Development and Application of a UK Sheep Production Simulation Model

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Declaration of Own Work

I, Thomas Clough, confirm that the work presented in this thesis is my own. Where information has been derived from other sources, I confirm that this has been properly cited within the thesis.

The data used in this research was collected by the Agriculture and Horticulture Development Board under the Challenge Sheep project. I have performed all subsequent analysis, interpretation, and writing of the thesis, under the supervision of my supervisors.

This thesis has not been submitted, either in whole or in part, for any degree or diploma at this or any other university.

List of Abbreviations

Abbreviation	Definition
AFRC	Agriculture and Food Research Council
AFT	Accelerated Failure Time
AHDB	Agriculture and Horticulture Development Board
AIC	Akaike Information Criterion
ARC	Agricultural Research Council
BCS	Body Condition Score
CCC	Concordance Correlation Coefficient
CI	Confidence Interval
CIEL	Centre for Innovation Excellence in Livestock
CNCPS	Cornell Net Carbohydrate and Protein System
CODD	Contagious Ovine Digital Dermatitis
CPH	Cox Proportional Hazards Model
CSIRO	Commonwealth Scientific and Industrial Research Organisation
DSS	Decision Support System
EID	Electronic Identification
INRA	Institut National de la Recherche Agronomique
KE	Knowledge Exchange
kg	Kilograms
KNN	K-Nearest Neighbour
KPIs	Key Performance Indicators
MAE	Mean Absolute Error
ME	Metabolisable Energy
NEB	Negative Energy Balance
NRC	National Research Council
NSA	National Sheep Association
NZ	New Zealand
PLF	Precision Livestock Farming
R^2	Coefficient of Determination
RMSE	Root Mean Squared error
ROI	Return on Investment
SVM	Support Vector Machines

TLPM	Teagasc Lamb Production Model
UK	United Kingdom
WFM	Whole Farm Model
XGBoost	Extreme Gradient Boosting

Abstract

Advancements in data collection, storage and analysis techniques have resulted in a recent surge in the potential to collect and utilise data on sheep farms. When used effectively, data can help support management decisions to make informed choices regarding animal health and performance.

Throughout the project the authors worked closely with the Challenge Sheep project. This was an Agriculture and Horticulture Development Board (AHDB) project to monitor the lifetime performance of ewes on a number of sheep farms throughout England. This thesis began with two main aims. An initial analysis of the Challenge Sheep project data would provide an insight into which variables affect ewe performance. These findings would then be used to build a series of models to analyse and predict key aspects of ewe performance, which would inform a simulation model to estimate total lifetime productivity. Key variables included within the analysis were; mating and lambing body condition score, pre-mating body condition score change, ewe age at first mating (either ewe lamb first bred at less than one years of age or shearlings first bred between one and two years of age) and parity. The analysis of ewe performance data focused on four areas: a reproductive analysis was conducted to model the rate at which ewes got in lamb; a wastage analysis, to observe the reasons and model timings of ewe losses throughout the production year; a predictive model for the number of lambs born to each ewe; and a predictive model of the impact of ewe performance on weaning weight of lambs. As body condition score is crucial to effective flock management, and will substantially inform the simulation model, an additional model was developed to predict body condition score using animal data including objective weight measurements. This was developed with the aim of reducing subjectiveness around body condition scoring, providing an objective measure for implementation on farm. An additional case study was conducted to observe scorer variability within body condition score measurements. The results from the case study were analysed independently to observe inter and intra rater variability and were also compared to the body condition scoring predictive model.

The reproduction analysis found key variables which had a significant effect on the interval between mating and lambing (indicates days to conception plus gestation

period, calculated from ram entry date and lambing date). For mature ewes (parity two or more), mating body condition score had a significant effect, with Low (BCS less than 2.75 out of 5) and High (BCS more than 3.5 out of 5) groups having a significantly increased mating to lambing interval, suggesting increased days to conception. Ewes which gained condition pre-mating (weaning to mating) got in lamb more quickly while ewes which lost condition took longer to get in lamb. These findings agree with AHDB recommended mating body condition score targets. In their first year of production, ewe lambs took significantly longer than shealings to get in lamb, which was to be expected due to their lower stage of maturity.

Within the wastage analysis, it was observed that lower BCS animals at mating (BCS less than 3.0 out of 5.0) had a significantly increased chance of loss (premature cull or death) throughout the production year compared with ewes in higher condition (BCS greater than 3.0). This suggests ensuring ewes are in a minimum BCS of 3.0 out of 5.0 at mating will minimise losses. Overall, from these data, ewes first lambed as shearlings had a higher incidence of wastage compared with ewes first lambed as ewe lambs. Wastage was lowest in one year old animals, peaking in two-year-old animals then gradually reducing as animals age further.

Systems dynamics models are one means of using farm data to simulate a production system, providing a measurable output. The individual models were incorporated within a simulation model that simulates how changes in ewe performance affect lifetime productivity. This allows the comparison of how parameters such as body condition score, age at first mating (ewe lamb or shearling) and breed combine at the individual ewe level to impact on flock productivity. Total lifetime lamb weaning weight was observed as a measure of performance within the simulation model. Findings from the simulation show that despite variation among breeds, effective management of body condition score is crucial to maximise lifetime performance. Ensuring body condition score is maintained on or above target at mating was estimated to yield an average increase of 26.7kg of weaned lambs over their lifetime. In addition, despite lower early life performance the model revealed first breeding as ewe lambs resulted in an average of 12.5kg greater weight of lambs over a ewes lifetime compared to first breeding as shearlings.

The body condition score prediction model was able to successfully predict body condition score from weight and additional predictor variables with the same accuracy as a human scoring. The best performing gradient boosting model had an RMSE of 0.406. Additionally, a regression chain model was used to improve predictions at extreme values, this resulted in a more generalisable model. If implemented on farm, the use of a model to predict body condition score, combined with electronic identification technologies, has the potential to save time and resources by avoiding the need to manually body condition score and improve the objectivity and reliability of measurements. This will help ensure farmers can manage individual ewes to increase farm productivity and profitability.

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1.1. The UK sheep industry

1.1.1. Overview

The UK Sheep industry consisted of approximately 32 million head of sheep in 2023 of which 15.4 million were breeding ewes and 16.3 million were lambs and other sheep (Department for Environment Food & Rural Affairs, 2023). The sheep population has remained relatively consistent over the past 20 years, after a substantial fall of 13% was observed in 2001 as a result of foot and mouth disease from which numbers did not recover (Zayed and Loft, 2019). The figures for 2023 are 4.3% lower than those of 2022, believed to be driven by rising feed prices (Department for Environment Food & Rural Affairs, 2023). The UK sheep industry had an estimated value of production of £1.3 billion in 2020, and worth approximately £290 million to the UK economy. 150,000 people are employed either directly on farm or within associated industries (NSA, accessed 23/01/2024). The UK sheep industry is focused on lamb production for meat with very few milking ewes kept in the UK unlike other European countries. The UK industry consists of a stratified system, which can largely be categorised into hill, upland and lowland systems. Hill flocks are kept at above 500m, upland flocks above 300m and lowland flocks below 300m. Each system utilises different management practices, which are often linked to how extensive the system is. The UK sheep industry plays an important economic role, particularly for rural communities, while also helping ensure food security. Sheep are one of the few animals with the ability to utilise low quality feedstuffs and produce high quality protein for human consumption. This often uses land which is unable to be utilised for other farming practices. The complex interactions between system, breed and management type make the UK sheep industry extremely diverse and constantly evolving.

1.1.2. Breeds

The stratified nature of the UK sheep industry results in variation in breed type depending on system. It is common for more extensive hill flocks to farm hardy breeds which can cope with the more extreme climate and variable nutrition. Maternal breeds such as Swaledale or Welsh Mountain are often used in these environments. Comparatively, upland systems often have increased forage quality, and less harsh weather conditions to contend with. Suitable breeds for these systems are sometimes composite ewes, often a cross between hill and lowland ewes such as the Mule or purebred ewes such as the Lleyn. Lowland breeds often include less hardy breeds, generally of a larger weight than upland and hill breed types and with the potential for higher fertility and offspring growth rates. Traditional lowland breeds include Suffolk and Texel. There are as many as 106 different sheep breeds represented in the UK industry (AHDB Beef and Lamb, 2018), however they can almost all be categorised into a system where their specific characteristics are desirable. Breed types are constantly evolving due to the introduction of new genetics, the use of composites and selective breeding. Farmers are constantly striving to find the right breed for their system to maximise productivity.

1.1.3. UK Systems

The nature of constantly changing breeds within the UK sheep industry is the result of market requirements and preferences, as well as changing systems throughout UK farming. Traditionally sheep may have been viewed as one component of a larger diverse farming enterprise which would often include arable and beef sections, particularly for lowland flocks. Sheep would often fit into the rotation, grazing arable land as a break crop, or grazing land unable to be used for crops. A shift in the industry to more intensive arable farming has resulted in sheep predominantly grazing land unable to be used for crops, often upland and hill areas.

The structure and size of the sheep industry in the UK has changed substantially over the past 30 years. These changes are largely a result of farmers managing disease risk and government policy. Stratification is reducing throughout the sector, this is due to an increase in closed flocks to reduce the disease and parasite risk, improving flock health status. Increasing interest in closed flocks has resulted in some of the shift in breed types observed, particularly an increase in Lleyn and Romney maternal genetics. In the 1990s support payments were calculated on a ewe headage basis, naturally this incentivised farmers to increase flocks size. More recent support payments including the 'basic payment scheme' focus on livestock units which may incentivise smaller sheep flocks. Increasing interest around the environmental impact of sheep production, particularly for upland and hill flocks has led to environmental schemes becoming popular. These schemes reduce ewe stocking density and have somewhat led to a reduction in ewe numbers.

1.1.4. Ewe Life Cycle

UK farms have two options for replacement ewes. Replacements are either bought in or bred on farm. Initially, ewes can be bred as either a ewe lamb or shearling. Ewe lambs are ewes which are first mated at less than one year old, while shearling are mated a year later at approximately 18 months old. The main benefits associated with first breeding ewes as ewe lambs include, higher potential lifetime productivity from an additional productive year and improved maternal ability in subsequent years, particularly in their second year of production. First breeding as shearlings allows the ewes to achieve a much higher percentage of mature liveweight before mating. This may improve first year performance when compared to ewe lambs and potentially mitigate any knock-on effect on performance associated with first breeding as ewe lambs. Within UK systems, mating occurs as photoperiod reduces in the autumn. This generally results in spring lambing. Mating dates can vary depending on the system, often with lowland systems choosing to mate, and therefore lamb, earlier than upland systems. The later lambing associated with upland systems increases the probability of good weather at lambing which reduces neonatal lamb mortality and allows for an increased reliance on grazed forage throughout the lamb rearing phase. Other key management events throughout the year occur at: pregnancy scanning; eight-weeks post lambing; and weaning. Ewes are pregnancy scanned approximately 80 days post-mating. This not only indicates whether ewes are in lamb but also the number of foetuses for each ewe. At eight-weeks post-lambing, ewe and lamb performance and health should be assessed. At this point lambs are starting to receive a substantial proportion of their energy intake from pasture due to ewe milk production starting to fall. At weaning, lambs are separated from the ewe. This is usually 12 to 16 weeks post-lambing. At this point ewe milk production has significantly reduced and most of the energy intake for lambs is received from pasture or concentrate. Ewes then have around 3 to 4 months to regain any lost BCS and ensure optimum health for next mating. Most ewes are removed from the flock at seven years of age as this is deemed the end of their productive life.

1.1.5. Flock productivity

Productivity throughout all areas of agriculture has seen substantial increases recently. Technological advancements, increasing knowledge and genetic improvement have led to increased productivity. The sheep industry in the UK has developed a range of extensive systems of small low input farms, with comparably low productivity, to larger, more productive systems in which genetics, management and nutrition play key roles in maximising productivity.

1.1.5.1. Measures of Productivity

There are multiple ways that performance can be assessed on sheep farms. Often this depends on the system and the desired output from that system. Ewe and lamb performance have multiple metrics to assess. Metrics to assess ewe performance often include fertility, number of lambs per ewe at scanning, lambing percentage, total lamb weaning weight, lamb growth rate up to eight-weeks of age, and lamb survival. Lamb performance metrics are often focussed around growth rates, particularly post-weaning and grade at slaughter. A series of key performance indicators (KPIs) have been established to observe the performance of both individual animals and a whole flock. Reference values can be used for each KPI to observe if a flock is under performing, or performing well (AHDB, 2024).

1.1.5.2. Genetics

An animal’s individual performance is closely linked to its genetic potential. Breed plays a large role in reproductive performance, lamb performance, and carcase conformation, however variations within breeds are also observed. Breeds can be categorised into maternal or terminal genetics. Terminal breeds produce lambs with optimal growth rates and carcass conformation traits, as their lambs are usually marketed for meat. Maternal genetics have traits associated with higher fertility and prolificacy, however good lamb carcass conformation and growth rates must also be maintained as most lambs will still be destined for slaughter. Selecting ewes and rams, using maternal and terminal indexes, is an effective way to improve overall flock productivity. Ewes with high maternal indexes have been shown to have higher litter size and reduced perinatal lamb losses. Improved terminal index resulted in heavier lambs post-weaning and reduced days to slaughter (Mchugh *et al.*, 2022). Flocks with maternal breed types have been shown to have higher productivity than that of hill or terminal breeds (Lima *et al.*, 2019).

1.1.5.3. Nutrition

Nutrition influences all aspect of sheep production including health, reproductive performance, wastage and lamb growth. Ewe and lamb nutrition is based around grazed forage, with supplemental concentrates and minerals at key stages of production. Nutrition around lambing is important to ensure optimal energy balance to mitigate metabolic diseases such as ketosis, as well as ensuring adequate mineral intake to reduce the incidence of conditions such as hypocalcaemia and hypomagnesaemia.

1.1.5.4. BCS & Weight

The use of weight and body condition scoring on farms as a measure of ewe performance, and to aid in management and nutritional decisions has been associated with an increase in productivity (Povey, Stubbings and Phillips, 2018). Estimating ewe subcutaneous fat reserves at key intervals throughout the production year provides farmers with an additional metric to monitor their flock. BCS throughout the production year and in particular BCS change between mating and scanning has been shown to effect litter size and the proportion of ewes that lamb (Wright, 2021). Weight is commonly used as a means to assess lamb performance, usually through eight-week and weaning weights. It is also used as the main metric to assess whether ewes should first be bred as ewe lambs or shearlings. Guidelines suggest ewe lambs should be at 60% of their mature liveweight before mating (AHDB Beef & Lamb, 2016).

1.1.5.5. Management

Management decisions on farm can greatly impact the productivity of a flock. One key management decision is made at pregnancy scanning, which usually occurs around 80 days post-mating. This provides farmers with information on which ewes are in lamb and an estimation of the number of lambs. The data can be used to group ewes depending on scanning number. Targeted nutrition post-scanning ensures ewes are meeting the correct nutritional intake to ensure adequate lamb growth, without leading to large lambs, which increase dystocia. Ewes not in lamb at scanning are often sold as cull ewes, this reduces forage and feed requirements for the flock and provides a source of income earlier in the year.

Additionally, management decisions regarding reproduction are important. Farmers must decide whether ewes should be introduced to the flock as ewe lambs or shearlings. The length of mating is then important to maximise reproductive performance without substantially increasing the lambing period.

Selecting cull ewes is another area where correct management decisions are vital to maximise productivity. Often ewes are selected for culling on a case-by-case basis, with poor health or poor performance being predominant factors for selection. Selection parameters and rate of culling are largely dependent on the specific system. Flock numbers must usually be maintained, therefore selectively culling ewes, or culling aging animals is important. This can sometimes result in ewes with less than desirable performance being retained to ensure replacement rate is not excessive.

1.1.5.6. Health & Disease Prevention

Disease prevention plays a large role in maximising flock productivity. Lima et al. (2019) investigated how disease prevention practices affect flock productivity. They used lamb sales data as a performance metric. They observed farms implementing preventative practices, including vaccination against abortion and clostridial agents, and administering anthelmintics during quarantine had greater flock productivity. Lameness can also substantially affect the productivity of a flock. It has been estimated that a lame ewe can see a reduction in BCS of 20% and a substantially reduced lambing percentage of 20% (Lovatt, 2015). The prevalence of lameness within English flocks has more than halved between 2004 and 2013, from 10.6% to 4.9% (Winter *et al.*, 2015). This may suggest that the negative impact on flock performance will also be reducing.

1.1.5.7. Future Productivity

Additional measures of productivity are likely to become common place in the future. Increasing pressure for ruminant production systems to reduce greenhouse gas emissions, and in particular methane emission is likely to lead to changes in how performance is viewed. The Centre for Innovation Excellence in Livestock (CIEL) reported the impacts of sheep production on greenhouse gas emission and discussed ways to reduce emissions (CIEL, 2022). They reported that more extensive systems have lower efficiency and therefore higher greenhouse gas emission per kilogram of lamb produced. Nutrition and management can be used to reduce methane emissions. Feeding higher grain diets and oilseed inclusion within the diet reduces methane production from rumen microbes. Genetically selecting ewes for lower emission may be an effective means to breed inherently low emissions animals. However, it is important to consider the financial impact of feeding higher concentrate diets or purchasing expensive genetics, particularly with the low margins associated with sheep production in the UK.

1.1.5.8. Profitability

The productivity of sheep farms is closely correlated with profitability. Volatility within the sheep industry, both within feed prices and lamb prices leads to large variations in yearly income. Lamb prices not only fluctuate each year but also throughout the year, with maximum prices observed in June (Clarke, 2023). Uncertainty around prices makes it difficult for producers to plan. Some use their system to their advantage to lamb early and target the highest lamb prices in June, while other, generally lower input systems utilise high grass growth from late spring into summer to fatten lambs for lower cost, however, often receive lower fat lamb prices in the autumn. The lowest input systems will often sell lambs as store lambs at approximately 30kg liveweight, where they will generally be finished on lowland farms where grass growth is higher later in the year.

Environmental schemes can limit the potential productivity of certain farms, however, can improve the profitability. These schemes are designed to limit the stocking density to minimise any effect on wildlife. Naturally incentivising farms to reduce stocking density will reduce the output and therefore the productivity of these farms. Overall profitability is often improved due to the subsidies from environmental stewardship schemes.

1.1.5.9. Summary

Although productivity and therefore profitability are key metrics on sheep farms, it is also important to balance economics and welfare. Stott et al. (2012) observed the relationship between economics and welfare. They suggested reducing extensification improved flock welfare. They also noted that flock expansion maximised productivity, largely due to a reduction in labour per ewe. As the sheep industry progresses it is vital to balance performance with welfare. A number of factors dictate the productivity and profitability of a sheep system. These are specific to each farm, and some are largely out of the control of the farmer. Maximising nutrition, genetic potential and health of a flock provides the best opportunity to increase productivity and profitability.

1.1.6. Data Collection and Implementation on UK Sheep Farms

Advancements in data collection, storage and analysis techniques has resulted in a recent surge in potential to collect data on sheep farms. Since legislation changes in 2009, all sheep in the UK not intended to be slaughtered before 12 months of age, must be electronically identified through the use of electronic identification tags (EID). These tags allow ewes to easily and effectively be traced throughout the industry, at each point within the supply chain. One additional benefit of EID tags for farmers is the ability to easily record individual animal data. Although data collection options are available, utilisation of this data is less common. Specific breeding programmes offer farmers financial incentives to collect data, however the wider industry appears to struggle to utilise animal performance data collected on farm. Out of 406 farmers surveyed to assess the use of EID technology to record animal information, only 87 utilised the technology (Lima et al., 2018). Perhaps the most common data collected is reproductive performance at pregnancy scanning, however this is rarely recorded.

The sheep industry as a whole is in its infancy in terms of data collection and utilisation. The increasing ease of data collection and encouragement from organisations such as the AHDB may result in a substantial uptake within the industry. Reasons for the current lack of uptake include; negative views of EID technology by farmers; lack of published evidence on the benefits of EID technology; cost of the technology; and lack of IT skills required for recording (Lima et al., 2018).

1.2. Challenge Sheep Project

The Challenge Sheep project is an Agriculture and Horticulture Development board (AHDB) funded project, started in 2016, to observe ‘the impact of the management of replacement ewes through their first pregnancy and lactation on their lifetime performance’ (Challenge Sheep | AHDB, accessed 20/10/2023). The project set out with four main objectives:

1. To identify best practice for management of replacement ewes from a network of producers, researchers and consultants using participatory action research techniques.
2. To monitor replacements brought into the flocks in 2017 and 2018 over their productive lifetime on ten farms through extensive analysis of EID data and benchmarking.
3. To communicate the activity through a planned KE programme with a range of approaches employed.
4. To collect additional information, such as DNA, health status and antimicrobial use, to complement other projects.

The Challenge Sheep project arose from findings from the Longwool project (Defra, 2007). High premature culling and mortality was observed for ewes in their first year of production (~11% of ewes bred). This results in a substantial production loss and therefore financial loss. It was estimated that £10.9 million per year is lost due to ewe losses in their first year of production. The Challenge Sheep project was designed to produce data to inform decision making for the management of ewe lambs and shearlings, resulting in the implementation of methods to reduce financial losses in their first year of production.

Data collection started in 2017, and continued for seven years, ensuring ewes were followed from entry as ewe lambs or shearlings to exit. Ewe performance was monitored at five key-stages throughout the production year. These included: mating, scanning, lambing, eight-weeks post-lambing, and weaning. Progeny performance was recorded at birth, eight-weeks of age, and weaning. All data-points were recorded using electronic identification (EID), to effectively record individual ewe data, and upload this data into each farm’s database.

7003 ewes, from eleven farms, entered the project in 2017, with an additional 721 joining within the first 4 years. 14 purebred and crossbred breed types were included within the project. These range from hefted hill flocks, farming predominantly Swaledale ewes to intensive lowland flocks. As would be expected the choice of breed is somewhat correlated with farm type, however most farms do include multiple breeds. The large range of breeds and management systems were chosen to help improve how generalisable the project data was for the wider industry. Farm size ranged from 252 ewes to 1190 ewes at the start of the project. Ewes exiting the project and replacements slightly alter these values throughout the seven years of the project.

The data collection focussed predominantly on the performance of ewes, with ewe factors such as body condition score, weight and survival data collected, alongside lamb performance data. At each of the five key-stages, ewe body condition score (BCS) and weight data were collected. BCS data were recorded by a single trained individual on each farm, who underwent a BCS calibration session at the start of the Challenge Sheep project. A five-point scale was used with 0.25-point increments, with the reading entered directly into EID readers. Weight was recorded on electronic weigh scales to an accuracy of 0.1kg, with either manual entry of the weight into EID readers or automatic recording from the weigh head. Lamb weights were estimated at lambing and recorded at eight-weeks post-lambing and weaning using the same method as that for the ewes.

All ewe exits from the project were recorded throughout the production year, with a date and reason for exit. This included ewes which were sold as breeding stock, ewes which were culled and ewes which died on farm. Farmers recorded the best-known reason for ewe exit. Lamb mortality was also recorded. At pregnancy scanning the number of lambs were recorded for each ewe.

Data on some management practices were not collected, this includes data regarding nutrition, reproductive management and day to day decisions. Additionally, data was not available for ewes before their project entry date, meaning the first data points were collected at first mating as a ewe lamb or shearling. Finally, paternal data was not recorded for any of the lambs.

1.3. Breeding from Ewe Lambs vs Shearlings

A large component of the Challenge Sheep project is to observe and compare the lifetime performance of ewes first mated as ewe lambs or shearlings. One key analysis required to achieve this is to observe the effect of first breeding as a ewe lamb vs a shearling on lifetime productivity. Ewe lambs are defined as ewes which are first bred within their first year of life, at approximately 7 months of age. shearlings are first mated in their second year of life, at around 18 to 20 months of age. Ewe lambs are mated at around 60 percent of mature weight while shearlings are usually at or extremely close to mature weight, with a minimum target of 80 percent. Reducing the duration that ewes are non-productive, through breeding as ewe lambs, has the potential to increase overall lifetime productivity of ewes, and reduces the period for ewes in which no revenue is generated. Although, initially it appears that producing an additional litter from a ewe could only have positive effects on productivity, it is important to account for the effects that breeding at a much younger age may have on lifetime reproductive performance of that animal. The high metabolic requirements during gestation and lactation, for animals which have not reached maturity, has the potential to impact overall performance in subsequent years. There may also be a higher degree of risk to the animal from breeding at a younger age, which also must be accounted for.

Some additional benefits of breeding from ewe lambs include: an overall increase in lambs weaned, with no increase in ewe numbers; a reduced generation interval which allows for rapid rates of genetic improvement, assuming that replacements are retained from ewe lambs; earlier replacement of poor performing ewes; and reduced environmental impact as a result of more lambs weaned per ewe (Kenyon and Corner-Thomas, 2022). Although on paper the rapid genetic turnover from retaining replacements from ewe lambs would allow quick introduction of new genetics into the flock, particularly for closed flocks, it is the authors experience that replacements are rarely retained from ewe lambs. This is likely due to ewe lambs often being mated later than the main flock to maximise mating weight and therefore their offspring have less time to reach a suitable mating weight, along with generally lower growth rates for offspring from ewe lambs.

There are many potential disadvantages associated with lambing as ewe lambs. Ewe lambs have variable reproductive performance in their first year of production, this results in a higher number of barren ewes which must be managed separately to the main flock. Ewe lambs must weigh at least 60 percent of their mature liveweight by mating, at seven to nine months of age. Ensuring a suitable weight is reached may require additional feeding throughout the summer months, depending on forage availability this could result in higher feed costs. Breeding from ewe lambs has been associated with increased labour requirements and therefore costs. These costs are a combination of increased labour for feeding and managing ewes and increased labour around lambing due to higher incidence of dystocia. The challenges around successfully mating and lambing ewe lambs can also increase the potential for higher mortality compared to mature ewes (Kenyon and Corner-Thomas, 2022).

1.3.1. Managing Ewe Lambs for Optimal Performance

The decision to breed from ewe lambs is largely dependent on the specific system. However, there are a number of factors which dictate the success of breeding from ewe lambs rather than shearlings.

1.3.1.1. Growth Rate

With the requirement for ewe lambs to weigh over 60 percent of their mature weight at first mating, it is important to maximise lamb growth rates post lambing, and to provide as long a period as possible for growth. Often replacements intended to be bred as ewe lambs will receive the best pasture at slightly reduced stocking rates. Some producers will choose to creep feed and then supplement these ewes to maximise the number that will reach the weight threshold. Ewe lambs are usually selected from animals which have lambed early in the season to maximise the time before mating. Similarly, ewe lambs are generally mated later than the main flock, resulting in later lambing dates. This further extends the interval from birth to first mating.

1.3.1.2. Selection of Ewe Lambs

Selection of replacements is an important factor to maintain the health and genetics of a flock. The AHDB has produced a series of guidelines for best practice when selecting ewe lambs for replacement. Ewe lambs should be at least seven months of age at first mating, should meet the minimum percentage of weight and not have any health issues such as lameness. Purchased replacements should be bought 6-8 weeks before mating, and undergo the same health checks as on farm replacements (Selecting ewe lambs for breeding | AHDB, accessed 24/01/2024).

1.4. Sheep Production Systems Research

1.4.1. Introduction to Systems Models

System dynamics models are a mathematical modelling technique used to better understand complex interactions within a system. They allow changes within a system to be observed over time. System dynamic models are of increasing interest within UK agriculture, already being extensively used in the arable sector with more recent introduction into livestock sectors through dairy farming. In livestock systems they provide a means to predict complex on farm interactions between livestock, nutrition, economics, and management. Systems models are often comprised of a series of sub models which interact together to help conceptualise the whole system. Within the specific area of sheep production models there are a wide variety of possible model types. Growth models; bio-economic models; wastage models and reproduction models are increasing in use within the sheep industry globally. They are usually supported by a nutritional model, often selected from a pre-existing model to best suit the systems model being developed. Systems models are usually designed to increase productivity, and therefore profitability of sheep enterprises. This often results in the inclusion of an economic component of the model, or a means of assessing changes in profitability.

The UK sheep industry currently has a very limited selection of dedicated system dynamic models. There have been attempts to adapt international models to suit the UK industry, however few have been built using UK based datasets. The structure of the UK sheep industry is almost unique, with a wide variety of management strategies and breeds. This increases the complexity of the model design and further increases the difficulty of adapting an international model. Our model will be almost unique in that a UK based dataset, collected from a significant number of UK farms, will inform the model. Internationally there are significantly more models in place, often originating in New Zealand and Australia. Consideration of the differences in farming practices, management and genetics between international flocks and UK flocks is important when designing our model.

1.4.2. Whole Farm Models

Whole farm models (WFM) usually consist of a series of predictive models, which interact to observe whole farm effects. They can include both biophysical models and a combination of biological and financial aspects (Robertson, Pannell and Chalak, 2012). There are a select number of WFM available within the sheep industry. These are often closely related to financial outputs, due to the benefit this can have for producers. The overall aim of WFM is to allow producers to increase productivity at a farm level. There are usually a series of inputs that ensure the model is specific to their farming system, and any outputs from the model are specific to variables on their farm. The overall design of some WFM will be discussed in this chapter, with a more in-depth investigation into the constituent predictive models in later chapters.

GrazPlan is a whole farm model developed in Australia (Donnelly, Moore and Freer, 1997). It incorporates a series of decision support systems (DSS) which interact together to predict flock performance. The constituent DSS include, MetAccess, LambAlive, GrazFeed and GrassGro (Freer, Moore and Donnelly, 1997). These DSS can either be used individually or within the larger GrazPlan DSS. GrazPlan was designed as an early computer package to be used by advisors to aid Australian sheep farmers in making key decisions. The suite of DSS are used in conjunction with local weather records and farm specific data to establish the effects of certain management decisions. The GrazPlan project incorporated results from grazing research into the individual packages. This allowed research on grazing management to be easily adopted by producers, while previously it would have been challenging to make the research specific to their farm. The inclusion of weather predictions within the GrazPlan DSS, utilising historical weather records, is almost unique. This allows chilling effects and grass growth to be more accurately predicted within the LambAlive and GrassGro DSS.

The Teagasc Lamb Production Model (TLPM) is a stochastic budgetary simulation model developed to observe the effects of changes within a lamb production system on profitability (Bohan et al., 2016). The financial aspect of this model is of key importance, using profitability to compare between different scenarios. Changes in cost per hectare and lamb sales per hectare are often used to compare different scenarios using this model. The model includes a series of inputs and outputs. Inputs include: land; capital; animal numbers and prices, while some outputs include: flock sales and purchases; grass supply and demand; and lamb growth. The TLPM was developed using an Excel spreadsheet, with the performance of each flock simulated on a monthly basis. Scanning rate was a key input for the TLPM, allowing mating success and weaning number to be determined. It also affected ewe energy requirements at late pregnancy and lamb growth rates post-partum. The proportion of breeding ewes culled or died were taken from experimental data with 25% lost at scanning and 75% pre-mating.

Validation of models is important to ensure they predict accurately under the conditions they were intended. The TLPM was validated using data collected from 20 commercial Irish sheep farms. The similarity between the model outputs and the real farm data supported the model and suggested the outputs were realistic. The application of the model was demonstrated through investigating two scenarios with differing average lambing dates. The model found that a mid-season lambing flock had a higher return on investment (ROI). Ewe prolificacy has also been evaluated using the model, finding that in general higher prolificacy resulted in higher profitability.

It is apparent from the literature that a number of models may be specific to international producers, and it is unknown how applicable these are to the UK industry. GrazPlan is specific to temperate pasture-based systems in Australia, however many concepts of the model may be applicable to a UK based system. The TLPM was validated on Irish data, therefore it may be more appropriate for the UK, however the large emphasis on budgetary simulation creates a different scope for the model compared to our model. The TLPM uses the inclusion of scanning number as an input to determine mating success and number of lambs. Instead, our model includes a predictive model to estimate the number of lambs born to each ewe from ewe parameters, rather than including this as a direct input into the model. Within our model, ewe wastage was determined from the existing dataset, then predicted within the simulation model, rather than including wastage at a predetermined rate. This should help improve the accuracy of our model.

1.4.3. Nutrition and Growth Models

The incorporation of a nutritional model into a WFM is important. The predictions and recommendations within the models will be closely associated with nutrition to ensure optimum productivity. There have been a significant number of small ruminant nutrition models developed to provide nutritionists, vets and farmers with a series of approximate parameters for ewe and lamb nutrition. Many of these models have undergone multiple iterations, utilising both previous versions of the same model and different models from around the world to improve the nutritional models.

Cannas et al. (2019) described the history of small ruminant nutrition models and explained the features of different models used throughout the world. One of the earlier nutrition models developed was from the Agricultural Research Council (ARC) in 1965. This model took the concepts of an existing cattle nutrition model and adapted it to make it suitable for sheep production. The ARC model was improved in the 1980s with significantly more rigorous analysis of protein utilisation, specifically by accounting for rumen degraded and undegraded protein. In the late 1990s the Agricultural and Food Research Council (AFRC) based a new model on the ARC model. In addition to the sheep nutrition models the AFRC model included goat specific data. The AFRC model is currently one of the few UK sheep nutrition models available and is often the building block for UK sheep nutrition.

The Institut National de la Recherche Agronomique (INRA) in France developed a sheep nutrition model as early as 1978. This model utilised many of the principles from the ARC model. The most recent update to the INRA model accounts for the reduction in rumen digestibility from increased feed intakes as well as correcting energy values for low pH associated with increased concentrate intake. One significant benefit of the INRA model is the inclusion of milking ewes. The European and African countries which utilise the INRA model often have a significant proportion of milking ewes. However, milking ewes make up a small minority of UK sheep systems, therefore, the use of the INRA model within a UK specific systems model may be non-optimal.

The ARC and AFRC models were also adapted and combined with research caried out on sheep in Australia. This formed the basis for the CSIRO model. This model was the first model to use degree of maturity to predict composition of gain, rather than using sex and breed categories.

In North America, the National Research Council (NRC) developed a basic sheep nutrition model in 1945. This model has undergone various iterations with the most significant in 2007. The 2007 model was based on Cornell Net Carbohydrate and Protein System (CNCPS), a cattle nutrition model. Equations from the ARC, INRA and CSIRO models were incorporated into the CNCPS model to produce a CNCPS model for sheep.

A significant amount of UK based nutritional decisions utilise the Agriculture and Horticulture Development Board's (AHDB) 'Feeding the Ewe' research (Povey, Stubbings and Phillips, 2018) . This advisory document includes a range of feed intakes, nutritional requirements, and management advice collated from the ARC (1993), and consultants' data. The AHDB 'Feeding the Ewe' contains UK specific requirements, including a range of common UK breeds and feed types, as well as being based around the UK sheep production cycle. The UK sheep industry is unique regarding the range of breeds, management systems and farm sizes. When compared to other prominent sheep producing countries such as New Zealand, the UK farms a much larger selection of purebred and crossbred ewes, over more varied land types (hill, lowland etc). The stratified UK system is unique, requiring a tailored nutritional model to ensure accuracy. Overall, it is important for the model to include a suitable nutrition model to incorporate the large variation within UK flocks.

GrazFeed and GrassGro are two decision support systems (DSS) included within the Australian GrazPlan DSS. Freer, Moore and Donnelly, (1997)discussed the GrazFeed DSS and the integration into the larger GrazPlan DSS. GrazFeed allows users to consider the nutritive value of pasture for specific animals and therefore to calculate the required supplementation to maintain a desired daily liveweight gain. The model relies on stage of maturity and body condition rather than liveweight values to make it more applicable to a wide range of breeds and ages. Feed intake is calculated from the potential intake of an animal and the proportion of that intake which is available from pasture and supplementation. A series of potential intake and relative intake equations are presented in Freer, Moore and Donnelly (1997). Energy and protein requirements are also evaluated with requirements for maintenance, pregnancy, lactation, wool growth, and environmental chilling all being considered. The GrazFeed model is dependent on the user providing data for some of the variables, for example the description of the pasture, breed and animal class.

Finlayson et al. (1995) developed one of the earlier sheep grazing system models. They initially developed a series of equations to calculate metabolizable energy (MEI) intake from a range of parameters such as, liveweight, reproductive status, digestibility and energy content of feedstuffs, and availability of feedstuffs. They utilised values from existing literature to select the model parameters and constraints. Rumen capacity was calculated as a function of liveweight, accounting for any increase due to reproductive requirements. Breeds were categorised into, meat, wool, or half, with differences in liveweight between the breed categories being included in the model. The selective grazing nature of small ruminants was accounted for by utilising a Michaelis-Menten function which determines the rate of consumption of leaf, dead and stem components. This series of equations account for pasture cover, resulting in higher digestibility and therefore intake, as pasture cover increases. Finlayson et al. went on to include the consumption of hay and milk into their MEI equation. It was assumed that hay was preferentially consumed when both pasture and hay were available, with equal intake from all animals within each group. Hay wastage was also accounted for. Milk intake by lambs was also calculated, with the assumption that lambs consume milk until metabolic requirements are met or the ewe’s milk supply is exhausted.

Finlayson et al. (1995) went on to produce a model for energy balance. They utilised the previous MEI model with the inclusion of specific energy requirements, these included: ME for maintenance; ME for pregnancy; ME for protein accretion; ME for wool growth and ME for lactation. Energy balance was then used to predict fat deposition and utilisation. The model predicts the influence of nutrition on protein accretion, wool growth, milk production and DNA synthesis. The inclusion of fat deposition and utilisation was one of the first instances where body condition was recognised to influence metabolic processes within the animal. Each ME requirement was modelled independently. Maintenance was determined to be a function of body weight. Additional variables such as temperature and energetic cost of grazing were not included due to the observation that temperature fluctuations in the study location were not extreme enough to warrant consideration.

Overall, it is important to consider that the correct nutritional model is used to inform whole farm models. For a UK focussed simulation model, the NRC and INRA models, although detailed in their approach, may not be specific enough to the UK industry because of the range of breeds and systems the UK has. It appears the AHDB recommended values in 'Feeding the Ewe' would be most suitable for the UK industry due to their close association with the UK specific AFRC (1993) model. Additionally, Finlayson et. al (1995) simulation model used a series of parameters from previous literature, including nutritional parameters from the ARC model, which later informed the AFRC model. The existing use of the ARC model within a grazing system model suggests the information within the ARC model, and therefore 'Feeding the Ewe', would be suitable.

1.4.4. Pasture Management Models

Pasture management is of key importance within predominantly grazing systems, such as the UK sheep industry. Specific models have been developed to aid producers with decision making regarding pasture management. Farmax is a whole farm feed planning model originally developed in New Zealand. It is designed to help producers manage pasture utilisation through predicting grass supply through growth forecasts, and demand through dry matter intake. The model predicts grass growth using regional grass growth curves, produced from historical data, and calculates grass demand from liveweight and growth rates. This review will focus on a report discussing and comparing the implementation of the Farmax model in England (Genver, 2013). A series of comparisons between English and NZ flocks were carried out. One of the most significant findings were that NZ ewes were on average 14% lighter. Overall, there were a significant number of similarities in terms of pasture growth between NZ and the UK. The differences in average ewe liveweight suggests current NZ based models may be inapplicable for the UK industry. These models may be able to be adapted to suit the UK, however the implementation of a UK based model should be more appropriate.

Another component DSS of the GrazPlan project is the GrassGro DSS (Freer, Moore and Donnelly, 1997b). This DSS has the ability to predict pasture growth from historical data, much like the Farmax model. This model then supports the GrazFeed

DSS and the larger GrazPlan WFM. The model is informed by the MetAccess model, allowing weather to effect pasture growth.

Although modelling pasture growth is an important area to consider, the inclusion of this within our model may add too much complexity. The variation between management strategies will have a significant effect on pasture availability, however the prediction of pasture growth curves would require a significant amount of historical and current data which is not currently available.

1.4.5. Lamb Growth Models

Lamb growth models are closely associated with the nutrition models previously discussed. Generally, the nutrition models do not account for variables such as breed. Within our systems model we included a predictive sub model to account for variation in growth rates depending on dam breed, BCS and birth status. We predicted lamb weaning weight using ewe parameters, creating a predictive sub model to inform the simulation model. The modelling of lamb growth is significant due to the potential for growth rates to increase farm productivity. Giving producers a means to accurately predict growth rates or lamb weaning weight from a range of ewe parameters will allow future planning to ensure optimum growth rates are achieved.

1.4.6. Environmental Models

The weather plays a significant role in all agricultural practices, often with extremes resulting in challenges for farmers. It is often accepted that farmers must adapt management practices in response to changes in weather. This is especially necessary within the UK sheep industry, specifically around lambing where weather can significantly impact lamb mortality.

Two decision support systems (DSS) from the GrazPlan project in Australia help farmers predict weather patterns and lamb mortality (Donnelly, Moore and Freer, 1997). The MetAccess and LambAlive DSS utilise a large database of historical Australian weather records, recorded by the Australian Bureau of Meteorology. The MetAccess DSS is designed to allow users to analyse typical weather patterns and calculate the probability of specific weather events occurring. This DSS is based on the frequency of each weather event occurring at a specific time of year and location. It is not designed as a statistical model to predict weather patterns. The MetAccess DSS then supports the LambAlive DSS, which is designed to estimate the risk of lamb mortality from the effects of chilling due to the weather. Using probability to estimate the chance of a specific weather event occurring is effective, however will struggle to encompass extreme weather events. Within the sheep industry it is often these extreme events which cause significant challenges around lambing, rather than the event which has occurred at the highest frequency in the past.

Similarly to the MetAccess DSS, White et al. (1983) used sampling from probability distributions to predict the probability of certain weather events in North Victoria, Australia. They used rainfall data to aid in the prediction of pasture growth, rather than lamb survival. Evapotranspiration was also estimated from time of year and probability of certain temperatures. Australian agriculture has a much larger risk of poor grass growth due to drought than the UK industry. Accounting for weather within Australian models appears to be a necessity due to a significant reliance on specific rainfall events.

Although the incorporation of historical weather records to predict weather event probability is important within some Australian models, it may not be necessary within an UK based model due to the lower reliance on specific rainfall events for grass growth. There would be significant challenges around predicting or estimating probabilities of weather occurring within the UK due to large annual variability. The requirements for a large weather database, and continual updates with current weather records is also challenging to include within systems models. This project will not include weather predictions due to the large fluctuations and significant data required to produce the predictive models.

1.4.7. Lamb Survival Models

Total lamb mortality has been estimated at around 10% with over 50% of that occurring within 24 hours after birth (Binns et al., 2002). This results in both a significant loss in productivity along with potential welfare concerns. The reduction in lamb mortality, resulting in a higher number of lambs weaned per ewe has the potential to increase profit. If lamb mortality can be reliably decreased, there is the potential to reduce flock size and maintain the same output per hectare.

The LambAlive DSS is one constituent of the larger GrazPlan DSS in Australia. The LambAlive DSS is designed to estimate the risk of lamb mortality due to chilling from adverse weather conditions. It is closely associated with the MetAccess DSS, used to estimate the probability of certain weather events occurring. The LambAlive DSS utilises an empirical model to predict the rate of heat loss from new-born lambs, with windspeed, rainfall and temperature as model variables. This allows the calculation of a chill index. The chill index, along with relative body condition and litter size is used to calculate the proportion of lambs that die in the first days of life. Merino and Merino x Border Leicester genotypes were used within the study to evaluate the effects of weather on neonatal lamb mortality. The purebred ewes had a higher lamb mortality within the study.

Oldham et al. (2011) predicted the birthweight and survival of Merino lambs using dam weight data. Lamb birthweight is closely associated with lamb survival, with the study finding that lambs which died within 48hr after birth were significantly lighter. However, there was no effect of birthweight on 48hr to weaning mortality. The study observed that increases in ewe liveweight between mating and lambing significantly increased lamb birthweight. They went on to predict lamb birthweight using a multivariable regression. The variables included were, ewe liveweight at joining, ewe liveweight change up to day 100 of pregnancy, ewe liveweight change from day 100 to lambing, lamb sex and lamb birth status (single or twin). The study also predicted lamb survival from ewe liveweight profile. Each additional kg of ewe joining weight resulted in a 0.5% increase in lamb survival for lighter lambs. Also, ewe weight gain during pregnancy resulted in twin lambs having increased survival rates, with the largest effect observed in twin lambs under 4.5kg. Overall, this study suggests it is possible to predict both birthweight and lamb survival from maternal factors. Within our study, the prediction of lamb survival through a multivariable analysis may be beneficial, with an emphasis on BCS change rather than weight changes. The relationship between lamb birthweight and lamb survival may be observed within our study as a basis for predicting lamb survival.

Binns et al. (2002) discussed the risk factors associated with lamb survival. They carried out an extensive study and developed a significant list of risk factors contributing to stillbirth, perinatal and postnatal mortality. When observing lamb survival data, it is important to consider the various risk factors associated with lamb mortality, this would ensure accurate predictions for the magnitude and timing of lamb mortality.

From the literature it is apparent that a significant number of variables can affect lamb survival. It is important to account for maternal factors such as BCS, BCS change, weight, and weight change within predictive models for lamb survival. It is apparent that breeds may also play a significant role in neonatal lamb survival rates (Freer et al., 1997). This could form a challenge within the UK industry due to the large range of maternal and paternal breeds. The effects of breed could be mitigated through the inclusion of a large range of common breeds to the UK. Lambing percentage also effects lamb mortality. The inclusion of weather variability, similar to the LambAlive DSS would also be beneficial, however poses a significant challenge within the UK due to extreme annual and local weather fluctuations. The data to support a predictive model for weather to inform a lamb survival model is not currently available within our study.

1.4.8. Reproduction Models

Reproductive performance is of key importance when increasing productivity on sheep farms. Earle et al. (2016) observed the effects of potential prolificacy and stocking rate in primiparous ewes. They observed an increase in carcass output per hectare when stocking rate and prolificacy were increased, however observed a decrease in lamb performance up to six weeks with higher stocking rates. It is important to match the reproductive performance and stocking rate of a flock to the management system in place to ensure optimum productivity. Within our model the relationship between ewe prolificacy and lamb growth will be considered.

White et al. (1983) included a reproduction model as part of a larger simulation model, focused on modelling the performance of Merino ewes. Ewe fertility was estimated from the product of ovulation, fertilisation, and embryo survival rates. Ovulation rates were calculated as a factor of ewe weight and time of year. It was assumed that 5% of ewes would not ovulate due to a variety of reasons. Pre-mating nutrition was accounted for through an assumed linear relationship between increased weight and ovulation rate. The probability of fertilisation was dependant on time of year; however, it was assumed that all ova were fertilised in fertilised ewes. Embryo survival was affected by ovulation rate, ewe mating weight and weight change up to 21 days post-mating. The GrazPlan model used white et.al (1983) model, with the addition of body condition, as a basis to determine conception rates.

The ability to predict conception rate within a simulation model is beneficial to determine number of lambs born. Scanning number is often recorded on farm to aid management decisions. The use of scanning number as an input within a WFM may be beneficial in terms of accuracy, however it still may be possible to predict reproductive performance from other factors such as, BCS, weight and time of year.

1.4.9. Ewe Wastage Models

Ewe wastage is defined as animals which are prematurely culled or died before the end of their productive life (Flay et al., 2021). There has been a significant amount of research in recent years, with the aim to evaluate and reduce ewe wastage, particularly within New Zealand flocks. New Zealand ewe wastage rates have been estimated in the range of 3 to 20% (Farrell *et al.*, 2019). This has a significant economic impact, especially when wastage rates are high in ewe lambs (Flay et al., 2021).

Farrell et al. (2019) constructed a bioeconomic model to investigate the effects of ewe wastage on profitability. The model was representative of a typical New Zealand North Island hill country sheep farm. The system dynamics model developed consisted of five separate modules to model each sub-system, these include ewe flock dynamics, wool production, feed demand, feed supply and economics. The simulation model developed was run over a 30-year timeframe and the outputs of the model analysed. The model was run over a range of wastage rates from 5-21% and the effect on flock productivity evaluated. Farrell et al. (2019) found that as wastage increases the average flock age decreases. This results in lower reproductive performance due to younger breeding animals within the flock. An increased end of year feed surplus was also observed when lower wastage rates were evaluated. Wastage rates can have a substantial impact on flock profitability, with Farrell et al. (2019) predicting a 17% increase in case profit from a 10% reduction in wastage. It is therefore vital to accurately predict ewe wastage within our model, with the hope to reduce wastage rates throughout the UK industry. The inclusion of a wool production sub model was required within Farrell et al. (2019) research, however, may not be required within our models. The UK has little reliance on the sale of wool for profit due to the low wool prices and meat specific breeds, therefore the inclusion of wool production may overcomplicate the models.

Flay et al. (2021) analysed and discussed annual and yearly ewe wastage of 13,142 ewes from three farms in New Zealand. They also described the relationship between BCS at mating and ewe wastage. They concluded that it was beneficial to increase pre-mating BCS to reduce ewe wastage. When predicting ewe wastage within this study the relationship between BCS and ewe wastage will be important to consider. The literature suggests that until recently very little was understood about the reasons for ewe wastage. Flay et al. (2021) has evaluated when wastage is occurring within NZ flocks, however there is still large variation between systems. It is important for us to initially analyse ewe wastage within our dataset before developing predictive models for wastage.

1.4.10. BCS and Weight Models

BCS is a subjective measure of subcutaneous fat coverage across the lumbar region of a ewe (Russel, Doney and Gunn, 1969). It allows estimation of energy reserves at key intervals throughout the reproductive cycle. There is increasing interest around the use of BCS within ewes, with the AHDB providing target values to maximise productivity and health. The uptake of BCS by farmers is increasing, however can sometimes be seen as a labour-intensive process for little return. The recording of individual BCS values for each ewe is rarer still, with this type of recording being almost unique to farms involved within research or breeding of replacements.

The relationship between BCS and weight has been observed within the literature, with some attempt to produce models to predict BCS. The relationship between weight and BCS was observed by Sezenler et al. (2011). They studied three Turkish breeds of sheep, recording weight and BCS data at three intervals throughout the year. They found that physiological state had a significant effect on weight and BCS. Ewes at lambing were significantly heavier and had higher BCS values than ewes at weaning. They found at all three intervals, weight and BCS had a significant positive relationship. It is important to consider weight as a significant predictor variable in our BCS predictive model.

Semakula et al. (2020a) produced a regression model to predict BCS from lifetime liveweight, liveweight change and previous BCS. Their results were promising and suggested using a multivariable predictive model could predict BCS significantly better than solely looking at liveweight. Our model will adopt a similar strategy to Semakula et al. (2020a), however will include additional variables in an attempt to further reduce predictive error.

1.4.11. Models Summary

The literature highlights a series of key relevant areas to focus on when designing a series of predictive models for the sheep industry. Reproductive performance is of key interest due to the significant increases in productivity which can be observed through relatively small increases in reproductive performance. The relationship between BCS, age, weight, parity, and breed are important to consider within our model. The ability to accurately predict BCS as a management tool to assess flock performance, may have the benefit of reducing labour associated with manually collecting BCS. It is apparent from the literature that there is some uncertainty around the extent of lamb mortality, this includes uncertainty around why it is occurring and when. One reason for the uncertainty around the extent of lamb mortality may be due to the lack of recording, and large variability between management systems. Ewe wastage has recently been analysed in NZ in an attempt to reduce ewe wastage through understanding the main risk factors. This project will analyse ewe wastage using a UK dataset, then build a predictive model to predict wastage. Although weather plays a significant role within lamb survival, it is unfeasible to include it within our study. The dataset required to calculate the frequency at which specific weather events occur is not available, and would likely be inaccurate for the UK.

1.5. Thesis Aims & Objectives

This thesis set out with two main aims:

1. To investigate some of the initial aims of the Challenge Sheep project through the analysis of the data and use of machine learning methods. These include: to identify best practice for management of replacement ewe; and to monitor replacement ewes throughout their productive lifetime using EID data collection (Challenge Sheep | AHDB, accessed 20/10/2023)
2. To build a series of predictive models for key events within sheep production systems, and evaluate how these models interact within a larger systems model

These aims were achieved through the building of a series of predictive models, informed from data collected during the Challenge Sheep project. Initially, the relationship between BCS and weight was observed. Predictive modelling techniques were used to predict BCS, using weight as the main predictor variable, alongside additional variables to improve model fit. The BCS predictions model could be used as a standalone model, as an objective means to predict BCS at any interval throughout the production year, or could be used to inform a larger systems model. It is well reported within the literature that the subjective nature of BCS leads to inconsistencies and bias within scoring. To further understand the effect of subjectivity within BCS measurements a pilot study was conducted, using the Challenge Sheep project farmers, to observe the inter and intra rater error. This indicated the accuracy and repeatability of scorers, and helped to validate the BCS measurements within the dataset.

Reproductive performance was observed. Similar techniques to that used within dairy production models to model days to conception were used. Survival analysis techniques allowed mating to lambing interval to be observed. This was then used to predict mating to lambing interval for individual ewes. These predictions were then integrated within a larger ewe simulation model.

Survival analysis techniques were used to observe wastage throughout the Challenge Sheep project farms. Initially the reasons for wastage was observed, alongside time of wastage. The probability of wastage was then calculated for each day of the production year. This allowed an estimation for the probability of survival for each individual ewe.

A ewe simulation model, observing the relationship between the sub-models was built to observe how the models interacted on a larger scale. The model observed the effects of BCS at key stages of production, ewe status at first mating and breed on lifetime performance. Lifetime performance was quantified by the total lifetime weaning weight of lamb from each ewe. The simulation was run over the expected productive life of an animal with comparisons of the outputs used to quantify the effect of ewe parameters on lifetime performance.

Chapter 2. Use of Machine Leaning to Predict Body Condition Score

2.1. Introduction

2.1.1. Body Condition Scoring

Body condition scoring is used throughout a wide variety of species, including livestock, companion, zoo and equine animals. Body condition scoring gives an indication of subcutaneous fat deposits, and an overall picture of the energy balance of an animal, particularly when changes in body condition score (BCS) are observed over a period of time. For production animals it is mainly used as a measure of performance, and to inform management decisions on farm. However, it can also be used to indicate health status and is one of the key indicators of disease such as ketosis in cattle and sheep. In companion and zoo animals it is largely used as a quick means to ensure the animal is not under or over-weight, again indicating health issues or poor nutrition. Methods of recording BCS vary depending on the species. It can be recorded through palpation, visual inspection or physical measurement, with one method often considered the “gold standard” for each species. Not only do the methods of collecting BCS vary between species, but the scale in which BCS is recorded can vary. Within livestock species BCS is usually recorded on a scale of 1 to 5 with 0.5 point-increments or 1 to 9. Measuring body condition gained traction within the livestock sector as a means to quickly assess and monitor the status of an animal, irrespective of breed, physiological state or age. Body condition scoring is also viewed as a cheaper option when compared to weighing each animal. The uptake of body condition scoring is variable across all livestock systems. Within ruminants, dairy systems have seen the largest use of regular BCS to maximise reproductive performance and yield. Body condition scoring in sheep was pioneered in the 1960s by Jefferies (1961) then further refined and evaluated by Russel, Doney and Gunn (1969), through the observation of the relationship between animal fat percentage and measured BCS. Since the conception of body condition scoring in sheep, the uptake on UK farms has gradually increased, largely due to vets and advisors advocating for the use of BCS and educating farmers around the benefits of body condition scoring. Although body condition on sheep farms is often observed or measured, it appears that recording BCS for individual animals is rare. Concerns with body condition score include high labour requirements and bias as a result of the subjective nature of the measurements. There is scope to increase the frequency, accuracy and recording of BCS on most farms throughout the UK.

2.1.2. Benefits of Body Condition Scoring

Depending on the species and the requirements from that species, body condition scoring can have varying uses. Generally, in livestock species body condition scoring is used as a means of measuring and optimising performance, with the utilisation of BCS targets at specific stages of the production cycle. For example, at mating the BCS target for ewes ranges from 3-3.5 to ensure optimal energy availability for reproductive processes (Wright, 2019). Some health issues can also be observed through body condition scoring, particularly health issues associated with a rapid loss of bodyweight, leading to emaciation. Although body condition scoring identifies potentially ill animals, it can also play a vital role in mitigating the onset of specific diseases. The dairy industry has effectively utilised BCS at calving to minimise negative energy balance post-calving and reduce the incidence of metabolic diseases (Heinrichs, Jones and Ishler, 2023). Often in companion species the emphasis of body condition scoring is placed on reducing obesity, which is a significant risk factor for many diseases. The uptake of body condition scoring in zoo species has also been substantial, with increased challenges due to the extreme differences in animal morphology. Similarly to companion species, body condition scoring is often used to reduce obesity, however, it can also highlight malnourished animals. Overall, body condition scoring provides an indication of an animal’s subcutaneous fat deposits, with different applications for varying species and systems.

2.1.2.1. Benefits of Body Condition Scoring in Sheep

The benefits of using BCS as a performance measure is well documented. BCS can be used to group ewes post-weaning for targeted nutrition (Povey, Stubbings and Phillips, 2018) , low BCS at weaning has been shown to negatively impact ovulation rates (Povey, Stubbings and Phillips, 2018), and low BCS at lambing has been shown to impact on lamb growth rates (Mathias-Davis *et al.*, 2013). Body condition score is an indicator of metabolic diseases, particularly around lambing. Ketosis occurs in ewes toward the end of pregnancy, slightly earlier than in dairy cows. This is due to the large energy demands of the growing foetus and reduced ruminal volume due to pressure from the foetus. The impact of reduced ruminal size is more pronounced in twin and triplet bearing ewes and is therefore often referred to as "twin lamb disease". Both low and high BCS pre-lambing are risk factors for ketosis. Low BCS results in reduced energy availability for foetal growth and has been observed to increase the risk of elevated BHB levels which indicates ketosis. High BCS pre-lambing is associated with reduced feed intake and therefore rapid mobilisation of fat again resulting in ketosis, often referred to as fat-ewe pregnancy toxaemia (Crilly, Phythian and Evans, 2021). A negative correlation between BCS and blood BHB levels has been observed in milking ewes (Marutsova, 2018). This suggests lower BCS might be an indicator of sub-clinical ketosis. It is important to optimise BCS throughout the whole production cycle. In the UK, the Agriculture and Horticulture Development Board (AHDB) have developed a series of recommended BCS values for ewes at different stages of production (Povey, Stubbings and Phillips, 2018). These BCS recommendations are included in Table 2.1. They were calculated to provide farmers with an appropriate BCS target for each stage of production. Ensuring ewes are in the correct BCS can help "improve fertility, increase lamb performance and reduce incidence of metabolic disease" (AHDB Beef and Lamb, 2019).

Table 2.1- Recommended BCS for Hill, Upland and Lowland ewes at each stage of production (Wright, 2019)

	Target BCS		
	Hill	Upland	Lowland
Mating	2.5	3.0	3.5
Scanning	2.0	2.5	3.0
Lambing	2.0	2.5	3.0
Eight Weeks post-lambing	2.0	2-2.5	2.5-3.0
Weaning	2.0	2.0	2.5

2.1.2.2. Benefits of Body Condition Scoring in Dairy Cows

Substantial research within the dairy sector has allowed body condition scoring to be developed as an essential routine tool for monitoring herd health and performance. Fertility within Holstein Friesian dairy cows has significantly reduced as milk production has increased (Wathes and Taylor, 2002). Rapid BCS loss post-calving results in significant negative energy balance (NEB). This reduces the concentration of insulin-like growth factor-I (IGF-I), and in turn downregulates reproductive processes. Metabolic diseases in dairy cows are also prevalent, and largely due to the effects of NEB during the post-calving period. Ketosis has been shown to be twice as prevalent in cows calving at a BCS greater than 3.5 compared to BCS equal to 3.25 (Heinrichs, Jones and Ishler, 2023). These results are also applicable to sheep production systems with ewes in a BCS of 2.5 to 3.5 shown to have a reduced risk of elevated beta-hydroxybutyrate (19.7%) compared to ewes with a BCS less than 2.5 (Ratanapob *et al.*, 2018). Research has shown that dietary energy intake of dairy cows cannot overcome the extreme energy demands during early lactation, and therefore optimising BCS at calving is vital (Heinrichs, Jones and Ishler, 2023).

Days from calving to conception is substantially lower in dairy cows than sheep, therefore it is essential to ensure a suitable calving BCS, to mitigate the occurrence of increased days to conception and the loss of production associated with this. Garnsworthy & Wiseman (2006) discussed BCS targets and whether existing targets were suitable for modern, high production dairy cows. They concluded that calving BCS should not be more than 0.5 units above the cow’s target BCS to mitigate extended periods of NEB post-partum. The Agriculture and Horticulture Development Board has outlined similar BCS targets for sheep production systems at key events throughout the year (Wright, 2019). Unlike dairy BCS targets which focus on reducing NEB after calving, the targets for sheep production systems often emphasise minimum BCS targets at each event, with many health and production issues stemming from low rather than high BCS. It appears that the effect of NEB post-partum on reproduction is less of an issue in sheep due to the extended period of recovery between weaning and subsequent mating. Extreme BCS loss can still result in ketosis, however can often be managed through increasing dietary energy through improved forage or supplementation.

2.1.2.3. Benefits of Body Condition Scoring in Other Species

The pig industry also utilises body condition scoring methods to ensure optimal sow performance. Low BCS has been associated with delayed oestrus, poor foetal development and poor performance during lactation. Alternatively, high BCS can cause difficulty farrowing, decreased litter size and low feed intake during lactation. Unlike sheep BCS targets, sow targets remain consistent at around 3 BCS units throughout the productive life of the animal, with a slight drop throughout lactation. (AHDB Pork, 2023).

2.1.3. Body Condition Scoring Methods

2.1.3.1. Methods for Body Condition Scoring Sheep

The methods associated with body condition scoring animals can significantly differ between species and region. Body condition scoring in sheep is a method of assessing subcutaneous fat coverage across the lumbar region. The technique was first developed by Jeffries (1961) (cited in Kenyon, Maloney and Blache, 2014) as a method to estimate body fat stores and therefore energy reserves of ewes. The process involves the palpation of the region between the spinous and transverse processes along the lumbar region of the ewe to assess subcutaneous fat deposits (Russel, Doney and Gunn, 1969). Scores are then allocated depending on the scale being implemented. BCS was designed as a means of assessing the condition of ewes irrespective of other traits such as skeletal size, breed, and physiological state (Kenyon, Maloney and Blache, 2014). This simplifies the assessment of ewes when compared to the use of other parameters such as weight, which is significantly influenced by breed and age. Commonly BCS is recorded on a 1-5 scale with 0.5 or 0.25 point increments or a 1-9 scale. Table 2.2 provides a description for each category. Other methods for assessing BCS in sheep are limited, largely due to variability of wool coverage throughout the season making visual techniques challenging. Often body condition scoring in sheep is performed alongside weighing if the technology is available or when management changes or treatments are implemented.

2.1.3.2. Methods for Body Condition Scoring Dairy Cows

Two traditional methods exist when evaluating body condition score in dairy cows. The first method is similar to that of sheep with palpation of the lumbar vertebrae to assess fat coverage. The second method is a visual assessment of the animal (Garnsworthy and Wiseman, 2006). Visual assessment can be effective for dairy cows, however, is not applicable to the sheep industry due to wool coverage impairing the view. With the increasing implementation of technology on livestock farms new methods of measuring BCS are being developed. The use of 3D cameras, image processing and regression models has provided a means to consistently assess cow BCS, while reducing labour requirements (Zin *et al.*, 2020). Two models were tested to analyse the 3D images. The models resulted in a mean absolute error (MAE) of 0.15 and 0.13 and a maximum error of 0.45 and 0.55, when tested against skilled scorers. These results suggest adequate levels of accuracy can be achieved using 3D imaging to estimate BCS. Unfortunately, utilising 3D imaging technology within the UK sheep industry faces many challenges. Wool coverage will substantially reduce the accuracy of the imaging. Zin et al. (2020) observed issues with imaging when cows were in close proximity to one another, this issue would be greatly exacerbated on sheep farms. The extensive nature of many sheep farms would make it difficult and time consuming to collect the images. Finally, the investment required for the technology may be prohibitive, especially with the small margins and financial uncertainty that many UK sheep producers face.

2.1.3.3. Methods for Body Condition Scoring in Other Species

Many body condition scoring techniques are used in other species. In pigs visual methods are often used to assess BCS, however with increasingly leaner breeds it has became more challenging to visually assess. Specific calipers for measuring sow BCS have been developed with the aim to objectively assess sow BCS, removing the subjective nature of the measurements (Knauer and Baitinger, 2015). Although this method is effective for individual sows, similar technology could not be implemented for sheep, again this is due to limitations from wool coverage, but also high labour requirements. Companion species are largely assessed using BCS charts which compare the shape of the animal to an average animal within each category. This appears effective to monitor health of the animals, however, would not be an accurate or practical means of assessing animals on farm, particularly if management decisions were to be made as a result of their measurements. When BCS is being measured by dog owners, the results have been significantly more subjective that that of veterinarians. Eastland-Jones et al. (2014) observed that 66%

of owner's scores were different to that of a primary investigator, with approximately 60% of these scores being an underestimate. This suggests owner bias can significantly impact body condition scoring accuracy, and is important to remember that bias may be present when farmers are assessing their own animals.

Table 2.2- Description of each Body Condition Score Category in Sheep (Kenyon, Maloney and Blache, 2014)

BCS Category	Description
Score 1	Prominent and sharp spinous and transverse processes. Little to no fat coverage. The animal will feel emaciated with shallow eye muscle. Animals in this category likely have underlying health issues or are extremely malnourished.
Score 2	Spinous and transverse processes are still prominent, however now appear smooth. A thin coverage of fat over the whole loin area, with moderate eye muscle depth. Usually, animals found in this category are at the end of the lamb rearing phase due to high energy demand for pregnancy and lactation. These animals need to regain condition before next mating.
Score 3	The spinous and transverse processes are now rounded and require some pressure to be felt. Eye muscle depth is full, with a good covering of fat across the whole area. This category is generally considered the ideal maintenance condition for ewes. Condition score will fluctuate from this level throughout the production cycle as energy demand changes, however, will return through good nutrition and management.
Score 4	The spinous processes can be felt with pressure applied, however the transverse processes cannot. Eye muscle depth is high with substantial fat coverage across the whole loin region. Animals in this category are generally considered to be above the ideal condition. At mating it is more usual for animals to be found within the category due to increased plane of nutrition pre-mating. Animals in this category at lambing are considered to be in too high a condition, potentially leading to increased dystocia and metabolic disorders.
Score 5	Both the spinous and transverse processes cannot be detected due to the high degree of fat coverage. Eye muscle depth is similar to that of Score 4, however fat deposits are higher. A depression above the spinous process may be present due to the nature of the fat deposits. Animals in this category are considered to have excessive fat deposits, which could impact on performance. Condition score should be managed so that animals do not deposit extreme levels of excess fat. Reproductive performance and general health can be impacted by high levels of fat deposition.

2.1.4. Adoption of Body Condition Scoring by Farmers

Despite the well documented benefits of body condition scoring, surveys carried out on Australian flocks suggest the uptake of body condition scoring by farmers is limited (Jones *et al.*, 2011). They reported that 96% of farmers monitored condition of their ewes, however only a small percentage of farmers (7%) carried out hands on condition scoring. This suggests that although the benefits of assessing BCS may be accepted, the physical process of condition scoring and recording may be too labour intensive and a barrier to use. In a more recent survey from the AHDB (Boon and Pollot, 2021), it was reported that 75% of UK farmers BCS their flocks at least once a year, 36% of which scored once a year, 25% twice, 18% three times and 21% four times. The nature of the BCS measurements are not discussed by Boon and Pollot (2021), therefore the extent that the farmers surveyed recorded or used the measurements is unclear. A survey of 105 British sheep farmers observed how body condition scoring was being assessed on farm. 67% of respondents reported using body condition scoring, however only 32% assessed BCS through palpation, using the methods discussed in section 2.1.3.1. Categorisation of BCS varied throughout the respondents, with 29% using three categories, 25% using a 1 to 5 scale and 19% using 2 categories (Owen *et al.*, 2017). Often body condition scoring is used as a quick means to group animals or highlight extremely poor condition animals, rather than as a tool to accurately measure and monitor BCS over a period of time. It still appears that there is a substantially higher percentage of farmers utilising body condition scoring in the UK compared to Australia. This is likely due to the benefits of body condition scoring being understood by farmers in the UK, however the opportunity to increase periodic scoring and recording is still available. Boon and Pollot (2021) observed significantly more body condition scoring occurring at mating than any other stage of production. Clearly, farmers place an emphasis on ensuring correct BCS at mating, to likely optimise reproductive performance of the animals, and ensure correct nutrition during the post-mating period and throughout gestation.

2.1.5. Predicting BCS

2.1.5.1. Benefits Associated with Predicting Body Condition Score

BCS by nature is a subjective measurement, as the scorer is evaluating the ewe based on their experience or training. This can result in variation both within and between scorers, resulting in challenges around repeatability (Kenyon, Maloney and Blache, 2014). Body condition scoring is also a labour-intensive process due to the requirement to handle every animal scored, multiple times per year. The current process of condition scoring ewes makes it challenging to compare BCS between flocks due to scorer subjectiveness and inconsistency. The use of predictive models to estimate BCS from specific predictor variables, may allow for an objective BCS to be calculated with little to no measurement error. Predictive models use known data to predict future outcomes. Historical BCS data along with predictor variables such as; weight, ewe age, breed, event, scanning number, and days since last lambing will be used to produce models to predict BCS. These models will then be evaluated using a range of error metrics.

2.1.5.2. Existing Literature

The relationship between BCS and weight in ewes is well documented. A positive relationship between BCS and weight for 25,246 ewes across 18 different farms in Ireland was observed (Mchugh *et al.*, 2019). They found an increase of 4.81 kg of liveweight for each additional unit of BCS. A similar, positive relationship between weight and BCS has been observed in smaller studies by Sezenler et al. (2011) and Morel et al. (2016) with regression coefficient of 0.73 to 0.82 and 0.81 respectively. The significant relationship between BCS and weight, observed throughout multiple studies, suggests that it is possible to use a predictive model to predict BCS from weight, using additional variables to improve model fit. Previously, machine learning models have been used to predict BCS in New Zealand Romney ewes (Semakula, Corner-thomas, *et al.*, 2021). They built nine machine learning algorithms to predict BCS from a ewe's current and previous liveweight. They found that a gradient boosting decision tree algorithm was most efficient, with an accuracy of >85% when predicting BCS between 43 and 54 months of age. Further research focussed on predicting BCS from ewe liveweight, age, and stage of production (Semakula, Corner-Thomas, *et al.*, 2021). They found that the combined model, including multiple predictor variables, improved model fit, however correcting liveweight for fleece and conceptus weights did not improve accuracy of the models. Although the potential effectiveness of using machine learning models to predict BCS has been established, it is still unclear as to whether additional variables would improve model fit. Additionally, the effectiveness of models to accurately predict BCS for the wide variety of breeds found within the UK sheep industry is currently unknown.

2.1.6. Aims and Objectives

This research aims to mitigate both the subjective nature and labour requirements of body condition scoring ewes through the production of predictive machine learning models to predict BCS as a continuous variable. Primarily weight will be used as a proxy for BCS, with the addition of commonly available individual animal characteristics.

2.2. Materials and Methods

2.2.1. Data Collection

This study uses data collected as part of the AHDB Challenge Sheep project (Challenge Sheep | AHDB, accessed 20/10/2023). The Challenge Sheep project was launched with the aim of evaluating the effects of the first breeding season on lifetime productivity of ewes. The ongoing project is monitoring 7003 ewes over seven production years (2017-2024), with this chapter using data from the first three years. Eleven commercial English farms were included within the project covering a range of management practices, locations and animal types for the UK. Breeds in the dataset included nine purebred and five crossbred types. Data were available for a range of variables. Animal data included breed, ewe date of birth and project entry status (ewe lamb or shearling). Scanning and lambing numbers were recorded. Exit date and reason were recorded for any ewes that left the project. All data were collected using electronic identification (EID) tags and readers to increase efficiency and help mitigate human error.

BCS and weight data were recorded at five key intervals throughout the season (mating, scanning, lambing, eight- weeks post- lambing and weaning), with the exception of weight records at lambing, due to challenges around physically recording pregnant ewes and accurately determining the effects of foetal weight on liveweight of ewes. The intervals were determined by the farmers, with dates being recorded at each scoring. It is highly labour intensive to record exact mating dates for each ewe, therefore, the date was recorded as the date that mating began (ram entry date). On each farm, BCS was recorded by a single trained individual who was also the flock owner or shepherd. At the start of the project the scorers underwent specific training to ensure accurate recording of BCS and weight data. BCS was recorded on a 1-5 scale with either 0.25- or 0.5-point increments, depending on scorer preference, based on the scoring methods described by Russel et al. (1969). The scorers took part in a BCS training and calibration session at the start of the project to mitigate intra- and inter-rater error. At each body condition scoring event, weight was recorded using calibrated EID weigh scales. In total 59,927 individual BCS records were recorded. The distribution of all BCS measurements is shown in Figure 2.0)

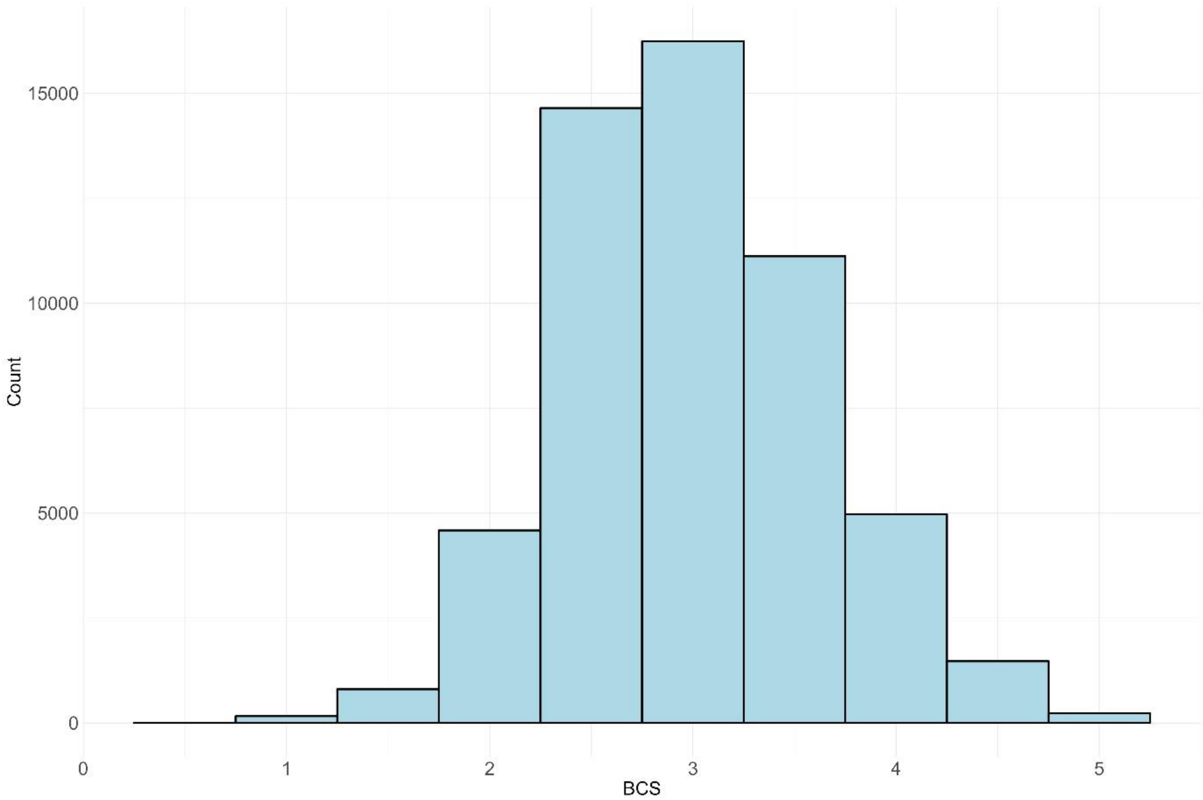

Figure 2.0 - Distribution of all BCS measurements collected throughout the first three years of the Challenge Sheep project

2.2.2. Data Cleaning

Data were manipulated and analysed using R version 4.1.0 (R: The R Project for Statistical Computing). Data were initially cleaned to remove missing values. These were the result of not recording weights when body condition scoring at lambing (total 6010 records), incomplete date records for when body condition scoring occurred, or failure to record datapoints for unknown reasons. Any weight values outside of +-3.sd for each breed were removed due to the high likelihood that these values were incorrectly recorded (372 records). The removal of missing values and weight values outside +-3 .sd, resulted in a clean dataset with 41,565 individual ewe records.

There were 14 unique ewe breeds and crossbreeds recorded within the project. We refined this number through grouping similar crossbred ewes and grouping biologically similar ewes. The final dataset included 11 grouped ewe breeds to ensure a suitable number of records for each breed group. Ewe age was calculated for each individual data record from the difference between the record date and ewe date of birth. Ewe age in days was calculated as a continuous variable. The lambing event was unique in that an exact date of the event was known, unlike records at mating. This resulted in a “days since last lambing” variable to be calculated as a timeframe within the model. This was determined by calculating the difference between each event and the previous lambing date. This was then grouped into a categorical variable, using groups of 10-day increments, with an additional category for ewes which had never lambed.

2.2.3. Variable Selection

Descriptive statistics and visualisation were used to explore the relationship between each of the variables (weight, age, days post-lambing and breed) and BCS. As weight was being used to predict BCS, the relationship between BCS and weight was initially explored at key stages of production. The effect of ewe age on the BCS weight relationship was then observed. As BCS is considered to be irrespective of breed (Kenyon, Maloney and Blache, 2014), yet weight is not, it was important to explore how breed affected the relationship between BCS and weight. The relationship between BCS and weight was also observed at each event throughout the production year. This was to observe whether the relationship was between BCS and weight was consistent as physiological state changed over time.

2.2.4. Predictive Modelling

Predictive models were built within R software 4.1.0 (*R: The R Project for Statistical Computing*, no date), using the caret package (Kuhn ,2021). Variables included as candidates in the models, largely selected from the results of the descriptive statistics, were weight, ewe age, days since last lambing and grouped breed category. The data were split into training and test sets at a ratio of 80:20. The Test split was used as a validation dataset to allow any model overfitting to be observed and help ensure generalisability of the model. Often Test datasets are taken from an external dataset in which the same parameters have been observed. When an external dataset is not available the existing dataset is split to ensure model performance is assessed on data not used for model training (Kuhn, 2008). When splitting the data, individual ewes were only included in either the training or test datasets to ensure the model was trained and tested on different animals. Ten-repeats of 10-fold cross validation were used during model training, with BCS predicted as a continuous outcome. Cross validation allows the performance of the model to be observed on each fold of the training dataset, further highlighting any overfitting.

A series of predictive models were trialled to assess which model gave the optimal performance. The models included, linear regression, random forest, support vector machines, K-nearest neighbour, and gradient boosted regression. Each model underwent hyperparameter tuning to optimise model performance. Tuning parameter plots were observed, along with the use of root mean squared error (RMSE) and Concordance Correlation Coefficient (CCC) metrics to assess model performance. RMSE provides an indication of overall model error, giving a larger weighting to higher residuals. Concordance correlation coefficient measures the deviation of predictions from a perfect prediction line (y=x). These metrics not only show model performance, they also ensure that the models are not overfitting on the training dataset by directly comparing the metrics from the training and test datasets. The results of the test dataset also provide an approximation of how the models will perform on out of sample datasets.

2.2.5. Model Overview

2.2.5.1. Linear Regression

Linear regression models describe the relationship between the dependent or response variable and one or more independent or predictor variables. The model fits a regression line which is the best fit line for the model. Benefits associated with linear regression models include low computational requirement and easy interpretation. This allows predictions to be generated in real time unlike some more computationally heavy models.

2.2.5.2. Random Forest

Random forest models are a supervised machine learning algorithm, utilising ensemble learning methods. This is a method to combine predictions from multiple models to create a more accurate prediction than any individual model. A series of decision trees are trained on independent subsets of data, with the predictions averaged across all trees. Random forest models differ from traditional decision trees due to no interaction between individual trees. This results in a model with a high degree of accuracy; however, random forest models can be prone to overfitting, particularly on noisy datasets (Segal, 2004).

2.2.5.3. Support Vector Machines

Support vector machines are a supervised learning algorithm in which a hyperplane is fitted on the training dataset. The hyperplane is fitted to maximise the margins from each datapoint, this minimises the generalisation error of the model. The hyperplane is then used to categorise specific values. (Cortes, Vapnik and Saitta, 1995). Support vector machines use some fundamental concepts to ensure accurate predictions. The separating hyperplane is used to separate datapoints belonging to different classes, maximising this margin is essential to improve generalisability of the model. Although in a perfect model the hyperplane would separate the data cleanly, this is often not the case, soft margins are used here to allow a certain degree of misclassification to occur, without affecting the model. User specified parameters are used to dictate the number of datapoints allowed to cross the hyperplane and the distance they are allowed to cross. For data which is one dimensional and non-separable, a hyperplane cannot be fitted, this is when the kernel function is implemented to add an additional dimension to the data (projects data from low dimensional space to a higher dimensional space) and often allows the data to be separated at the higher dimensional space (Noble, 2006). SVM can also be use for regression where a continuous output is predicted from the hyperplanes (Ashwin, 2020).

2.2.5.4. K- Nearest Neighbour

K nearest-neighbour is a non-parametric modelling technique. It uses distance functions to predict values using the available data points. The value of K determines the number of data points used to calculate the prediction. When the value of K exceeds one, the prediction is taken from an average of the nearest datapoints. It is important to optimise the value of K to ensure that the model is not oversensitive to outliers, or using datapoints with a higher distance function than necessary (Ahmed, no date).

2.2.5.5. Gradient Boosting Regression

Gradient boosting regression models are similar to random forest models in that they are also ensemble techniques that use a series of decision trees to estimate the result. They differ in that random forest models create a series of decision trees through randomly splitting the dataset then averaging the predictions from each decision tree. Gradient boosting models use the addition of decision trees to correct the error from the last tree. Additional trees are added until an acceptable degree of error is reached, or the maximum number of trees are used. Extreme gradient boosting, used within this study, takes the basic gradient boosting algorithm and uses advanced regularization techniques. This results in a model which prevents overfitting. Although random forest models can be extremely accurate, they have a tendency to overfit. This is minimised in gradient boosting models as each tree is not constructed to its full depth (Yokotani, 2021).

2.2.5.6. Hyperparameter Tuning

Hyperparameters are configurations which can be selected within specific ranges to improve model performance. Hyperparameter tuning is the process of selecting hyperparameters to ensure optimal model fit (Bartz *et al.*, 2023). The tunability of the model is determined by the difference between the model performance for reference values and optimised values. Each algorithm has a specific set of hyperparameters which can be tuned (Table 2.3).

Table 2.3- Summary and description of the hyperparameters for each model

Model	Hyperparameter	Description
KNN	K	Determines the number of neighbours included within the model
	p	Determines the distance to each neighbour
Random Forest	num.trees	States the number of trees included within the ensemble. Increasing the number of trees generally improves model performance, however increases model runtime
	mtry	Controls the randomization of individual trees through dictating how many features are randomly chosen.
	sample.fraction	Number of observations used to train one tree
	Replace	States whether samples can be drawn multiple times for training of one tree
Extreme Gradient Boosting (XGBoost)	n.rounds	Controls the number of trees in the ensemble
	eta	Alters the influence of individual trees in the ensemble
	lambda, alpha gamma	Regularization parameters to prevent overfitting

2.2.5.7. Regression Chain Model

A recurring theme when observing the outputs of the predictive models were that at the extreme BCS predictions (BCS <2.5, BCS >4) the models were consistently predicting poorly (high BCS values were underpredicted with low BCS values overpredicted). This resulted in a degree of bias throughout the model. The observation of model bias led to the use of a regression chain model in an attempt to reduce overall model bias. Multiple model machine learning, and subsequently the implementation of regression chain models is outlined in ‘A Gentle Introduction to Multiple-Model Machine Learning’ (Brownlee, 2022). Regression chain models result in a model which is conditional on the predictions from previous models in the chain. The fitted BCS values were taken from the gradient boosting model, then an average fitted BCS for each observed BCS category was calculated. A linear regression model was then fitted to predict BCS from the average gradient boosting fitted values. The linear model was then used to predict a second fitted value on the training dataset from the initial fitted values. This gives a model which has the ability to correct model predictions, depending on the previous predicted value. The degree of which the initial predictions are corrected is independent of the observed BCS values.

2.2.6. Evaluating Model Performance

Model performance was assessed on the test set using four metrics, mean absolute error (MAE), root mean squared error (RMSE), coefficient of determination (R^2), and concordance correlation coefficient (CCC). Models with the lowest RMSE and highest R^2 were determined to perform the best. The model performance was also evaluated via visualisation using quantile-quantile plots and scatterplots of the predicted vs observed BCS values. To evaluate model performance, observed vs predicted plots were used to observe model fit throughout the whole BCS range. This provides a means to assess both model fit and can indicate model bias. Boxplots of the model residuals were used to observe both error and bias within the model. For each observed BCS value, a boxplots of the error between observed and prediction values was plotted. This allows the observation of which BCS values the model was struggling to predict, and whether the model was biased at the extreme predictions. Bias could be observed when median residuals were not equal to 0. Variable importance plots and model coefficients were used to observe the relative importance of each predictor variable for each model.

2.2.6.1. Descriptive Statistics

A range of descriptive statistics were used to observe relationships between different variables. Initially, the relationship between BCS and weight was plotted. The effect of the additional predictor variables on the BCS weight relationship was then observed. These plots were used to help select the appropriate predictor variables to include within the predictive modelling.

2.3. Results

2.3.1. Descriptive Statistics

Table 2.4- Mean BCS and standard deviation for each breed grouping

Breed	Mean BCS	Standard Deviation
AberField	2.89	0.55
AberField X	3.41	0.70
Highlander	3.36	0.58
Lleyn	2.92	0.45
Mule	3.18	0.56
Mule X	2.87	0.86
Other	3.01	0.81
Romney	3.32	0.56
Swaledale	2.57	0.42
Texel	3.07	0.83
Texel X	3.30	0.73

An overall positive relationship between BCS and weight was observed (Figure 2.1 and Figure 2.2), however the relationship differed depending on stage of production. The positive relationship between BCS and weight was apparent throughout four ewe age groups, however the relationship changed depending on ewe age. As age increases, ewes are in a lower BCS for their weight. Breed also affected the BCS weight relationship.

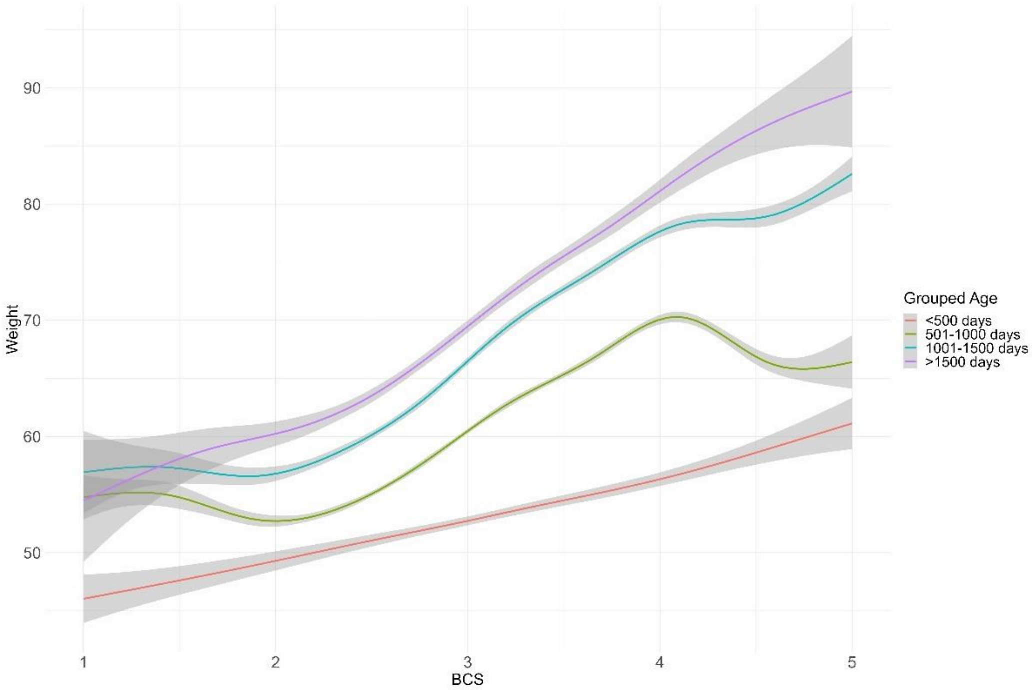

Figure 2.1- Scatter plot showing the relationship between weight (kg) and BCS for four ewe age categories. Each age category is shown by a single line of best fit. 95% confidence intervals are highlighted by shading around each line of best fit.

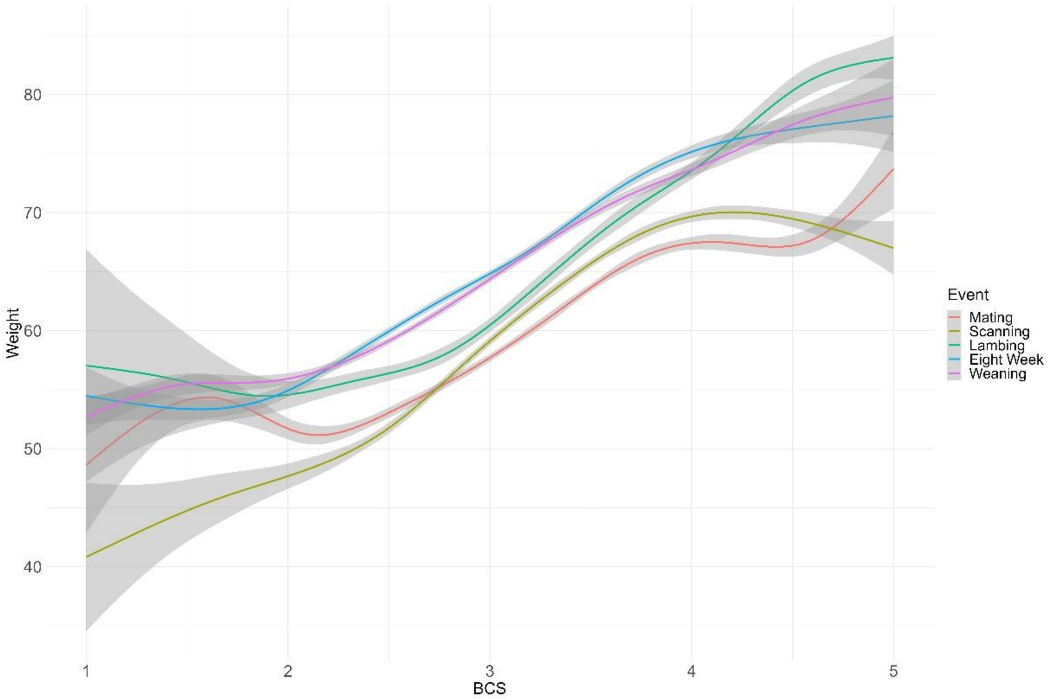

Figure 2.2- Scatter plot showing the relationship between weight (kg) and BCS for five stages of production. Each stage of production is shown by a single line of best fit. 95% confidence intervals are highlighted by shading around each line of best fit.

2.3.2. Model Performance

A summary of model performance is provided in Table 2.5. The best performing singular model was gradient boosting regression (RMSE = 0.406 and CCC = 0.752), whilst the worst performing model was linear regression (RMSE = 0.478 and CCC = 0.608). The difference in RMSE from best to worst performing models were 0.072 units and gradient boosting regression had an R^2 value 0.141 units higher than linear regression. The random forest model performed similarly to the linear gradient boosting model, whilst support vector machines and K-Nearest Neighbour models were mid-performing.

Table 2.5- RMSE, MAE, R2 and CCC values on training and test datasets for all models

Error Metric	Linear regression	Support Vector Machines	Gradient Boosting regression	K-Nearest Neighbour	Random Forest	Regression Chain model
Training Dataset						
RMSE	0.474	0.468	0.358	0.414	0.385	0.392
MAE	0.365	0.473	0.258	0.312	0.297	0.306
R^2	0.432	0.448	0.722	0.577	0.651	0.722
CCC	0.601	0.621	0.850	0.731	0.748	0.862
Test Dataset						
RMSE	0.478	0.464	0.406	0.447	0.423	0.464
MAE	0.367	0.355	0.304	0.338	0.325	0.357
R^2	0.417	0.457	0.599	0.503	0.557	0.599
CCC	0.608	0.627	0.752	0.680	0.688	0.766

Abbreviations; RMSE = Root mean squared error, MAE = Mean absolute error, R^2 = Coefficient of determination, CCC = Concordance corelation coefficient.

Figure 2.3 shows the distribution of residuals for each BCS category. The model predicts well throughout BCS values 2 to 4, however appears to have substantial bias within the prediction, shown by the higher residuals at extreme BCS values. This bias was apparent for all five models initially tested.

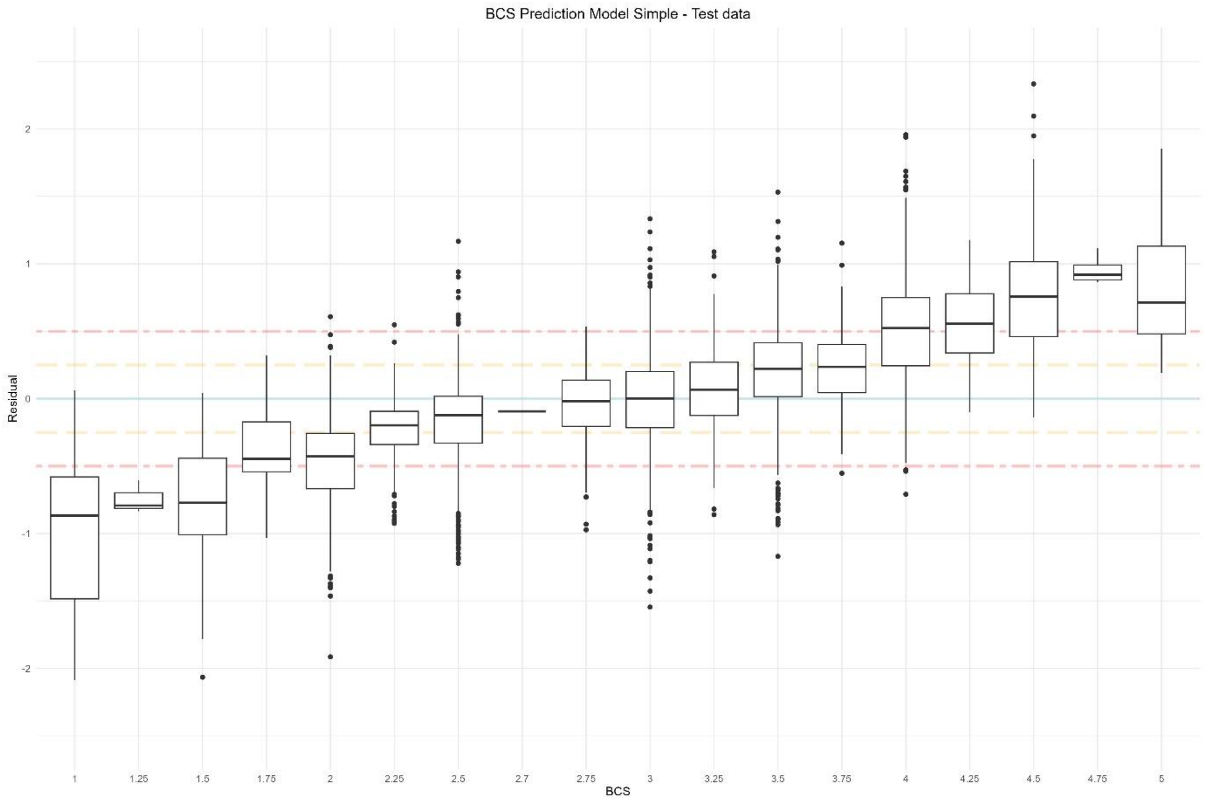

Figure 2.3- Observed BCS against model residuals for Linear Gradient Boosting model on test dataset, where boxes represent the minimum and maximum residuals, first and third quartile and median residuals.

Comparison of error metrics between training and test datasets for the linear gradient boosting model suggest a small degree of overfitting. There was higher RMSE on the test dataset than the training dataset by 0.048 units. This indicates overfitting of the model on the training dataset, however, is not excessive. Figure 2.4 shows a variable importance plot for the gradient boosting model. This highlights which predictor variables had the largest effect on the predictions. Weight was the most important variable, followed by ewe age.

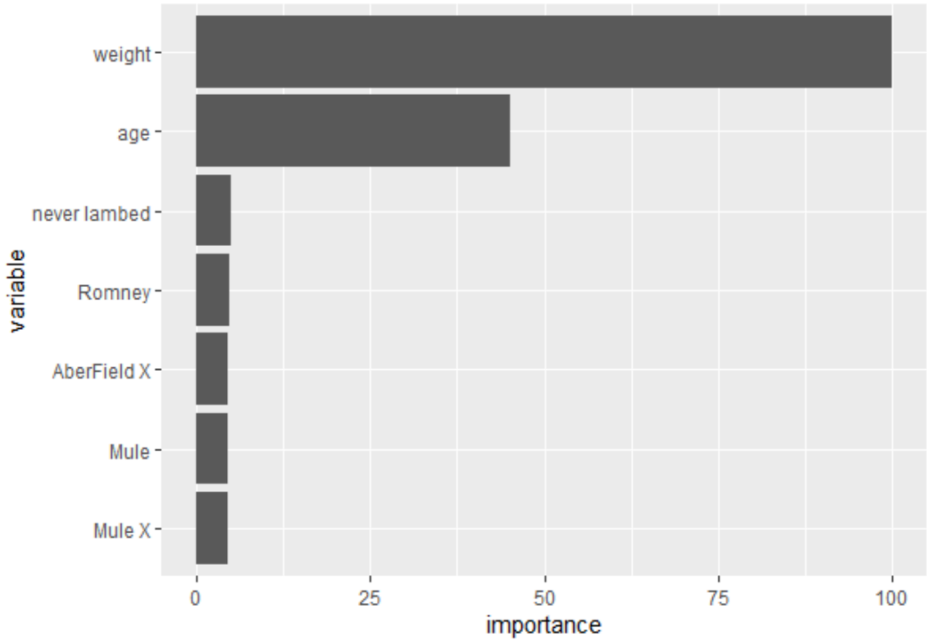

Figure 2.4- Variable importance plot for the Gradient Boosting model

2.3.3. Regression Chain Model

Due to the bias in extreme predictions from the gradient boosting model, a regression chain model was built. The linear model built as part of the regression chain model had an intercept of -2.01 and BCS coefficient of 1.65. The regression chain model has a higher test RMSE than the gradient boosting model (0.464), identical R^2 value (0.599) and improved CCC (0.766). The distribution of residuals for the regression chain model (Figure 2.5) shows a reduced bias across the extreme predictions (BCS <2 and BCS > 4) compared to the gradient boosting model distribution (Figure 2.3). It can be observed that error has increased throughout the central BCS values, however the extreme predictions have lower bias and reduced error. We observe a positive relationship between weight and predicted BCS from the regression chain model (Figure 2.6). This is the same relationship observed within the dataset collected on farm, presented in Figure 2.1.

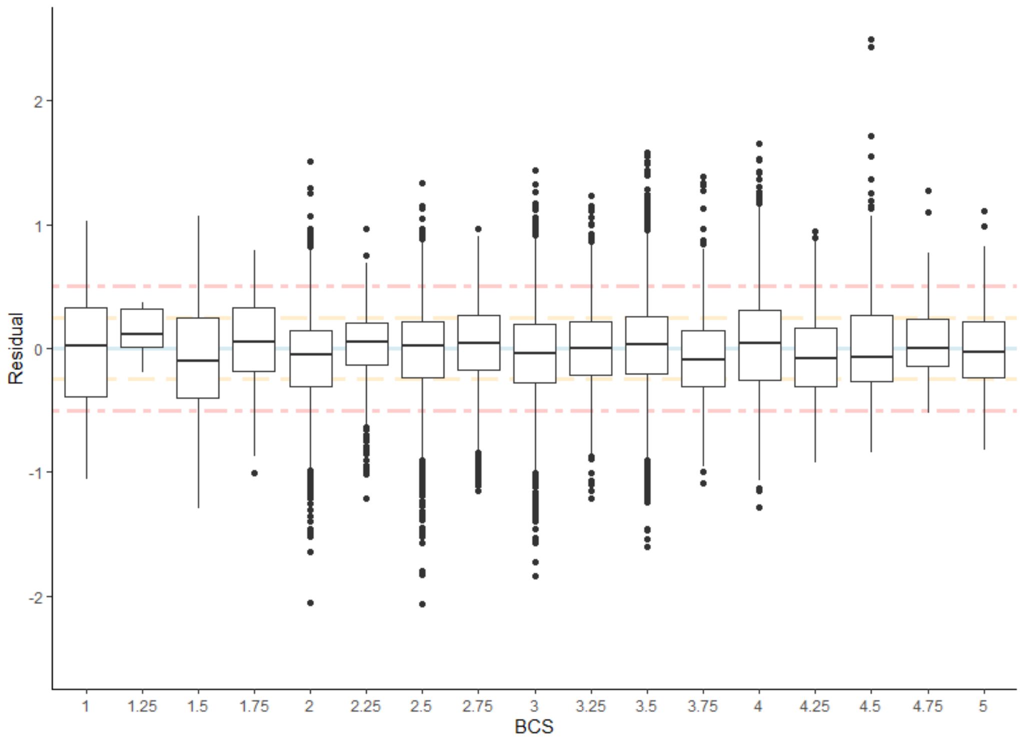

Figure 2.5- Distribution of residuals for Regression Chain model on Test dataset, where boxes represent the minimum and maximum residuals, first and third quartile and median residual. Outliers are displayed as points.

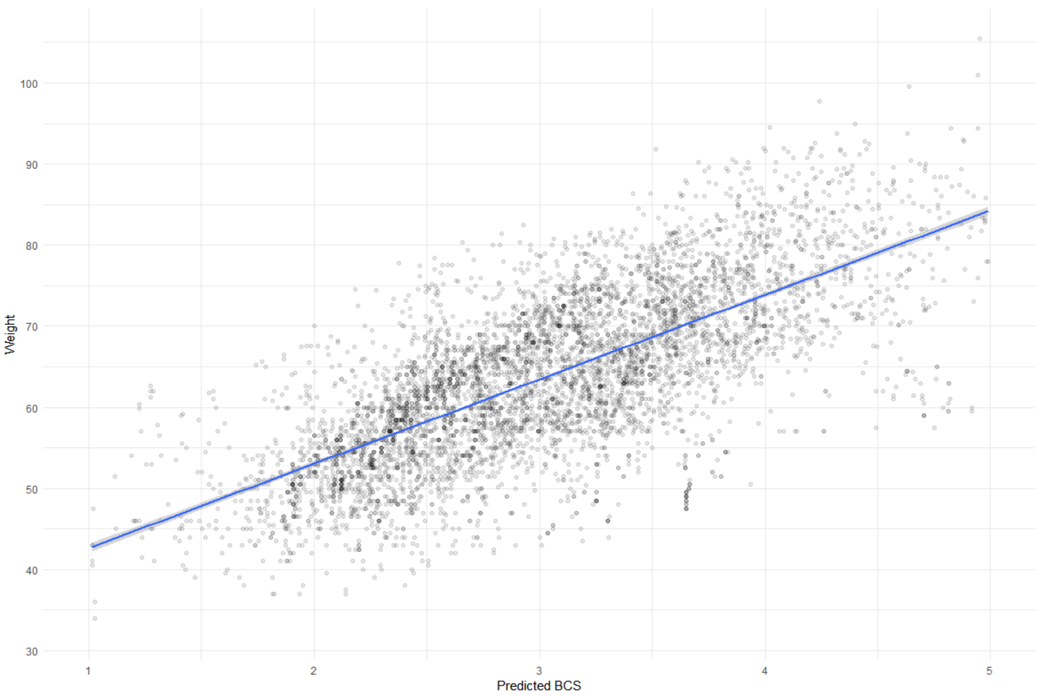

Figure 2.6- Scatter plot showing weight (kg) against predicted BCS on the test dataset for the Gradient Boosting with Regression Chain Model. The blue line shows the line of best fit.

2.4. Discussion

2.4.1. Model Evaluation

The aim of this study was to evaluate a series of machine learning models to predict BCS from weight with the addition of other predictor variables to improve predictive ability. This would be achieved through the use of ewe data as predictor variables. Historical ewe performance data would not be used to predict BCS, this mitigates the need for previous data within predictions and allows predictions to be produced from an individual timepoint. The findings suggest that BCS can be predicted from variables; weight, age, days since last lambing, and breed, using a range of common machine learning models.

2.4.2. Results Summary

The results show that out of the singular models the gradient boosting regression model performed best (RMSE = 0.406, CCC = 0.752). Random forest models performed similarly, with slightly higher predictive error (RMSE = 0.423) and lower CCC (CCC=0.766). KNN, SVM and linear models all performed consistently worse, resulting in a greater predictive error. The regression chain model has a higher overall error than singular machine learning models, however bias was significantly reduced. The results from the final model (regression chain model) are consistent with RMSE values produced by Semakula et al. (2021), who used linear regression to predict BCS in Romney ewes using adjusted liveweight and previous BCS values. Their results showed RMSE varied from 0.33 to 0.54 depending on the use of combined models and stage of production. The results from our final model is comparable to Semakula et al. (2021) , without the requirement for previous BCS values.

2.4.3. Linear Gradient Boosting

The findings suggest the linear gradient boosting model, on average, is predicting well throughout the central BCS values (BCS 2 - 4), however is overpredicting for low BCS ewes and underpredicting for high BCS ewes. This trend was not unique to gradient boosting models with all models exhibiting a similar pattern. This suggests the machine learning models are struggling to capture some of the more extreme

BCS ewes. This may be due to additional variables influencing BCS at the extremes, for which data were not available, a result of the subjective nature of the BCS measurements or a lack of training data at the extreme values. Gradient boosting models are susceptible to overfitting (Natekin and Knoll, 2013), however, the comparable error metrics between the training and test datasets suggests little overfitting, resulting in a largely generalisable model.

2.4.4. Regression Chain Model

The use of a regression chain model significantly improved the residuals for extreme predictions, however decreased the predictive accuracy throughout the central BCS values. High observed BCS values were underpredicted by the model while low observed BCS values were overpredicted. Although model error is slightly worse for the regression chain model, the CCC is improved, partly as a result of reduced bias at the extreme predictions. Ensuring reduced bias at the extremes of the model is important when applying the model to a practical situation. BCS can be used as a selection tool to help implement targeted nutrition or targeted selective treatments. Cornelius, Jacobson and Besier, (2014) discussed the benefits of using BCS to group ewes for nematode control. This is one example where effective BCS grouping is essential, it is vital that ewes in extreme conditions are captured within the model to maximise productivity but also mitigate health risks.

Similar to the current study, Semakula, Corner-Thomas, S. T. Morris, et al. (2020a) used a range of linear regression and machine learning models to try to predict ewe BCS. Initially they observed the effects of ewe liveweight, liveweight change and previous BCS records on predicted BCS (Semakula, Corner-Thomas, S. T. Morris, *et al.*, 2020a). They found univariable analysis using lifetime weight to predict BCS resulted in weak predictions, however the addition of liveweight change and previous BCS in a multivariable approach somewhat improved their predictions. The study focussed specifically on 11,798 Romney ewes which were recorded between 8 – 67 months of age. Univariable and multivariate linear regression models were used to predict BCS. Their results showed that even with a multivariable linear regression a significant amount of variability remained unaccounted for. Semakula, Corner-thomas, et al. (2021a) further developed their research and used similar machine learning methods as this study for predicting BCS. They predicted grouped BCS using previous and current liveweight. A series of models were built and evaluated to determine which model performed best. Similar to this research, they found that gradient boosting models were most accurate. In comparison our model does not use previous BCS values within the prediction. This gives the model the ability to predict each value independently of previous scores, allowing BCS to be assessed without the requirement for previous records which may not be available.

2.4.5. Variable Selection

The initial linear regression model found weight to be the main predictor variable for BCS. This finding is consistent with previous research observing a positive relationship between BCS and weight. Kenyon et al. (2014) showed a positive linear relationship between BCS and weight throughout 11 separate studies, with one study observing a curvilinear relationship. Sezenler et al. (2011) observed a similar linear relationship in 156 ewes from three Turkish breeds. Finally, McHugh et al. (2019) observed a positive linear relationship between weight and BCS. Semakula, Corner-Thomas, et al. (2021b) adjusted liveweight for fleece and conceptus weight. Both conceptus weight and fleece weight can vary significantly, therefore it was thought that adjusting for these factors would improve predictive ability. However, they did not observe a significant improvement in predictions with the adjusted liveweight. This suggests there would be little to no gain in predictive accuracy if liveweight was adjusted in the current study.

The inclusion of breed as a predictor variable was important, considering the wide range of breeds within UK sheep systems and the influence of breed on weight. Jeffries (1961) (cited in Kenyon et al., 2014) suggests that one of the benefits of BCS ewes over weighing was that BCS is independent of skeletal size both within and between breeds. Figures from the AHDB suggest the UK has 99 different breeds (Boon and Pollot, 2021), however it appears a significant proportion of ewes are derived from a select few breeds. Some common breeds include, Texel crosses, Mules, Scottish Blackface, Welsh Mountain, Swaledale and Lleyn. This study included 11 of the most common UK breeds, which is important in relation to generalisability of study findings, however not all breeds were included and results should be interpreted in this context. It is important to note the constant development of breeds within the UK with a current increasing trend of Texel and

Lleyn breeds according to the 2020 Sheep Breed Survey (Boon & Pollot, 2021). The large variation of breeds within the UK industry poses a significant challenge when selecting breed as a predictor variable, to ensure model generalisability on a UK scale. The grouping of breeds dependant on biological factors may circumvent this issue and make a more largely applicable model. When predicting on breeds not included within this study, it may be necessary to group the breeds into similar categories using ewe traits.

This study found the relationship between BCS and weight is dependent on ewe age. This is likely due to the stage of maturity of the ewes, with older ewes exhibiting a lower BCS to weight ratio (Figure 2.1), also shown in the research as a larger incremental change in weight for each BCS category in older ewes (Semakula, Corner-Thomas, S. Morris, et al., 2020a). Stage of production also affected the BCS weight relationship (Figure 2.2). A timeframe needs to be included within the model to account for variation in the BCS weight relationship due to stage of production. Although it can be observed that the relationship is dependent on event, the inclusion of event within the model could be inaccurate. This is due to variation around the timing of each event and their correlation to time of year, for example mating, may be confounded by another factor not observed in this study. Days post lambing was included within the final model. This was selected due to an exact date of recording at lambing, giving the option to accurately reflect this stage of production for each ewe. The use of days in lamb would also be a useful parameter to reflect stage of production, however within this dataset it was not possible to calculate this with a high degree of accuracy. Semakula, Corner-Thomas, S. Morris, et al. (2020b) observed the effect of age, stage of production cycle and pregnancy rank (number of lambs at scanning) on the relationship between liveweight and BCS. They found that these three variables significantly affected the relationship between liveweight and BCS for the sample of Romney ewes. They concluded that age, stage of production and pregnancy rank should be included within a predictive model for BCS. The current study did not include pregnancy rank as a variable for two main reasons. Initially, there was little to no increase in model predictive performance with the inclusion of scanning number. Additionally, after considering the applicability of the model to the wider industry, it was decided that the requirement to record pregnancy scanning data to use in the model would limit opportunities for application, especially for a small gain in model performance.

2.4.6. Model Generalisability

The Challenge Sheep project dataset includes 11 farms from a range of different areas throughout England. This study is comparable in scale to other similar studies. Semakula, Corner-Thomas, S. T. Morris, et al. (2020a) observed 11,798 ewes, from only two commercial farms in New Zealand, while McHugh et al. (2019) observed 36,424 BCS and weight records from 25,246 ewes across 18 farms. Ensuring a large range of different flocks are included within the data helps increase the generalisability of the model when applied to UK systems, particularly due to the large variation in systems discussed in section 1.1.3. Not only does the data include a substantial number of farms, the range of breeds across these farms are highly varied. There were 14 different breeds recorded, which were refined to 11 grouped breeds during the initial data manipulation. Again, this increases model generalisability. Additional testing using an external dataset, not included as part of the Challenge Sheep project, would be beneficial to further observe the performance of the model on different flocks. When constructing machine learning models, it is important not to overfit the model on the training dataset. Commonly a training and test data split is used to mitigate overfitting with the aid of 10-fold cross-validation with 10 repeats. Low degrees of overfitting were observed throughout all models with no observed difference between training and test dataset RMSE values. Each model has unique tuning parameters which were used to help reduce overfitting. Plotting the tuning parameters for each model allowed each parameter to be observed and optimised.

2.4.7. Implications

Body condition scoring is viewed as an important management tool to improve overall flock performance. The benefits of BCS are well documented, with reports of low BCS and BCS loss impacting ewe performance, lamb growth and birth weight (Wright, 2019). The ability to predict BCS could significantly reduce labour requirements, as weighing is viewed as a quicker and more accurate parameter to record. Currently 75% of UK sheep farmers carry out BCS at least once a year, with a large weighting towards scoring at mating (Boon and Pollot, 2021). This is a substantial number of farmers and suggests the benefits of BCS are accepted in the industry. However, the current BCS system allows for an unknown degree of error both within and between scorers. In the writer's experience this is likely exacerbated by infrequent and rushed scoring which appears to be the case on many farms. Boon & Pollot (2021) also stated that although a significant number of farms condition score, the degree of recording is unknown. This results in a parameter which may be difficult to utilise on farm and even more challenging when comparing between farms. Although the prediction of BCS using both gradient boosting models and gradient boosting models with regression chains, results in RMSE of 0.402 and 0.460 respectively, it is important to consider the error within and between scorers. Kenyon et al. (2014) discussed the repeatability of BCS, highlighting a significant variation throughout different studies. They suggested that consistency was closely linked to scorer experience and frequency. An advantage of machine learning models is that the impact of scorer experience is negated and allows for a repeatable process.

2.5. Conclusion

It is possible to predict BCS in ewes with an acceptable level of error using machine learning models, weight recording and a limited number of commonly available ewe parameters including age, breed and days post lambing. A linear gradient boosting model produced the best predictions out of the five singular machine learning models tested. All models tended to under and over predict at the extremes, this made be due to an additional factor, not included in the model, a result of human error within the data collection, or a lack of training data at the extremes. The use of regression chain models significantly reduced the bias within the results, decreasing the under and over predicting at extreme BCS, however slightly increased the overall error. The use of a machine learning model on farm may significantly reduce subjectivity associated with condition scoring, while also reducing labour requirements of physically scoring each ewe. The final model will provide a means of quickly and accurately and consistently assessing the body condition of ewes, with comparable results between farms. Currently the model is designed to predict BCS as a continuous variable. There is the potential scope to group these variables into low, moderate and high categories to be used practically on farm. This would align closer to the current BCS system many farmers use and could potentially increase uptake on farm. In terms of integrating BCS predictions within a larger simulation model it was important to ensure BCS was predicted throughout the full scale.

Chapter 3. Case study: A Comparison of Manual Body Condition Scoring among Farmers, Experts and Machine Learning Prediction Models

3.1. Introduction

Body condition scoring was developed as a subjective assessment of body fat in a live sheep (Russel, Doney and Gunn, 1969). Shortly after the development of body condition scoring in sheep, the consistency and repeatability were questioned, with comparisons being made to objective measurements such as weight to estimate fat deposits. Russel et al., (1969) conducted a study to assess the repeatability of BCS measurements both within and between scorers. Results showed that repeatability within scorers was over 80%, with repeatability between scorers showing over 70% absolute agreement. This study showed high levels of repeatability and suggested that body condition scoring ewes can provide a suitable estimation of body fat. In the 64 years since this study was conducted the sheep industry has undergone significant changes with the adoption of new breeds and management practices. These changes, along with the potential for other body condition scoring methods (Chapter 2), may warrant an up-to-date evaluation of body condition scoring.

3.1.1. Influence of BCS on Performance

The use of BCS measurement and recording has been promoted on sheep farms as a performance measure and to assess flock health. The AHDB states “Regular condition scoring of ewes and acting on the results will increase the performance of a flock.” (Wright, 2019). BCS has been shown to impact specific production characteristics. Aliyari et al., (2012) observed a reduction in the duration of the oestrus cycle for ewes with lower condition scores. Mathias-Davis et al. (2013) observed that ewes in high condition at lambing which lost condition between lambing and weaning , or ewes in low condition at lambing which gained condition had higher lamb growth rates. It is clear from the literature that BCS can significantly influence the performance of ewes and their offspring. However, when implementing these findings, it is important to ensure that BCS measurements are collected accurately and consistently on farm. Commonly, a BCS range of 3.0 to 3.5 is considered ideal, with lower and higher values considered suboptimal. This does fluctuate with stage of production, often with ewes requiring a slightly increased BCS at mating. Generally, the difference between good condition and poor condition is as little as 0.5 to 1.0 units. The small difference between an ideal BCS and suboptimal BCS further highlights the need for accurate body condition scoring to maximise performance and production. An incorrect score at an extreme BCS may have more significant effects. Incorrectly allocating BCS pre-lambing could lead to incorrect nutrition and an increased risk of metabolic diseases.

Since the initial evaluation of body condition scoring by Russel et al., (1969), a substantial number of studies, both on livestock and zoo species have been conducted. The repeatability of body condition scoring in sheep was evaluated by Refshauge and Quin (2007). They conducted three trials on adult Merino ewes. Across the three trials 15 assessors scored a total of 409 ewes, however each assessor only took part in one trial. Ewes were scored twice in all trials. RMSE and R^2 values were used to assess scorer performance, along with a histogram of each assessor's scores. Mean BCS within each trial showed a range of 0.5 to 1.2 BCS units. They also found that although some scorers had low RMSE and high R^2 values, which suggests high accuracy and repeatability, they did not necessarily detect the full range of BCS values that other scorers had observed. Fitzgerald et al. (2009) observed the effect of different experience levels on the ability to BCS sows. They found that individuals tended to allocate BCS measurements on their own scale, suggesting measurements were not calibrated between scorers. This resulted in consistent under or overpredictions for each individual scorer. They found experience level had little effect on the ability to assign BCS. A study conducted on Danish Holstein cows compared the ability of students and instructors to allocate BCS. They found experience had a large effect on the ability to accurately perform body condition scoring. Experienced scorers provided BCS measurements which were comparable across herds while less experienced scorers struggled (Kristensen *et al.*, 2006). The literature suggests there is substantial error when manually scoring BCS across a range of species. The results from previous studies observing the accuracy and repeatability of BCS measurements highlight key areas for observation. It appears that scorers that have high repeatability, may still be inaccurate due to consistent bias within their measurements, additionally bias appears to be difficult to assess without a 'gold standard' BCS. Within an experienced group of scorers, it is likely that the average BCS is the best estimate of a 'correct' score.

Using the concepts outlined by Russel et al. (1969), a pilot study was conducted to assess the repeatability of BCS measurements within the Challenge Sheep farmers and advisors. The evaluation of body condition scoring error within the Challenge Sheep project farmers not only allowed for scoring accuracy to be observed, but also allowed for the comparison of the BCS predictions models (outlined in Chapter 2), against manual scoring. Differentiating between prediction error and measurement error within the BCS predictions model is challenging. This is a result of the subjective nature of manually body condition scoring ewes. The pilot study begins to quantify within and between scorer error for the Challenge Sheep farmers. A sample of ewes were scored multiple times over two sessions. This allowed errors to be calculated for each ewe and each scorer, and allowed the repeatability between sessions to be observed. The results will not only allow repeatability and consistency of the scorers to be evaluated, but also provide an indication of the degree of error within the BCS predictions model that is accounted for by measurement and predictive error.

3.2. Materials and Methods

3.2.1. Data Collection

A subset of ewes taken from one of the Challenge Sheep project farms were selected for body condition scoring. 20 ewes, split between three breed categories (Mule, Texel and Texel x Mule) were included within the study. Ewes were selected by the farmer from the main flock, ensuring an approximately equal number of ewes from each breed were chosen. This provided a manageable sample size for the pilot study while ensuring a suitable number of individual BCS records were collected for analysis. The data was collected pre-mating. 17 trained farmers and advisors from within the Challenge Sheep project scored the 21 ewes twice across two sessions (morning and afternoon sessions). All data were initially recorded on paper by the individual scorers, before being manually entered into the dataset. A total of 714 individual BCS records were collected. Ewes were divided into three pens and numbered for identification. In between the two sessions ewes were mixed, numbers changed and re-penned. BCS was recorded on a 1-5 scale with 0.25-point increments, as outlined by Russel et al. (1969) and Kenyon et al. (2014). No formal BCS training was undertaken on the day, however all scorers had undertaken previous training at the start of the project and were regularly involved in scoring their own flocks. The scorers were instructed to use a 1-5 scale with 0.25-point increments as they usually would on farm. The rate of scoring (time spent scoring each ewe) was consistent with that of the usual scoring practices for each scorer, this helps to ensure the results are applicable to a practical setting.

3.2.2. Data Analysis

The BCS were analysed to assess within scorer error, between scorer error and error around the mean for each ewe. Boxplots for each scorer were plotted to observe the distribution of scores, indicating calibration between scorers. MAE was calculated for within and between scorer error, using mean BCS to calculate the residual of each score. Due to the nature of BCS measurements in ewes, and the lack of method to provide objective BCS measurements, the ‘correct’ BCS measurement was assumed to be the mean of all scores for each ewe. A comparison between scorer error and model error was made.

3.2.3. Predictive Models

Two BCS predictive models, (gradient boosting model and gradient boosting with regression chain model), outlined in Chapter 2 were used to predict BCS values for each ewe. One ewe had to be removed from the study due to incomplete data. Two methods were used to assess performance of the model. Firstly, each individual score was taken as an observed value, with the residuals calculated as the difference of each observed value and the predicted value for each ewe. Secondly the mean value of all scores for each ewe was taken as the observed value, then a single residual was calculated for each ewe. The RMSE from these predictions was then compared to the scorer error and boxplots of the scores were overlayed with the model predictions for comparison.

3.3. Results

3.3.1. Repeatability Within and Between Scorers

Table 3.1- Average error from the mean score and error between each session for each scorer

Scorer Number	Average error from the mean score	Average error between sessions
1	0.35	0.42
2	0.28	0.43
3	0.33	0.56
4	0.63	0.50
5	0.36	0.50
6	0.57	0.35
7	0.58	NA
8	0.30	0.46
9	0.44	NA
10	0.28	0.38
11	0.44	0.41
12	0.37	0.29
13	0.36	0.45
14	0.47	0.34
15	0.30	0.60
16	0.30	0.34
17	0.39	0.46
Mean	0.41	0.44

Table 3.2- Mean error calculated for each ewe

Ewe number	Mean error	Ewe number	Mean error
1	0.39	12	0.38
2	0.33	13	0.34
3	0.4	14	0.34
4	0.37	15	0.46
5	0.49	16	0.42
6	0.43	17	0.39
7	0.45	18	0.35
8	0.51	19	0.54
9	0.4	20	0.37
10	0.41	21	0.44
11	0.48	Mean	0.41

The average error from the mean score for each individual scorer (Table 3.1) ranges from 0.28 to 0.63. With an average of 0.41 for all scorers. The consistency between session one and session two showed an average error of +- 0.44 units (Table 3.1). The error ranged from 0.29 to 0.60. The average error for each ewe was reasonably consistent ranging from 0.33 to 0.54 units, with an average error for all ewes of 0.41 BCS units (Table 3.2). Results from Table 3.1 are presented graphically in Figure 3.1.

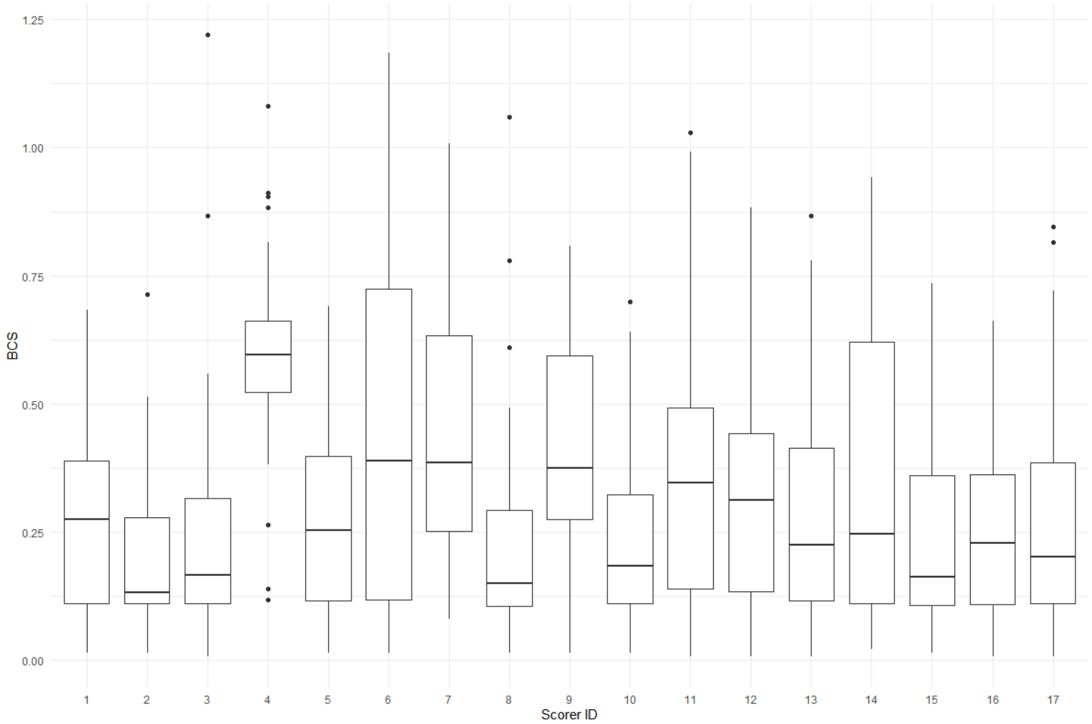

Figure 3.1- Boxplot showing the error for each scorer from the mean BCS for each ewe

3.3.2. Model Predictions

When predicting BCS for the 20 ewes in this study, the RMSE from the gradient boosting model and regression chain model were 0.44 and 0.65, respectively. Figure 3.2 shows the predictions for the gradient boosting model and regression chain model overlaid on the distribution of body condition scores for each ewe. This highlights the variation in predictive accuracy for each animal. Table 3.3 shows the RMSE values for each median BCS category using predictions from the gradient boosting model. RMSE ranged from 0.411 to 0.933, however we did observe low numbers of ewes in multiple categories due to the small animal sample size.

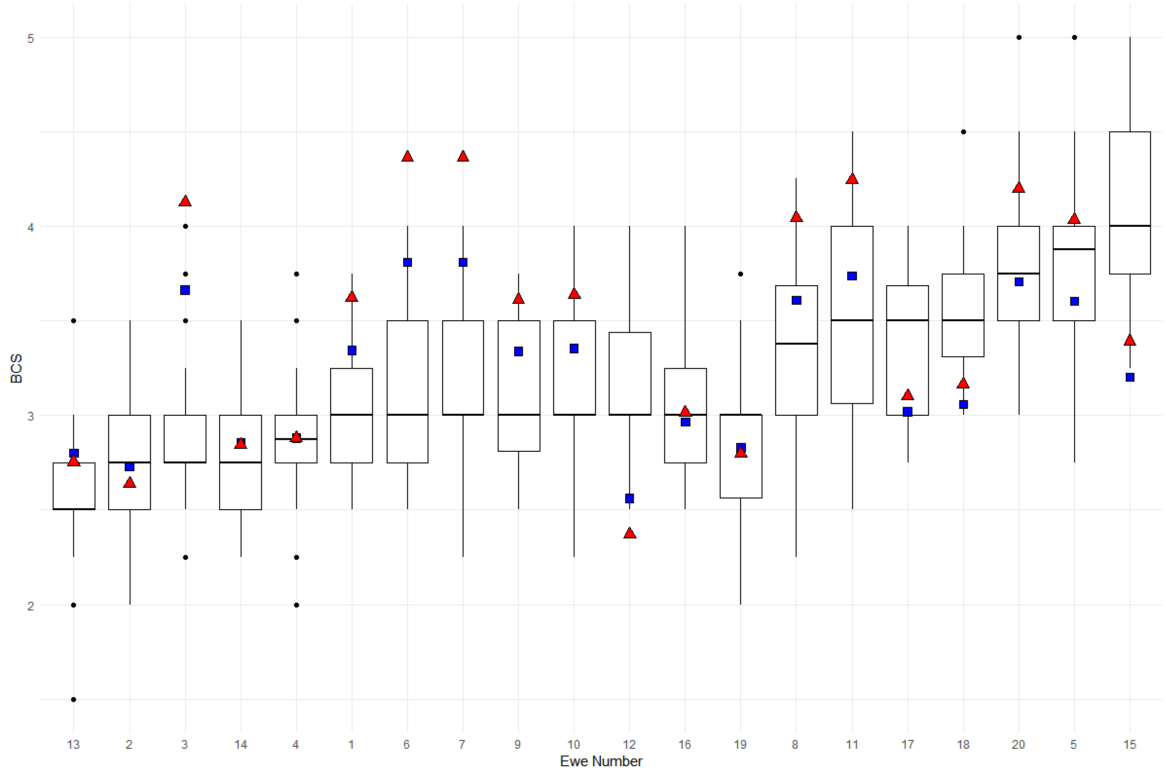

Figure 3.2- Boxplot showing BCS distribution for each ewe overlaid with predictions from the gradient boosting and regression chain models for each ewe. Boxplots are ordered by mean BCS for each ewe. ■ = Gradient Boosting Model Predictions, ▲= Regression chain model predictions

Table 3.3- RMSE for each BCS category using median BCS. RMSE calculated using measured BCS and gradient boosting model predictions

Median BCS	Number of Ewes	Gradient Boosting RMSE
2.5	1	0.411
2.75	3	0.563
3.0	9	0.559
3.5	4	0.562
3.75	1	0.426
4.0	2	0.933

3.4. Discussion

3.4.1. Inaccuracies when Measuring BCS

Many factors can affect the ability of an individual to accurately record BCS. Scorer experience significantly impacts the repeatability of scorers. Burmeister (2006) discussed the repeatability of BCS measurements in beef cattle across three scorer experience groups. They grouped scorers on experience, providing no training to the untrained group, moderate training to the trained group and substantial training to the experienced group. The amount of previous experience was also considered. Results showed that scoring was significantly worse for the untrained group, but showed little difference between the trained and experienced groups. Burmeister (2006) concluded that trainees needed to observe a large range of different cow body condition scores to become proficient and record repeatable, reliable measurements.

Within our study it is difficult to specifically determine scorer experience, however it is known that the scorers regularly recorded their own flocks up to five times a year. Using this practical experience along with the BCS training course which all scorers underwent at the start of the project, it is a safe assumption that the scorers could be regarded as experienced.

From the writer's personal experience and through discussions with farmers, some scorers claim to require a period of calibration at the start of each scoring session. This is often discussed as scoring the initial animals to "get their eye in" and adjusting the initial scores slightly depending on fat coverage. Although this may be an effective means to score animals relative to one another, it means that the data collected is highly subjective and may make it challenging to compare between flocks and even implement recommended values from the literature.
The adoption of measuring BCS is high in the UK, with studies suggesting 74% of UK sheep farmers score their animals once a year (Boon & Pollot, 2021). However, it is not clear of the methods used, or whether recording of scores occurs. Wright (2021) observed that over 99% of farmers surveyed observed condition of their ewes at mating, however only 77% used weight and BCS or only BCS methods. Body

condition scoring rates were lower at scanning, lambing, 8 -weeks and weaning at 61%, 61%, 34% and 65% respectively. Overall, this suggests farmers understand the benefits of observing the condition of their ewes, particularly at mating, however, do not necessarily use specific scoring methods or recording. It is vital to ensure the accuracy of these measurements across the whole industry to optimise the use of BCS targets and allow comparison between scorers.

It is possible to mitigate the subjective nature of BCS. This can be achieved through the regular calibration between scorers, regular training and increased experience. Even with these changes, the nature of collecting BCS means a certain degree of error is always present. Although the scorers involved within the Challenge Sheep project have substantial experience collecting BCS measurements, the accuracy of these measurements were largely unknown. This pilot study provides an indication of the accuracy of scorers within the project. This not only helps to validate the data collected, but also provides some understanding of the degree of measurement error and prediction error within the models in Chapter 2.

The issues of quantifying BCS measurement error is not specific to the sheep industry. There are many studies, throughout a range of species which attempt to quantify error. Within pigs, a study to observe the accuracy and repeatability of BCS measurements within sows was conducted (Fitzgerald et al., 2009). They found that measurement error was largely a result of scorers having poor repeatability, rather than scorer bias or subjectiveness. 70.6% of test variability was associated with scorer repeatability. Within our study, the average RMSE between the two sessions was 0.44, slightly higher than that of the RMSE for each scorer from the mean score of 0.41. However, this difference is not as substantial as that observed by Fitzgerald et al. (2009).

3.4.2. Evaluating Scorer Error

3.4.2.1. Within Scorer Error

Within scorer error ranged from 0.29 - 0.60. This is comparable to Refshauge and Quin (2007) where they observed RMSE ranging from 0.16-0.6 within a trial conducted on Merino ewes. This variation suggests that consistency is variable between scorers. Four of the scorers had an average error between the two sessions of 0.5 or more. Errors of more than 0.5 may affect management decisions on farm, particularly when referring to the recommended BCS values outlined in Table 2.1, where half a condition score of error could result in missed BCS targets. The overall error between the morning and afternoon sessions of 0.44 BCS units indicates that on average for all the scorers, BCS measurements were within half a condition score from each other, this is still a substantial error when implementing BCS measurements to inform management decisions.

3.4.2.2. Between Scorer Error

Between scorer error was observed through calculating average error from the mean score. Error ranged from 0.26 to 0.63 units, with an average of 0.41 units. This suggests that on average all scorers were 0.41 BCS units from the mean BCS score for each ewe. Similar to within scorer error, scorers averaging more than 0.5 BCS units of error may be considered inaccurate, and could struggle to categorise ewes on farm for management.

3.4.2.3. Error Around Each Ewe

The error around the mean values for each ewe ranged from 0.33 to 0.54, with an average error of 0.41 BCS units. This would suggest that calibration between farmers is moderate. Calibration between farmers is important when applying recommended values to management practices, however may be less important when using BCS as a performance error on farm, provided that the error is consistent for all animals scored.

The Challenge Sheep farmers generally farm between 1-3 breeds on each farm. It is assumed that some of the error observed may be the result of individual farmers being incorrectly calibrated to their specific breeds or animal type. For example, if a scorer is regularly observing high BCS values within their flock, it is more likely that these values will be classified as average values, with anything lower being observed as a low BCS, although this does go against the body condition scoring methods outlined in section 2.1.3.1. It had also been approximately three years since the assessors had undertaken any formal BCS training through the Challenge Sheep project. Although the aim was to calibrate all the scorers at the start of the project to create consistency throughout the whole seven-year project, there is a high chance that variability in scores has developed since the initial calibration and training session. Additionally, it is unknown whether individual scorers had undergone training outside of the project.

3.4.3. Next Steps

This pilot study appears to highlight substantial inter and intra rater error, that could suggest body condition scoring measurement errors on a broader level within the sheep industry. Quantifying error throughout the industry is important, particularly if body condition scoring is to continue to be used and promoted as a means of assessing individual animal performance. A larger study would be required to observe a range of scorers, over a range of management systems throughout the UK. It would be beneficial to collect an experience profile of each scorer, along with background information, particularly on their farming system if applicable. This pilot study had some limitations that could be easily mitigated within future studies.

3.4.3.1. Breed

One substantial limitation of the pilot study is the number of ewes and breeds included within the study. There were 21 ewes across 3 breed types (Mule, Texel and Texel X Mule), all located on one farm, included within the sample group. Ideally a larger sample size, including a range of breeds encompassing the majority of breeds within the Challenge Sheep project would have been scored. Comments were made on the day that individuals had more confidence scoring their own animals, rather than scoring uncommon breeds to them. This was unsurprising, however body condition score was designed to be irrespective of breed, therefore this may highlight an underlying breed bias within the scorers. Within a larger study observing the relationships between scorer accuracy for each individual breed type may highlight any breed biases. Due to time constraints on the day and the inability to move sheep between farms, both practically and from a biosecurity standpoint it was not possible to score a larger group with an increased number of breeds. The decision to include more scorers rather than more animals within the study appears to beneficial, as substantial variations between scorers can be observed within the results.

3.4.3.2. Experience Level

Experience level was an unknown factor within the pilot study, with scorers including farmers, advisors and project managers. Records of previous scorer experience, collected through a survey, would have been beneficial for this study. Although all scorers were either farmers involved with regularly collecting BCS for the Challenge Sheep project or advisors with significant experience in sheep, it may have been beneficial to group the scorers depending on experience. Some methods to group the scorers would have been via self-categorising, or the use of a survey to determine prior experience, however this could have resulted in highly subjective groupings. Observations on the day suggest that the scorers all had substantial experience and would most likely all be grouped into an experienced category. If a larger study was to be conducted, the addition of less experienced scorers may provide results more applicable to that of the industry. The study chose not to provide any additional training on the day to ensure the scores were consistent with that of which the scorer would usually allocate. Providing training on the day to a specific group would indicate whether regular training improves the ability to accurately record BCS, however with the scorer sample size (n=17) it would have resulted in groups which were too small for an accurate comparison.

Often studies have used experienced assessors or instructors as a “gold standard” BCS measurement to compare to. In this study the mean BCS from all results was used to calculate the BCS for each ewe to calculate error. Although this has the benefit that BCS is not calculated from one individual, who may have their own bias, it also has the negative effect of ‘incorrect scores’ impacting the mean.

3.4.3.3. Time Constraints

On farm scoring is usually a fast-paced process which involves the scorer quickly assessing BCS, then moving onto the next animal. Within this study we had no specific time constraints for scorers. This allowed scorers more time than usual to consider the groupings, and could have potentially increased scoring accuracy. Observing how the rate of scoring effects scoring accuracy may be of interest, however may not be applicable on farm where labour requirements can be a large concern of body condition scoring ewes. One point of interest was many scorers backtracking to previous animals to compare condition scores, then using this comparison to decide on the score for the next animal, relative to previous scores. Scorers also commented that often when scoring their own animals they would ‘get their eye in’ on the initial animals, and felt that scoring accuracy would increase after that. Using this technique has the potential to significantly bias results for the group of animals being scored, however likely has little to no impact on management practices, as the low and high BCS animals are still being observed. More issues are likely to occur if management practices are changed using recommended BCS values.

3.4.3.4. Weight Measurements

Within the pilot study, two scoring sessions were conducted, one late morning and one mid-afternoon. Weighing of the ewes occurred at a single point prior to the morning session and were not repeat weighed before the afternoon sessions. The ewes were kept indoors between sessions with no access to feed. The liveweight of the ewes may have changed between morning and afternoon session, due to fluctuations in gut fill. This is unavoidable and is one of the many reasons body condition scoring was developed. Taking an average between weights between each session may be beneficial to improve the ability of the model to predict accurately and highlight any incidences of incorrect weight measurements.

3.4.4. Predictive Model Evaluation

3.4.4.1. Measurement Error vs Predictive Error

To test the performance of the BCS predictions model on an additional dataset, the two best performing models were tested (Gradient boosting model and gradient boosting model with regression chain). This testing indicates the generalisability of each model, and allows a comparison between predicting BCS and manually recording. The average BCS measurement error from the mean score on each ewe was 0.41 (Table 3.2). The gradient boosting model, predicting on the 20 ewes, had an RMSE of 0.44 when the observed value was taken as the mean of all scores on each ewe. The equal error in the predictive model and the measurements may suggest that a large degree of error is associated with measurement error, rather than predictive error, however it is still challenging to determine the exact cause of error due to the subjective nature of the data. Figure 3.2 shows a boxplot of scores for each ewe overlayed with predictions from the gradient boosting model. It is clear from this plot that the gradient boosting model predicts certain ewes well, however overpredicts a proportion of ewes. The model appears to be overpredicting heavy ewes, which is exacerbated by the regression chain model.

Although the gradient boosting model with regression chain reduced bias compared to the gradient boosting model (Section 2.2.5.7), it struggled to predict on this dataset, with increased overall RMSE values of 0.65 compared to 0.44. This appears to be a result of the nature of the data collected within this study. The gradient boosting model with regression chain was designed to increase the performance of the model at extreme predictions, where the gradient boosting model was struggling, while slightly increasing error across the central BCS values (2.5-3.5). This dataset had a mean BCS of 3.23, with an interquartile range of 0.75. A comparison of the predictions from the two models in Figure 3.2 show that ewes which were overpredicted in the gradient boosting model had increased error within the gradient boosting model with regression chain.

Chapter 4. Use of Survival Analysis Techniques to Model Reproductive Performance in Ewes

4.1. Introduction

4.1.1. Overview

Reproductive performance is one of the key drivers for efficiency on sheep farms in the UK. Advancements in genetics, nutrition and management has led to an increase in reproductive performance of ewes. Breed selection and the selective breeding of individuals within these breeds has led to advancements in ewe prolificacy and fertility. There are several common parameters used to quantify reproductive performance in ewes. Commonly observed parameters include, fertility (the percentage of ewes which lamb after being exposed to the ram), lambing percentage (number of lambs born to each ewe exposed to the ram), scanning percentage (number of foetuses per ewe as a percentage) and perinatal lamb losses (preferably observed separately as prenatal and neonatal losses)(Larsen, 2021). Reproductive performance can be assessed at both an individual animal and group level, with the later more common when comparing lambing group or flock performance. It could be argued that within the dairy sector, measurement of reproductive performance is more common and robust than the sheep sector, particularly when observing individual animals. Challenges around the large increase in metabolic requirements for milk production coinciding with insemination, has led to significantly reduced fertility in modern high yielding dairy cows (Crowe, Hostens and Opsomer, 2018). This reduction in fertility led to an industry wide effort to improve the management of cows around insemination. More reproductive parameters are recorded and observed within the dairy sector than the sheep sector. These include but are not limited to calving interval and days to conception. Using previously gained knowledge from research on dairy reproduction, it may be possible to use similar techniques to observe timeframes within sheep reproduction, and observe specific variables which impact on reproductive performance. Days to conception is utilised as a fertility metric within dairy cows. Observing days from ram entry to lambing may provide a similar metric to days to conception and indicate how fertility rates may be increased within sheep production systems. The comparison of the reproductive performance between ewes first bred as ewe lambs and shearlings in their first year of production and subsequent years is also of interest, and one of the key aims of the Challenge Sheep project. The prediction of ram entry to lambing interval will also play a significant role within a larger systems model, in which lambing date will be estimated from mating date and other ewe factors.

4.1.2. Factors that Affect Reproduction in Ewes

4.1.2.1. Body Condition Score

Reproductive performance in sheep is affected by management, genetic and nutritional factors. Mating liveweight and condition score of ewes have been observed to have a positive relationship on reproductive performance (Kenyon, Morel and Morris, 2011). They observed a negative effect of low condition score (BCS < 2.0) on reproductive performance, however found no improvement over a BCS of 2.0 and 3.0 for composite and Romney breeds respectively. Ewes gaining condition pre-mating has been shown to significantly increase rates of ovulation and potential lambs per ewe pregnant (Gunn *et al.*, 1991).

4.1.2.2. Weight

Currently the main use of liveweight in regards to reproductive performance is during the selection of ewe lambs for breeding. Ewe liveweight is the main indicator of whether ewes should be bred as ewe lambs or retained for breeding as shearlings. As discussed in section 1.3, ewe lambs should weigh at least 60% of their mature weight at first mating. It has been reported that increased ewe lamb live weight at mating significantly increases fertility and lambing percentage (Haslin, et al., 2022b). They observed the effect of heavy ewe lambs (47.9 +- 0.36 kg at mating) and a control group (44.9 +- 0.49kg at mating) on fertility and lambing percentage. The heavy group had 28% increased fertility and 59% increased lambing percentage compared to the control group. Interestingly, the higher first mating weight and resulting increase in fertility and lambing percentage did not impact subsequent production years (Haslin, et al., 2022b).

4.1.2.3. Nutrition

Nutrition around mating has a significant effect on reproductive parameters. Higher ovulation rates and a higher percentage of ewes conceiving at first oestrus, have been observed in ewes on a high plane of nutrition (Fletcher, Geytenbeek and Allden, 1970). Additionally, studies suggest a high plane of nutrition (1.5x estimated ME requirement), can significantly increase ovulation rate during induced oestrus for more prolific breeds (2.26 compared to 1.78 for the lower ME group) (Lassoued *et al.*, 2004). For less prolific breeds no significant effect on ovulation rate was observed. The nutritional requirement around mating appears to be highly dependent on the prolificacy of each specific breed. Flushing ewes is the process of increasing the plane of nutrition pre-mating with the aim to optimise ovulation, conception and embryo implant rates.

4.1.2.4. Status at First Mating

There is substantial discussion around how to improve lifetime productivity of ewes, with a lot of interest around whether ewes should be initially bred as ewe lambs or shearlings. Answering this question was one of the main aims of the Challenge Sheep project. Although breeding from ewe lambs provides the opportunity for an additional litter, and therefore a higher total number of lifetime progeny, it is unclear whether breeding as a ewe lamb, before mature weight is reached, could have a negative effect in subsequent production years. As ewes age, fertility generally increases, with a particularly large increase between first breeding as a ewe lamb and subsequent mating. Edwards and Juengel, (2017) observed the number of lambs born and weaned for a sample of New Zealand ewes. As age of the ewe increases from one to four years of age, so did average number of lambs born and weaned. In year one approximately 0.9 lambs were born per ewe while in years two, three and four, 1.7, 1.8 and 1.9 lambs were born per ewe, respectively. It is clear that ewe lambs have a substantially lower average number of lambs born compared to two-, three- and four-year-old ewes. There does not appear to be any effect of ewe age on number of lambs weaned, with a consistent reduction in number of lambs between birth and weaning for all groups.

To ensure optimum productivity and health from ewe lambs it is important that management practices are implemented carefully. This largely involves the careful monitoring of both BCS and liveweight to ensure ewe lambs are ready for mating. Body condition score and liveweight has been shown to significantly affect ewe lamb reproductive performance (Corner-Thomas *et al.*, 2015). Ewe lambs in a 47.5-52.5kg liveweight category at mating had the highest reproductive rate at 138%. Reproductive rate peaked at a mating BCS of 3.0, with no improvements seen at higher condition scores. It is understood that ewe lamb reproductive performance is largely dictated by the percentage of total liveweight at first mating, and less so by the condition of that animal. It is recommended that ewe lambs must weigh at least 60% of their mature weight at mating to be mated. (Selecting ewe lambs for breeding | AHDB, accessed 06/02/2024). A percentage of mature weight is used to allow for variations in breeds. A similar recommendation exists for shearlings at first mating, in which it is advised that they should weigh at least 80% of mature liveweight.

4.1.2.5. Effect of First Mating as a Ewe Lamb on Future Reproductive Performance

The effect of ewe lamb first mating weight on reproductive performance in year 2 and year 3 has been observed in Romney ewes (Haslin *et al.*, 2021). A control group with average first mating weight of 44.9 ± 0.49 kg, and a heavy group with average first mating weight of 47.9 ± 0.38 kg were observed. They found that first mating weight had no effect on ewe liveweight, BCS, reproductive performance or lamb performance in their second and third years. This suggests that breeding from a ewe lamb does not negatively impact mature ewe performance. Similar to Corner-Thomas et al. (2015) , it was observed that heavier ewe lambs performed better in their first year of production (Haslin *et al.*, 2021). Reproductive and lamb performance are not the only factors that farmers must consider when breeding from ewe lambs.

4.1.2.6. Genetics

Genetic differences between different breeds can significantly affect reproductive performance, with more prolific breeds having significantly higher fertility (Petrović *et al.*, 2012). Some examples of highly prolific breeds include Lleyn, Blue Faced Leicester, Romney and Merino. Modern composite breeds such as the ‘Aberdale’ have been bred to optimise some of the characteristics from these highly prolific breeds, specifically the Inverdale gene mutation has been bred into Welsh mountain ewes. There are many gene mutations within sheep which can result in increased prolificacy, however perhaps the two most common are the boroola mutation (FecB), commonly found in Merino breeds, and the Inverdale (FecX), found in Romneys (Davis, 2004). Ewes which are heterozygous for the Inverdale gene have been shown to ovulate an average of one more egg than noncarriers (Smith *et al.*, 1997). Care must be taken when breeding ewes with the FecX mutation as homozygous ewes are infertile due to ‘streak’ ovaries. Often rams are used to carry the gene mutation on the X chromosome, to ensure homozygous ewes are not bred.

4.1.2.7. Environmental Factors

Thermally stressed ewes have been shown to exhibit oestrus later and for a shorter period (Dobson *et al.*, 2012). In their study, ewes subjected to temperatures of 40 degrees Celsius for 6 hours per day exhibited oestrus 5 hours later than a control group at 19 degrees Celsius. Ewes subjected to increasing periods of high temperatures (>32 degrees Celsius) saw a 2.7% decrease in fertility for each subsequent day exposed at that temperature (van Wettere *et al.*, 2021). Climate change is a concern for sheep producers in extreme environments. Producers are likely to observe an increased frequency of days in which animals are experiencing heat. If these occurrences of heat stress coincide with mating, a detrimental effect on fertilisation and embryo survival has been observed (Comparative Endocrinology of Animals, 2019). Although the effects of heat stress on reproduction in ewes is of great concern for more arid areas, the UK rarely experiences extreme, high temperatures around mating. Although with ever changing climates and increase occurrence of extreme events increased seasonal temperature changes around mating are possible in the UK.

4.1.3. Manipulating Ewe Reproduction

Although the onset of oestrus is largely dictated by reducing photoperiod, there are many techniques which can be implemented to improve reproductive performance. Synchronising oestrus in ewes can be an effective way to condense ram entry to lambing interval. Progesterone sponges can be used to synchronise oestrus cycles and are particularly useful pre artificial insemination (Hameed *et al.*, 2021). Teaser rams are commonly used to improve the rate of successful first cycle mating. It has been observed that 62.6% of teased ewe lambs were mated in the first 17 days while only 32.1% of unteased ewe lambs were mated. After 2 cycles, 17.8% of unteased ewe lambs were unmated while only 11.2% of teased ewe lambs were not mated (Kenyon *et al.*, 2005). Artificial insemination is beginning to gain traction within the sheep industry. The dairy industry has utilised artificial insemination to maximise genetic gain and improve fertility. Cows can be inseminated at a specific timepoint when oestrus is detected or induced. This has improved the low fertility often associated with dairy cows. Similar techniques are starting to be implemented on sheep farms, but not necessarily to increase fertility. The increasing focus on genetic improvement has led some producers to source the best paternal genetics through the use of artificial insemination. This is most often utilised by ram breeders, however, can reduce biosecurity risk for some closed flocks. For commercial flocks the cost associated with artificially inseminating large numbers of ewes is often prohibitive. Similar to artificial insemination, ram breeders sometimes use embryo transplants. This gives the option to introduce new ram and ewe genetics, from high performing animals, into an existing ewe with good maternal ability. Harvesting many embryos from high performing ewes allows higher number of offspring with those genetics.

4.1.4. Survival Analysis

Survival analysis is a collection of statistical techniques used to analyse changes over time of a specific event (Dudley, Wickham and Coombs, 2016). Initially these techniques were developed for use within medical studies to observe the time from treatment to death. However, are now used as a means to assess time to event data in many research areas. Kaplan-Meier analysis (K-M) and Cox proportional hazards model (CPH) are the two most common techniques.

4.1.4.1. Kaplan-Meier Analysis

Kaplan-Meier analysis is a univariate approach to observe the effect that one variable has on an event. Events are classified as binary variables, in which the event does or does not occur. Outputs from K-M Analysis include a predicted survival curve. The x-axis indicates the time variable, starting when the study commenced, with the y-axis indicating the probability of the event occurring. The K-M curves have a stepped appearance with the horizontal drop indicating the occurrence of the event between two subsequent individuals. Censored data appears as tick marks on the K-M plot.

4.1.4.2. Cox Proportional Hazard Models

Cox models allow the investigation of multiple continuous and categorical variables simultaneously. The main output from the Cox model is the hazard ratio. The hazard ratio is the ratio of the event rate in any one group. For example, the ratio of a low BCS group to a high BCS group. All hazard ratios are relative to a reference group.

The Cox model has three main assumptions. Firstly, the hazard ratio is assumed to remain constant throughout the follow-up. Secondly, the survival time of each individual is not dependant on another. Finally, any individuals who were censored must have had the same likelihood of the event occurring (Deo, Deo and Sundaram, 2021). A benefit of using survival analysis over more common techniques such as logistic regression is the ability of survival analysis to process censored data.

4.1.4.3. Survival Analysis to Observe Reproductive Performance in Livestock Species

Survival analysis has been used within the livestock sector to evaluate longevity. (Szabó and Dákay, 2009) used survival analysis techniques to evaluate how specific parameters at first calving affected longevity. They observed breed, age at first calving, season at first calving and level of calving difficulty. K-M analysis was used to plot the estimated survival distributions, allowing comparison of the groups within each variable. They found that cows which calved without assistance had a longer productive life than those which had still born calves or required veterinary assistance. This indicated that dystocia is a significant factor for reduced longevity in cattle. Breed had a significant effect on longevity with Herfeord having the highest longevity. It is important to include the influence of breed within models and analysis of ewes due to the extensive range of breeds, with significant phenotypic differences. Similar trends were observed using a Cox regression model on composite beef cows. Rogers et al. (2004) observed the risk factors affecting the longevity of beef females and evaluated the ability to predict longevity using measures collected in early life. They observed similar findings as Szabó and Dákay (2009), with risk ratio increasing when cows had been assisted at first calving. Additionally, they observed that changing herd sizes affected longevity, with increasing herd sizes resulting in increased longevity. K-M analysis was used to model days open in a sample of 385 dairy cows in Ethiopia (Temesgen *et al.*, 2022). They observed the median days open (154 days) and the percentage of cows open at 210 days post-partum (16%). Additionally, a Cox model was built to observe the effect of multiple variables on days open. They observed the effects of season; breeding system; calving-to-insemination interval and herd milk yield, with hazard ratios calculated for each subset of the variables. All variables have a significant effect on days open, particularly cows inseminated in autumn with a hazard ratio of 4.45. Similarly, the effects of disease on days open was observed in 467 Holstein dairy cows (Lee, Ferguson and Galligan, 1989). Five diseases were included within a Cox proportional hazards model. All diseases had a low hazard ratio (<1), resulting in increased days open. Transition cow diseases can have a large influence on reproductive performance and particularly fertility. Bogado Pascottini et al. (2020) studied the effect of a range of transition diseases on days open. Variables included, twinning, milk fever, retained placenta, metritis, ketosis, displaced abomasum and mastitis. They ran a Cox proportional hazards model to observe the effect of each variable on days open. Healthy animals were used as the reference value for calculation of hazard ratios. Primiparous and multiparous ewes were modelled separately.

It is apparent that the use of survival analysis is common practice to analyse reproductive performance in dairy cows, with a particular emphasis on the risk factors associated with increased calving to conception interval. The focus on days open appears to be a result of significant production losses for each day a cow is not lactating (Louca and Legates, 1968). Although within sheep, days open is not used as a measure of reproductive performance, similar techniques could be used to observe days to conception or days to lambing from a ram entry date.

4.1.5. Analysing Ram Entry to Lambing Interval

Survival analysis or more generic time to event analysis had been used to model gestation length and calving interval in dairy cows (Safa Gürcan and Akçay, 2007). Kaplan-Meier analysis was used to observe the effects of maturity on gestation length. Cows were grouped into two age categories and compared using Kaplan-Meier analysis. It was concluded that survival analysis was an appropriate means of analysing reproductive data in dairy cows. The success of utilising survival analysis to evaluate reproductive performance in dairy cows indicates that similar techniques may be useful to analyse sheep reproduction. This study will model the effect of ewe parameters on the interval from ram entry to lambing date using Kaplan-Meier analysis and Cox Proportional Hazard models.

4.1.6. Aims and Objective

The aim of this section is the development of a model to predict ram entry to lambing interval, referred to as mating to lambing interval in this chapter. This will indicate the days to conception and gestation length of each ewe. This will be achieved through the initial analysis of the Challenge Sheep project dataset to observe the effects of specific variables on mating to lambing interval using survival analysis techniques. The results from this initial analysis will indicate which factors positively and negatively affect mating to lambing interval. Ewes which have a lower mating to lambing interval are considered to have higher fertility and therefore the performance measures resulting in this are desirable. Accelerated failure time models will be used to predict a specific interval for each ewe to use within larger systems models. The prediction of mating to lambing interval is important within a systems model to estimate the date of lambing dependant on the management decision of ram entry. Having an approximation for lambing date allows a larger systems model to correctly predict lamb performance, sales dates and ewe recovery period before next mating.

4.2. Materials and Methods

4.2.1. Data

4.2.1.1. Data Collection

Data collected as part of the AHDB Challenge Sheep project (Challenge Sheep | AHDB, accessed 06/02/24) was used to model reproductive performance in ewes. The dataset included data collected from 11 commercial sheep farms across England over four production years. 14 breeds were observed from a total of 7724 ewes. Ewe and progeny performance data were collected at five stages throughout each production year, mating, scanning, lambing, eight weeks post-lambing and weaning. All ewes entered the project as ewe lambs or shearlings. Dates were recorded at each event, providing ram entry dates and lambing dates. Exact mating dates were not collected as part of the project. BCS and weight records were recorded for each ewe, with progeny weight records recorded at lambing, eight-weeks and weaning. Ewe birth date was recorded allowing age to be calculated at specific timepoints. BCS was recorded by a single trained individual on each farm, with the use of electronic identification (EID) tags and readers to accurately record data points for each ewe. All scorers had undergone a BCS calibration session at the start of the project to minimise subjectivity.

4.2.1.2. Data Manipulation

The survival analysis required specific variables to be manipulated or categorised from the raw data. Mating BCS was grouped into three categories, Low (BCS < 2.5), moderate (2.5 ≤ BCS ≤ 3.5) and high (BCS > 3.5). BCS categories were determined on biological factors, utilising recommended values outlined in by Wright (2019) in 'Managing ewes for better returns'. The range of moderate BCS values includes the recommended mating BCS values for lowland, upland and hill ewes. This resulted in 812 low BCS records, 10174 moderate BCS records and 3891 high BCS records. Breeds were refined to 11 breed groupings from an initial 14 breeds recorded within the project, this included the grouping of some crossbred ewes into larger categories. BCS change (∆ BCS) pre-mating was calculated as the difference from weaning in the previous production year to mating in the current production year. This was then grouped into three groups: loss (∆ BCS <0), maintain (∆ BCS = 0) and gain (Δ BCS > 0). This resulted in groups of 805, 1555 and 5397 records, respectively. 7120 records did not have a previous weaning BCS, largely a result of ewes in their first year of production. Age at mating was calculated in days. Where applicable previous number of lambs were calculated using data from the previous production year, this included total number of live lambs born. Parity was calculated from the total number of times the ewes had lambed within the project. As all ewes joined the project as ewe lambs or shearlings, this provides an accurate measure of parity.

4.2.1.3. Data Censoring

One significant benefit of using survival analysis over more common techniques such as logistic regression is the ability of the survival analysis methods to process censored data. Censored data was defined as any ewes which did not lamb within the desired timeframe (right censored), or ewes that were lost to the project before recording began (left censored). In the case of this study all ewes were considered as right censored. A total of 1815 datapoints were censored from a total of 15,807 usable entries.

4.2.1.4. Data Analysis

Two survival analysis techniques and an accelerated failure time model were used to investigate mating to lambing interval. Kaplan-Meier Analysis was used to determine the association of individual variables on the mating to lambing interval, and provided an indication of which variables to include within the final model. Two Cox proportional hazards models were built. One to analyse primiparous ewes, and one for multiparous ewes. These models allowed the comparison of variables through a multivariate approach.

The K-M analysis was used to determine the association between individual predictors on mating to lambing interval. A series of variables were observed including, ewe BCS at mating, parity, weaning to mating BCS change, breed, and previous lambing number (the number of lambs born to each ewe in the previous production year). The results of these plots provided a graphical representation of the association between each variable and informed the decision of which variables to include within the Cox proportional hazards model.

Two individual Cox Proportional Hazard models were built to differentiate between primiparous ewes and multiparous ewes. The primiparous model included variables: grouped BCS at mating and age (ewe lamb or shearling), with breed included as a random effect and stratified by project year. The second multiparous model not only included variables collected at the point of mating, but also variables collected from the previous production year. These include, grouped BCS at mating, grouped pre-mating BCS change, previous number of lambs (number of live lambs born to each ewe in the previous production year), age, and parity. Again, breed was included as a random effect with the model stratified by project year. Hazard ratios were observed to assess the effect of each variable on the event. P-values were used to determine significance. Hazard ratios greater than one suggest the predictor is associated with decreased mating to lambing interval.

4.2.2. Accelerated Failure Time model

The nature of Cox proportional hazards models makes it challenging to predict intervals directly from the analysis, largely due to the nature of the results being relative to a reference value. Accelerated failure time models can be used to predict a survival time from time to event data, using the results from Cox proportional hazards models to decide which variables to include. Accelerated failure time models are a parametric method for predicting continuous time data. The probability that an individual can survive beyond a given time (t) is denoted by S(t).

Similar to the two distinct Cox proportional hazards models produced to model first parity and multiple parity ewes separately, parametric distributions were used to model both groups, again allowing for the use of data from previous production years within the multiple parity model. A series of parametric distributions were plotted using the important variables highlighted from the results of the Cox proportional hazards models. These included, weibull, loglogistic, exponential, gaussian, logistic, and lognormal. Akaike information criterion (AIC) was used to estimate prediction error and allow for relative comparison between the models. The model with the lowest AIC was used for the time to event predictions. Out of the six parametric distributions tested, the loglogistic distribution provided the lowest AIC for first and multiple parity ewes, and therefore was used for prediction.

4.3. Results

Figure 4.1 shows first parity animals that are in a lower mating BCS (<2.75) have a shorter mating to lambing interval with more animals lambing earlier in in the production year. This can be observed through the initial steeper gradient in the Low BCS group, starting at around 145 days post-mating. High BCS ewes lamb at a similar rate to moderate BCS ewes throughout the interval, with the rate slowing at around 165 days post-mating where the remaining high BCS animals take longer to lamb. In their first year of production, shearlings appear to get in lamb quicker, resulting in a shorter mating to lambing interval than ewe lambs (Figure 4.2). Ewe lambs begin lambing later, then continue to lamb slowly up until approximately 165 days post-mating, where the rate increases.

4.3.1. Kaplan-Meier Analysis for First Parity Ewes

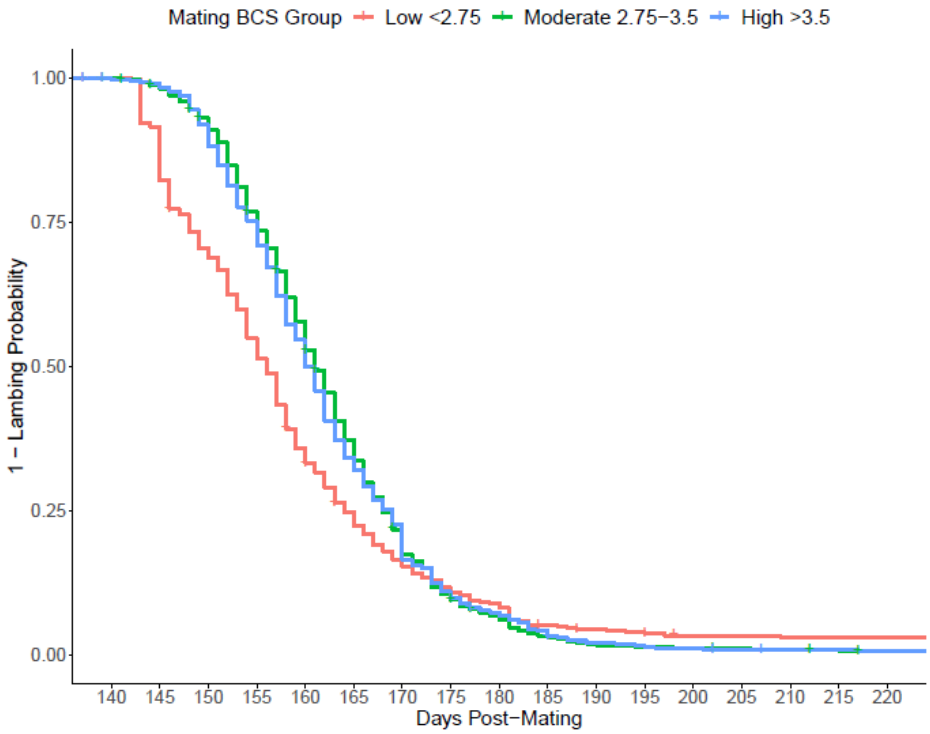

Figure 4.1- Kaplan-Meier plot showing the probability of lambing for first parity ewes in either Low, Moderate or High mating BCS groups

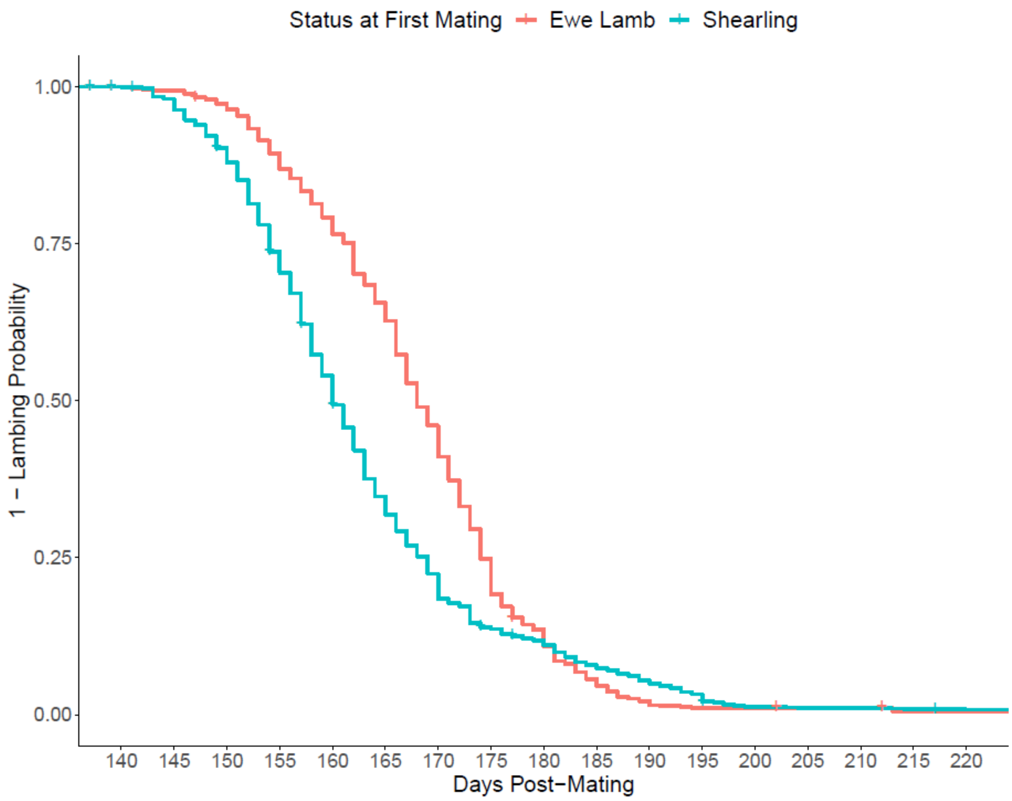

Figure 4.2- Kaplan-Meier plot showing the probability of lambing for ewes in their first year of production as either ewe lambs or shearlings

4.3.2. Kaplan-Meier Analysis for Multiple Parity Ewes

In mature ewes the Kaplan-Meier Analysis (Figure 4.3) suggests that High BCS at mating has a negative effect, increasing mating to lambing interval. Lambing appears to begin later in the High BCS group and continue for longer (up to 200 days post-mating). The Low and Moderate BCS groups have a similar curve and therefore intervals. The Low group appears to initiate lambing earlier, however by 155 days post-mating the same proportion of ewes have lambed in both the Low and Moderate Groups.

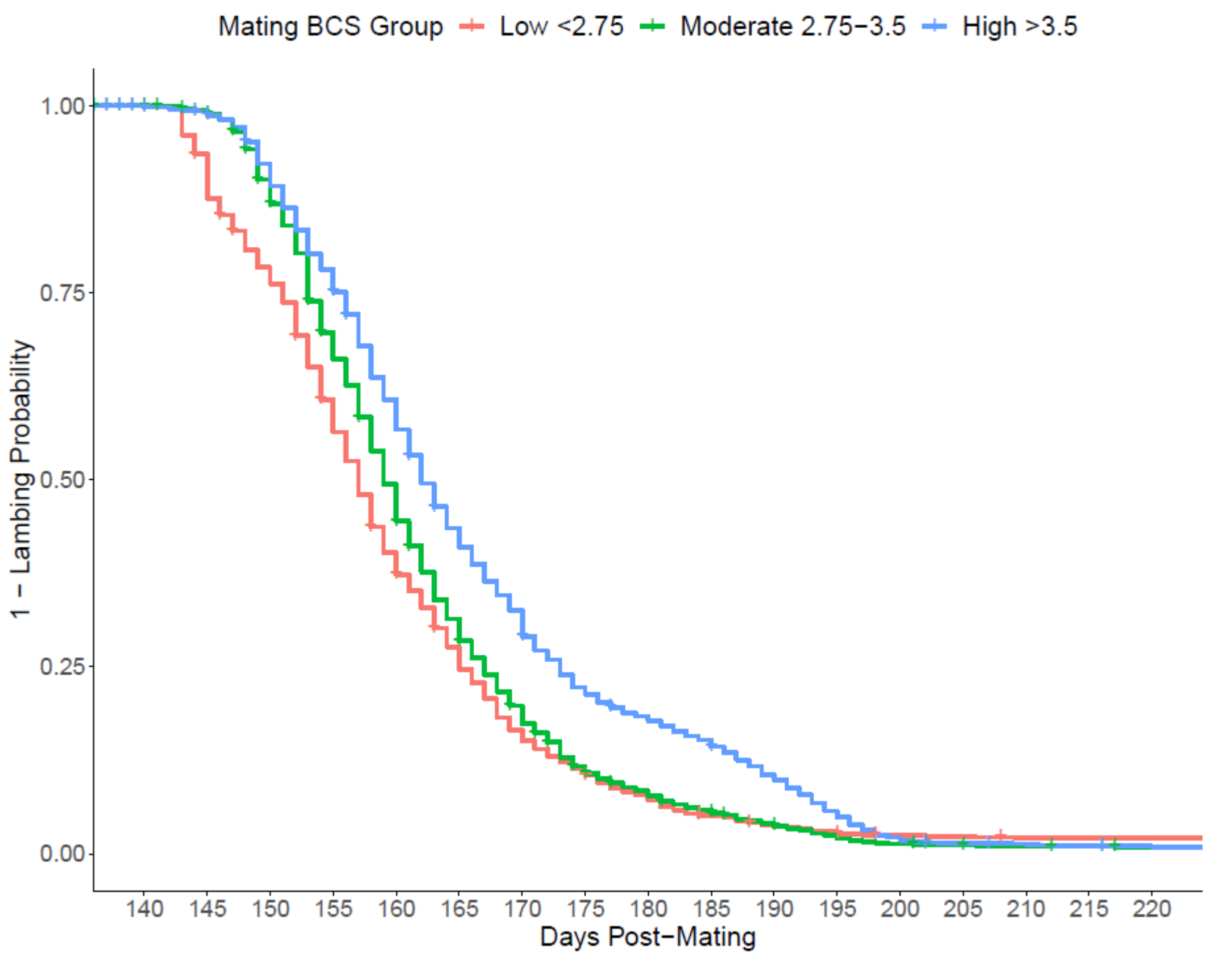

Figure 4.3- Kaplan-Meier plot showing the probability of lambing for multiple parity ewes in either Low, Moderate or High mating BCS groups

4.3.3. Kaplan-Meier Analysis for All Ewes

When observing the effect of age on mating to lambing interval (Figure 4.4) it is clear that younger animals have an increased mating to lambing interval. Ewes at less than one year of age at first mating (ewe lambs) initiate lambing at a later interval, with a larger proportion left to lamb compared to the other groups throughout the whole interval. One year old ewes exhibit a slightly increased interval with less animals lambed at 160 days post-mating than the older groups. Two, three, and four year old ewes at mating exhibit similar curves, maybe suggesting age is less of a factor in older animals.

The relationship between age and parity is shown in Figure 4.5. For parity one animals, age at mating appears to have a substantial effect on mating to lambing interval. Ewes under one year of age (ewe lambs) had an obviously increased mating to lambing interval compared to ewes at one (shearlings) and two years of age at first mating. Parity two ewes at two years of age appears to have the shortest mating to lambing interval, with parity one slightly increased. Parity two ewes at three years of age had a substantially increased mating to lambing interval, with over half the animals lambing after 165 days post-mating. For parity three animals at three years of age at mating have the shortest mating to lambing interval. Four-year-old animals in parity three have an increased mating to lambing interval with over 30% still left to lamb after 180 days post-mating. Ewes at four years of age at parity four performed best with ewes at three years of age taking slightly longer to initially start lambing. An interesting observation is that for multiple parity animals, when the age in years coincide with parity the mating to lambing interval appears to be reduced. Generally, this grouping would include ewes that were first mated as shearlings at one years of age.

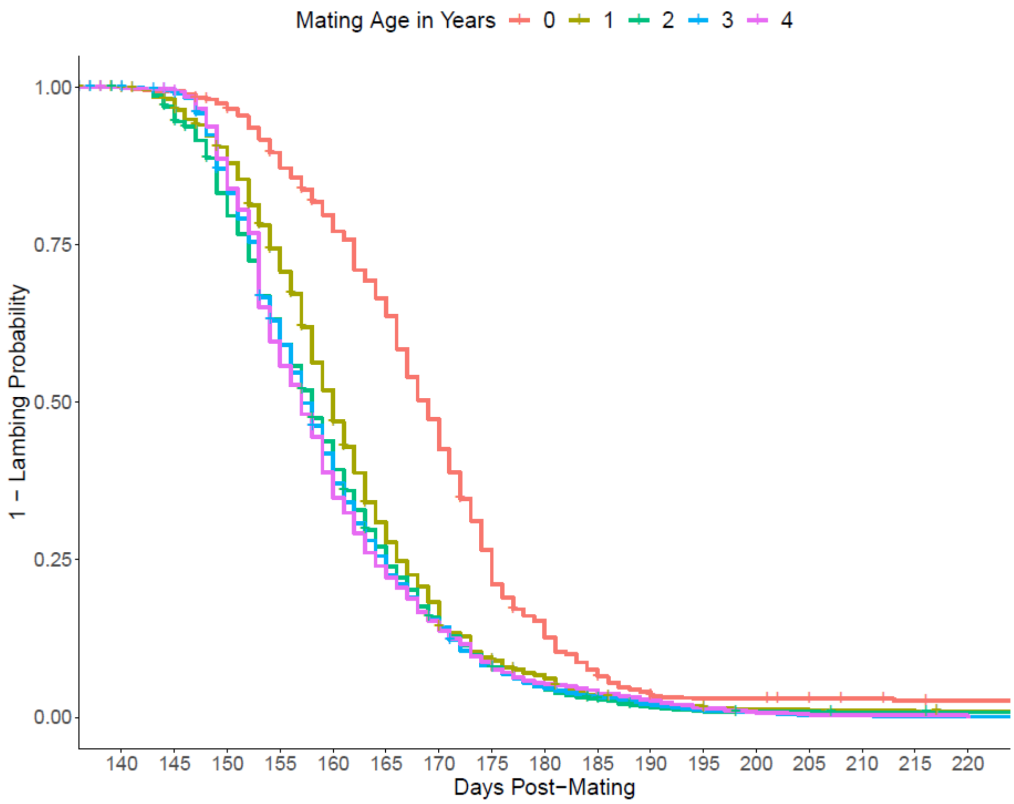

Figure 4.4- Kaplan-Meier plots showing the effect of Age on mating to lambing interval

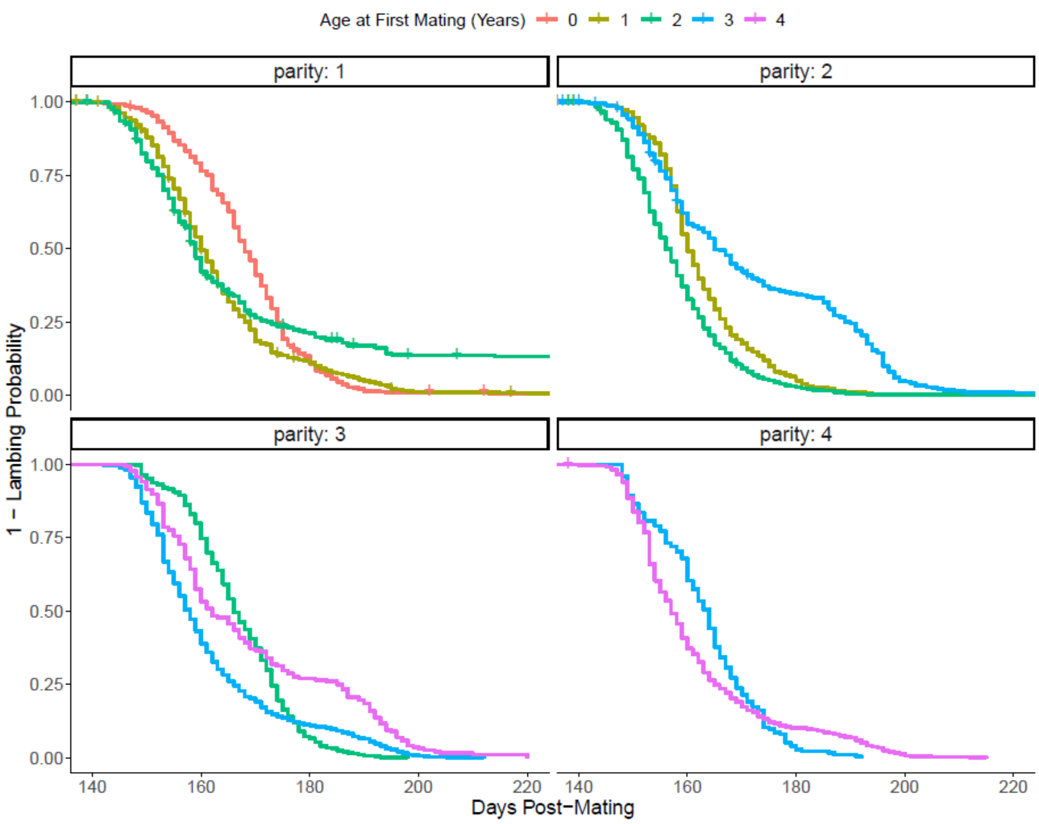

Figure 4.5- Kaplan-Meier plots showing the effect of Age and Parity on mating to lambing interval

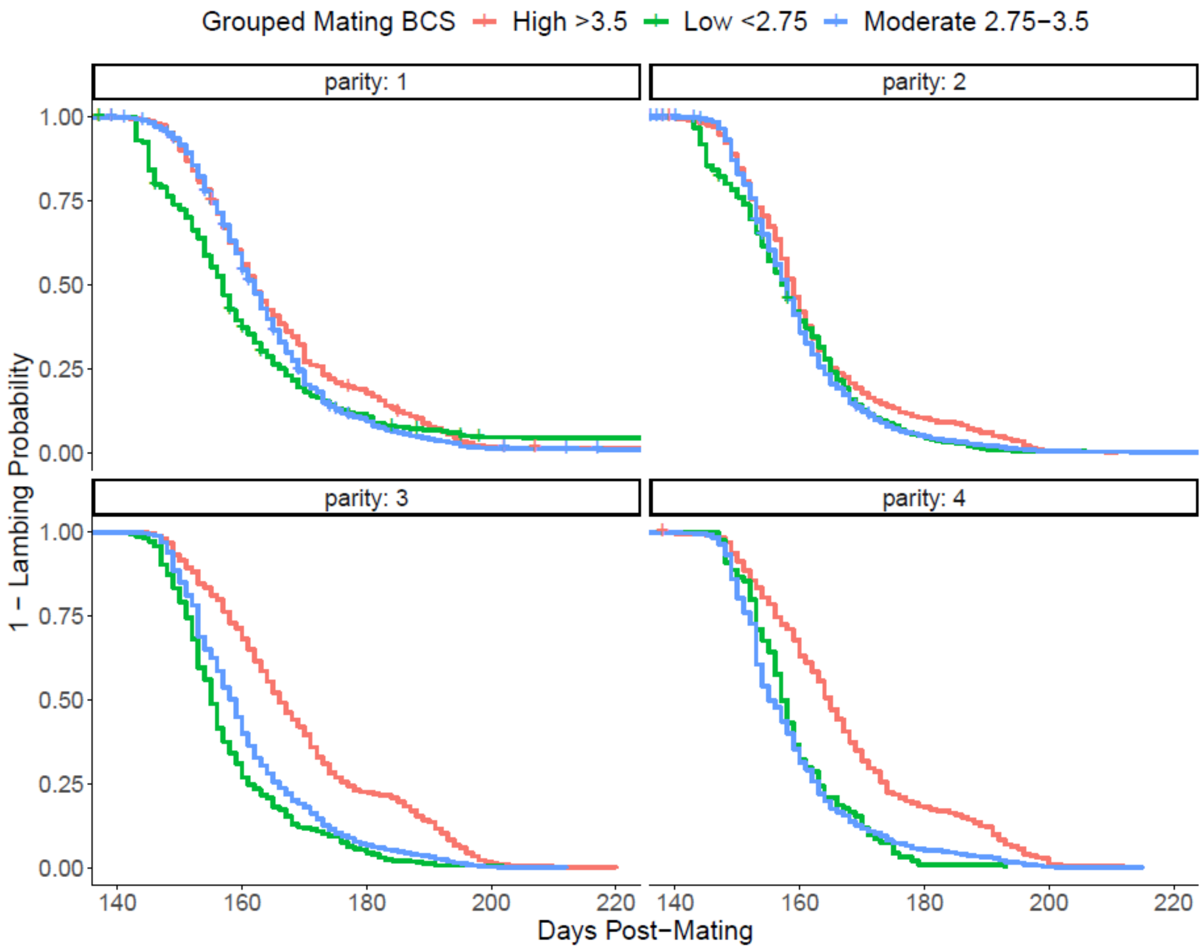

Figure 4.6- Kaplan-Meier plots showing the effect of Mating BCS and Parity on mating to lambing interval

As parity increases the effects of a High mating BCS become more prominent (Figure 4.6). For parity three and four animals, High mating BCS has a substantial negative effect on mating to lambing interval. Low and moderate groups have a similar performance across all parities, with the exception of first parity ewes where Low mating BCS seems to reduce mating to lambing interval.

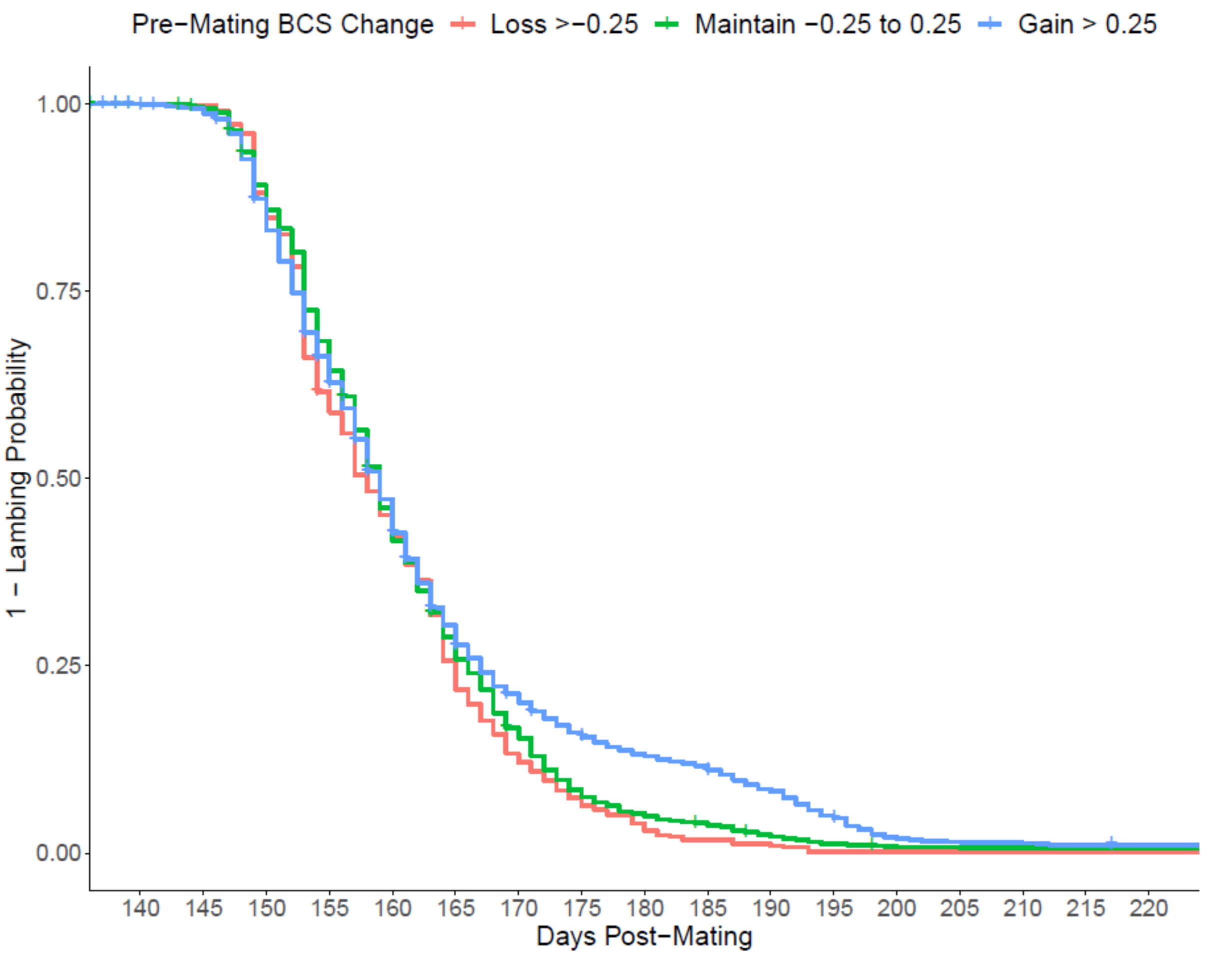

Figure 4.7- Kaplan-Meier plot showing the effect of pre-mating BCS change on mating to lambing interval

BCS change from weaning to mating appears to have little effect on mating to lambing interval up until 170 days post-mating. The Gain group appears to have more ewes remaining after 170 days post-mating, with a substantially reduced lambing rate, resulting in a drawn-out interval. It appears that around 15% of ewes in the Gain category took substantially longer to lamb than other ewes.

4.3.4. Cox Proportional Hazards Model

Low and High mating BCS groups both had a significant negative effect on mating to lambing interval for multiple parity ewes, with hazard ratios of 0.91 and 0.71 respectively (Table 4.1). Pre-mating BCS change was shown to have a significant effect on mating to lambing interval with ewes that lost and gained condition having hazard ratios of 0.88 and 1.13 respectively. The number of lambs born to a ewe in the previous production year only had an effect for ewes which had three lambs in the previous production year. These ewes showed a reduced hazard ratio and therefore increased mating to lambing interval. Mating to lambing interval increases with parity, with higher parity ewes showing a significantly reduced interval. Age had less of an effect, the only significant effect was ewes at 1 year old had an increased mating to lambing interval.

Table 4.1- Cox proportional hazards model results for the multiple parity model

Variable	Category	Coefficient	Hazard Ratio	Lower .95	Upper .95	p-value
Previous Number Lambs Born	0	0.05	1.05	0.73	1.50	0.79
	1	-0.00	1.00	0.95	1.05	0.99
	2	**ref**	**ref**	**ref**	**ref**	**ref**
	3	-0.21	0.80	0.71	0.91	<0.05
Grouped Mating BCS	Low <2.75	-0.10	0.91	0.84	0.98	<0.05
	Moderate 3 to 3.5	**ref**	**ref**	**ref**	**ref**	**ref**
	High >3.5	-0.34	0.71	0.67	0.76	<0.05
Pre-Mating BCS Change	Loss > – 0.25	-0.13	0.88	0.80	0.98	<0.05
	Maintain -0.25 to 0.25	ref	ref	ref	ref	ref
	Gain > 0.25	0.12	1.13	1.07	1.09	<0.05
Mating Age (years)	1	-0.14	0.87	0.79	0.96	<0.05
	2	**ref**	**ref**	**ref**	**ref**	**ref**
	3	0.03	1.03	0.94	1.12	0.54
	4	0.07	1.07	0.92	1.24	0.38
Parity	**2**	**ref**	**ref**	**ref**	**ref**	**ref**
	3	-0.12	0.89	0.82	0.97	<0.05
	4	-0.17	0.84	0.73	0.98	<0.05

Table 4.2- Chi squared output for multiple parity model

Category	Reference value	Df	p-value
Previous Number Lambs Born	2	4.00	<0.05
Grouped Mating BCS	Moderate	2.00	<0.05
Pre-Mating BCS Change	Maintain	2.00	<0.05
Mating Age (years)	2	3.00	<0.05
Parity	2	2.00	<0.05
Frailty= Breed	-	11.00	<0.05
Strata= Project Year	-	0.0017	<0.05

Table 4.3- Cox proportional hazards model results for first parity model

Variable	Category	Coefficient	Hazard Ratio	Lower .95	Upper .95	p value
Grouped Mating BCS	Low <2.75	0.19	1.21	1.10	1.32	<0.05
	Moderate 3 to 3.5	ref	ref	ref	ref	ref
	High >3.5	0.16	1.17	1.09	1.26	<0.05
Mating Age (years)	0 (Ewe lamb)	-0.66	0.52	0.47	0.57	<0.05
	1 (Shearling)	ref	ref	ref	ref	ref
	2(2 Shear)	-0.05	0.96	0.84	1.09	0.49

Table 4.4- Chi Squared output for first parity model

Category	Reference value	Df	p-value
Grouped Mating BCS	Moderate	2.00	<0.05
Mating Age (years)	1	1.99	<0.05
Frailty=Breed	-	10.89	<0.05
Strata= Project Year	-	0.011	<0.05

Low and High mating BCS in the first parity model had a significant positive effect on mating to lambing interval. Age at lambing had a significant effect. Shearlings performed best with ewe lambs having significantly lower hazard ratio, and two-year-old ewes showing no significant difference. Breed as a whole had a significant effect within the model on mating to lambing interval (Table 4.4).

4.3.5. Accelerated Failure Time Model

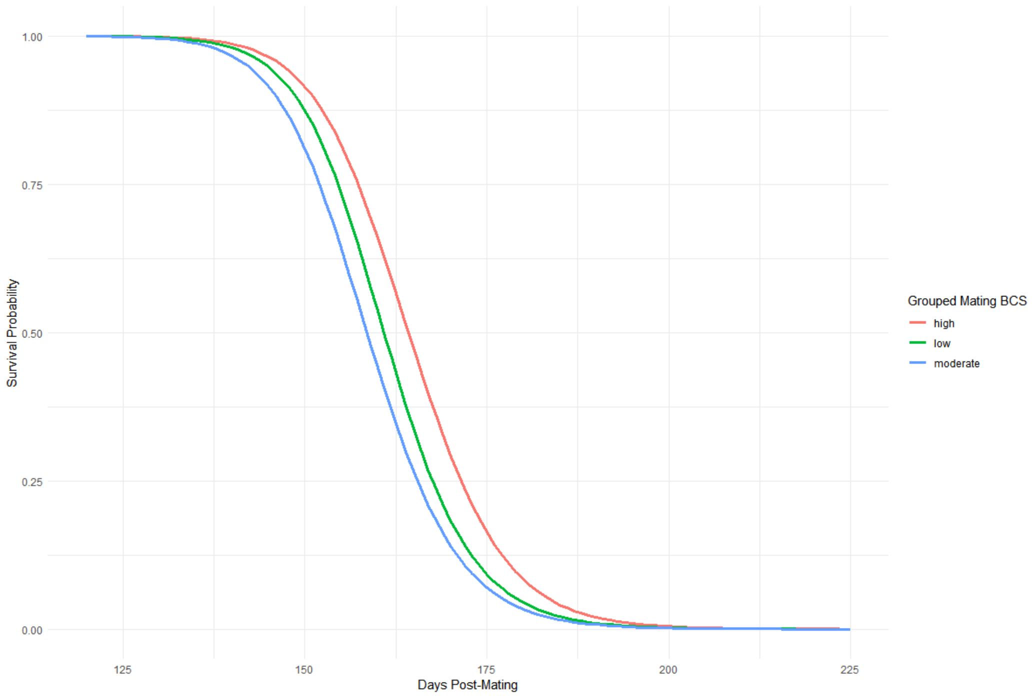

Figure 4.8- Effect of Grouped Mating BCS within the Accelerated Failure Time Model for multiple parity ewes

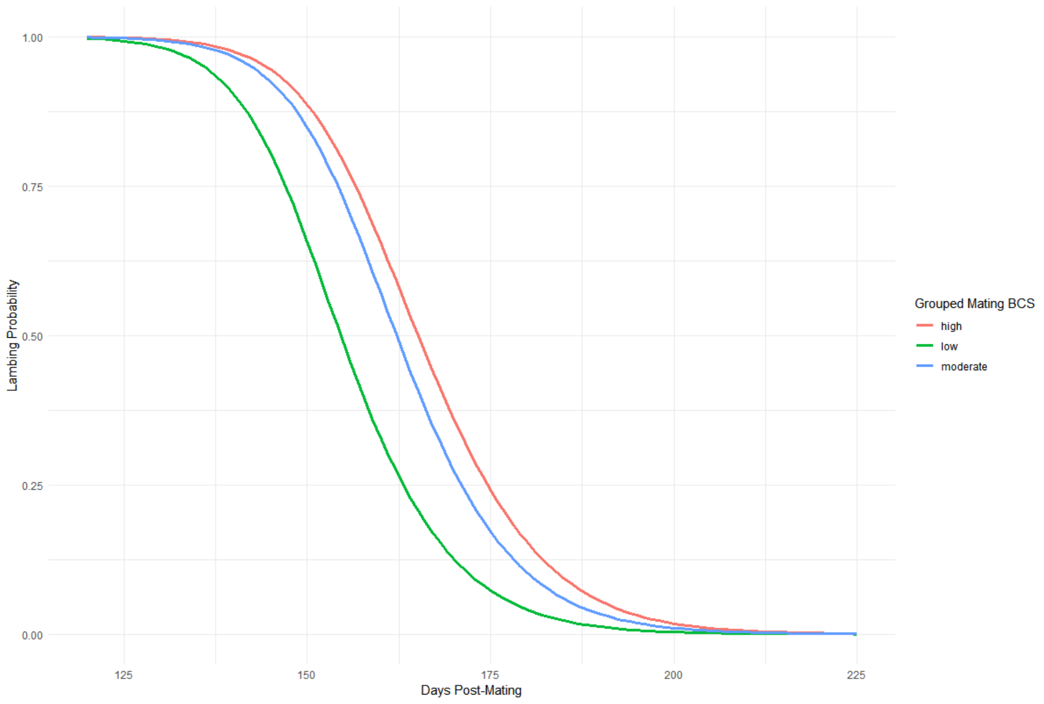

Figure 4.9- Effect of Grouped Mating BCS within the Accelerated Failure Time Model for first parity ewes

The plots from the accelerated failure time models show the effect of mating BCS when estimating mating to lambing interval. The multiple parity model (Figure 4.8) shows moderate mating BCS ewes have a shorter mating to lambing interval, suggesting increased conception rates. Low mating BCS ewes performed slightly worse with High mating BCS ewes having the highest mating to lambing interval of all groups. The trend differed within the first parity model (Figure 4.9). Low mating BCS ewes performed best with the shortest mating to lambing interval. High and Moderate mating BCS groups performed similarly, with a slight improvement within the Moderate group.

Table 4.5- Percentage lambed at each interval for Low, Moderate and High BCS ewes at mating

	Percentage lambed at each interval			
	All ewes	Grouped Mating BCS		
Interval (days)		Low	Moderate	High
150	14.5	29.5	14.6	10.8
170	81.1	88.7	83.9	71.7
>170	100	100	100	100

4.4. Discussion

Within the survival analysis it was observed that certain variables had a significant effect on mating to lambing interval while others had no effect. Grouped mating BCS had a significant effect in both first parity and multiple parity ewes. Multiple parity ewes in Low or High mating BCS had a significantly decreased hazard ratio and therefore increased mating to lambing interval relative to the moderate group (Table 4.1). The opposite trend was observed for first parity ewes with the Low mating BCS group exhibiting the shortest mating to lambing interval (Table 4.3). Pre-mating BCS change from weaning to mating had less of an effect than expected, with no significant influence within the model. Ewes which had three lambs in the previous production year appeared to have a follow-on effect, with lower hazard ratios observed within the model. Ewes first mated as shealings had better performance than that of ewe lambs or two-year-old ewes. As parity increases within the multiple parity model, so does ewe performance. Certain breeds such as the highlander and Romney had significantly increased hazard ratios. The effect of breed appears to be significant, however largely irrelevant from a practical application.

4.4.1. Mating to Lambing Interval for Multiple Parity Ewes

4.4.1.1. Grouped Mating BCS

Often the concept of optimal BCS at each stage of production is discussed within the literature, with specific recommendations provided for ewes at mating. The AHDB recommend that the optimal mating BCS for lowland and hill ewes is 3.5 and 2.5 respectively (Povey, Stubbings and Phillips, 2018). This is to optimise the energy available for reproduction, while also ensuring sufficient energy deposits throughout the winter period. The survival analysis for multiple parity ewes suggests there is an optimal mating BCS to minimise mating to lambing interval, and therefore optimise conception rates. Mating BCS values of <2.75 or > 3.5 significantly increased the interval. Vatankhah et al. (2012) observed the effect of mating BCS on reproductive parameters. They studied the effect of BCS at mating, ranging for 1 to 4 units on conception rate. They found that as BCS increases conception rate also increases, however at a BCS of 3 and above the increase in conception rate was not significant.

Yilmaz et al. (2011) similarly found that low BCS at mating (BCS ≤ 1.5) significantly reduced pregnancy rate when compared to ewes in a BCS of more than 2.0. Interestingly, they also observed a decrease in pregnancy rate above a BCS of 3.0. This follows a similar trend to the observations within this study, with BCS 3.5 and above ewes having an increased mating to lambing interval.

4.4.1.2. Pre-Mating BCS Change

Nutrition both pre and post mating is vital in maximising reproductive performance. The Challenge Sheep project did no collect specific data regarding the ewe's plane of nutrition or specific supplements provided, therefore could not be included within the models. It is essential that deficiencies are mitigated throughout the whole production year, especially at mating where trace element deficiencies can significantly impact on reproduction rates. Often risk of deficiency is highly breed specific, with bioavailability varying significantly. It is assumed that deficiencies within the Challenge Sheep project farms are rare due to the nature of the farms, and when present are adequately resolved, therefore it is not considered to be a large concern on model performance. Ewe energy balance between weaning and mating is also a significant factor when assessing reproductive performance. Energy profile of the ewes' feed was unknown, therefore the use of BCS change between weaning and mating was used as an indicator of net energy balance. Although this does not provide a precise energy balance at mating, or allow for calculation of energy availability for reproduction, it does provide an approximation for overall energy profile between weaning and mating. The energy availability during the implantation period post-mating is unknown within the dataset. The Cox proportional hazards model suggests that BCS change has no effect on mating to lambing interval, with no significance within the results (Table 4.1). Similar results have been observed within the literature with early pregnancy nutrition having no significant effect on conception rate and therefore total lamb birth weight in mature ewes (Annett and Carson, 2006). With BCS change pre-mating having no effect on mating to lambing interval, it is likely more important to optimise mating BCS, irrespective of the changes in BCS required.

It is still important to ensure the correct plane of nutrition post-mating. One benefit of increased plane of nutrition in early pregnancy is that female offspring eight-week weight and sixteen-week weight have been observed to increase when ewes were on a higher plane of nutrition (Muñoz *et al.*, 2009). This could result in an increased number of ewe lambs reaching required weight pre-mating.

4.4.1.3. Breed

The choice of which breed a farm uses is specific to their management practices, and what the producer requires from the animals. Traditionally UK sheep breeds were largely split into categories depending on whether they were bred for meat or wool production, with an additional smaller category for milk producing animals. These categories were then split into lowland, upland and hill breeds, often based on level of hardiness. The current nature of the UK sheep industry means that sheep are predominantly bred for their meat production characteristics. Maternal and terminal breeds often differ, with a focus on growth rates within terminal breeds and reproduction and maternal ability within maternal breeds. The results from the survival analysis showed that breed had a significant effect when included as a frailty in both the multiple parity model (Table 4.2) and the first parity model (Table 4.4), however the effect of individual breeds was not observed.

4.4.1.4. Parity and Age

Three parities of ewe were included within the multiple parity model. As parity increased so did the hazard ratio, reducing mating to lambing interval. This would be expected with reproductive performance increasing as parity increases, particularly with the relatively young distribution of ewes within the dataset. When observing age, two-year-old ewes had the best performance, with three- and four-year-old ewes performing worse. This may suggest that peak reproductive performance in terms of conception rate occurs in two years old ewes. These could either be ewes that joined the project as ewe lambs and are now in parity three, or ewes that joined the project as shearlings now in parity two.

4.4.1.5. Previous Number of Lambs

Within the mature ewe model, number of lambs in the previous production year had a significant effect on mating to lambing interval for ewes which had triplets. This is likely due to a higher energy demand for reproduction in the previous production year, which is having a subsequent knock-on effect. The effects observed for previous number of lambs are potentially less than expected. This is probably due to the relatively long period of recovery from weaning to mating in ewes compared to other species. Studies have however shown that number of lambs affects gestation length. Within Konya Merino ewes triplet births had the longest gestation length (153.7 ± 0.73 days), with twins approximately one day shorter (152.8 ± 0.16 days) and singles the shortest (151.6 ± 0.22 days). (Öztürk and Aktaş, 1996). Additionally, offspring sex and litter size have both been shown to significantly impact gestational length in ewes (Tozlu Celik *et al.*, 2021). Data on number of lambs in the current production year was not included within the model as it would not be available at mating for use in predictions.

4.4.2. Mating to Lambing Interval for First Parity Ewes

4.4.2.1. Grouped Mating BCS

Within the parity one model, Low BCS appeared to reduce mating to lambing interval (Table 4.3). A significant hazard ratio of 1.3 was observed for the Low BCS category. The Kaplan-Meier plot showing the effects of mating BCS on mating to lambing interval (Figure 4.1) shows an obvious increase in the rate at which lower mating BCS ewe lambs and shearlings lamb. There is very little recorded in the literature regarding this. It may be due to immature animals having more energy available for reproduction if they are not storing energy in the form of fat reserves, or potentially a higher appetite around mating having the same effect. It does appear that recommended mating BCS values for first parity and multiple parity ewes should differ.

4.4.2.2. Ewe Lambs and Shearlings

Figure 4.2 shows a distinct difference between the performance of ewe lambs and shearlings in their first year of production. Ewe lambs have an increased interval compared to shearlings, highlighting the lower conception rates within ewe lambs. This observation was expected as energy available for reproduction will be lower within ewe lambs which still have a large requirement for growth. Interestingly within the Cox proportional hazards model (Table 4.3), the same trend was observed with ewe lambs performing significantly worse than shearlings (hazard ratio 0.7), however any ewes that remained parity one at two years of age also had significantly worse performance than shearlings. It is assumed that parity one ewes at two years of age have had poor reproductive performance earlier in their productive life. This appears to be having a continued effect, shown through the increased interval.

4.4.3. Predicting Mating to Lambing Interval

Predicting time to event directly from the Cox proportional hazards Models is not possible. The use of an accelerated failure time model allows the estimation of a specific date of lambing and therefore mating to lambing interval. Separate models were developed for parity one and multiple parity ewes. The distribution observed in Figure 4.8 and Figure 4.9 show the effect of BCS within each accelerated failure time model. The results observed are in line with that of the Cox proportional hazards models.

4.4.4. Limitations

Mating to lambing interval can also be affected by a number of other variables not included within the analysis. Many of these variables were not included due to limitations around data collection and recording. Ram factors were not recorded within the project. This makes it difficult to discern the effects of ram performance on days to conception. Ram age has been shown to effect ewe hogget reproductive performance (Kenyon *et al.*, 2007). More ewe hoggets were mated by mature rams in the first 17 days compared to ram hoggets. However, a larger proportion of the ewe hoggets mated by mature rams returned to service, resulting in similar pregnancy rates between mature and hogget rams at 17 days. Ram performance data is challenging to collect and utilise, due to difficulties discerning which rams mated with which ewes. Crayon markers have been used, however recording these are labour intensive and often multiple marks can be observed on one ewe. Although there is variability between all ewes, from the authors experience it is likely that high quality rams were used on all farms within the study. Ram to ewe ratio will have been maintained at suitable level to ensure optimum conception rates.

Ewe reproductive performance can be somewhat dependant on year of production. Many on farm factors such as, weather, nutrition from pasture, and flock disease risk, can vary from one production year to the next. Understanding the intricacies of each of these factors is challenging and leads to added complexity when predicting future reproductive performance. For example, in 2018 the UK was hit by Anticyclone Hartmut, which led to extreme snowfall and cold temperature during February and March, this coincided with lambing for many farmers and led to considerable lamb losses across the country. Events of this nature are impossible to predict at mating, and therefore can never influence a predictive model for reproduction.

Nutrition was not recorded within the Challenge Sheep project dataset. Like many UK sheep farms the project farms were largely low input systems, focussed on maximising nutritional intake from pasture. This is the system that many UK farms have adopted, rather than feeding a high input, concentrate and forage crops diet. The different systems within the Challenge Sheep project farms, including lowland, upland and hill farms help to ensure the models are somewhat generalisable within the UK industry. Although ewe nutrition was not directly recorded, BCS change pre-mating can indicate net energy balance at mating. Ewes on a high plane of nutrition throughout gestation have been reported to have significantly shorter gestation periods that ewes on a low plane of nutrition (Holst, Killeen and Cullis, 1986), therefore the option to include nutritional categories into a predictive model may be beneficial, if the data were to become available. Within the Challenge Sheep dataset breed is closely correlated to farm which introduced a farm effect which could be influencing the results. It is challenging to mitigate these farm factors due to the small number of breeds utilised on each farm.

4.4.5. Summary

This chapter focuses on the analysis of the variables which affect reproduction within the Challenge Sheep project data, and how this analysis can be used to estimate mating to lambing interval. Some variables which were observed to have a significant effect were grouped mating BCS, mating age, parity, breed and previous number of lambs. An important aspect of the analysis was the requirement to build two separate models. This improved performance of the multiple parity models through the use of variables not available for first parity animals. Using mating to lambing interval provides an indication of days to conception plus gestation length, this can be used to calculate the probability of a ewe lambing on a specific day post-mating within the simulation model.

5.1. Introduction

5.1.1. Reasons for ewe wastage

Ewe wastage is a combination of on farm mortality and premature culling (Farrell *et al.*, 2019). Premature culling is often the result of poor performance, or health issues, with mortality being almost solely linked to poor health. Naturally, farmers have always tried to mitigate wastage through ensuring optimum flock health and performance. This increases longevity and lifetime productivity of each ewe. Ewes culled at the end of their productive life are not considered wastage as productive years from that animal have been maximised. There is a substantial financial cost in raising a ewe before any return is seen (AHDB Beef and Lamb, accessed 12/02/2024), or a significant investment if replacements ewes are bought in. Ensuring the maximum return on each ewe is vital to maximise flock productivity. Overall replacement rates on sheep farms are around 23%, with a small amount of variation depending on management and farm profitability (AHDB Beef and Lamb, accessed 12/02/2024). On low wastage farms the replacement rate is expected to be controlled through the culling of poor performing or older animals. On higher wastage farms there is more emphasis on replacement rate being driven by dead animals or animals culled due to health issues. Lower wastage rates provide the opportunity to selectively cull ewes, giving more scope to improve flock health and performance, while reducing overall costs.

Quantifying wastage on UK sheep farms has significant challenges due to the lack of performance recording within most commercial flocks. Throughout this chapter ewes which left the flock due to premature culling, on farm mortality or sold as cull ewes are referred to as ewe losses. Usually, the reasons for ewe loss and specific time of ewe loss would not be recorded. Overall losses throughout the production year are often easier to calculate by using ewe numbers at the start and end of the production year, however this provides very limited information. The extensive nature of many UK sheep farms, along with small economic margins, make it extremely difficult for individual farmers to justify spending time assessing ewe losses. In cases where a substantial number of ewe losses are occurring for the same reason it is likely this would be observed, however recording individual ewes is rare. In research settings ewe losses have been recorded and analysed, with the aim to estimate wastage on an average farm.

Flay et al. (2021) observed ewe wastage on New Zealand commercial sheep farms. They calculated levels of wastage across three farms, along with observing the factors affecting both mortality and premature culling. They observed that pre-mating body condition score (BCS) had a negative correlation with wastage rates in ewes. Quantifying wastage rates and understanding the risk factors associated with higher levels of wastage, allows for a multifaceted approach to reducing ewe wastage on farm.

Within this study, reasons for loss and timings of loss will be observed throughout the Challenge Sheep project farms, with the effects of specific variables on wastage observed. Time of loss will then be predicted to estimate the probability of loss for each day of the production year for a specific animal.

5.1.1.1. Culling

Culling on sheep farms can be categorised into ewes which have reached the end of their production life, or ewes that have been culled prematurely. Wastage on farms focusses on the ewes which have been culled prematurely, as this is where culling rates can often be reduced. Often culling decisions are the result of a multifactorial approach, with a large number of variables contributing to the culling rates on each farm. There is usually a hierarchy when culling decisions are made. Initially animals which have reached the end of their productive lives are culled, often at around seven years of age. Although animals which have reached the end of their productive lives are not included within wastage analysis, it accounts for around 23% of culls on UK sheep farms (McLaren *et al.*, 2020). Poor teeth account for 39.9% of all culls, this can be a result of poor genetics, however, is usually closely correlated with ewe age. Reproductive performance is also an important factor in culling decisions. Often animals which are barren when pregnancy scanning are removed from the main flock and sold as cull ewes, often with the exception of ewes mated as ewe lambs. A seasonal peak in wastage rate can be observed during scanning due to levels of infertility. Factors affecting the health and welfare of animals such as lameness, prolapses, and udder problems are often initially treated and if treatment fails the animals are then culled. It has been reported that 63% of farmers cull ewes after two or three bouts of lameness, with larger farms more likely to cull animals (Best *et al.*, 2020). Body condition scoring can also be used to assess which animals to cull, however this will often be linked to underlying health conditions or a general poor performance. Farmers would select extremely low condition ewes relative to the rest of the flock. It is extremely uncommon to cull ewes solely on condition score due to the plethora of other factors to select from, particularly if ewes are only marginally under target BCS.

5.1.1.1.1. Disease

Individual events can affect ewe wastage, and potentially make it extremely difficult to predict for a specific year. Epidemics can substantially increase ewe wastage for an individual production year. For example, the 2001 outbreak of foot and mouth in the UK led to extremely high incidence of culling (Keeling *et al.*, 2001). It is not possible to predict specific events of this nature, therefore there will always be a certain degree of uncertainty within predictive models for wastage. However, survival analysis techniques can still be an extremely useful tool to observe the affect or impact of specific events after they have occurred.

5.1.1.1.2. Lameness

Lameness on UK sheep farms is an extremely common and persistent disease problem, with both economic and welfare concerns (Page et al., 2023). Lameness is predominantly caused by either footrot or contagious ovine digital dermatitis (CODD). The exact economic impact of lameness within UK flocks is largely unknown, however, is estimated in the range of £20-80 million each year (Lameness in sheep | AHDB). The total cost of footrot has been estimated at £24 million, £7 million of which is due to lost performance, £3 million due to treatment and culling, and £14 million due to costs associated with prevention (Wright, 2013). Ignoring the obvious and often severe health and welfare issues associated with lame animals, the economic impact alone highlights the needs to initially understand and subsequently reduce lameness across UK flocks. It is often the case that although incidence of lameness is high, culling due to lameness is significantly lower than expected. This is due to other culling reasons taking precedence and the effective treatment of the disease. Only 20% of farms in the UK are culling lame sheep promptly (Farm Animal Welfare Council, 2011), decreasing the incidence of wastage due to lameness. Since 2011 the Five-Point-Plan for the prevention and treatment of lameness has been introduced. This has introduced best practice for management of lameness in flocks. The prevalence of lameness is currently around 3.2%, this may suggest than an increased number of farms are now using lameness as a culling parameter.

5.1.1.1.3. Mastitis

Unlike lameness, ewes with mastitis are often culled in the same production year as the disease is discovered. This can be attributed to the severe impact on health and production. Mastitis is the inflammation of the mammary gland, caused by bacterial infection. Treatment is often difficult, and even when successful can often result in loss of mammary function to at least one half of the udder. High rates of culling when mastitis is detected lead to mastitis being one of the main reasons for premature culling of ewes, particularly within lowland flocks (McLaren et al., 2020). Although specific cases of mastitis would be extremely difficult to predict, a wastage analysis can highlight if farms have higher incidence of mastitis. If this is the case a specific treatment and preventative plan can be put in place.

5.1.1.1.4. Fertility

Sheep production systems rely on high fertility to ensure all ewes are productive. Within UK systems mating occurs in the autumn, with lambing in the spring. It is important for ewes to have high fertility as if they do not conceive in the autumn, they would be unproductive for a whole season. Around scanning, culling of barren ewes is common practice with advice that infertile ewes should be culled to allow for more productive animals to enter the flock (Genever and Wright, 2016). Ewes first bred as ewe lambs are often retained for a subsequent year if they are barren at first scanning, this is due to the high likelihood that these animals had not reached a suitable age or weight at mating for conception. Infertile ewe lambs are often culled in their second year of production.

5.1.1.2. Mortality

Ewe mortality is defined as the percentage of females that died on farm, calculated as the total number of females mated in that production year (Key performance indicators (KPIs) for lamb sector | AHDB, Accessed 10/02/2024). Although there are many similarities between the reasons for culling and causes of mortality, mortality by nature is less controlled and selective than culling. This results in high level of uncertainty regarding the reason for death. Across the UK sheep industry average ewe mortality is approximately 5%, however it is highly variable and can range from 2% to 10% depending on individual farms (Wright, 2013). Key performance indicators (KPIs) for ewe mortality suggest that farms with a mortality of <2.5% are performing well, 2.5 to 5% have room for improvement and >5% requires a review of performance (Key performance indicators (KPIs) for lamb sector | accessed 10/02/2024). Wastage analysis can highlight specific events leading to higher mortality and may provide an insight into how to reduce this. A certain level of ewe mortality will always be present on farm, however any reduction in mortality allows for more selective culling while maintaining the replacement rate or allows replacement rate to be reduced. Managing replacement rate effectively, leads to more productive animals and an overall healthier flock.

5.1.1.3. Factors Affecting Wastage Rates

As previously established, ewe wastage is a combination of multiple reasons for both culling and mortality, however there are a number of risk factors associated with increased wastage rate. Flay et al. (2021) established a relationship between pre-mating BCS and wastage rates, while Kenyon, Maloney and Blache (2014) observed that low BCS can reduce reproductive performance, which would in turn lead to increased culling and wastage. First breeding as a ewe lamb vs as a shearling is believed to have an impact on lifetime productivity, however it is unclear from the literature of its extent. Breeding from ewe lambs provides the opportunity for an additional litter, and therefore additional lamb sales at an earlier age. However, some people believe the metabolic stress required during gestation and lamb rearing has a long lasting impact on ewe performance as parity increases. First breeding as a shearling allows ewes to reach a larger percentage of mature weight before breeding, this results in a smaller metabolic requirement for ewe growth, and therefore more energy is available for reproduction.

It is clear that failing to maximise the productive lifespan of a ewe is going to have an economic impact on the flock, however there are key factors which lead to reduced profitability. Ewe wastage, particularly in ewes during their most productive mature years, leads to a reduction in the mean flock age. Generally younger animals have lower reproductive performance, therefore the average flock reproductive rate can be impacted, leading to an overall reduction in lamb sales. This can also contribute to a reduced feed efficiency and therefore higher feed wastage, particularly from pasture (Lydia Farrell, 2020).

5.1.1.4. Survival Analysis in Sheep

Within the literature a large emphasis appears to have been placed upon lamb mortality, rather than ewe wastage. This appears to be due to the direct correlation between lamb survival and productivity, and the welfare concerns associated with high mortality. High perinatal lamb mortality has been associated with more intensive systems, poor hygiene at lambing, increased foster rate, and poor nursing of sick lambs. Poor ewe condition and flocks with higher replacement rates were also associated with increase postnatal mortality (Binns et al., 2002). Lamb survival in Harnali sheep has been observed by Gaur et al. (2022). They used Cox proportional hazards models and Kaplan-Meier Analysis to observe the effect of each variable on lamb survival. They found that year of birth, lamb sex and birth weight all significantly affected lamb survival until weaning. Similarly, in Turkish sheep, lamb survival was observed using Cox regression and Kaplan-Meier techniques (Ceyhan and Kozaklı, 2023). Year, season, lamb sex, types of birth (single or twin) and birth weight all had a significant effect on survival within the Cox model. Similar Cox proportional hazards models and Kaplan Meier analysis have been used to observe ewe wastage in New Zealand flocks (Flay et al., 2021). They observed lifetime and annual wastage of 13,142 commercial ewes. Key findings included a positive relationship between pre-mating BCS and reduced wastage, with the ability to predict wastage from pre-mating BCS. They also highlighted the importance of reducing hogget wastage through reducing hogget on farm mortality and improving hogget reproductive performance (Flay et al., 2021).

5.1.2. Aims

One of the first steps to effectively reduce ewe wastage is to understand where wastage is occurring within the system. This will provide an overview of overall wastage, but also pin-point specific events, or causes of high wastage. One of the aims of the Challenge Sheep project was to compare the lifetime performance of ewe first mated as ewe lambs vs shearlings. Understanding lifetime wastage rates for each of these categories, and the risk factors associated with wastage is important when observing lifetime productivity. This will initially be achieved through descriptive statistics, comparing the reasons for loss with variables such as the status of the ewe when joining the project (ewe lamb or shearling), the BCS of the animals at mating, the breed of the animals and age. The results from the loss analysis will help inform the survival analysis model to observe time to wastage. This will include Kaplan-Meier Analysis to observe the effects of specific variables on time to loss and Cox proportional hazards models to determine the interactions between each variable. The results from the Cox proportional hazards model will then be used to inform an accelerated failure time model which will be used to predict ewe exit dates.

5.2. Material and Methods

5.2.1. Data Collection and Manipulation

The Challenge Sheep project not only collected data on ewe and lamb performance, but also collected a substantial subset of data on ewe losses. Exit reasons and dates were recorded for every ewe that left the project, whether that was due to sales, mortality or culling. Farmers recorded the main reason for loss for each ewe that exited the project, in cases where multiple reasons were observed the most likely cause was recorded. Reasons for loss were then grouped into a selection of fate codes for consistency within the dataset. Any ewes with uncertainty around the cause of mortality were recorded as 'unknown'. The overall number of losses for each fate code are shown in Table 5.1. A total of 2167 ewes were lost over the first three years of the project. BCS was recorded at five intervals throughout the production year including, mating, scanning, lambing, 8-weeks post-lambing, and weaning. As discussed in Chapter 2 body condition scoring is a subjective measurement, however measures were taken to mitigate the effect of bias and scorer error within the data collection process. Ewe factors such as date of birth and project entry status (ewe lamb or shearling) were recorded for each ewe when they entered the project. All data was recorded using EID tags and readers to ensure accuracy and help mitigate human error.

Initially data were tidied and manipulated using R (*R: The R Project for Statistical Computing*, no date). For a ewe to be included in the model it had to have complete data including: exit date; fate code and event dates. Specific ewes were removed from the dataset due to inconsistencies within the scoring, or extremely low number of ewes within a group. Additional variables for the analysis were then manipulated, including, censoring status and interval for each ewe over each production year. The start of the production year was set at mating, with all intervals calculated as days post-mating. The date at which the ram entered is referred to as mating date throughout this chapter. Age at mating was calculated from mating date and ewe date of birth, and was included as years within the analysis. BCS at mating were grouped into five categories: <2.5, 2.5 to 2.75, 3.0 to 3.25, 3.5 to 3.75, and ≥ 4.0. Fate codes from the raw data were refined into eight categories to group similar reasons for loss. These groups included, Infertility, Lameness, Mastitis, Lambing difficulty; Health, Poor performance, Sold, and Unknown (Table 5.1). The number of ewe records in each group ranged from 11 to 639, with total ewe exits of 2167.

5.2.2. Analysing Reasons for Loss

Descriptive analysis was used to observe the number of losses within the dataset. Histograms of overall losses, along with histograms for each category of loss throughout the production year were plotted. This allowed observation of specific time points of higher losses. To observe the relative losses within each fate category, percentages were calculated for each fate code, then compared within the histograms. Variables which may affect rate of loss were then plotted against the reasons for loss, providing an indication of which mating variables led to increased wastage within a specific category. Exit reasons were then observed on an individual farm basis to highlight specific causes of high culling or mortality on each farm. A large farm effect was expected due to subjective recording of exit reasons, as well as health issues often having higher incidence on specific farms (e.g. mastitis).

5.2.3. Survival Analysis

The techniques for quantifying wastage share a lot of similarities with the methods outlined in section 4.2 for observing mating to lambing interval, however, they are used in a more traditional way to observe wastage. Mating date was used as the start of the production year, with all intervals calculated in days from the mating start point.

Kaplan Meier plots were used to observe the effect of each variable on ewe wastage. Initially, an overall survival plot was produced to show the losses for each production year starting at mating. The variable `entry status` was included to show the effects of ewes first mated as a ewe lamb or shearling. Age at mating was included to show the effects of age for each of the ewe lamb and shearling categories. Age was considered independently with four age categories at mating being included (1, 2, 3, and 4 years of age). The five BCS categories were plotted to show the effects of BCS at mating on survival throughout the subsequent production year. Results from the Kaplan-Meier plots were used to observe differences between survival probability for each variable. The results from the Kaplan-Meier plots allowed comparison of survival probability between variables, highlighted specific high loss events throughout the production year, and indicated the important variables to include within the Cox proportional hazards model.

A Cox proportional hazards model was built using variables including, BCS at mating, entry status (ewe lamb or shearling), and age, to analyse the effects of each variable in the Challenge Sheep project data. Unlike the Kaplan-Meier analysis, Cox proportional hazards models are a semi-parametric model and allow for multiple predictors within the model. The output of the Cox proportional hazards model gives a hazard ratio for each variable, which is relative to a reference value. Higher hazard ratios indicate increased ewe losses. Confidence intervals and p-values are also provided to show the variation within the estimate and significance.

5.2.4. Predicting Exit Date

Similar to predicting the interval from mating to lambing in section 4.2, it is not possible to predict a specific date of ewe exit using the Cox proportional hazards model. Therefore, the results from the Cox proportional hazards models were used to build an accelerated failure time model (AFT model). Accelerated failure time models are a parametric method for predicting continuous time data. The probability that an individual can survive beyond a given time (t) is donated by S(t). Within the model a series of distributions were tested to select the type of distribution which best fit the data. Parametric distributions tested included, Weibull, loglogistic, exponential, gaussian, logistic, and lognormal. The model with the lowest AIC was the loglogistic model and was therefore deemed to have the best fit and used to predict days to exit.

5.3. Results

5.3.1. Distribution of Ewe Exit Reason

Table 5.1 shows that certain ewe exit reasons were more prevalent than others. Mastitis was the main reason for ewe exits at 19% (Table 5.1). Sold for slaughter and poor performance were the second and third main reasons for loss at 15% and 14% respectively. 29% of ewes had an unknown exit reason, either due to uncertainty around cause of death or incomplete scoring. BCS appears to be related to higher incidence of certain exit reasons (*Figure 5.2*). Within the "Sold" category it appears that low mating BCS ewes (BCS <2.5) and ewes which would be considered in a good BCS at mating (BCS 3-3.25 and BCS 3.5-3.75) are being sold at a higher rate than the other two groups. Low mating BCS ewes have an increased incidence of loss due to poor performance, however have lower incidence of mastitis. There is little effect of mating BCS on loss for infertility. The distribution of exit reasons for each age group (Figure 5.3) suggest mastitis is the most prevalent exit reason for three-year-old ewes with over 30% of losses due to mastitis. While in one-year-old and two-year-old ewes, losses are spread more evenly across exit reasons. Only one loss reason (poor lambing) was recorded for four-year-old ewes, largely due to the small number of four-year-old ewes within the dataset.

Table 5.1- Number and percentage of ewes which exited project for each fate code

Exit reason	Number	Percentage
Other Poor performance	302	14
Infertility	268	12
Lambing	61	3
Lameness	11	1
Mastitis	417	19
Other Health	149	7
Sold	320	15
Unknown	639	29
Total	2167	100

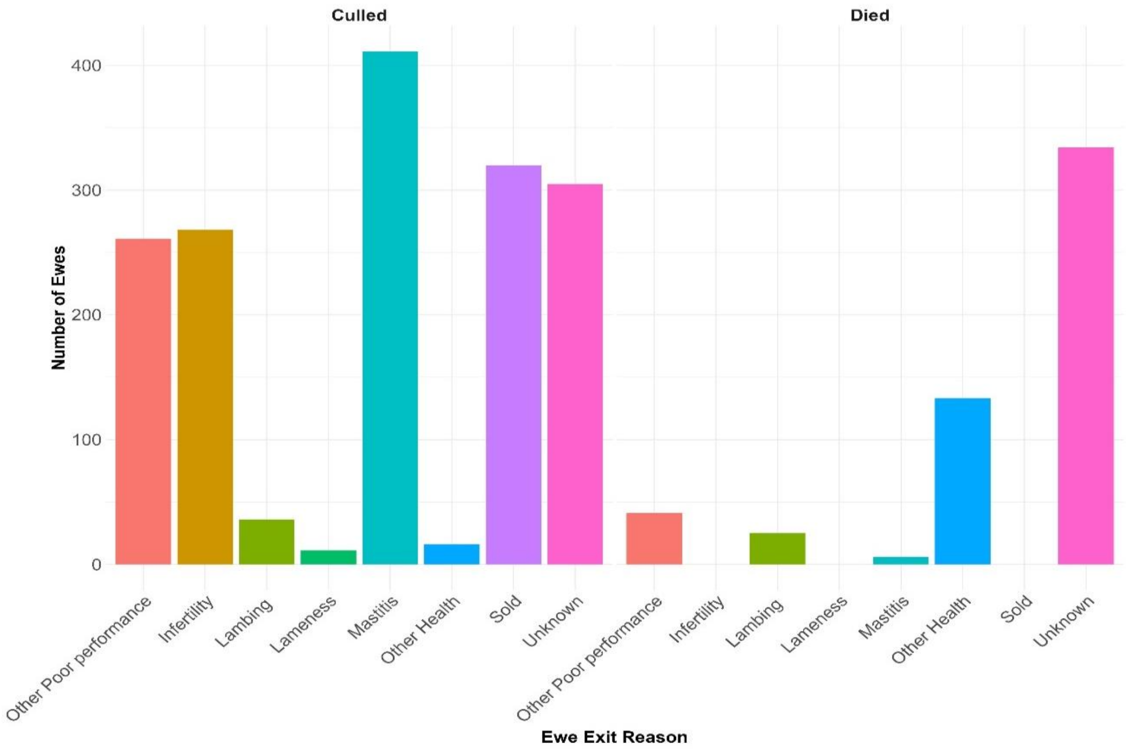

Figure 5.1- Bar chart showing the number of ewe exits for each exit reason. Split by ewes which were culled and died on farm.

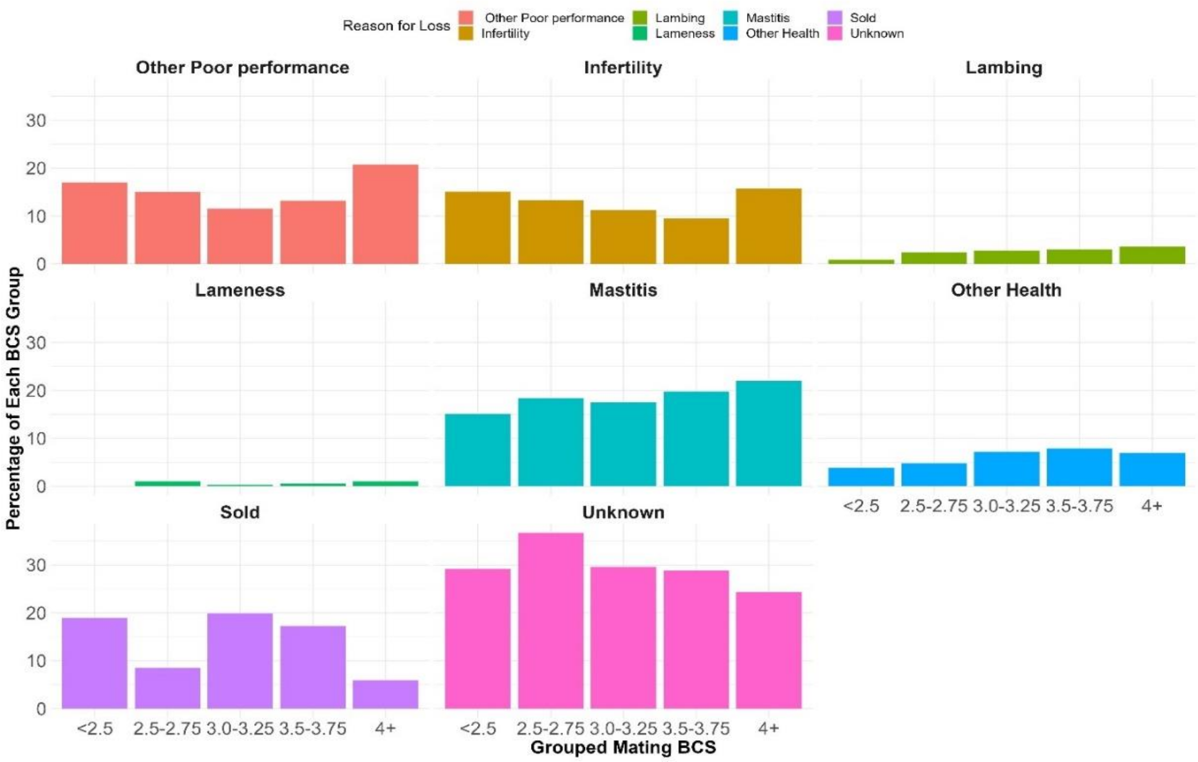

Figure 5.2- Graph showing the percentage of losses from each BCS group at mating attributed to each exit reason

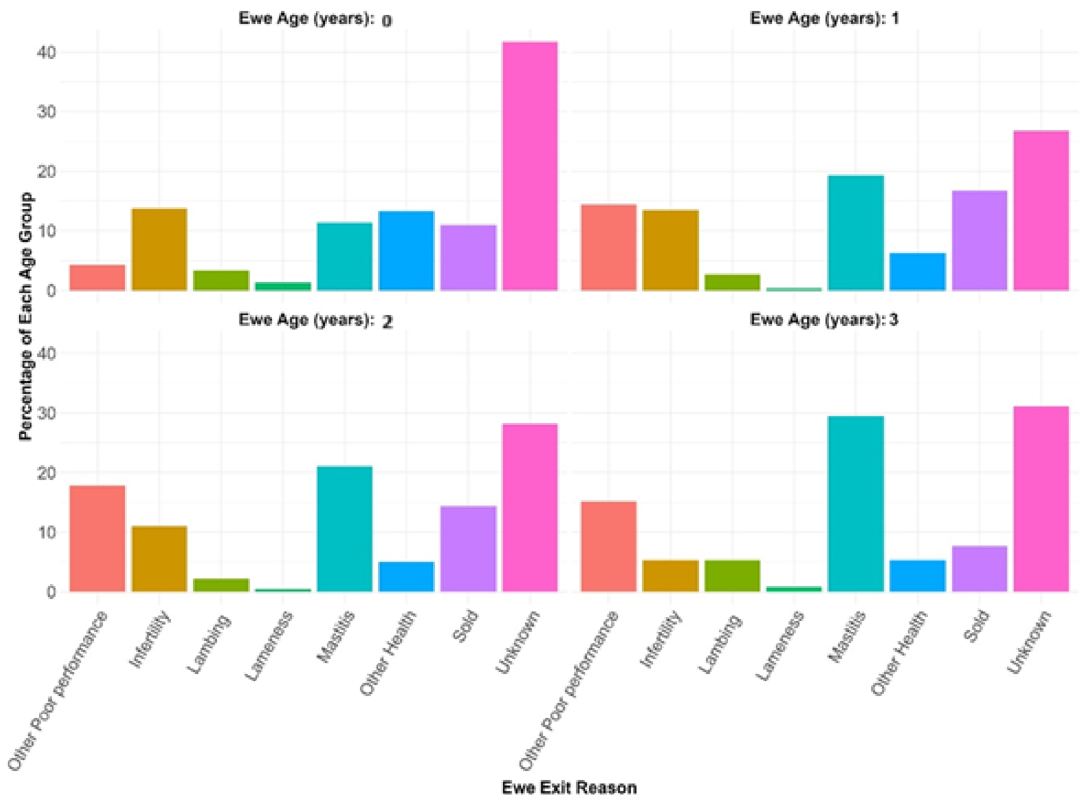

Figure 5.3- Graph showing the percentage of total losses for each ewe age at mating for each exit reason.

The total number of losses from each farm varies substantially due to differences in flock size and management practices (Figure 5.4). Observing the effect of farm on exit reasons, shows that exit reasons are often associated with individual farms. Farms 9, 10 and 11 lose a disproportionately higher number of ewes to mastitis than the other farms, while Farm 3 appears to be culling significantly more due to poor performance. Poor performance is largely associated with farms 2, 3 and 5, while unknown reasons for loss were heavily associated with farms 6 and 7. Although losses such as mastitis and infertility were prevalent, the distribution of these is more even across all farms.

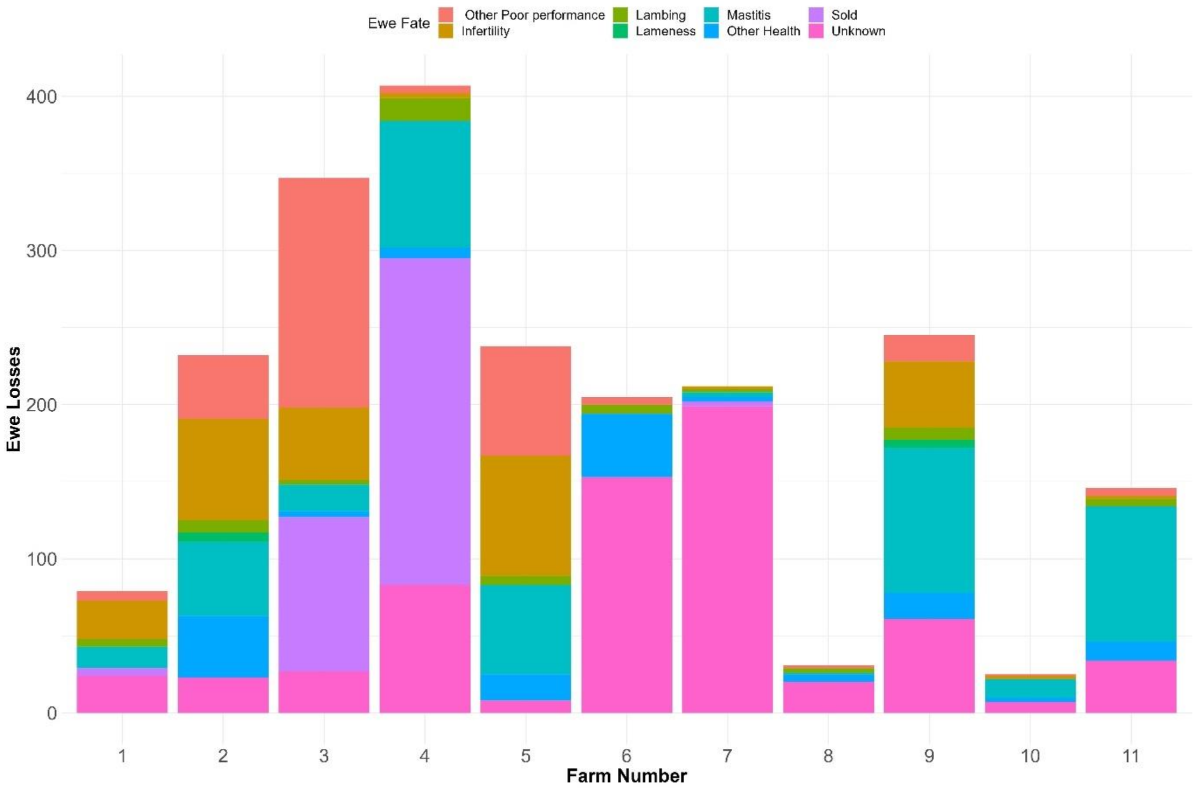

Figure 5.4- Distribution of the reason for ewe losses for each project farm

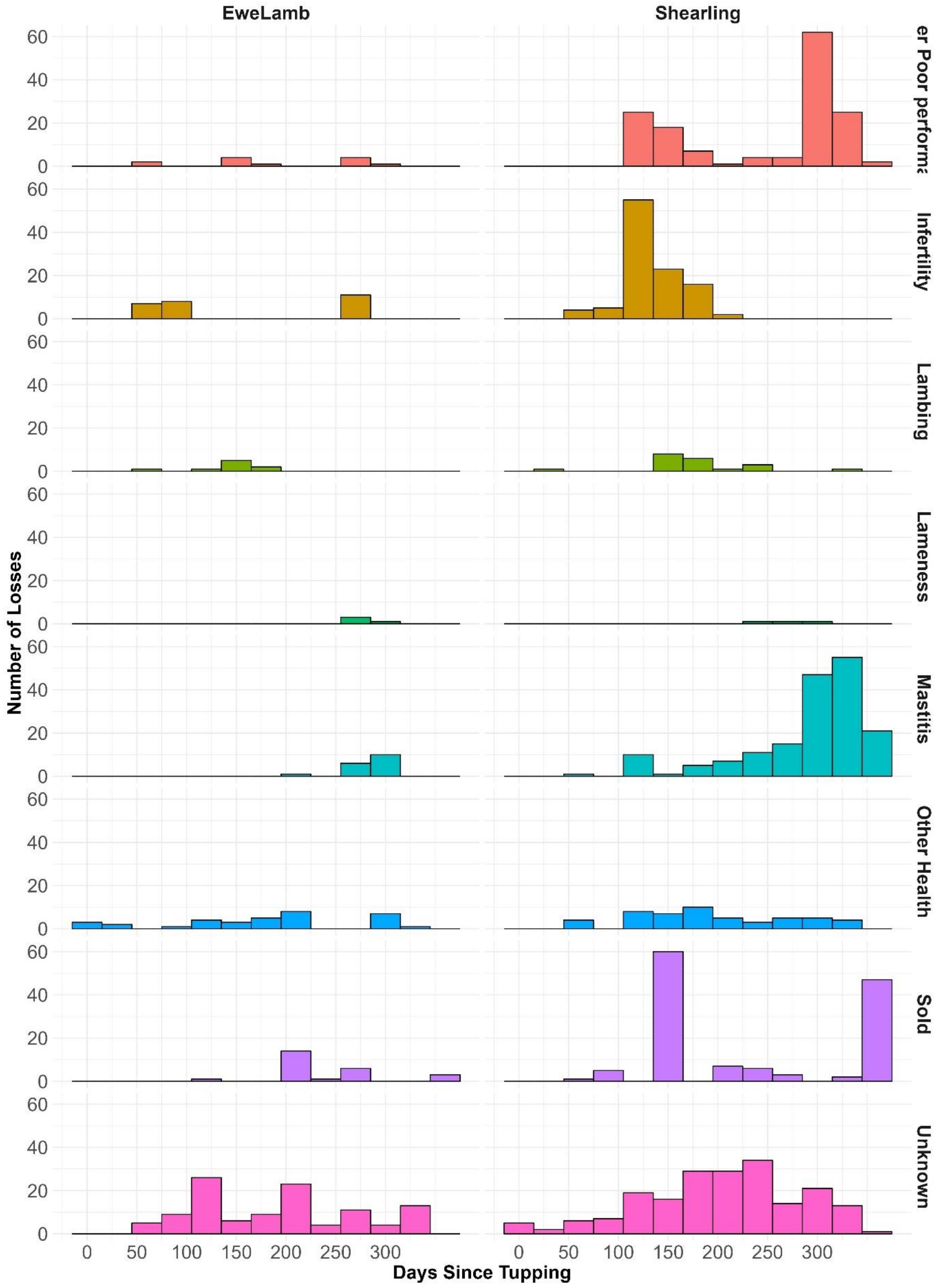

Figure 5.5- Distribution of ewe losses throughout the production year for each exit reason, for ewes first mated as ewe lambs or shearlings.

The point in the production year in which losses are occurring is shown in Figure 5.5. Losses are closely associated with management events such as pregnancy scanning and pre-mating health checks with peaks at approximately 120 days and 330 days post-mating (Figure 5.5). The time of loss is often dependent on reason for loss. Mastitis losses occur later in the year between weaning and mating, while ewe losses due to infertility are much more prevalent around scanning. Other health issues are reasonably consistent throughout the production year.

5.3.2. Kaplan Meier Analysis

The Kaplan-Meier plots show the overall survival curves, and a comparison of the survival curves of different categories for ewes within the Challenge Sheep project. They provide an indication of when ewes are exiting the project and highlight any specific events or intervals of increased rate of exit. Figure 5.7 shows that throughout the first four years, approximately 45% of ewes enrolled had left the project due to either culling or mortality. Each production year there is approximately an 8% loss of ewes (Figure 5.7), with substantial events at approximately 120 days, 150 days and 300 to 350 days post-mating. This is observed by the steeper gradient of the Kaplan-Meier curves at these times. These coincide with scanning, lambing and pre-mating, respectively. Ewes that joined the project as shearlings rather than ewe lambs have lower survival probabilities, with a particularly pronounced effect over 300 days into the production year. BCS at mating appears to substantially affect the survival probabilities for low and high BCS groups (BCS< 2.5 and BCS≥ 4) (Figure 5.9), with both these groups having lower survival probabilities by the end of the production year. However, the interval in which each group are exiting differs. The BCS < 2.5 group appears to have higher exit rates earlier in the production year (140 days post-mating) while the BCS ≥ 4 group appears to exit later in the production year (300 days post-mating). The middle three mating BCS groups (BCS 2.5 to 2.75, BCS 3.0 to 3.25, and BCS 3.5 to 3.75) have similar survival curves throughout the whole production year, possibly with the highest BCS group of the three having slightly higher survival probability earlier in the production year. Four age categories ranging from 0 to 3 years of age at mating were plotted (Figure 5.10). Group 0 ewes had a much higher survival probability throughout the whole production year. Groups 1, 2 and 3 ewes had similar survival curves, with older ewes performing slightly better overall. Ewe lambs in their second year of production had a much lower survival probability than those in first and third years of production (Figure 5.12). Shearlings observed a different trend in which they had higher losses in their first year of production compared to their second and third years.

5.3.2.1. Overall Survival

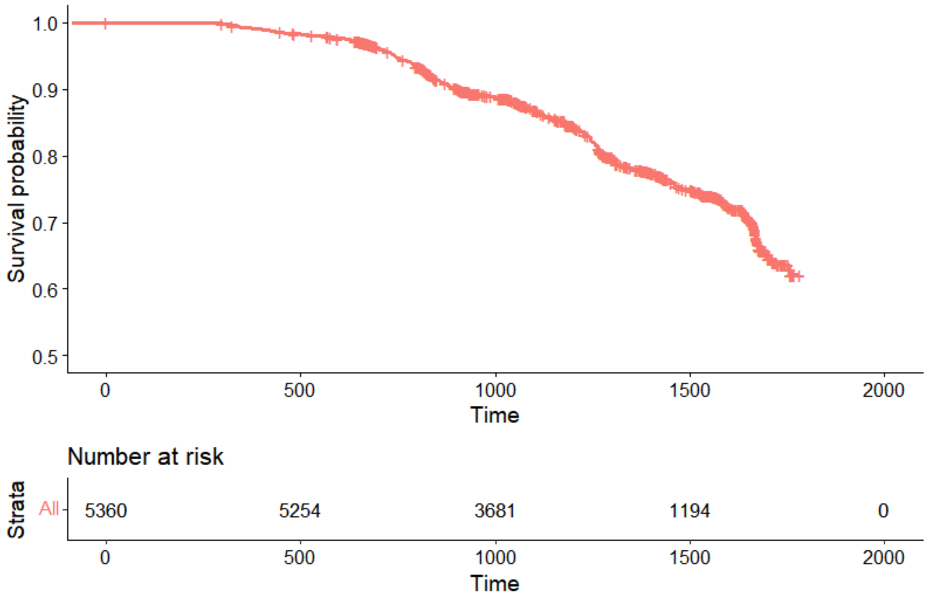

Figure 5.6- Kaplan-Meier plot showing the overall survival curve and the number of ewes at each timepoint.

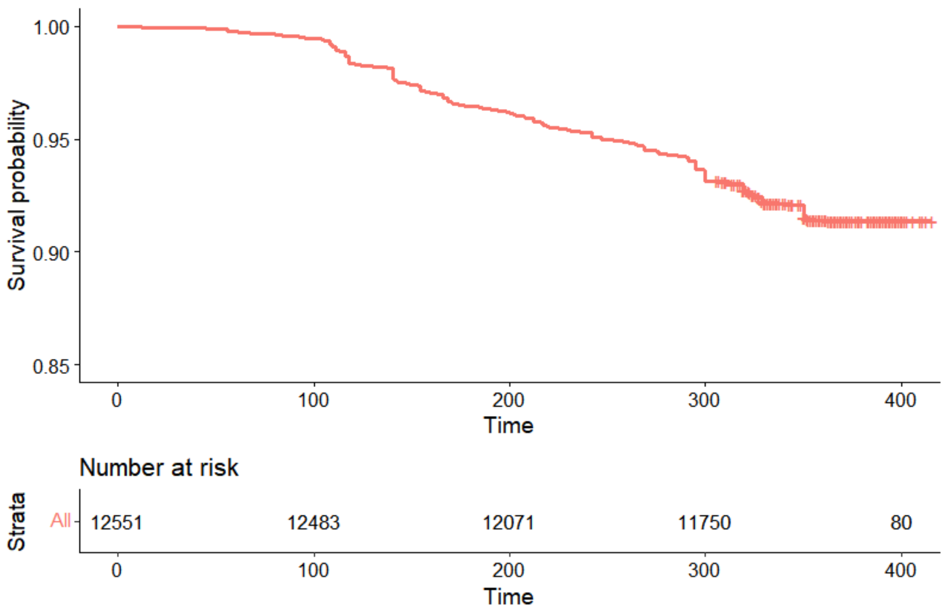

Figure 5.7-Kaplan-Meier plot showing the survival curve for the production year starting at mating

5.3.2.2. Ewe Lambs vs Shearlings

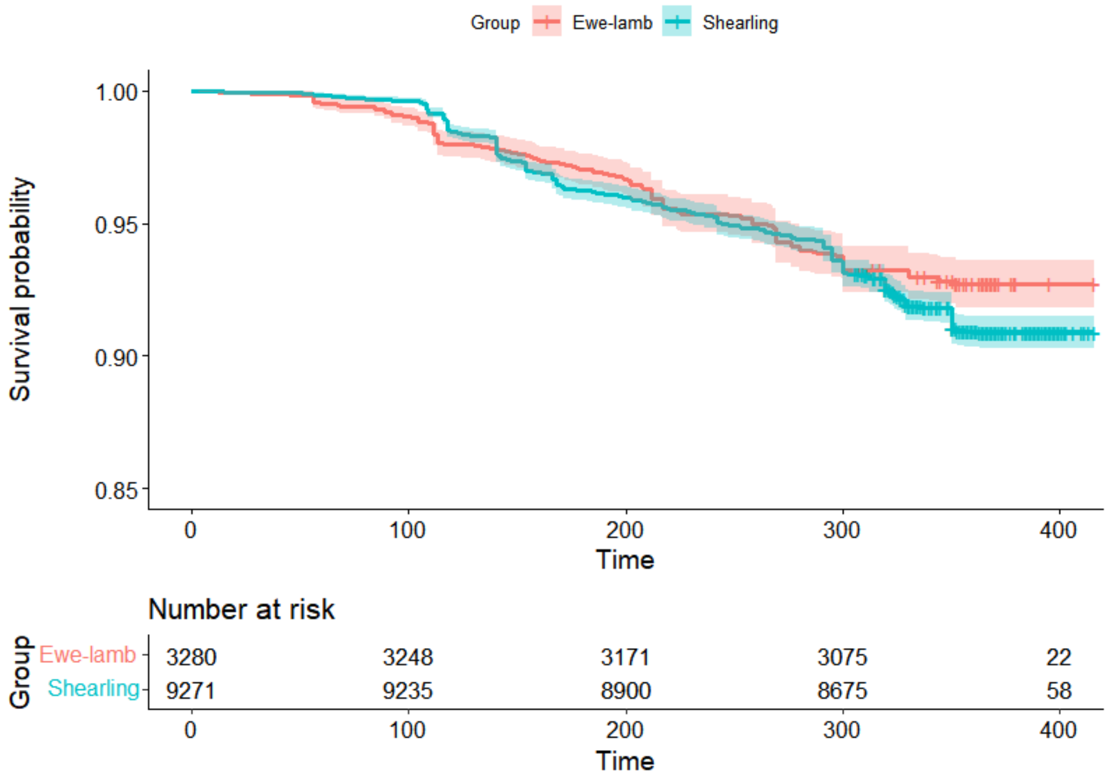

Figure 5.8- Kaplan-Meier plot showing the survival curves for ewes which entered the project as ewe lambs compared to shearlings

5.3.2.3. Mating BCS

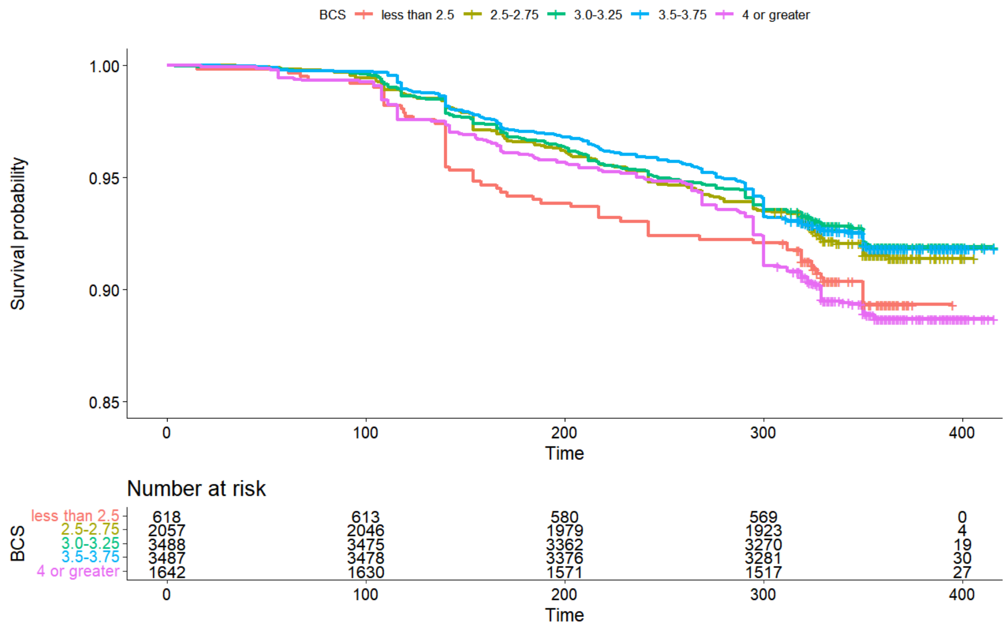

Figure 5.9- Kaplan-Meier plot showing survival curve for each mating BCS category for one production year from mating

5.3.2.4. Age

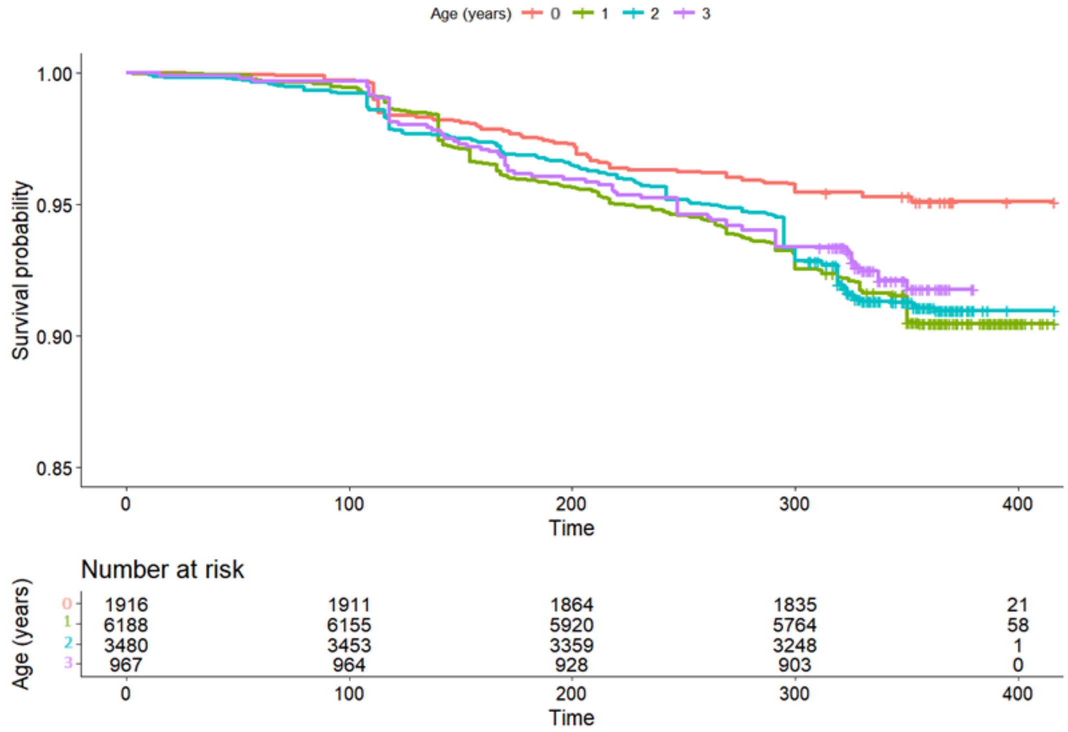

Figure 5.10- Kaplan-Meier plot showing the effect of age on survival probability over one production year

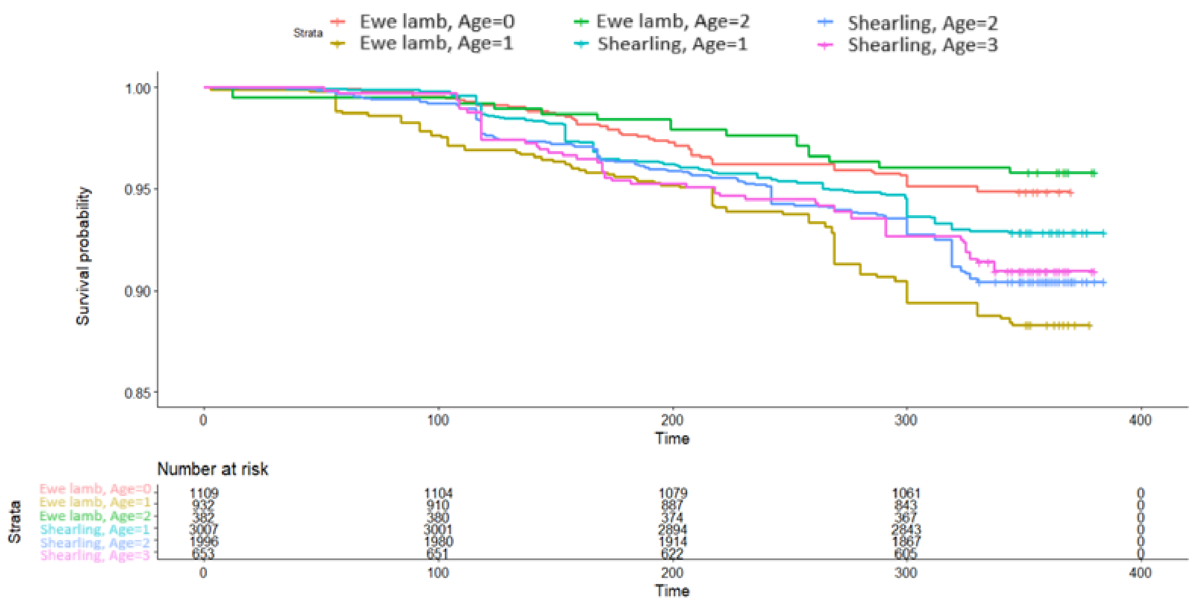

Figure 5.11- Kaplan-Meier plot showing the effect of age and status at first mating on survival probability over one production year

5.3.3. Cox Proportional Hazards Model

Table 5.2- Output from the Cox proportional hazards Model to observe the relationship between each ewe parameter on wastage.

Variable	Term	Coefficient	Hazard ratio	Lower .95	Upper .95	P value
Age (years)	**0**	**Ref**	**Ref**	**Ref**	**Ref**	**Ref**
	1	0.61	1.84	1.30	2.6	<0.05
	2	0.36	1.43	1.02	2.04	<0.05
	3	0.05	1.05	0.68	1.61	0.81
Entry Status	**Ewe Lamb**	**Ref**	**Ref**	**Ref**	**Ref**	**Ref**
	Shearling	0.32	1.37	0.99	1.80	<0.05
Grouped BCS at Mating	< 2.5	0.57	1.77	1.28	2.40	<0.05
	2.5-2.75	0.35	1.42	1.15	1.74	<0.05
	3.0-3.25	**Ref**	**Ref**	**0.86**	**Ref**	**Ref**
	3.5-3.75	0.02	1.02	0.88	1.21	0.83
	>4	0.06	1.06	0.50	1.34	0.58

Results show that the lowest two mating BCS groups had a significantly higher hazard ratio that the reference group (BCS 3.5- 3.75). BCS groups of less than 2.5 and 2.5 to 2.75 had hazard ratios of 1.77 and 1.42 respectively. Higher BCS groups of 3.5 to 3.75 and greater than 4 had hazard ratios close to the reference of 1.02 and 1.06 respectively, however these were not significant with p > 0.05. Entry status had a significant effect with hazard ratio of 1.38 for shearlings compared to the ewe lamb reference. Age of the ewe at mating had a significant effect on ewe wastage within one- and two-year-old ewes, with hazard ratios of 1.84 and 1.43 respectively. There was no significant difference between three-year old ewes and the reference group (0 year old ewes).

5.3.4. Accelerate Failure Time Model

The results from the accelerated failure time model show that BCS group at mating has a substantial effect on ewe survival. A similar trend to that of the Kaplan-Meier plot shown in Figure 2.1. Low BCS ewes at mating showed poor survival compared to that of more moderate BCS groups (BCS 3.0 to 2.25 and BCS 3.5 to 3.75). Shearlings also performed worse than ewe lambs within the accelerated failure time model with overall higher losses throughout the production year. This reinforced the findings from the Kaplan-Meier plot shown in Figure 5.8. The Accelerated Failure Time models provide a good foundation for predicting survival time within the simulation model.

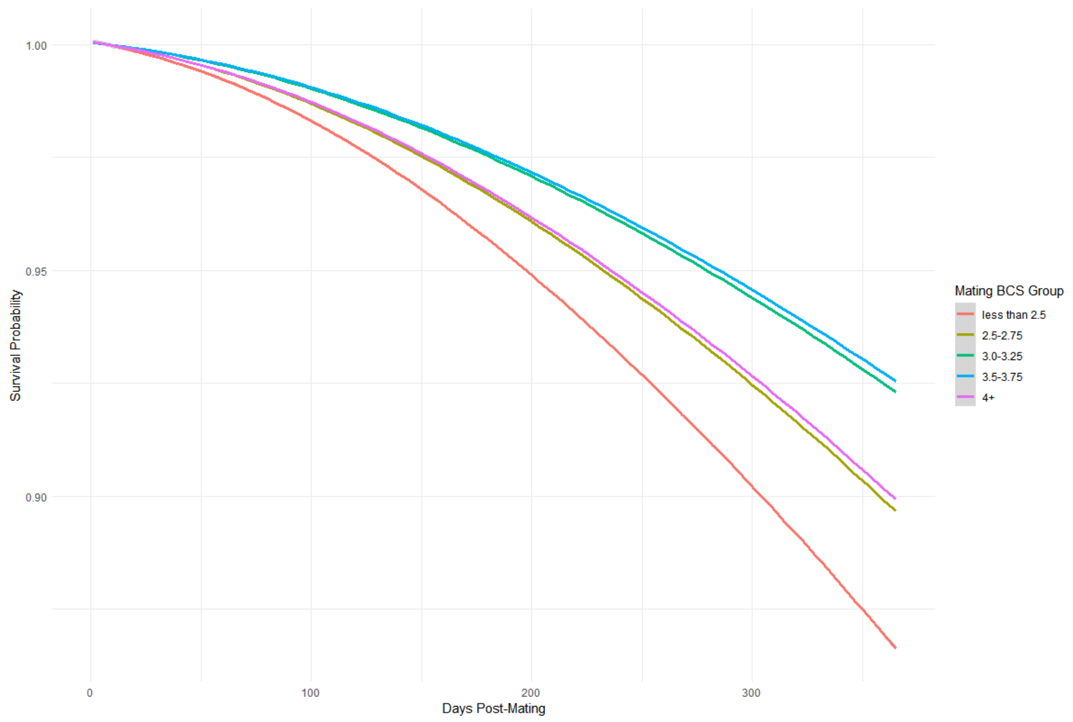

Figure 5.12- Effect of Grouped Mating BCS within the Accelerated Failure Time Model

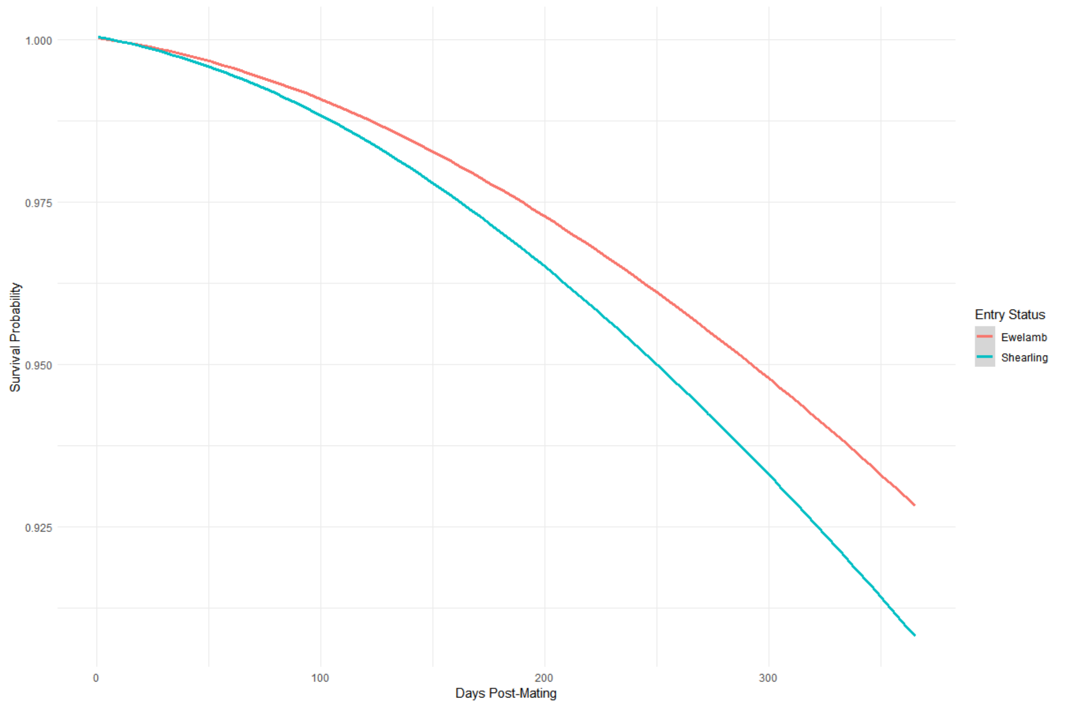

Figure 5.13- Effect of Entry Status within the Accelerated Failure Time Model

5.4. Discussion

5.4.1. Introduction of Main Findings

The wastage analysis showed that within the Challenge Sheep project farms, reasons for loss including, mastitis, infertility and poor performance were most prevalent. The timings of loss showed a correlation with management decisions throughout the year, particularly for ewes which were culled. The survival analysis showed approximately an 8% ewe loss throughout each production year. Again, specific periods of high loss occurred around scanning and pre-mating, where culling decisions were being made. The survival analysis gave a comparison between different groups within the data. Age, entry status and mating BCS all had a significant effect on wastage. Ewes in a lower BCS than 3.0 at mating saw a significantly increased hazard ratio and therefore increased incidence of wastage. There was no significant difference observed for ewes with a BCS more than 3.0 at mating. Throughout all production years observed ewes which entered as shearlings had higher wastage than ewes which entered as ewe lambs. Two-year-old ewes had significantly higher wastage than one year old ewes. As ewes age the hazard ratio reduced, suggesting older animals experienced lower incidence of wastage.

5.4.2. Overall Wastage

Overall exit rates within Challenge Sheep project farms over the first four years of recording are approximately 8% per year. As expected, reason for loss is often correlated with stage of production year (Figure 5.5). For example, relatively high levels of culling for infertility occur around 110 days post-mating or when pregnancy scanning is carried out. Similarly, culling for mastitis increased throughout lactation with most ewes culled before the start of the next production year. Ewes recorded as 'Sold' increased substantially pre-mating, likely due to ewes not being selected for breeding in the next production year.

It is important to note that only the main reason for loss was recorded by the farmers. This may lead to bias within the data due to farmers recording the most visually obvious reason, rather than multiple causes of mortality or culling. The extremely low number of ewes culled for poor feet (n=5) (Table 5.1) may be an example of this.

Ewes with poor feet have a higher chance of performing poorly, therefore there is a high likelihood that these animals could have been recorded as poor performance or poor condition. The categories of loss (Table 5.1) are subjective due to farmers being given the freedom to record the most probable cause of death or culling. This makes the accuracy dependant on the experience of each farmer. It is impractical to have each ewe categorised by a trained individual due to the randomness of ewe losses on farm. The infertility, lameness and mastitis groupings are self-explanatory, with these being the main observable causes of loss. The categories, lambing, other health and other poor performance indicate the reason for exit, however, do not provide a specific cause. The lambing category includes both losses from death at lambing and culling because of poor lambing. Other health includes all health-related issues which were not categorised as lameness or mastitis, this includes, neurological issues, accident/Injury, flystrike and pneumonia. Other poor performance includes, teeth, poor condition and poor mothering ability. The final two categories; sold and unknown largely include ewes where specific reasons for exit were not recorded. The "sold" category is ambiguous in that it could include ewes sold for slaughter or sold as breeding stock, however we know they left the farm alive. The unknown category includes all ewes in which the cause of death was unknown or that exit reasons were not recorded. It is important to note that due to the subjective nature of the recording, the exit reasons are specific to each Challenge Sheep project farm, however the overall wastage and time of wastage is more generalisable.

5.4.2.1. Wastage by Farm

Although the overall wastage is consistent with values from the literature, the reasons for losses on each farm (Figure 5.4) show a large amount of variation. The "unknown" ewe fate category is substantially more prevalent in farms 5 and 6. This category includes ewes which died on farm from an unknown cause of death and ewes which a cause of death or culling was not recorded. It is difficult to distinguish specific reasons for higher unknown losses within these two farms, however it is likely a result of inability to record reason for loss at time of loss, due to more extensive systems.

5.4.3. Reasons for Loss

5.4.3.1. Mastitis

Mastitis was the largest reason for ewe wastage within the Challenge Sheep project farms, with 19% of ewe exits a result of mastitis. McLaren et al., (2020) observed the main factors affect ewe longevity on UK, Irish and Norwegian sheep flocks. They found a large variation within reasons for culling between each country. They also found the main reason for culling in Norwegian flocks was mastitis at 19.9%, while Irish and UK flocks were 13.5% and 3.4% respectively. The results for the UK clearly differ from the 19% observed within this research, however the result from Norwegian flocks are highly comparable. The author suspects the difference in number of ewes culled for mastitis is largely a result of breed, with Norwegian flocks having higher fertility than the UK hill flocks observed. Within the Challenge Sheep project farms the breed types and systems are largely comparable to the Irish farms observed, therefore it would be expected that health issues such as mastitis would have similar incidence, however it does appear to be slightly higher within the Challenge Sheep project dataset, likely due to the relationship between prolificacy and mastitis.

Mastitis is caused by a selection of environmental and animal related predisposing factors. Environmental factors such as temperature and wet weather have been shown to affect the cases of mastitis (Vasileiou *et al.*, 2019). Good hygiene and biosecurity during lambing, particularly for indoor lambing systems, may have a substantial impact on cases of mastitis. Housed ewes have been shown to have increased cases of clinical mastitis (Cooper *et al.*, 2016), with bedding and floor type effecting cases. Poor BCS has been associated with an increased risk of mastitis (Arsenault *et al.*, 2008), however it is unclear if this is an effect of low milk production leading to over-suckling. Increased litter size may have a positive correlation with incidence of mastitis. *Figure 5.2* suggest that as mating BCS increases, culling due to mastitis also increases. This may be an effect of increased mating BCS resulting in higher fertility and therefore an increased number of lambs suckling. Bacteria (M. haemolytica) has been shown to pass from the lambs mouth to ewes teat during suckling (Fragkou *et al.*, 2011), increased suckling will lead to an increased rate of bacterial transfer. It is clear from the literature that the cases of mastitis are dependant on many environmental and animal factors, and therefore may be specific to the farm. The losses by farm shown in Figure 5.4 highlight that mastitis is a predominant cause of loss on 8 of the 11 farms, however a larger proportion of losses were attributed to mastitis on some farms (e.g. farms 2, 4, 5, 9 and 11), reiterating the effects of breed and system on losses due to mastitis.

5.4.3.2. Teeth

McLaren et al. (2020) found that teeth were the cause of the highest percentage of culling on UK sheep farms at 38.9%, however were not a factor within Norwegian or Irish flocks. Due to the nature of this dataset only including the first three years data from the challenge sheep project, the incidence of culling for poor teeth is reduced at approximately 1% of overall losses. Again, the nature of the Irish flock is likely more comparable to the flocks within the Challenge Sheep project farms, therefore it is not surprising that teeth account for a small proportion of ewe losses.

5.4.3.3. Lameness

Culling due to lameness accounted for 1% of losses (n=11) (Table 5.1). This is clearly a low number of ewes compared to the more prevalent exit reasons. The average percentage of lame ewes on UK flocks has been recorded as 3.2%, however this is variables with some farmers observing >30% (Best *et al.*, 2020). All farms within this study appear to have low rates of culling due to lameness (Figure 5.4), with only farms 2 and 9 recording any losses due to lameness as the main factor. Although this may indicate a low prevalence of lameness within the project farms, traditionally culling specifically due to lameness is rare. In 2011 it was reported that only 20% of farms in the UK are culling lame sheep promptly (Farm Animal Welfare Council, 2011). A combination of the low number of lame sheep in the UK, along with the reluctancy to cull lame animals explains why the losses due to lameness are low within the Challenge Sheep project. Treatments for lameness have developed significantly, with current best practice stating that lame animals should receive prompt treatment with antibiotics, with no routine foot trimming or footbathing (Lewis and Green, 2020) .It is assumed that the Challenge Sheep project farmers are well informed on how to effectively prevent and treat lameness before it has a significant impact on the flock.

5.4.3.4. Infertility

Infertility was one of the leading causes of ewe losses within the project (12%, n=268). There is no universal value for fertility targets in ewes with, breed, ewe age, and system all affecting an individual farms target. KPIs are available for number of lambs reared per ewe. These KPIs are dependent on lambing system (indoor or outdoor) and ewe status at mating (ewe lamb, shearling or mature ewe) (AHDB, 2024).

There is a significant peak in losses due to infertility from 100 to 130 days post-mating (Figure 5.5). This coincides with pregnancy scanning and the presumed sale of barren animals for slaughter. Interestingly the sold loss category also observes a significant peak post-scanning, therefore it is likely that the reason for sale of these animals was also liked to poor reproductive performance. As reproductive performance and mainly fertility is a driver for overall productivity on sheep farms. It is advised that infertile ewes should be culled to allow for more productive animals to enter the flock. (Genever and Wright, 2016).

5.4.3.5. Poor Performance

Although low BCS was not included as a specific reason for losses within the data. It is advised that any ewes with a condition score of <2 at weaning and which fail to regain at least 0.5 BCS units post-weaning should be culled (Genever and Wright, 2016). This suggests that poor performance and mating BCS are closely correlated with significantly higher numbers of ewes being culled for poor performance that were in low condition at mating (BCS <2.5) than higher conditions (BCS > 4). It is likely that these animals failed to regain condition throughout gestation, leading to poor reproductive performance. Culling for poor performance appears to occur at two distinct points throughout the production year. Initially ewes are culled at pregnancy scanning around 100 days post-mating, likely due to infertility caused by overall poor performance, hence the categorisation. The second period of culling due to poor performance is pre-mating in the subsequent year, likely during pre-mating health check. Ewes culled at this point may have struggled to rear lambs effectively or may be in a lower condition than mating BCS targets advise.

It is clear from analysing the reasons for losses that it is difficult to determine specific reasons for each loss, particularly due to the range of breeds and managements systems within the project. It does still however provide a general overview of wastage on a larger UK flock scale.

5.4.4. Survival Analysis

Although the reasons for wastage appear to be somewhat farm specific, with some ambiguity between the categorisation of reasons for loss, using survival analysis to observe the timings of loss and the ewe factors which effect wastage is still effective. As data was collected at specific intervals throughout the production year, and most farmers make management decisions at these intervals, the data shows peaks post-scanning and pre-mating (Figure 5.5). The overall loss of ewes throughout the first three years of the Challenge Sheep project is shown in Figure 5.6. Approximately 40% of ewes exited over this period. It appears that the rate of loss has two distinct periods shown by two differing negative gradients. From 0 to 700 days the Kaplan-Meier plot is linear with a slight negative gradient. From 700-1750 days of age the gradient is significantly steeper, indicating a higher probability of loss each day. This is a result of animals having greater losses due to both deaths and culling after their first lambing (at either zero or one years of age). The losses for each production year, starting at mating are shown in Figure 5.7. There are two clearly observable periods of higher loss at 140 and 320 days post mating. This coincides with scanning and pre-mating respectively. Yearly losses are around 8% of ewes mated.

Deaths throughout the year were recorded on the date of death therefore these are less affected by management decisions. mating BCS, ewe age and ewe status at first mating (ewe lamb or shearling) all affect the incidence of wastage throughout the production year (Table 5.2). The survival analysis indicates the probability of loss each day post-mating, irrespective of the reason for loss, and informs producers of the main variables affecting wastage. Overall, approximately 40% of ewes which entered the project were lost.

5.4.5. Losses over Time

5.4.5.1. Effect of BCS at Mating

Lower condition ewes (BCS < 2.5) had significantly increased hazard ratios and therefore increased chance of wastage than higher condition ewes (Table 5.2). These results are consistent with findings by Flay et al. (2021) where they found that ewes in low BCS pre-mating (BCS 2.0) had a higher wastage due to premature culling and dead or missing, than ewes in higher BCS pre-mating (BCS 3.5) for the majority of cohorts. The Kaplan- Meier plot showing the effects of mating BCS (Figure 5.9) shows that within the first 300 days post-mating, the low BCS group had substantially lower survival probability that all other groups, however after 300 days post-mating the difference is less pronounced with the high BCS group (BCS ≥ 4.0) having a similar survival curve. The nature of the low BCS group curve may be explained by a couple of factors. Low BCS ewes at mating may have an underlying health issue resulting in the low BCS, these ewes may struggle throughout the production year, resulting in mortality or culling due to health issues. Also, these ewes may have poorer fertility due to less energy availability for reproduction, resulting in barren ewes at scanning and therefore higher exit rates. Interestingly, the higher BCS ewes appears to perform similarly to the middle BCS groups, then have a period of extremely high exit rates at around 280 days post-mating. This is likely the result of culling ewes with non-fatal health issues, such as mastitis or lameness at the end of the production year. It is unclear why exit rates would be substantially higher than other groups at this stage however, Haslin, et al. (2022b) found that higher BCS pre-lambing improved the survival of triplet bearing Merino ewes, however, there was no significant effect on a maternal breed. They found that pre-lambing BCS change had a larger impact on ewe survival than BCS at a fixed point.

5.4.5.2. Effect of Ewe Age

Within the analysis of the Challenge Sheep project data, year one ewes, had a substantially higher survival probability over the whole year compared to year two, three, and four ewes (Figure 5.10). This is likely due to the reluctancy to cull ewe lambs, particularly for poor reproductive performance. It is likely that farmers are reluctant to cull barren ewe lambs which have the potential to perform well once a mature weight is reached. The reluctance to cull ewe lambs is also shown with the lower survival probability of ewes at one year of age or more at mating (Figure 5.10). From the Kaplan-Meier plot it appears that around 130 days post mating there is a substantial increase in ewe exit rate for one year old ewes or more at mating. This is likely the result of culling due to infertility, observed through pregnancy diagnosis at scanning. The effects of culling at scanning are less pronounced in year three and four ewes. This is likely due to the effects of not culling ewe lambs in their first production year. Figure 5.11 further clarifies this when comparing the survival probabilities of year one ewe lambs and years two ewe lambs, in which year two ewe lambs have a much lower overall survival probability, and therefore higher exit rates. The higher exit rates within two and three year old ewes is further highlighted within the results from the Cox proportional hazards model (Table 5.2). Year two ewes had the highest hazard ratio (1.86), suggesting a higher likelihood of exit from the flock.

5.4.5.3. Effect of Breeding as a Ewe Lamb or Shearling

One of the main aims of the Challenge Sheep project was to observe the effects of first breeding as a ewe lamb or a shearling on lifetime productivity. When comparing the survival probability of ewe lambs and shearlings, shearlings have a lower overall survival probability (Figure 5.8). It appears that this difference in overall survival probability is largely due to increased exit rates around pregnancy scanning and 300 days post-mating. For ewes exiting before the next breeding season, the decision has often been made by the farmer not to breed these animals again therefore they’ve been sold as cull ewes. Increased culling of shearlings around pregnancy scanning suggests that ewes which joined as shearlings are more likely to be culled for infertility. This is possibly a result of ewe lambs not being culled for infertility in their first year of production and therefore mated again as shearlings. The Cox proportional hazards model (Table 5.2) shows a significantly higher hazard ratio for ewes first enrolled as shearlings than ewe lambs.

5.4.6. Limitations

5.4.6.1. Data Recording

The data collected by the challenge sheep farmers showed some inconsistencies throughout the recording of ewe exit reasons. Farmers were required to input the main reason for death or culling for each ewe that exited the project. This is somewhat subjective, and in the event that multiple reasons were present the most visually obvious reason was likely recorded. Requiring the farmers to decide the exit reasons also led to a substantial number of ewes where the true exit reason was not recorded. For example 320 ewes (15%) were categorised as `sold for slaughter` (Table 5.1). Although this records the fate of the ewe, there is not enough data to distinguish the true cause of the sale. It is likely that these ewes had poor reproductive performance or general poor performance, therefore removal of this category would lead to bias within other exit reasons.

The nature of some of the exit reasons leads to a substantial farm effect within the data, particularly for some health related exit reasons such as mastitis. Mastitis is usually more prevalent in flocks with higher reproductive performance. These are often the lowland flocks, therefore there is a certain amount of bias when observing the prevalence of specific exit reasons. The results do however indicate an overall picture of the UK sheep industry, especially due to the large variation of systems included within the project.

The dataset received only included data collected over the initial three years of the Challenge Sheep project. It is important to note that as ewes age, predominant exit reasons may also change. It is likely that in ageing ewes, reproductive performance will be less of an issue due to early removal of these animals, however health related issues such as mastitis and poor feet will become more prevalent. Three year old ewes at mating were the oldest animals included within the dataset, these animals would often be considered the optimum age for productivity.

29% of ewes had an unknown exit reason (Table 5.1). It is unclear from the data whether these ewes were initially recorded as unknown by the farmers due to uncertainty around a specific cause of death, or whether these were datapoints with missing exit reasons. This does not affect the survival analysis as dates of exit were still recorded, however does raise issues when determining relationships between ewe variables (e.g. mating BCS) and exit reasons.

5.4.7. Summary

Higher ewe wastage leads to fewer lambs weaned, lighter ewes at weaning and ewes born later into the season, due to a younger flock demographic. This chapter observed that wastage is significantly affected by ewe age, entry status into the flock and mating BCS. One- and two-year-old ewes at mating had a significantly higher wastage rate than ewes mated at less than one year old. Ewes first mated as shearlings observed a higher wastage rate than that of ewes first mated as ewes lambs. When BCS was observed to be lower than recommended at mating (BCS <3.0) a substantially higher hazard ratio and therefore risk of wastage was observed. The results from the Accelerated Failure Time model agreed with that of the survival analysis models, providing an effective means of predicting time to wastage within a larger simulation model.

Chapter 6. Ewe Simulation Model

6.1. Introduction

A ewe simulation model was developed to observe the interactions between status at first mating, body condition score and body condition score change throughout production, on ewe lifetime productivity. The reproduction model (Chapter 4) and wastage model (Chapter 5) create the foundation for the ewe simulation model. These models can be used as standalone models to estimate days from mating to lambing and predict the probability of survival on a specific day, or can be combined to predict lifetime output of a ewe. Two additional models were developed to quantify ewe performance, these were a number of lambs model and a lamb weaning weight model.

6.1.1. Estimating Number of lambs

When observing number of lambs within a systems model there are two options. Firstly you can include scanning number as an input within the model at mating, this would allow for accurate predictions of the number of lambs born to each ewe, however would not provide accurate simulations over multiple production years. Secondly you can predict the number of lambs born to each ewe from known parameters. The concept of predicting ewe fertility from ewe parameters is not new. White et al. (1983) predicted ovulation rate in merino ewes in Australia as part of a larger simulation model. They found that ovulation rate increased with liveweight and concluded that the relationship between mean ovulation rate and mean liveweight of the flock was approximately 0.025 in the autumn and 0.015 in the spring. Similarly, (Saul, Kearney and Borg, 2011) observed that increasing BCS had a positive effect on lambing percentage. Ewes which joined at a BCS of 3.0 observed a 16% higher lambing percentage than that of ewes which joined at a BCS of 2.3 (111% and 95% respectively.

Within the ewe simulation model the number of lambs was predicted using a multinomial model to estimate the number of lambs born to each ewe. Predictor variables included grouped mating BCS, breed and age at mating. The output variable was a categorical prediction of whether ewes would produce one, two or three live lambs at lambing.

6.1.2. Modelling Lamb Growth and Weaning Weight

Within the literature there are a number of models that have been designed to predict and model lamb growth rates, using lamb and ewe parameters. Amaral et al. (2024) developed a model to simulate lamb growth, nutrient requirement and body composition within a feedlot system. The model observed the nutritional requirement for maintenance and growth for lambs during the pre-weaning period. The input variables within the predictive model include; body mass, standard final mass, age and dietary energy composition. Final body mass was observed with simulated results being compared to measured weight. They observed at R^2 value of 0.89 when comparing simulated final body mass to observed final body mass. They discuss that their model provides an effective means to be used a decision support tool to estimate final body mass of lambs. The requirement for dietary energy composition as an input within Amaral et al. (2024) model means that it is outside the scope of this project, as dietary composition was not recorded within the data collection process. It is likely that developing a similar model would provide a more accurate estimation of specific lamb weaning weight, and would allow the comparison between different planes of nutrition, but would require additional inputs and therefore complexity within our ewe simulation model. The TLPM (Bohan *et al.*, 2016) estimated lamb growth rates initially from ewe milk yield, then from previously collected Irish sheep data. Energy requirements for a set rate of growth were established for each stage of the animals production cycle, then an economic cost calculated for this. This differs from our model in that we estimated the average weaning weight of lambs from ewe parameters, rather than observing the requirements for lamb growth. This allows our ewe simulation model to make comparisons between ewe performance, rather than observing the economic benefit of different management systems on farm. The prediction of average lamb weaning weight within our model provides one of the outputs required to estimate a total lifetime weaning weight within the ewe simulation model. It was not deemed necessary, or possible to include a nutritional component within this model without increasing complexity within the larger ewe simulation model through an increase number of required inputs.

6.1.3. Quantifying Lifetime Performance

Lifetime performance of a ewe is somewhat difficult to quantify with both economic and biological metrics being used. As discussed in section 1.1.5 there are many variables which affect flock performance, but also many measures of flock productivity. Metrics to assess ewe performance often include, fertility, number of lambs per ewe at scanning, lambing percentage, total lamb weaning weight, lamb growth rate up to eight-weeks of age, and lamb survival. These metrics are affected by factors such as, ewe genetics, nutrition and management. Often an economic output can be used to quantify the overall lifetime performance of an animal, or more likely, the overall performance of a flock. The TLPM model provides a good example of using economic outputs to evaluate overall performance of a flock over an extended period. Outputs included variable cost, net profit and return on total capital (Bohan *et al.*, 2016). Economic outputs are useful when comparing whole systems, however less so when comparing one aspect of a system, such as ewe lifetime performance, as there are a number of other factors which effect the economic output not captured by a ewe simulation model.

To quantify lifetime performance within the ewe simulation model a total lifetime lamb weaning weight was used as a metric. This provided an indication of the performance attributed to the ewe, and accounted for lamb growth rates, ewe fertility and lamb survival. The ewe simulation model allows the comparison of the output of ewes managed under different conditions, and indicates the best management practices for individual animals. Practically, the simulation model would allow UK farmers to simulate their ewes by inputting breed, entry status and BCS. This could help make informed decisions on whether to first breed ewes as ewe lambs or shearlings, or to observe the impact of poor BCS throughout the production year. The outputs from the model could then be used alongside the farmers knowledge of their own system and production costs, to ensure best management decisions, however a bio-economic component was not directly included.

6.2. Materials and Methods

6.2.1. Model Structure

The structure of the simulation model is shown in Figure 6.1. The inputs for the model include, breed, age, mating date and length, ewe entry status, mating BCS, lambing BCS and pre-mating BCS change. The model uses a mechanistic stochastic approach to predict the total lifetime lamb weaning weight of each animal. Using the reproduction model for first parity animals, the probability of getting in lamb on each day is calculated. The probability of mortality is calculated for each day of the production year using the wastage model. In the second year of production, the multiple parity reproduction model is used. The model simulated the animal over a maximum of six years or until lost from the flock. Ewes which are first mated as ewe lambs therefore have an additional potential year of production, than that of ewes which entered as shearlings. The model was ran over 400 iterations due to the stochastic nature of its design. This ensured that all the range of possible outcomes was explored, allowing for improved accuracy and reliability in the model's predictions. Increasing the number of interactions within stochastic simulation models often captures the variability between each iteration and may better reflect real world dynamics.

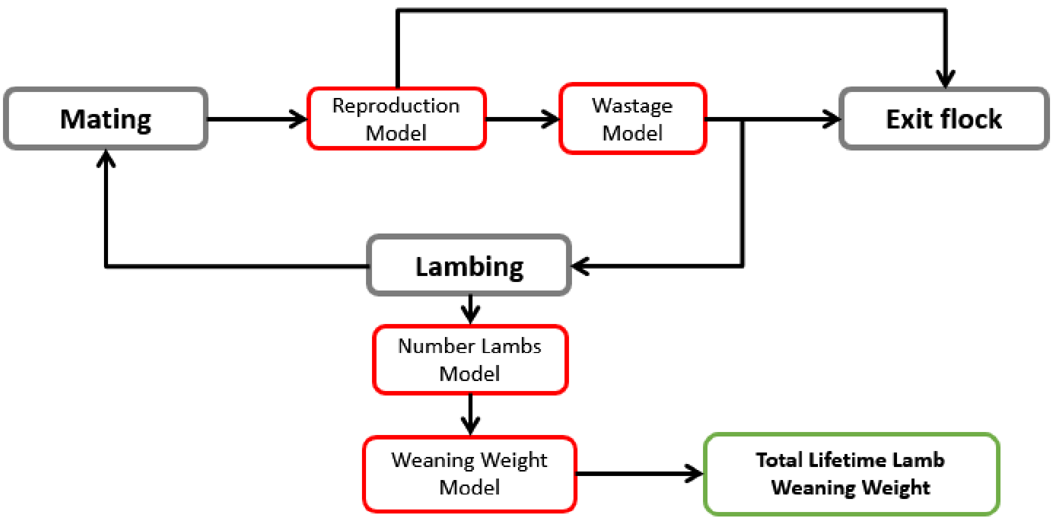

Figure 6.1- Flow diagram showing the overall structure of the flock simulation model. Individual component models are shown in red, with events shows in grey and outputs shown in green.

6.2.2. Model Output

Total lifetime lamb weaning weight was used to quantify ewe performance within the model. This was chosen due to the relationship between ewe performance and total lamb weaning weight, and the availability of robust weaning data within the dataset. The model observes the effect of ewe parameters on total lifetime lamb weaning weight and does not account for the effects of paternal genetics or nutrition during the lamb growth phase.

6.2.3. Additional Models

To calculate the output 'total lifetime lamb weaning weight' for each ewe, an additional two models were built. A predictive model for number of lambs born to each ewe, and a predictive model to estimate lamb weaning weight were developed. These models were also built using the Challenge Sheep project data.

6.2.3.1. Prediction of Number of Lambs

6.2.3.1.1. Multinomial models

Multinomial models are used when the dependant variable has more than two categories. The categories are nominal, therefore do not have a natural order. The predictor variables can be either continuous or categorical. Probabilities are estimated for each category which are relative to the reference value. Some of the key assumptions that multinomial models make are that the categories within the dependent variable are mutually exclusive, the observations are independent and that the dependent variable is nominal.

Model coefficients represent the relationship between each predictor variable within the model, relative to a reference category. Standard error is observed for each of the coefficients to indicate how precise the estimate is. High standard error relative to the coefficient suggests that the model has low precision. 95% confidence intervals are observed to indicate the reliability of the predictions.

6.2.3.1.2. Methods

The multinomial model was built using data collected from the first four years of the Challenge Sheep project. The model was built in R (*R: The R Project for Statistical Computing*, no date), utilising the nnet package. The output from the model was number of lambs, included in three categories (1, 2 and 3), with category one being included as the reference value. The predictor variables included, grouped mating BCS (Low <2.75, Moderate 3.0 to 3.25, and High >3.5), breed and age at mating in years. This provides ewes which conceive, an output of either one two or three lambs. Barren ewes were observed within the reproduction model.

6.2.3.2. Prediction of Average Lamb Weaning Weight

6.2.3.2.1. General Linear Models

General linear models are used to describe the relationship between a continuous dependent variable and a series of predictor variables. They assume that there is a linear relationship between the predictor variables and the dependent variables. There are a number of metrics used to interpret the output of a general linear model. Initially the intercept is used to provide a baseline value for all predictions. It is calculated from output in which the predictor variables are all 0 or the reference value. An estimate is calculated for each category within the predictor variables. This shows the effect that each category has on the dependant variable relative to the reference value. Standard errors are used to indicate the degree of uncertainty around the estimate. The larger the standard error the less precise the estimate is. Finally, the p-value indicates whether the effect shown in the estimate is having a significant effect within the model.

6.2.3.2.2. Methods

A multiple linear regression model was used to predict average lamb weaning weight from number of lambs born, grouped lambing BCS (Low <2.75, Moderate 3.0 to 3.25, and High >3.5), breed and age at mating in years. Lambing BCS was used to provide the most recent datapoint to predict from, and was deemed likely to have the largest effect on lamb weaning weight. There is a correlation between weaning weight and number of lambs born to each ewe therefore, number of lambs was included within the model to account for this. These values were taken from the outputs discussed in section 6.2.3.1. Within the model the average weaning weight of lamb was predicted, total lamb weaning weight can then be calculated within the simulation. The effect that each category within the predictor variables has within the model is presented as the estimate, and highlights the effect on average lamb weaning weight.

6.2.4. Simulated Scenarios

Simulations were run to compare the effects of mating BCS and entry status for two breed categories (Lleyn and Mule). In total 400 iterations of the simulation were run for each possible combination of model inputs. This resulted in 43,200 datapoints for analysis. To observe the effects of each variable within the simulation model, total lifetime lamb weaning weight was plotted against all variables. A linear regression model was built to summarise the relationship between each variable and the total lifetime weight of weaned lambs from the simulation model.

6.3. Results

6.3.1. Additional Models

6.3.1.1. Number of Lambs

The results from the number of lambs model (Table 6.1) show that Low BCS at mating decreases the chance of multiple lambs when compared to the reference of one. High mating BCS increases the chance of having two or three lambs. As mating age increases, the number of lambs also increases with 3-year-old animals having a higher coefficient for both two and three lambs (1.88 and 4.27 respectively). Breeds exhibited a difference in number of lambs born. Mules and Mule X ewes had high coefficients for both two and three lambs born, while Swaledale ewes had a lower coefficient, with a particularly low incidence of three lambs born.

Table 6.1- Output from the Multinomial model to predict number of lambs from ewe parameters. All coefficients are relative to the reference value of Number of lambs = 1.

	Number Lambs	2				3			
		Coefficient	Std. Error	0.95 CI Lower	0.95 CI Upper	Coefficient	Std. Error	0.95 CI Lower	0.95 CI Upper
	(Intercept)	-1.39	0.09	-1.56	-1.22	-6.29	0.38	-7.04	-5.55
Mating BCS	High	0.40	0.05	0.31	0.49	0.87	0.11	0.66	1.08
	Moderate	ref	ref	ref	ref	ref	ref	ref	ref
	Low	-0.42	0.06	-0.53	-0.30	-0.51	0.16	-0.83	-0.19
Breed	AberField	ref	ref	ref	ref	ref	ref	ref	ref
	AberField X	0.20	0.07	0.07	0.33	0.33	0.15	0.05	0.62
	Highlander	0.80	0.10	0.60	1.00	0.16	0.25	-0.34	0.66
	Lleyn	0.29	0.09	0.11	0.47	0.55	0.20	0.17	0.94
	Mule	0.80	0.07	0.67	0.93	1.76	0.13	1.51	2.00
	Mule X	0.81	0.09	0.64	0.98	1.36	0.17	1.02	1.70
	Other	0.60	0.33	-0.06	1.25	0.82	0.65	-0.46	2.10
	Romney	0.35	0.07	0.21	0.48	-0.58	0.22	-1.00	-0.15
	Swaledale	-0.46	0.07	-0.60	-0.32	-2.26	0.46	-3.16	-1.35
	Texel	-0.22	0.10	-0.41	-0.02	0.21	0.21	-0.20	0.63
	Texel_X	0.50	0.12	0.26	0.73	1.74	0.20	1.34	2.14
Mating Age Years	0	ref	ref	ref	ref	ref	ref	ref	ref
	1	1.25	0.08	1.10	1.41	2.77	0.37	2.05	3.49
	2	1.50	0.08	1.34	1.67	4.03	0.37	3.31	4.75
	3	1.88	0.09	1.71	2.06	4.27	0.37	3.54	5.00

6.3.1.2. Average Lamb Weaning Weight

The results from predicting average lamb weaning weight are shown in (Table 6.2). Number of lambs born had a significant effect on average weaning weight. Ewes with two and three lambs born observed significantly lower average weaning weights (-3.69kg and -3.74kg respectively). Lambing BCS had a significant effect on average lamb weaning weight. High BCS ewes at lambing showed an increase of 1.89kg average weaning weight than Moderate BCS ewes, while Low BCS ewes had a 0.86kg lower average weaning weight than the moderate group. As ewes age it appears that average lamb weaning weight increases, with the exception of ewe lambs (0 at first mating) which exhibit an unusually high average lamb weaning weight. Breed plays a significant effect on average lamb weaning weight. Swaledale ewes show the lowest average weaning weight (7.51kg lower than Aberfield reference) while Texel X ewes have the highest average lamb weaning weight (2.24kg higher than Aberfield reference).

Table 6.2- Output from the general linear regression model to predict lamb weaning weight from ewe parameters

		Estimate (kg)	Standard Error	P Value
	(Intercept)	34.17	0.19	<0.05
Number Lambs Born	1	ref	ref	ref
	2	-3.69	0.14	<0.05
	3	-3.74	0.28	<0.05
Breed	AberField	ref	ref	ref
	AberField X	0.65	0.21	<0.05
	Highlander	-5.60	0.28	<0.05
	Lleyn	-2.42	0.34	<0.05
	Mule	-1.48	0.23	<0.05
	Mule X	0.66	0.30	<0.05
	Other	1.19	0.93	<0.05
	Romney	-4.87	0.22	<0.05
	Swaledale	-7.51	0.22	<0.05
	Texel	1.97	0.33	<0.05
	Texel X	2.24	0.40	<0.05
Lambing BCS	High	1.89	0.16	<0.05
	Moderate	ref	ref	ref
	Low	-0.86	0.17	<0.05
Age at Mating	0	-0.19	0.31	<0.05
	1	-2.07	0.16	<0.05
	2	ref	ref	ref
	3	1.24	0.16	<0.05

6.3.2. Ewe Simulation

The results from the simulation (Table 6.3) showed that Low mating BCS had a significant negative effect on total lifetime lamb weaning weight compared to the Moderate and High groups. The Low mating BCS group weaned on average 27kg less over their productive life. Lambing BCS showed a similar trend with Low BCS animals showing a lower average total lifetime lamb weaning weight. Mules weaned a significantly higher weight of lambs than Lleyns at approximately 60kg more. Over the lifetime of the animal, ewes which first lambed as ewe lambs weaned a significantly higher weight of lambs than ewes which were first mated as shearlings. This is due to the additional year of productivity possible from ewes first bred as ewe lambs. This resulted in around 12.5kg more lamb weaned from ewes first mated as ewe lambs over their lifetime.

Table 6.3- Regression model showing the effect of each variable on total lifetime lamb weaning weight within the ewe simulation model

		Estimate (kg)	Standard Error	P-value
	Intercept	168.70	1.46	<0.05
Breed	Lleyn	Ref	Ref	Ref
	Mule	59.24	0.98	<0.05
Mating BCS	Low	Ref	Ref	Ref
	Moderate	26.71	1.19	<0.05
	High	26.95	1.19	<0.05
BCS Change	Loss	Ref	Ref	Ref
	Maintain	2.31	1.19	0.053
	Gain	2.05	1.19	0.085
Lambing BCS	Low	Ref	Ref	Ref
	Moderate	5.65	1.19	<0.05
	High	13.20	1.19	<0.05
Entry Status	Ewe lamb	Ref	Ref	Ref
	Shearling	-12.47	0.98	<0.05

Figure 6.2 shows a boxplot of the simulation results. When breed, mating BCS and entry status are observed, ewes in a Low BCS at mating appear to have lower total lifetime lamb weaning weight that that of Moderate or High mating BCS. Ewes first bred as ewe lambs have a higher total lifetime lamb weaning weight than ewes first bred as shearlings for all mating BCS groups observed, with the exception of Lleyn ewes in high mating BCS. Within the simulation, Mules had a higher total lifetime lamb weaning weight than Llyens, for both entry statuses and all mating BCS groups. Table 6.4 shows the mean total lifetime lamb weaning weight for each category of animal. It ranges from 167kg to 268kg, depending on entry status, breed and mating BCS.

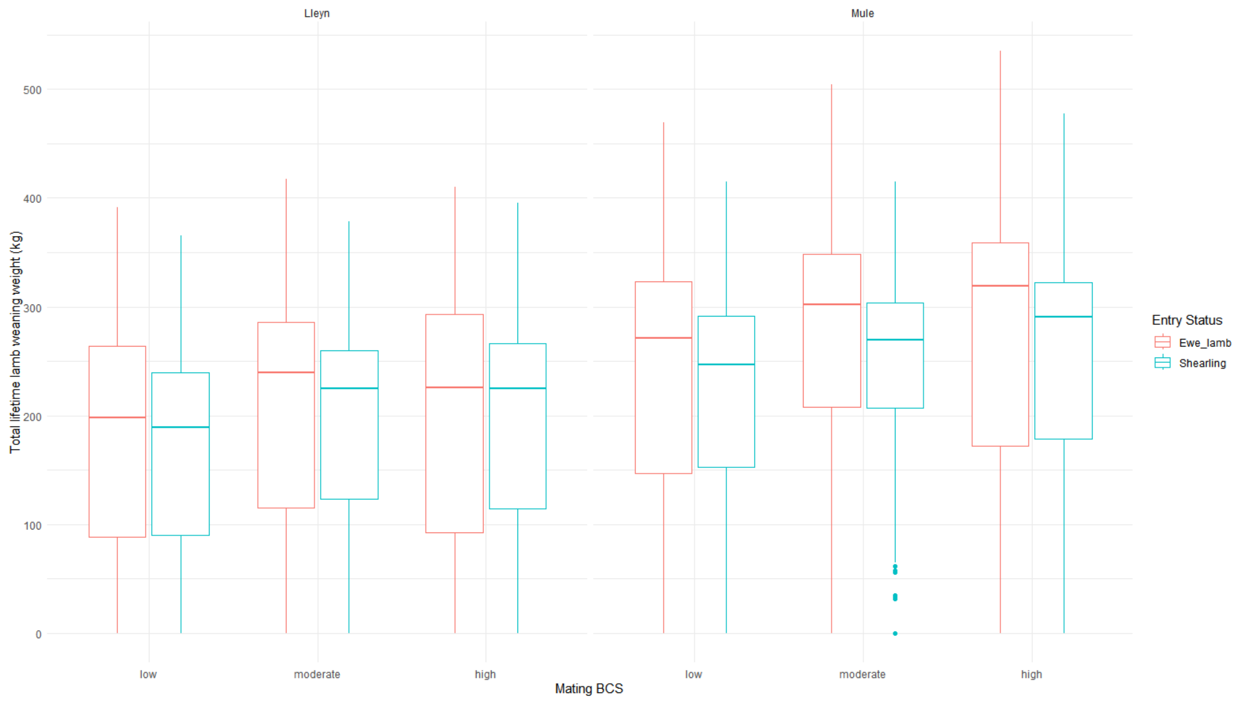

Figure 6.2-Boxplot showing predicted total lifetime lamb weaning weight for ewes in different mating BCS groups. Ewe entry status and two breeds (Lleyn and Mule) are included.

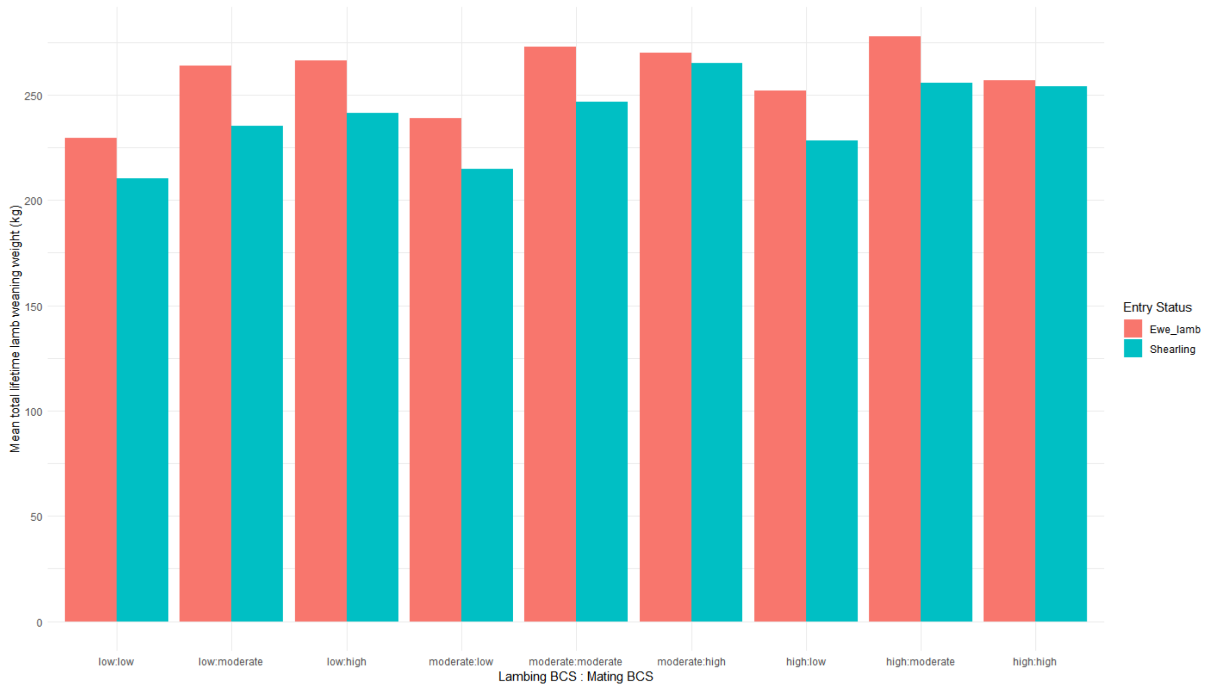

Figure 6.3- Bar chart showing the effect of lambing and mating BCS on mean total lifetime lamb weaning weight for different ewe entry status.

Table 6.4- Mean total lifetime lamb weaning weight for each group of ewes ran within the simulation model.

Entry Status	Mating BCS	Breed	Mean (kg)	Standard Deviation
Ewe lamb	low	Lleyn	177	102
Ewe lamb	moderate	Lleyn	200	105
Ewe lamb	high	Lleyn	196	112
Shearling	low	Lleyn	167	87.4
Shearling	moderate	Lleyn	195	86.4
Shearling	high	Lleyn	193	93.6
Ewe lamb	low	Mule	235	110
Ewe lamb	moderate	Mule	267	108
Ewe lamb	high	Mule	268	122
Shearling	low	Mule	220	92.5
Shearling	moderate	Mule	244	90.6
Shearling	high	Mule	250	100

6.4. Discussion

The simulation model provided a means to observe the overall interactions between each of the individual models throughout the lifetime of an animal. Total lifetime lamb weaning weight was used as the main output from the simulation. This was considered an appropriate metric for comparing the lifetime performance of individual ewes. Running the simulation 400 times for each combination of ewe parameters provided a suitable number of simulations for analysis.

It was observed that mating BCS had a substantial effect on the total lifetime lamb weaning weight. Low BCS animals at mating, saw a substantially reduced total lifetime lamb weaning weight than those in Moderate or High mating BCS groups. This was apparent for both breeds simulated (Lleyn and Mule). The negative effects associated with Low mating BCS are likely a combination of poor fertility and conception rates within this group. Low mating BCS may also be associated with higher incidence of wastage as discussed in Chapter 5. The simulation supports the AHDBs recommended mating BCS values suggesting ewes should be in a BCS of more than 3.0 at mating (Povey, Stubbings and Phillips, 2018). One of the key aims of the Challenge Sheep project was to investigate best management practices for rearing replacement ewes. A large part of this is the decision of whether to first mate ewes as a ewe lamb or shearling. There are concerns around whether mating as a ewe lamb before maturity is reached may have a knock on effect and reduce lifetime productivity. The obvious advantage of breeding from a ewe lamb is the additional year of production available. The simulation model suggested that breeding from ewe lambs had an overall positive effect on total lifetime lamb weaning weight compared to shearlings. This is the result of the additional crop of lambs produced in their first year of production. Differences were observed between breeds within the simulation model. Mules had a total lifetime lamb weaning weight around 60kg higher than Llyens. This is in line with results from the 'Sheep KPI Validation Project' showing that on average Mule lambs have a heavier weaning weight than that of Llyen lambs (Sheep KPI Validation Project, AHDB, EBLEX, 2014).

6.4.1. Model Validation

Validating the model using data observations was not possible due to the novelty of the model and complexity of the data required to validate the simulations. An external dataset including overall ewe lifetime productivity (total lifetime weight of weaned lambs) and all the parameters included within the simulation was not available. The simulation was built on only the first four years of the Challenge Sheep project data, therefore we could not compare the simulation results to the lifetime productivity of animals within the dataset. To validate the model the approach was to ensure that each component of the simulation was robust and independently validated and that the structure was logical when compared to UK sheep production systems.

Each sub model was built on a large dataset, including records from 14 breeds across 11 farms throughout England. This improved the generalisability of the simulation model. The reproduction component of the simulation model was developed using Kaplan-Meier, Cox proportional hazards and accelerated failure time models to ensure the accuracy of predictions within this model. The Cox proportional hazards model showed the effects of each variable and whether they had a statistically significant effect on mating to lambing interval. Similarly the wastage model used Kaplan-Meier, Cox proportional hazards and accelerated failure time models. Descriptive statistics helped validate the wastage model as reasons for loss were plotted over time, highlighting any substantial events of loss, this was then used to ensure the Cox proportional hazards and accelerated failure time models appeared accurate. The statistical significance of each variable on ewe survival was observed within the Cox proportional hazards model. This ensured all variables included within the accelerated failure time model improved predictions. For both the reproduction and wastage models, when building the accelerated failure time models, five distributions were tested for each. AIC was used as a metric to determine the relative quality of the models, with the best performing model selected for prediction. The overall structure of the model followed established principles followed on UK sheep farms regarding the management component. Care was taken to ensure the simulation model was applicable to the UK industry, particularly when selecting breeds and management decisions. Each sub model was built on data collected from 11 commercial farms, therefore the timing of management decisions were largely extrapolated from the dataset.

The results from the simulation model were consistent with findings within the literature. In a study on Romney ewes, total lifetime weaning weight was observed for ewes selected from either ewe lambs or mature ewes. Total lifetime weaning weight over six production years ranged from 203kg to 232 kg (Pettigrew *et al.*, 2019). This is highly comparable to the average total lifetime weaning weight within the simulation of 225kg. Within the literature it is apparent that breed has a substantial effect on lamb weaning weight. It has been observed that the average lamb weaning weight in Mules is approximately 5kg per lamb greater than Lleyns (Sheep KPI Validation Project, 2014). Extrapolating this heavier average lamb weaning weight across the lifetime of the animal would account for the breed differences observed within the simulation model.

6.4.2. Limitations

The simulation model was designed to observe how ewe factors, with an emphasis on ewe BCS, affect lifetime performance of the animal. It focusses on ewe factors and does not account for management or economic aspects. There are a number of additional models and inputs that would be required to produce a full systems model. These include management factors such as, ewe nutrition, management of health and mating practices. Additionally, environmental factors which are somewhat disconnected from management such as, grass growth and weather could play a vital role within a full systems model.

The development of a bioeconomic model, similar to that of the Teagasc Lamb Production Model (Bohan *et al.*, 2016) has the benefit in that a whole systems model can be developed with an economic evaluation of each model output. The ewe simulation model did not include an economic output due to unknown variables within the data including the management practices previously discussed. It was deemed that the added complexity of an economic output within the model would reduce the generalisability of the simulation, particularly with the large range of farm types and management practices observed within the data.

6.4.3. Summary

Overall, the simulation model provides an effective means of comparing ewe performance under different conditions. It largely shows the importance of ensuring correct BCS at key stages of production, however, integrates this into a model which accounts for reproductive performance and ewe wastage across the lifetime of a ewe. Although ewe performance is observed within the model, the economic cost and output is not included. The simulation model shows that ensuring recommended BCS values are met throughout the productive life of the animal, can result in a significantly greater lifetime lamb weaning weight. This project has developed a novel ewe simulation model unique to the UK industry. The methods used within this research has created a series of robust models which were combined to produce the final simulation model.

Chapter 7. General Discussions and Conclusions

7.1. General Discussions

7.1.1. Project Aims

The first aim of the project was to investigate some of the aims of the Challenge Sheep project through an initial analysis of the Challenge Sheep project dataset followed by the development of a series of models for key areas of production. This research focused on the Challenge Sheep project aim of identifying best practice for the management of replacements, through observing the variables which effect the performance of ewes throughout their productive lives. Throughout this research the importance of effectively managing BCS at all stages of production, and in particular at mating is vital to maximising lifetime productivity. Ensuring ewes are in a moderate or high BCS at mating throughout their productive lives resulted in a significant increase in lifetime productivity in the ewe simulation model (Table 6.4). The simulation agreed with the literature, particularly regarding recommended BCS values around mating which often suggest ewes should be in a higher condition at mating (Wright, 2019). The differences observed between ewes first bred as ewe lambs and shearlings within the simulation is of interest when assessing the Challenge Sheep project aims. The simulation showed that ewe lambs had a significantly higher lifetime productivity when simulated over six years than shearlings, with an average of 12.47kg higher lifetime lamb weaning weight.

The results from the simulation (Table 6.3) showed that Low mating BCS had a significant negative effect on total lifetime lamb weaning weight compared to the Moderate and High groups. The Low mating BCS group weaned on average 27kg less over their productive life. Lambing BCS showed a similar trend with Low BCS animals showing a lower average total lifetime lamb weaning weight. Mules weaned a significantly higher weight of lambs than Lleyns at approximately 60kg more. Over the lifetime of the animal, ewes which first lambed as ewe lambs weaned a significantly higher weight of lambs than ewes which were first mated as shearlings. This is due to the additional year of productivity possible from ewes first bred as ewe lambs. This resulted in around 12.5kg more lamb weaned from ewes first mated as ewe lambs over their lifetime (Table 6.3).

This suggests that industry concerns regarding first breeding ewes before they meet a mature weight on lifetime productivity may be inconsequential. The simulation did however suggest that on average, ewes first bred as ewe lambs were less productive than that of shearlings in a single production year, but due to an additional year of production from ewe lambs the effect of this was mitigated. Similarly, (Thomson, Smith and Muir, 2021) observed an increase in total lifetime lamb weaning weight for ewes first mated as ewe lambs, and also concluded this was due to an additional year of productivity resulting in more lambs born per ewe. A significant increase in total number of foetuses over the lifetime of the ewe has been observed for animals first bred as ewe lambs (Kenyon et al., 2011), further highlighting a potential increase in productivity as a result of additional productive years. It is important for farmers to ensure the correct management of replacements for their individual farms. It appears that post-mating nutrition is important to maximise the lifetime productivity of ewe lambs (Kenyon et al., 2011). Overall this research shows that there is a potential higher lifetime productivity from first breeding as ewe lambs, rather than shearlings, however correct BCS must be maintained throughout.

7.1.2. Predicting Body Condition Score on Farm

Body Condition Score has been consistently promoted as a useful management tool since Russel, Doney and Gunn, (1969) developed and validated the methods used today. The AHDB promotes the use of BCS throughout the whole production year (Wright, 2019), but particularly at mating to help make informed management decision and monitor the health of the flock.

The question of whether weight could be used as a proxy for BCS, within a machine learning model, was raised. This would make it possible to predict BCS from weight and additional predictor variables at key stages of production. Chapter 2 discussed the ability to predict BCS from common ewe factors collected on farm. Predicting BCS has an advantage in that issues around the accuracy of measurements, as a result of subjectivity can be overcome. It may also be a means to reduce labour requirements on farm from manually scoring each animal. The best performing model predicted ewe BCS to approximately half a BCS unit, with an RMSE of 0.46. It was concluded that this was a suitable degree of accuracy to make effective management decisions from predicted BCS values.

The benefit of predicting BCS is not limited to labour savings. It also provides a means to objectively assess BCS values without any of the measurement error traditionally associated with subjective BCS measurement. This allows the comparisons of BCS values between farms which is currently difficult. Within the case study outlined in Chapter 3 it was observed that there was a substantial amount of intra and inter rater variability within the Challenge Sheep project farmers and advisors with an average error from the mean BCS scores of 0.41 units.

Challenges around predicting BCS on farms are largely associated with difficulty in effectively collecting weight measurements and electronically linking these measurements to each ewe. To make the process efficient, technology would have to be implemented in which ewes are weighed on scales with integrated EID weigh heads to automatically record a weight value for each animal. BCS could then be predicted in real time, allowing for an effective means to rapidly predict BCS values to use within management decisions. It is likely not economically viable to use BCS prediction alongside manual weigh scales and manual input of weights into an EID reader, as this would substantially increase labour requirements over traditional body condition scoring.

The future success of using a BCS predictions model rather than manual scoring techniques largely depends on the rate of uptake of technology on sheep farms throughout the UK. The uptake of precision livestock farming (PLF) on small ruminant farms is in its infancy and often not specific enough for effective utilisation. (Morgan-Davies et al., 2024). The effective uptake of PLF is largely dependent on practicality, usefulness and, external pressure and negative feelings (Lima *et al.*, 2018b). When sharing the benefits of predicting BCS over manual recording it is important to not only highlight the potential gains in productivity and labour savings, but also ensure that farmers do not feel under pressure to adopt the technology which could result in lower uptake (Lima et al., 2018). As the industry naturally begins to utilise EID technology as not only a means to track the movement of animal but to record data to aid in effective management decisions, it is much more likely that a BCS predictive model could be integrated into the industry. The ability to compare performance between farms, using an objective measure of BCS may provide a useful performance metric for the industry.

7.1.3. Applying the Ewe Simulation Model as a Management Tool

As the simulation model stands, it is useful in that it highlights the effects of entry status, breed and BCS throughout production on the lifetime performance of a ewe. This may be a useful tool when management decisions regarding the impact of first breeding animals as ewe lambs or shearlings are made, or how BCS and BCS change should be managed throughout production. The wastage model and reproduction model formed the foundation of the ewe simulation model. Each sub model functioned as an individual model, and the performance of each of these models was observed (Chapter 4 and Chapter 5). The process of building each model individually and following a commonly accepted structure for UK sheep production ensured that the model was generalisable to the UK industry. The initial eleven farms were commercial sheep farms, covering a range of management types, which makes the individual models and final ewe simulation model applicable to a wider range of farms. The data collection on farm followed a rigorous process with each scorer receiving training at the start of the Challenge Sheep project, this ensured a high quality of data to form the foundations of the models. Although, as previously discussed, BCS were subjective, it is important to note that the farmers involved in collecting the data were highly trained in measuring BCS and likely substantially better than that of average UK farmers. Overall the process of building the ewe simulation model was rigorous and should provide a largely generalisable model for UK sheep production.

7.1.3.1. Barriers to Use

Similar challenges face the implementation of a ewe simulation model as that of a BCS predictions model (sections 7.1.2). As the industry moves further towards the routine use of PLF, the integration of a ewe simulation model would be efficient. As a standalone model it is useful to compare the lifetime performance of different ewes, and could help inform management decisions. If the model were to be integrated in a larger systems model it could provide the foundation for a powerful tool to aid on farm decision making. Often farm models include an economic which allows easy comparisons between different inputs component (Lydia Farrell, 2020) (Bohan *et al.*, 2016). The lack of an economic component to the ewe simulation model may form a barrier to use, however this would be added within any future research.

7.1.4. Novelty of Research

The concepts used within this research are well understood within the literature. Survival analysis techniques have been effectively used to observe ewe wastage (L Farrell, 2020). Survival analysis or time to event analysis techniques have not previously been used to observe reproductive performance in sheep, however, have been used to observe days open in dairy cows. This research project took a novel approach to simulating aspects of sheep production in the UK. Within our study, using the wastage analysis to estimate the probability of wastage for each day post-mating is unique. Other models often make assumptions on when mortality and culling occurs. Farrell (2020) assumed all ewe deaths occurred at lambing, with 20% of culling at pregnancy scanning and the remainder at weaning. Our approach to predicting the probability of wastage should provide a more accurate estimation of when wastage is occurring for each ewe. The stochasticity of the model accounts for unpredictability both when predicting the probability of wastage and probability of lambing on a specific day. There does not appear to be another UK specific ewe simulation model which takes a mechanistic, stochastic approach to predicting the lifetime performance of an animal. Using the Challenge Sheep project data to inform the simulation model was a unique opportunity to develop a model that is widely generalisable. The large number of datapoints, collected from a substantial number of breeds and different commercial farms gave a unique dataset for analysis.

7.2. General Conclusions

Simulation models within livestock production provide a means to predict the performance of animals while observing interactions within the system. This research developed an effective simulation model for observing the effects of ewe BCS, status at first mating and breed on lifetime productivity. The combination of a reproduction model and wastage model formed the foundation for the simulation model.

The simulation model showed that maintaining ewe BCS throughout production is important to maximise lifetime weaning weight of lambs. Ewes in a lower BCS at mating weaned a significantly lower weight of lambs than that of the Moderate or High groups. Ewes in a moderate and high BCS groups performed similarly, therefore highlighting the importance of ewes not being below the recommended body condition scores. Ewe lambs performed significantly better than shearlings throughout their productive life. This is largely a result of the additional year of production available from ewes first bred as ewe lambs rather than shearlings. This study suggests that concerns regarding the negative knock-on effect from breeding immature ewes may be unfounded as neither reproduction, wastage nor lifetime productivity appears to be impacted within ewe lambs. This is an important consideration for farmers when making management decisions on when to first breed ewes.

Using survival analysis techniques was an effective means to assess both reproductive performance and wastage in ewes. The reproduction analysis showed that in mature ewes, both High and Low mating BCS increased mating to lambing interval, suggesting these groups took longer to conceive. Mating BCS also significantly affected ewe wastage. BCS groups lower than 3.0 had a significantly higher hazard ratio and therefore higher incidence of wastage. Ewes first mated as shearlings experienced higher wastage throughout their lives than that of ewes first mated as ewe lambs. It appears this was largely due to higher exit rates of shearlings pre-mating. Reasons for loss were variable within the data, however certain causes were more prevalent. Mastitis was observed as a substantial reason for loss, particularly towards the end of the production year.

The ability to accurately predict body condition score has the potential to improve management practices on farm. One of the challenges associated with body condition scoring is the degree of subjectivity associated with the scores. This makes it difficult for BCS to be used as a performance metric, and also challenging when using target BCS values during production. The BCS predictive model shows that it is possible to predict BCS to a suitable degree of accuracy to use during management decisions, and appears to predict to a similar degree of consistency as manually scoring. If this was to be used as a tool on farm to quickly predict BCS from weights, a larger selection of breeds would be beneficial to inform the model. The case study observing inter and intra scorer variability when body condition scoring highlights the need for further research into the accuracy and subjectiveness associated with BCS measurements. A more detailed study incorporating previous scorer training and experience would be beneficial.

Overall, this research has provided an insight into the data collected as part of the AHDB Challenge Sheep project. The models developed highlight key factors important for maximising ewe performance. The simulation model shows how ewe wastage and reproductive performance interact to effect lifetime performance of the animal. The final simulation model can be used as a management tool to compare the performance of different ewe entry statuses, to compare breeds and to compare the effects of BCS and BCS change for farmers within the UK industry.

7.3. Further Research

7.3.1. Improving the Prediction of Ewe Body Condition Score

Although within this study BCS was predicted to a suitable degree of accuracy to be used as a useful metric to aid management decisions, the opportunity to improve model performance through the use of additional predictor variables is available. Number of lambs at scanning may improve model fit as it would more accurately account for conceptus weight. Semakula, et al. (2020) concluded that number of lambs at scanning was an important factor to include within a predictive model for BCS. Including further breed types would make the model more generalisable, however the number of breeds included, alongside the range of breeds does encompass a large proportion of ewes in the UK. The subjective nature of BCS measurements made it difficult to estimate error within measurements in the dataset. Even with assessing error in the case study it was still difficult to determine the error in the original dataset in which farmers has solely scored their own animals. Collecting a large dataset using experts who scored each and every animal may help mitigate issues around subjectivity, increasing predictive accuracy. In this study the model was tested on a subset of the original dataset. In future research, testing the predictive model on an out of sample dataset would provide a more accurate indication of the generalisability of the model. Unfortunately, such a dataset was not available for this study.

7.3.2. Using Survival Analysis Techniques to Observe Animal Performance

This study proved that using survival analysis techniques, including Kaplan-Meier analysis and Cox proportional hazards models were an effective means to observe the timing of wastage and the factors affecting ewe wastage on the Challenge Sheep project farms. It was possible to predict the incidence of wastage using a series of predictor variables within an accelerated failure time model. Further research utilising the same survival analysis methods, with additional variables could provide further insight into the causes of ewe wastage. The wastage analysis used data collected over the first four production cycles. To improve the accuracy of wastage in older ewes reaching the end of their productive lives, it would be beneficial to run the analysis on a dataset which followed all ewes to mortality or culling.

The approach to modelling reproductive performance was novel in this study in that traditional reproduction metrics were not observed. Instead mating to lambing interval was observed, which indicated the rate at which ewes conceived, and accounted for any animals which were not in lamb.

7.3.3. Developing a Systems Model for Sheep Production

Within this research the effect of ewe factors on lifetime productivity was simulated. There is substantial scope for simulating other aspects of sheep production to form the foundations of a whole flock systems model. The addition of an economic component to the model would provide an easily understandable metric for farmers. Similar to the TLPM (Bohan *et al.*, 2016), the use of a 'net profit per hectare' metric would be beneficial. This component would require data on lamb and ewe sale prices, feed costs, management and land costs and replacement costs. A nutritional component to the simulation would be highly beneficial as many management decisions revolve around nutrition. The impact of environmental conditions were outside the scope of this project, however the potential benefit from predicting environmental conditions, particularly regarding nutrition (grass growth) and lamb mortality, could be an important metric for farmers to utilise. A similar model to the environmental component of the Grazplan DSS (Donnelly, Moore and Freer, 1997) may be effective.

7.3.4. Additional Data Requirements

Due to the nature of the Challenge Sheep project focussing predominantly on the effects of ewe performance on lifetime productivity, it was challenging to develop some of the components that a larger systems dynamics model would require. Within this study, data collection started at first mating, therefore management of these animals before this point was largely unknown, except for some replacements which were retained from previous animals within the study. This study provides some information on how to best manage ewes during their productive lives after first mating, however does not indicate how to manage replacements in their early life before first mating. A separate study observing the effects of different management practices before first mating would be beneficial, and may help inform the ewe simulation model, particularly regarding the performance of ewe lambs and shearlings.

The analysis were mainly conducted on the first four years of the Challenge Sheep project data. Although the project ends in 2024, the data was not available at the time of analysis. It was impractical to include any subsequent years retrospectively. Building the components of the simulation model on data collected over a ewe's whole productive life may have increased the accuracy of the model, particularly for older animals.

An external dataset for validating the individual models and the ewe simulation model was not available. Testing the model against an external dataset would give a more accurate measure of generalisability, and further ensure the applicability to the UK industry. The dataset would need to include both ewe and progeny data over the lifetime of the animal.

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