitably over the long term.

To ensure economic sustainability, successful farmers commonly adopt risk mitigation practices. These may include low debt to asset ratios, diversification and taking time to understand market forces. Remaining economically viable over the long term depends on regularly having sufficient income to cover both fixed and variable costs and for UK sheep farms, it is reported that net margins are tight (AHDB, 2016). It is therefore critical to maximise income whilst controlling costs and the most important source of income in sheep flocks is that derived from lamb production (AHDB, 2016). Although many factors are likely to influence the magnitude and efficiency of lamb production few studies have identified factors associated with between-farm differences. Such information would be of substantial benefit to the industry; it could lead to more efficient production, increased revenue and therefore enhanced sustainability of the sheep sector.

Previous reports from experimental studies have identified individual factors that impact on flock productivity, including genetics (Walkom et al., 2016), nutrition (Fraser et al., 2004), disease (Green et al., 1998), and reproduction (Kelly and Johnstone, 1982). However, from such studies it is virtually impossible to identify the relative importance of different factors; this is key for making improved on-farm decisions. A small number of field studies have identified a limited number of factors that influence productivity such as stocking rates (Bohan et al., 2018), farming a greater ratio of cattle to sheep (Townsley and Parker, 1987) and indoor lambing (Doré et al., 1987). However, many drivers of productivity on sheep farms remain unexplored. One recent study of British sheep farms used a more holistic set of variables to evaluate associations between disease prevention strategies and the number of lambs produced (Lima et al., 2019). This study reported that vaccination/anthelmintic strategies, regular weighing of lambs, treating individual lame ewes with an antibiotic injection, and carrying out faecal eggs counts were all associated with increased lamb numbers but the model only explained 26% of total variability indicating that additional factors need to be identified to elucidate this unexplained variation.

Although it appears necessary to widen the search for factors that influence lamb production, when investigating a large number of possible explanatory variables, statistical model construction becomes challenging. Multiple correlations between individual or subsets of variables become more likely and under these circumstances it is known that conventional least squares modelling approaches tend to fail, resulting in inflated coefficients and over fitting (Hastie et al., 2015; Kuhn and Johnson, 2013). Furthermore, as the number of predictors (p) approaches or is greater than the number of subjects (n), parameter estimates may again become unreliable or impossible to make (Hastie et al., 2015; Kuhn and Johnson, 2013). Regularised regression methods can be used to mitigate these limitations and are particularly useful where multiple correlations are present in data or where p~n or p>>n (Tibshirani, 1996; Zou and Hastie, 2005). In brief, these methods contain parameters to penalise model coefficients which means coefficients only become large if there is a proportional improvement in model fit (generally assessed by cross validation error) (Kuhn and Johnson, 2013). The bootstrap is a useful addition to regression modelling, particularly to provide robust coefficient estimates (Breiman, 1996; Dallah, 2012) and allow evaluation of coefficient stability (Austin and Tu, 2004; Hastie et al., 2015).

The aim of this study was to identify influential factors from a large number of explanatory variables that were likely to have the largest, most reliable associations with lamb-derived revenue on sheep farms. To achieve this we implemented bootstrapped, regularised regression (via the elastic net (Zou and Hastie, 2005)) that incorporated both variable stability (an estimate of the likely reproducibility of the effect of each variable in the target population) as well as variable coefficient distributions. We believe this is the first use of such methodology in animal health and production research.

2. **Materials and Methods**

The study was approved by School of Veterinary Medicine and Science Ethics Committee (no: 1537 150907).

2.1. Target population

The target population was commercial sheep farms with ≥50 breeding ewes that supplied homebred, finished lambs to a British retailer through two specified abattoirs (n=830). All farms within the target population were asked to participate by filling in an online questionnaire and by providing permission for the researchers to obtain details of their lamb sales directly from an abattoir.

2.2. Questionnaire design

A questionnaire was developed based on a review of literature. The purpose was to capture a large variety of relevant farm and farmer demographic features and management processes and decisions that could impact lamb production. The questionnaire related to practices implemented between autumn 2016 and autumn 2017. The wording of the questions was formulated according to the guidelines described by Dillman et al. (2009) and questions were mostly formulated in a close-ended format. The visual aspects of the questionnaire were curated according to the visual presentation guidelines from (Dillman et al., 2009) in order to improve the user experience and increase question response rate. The full questionnaire is available in Supplementary Materials, an outline of questionnaire themes is provided below.

2.2.1 Farm characteristics

This section comprised general information about the enterprise including farming system as applicable between autumn 2016 and autumn 2017. It included questions on flock size, breed, type of lambing (indoor/outdoor), area available for grazing, farm altitude (lowland, upland or hill), main farm income streams (e.g. lambs sold for meat production or breeding) and non-sheep related income streams.

2.2.2 Farmer demographic characteristics

Demographic features such as age, gender and education level of the farmer were included in this section.

2.2.3 Grassland and nutritional management

This section incorporated questions on the type of pasture (permanent/reseeded), type of grazing (set stock/ rotational), type of feed available at key stages of the production cycle (e.g. mating, late pregnancy, lactation), use of fertilisers and amounts of concentrate feed used.

2.2.4 Practices at lambing time

Information collected included the month of the year in which lambing started, duration of the lambing period, the number of lambing groups, types of records collected and the number of lambs weaned.

2.2.5 Flock health and disease control practices

Questions were developed to identify actions taken to control or prevent specific diseases including coccidiosis, sheep scab, liver fluke, intestinal endoparasites and clostridial diseases. Estimates were requested of annual disease prevalence for adult ewes (e.g. mastitis, lameness, vaginal prolapses) and lambs (e.g. watery mouth, bacterial arthritis).

2.2.6 Record keeping practices and animal selection criteria

These questions focused on whether specific records were kept (e.g. pregnancy scanning figures, number of abortions, numbers of lambs born alive) and which data were used for selecting animals for sale, breeding and culling.

2.2.7 Animal production data (lamb sales)

Information was collected on the number of lambs the farmer sold as ‘stores’ (lambs sold to be reared elsewhere for slaughter) and as breeding stock. This information was included in the calculation of the metric for flock productivity (Section 2.5).

2.2.8 Farmer managerial beliefs

Based on concepts from previous research and adapted from the work of Mäkinen (2013), Willock et al., (1999) and Nuthall (2001), farmer managerial beliefs were included as twenty statements to capture on the respondents' attitudes towards areas of farm management. The purpose was to identify constructs previously defined as "entrepreneurial orientation", "strategic thinking", "appreciation of profession" and "locus of control". Farmers were asked to describe their attitudes towards specific aspects of farm management that reflected these traits, using a 5-point Likert scale (1 = strongly disagree, 2 = disagree, 3 = neutral, 4 = agree, 5 = strongly agree. The full set of statements and related managerial beliefs are provided in Supplementary Materials Table I.

Latent class analysis was conducted using multivariate normal mixture models (Fraley and Raftery, 2002) to identify groups of farmers with similar managerial attitudes. Latent class models were fitted using the R-package "*mclust*" (Scrucca et al., 2016), the number of classes selected was based on maximising the Bayesian Information Criterion (Fraley and Raftery, 2002). The latent class attributed to each farmer was used as an explanatory covariate for subsequent modelling of lamb-derived revenue. Non-respondents (n=74) were allocated to an "undefined" class to avoid missing data in the final dataset.

2.3. Piloting and distribution of the questionnaire

The questionnaire was pilot-tested with 12 sheep farmers and improvements made to the text. It was estimated that the final version of the questionnaire would take approximately 40 minutes to complete. Farmers in the target population were contacted by the two participating abattoirs through which they sold lambs and asked to join the study. The questionnaire was made available in a specialised platform designed for online surveys (Smartsurvey™), to the entire target population. The questionnaire was available online for

12 weeks (from beginning of November 2017 to end of January 2018) and a reminder was sent to farmers in early January.

2.4. Data cleaning, coding and imputation

A total of 480 responses to the online questionnaire were received but not all were used in the analysis. Thirty farms were excluded because their abattoir data were missing and 11 because flock size was too small (< 50 breeding ewes). Farmers specialised in finishing store lambs (defined as enterprises where the number of store lambs purchased exceeded the number of breeding ewes in 2017) were also omitted (n=24).

The data were checked for outlying or implausible values. A stocking rate above 6 ewes per acre was deemed implausible and more than 1.5 breeding lambs kept per ewe was considered highly unlikely; 7 farms were excluded for one of these two reasons.

Six farms did not provide a figure for flock size and were therefore excluded from the analysis of lamb-derived revenue per ewe. The final dataset comprised 408 sheep farms for Model 1 (outcome; lamb-derived revenue per acre) and 401 observations for Model 2 (outcome; lamb-derived revenue per ewe).

Three explanatory variables with ≥10% of missing observations were excluded ("*Number of rams on farm"*, *"Total number of empty ewes"* and *"% of lambs with scour*"). Of the other variables, relatively few had missing data (n= 31) and these had a very small proportion of missing data points (mean = 1.7%). For these variables, data imputation was conducted using the K nearest neighbours method (Altman, 1992) with the R package "*DmWR"* (Torgo, 2010). Numeric and categorical variables were imputed in separate steps and the number of nearest neighbours used (K) was set to 10 (Troyanskaya et al., 2001).

The total number of all species of animals farmed per acre was converted to livestock units per acre (LU); values of 1, 0.8 and 0.1 were used to convert the numbers of dairy cattle, beef cattle and adult sheep to LU respectively (Eurostat, 2019).

The number of explanatory variables in the final dataset was 193 but since many categorical variables contained multiple groups, the effective number of covariates considered in the final models was 337.

2.5. Estimation of lamb-derived income

A total lamb-derived revenue was calculated for each farm for the year 2017. Lamb-derived revenue for each farm was estimated by adding the different sources of income available to the farm; lambs sold to the abattoir, lambs sold to slaughter elsewhere (i.e. not to the two abattoirs participating in the research), lambs sold or kept for breeding purposes and lambs sold to other farmers for fattening (stores). Most lambs were sold through the participating abattoirs and the value of these lambs was calculated using individual lamb carcass grade, fatness type and non-condemned-weight, alongside weekly mean published prices for lamb deadweight based on carcass conformation (AHDB, 2019a) There were a small proportion of missing data points for some of the less common carcass grade categories (<5% of data points) and these values were imputed using the K nearest neighbours method (Altman, 1992; Troyanskaya et al., 2001). A price reduction was applied to carcasses <15 kg (8% of the carcasses (59,555 of 696,768) and >25 kg (9%, 65225 of 696,768) in line with abattoir policy; a penalty of 32.5 pence per kilo was applied below 15 kg and carcasses >25kg were valued at a weight of 22 kg. In addition, carcasses over one year of age were given a set price of 250 pence per kg, also according to abattoir policy.

The value of lambs sold to slaughter elsewhere was based on the annual mean price paid per finished lamb to that farm for lambs sold through the participating abattoirs (i.e. the same mean value for lambs was attributed as if they had been sold through these abattoirs). The value of lambs sold as stores was based on prices published by AHDB for the mean average monthly price paid for store lambs (AHDB, 2019b). However, no price estimates for store lambs were available for months March to July and therefore the price paid in these months was estimated as the mean price during the months February and August. The value of lambs kept for breeding was estimated using prices from the Livestock Auctioneers Association and attributed as the average price paid in 2017.

A total farm lamb-derived revenue was calculated by summing the value of all lambs sold by the farm in 2017. This value was divided by flock size (number of breeding ewes) to obtain the outcome variable 'lamb-derived revenue per ewe' and separately was divided by the amount of farm area used for sheep production in acres to obtain the outcome variable 'lamb-derived revenue per acre'.

2.6. Statistical analysis

2.6.1. Identification of potential non-linearities and interactions; Multivariate adaptive regression splines (MARS)

Before running inferential elastic regression models, multivariable adaptive regression spline models (Friedman, 1991) were conducted to explore the presence of non-linear and interaction terms within the data. Two separate MARS models were run, one for each outcome variable; lamb-derived revenue per acre and lamb-derived revenue per ewe. The predictor variables used for MARS comprised all variables in the cleaned dataset. The MARS models were constructed using the "*earth*" package (Milborrow, 2019) within the caret package platform (Kuhn et al., 2019) in R (Team, 2018). Ten-fold cross validation repeated 10 times was used to explore a wide set of the two tuning parameters (degree of interactions and number of terms retained in the model, (Friedman, 1991)); the best model was identified as that minimising the mean absolute error (MAE) on cross validation. For both outcomes, no interaction terms were identified and up to 6 variables contained non-linear relationships with the outcome. Therefore to check for non-linear relationships in subsequent elastic net regression models, these variables were included as polynomial terms up to power 4.

2.6.2. Elastic net regression

Since the data contained a large number of explanatory variables (337) relative to the number of farms (408) and was likely to contain multiple correlations, a conventional least squares modelling approach was deemed unsafe since it could be expected to result in substantial over fitting of the models (Hastie et al., 2015; Kuhn and Johnson, 2013). To mitigate this, regularised regression in the form of elastic net (Tibshirani, 1996; Zou and Hastie, 2005) was used. Regularisation works through a penalty term applied to model coefficients, which comprises part of the loss function to be minimised. This has the impact of shrinking covariate coefficients towards zero and limiting model over fitting by i) identifying a relatively sparse model (some coefficients are set to zero) and ii) preventing over-inflation of coefficients. Elastic net incorporates a mixture of two penalty terms, the lasso (known as the L1 penalty; a penalty on the sum of the covariate coefficients) and ridge (known as the L2 penalty; a penalty on the sum of the squared covariate coefficients). The models took the form:

$$SSE_{enet} = \frac{1}{2n} \sum_{i=1}^{n} \left(y_i - \hat{y}_i\right)^2 + \lambda \ [\sum_{j=1}^{P} (\frac{1}{2} \ (1 - \alpha) \ \beta_j^2 \ + \ \alpha \, \beta j \ ]$$

where SSE_{enet} represented the elastic net loss function to be minimised, i denoted each subject (farm) and n the number of farms, y_i was the observed outcome for the ith farm and $\hat{y}_i$ the predicted outcome for the ith farm, λ was the penalisation parameter, j denoted a predictor variable with p the number of predictor variables in total, α was a mixing parameter that defined the relative proportion of penalisation on either the sum of the square of the coefficients (β_2) or the unsquared coefficients (β).

Elastic net models were built using the "*glmnet"* package (Friedman et al., 2010) within the "*caret"* package platform (Kuhn et al., 2019) in R (R Core team, 2014). Before parameter estimation, continuous variables were centred and rescaled by subtracting each from the variable mean and dividing by 2 standard deviations; rescaling variables is important in elastic net regression and this method has been recommended to facilitate direct comparison between coefficients of continuous and categorical variables (Gelman, 2008). The tuning parameters α and λ were optimised by evaluating a dense grid of these terms using 10-fold cross validation repeated 10 times, to identify parameter values that minimised mean absolute error (Kuhn and Johnson, 2013). Model coefficients were extracted at these optimised values of α and λ.

2.6.3. Elastic net bootstrap parameter estimation

The bootstrap (Efron, 1992) has been shown to be an effective method to produce robust estimates of parameter distributions in regression models (Austin and Tu, 2004; Freedman and Peters, 1984), and useful for inference in elastic net models (Hastie et al., 2015). Aggregation of parameters across bootstrap samples has been shown to give substantial increases in accuracy of parameter estimation, particularly in situations where small changes in the data can lead to large alterations of coefficient estimates (Breiman, 1996). In outline, the method involves taking multiple samples of a dataset, with replacement, and estimating model parameter distributional characteristics using parameter values across all bootstrap samples. For our elastic net model, we implemented a previously reported bootstrap procedure (Hastie et al., 2015), as follows;

- A bootstrap sample was selected at random from the full dataset
- An elastic net model was fitted to this dataset using a wide grid of values of α and λ; (α = 0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8. 0.9, 1.0), (λ = 0, 001, 0.25, 0.5, 1, 1.5, 2, 2.5, 3, 4)
- Ten-fold cross validation, repeated 10 times, was undertaken to identify values of α and λ that minimised model prediction error (MAE)
- Coefficient parameter values were returned and stored for these values of α and λ
- The procedure was repeated 500 times and coefficient distributions were estimated by evaluating values across the 500 bootstrap samples.
- The distribution of values for λ were checked post hoc to ensure there was a sufficient range to encompass the optimal value (i.e. the value used to produce a model with the lowest MAE) for each bootstrap sample

2.6.4. Model inference

To facilitate selection of variables most likely to be important in our target population, and to identify a relatively sparse model that retained near-optimal performance, we used two metrics for inference; parameter stability and parameter coefficient distributions. These were estimated as follows.

2.6.4.1. Parameter stability

Using the bootstrap, we estimated covariate stability as the probability that each covariate was selected in the elastic net model (i.e. with a non-zero coefficient), in each bootstrap sample. This was calculated as the proportion of non-zero coefficients that were identified for each covariate across all 500 bootstrap samples. A low stability indicates that a covariate effect is not consistent across all farms because it requires specific farms (or groups of farms) to be included for the covariate to be selected. Conversely, covariates with high stability are selected in the vast majority of bootstrap subsets which indicates a consistent, reproducible effect across most of the data. Therefore, stability in this context gave an indication of the consistency and reproducibility of a covariate effect (Meinshausen and Bühlmann, 2010; Sauerbrei, 1999) and thus reflected the importance and likely generalisability of the covariate in our target population.

2.6.4.2. Parameter coefficient distributions

The distribution of predictor variable coefficients was estimated from the elastic net bootstrap procedure. All non-zero coefficients for each parameter were aggregated across 500 bootstrap samples and used to calculate a central estimate (median) and probability distributions for each parameter.

2.6.4.3. Final model inference

To identify a robust final model, both variable stability and coefficient distributions were used to select variables most likely to have important associations with lamb-derived revenue. Variables deemed to be eligible and included in a final model had a stability >80% and a coefficient with a 95% probability of being < or > 0.

To compare the performance of increasingly sparse models, and to judge how these models over or under fit the data, further (non-bootstrapped) elastic net models were constructed using three reduced sets of variables from within the data. These sparse sets comprised variables as follows; Sparse set 1: variables with a stability >80% and a coefficient with a 0.95 probability of being < or > 0; Sparse set 2: variables with a stability >90 and a coefficient with a 0.95 probability of being < or > 0; Sparse set 3: variables with a stability >95 and a coefficient with a 0.95 probability of being < or > 0. A comparison of performance was made between these sparse models, and the sparse models were also compared to the initial elastic net model that incorporated the entire set of predictor variables.

2.6.5. Model fit and final model selection

Residuals from the initial elastic models were approximately normally distributed for both outcomes but both contained a small number of outliers (<3% of data points). Although bootstrapping is recognised to produce robust coefficient estimates even when model distributional assumptions, are not met (Stine, 1985), for added security, we conducted a full bootstrap elastic net analysis on two further datasets for each outcome; one with outlying farms removed and one with the inclusion of an over dispersion parameter (a dummy variable to label outlying data points). All three models were run for 500 bootstrap samples as described above, and model stability parameters and coefficients were compared between models. For all three models, variable stability and coefficient distributions showed great similarity but the model containing the over-dispersion parameter was chosen for main inference for the following reasons. Firstly, model residuals were approximately normal which meant that outlying points were least likely to have a major influence on model parameters. Secondly, this model was the most sparse but maintained performance characteristics (R_2 and MAE) on a par with the other models. Thirdly, the model used all the data which theoretically maximised power. In summary, the model with the over-dispersion parameter was a good fit to the data, was the least likely to be over-fit and thus was chosen for model inference.

3. **Results**

3.1. Response rate and farm characteristics

The final dataset comprised information from 408 farms giving a questionnaire response rate of 49% (408/830). Seventy-six per cent of farms were located in Wales, 18% in England and 4% and 2% in Scotland and Northern Ireland. The median area used for the sheep enterprise was 265 acres (IQR 150-450) and the median flock size was 560 breeding ewes (IQR 329-

873). Eighteen per cent (72/408) of farms were located in lowland areas with all ewes lambing indoors, 4% in lowland areas with all ewes lambing outdoors (48/408), 24% in upland areas with all ewes lambing indoors (97/408), 12% (34/408) in upland areas with all ewes lambing outdoors, 5% (20/408) in hill areas with all ewes lambing indoors and 6% (24/408) in hill areas with all ewes lambing outdoors. Nineteen per cent (78/408) of farms were lambing part of the flock indoors and 12% (50/408) of flocks had a large range of altitude in which sheep were farmed. Although there was a wide range of housing and altitude combinations, these system categories were included in the models to control for potential confounding. Fifty-three per cent and 5% of the farms also had beef and dairy cows respectively. The median revenue per acre for lambs sold in 2017 was £197 (IQR 120-296) and the median revenue per ewe £95 (IQR 72 – 123).

3.2. Latent class analysis of farmer attitudes

Three latent classes of farmers were identified and these are illustrated in Figure 1. A summary of results for all of the 20 statements is provided in Supplementary Materials Table I. For each area of management attitude explored, "entrepreneurial orientation", "strategic thinking", "appreciation of profession" and "locus of control", Latent Class 1 tended to score lowest and Latent Class 3 highest.

Figure 1. An illustration of the latent class analysis to explore farmer managerial attitudes. The analysis was based on responses to 20 statements on attitudes and opinions about farm management. Responses were made on a five-point scale; 'strongly disagree', 'disagree', 'neutral', 'agree' and 'strongly agree' and were numbered 1 to 5 respectively. Three latent classes (labelled Cluster 1 to 3) of farmers were identified. The x axis depicts each statement numbered from 1 to 20 and the y axis illustrates the mean rating of the statements in each latent class. While some statements showed very little difference between classes (such as statement 3) others were more discriminant.

3.3. Model 1 - Outcome; lamb revenue per acre

Four variables were identified in the preparatory MARS analysis as having a non-linear relationship with the outcome and polynomial terms up to power four were subsequently added to the dataset to account for this.

Parameter estimates from the bootstrapped elastic net analysis are provided in Table 1; covariates with a stability >80% and coefficients with a 95% bootstrap interval greater or less than zero are shown in the table. Whilst the effect size (median coefficient estimate) was small for some covariates (e.g. tonnes of concentrate feed used) it was relatively large for others. Covariates with relatively large effect sizes were; attending technical college or university compared to having solely a secondary education (increased median revenue of £23 (5–48) and £20 (2-54) per acre respectively); farmers being in Latent Class 2 as opposed to Latent Class 1 (increased median revenue £15 (0.2 – 38) per acre); an increase in stocking rate of ewes (increased median revenue of £13 (6-17) per acre for each 0.2 increase in ewes per acre), fertilizer being used on most as opposed to none of the grazing land (increased median revenue of £18 (0.1-37) per acre), the use of rotational grazing for most grassland areas as opposed to use of entirely set stocking (increased median revenue of £13 (0.3-34) per acre); an absolute increase of 0.1 in the proportion of ewes with prolapses (reduced median revenue of £4 (0.3-9) per acre); sometimes separating lame sheep from the rest of the flock as opposed to always doing (reduced median revenue of £16 (0.9-37) per acre); farmers that took routine action to control *Haemonchus* worms in the flock, as opposed to no action (decreased median revenue of £25 (2-54) per acre); selecting ewes for culling based on prolapses (increased median revenue of £20 (0.2-55) per acre) or infertility (increased median revenue of £20 (2-46) per acre) and farmers who provided figures of scanning during pregnancy in the questionnaire had an increased median revenue of £14 (0.04-38) per acre compared with farmers not doing so.

The relationship between the body condition scoring of ewes and revenue per acre was not straightforward. Compared to farms that did not undertake body condition scoring, farms that conducted body condition scoring on 51-90% of ewes at lambing or body condition scoring on >90% ewes in early lactation or at weaning had a relatively large increase in lamb-derived revenue. However, conducting body condition scoring on 10-50% ewes during pregnancy (scanning time), compared to not conducting body condition scoring, was negatively associated with revenue per acre.

3.3.1. Sparse elastic net models of revenue per acre

An initial elastic net model built using all explanatory variables resulted in a model with parameters α= 0.99 and λ= 2.5. The model performance suggested slight overfitting with an internal R^2 of 0.74 (MAE = 56.5) and a cross validation R^2 of 0.65 (MAE = 64.6). Subsequent elastic net models conducted on the reduced subsets of variables were found to have performance characteristics as good as or better than the elastic net model conducted on the full dataset. For the subset of covariates with a stability >80%, the cross validation R^2 was 0.69 but this model shows slight signs of overfitting since the internal R^2 was 0.75. For the subset of covariates with a stability >95%, the internal model R^2 was 0.67 and the cross validation R^2 0.68; this model showed least signs of over-fitting (R^2 values most similar) of the subset models. For the subset of covariates with a stability >90%, the internal model R^2 was 0.72 and the cross validation R^2 0.67.

3.4. Model 2 - Outcome; lamb revenue per ewe

Seven variables were identified in the preparatory MARS analysis as having a non-linear relationship with the outcome and polynomial terms up to power four were subsequently added to the dataset to account for this.

Parameter estimates from the bootstrapped elastic net analysis are provided in Table 2; covariates with a stability >80% and coefficients with a 95% bootstrap interval greater or less than zero are shown in the table. Covariates with relatively large effect sizes were; attending technical college compared to completing education at secondary school (increased median revenue of £6 (0.6-15) per ewe); a 0.3 increase in the number of livestock units per acre (increase median revenue of £5 (0-13) per ewe); purchasing store lambs (increased median revenue of £12 (2-28) per ewe); selecting home-bred replacement ewes based on the criteria “appearance” or “fertility of the mother” (increased median revenue per ewe of £7 (0.2-17) and £6 (0-16) respectively); selection of ewes for culling based on infertility (increased median revenue of £6 (0.7-15) per ewe); never trimming diseased feet of lame ewes compared to always doing (increased median revenue of £9 (0.8-22) per ewe); recording flock information, using records as a basis for culling decisions and providing a figure for the number lambs present at weaning (increased median revenues of £6 (0.3-15), £5 (0.3-13) and £6 (0.1-13) per ewe respectively).

As with Model 1, the relationship between body condition scoring and farm revenue per ewe was variable. While performing body condition scoring of 10-50% ewes in early lactation or 51-90% at weaning was associated with increased farm revenue per ewe, carrying out body condition scoring in 10-50% ewes in mid pregnancy (at scanning time) was negatively associated with revenue per ewe. Conducting body condition scoring at lambing gave contradictory results; compared with not conducting body condition scoring, if performed on >90% ewes it was associated with an increase in revenue but if performed on 51-90% ewes it was associated with a reduction in revenue per ewe.

3.4.1. Sparse elastic net models of revenue per ewe

An initial elastic net model built using all explanatory variables resulted in a model with parameters α= 0.99 and λ= 0.50. The model performance suggested substantial overfitting with an internal R_2 of 0.62 (MAE = 19.7) and a CV R_2 of 0.32 (MAE = 25.4). Of the sparse models, the elastic net model that included all covariates with a stability of >80% performed best in terms of cross validation, with internal and cross validation R^2 values of 0.53 and 0.41 respectively. This subset model was less over-fit and had substantially better cross validation performance than the original elastic net model that included all explanatory variables. For the sparse models comprising covariates with a stability >90% and >95%, the internal R^2 values were 0.48 and 0.43 and cross validation R^2 values 0.40 and 0.37 respectively.

4. **Discussion**

4.1. Key findings

The aim of this study was to identify, from a large number of candidate variables, factors that were likely to have the largest, most reliable associations with lamb-derived revenue on commercial sheep farms and hence be considered prime candidates for future intervention studies. The bootstrapped regularised regression provided a platform to evaluate a large set of potentially correlated explanatory variables and identify variables that were most stable and with largest effect sizes. Factors with high stability and a relatively large positive effect on revenue per acre were; increased stocking rate, fertilizer being used on most of the grazing land, the use of rotational grazing, separation of lame sheep from the rest of the flock, selecting ewes for culling based on prolapses and infertility, conducting body condition scoring of ewes at lambing, early lactation or weaning, decreased proportion of ewes with prolapses, increased farmer education and farmers with a positive business attitude. Additional factors with a high stability and relatively large effects on revenue per ewe were; purchasing of store lambs, never trimming diseased feet of lame ewes and keeping good farm records. As an overview from the whole data, from a list of over 300 candidates, the six factors that appeared to have a substantive impact on both lamb-derived revenue per acre and per ewe were; farmers receiving an education above secondary school level, increasing stocking rates, using infertility as a reason for culling ewes, managing lameness in ewes and conducting BCS in early lactation and at weaning. These could be considered the most important to evaluate in future intervention studies.

4.2. Management factors associated with increased lamb-derived revenue

A variety of management factors were associated with relatively stable and large effects on lamb revenue either per acre or per ewe. Methods of land management were associated with lamb-derived revenue per acre with factors related to increased intensification such as rotational grazing of sheep, increased application of fertilizer and increased stocking rates being associated with increased revenue. The importance of grassland management, and stocking rates has been documented for improved the sheep productivity (Bohan et al., 2017; Kilkenny and Read, 1974), but this is the first study evaluate these effects individually and estimate a financial value for each practice. Since grass generally represents a very high proportion of the sheep's diet, it is unsurprising that more intensive and efficient management of the grazing area is associated with greater revenues and the large effect sizes and high stability of these variables suggest they may be an important and consistent effect across many farms. These results are in agreement with previous dairy cow research that reported that pasture management variables (stocking rates and fertiliser use) were positively associated with enterprise performance (financial margin per hectare) (Solano et al., 2006). Notably, in contrast to the relatively large effect sizes of these grassland-related variables, only a very small effect size was identified between feeding concentrate feed and lamb-derived revenues; each additional tonne of concentrate used was associated with an increased lamb-derived revenue per acre of only £0.86. Since a tonne of concentrate will cost approximately £150-£250 per tonne (AHDB, 2016a), this estimated return of less than £1 per acre for an average 200 acre farm would barely be cost-effective.

Management related to aspects of flock health presented some interesting associations with financial revenue per acre. Farms that “sometimes” separated lame sheep from the rest of the flock (as opposed to always) were associated with lower lamb-derived revenues. Lameness remains an important condition in UK flocks (Prosser et al., 2019) and separating sheep affected by lameness has been observed to be associated with a decreased prevalence of the disease in a large scale survey of 809 sheep farms (Kaler and Green, 2009). A second lameness management practice, trimming the feet of lame ewes, was associated with a reduced lamb-derived revenue per ewe and this could be because for footrot, the most common cause of lameness, trimming has been shown to delay recovery (Kaler et al., 2010). In our study farms, trimming may have resulted in prolonged ewe lameness, which could in turn have resulted in reduced pregnancy rates, reduced numbers of lambs born and poorer lamb growth rates, all of which could affect lamb-derived revenue. Therefore, in this sample of sheep farms, adoption of recognised best practices to manage flock lameness was associated with substantive increases in lamb revenue and this would appear an important route to enhance farm income as well as animal welfare in the future.

Another management factor related to flock health, body condition scoring (BCS), presented positive although slightly contradictory results. Whilst BCS of ewes at the time of lambing, early lactation and weaning were associated with improved lamb-derived revenues, BCS of 10-50% ewes at the time of scanning was associated with a reduction in revenue. It is unclear as to why BCS of ewes at scanning could result in reduced revenue unless, in certain circumstances, the act of scoring at this time could lead to pregnancy losses. Undertaking BCS is generally accepted as good practice, so that corrective grouping and feeding of ewes can be undertaken as necessary, therefore the unexpected findings related to BCS at scanning warrant further investigation. However, at other times in the management cycle BCS appears to be an important management tool that is associated with increased farm revenue; the exact financial benefits of BCS would be worthy of study in future intervention studies.

Management decisions around selection of ewes for culling was associated with increased with lamb-derived revenue per acre. Culling decisions based on criteria such as infertility or previous cases of vaginal and/or uterine prolapse were positively associated with lamb-derived revenue per acre suggesting that the exclusion of ewes with reproductive problems from the flock resulted in greater returns. High net margin sheep producers have previously been reported to have relatively few empty ewes (AHDB, 2016) which aligns with our results on culling ewes with reproductive issues.

As well as culling decisions, management decisions on selection of home-bred replacements was also associated with increases in lamb-derived revenue. Selection decisions based on appearance or recorded fertility was associated with increase revenue per ewe. These results suggest that fertility management is important for farm productivity, probably because of the impact numbers of lambs born which in turn will generally lead to greater numbers of lambs sold.

Four management variables related to data recording were associated with increased lamb-derived revenue (recording flock information, keeping records of pregnancy scanning, recording of number of lambs present at weaning and using records for culling decisions). Record keeping is likely to be of benefit in providing information to make better management decisions (Lima et al., 2018) and therefore these associations are unsurprising. Good record-keeping practices may provide a clear, objective basis for farm decision making which should lead to better financial returns. This finding is in line with previous research reporting a positive relationship between recording keeping and dairy cow farm performance (Solano et al., 2006).

Management decisions on the routes through which lambs were sold was found to be associated with lamb-derived income; an increased number of lambs sold finished or for breeding, as opposed to being sold as stores (i.e. to be finished elsewhere), was associated with higher revenues. Store lambs generally attract a lower price than finished lambs (AHDB, 2016) and an increased proportion of store lambs being sold probably reflects farms with relatively large variation on lambing period or relatively poor lamb growth rates.

Management practices for controlling the nematode *Haemonchus* gave results that were difficult to interpret. Flocks that routinely took action to control *Haemonchus* had lower financial revenues per acre than flocks where no routine action was taken. This could be because flocks in which no action was taken did not have any significant challenges from this parasite and therefore no losses. Even when farmers took action to control *Haemonchus* it may be that losses still occurred that were greater than on farms without problems. It could also be that routine control of the parasite was ineffective, for example because of resistance to anthelmintics of this parasite (Coles et al., 2005). It should be noted that current recommendations for nematode control are to use worm egg counts to monitor parasite burden alongside strategic treatments rather than using blanket therapy (Abbott et al., 2012). Since *Haemochus* is a severe (Besier et al., 2016), and relatively widespread infection (Burgess et al., 2012) further research on the financial impact of *Haemonchus* control is warranted.

4.3. Reported disease prevalence associated with lamb-derived revenue

Several health-related variables were associated with lamb-derived revenue. An increase in the reported proportion of ewes affected by prolapses was associated with reduced lamb-derived revenue per acre. Although several risk factors seem to play a role in the aetiology of this condition (genetics, litter size, diet and topography of terrain (Jackson et al., 2014)), there is little information about the current prevalence of this disease in the UK; the last estimates date from 1987 (Low and Sutherland, 1987). Our results suggest that this condition may have a negative impact on lamb-derived revenue, possibly a result of a poorer reproductive performance of ewes.

A reported increase in the prevalence of pregnancy toxaemia in ewes was associated with reduced revenue per ewe. Pregnancy toxaemia arises from poor management of ewe nutrition and is a form of ketosis that can result in severe disease and death (Andrews, 1997). It is therefore likely to result in lower revenues per ewe in the flock. Pregnancy toxaemia can also act as a predisposing factor for mastitis in the immediate post-partum period (Mavrogianni and Brozos, 2008) and this is known to affect lamb growth (Grant et al., 2016), which could lead to lower lamb-derived revenues.

In terms of reported lamb health, increased bacterial arthritis was associated with reduced revenue per ewe. Previous research has reported that age at slaughter increased in lambs affected by arthritis (Green et al., 1995) suggesting a negative impact of this condition on lamb development. Lower growth rates and arthritis lesions are likely to affect both the time of sale and the quality of a lamb carcass, both of which could explain the lower revenues per ewe observed in flocks with a greater proportion of lambs affected by this condition.

4.4. Farmer traits associated with increased lamb-derived revenue

Several farmer-related variables were found to be associated with lamb-derived revenue and this generally aligns with previous evidence from agricultural economics on the associations between farmer beliefs and attitudes and enterprise performance (Gasson, 1973; Mäkinen, 2013; Nuthall, 2001; Willock et al., 1999). This is the first time, however, that such relationships have been observed in the UK sheep farming sector. Interestingly, our results also indicate that farmers that were part of a group with relatively positive and proactive beliefs towards farm management had enterprises with the highest financial revenues per acre confirming the relationship between intrinsic personal beliefs and increased farm productivity.

The greater farm productivity observed in this group may have resulted from the application of superior managerial principles, although in this study only opinions, and not actual managerial practices, were captured. It could also be that these beliefs were generated through success rather than being the reason for it. These results concur with previous reports in which a farmer's managerial ability was considered to be a major resource in parallel with nature and labour (Nuthall, 2009). Further research would be beneficial to understand how these beliefs are formed, whether coaching could be an effective means of developing farmer managerial skill sets and whether this leads to improved farm revenues.

Higher education was positively associated with lamb-derived revenue per acre and per ewe. This is a plausible causal relationship if learned practices are incorporated in farm management strategies and this is in agreement with previous studies relating education attainment to farm productivity (Leary and Gate, 2017; Wilson et al., 2001). This is also a promising area for change; if education can be increased to the farming population it is possible financial sustainability of the sector could increase.

Farmer age was associated with lamb-derived revenue, being higher for farmers aged between 36 and 45 years than those aged 25 or less. It is unclear why this specific age group should obtain greatest financial returns but both age and farming experience have been reported to be important in previous research on general flock management (Corner-Thomas et al., 2015; Wilson et al., 2001). Further research is needed to explore the reasons behind this finding.

4.5. Farm characteristics associated with increased lamb-derived revenue

Farm characteristics such as location, flock type, main breed and flock size were associated with differences in revenue from lamb sales, although none of these were unexpected and these are generally system-dependent and therefore difficult to change. Farms with maternal breeds had increased lamb-derived revenues per acre compared to farms with pure hill breeds; this is likely to a result of the higher fertility and mothering skills from these breeds (Bradford, 1972).

4.6. Variable selection and stability; identification of most important covariates

The use of bootstrapped parameter estimates and stability provided useful insights into the robustness and relevance of model covariates. The bootstrapped stability values, that represented the probability that each covariate was selected in the elastic net model when different subsets of data were used, provided an estimation of the consistency of the effect of each covariate. That is, covariates with a high stability had a consistent association with the outcome across a relatively large number of farms (i.e. the effects remained no matter which farms were omitted) and are therefore candidates to have a consistent and reproducible effect on farms in the target population. Under the assumption that our sample was representative of our target population, bootstrap stability can be considered to be a ranked estimate of the generalisability of each covariate; how likely it is to have an effect on farms throughout our target population (and on other similar farms). Although covariate stability appears to have rarely been used in veterinary epidemiology, it is not a new concept and has been previously considered in the context of model selection and covariate reproducibility (Baldassarre et al., 2017; Meinshausen and Bühlmann, 2010; Sauerbrei, 1999). With this study being a cross sectional design, however, it is important to recognise that the relationships identified cannot be considered causal, therefore stability in this context should be treated as a means to rank candidate variables in terms of suitability for follow up intervention studies; if causal, the highest stability variables would be expected to have the largest impact across the population of tested farms.

Further elastic net modelling of lamb-derived revenue per acre, incorporating only subsets of covariates with a bootstrap stability >80%, provided additional understanding of the importance and robustness of the explanatory covariates. For both outcome variables, the cross validation R^2 values were higher for these reduced covariate models than for the elastic net models that were built from the entire data set of covariates. This indicated that the covariates identified with high stability and included in these reduced models explained most of the variability in outcomes when assessed by cross validation. Again, this suggests these explanatory variables may be important in affecting lamb-derived revenue and could therefore be considered the best candidates for future intervention studies; further research is needed to establish causality.

Interestingly all reduced covariate models, for both outcomes, had better cross validation performance (R^2 and MAE) than the initial elastic net models using the full data set. The full elastic net models had a tendency to over fit the data when all covariates were offered, presumably because of the difficulty in filtering useful from non-useful information; that is, despite optimising the regularisation parameters, some covariates with relatively small and uncertain effects were still selected in the final models. It is known that reducing the number of predictor variables often results in improved model performance for regression-based or machine learning algorithms (Kuhn and Johnson, 2013) and automated methods have been developed to address this such as recursive feature elimination (Guyon et al., 2002). Regularisation is a recognised procedure for automatic variable selection that is known to reduce over fitting (Hastie et al., 2015) however, in this analysis, the use of covariate stability through bootstrapping alongside a regularised model framework, produced even more sparse models with better performance than regularisation alone.

4.7. Study limitations

It is difficult to be sure how representative our sample of farmers was of the population under study and some caution is needed in case bias has arisen. All farmers present in the target population were given the opportunity to participate in the study and a good response rate (49%) indicated the target population was well represented. A lack of available data on farm characteristics (e.g. flock size, location) hampers a direct comparison between the study and target populations that could help confirm representativeness. A systematic bias could have resulted from ‘volunteer bias’ (farms volunteering to participate being different from those not volunteering) or the administration mode of the survey online (with a potential under-representation of farmers with no access to the internet). Such biases are difficult to evaluate without data from non-participating farms and this was not available. However, since this study was a cross sectional design and further research is needed to evaluate whether the factors identified are truly causal, such follow up intervention studies should not suffer from the potential biases of this observational study and further confirms their importance to evaluate causality.

An important limitation of this study was that farm costs could not be included and that income rather than profit was used to evaluate farm productivity. A suggestion for further research is a detailed economic assessment of sheep farms financial inputs and outputs to evaluate the hypothesis that the identified practices are not only associated with farm revenue but also with profit. It is recognised that many the of practices identified as associated with increased revenue would have associated costs (for example, increased fertiliser or concentrate feed use) and even if causality is established, there is a further need to establish the economic impact; whether the increased income outweighs the costs involved. However, within these limitations it is worth noting that many relatively low cost practices, such as the use of rotational grazing, the selection of ewes for culling based on prolapses and infertility and undertaking body condition scoring of ewes, would yield a relatively large return at relatively low cost and are therefore likely to be profitable.

As final limitations, it should be recognised that although many explanatory covariates were explored in this study, some unexplained variation remained in both models suggesting that there are additional factors, yet to be identified, that also influence lamb-derived revenue on sheep farms. Furthermore, despite the use of a robust method for variable selection in this research, a variety of alternative automated covariate selection methods are available and it is unknown whether the use of different methods would have resulted in the selection of slightly different covariate subsets. Since methods of covariate selection will become increasingly important as the size of datasets available for research continues to increase, further research exploring differences between such selection methods would be worthwhile.

4.8. Conclusions

Six general areas associated with lamb derived financial revenue have been described; feed and grassland, strategy of lamb sales, flock health, flock record keeping, farm attributes and farmer characteristics. From within these categories, a small set of variables with the largest potential influence on lamb-derived revenue have been identified and these are candidates for future intervention studies to assess causality. Bootstrapped regularised regression proved useful in dissecting a wide dataset and we recommend this approach to provide a robust method to rank the importance of explanatory covariates in large scale observational animal health epidemiology.

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List of references

Abbott, K.A., Taylor, M., Baber, P., 2012. SCOPS - Sustainable worm control strategies for sheep - 4th Edition.

Adams, W.N., 2006. The future of sustainability: Re-thinking Environment and Development in the Twenty-first Century, The Future of Sustainability. https://doi.org/10.1007/1-4020-4908-0

AHDB, 2019a. Deadweight sheep prices [WWW Document]. URL http://beefandlamb.ahdb.org.uk/markets/deadweight-price-reports/deadweight-sheep-price-reporting/ (accessed 7.29.19).

AHDB, 2019b. Market Intelligence Publications - Cattle and sheep weekly [WWW Document]. URL http://beefandlamb.ahdb.org.uk/markets/market-intelligence-publications/ (accessed 7.29.19).

AHDB, 2016. Stocktake report 2016.

Altman, N.S., 1992. An Introduction to Kernel and Nearest-Neighbor Nonparametric Regression. Am. Stat. 46, 175–185.

Andrews, A., 1997. Pregnancy toxaemia in the ewe. In Pract. 19, 306–314. https://doi.org/10.1136/inpract.19.6.306

Austin, P.C., Tu, J. V, 2004. Bootstrap Methods for Developing Predictive Models. Am. Stat. 58, 131–137. https://doi.org/10.1198/0003130043277

Baldassarre, L., Pontil, M., Mourão-miranda, J., 2017. Sparsity Is Better with Stability : Combining Accuracy and Stability for Model Selection in Brain Decoding. Front. Neurosci. 11, 62. https://doi.org/10.3389/fnins.2017.00062

Besier, R.B., Kahn, L.P., Sargison, N.D., Van Wyk, J.A., 2016. Chapter Four - The Pathophysiology, Ecology and Epidemiology of Haemonchus contortus Infection in Small Ruminants. Adv. Parasitol. 93, 95–143. https://doi.org/https://doi.org/10.1016/bs.apar.2016.02.022

Bohan, A., Shalloo, L., Creighton, P., Boland, T.M., Mchugh, N., 2017. A survey of management practices and flock performance and their association with flock size and ewe breed type on Irish sheep farms. J. Agric. Sci. 155, 1–10. https://doi.org/10.1017/S0021859617000399

Bohan, A., Shalloo, L., Creighton, P., Earle, E., Boland, T.M., McHugh, N., 2018. Investigating the role of stocking rate and prolificacy potential on profitability of grass based sheep production systems. Livest. Sci. 210, 118–124. https://doi.org/10.1016/j.livsci.2018.02.009

Bradford, G.E., 1972. The Role of Maternal Effects in Animal Breeding: VII. Maternal Effects in Sheep. J. Anim. Sci. 35, 1324–1334. https://doi.org/10.2527/jas1972.3561324x

Breiman, L., 1996. Bagging predictors. Mach. Learn. 24, 123–140. https://doi.org/10.1023/A:1018054314350

Burgess, C.G.S., Bartley, Y., Redman, E., Skuce, P.J., Nath, M., Whitelaw, F., Tait, A., Gilleard, J.S., Jackson, F., 2012. A survey of the trichostrongylid nematode species present on UK sheep farms and associated anthelmintic control practices. Vet. Parasitol. 189, 299–307. https://doi.org/10.1016/j.vetpar.2012.04.009

Coles, G.C., Rhodes, A.C., Wolstenholme, A.J., 2005. Rapid selection for ivermectin resistance in Haemonchus contortus. Vet. Parasitol. 129, 345–347. https://doi.org/https://doi.org/10.1016/j.vetpar.2005.02.002

Corner-Thomas, R.A., Kenyon, P.R., Morris, S.T., Ridler, A.L., Hickson, R.E., Greer, A.W., Logan, C.M., Blair, H.T., 2015. Influence of demographic factors on the use of farm management tools by New Zealand farmers. New Zeal. J. Agric. Res. 58, 412–422. https://doi.org/10.1080/00288233.2015.1063513

Dallah, H., 2012. A Bootstrap Approach to Robust Regression. Int. J. Appl. Sci. Technol. 2, 114–118.

Delgado, C., Rosegrant, M., Steinfeld, H., Ehui, S., Cour, C., 1999. Livestock to 2020 Revolution, Food and Agriculture Organization of the United Nations. https://doi.org/10.5367/000000001101293427

Dillman, D.A., Smyth, J.D., Melani, L., 2009. Internet, mail, and mixed-mode surveys: The tailored design method, 3rd ed. Wiley & Sons, Hoboken, NJ, US.

Doré, A.C., Meek, A.H., Dohoo, I.R., 1987. Factors associated with productivity in Canadian sheep flocks. Can. J. Vet. Res. 51, 39–45.

Efron, B., 1992. Bootstrap Methods: Another Look at the Jackknife. pp. 569–593. https://doi.org/10.1007/978-1-4612-4380-9_41

Eurostat, 2019. Glossary: Livestock unit (LSU) [WWW Document]. https://doi.org/ISSN 2443-8219

Fraley, C., Raftery, A.E., 2002. Model-Based Clustering, Discriminant Analysis, and Density Estimation. J. Am. Stat. Assoc. 97, 611–631. https://doi.org/10.1198/016214502760047131

Fraser, M.D., Speijers, M.H.M., Theobald, V.J., Fychan, R., Jones, R., 2004. Production performance and meat quality of grazing lambs finished on red clover, lucerne or perennial ryegrass swards. Grass Forage Sci. 59, 345–356. https://doi.org/10.1111/j.1365-2494.2004.00436.x

Freedman, D.A., Peters, S.C., 1984. Bootstrapping a Regression Equation: Some Empirical Results. J. Am. Stat. Assoc. 79, 97. https://doi.org/10.2307/2288341

Friedman, J., Hastie, T., Tibshirani, R., 2010. Regularization Paths for Generalized Linear Models via Coordinate Descent. J. Stat. Softw. 33, 1–22.

Friedman, J.H., 1991. Multivariate Adaptive Regression Splines. Ann. Stat. 19, 1–67.

Gasson, R., 1973. Goals and values of farmers. J. Agric. Econ. 24, 521–542. https://doi.org/10.1111/j.1477-9552.1973.tb00952.x

Gelman, A., 2008. Scaling regression inputs by dividing by two standard deviations. Stat. Med. 27, 2865–2873. https://doi.org/10.1002/sim.3107

Grant, C., Smith, E.M., Green, L.E., 2016. A longitudinal study of factors associated with acute and chronic mastitis and their impact on lamb growth rate in 10 suckler sheep flocks in Great Britain. Prev. Vet. Med. 127, 27–36. https://doi.org/10.1016/j.prevetmed.2016.03.002

Green, L.E., Berriatua, E., Cripps, P.J., Morgan, K.L., 1995. Lesions in finished early born lambs in southwest England and their relationship with age at slaughter. Prev. Vet. Med. 22, 115–126. https://doi.org/10.1016/0167-5877(94)00392-V

Green, L.E., Berriatua, E., Morgan, K.L., 1998. A multi-level model of data with repeated measures of the effect of lamb diarrhoea on weight. Prev. Vet. Med. 36, 85–94. https://doi.org/10.1016/S0167-5877(98)00086-5

Guyon, I., Weston, J., Barnhill, S., 2002. Gene Selection for Cancer Classification using Support Vector Machines. Mach. Learn. 46, 389–422. https://doi.org/10.1002/bip.360320308

Hastie, T., Tibshirani, R., Wainwright, M., 2015. Statistical learning with sparsity: the lasso and generalizations. Chapman and Hall/CRC.

Jackson, R., Hilson, R.P.N., Roe, A.R., Perkins, N., Heuer, C., West, D.M., 2014. Epidemiology of vaginal prolapse in mixed-age ewes in New Zealand. N. Z. Vet. J. 62,

328–337. https://doi.org/10.1080/00480169.2014.925788
Kaler, J., Daniels, S.L.S., Wright, J.L., Green, L.E., 2010. Randomized clinical trial of long-acting oxytetracycline, foot trimming, and flunixine meglumine on time to recovery in sheep with footrot. J. Vet. Intern. Med. 24, 420–425. https://doi.org/10.1111/j.1939-1676.2009.0450.x
Kaler, J., Green, L.E., 2009. Farmers' practices and factors associated with the prevalence of all lameness and lameness attributed to interdigital dermatitis and footrot in sheep flocks in England in 2004. Prev. Vet. Med. 92, 52–59. https://doi.org/10.1016/j.prevetmed.2009.08.001
Kelly, R.W., Johnstone, P.D., 1982. Reproductive performance of commercial sheep flocks in south island districts. New Zeal. J. Agric. Res. 25, 519–523. https://doi.org/10.1080/00288233.1982.10425215
Kilkenny, J.B., Read, J.L., 1974. British sheep production economics. Livest. Prod. Sci. 1, 165–178.
Kuhn, M., Johnson, K., 2013. Applied predictive modeling. Springer publishing, New York.
Kuhn, M., Wing, J., Weston, S., Williams, A., Keefer, C., Engelhardt, A., Cooper, T., Mayer, Z., Kenkel, B., Team, the R.C., Benesty, M., Lescarbeau, R., Ziem, A., Scrucca, L., Tang, Y., Candan, C., Hunt, T., 2019. caret: Classification and Regression Training.
Leary, N.O., Gate, E., 2017. Farmer Attitudes Predictive of Profitability. 91st Annu. Conf. Agric. Econ. Soc. R. Dublin Soc. Dublin, Irel. 1–29.
Lima, E., Hopkins, T., Gurney, E., Shortall, O., Lovatt, F., Williamson, G., Kaler, J., 2018. Drivers for precision livestock technology adoption: a study of factors associated with adoption of Electronic Identification technology by commercial sheep farmers in England and Wales. PLoS One 13, 1–17. https://doi.org/10.1371/journal.pone.0190489
Lima, E., Lovatt, F., Davies, P., Kaler, J., 2019. Using lamb sales data to investigate associations between implementation of disease preventive practices and sheep flock performance. Animal 1–9. https://doi.org/10.1017/s1751731119001058
Low, J.C., Sutherland, H.K., 1987. A census of the prevalence of vaginal prolapse in sheep flocks in the Borders region of Scotland. Vet. Rec. 120, 571–575. https://doi.org/10.1136/vr.120.24.571
Mäkinen, H., 2013. Farmers ' managerial thinking and management process effectiveness as factors of financial success on Finnish dairy farms. Agric. Food Sci. 22, 452–465. https://doi.org/10.23986/afsci.8147
Mavrogianni, V.S., Brozos, C., 2008. Reflections on the causes and the diagnosis of peri-parturient losses of ewes. Small Rumin. Res. 76, 77–82. https://doi.org/10.1016/j.smallrumres.2007.12.019
Meinshausen, N., Bühlmann, P., 2010. Stability selection. J. R. Stat. Soc. Ser. B 72, 417–473. https://doi.org/10.1111/j.1467-9868.2010.00740.x
Milborrow, S., 2019. R Package ' earth ' - Multivariate Adaptive Regression Splines. https://doi.org/10.1214/aos/1176347963>.)
Nuthall, P.L., 2009. Farm business management: the human factor. CABI.
Nuthall, P.L., 2001. Managerial ability—a review of its basis and potential improvement using psychological concepts. Agric. Econ. 24, 247–262. https://doi.org/10.1016/S0169-5150(00)00069-4
Poore, J., Nemecek, T., 2018. Reducing food's environmental impacts through producers and consumers. Science (80-.). 360, 987–992.
Prosser, N.S., Purdy, K.J., Green, L.E., 2019. Increase in the flock prevalence of lameness in ewes is associated with a reduction in farmers using evidence-based management of prompt treatment: A longitudinal observational study of 154 English sheep flocks 2013–2015. Prev. Vet. Med. 173, 104801. https://doi.org/10.1016/j.prevetmed.2019.104801

Sauerbrei, W., 1999. The Use of Resampling Methods to Simplify Regression Models in Medical Statistics. J. R. Stat. Soc. 48, 313–329. https://doi.org/10.1111/1467-9876.00155

Scrucca, L., Fop, M., Murphy, B.T., Raftery, E.A., 2016. mclust 5: clustering, classification and density R, estimation using Gaussian finite mixture models. R J. 8/1, pp. 205-233 205–203.

Solano, C., León, H., Pérez, E., Tole, L., Fawcett, R.H., Herrero, M., 2006. Using farmer decision-making profiles and managerial capacity as predictors of farm management and performance in Costa Rican dairy farms. Agric. Syst. 88, 395–428. https://doi.org/10.1016/j.agsy.2005.07.003

Stine, R.A., 1985. Bootstrap Prediction Intervals for Regression. J. Am. Stat. Assoc. 80, 1026–1031. https://doi.org/10.1080/01621459.1985.10478220

Team, R.C., 2018. R: A language and environment for statistical computing.

Tibshirani, R., 1996. Regression Shrinkage and Selection via the Lasso. J. R. Stat. Soc. 58, 267–288. https://doi.org/10.1111/j.2517-6161.1996.tb02080.x

Tilman, D., Cassman, K.G., Matson, P.A., Naylor, R., Polasky, S., 2002. Agricultural sustainability and intensive production practices. Nature 418, 671.

Torgo, L., 2010. Data Mining with R, learning with case studies.

Townsley, R.J., Parker, W.J., 1987. Regression analysis of farm management survey data. New Zeal. J. Exp. Agric. 15, 155–162. https://doi.org/10.1080/03015521.1987.10425554

Troyanskaya, O., Cantor, M., Sherlock, G., Brown, P., Hastie, T., Tibshirani, R., Botstein, D., Altman, R.B., 2001. Missing value estimation methods for DNA microarrays. Bioinformatics 17, 520–525.

Walkom, S.F., Brien, F.D., Hebart, M.L., Fogarty, N.M., Hatcher, S., Pitchford, W.S., 2016. Season and reproductive status rather than genetic factors influence change in ewe weight and fat over time. 4. Genetic relationships of ewe weight and fat score with fleece, reproduction and milk traits. Anim. Prod. Sci. 56, 708–715. https://doi.org/10.1071/AN15090

Willock, J., Deary, I.J., Mcgregor, M.M., Sutherland, A., Edwards-jones, G., Morgan, O., Dent, B., Grieve, R., Gibson, G., Austin, E., 1999. Farmers ' Attitudes , Objectives , Behaviors , and Personality Traits : The Edinburgh Study of Decision Making on Farms 36, 5–36.

Wilson, P., Hadley, D., Asby, C., 2001. The influence of management characteristics on the technical efficiency of wheat farmers in eastern England. Agric. Econ. 24, 329–338. https://doi.org/10.1016/S0169-5150(00)00076-1

Zou, H., Hastie, T., 2005. Regularization and variable selection via the elastic net. J. R. Stat. Soc. 67, 301–320. https://doi.org/10.1111/j.1467-9868.2005.00503.x

Table 1. Results of the elastic net bootstrapped model with outcome variable "farm revenue per acre" (£/acre). Results for variable stability (percentage of bootstrap samples in which each variable was selected) and coefficient distributions (median and 95% bootstrap probabilities) are provided. The elastic net models were run for 500 bootstrapped samples and variables with both a stability >80% and a 95% bootstrap probability of being > or < zero shown. The asterisk indicates variables where a 10% change in the coefficient is shown rather than a change in 1 unit, to facilitate interpretation of the results.

Group	**n (number in variable category**	**Variable**	**Reference category (unless continuous predictor) (n = number in reference category)**	**Stability (%)**	**50%**	**5%**	**95%**	**Median effect size for 2 SD change in continuous predictors**	**Value of 2 standard deviations of continuous predictors**
	408	Intercept		100.00	150.98	55.60	230.50		
Farm characteristics	127	Main breed of the flock – maternal type	Hill breed type (190)	94.04	16.39	0.61	39.40		
	310	Region - Wales	England (74)	89.07	-17.15	-49.65	-0.25		
	408	Flock size (ewes tupped)		98.21	-0.04	-0.11	-0.01	-44.26	1087.88
Farmer characteristics	180	Education Level – Technical college	Secondary school (156)	97.42	23.34	5.34	48.13		
	72	Education Level – University	Secondary school (156)	89.86	20.30	1.52	54.44		

	64	Age category – between 36 and 45	Below 25 y (17)	89.86	17.44	1.02	46.52		
	83	Managerial cluster 2 (“medium” managerial profile)	Managerial cluster 1 (“low” managerial profile) (108)	85.29	15.18	0.20	37.95		
Grassland management	408	Stocking rate – number of ewes per acre for sheep		100.00	62.90	30.73	86.26	151 .0	2.40
	408	Livestock unit per area sheep		95.83	46.37	4.08	99.92	30.14	0.65
	408	proportion sheep area out of total area		92.64	-12.99	-63.96	-0.14	-12.99	1.00
	205	Sheep were rotationally grazed – most or all of the sheep area	None of the sheep area (72)	89.07	12.55	0.27	34.05		
	223	Fertiliser was spread on the ground- most or all of the sheep area	None of the sheep area (38)	94.23	17.54	0.13	36.77		
	408	Number of tonnes of concentrate used to feed ewes		99.60	0.86	0.30	1.53	36.00	41.87
Lamb sales strategy	408	Ratio of lambs sold finished (to abattoirs) per		89.86	4.01	0.1	9.93	2.36	0.59

		lamb crop (per change of 0.1)							
	408	Ratio of lambs sold finished elsewhere per lamb crop (per change of 0.1)		91.05	6.88	0.90	15.55	2.82	0.41
	408	Ratio of lambs sold for breeding per lamb crop (per change of 0.1)		93.24	9.56	2.21	20.53	2.77	0.29
Animal selection	76	Infertility selected as the most important reason for culling	Infertility not selected as the most important reason for culling (332)	92.45	20.38	2.14	45.54		
	28	Prolapse selected as the most important reason for culling	Prolapse not selected as the most important reason for culling (380)	80.52	19.87	0.16	55.01		
Flock Health	408	% of ewes affected by prolapses		90.06	-3.64	-9.36	-0.28	-17.60	4.84

	195	Did you separate lame sheep from the rest of the flock? – Sometimes	Always (80)	90.85	-15.82	-36.79	-0.85
	68	Haemonchus worms – “I routinely took action to control this disease in my flock”	No routine action (340)	92.84	-24.52	-54.32	-2.38
BCS	43	BCS conducted at lambing time – majority of the ewes (51-90%)	None of the ewes (56)	90.85	27.97	2.96	58.02
	72	BCS conducted at weaning time - most of the ewes (>90%)	None of the ewes (67)	84.49	24.67	2.12	69.46
	80	BCS conducted in mid pregnancy (e.g. scanning time) some ewes (10-50%)	None of the ewes (23)	91.25	-22.04	-52.05	-2.84
	83	BCS conducted in early lactation - Some ewes (10-50%)	None of the ewes (95)	92.25	20.56	1.43	54.11
Records	295	Farmer provided scanning figures	Did not provide scanning figures (113)	88.07	14.00	0.04	38.13

Non-inferential parameters	Lowland farms with indoor lambing	All other systems (upland or hill farms lambing indoors or outdoors)	42.95
	Over-dispersion parameter		190.27

Table 2. Results of the elastic net bootstrapped model with outcome variable “farm revenue per ewe” (£/ewe). Results for variable stability (percentage of bootstrap samples in which each variable was selected) and coefficient distributions (median and 95% bootstrap probabilities) are provided. The elastic net models were run for 500 bootstrapped samples and variables with both a stability >80% and a 95% bootstrap probability of being > or < zero shown. The asterisk indicates variables where a 10% change in the coefficient is shown rather than a change in 1 unit, to facilitate interpretation of the results.

Farm management area	**n (number in variable category)**	**Variable**	**Reference category (unless continuous variable) (n = number in reference category)**	**Stability**	**50%**	**5%**	**95%**	**Effect size for 2 SD change in the predictor**	**Gelman SD**
		(Intercept)		100.00	56.50	19.60	86.70		
Farm characteristics	304	Region - Wales	England (74)	96.40	-9.60	-21.00	-1.70		
	401	Flock size (ewes tupped)		95.80	-0.01	-0.03	<0.01	-13.9	1082.70
Farmer characteristics	175	Education Level – Technical college	Secondary school (156)	94.70	6.10	0.60	14.70		
	64	Age category – between 36 and 45 years	Below 25 years (17)	96.50	10.30	2.80	20.70		
Grassland management	401	Stocking rate – number of ewes per acre for sheep		89.30	-1.20	-3.29	-0.04	-2.8	2.34
	401	Number of tonnes of concentrate used to feed ewes		99.60	0.01	0.00	0.02	0.4	40.00

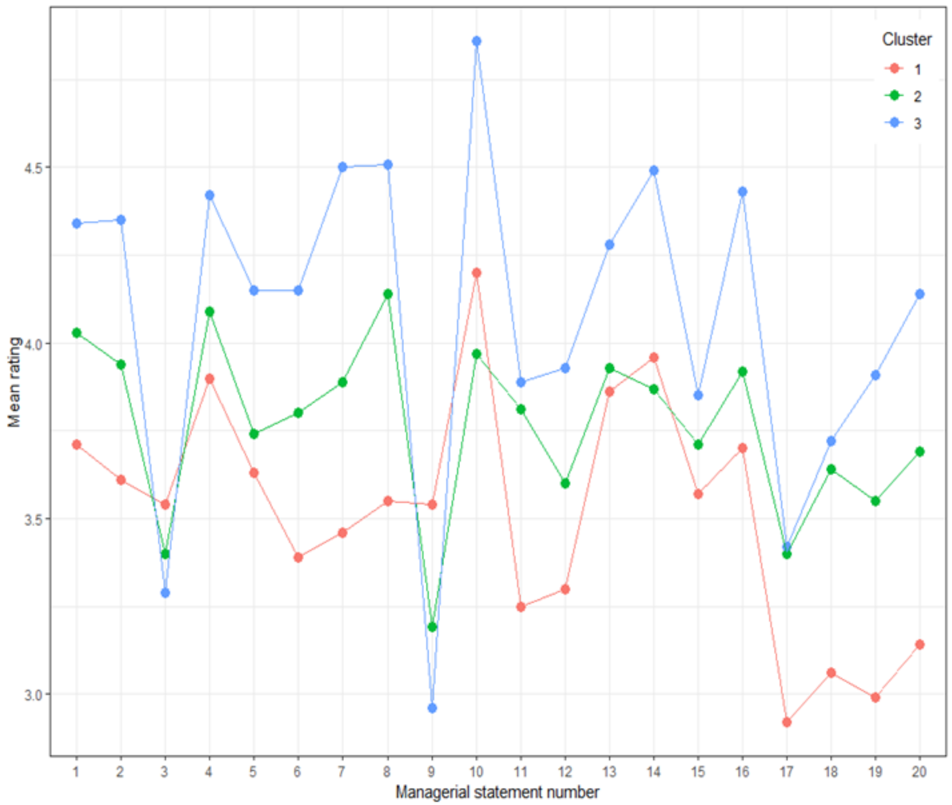
	401	Number of other livestock on farm		84.70	<0.01	-0.01	<0.01	-0.1	50.00
	401	Livestock unit per area sheep		84.50	17.00	0.00	43.67	10.2	0.60
Lamb sales strategy	36	Farmer purchased store lambs	Farmer did not purchase store lambs (365)	93.50	11.60	1.90	28.10		
	401	Ratio of lambs sold finished (to abattoirs) per lamb crop (per change of 0.1)		96.50	3.03	0.55	6.73	18.2	0.60
	401	Ratio of lambs sold finished elsewhere per lamb crop (per change of 0.1)		96.40	7.63	1.33	15.43	30.5	0.40
	401	Ratio of lambs sold for breeding per lamb crop (per change of 0.1)		95.50	11.97	2.10	23.97	35.9	0.30
Animal selections strategy	124	Lamb weight was the factor with the strongest influence on the decision to sell lambs	Time of the year was the factor with the strongest influence on the decision to sell lambs (12)	86.50	4.90	0.20	12.60		

	302	Appearance was selected as important when selecting home bred replacement ewes	Appearance was not selected as important when selecting home bred replacement ewes (99)	94.70	7.10	0.20	17.40		
	69	Fertility was selected as important when selecting home bred replacement ewes	Fertility was not selected as important when selecting home bred replacement ewes (332)	87.60	5.90	0.00	16.00		
	75	Infertility selected as the most important reason for culling	Infertility not selected as the most important reason for culling (326)	92.70	6.30	0.70	14.80		
	39	“Other” factors were important when selecting replacements ewes	“Other” factors not important when selecting replacements ewes (362)	85.50	7.90	0.40	20.10		
Flock health	401	Percentage of lambs with joint ill		96.20	-0.22	-0.43	-0.02	-1.3	6.00

	137	Did you trim diseased feet? – Never	Always (32)	86.00	8.90	0.80	22.40		
	401	Percentage of ewes with twin lamb disease		92.40	-0.40	-1.00	<0.01	-1.6	4.00
BCS	78	BCS In mid pregnancy e.g. scanning time – some ewes (10-50%)	None of the ewes (23)	96.90	-10.50	-20.40	-1.00		
	82	BCS In early lactation – some ewes (10-50%)	None of the ewes (94)	94.70	8.10	0.20	16.20		
	64	BCS At lambing time – most of ewes (>90%)	None of the ewes (56)	89.10	10.20	1.40	22.10		
	71	BCS At weaning time – majority of ewes (51-90%)	None of the ewes (66)	88.00	7.10	0.00	20.30		
	42	BCS At lambing time – majority of ewes (51-90%)	None of the ewes (56)	83.50	-6.50	-18.00	0.00		
Record keeping	227	Farmer provided a figure of the number of lambs at weaning	Farmer did not provide a figure of the number of lambs at weaning (174)	93.10	5.90	0.10	12.70		
	182	Culling source of information - records	Culling source of information - no	92.90	5.40	0.30	12.50		

			records, memory only (219)				
	49	Recorded flock information using “any piece of paper”	Did not record flock information using “any piece of paper” (352)	86.70	6.40	0.30	15.30
Non-inferential parameters		Lowland farms with indoor lambing	All other systems (upland or hill farms lambing indoors or outdoors)		15.00		
		Overdispersion parameter			56.50		

Figure 1


Cluster
1
2
3
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SUPPLEMENTARY MATERIALS

Supplementary Table 1. Results of the latent class analysis to explore farmer managerial attitudes, based on responses to 20 statements on attitudes and opinions about farm management. Responses were on a five point scale; ‘strongly disagree’, ‘disagree’, ‘neutral’, ‘agree’ and ‘strongly agree’ and were numbered 1 to 5 respectively. Three latent classes (labelled Latent Class 1 to 3) of farmers were identified and mean statement ratings per latent class are provided in the table.

Managerial construct	**Belief statement**	**Mean rating per Latent Class**		
		Latent Class 1 – “Lower managerial attitude”	*Latent Class 2 – “Medium managerial attitude”*	*Latent Class 3 – “High managerial attitude”*
Strategic thinking (adapted from (Mäkinen, 2013))	1. I have a vision how to develop the farm in the long run	3.71	4.03	4.34
	2. I have plans for investments on machinery buildings or grassland	3.61	3.94	4.35
	3. It is difficult to set goals for a period of a couple of years	3.54	3.40	3.29
Entrepreneurial orientation (adapted from (Mäkinen, 2013))	4. A farmer today should be regarded as a business manager	3.90	4.09	4.42
	5. My managerial skills are good	3.63	3.74	4.15
	6. I follow business principles in managing my farm	3.39	3.80	4.15
Appreciation of profession (adapted from (Mäkinen, 2013))	7. It is rewarding to be a farmer	3.46	3.89	4.50
	8. Young people should be encouraged to a farming career	3.55	4.14	4.51
	9. Farming in UK does not pay	3.54	3.19	2.96
Appreciation of profession (adapted from (Mäkinen, 2013))	10. A farmer can be proud of his her job	4.20	3.97	4.86
Planning (adapted from (Mäkinen, 2013))	11. Keeping records on just about everything is very important	3.25	3.81	3.89

Planning (adapted from (Mäkinen, 2013))	12. It is very important to stick to management principles no matter what the pressure to do otherwise	3.30	3.60	3.93
Planning (adapted from (Mäkinen, 2013))	13. I am much happier if everything is planned well ahead of time	3.86	3.93	4.28
Planning (adapted from (Mäkinen, 2013))	14. I normally do not rest until the job is fully completed	3.96	3.87	4.49
Decision making and information seeking (adapted from (Nuthall, 2009)	15. I tend to mull over decisions before acting.	3.57	3.71	3.85
Decision making and information seeking (adapted from (Nuthall, 2009)	16. I usually find discussing everything with members of my family and or colleagues very helpful	3.70	3.92	4.43
Decision making and information seeking (adapted from (Nuthall, 2009)	17. I find it easy to ring up strangers to find out technical information	2.92	3.40	3.42
Decision making and information seeking (adapted from (Nuthall, 2009)	18. I tend to seek the views of many people before making changes to my operations	3.06	3.64	3.72
Productivity-oriented (Leary and Gate, 2017)	19. My farm is completely oriented towards maximizing productivity	2.99	3.55	3.91
“Locus of control” (adapted from (Leary and Gate, 2017)	20. It is within my control whether or not my farm will be successful in the long term	3.14	3.69	4.14