Methods to Improve Our Understanding of the Health and Welfare Status of Sheep (*Ovis Aries*) and the Influences of their Immediate Environment

Submitted by

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I certify that all material in this thesis which is not my own work has been identified and that any material that has previously been submitted and approved for the award of a degree by this or any other University has been acknowledged.

Signature: ………………………………………………………………………

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I hope others can continue the research and develop the many other concepts that formed a part of my original PhD outline, that are clearly achievable with today's technology and crucial to support the industry in the future. I am devastated my research ends here but I remain grateful to have been given such an incredible opportunity and thankful to be adding to this novel research area.

To Amber, mum, Hannah and Lewis your ears can finally have a rest! To Darren and Tim, thank you very much for allowing me the time.

Abstract

Studies into the effective use of accelerometers in the automated assessment of sheep behaviour to improve welfare has increased exponentially with promising preliminary results. Previous research has focused primarily on explicit behaviour classification, for example, parturition and urination events, with a view to create a commercial tool that will provide health warnings for farmers. Yet the majority of trials have not been conducted in a farm environment. This study aims to provide essential primary research investigating environmental variables that may influence the behavioural patterns of a commercial flock. This vital information has been largely overlooked and crucial when considering tools that provide health warnings, due to the many factors that influence sheep behaviour such as weather, vegetation, soil type, land typography and breed (Hinch, 2017).

The primary aim of this study was to assess the most appropriate model to predict the behaviours of commercial ewes. This was achieved by deploying accelerometers on a commercial flock and simultaneously collecting manual observations and video recordings of flock's individual activity. The raw acceleration data was processed to create 6 variables. Behaviour classification was also evaluated using three ethograms, each with two mutually exclusive behavioural/postural states: 1. Head Position (head up/down), 2. Posture (standing/lying), 3. Activity (resting/grazing). Three Window setting (3, 5 and 7 seconds) and five machine learning algorithms

(Linear Discriminate Analysis (LDA), Classification and Regression Trees (CART), K Nearest Neighbour (KNN), Support Vector Machines (SVM) and Random Forest (RF)) were evaluated. Results indicated a RF with a 7 second window the optimal model across all ethograms. (Accuracy by ethogram; 1) 91.5%, 2) 91.0% and 3) 99.3%).

The secondary aim of this study was to use a Linear Mixed Model (LMM) to investigate the influence of temperature and rainfall on grazing and resting behaviours. This was accomplished by using the initially developed model (RF) on data collected from an unsupervised commercial flock, recorded in a second trial. Results indicated that there was a significant positive relationship between grazing durations and rainfall (p.001), this finding conflicts with previous research observations and is yet unpublished. In addition, prior sheep behaviour research has suggested ‘foraging’ as the dominant activity, results from this trial indicate the dominant daily activity was resting (67% of daily activity).

In conclusion this study highlights the difficultly of defining what ‘normal’ sheep behaviour is and that it is not viable to implement a ‘one-size fits all’ approach. Further research is required in the behavioural assessment for this particularly malleable species.

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Chapter 1 Overview of the Sheep Industry and Novel Approaches to Improve Production, Health and Welfare

1.0 Introduction

In 2019, the sheep industry in the United Kingdom (UK) achieved the highest price in recent years (£1.3m). This was due in part to the export market being supported by the weakness of the pound (DEFRA, 2019). Despite this, there are many challenges that impact the UK sheep industry and remarkably a rise in novel influences. Brexit, the name given to Britain's separation from the European union (EU) and the unprecedented challenge of Coronavirus (Covid-19) disease, has significantly impacted consumer behaviours and the economy worldwide (AHDB, 2019; Georgalakis, J., 2020; Malley, 2020; Wright, 2020; Vegas, 2020). The Covid-19 disease is a pandemic that emerged in late 2019, identified in Wuhan City in December. There were approximately 2.2m confirmed cases worldwide by mid-April 2020 (Ibarra-Vega, D., 2020). The start of 2020 was an extraordinary time in UK history, as the country went into lockdown; whereby the population was requested to remain indoors, work from home and only go to supermarkets 'when absolutely necessary'. The rules were implemented to 'flatten the epidemic curve' of Covid-19. (Wright, 2020; Ibarra-Vega, D., 2020). Apart from some takeaway services, all other eateries across the UK closed their doors to consumers. Eating out makes up approximately 80% of UK foodservice revenue and it is worth noting that the agricultural industry supplies both the retail and foodservice sectors, which contribute billions annually to the UK economy (Wright, 2020). Lamb meat performs particularly well in both pubs and restaurants as compared to the standard retail environment thus their closure is specifically detrimental to the sheep industry as suggestibly this would result in a significant reduction in UK lamb consumption. (Malley, 2020; Wright, 2020).

Furthermore, the unknown quality of husbandry practices and meat products from a changing market, as a result of Brexit, caused worries for consumers. Combined with the Covid-19 pandemic, a disease that can spread from animals to humans worldwide, unavoidably amplified the already evident concern for food security. Along with existing challenges, climate change, population growth and disease threats that present risks for the UK sheep industry, there is a clear requirement and opportunity to improve transparency, animal health, welfare and production in the livestock sector (Berckmans, D., 2014; Dwyer, C. M, 2008; Georgalakis, J., 2020; Grant, E.P. et al., 2018; Krebs, 2015; Malley, 2020; Montossi, F. et al., 2013; Morris, S. T., 2017; SHAWG, 2018).

The aforementioned challenges are believed to individually and collectively alter the future of agriculture and offer many reasons to explore new approaches to improve farming practices, that will in turn allow for greater transparency to consumers and chiefly a higher standard of animal welfare. The most accepted and successful means to monitor livestock health for many years has been by manually observing their behaviour. This labour-intensive practice has been employed since livestock domestication and is subject to human error and harder to accomplish on larger farms, specifically in the sheep sector where flocks may be distributed over a large area. Therefore, better means for observing livestock have been considered and one that has gained recognition for its use in improving animal health management is an automated behavioural identification method using biosensors (Barwick, J. et al., 2018; Fogarty, E.S. et al., 2020; Learmount, J. et al., 2018; Living Countryside, 1999; NSA, 2020b; Royal Duchy College, 2018; Walton, E. et al., 2018).

Biosensors including and not limited to accelerometers, placed in wearable tools, have enhanced our understanding of animal behaviours by monitoring in field movements of the flock/herd member via gravitational and inertial acceleration signals on three axis (x,y,z). Activities collected and stored in these tools are combined with predictive models and have been evidenced and heavily implemented for many years in the cattle industry, to compliment traditional farming methods. Animal health management tools available commercially, include MooMonitor and Silent Herdsman, the latter utilises a collar to record the activities of each cow and then detects any variability from the individual’s normal behaviour, which are identified to infer onset of illness and oestrus by proxy (Jukan, A. et al., 2017; Neethirajan, S. 2017; Walton, E. et al., 2018).

Biosensors have some clear advantages, enabling objective quantification of the physical activities of sheep without the need to physically observe the flock, allowing sheep to be continued to farm traditionally in an extensive setting. Developing these tools to monitor sheep behaviour could provide a wealth of information, like silent herdsman, potentially detecting behavioural changes correlating to the individual flock members health and welfare fluctuations. (Phythian, C. et al, 2013; Burgunder, J. et al., 2018; Walton, E. et al., 2018). As yet there have been some successful studies identifying basic sheep behaviour; grazing, standing, and walking events (Barwick, J. et al., 2018; Giovanetti, V. et al., 2017). In addition to isolated behaviours such as; urination, (Lush, R. et al., 2018) gastrointestinal parasite infection, (Burgunder, J. et al., 2018) and onset of parturition (Fogarty, E.S. et al., 2020b) all with high levels of accuracy. However, research is still in its initial stages and a commercial tool has yet to be developed. Studies into the effective use of biosensors in the assessment of sheep welfare offers the sector huge potential for improvements and is a developing and an exciting research area (Barwick, J. et al., 2018; Fogarty, E.S. et al., 2020b; Jukan, A. et al., 2017; Neethirajan, S. 2017; Walton, E. et al., 2018).

2.0 Legislation and Leaving the Common Agriculture Policy

Britain's 'world class' and 'world leading' welfare practices are expected to continue to strengthen in the post-Brexit agricultural policy. The UK is considered a 'global leader' in animal welfare, it passed the first animal protection laws in the Martin's Act in 1822. In 1824 it established the first humane society for the protection of sentient creatures, still active today, termed Royal Society for the Prevention of Cruelty to Animals (RSPCA) (DEFRA, 2018; Parliment. House of Commons, 2018). Furthermore, the UK abides by a regulatory standard of animal welfare (DEFRA, 2018). In 2005, the Single Farm Payment (SFP) scheme was implemented to reduce over-production and support farm incomes. The additional benefit of the SFP was to ensure rules were being adhered to, by governing; environmental conservation, food safety, high standards of welfare and husbandry (Parliment. House of Commons, 2007). In 2015, the single farm payment was changed to the Basic Payment

Scheme (BPS), this was designed to be more stringent with added emphasis on food security, sustainability and good husbandry practices (RPA, 2015).

Following a referendum in 2016, the public voted to leave the EU and with it the European Communities control of UK agricultural production (McCulloch, S. P, 2019). The EU commonly set minimum standards of welfare as a basis for member states to form regulations (DEFRA, 2018; McCulloch, S. P, 2019). The UK took this opportunity to view the EUs minimum guidelines and make more 'progressive rules' evidenced by; providing broilers more space, prohibiting veal crates (1990) and banning the use of sow stalls (1999) (DEFRA, 2018; Parliment. House of Commons, 2018; McCulloch, S. P, 2019). It has been suggested that for 40 years the EU framework held back productivity, negatively impacted the environment and as subsequence impacted public health. The new Domestic Agricultural Policy (DAP) is designed to coherently and sensitively, encourage on-farm environmental and technological developments, support profitable food production and inspire a healthier culture (DEFRA, 2018). Despite leaving the EU in 2020, the BPS will remain unchanged until 2021. In September 2018, DEFRA released the new DAP framework set out in the Agricultural Bill, the first key piece of law guiding UK agriculture since 1947. The bill stipulated that from 2021, the direct payments provided to farmers in both England and Wales will be phased out over a total of 7 years, possibly leading to further challenges for livestock producers (AHDB, 2018; DEFRA, 2018; NFU, 2020b).

Compared with its predecessor the DAP has been suggested to have a much greater emphasis on traceability and transparency from 'farm to fork', with an aim to implement publicly funded schemes for 'public goods' to include improvements to air and water quality, boosting wildlife, tackle climate change and for livestock producers to meet higher welfare standards (AHDB, 2018; DEFRA, 2018). Consumer confidence in Britain's husbandry practices could enable a greater return in investments to raise welfare. The policy is set out to encourage producers to go above the minimum premium standard and instead rewards farmers that exceed the benchmark. The policy is utilising the UKs stringent welfare standards as a niche product to sell in our developing market. This has unlocked an opportunity to review and improve current farm management practices to aid in achieving the DAPs refreshed requirements (Parliment. House of Commons, 2018).

3.0 A Review of UK Farming Systems and Stratification

The UK landscape is made up of varying regional terrains. This led to the development of a stratified system of sheep production, which are dictated by locations of lower and upper ground (Allen, N, 2010; NSA, 2020b; Royal Duchy Collage, 2018; Rodriquez-Ledesma, et al., 2011). An essential part of sheep husbandry is to understand the UK stratification and the associated impacts of the various production systems and husbandry practices, before they are adopted (DEFRA, 2002). These variables expose sheep to a range of challenges, for example: varying environmental conditions, geographic locations, typography of the land and grazing strategies. Along with management changes; lambing systems and chosen production calendar. As well as; social structures; flock size, stocking rates, breed variations and their overall performance. A failure to adapt to these challenges may compromise health, reduce production, and impact returns (AHDB, 2015; DEFRA, 2002; Dwyer, CM & Lawrence, AB., 2005; Hargreaves, A.L. & Hutson, G.D., 1990). The stratified system is unique to the UK and enables producers to have a pragmatic and sustainable approach to the differing regional conditions, by exploiting the various breeds, crossbreeds and heterosis, which are better suited to specific environments and farm systems. This is crucial for optimum efficiency and productivity, it is suggested that should one of the tiers collapse, it would alter the UK sheep industry significantly (Allen, N, 2010; Living Countryside, 1999; NSA, 2020b).

The stratification system is divided into three tiers; the lowland flocks, upland flocks, and hill flocks, all of which have adapted to occupy their associated environments and yet remain interdependent as defined below (NSA, 2020; Royal Duchy Collage, 2018):

- Lowland systems

The lowlands are the favourable climates of the low-lying parts of Wales and England. The better conditions allow for a longer overall lambing period, with some lambing enterprises starting as early as December (NSA, 2020b; Royal Dutchy College, 2018). The lowlands typically utilise rotational grazing management strategies, referred to as paddock grazing. Early lambing enterprises will adopt indoor lambing systems. Indoor lambing systems are said to provide shelter from adverse weather conditions and allow for increased supervision for both the ewe and her neonate. Housing ewes enables farmers to rest pasture and increase stocking densities. However, indoor lambing systems have a higher labour costs and are often associated with confinement or significantly reduced space availability (AHDB, 2015; Averós, X. et al., 2014; Berckmans, D., 2014; Centoducati, P. et al., 2015; Dwyer, CM & Lawrence, AB., 2005; Living Countryside, 1999).

The lowlands benefit from an undemanding environment, that allows for desirable grass growth, it is for this reason that its more likely to see a greater volume of intensive farming practice. The main characterisation for intensive farming is 'maximising' production whereby either housed or per acre, there is more livestock per unit of space (Dwyer, CM & Lawrence, AB., 2005; Living Countryside, 1999; NSA, 2020b). Commonly, Mule lambs are sold to the lowlands to mate with terminal sire breeds. Terminal sires are used for their prolificacy to boost lambing percentage targets and for their larger frame, which in turn improves carcase conformation, enabling lambs to be fattened and finished on summer pasture (Allen, N, 2010; NSA, 2020b; Rodriquez-Ledesma, A. et al., 2011; Royal Dutchy College, 2018). In addition to breeding enterprises, the lowland producers will purchase slower growing lambs from hill and upland regions to graze over winter, referred to as store lambs. The store lambs will be fattened on saved grazing or root crops throughout the autumn and winter months, approximately 50% of the store lamb crop will be finished before December and the rest will be sold the following spring, these lambs are then referred to as “hoggets”, this historically is quite a lucrative enterprise (Allen, N, 2010; Living Countryside, 1999; NSA, 2020b; Royal Dutchy College, 2018).

- Upland systems

The uplands are the regions of the Lake District and the Pennines, in addition to Dartmoor and Exmoor in the South West. The soil and lands aren't as productive as the lowlands, with less grass, sword density and variety. The conditions are less unforgiving than some of the higher hill regions and the land is more manageable. The majority of farms in the upland regions will adopt extensive farming systems, often perceived by some to provide higher standards of welfare due to the availability of space and a decrease of restrictions (Dwyer, CM & Lawrence, AB., 2005).

The typography of the land in these areas include, larger flatter fields that allow for cultivation, sward improvement and the use of inputs such as fertilisers and lime (Allen, N, 2010; Living Countryside, 1999; NSA, 2020b; Royal Dutchy College, 2018). The land management and capability to conserve forage for winter feeding, such as haylage or silage, has been linked to a 30-40% increase in lambing percentage of upland flocks, as compared with Hill flocks (Royal Duchy College, 2018). Strip grazing is one of the more popular upland grazing management strategies, allowing the flock to have fresh area of grazing each day.

The common lambing time is late spring and often ewes are lambed outdoors (Living Countryside, 1999). Outdoor lambing systems benefit from a reduction in feed and labour costs, there is also limited handling and interference of ewes and a clear decrease in infectious diseases. Contrastingly it may be harder to catch lambs and or ewes for data collection, tagging, fostering, and administering necessary health checks. There is a risk that poorer weather may cause high losses of new-born lambs, detrimental from a welfare perspective and financially for a breeding enterprise (AHDB, 2015; Dwyer, CM & Lawrence, AB., 2005; Royal Duchy College, 2018). One of the important sources of income for upland farmers is the breeding of Mule ewe lambs to sell to lowland farmers where they are mated to ‘meaty’ terminal sires to produced lambs for meat, referred to as finishers (Allen, N, 2010; Rodriquez-Ledesma, A. et al., 2011). One of most typical parentages of the Mule, is crossing a Swaledale ewe drafted from the hills, to be mated with a Blue-faced Leicester, a long-wool upland breed (Living Countryside, 1999; NSA, 2020b; Royal Dutchy College, 2018; Rodriquez-Ledesma, A. et al., 2011). Mule ewe lambs maximise in heterosis for maternal traits such as rearing ability and survivability and paternal traits such as prolificacy and body weight (Allen, N, 2010; Rodriquez-Ledesma, A. et al., 2011).

- Hill Systems

Hill flocks reside in the Highlands and islands of Scotland and the Welsh mountains. The unforgiving conditions and longer winters reduce growing seasons of forage. The poor quality of soil and low-quality vegetation reduces the ability to conserve forage for winter feeding (NSA, 2020b; Royal Dutchy College, 2018). The most common grazing management of hill flocks is exclusive to extensive farming systems and referred to as set or continuous stocking, this is suggested to be the simplest grazing strategy, whereby a flock will graze one area of grassland for a whole season. Hill flocks are often lambed outdoors in late spring (Royal Duchy College, 2018). Hill and mountain sheep such as Swaledale and Scottish Blackface are mostly kept as pure breeds, these small ewes have adapted to life and are physiologically suited to the hard environment and can function on low inputs and low-quality vegetation boasting attributes such as, hardiness, rearing efficiency and excellent mothering ability (Living Countryside, 1999; NSA, 2020b; Royal Dutchy College, 2018).

Hill breeds generally don’t thrive beyond four lamb crops in the hill regions, due to the exposure of harsher conditions, and therefore pure-bred lambs are kept as replacements and older ewes are drafted to the more sympathetic conditions of the uplands for cross breeding. Crossbred ewe production is very successful and accounts for up to 56% of the UK flock (Allen, N, 2010; Moore, K & Kaseja, K., 2015; Royal Duchy Collage, 2018; Rodriquez-Ledesma, A. et al., 2011). In order to produce Mules, pure-bred hardy hill ewe breeds are drafted to the uplands and classically mated with a Blue-faced Leister or a similar prolific ram of the long-wool breed variety. The resultant Draft ewes and store lambs are a vital income for hill farmers (Living Countryside, 1999; Royal Dutchy College, 2018).

It would be unfair to say which farm management strategy is superior for the animal from a welfare perspective, without a more granular investigation, as there are numerous pros and cons in all system types. Historically the farm environment, group size and stocking density are often dictated by production goals and not what may be ideal from a welfare standpoint (Dwyer, CM & Lawrence, AB., 2005; Averós, X. et al., 2014). Due to consumer awareness, the rise in interest in animal welfare groups and new agricultural policy implementation, there is palpable pressure to improve the life experienced by animals for meat production and boost welfare, using novel faming approaches (DEFRA, 2018; Grant, E.P. et al., 2018; Hargreaves, A.L. & Hutson, G.D., 1990).

4.0 Novel Approaches to Improve Health and Welfare

The term ‘welfare’ refers to the ‘ethical concerns’ about the ‘quality of life’ experienced by animals (Duncan, I. & Fraser, D, 1997; Hansen, B. G. & Osteras, O, 2019). In addition to abiding to the framework of the DAP and its predecessors, the farm council designed a code for the welfare of sheep. The main emphasis is to encourage keepers to have high standards of husbandry to safeguard livestock (DEFRA, 2002). The code includes guidance on the day-to-day management of sheep, farm buildings and stocking densities for housed systems. The code provides general recommendations for good agricultural practice and features the potential risks and impacts of differing systems, as well as highlight the five principles of animal welfare. The five principles were developed by Brambell in 1965 and referred to as the ‘Five Freedoms’; freedom from hunger and thirst, freedom from discomfort, freedom from pain, injury or disease, freedom from fear and distress and freedom to express normal behaviour. (Brambell, 1965; DEFRA, 2002). Brambell’s principles and Duncan and Fraser’s definition highlight that the welfare of sheep encompasses the animal’s health and disease status, along with optimum behavioural expression and an understanding of the impacts of husbandry and management practices. As a result, sheep welfare is arguably difficult to quantify (Brambell, F. W. R, 1965; Duncan, I. & Fraser, D, 1997; Gougoulis, A. et al., 2010).

Poor animal health and welfare is potentially devastating to the keeper and UK sheep industry. In 2005 gastro-intestinal parasites were recorded to have cost the industry £84 million annually, due in part to the increase of multiple resistance of broad-spectrum anthelmintic classes. Loss of parasite control due to anthelmintic resistance may result in the farming livestock in the UK becoming increasingly uneconomical, without effective intervention. (Learmount, J. et al., 2018; SHAWG 2016). Further health and welfare challenges include Liver fluke at an estimated £3-5s per head annually of infected flock members, abortion caused by three main infections, Enzootic abortion, Chlamydia abortus and Toxoplasmosis at an annual estimate cost of £30 million. Furthermore, the annual cost of footrot was recorded at £24 million, due in part to the additional farm labour for providing treatment and that of the reduced performance of the lame sheep (AHDB, 2015). In addition to lameness from contagious ovine digital dermatitis (CODD) that has been recorded on 35–53% of farms in England and Wales (AHDB, 2019). This exhaustive list of health challenges and the rise in adopting intensive farming practices across the livestock sector led to considerable research undertaken to investigate whether housing and higher stocking densities may inhibit health and welfare, results in the sheep sector include; a strong relationship between stocking rates and microbial air quality, higher incidence of mastitis, higher aggression levels, mis-mothering and a decrease in feed efficiency and growth of young lambs (Averós, X. et al., 2014; Barwick, J. et al., 2018a; Boe, K. E. et al., 2006; Centoducati, P. et al., 2015; Estevez, I. et al., 2007).

Efforts over the past few years to improve production and welfare by the development of precision sheep management (PSM), a system in which sheep are managed at an individual level utilising 'walk over weight' scales, EID tags and remote drafting systems as reviewed by Morris, J.E. et al, (2012) have gone a long way to improve farming strategies and have encouraged British sheep farmers to consider various technologies to complement traditional husbandry practices. The DAP objective to collaborate with veterinary professionals and industry representatives in the investigation and assessment of novel tools, that may be better placed to reduce both the animal welfare and economic impacts of endemic disease and poor health, has the potential to offer prodigious support to the sheep industry (DEFRA, 2018, Paterson MP, R. H. O, 2017).

The augmentation of precision farming tools has been implemented widely in the cattle industry evidenced in research and subsequent adoption of commercial tools to boost performance, welfare and aid husbandry practices. Adoption of animal-borne sensing devices has increased over the last decade and well established in the cattle industry, markedly diary. Due to the advances, most notably in the miniaturisation of sensing technology and improved battery life their use has broadened across the livestock industry. Commonly these innovative wearable tools utilise accelerometers. As mentioned previously, accelerometers are a mechanism designed to use gravitational and inertial acceleration signals, typically on three axis (x,y,z). Signals are generated by movement of host animals and later activities and postural states are identified when combined with a classification tree model (Barwick, J. et al., 2018; Fogarty, E.S. et al., 2020). These models use observed behaviours (categorical variables) as training data which is then used to perform predictive analysis on unclassified data collected from unobserved animals, by way of an regression analysis (Dutta , R. et al., 2015; Gonzales, L. A. et al., 2015; Rahman, A. et al., 2018; Valletta, J.J. et al., 2017). Tree based learning algorithms are suggested to be one of the leading supervised learning methods, capable of achieving high accuracy (Dutta, R. et al., 2015; Gonzales, L. A. et al., 2015; Rahman, A. et al., 2018). There have been many findings to demonstrate that there is a higher evidence of suffering stress from qualitative behavioural assessment than that of endocrine biochemical results (Centoducati, et al., 2015; Phythian, et al., 2013). Technological advances are believed to go a long way in enabling the enhancement of welfare and in turn maximising productivity. With evidence to suggest that behavioural data can be used efficiently to improve welfare, performance, productivity and traceability at the farm level. As well as identify disease threats, it is considered that this collation of qualitative and quantitative data will create a superior quality of welfare which will contribute towards future bench marks and policy implementation in the UK and potentially drive a global standard (DEFRA, 2018). Barwick, et al., (2018) advocates that animal behaviour can be a valuable metric of an animal's health status. Behavioural data at a commercial level may provide an enhanced understanding of the welfare status of sheep and aid keepers to maximise production, due to the capabilities to overcome their restrained habitual behaviour (Gougoulis, A. et al., 2010). Sheep are impassive in their behavioural expression and at an individual level it is difficult to assess pain, fear or suffering (Barwick, J. et al., 2018a; Hinch, G. N, 2017).

Studies into the effective use of accelerometers in the assessment of sheep welfare is a developing research area with promising preliminary results, that suggest their future use in non-invasive and non-disruptive farm tools is viable, yet research to validate these tools in commercial environments is still in its infancy (Phythian, C. et al, 2013; Burgunder, J. et al., 2018). Barwick, J. et al., (2018a) validated that ear tag deployed accelerometers were capable of identifying basic sheep behaviour with >90% accuracy for grazing, standing and walking events, as also demonstrated by Giovanetti, V. et al., (2017) that recorded sheep grazing behaviour with high levels of accuracy. Additionally, Lush, R. et al., (2018) were similarly able to detect sheep urination events using accelerometers with high precision. Burgunder, J. et al., (2018) successfully recorded activity variations of untreated individuals that suffered from a gastrointestinal parasite infection. These results provide evidence that distinct behaviours can be measured, classified, and subsequently predicted.

Despite the rise and popularity of implementing accelerometer technology in the sheep sector, their utilisation in research to gain a better understanding of the many variables that influence activity such as; farm system, climate, environment and breed type, in addition to health and welfare status of commercially reared sheep, has been largely unsubstantiated, as concluded by Fogarty, E.S. et al., (2020a) following a recent study. Furthermore, breed variation needs to be taken into account due to potential biomechanical variation, as well as individual behavioural idiosyncrasies. There is a documented disparity in the expression of natural behaviours, due largely to the extensive and varying genotypes across the 2000 sheep breeds (Barwick, J. et al., 2018a; Fogarty, E.S. et al., 2020a; Hinch, G. N, 2017). In addition, in previously published research that have examined specific behaviour classification, there have been various study designs, farm environments and interpretations and classifications of a wide-range of behavioural states as a result acceleration signatures of recurrent behaviours may differ (Fogarty, E.S. et al., 2020a; Barwick, J. et al., 2018a).

The author suggests that it is vital to understand how the behaviours of a healthy flock are influenced by their environment, to assure the efficacy of the predictive models before they are utilised to provide performance information such as; lameness or the onset of parturition, in a research or commercial capacity.

5.0 Aims

The key objective of this study is to use accelerometer technology to establish the best technique of; recording, processing and classifying sheep behaviour of an unsupervised commercial flock of sheep. Furthermore, the data collected is hoped to provide a wealth of information resulting in a wider understanding of flock activity over an extended period. It is an opportunity to compare results to previous studies where flocks were monitored using traditional methods of observation to investigate whether there are some new insights gained from the novel approaches of assessing sheep by limiting the use of human intervention and observation, which in itself may have modified animal behaviour (Barwick, J. et al., 2018a).

The overarching aim of this study is to select the most appropriate model and later investigate environmental variables that may influence the behaviour of a commercial flock. Findings may contribute to improving the efficacy of predictive models by doing essential primary research, that seems to have been overlooked. It is crucial to understand any influences, so that we can be sure that outliers detected in future farm tools are not misclassified as specific health or welfare issues. Based on the lack of literature investigating environmental influence of an unsupervised commercial flock, we can assume it is yet to be investigated and provides a novel and truly exciting area of study.

6.0 Thesis outline

The thesis is structured to include two standalone data chapters and a final chapter for general conclusions:

- Chapter 2 Methods to classify sheep (Ovis Aries) behaviour

In this chapter, we will record and evaluate three areas: window setting, model type and behaviour type. We will then use these results to investigate and classify sheep behaviour to create the most appropriate model in an extensive environment using a tri-axial accelerometer.

- Chapter 3 Using accelerometer technology and a random forest algorithm to predict the behaviours of unsupervised sheep and explore the effects of temperature and rainfall on daily behaviour durations

We will utilise tri-axial accelerometers and the classification model developed following the initial trial in chapter 2, to predict behaviours of an unsupervised commercial flock of sheep and as a result later draw insights on the effects of temperature, rainfall and their interaction. It would be essential to investigate the relationships between environment and behaviour further, to better understand the influence this has on their overall welfare status of sheep in a commercial environment.

- Chapter 4 General Conclusions

This chapter is a collation of the thesis findings and discusses them in a broader context.

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Chapter 2 Methods to classify sheep (*Ovis Aries*) behaviour

1.0 Introduction

The sheep industry in the United Kingdom (UK) suffers from three primary and inherently linked challenges: production demand, optimisation of animal health and welfare and the prevalence of disease. In 2020 it was recorded that endemic disease in livestock cost the industry approximately £7 billion a year, as well as being devasting at a farm level due to production loss and additional labour costs (DEFRA, 2020; AHDB, 2015). Notable health and welfare issues in the sheep sector such as anthelmintic resistance and footrot cause huge financial implications, £84 million and £24 million respectively (AHDB, 2015; Learmount, J. et al., 2018; SHAWG, 2018). A rising population and with it the growing pressure for animal products worldwide demonstrate a need to increase lamb yield. This anticipated population growth and in addition to impacts on growing seasons predicted by climate change may in turn reduce available grazing, all of which may result in the motivation to implement intensive farming systems. The results of this highlights many obstacles for the future of the sheep industry, of a nature that could present further welfare challenges. Farmers will need to focus on meeting the desired production levels required whilst adapting to ever-changing demands without compromising animal health and welfare. Furthermore, along with what was already an exhaustive list of pressures, there has been a growing rise in consumer concern with regards to the operation of the agriculture industry with a desire to improve and evidence animal welfare standards across all livestock sectors (Berckmans, D., 2014; Learmount, J. et al., 2018; Krebs, 2015; SHAWG 2017).

At present extensive systems are more commonly adopted in the sheep sector. In extensive farming systems, lower stocking densities are adopted in both fields and housing, enabling more space availability (Dwyer, CM & Lawrence, AB., 2005). Even though these systems utilise sheds for lambing, the majority of UK flocks spend much of their production calendar at grass. Although this may seem optimum for ewe health by reducing disease prevalence, in contrast when animals are kept in high volumes or kept over vast distances, it becomes incredibly difficult to reliably monitor animals individually which presents a welfare issue (Berckmans, D., 2014; Learmount, J. et al., 2018; SHAWG 2017). In the case where sheep are not yet showing clinical signs of disease or remain able to uphold synchronous behaviours some health issues may be missed, research has shown that the individual animal's posture and locomotion can be used as key indicators of overall health and welfare (Barwick, J. et al., 2018a; Barwick, J. et al., 2020; Berckmans, D., 2014; Dutta, R. et al., 2015; Dwyer, C.M, 2008; Fogarty, E.S. et al., 2020a; Gonzales, L.A. et al., 2015; Martiskainen, P. et al., 2009; Montossi, F. et al., 2013; Morris, S.T, 2017; Moreau, M. et al., 2009; Rahman, A. et al., 2018; Weary, D. et al., 2009).

Understanding how posture and locomotion is represented in the activity and thus behaviours of sheep could be especially useful in understanding their health status, by refining observational assessments. Over the last decade studying the movement, physiology and behaviour of free-ranging animals has been demonstrated to underpin the performance goals of commercially farmed livestock, most notably in cattle and is considered to be one of the most common and sensitive indicators of animal health. For example; activity levels based on walking, standing and lying behaviours of dairy cows have been collated and examined to determine the health status and comfort of cows in their environment, as well the stage of their oestrus cycle (Elischer, M.F., et al. (2013).

There has been a notable increase in behavioural research in the sheep sector due to the adoption and success of various micro-electromechanical technologies, such as accelerometer sensors following continued development yielding smaller and more affordable units (Nathan, R. et al., 2012; Walton, E. et al., 2018). In multiple research trials, both collar and ear tag application, have been evidenced to successfully capture behavioural changes correlated to variations in the health and welfare status of sheep (Barwick, J. et al., 2018a; Fogarty, E.S. et al., 2020a, Giovannetti, V. et al., 2017; Walton, E. et al., 2018, Lush, R. et al., 2018). In addition, there have been further studies using accelerometers for specific application to effectively record; lameness (Barwick, J. et al., 2018b) parturition (Fogarty, E.S. et al., 2020b) and individuals suffering from a gastrointestinal worm burden (Burgunder, J. et al., 2018). While furthering this research has huge benefits from the perspective of cascading these findings at all levels in the sheep sector, the commercial prospect is invaluable. Remote sensing technology could be utilised to indicate the onset of health and welfare issues by highlighting alterations in behavioural activity without potentially disruptive and persistent human intervention. (Fogarty, E.S. et al., 2020a; Fogarty, E.S. et al., 2020b; Bailey, D. et al., 2018; Müller, R. & Schrader, L., 2003; Neethirajan, S., 2017; Schoenig, S.A. et al., 2004; Trotter, M, 2013; Vázquez, A.I et al., 2019).

Producing an early warning system by expanding on this research would allow the farmer the opportunity to streamline decision making, potentially enabling earlier diagnosis and treatment, and subsequently improving welfare and profitability. Further research and development are required to ascertain the best method of recording and processing sheep behaviour. Breed variation needs to be taken into account due to potential biomechanical variation, as well as individual behavioural idiosyncrasies. It is also imperative to note that in previously published research there have been multiple variations of study designs, e.g. farm environment, along with varied interpretations and classifications of wide-ranging behavioural states, these variables may result in differing signatures in acceleration of common behaviours (Fogarty, E.S. et al., 2020a; Barwick, J. et al., 2018a).

The overarching aim is to select the most appropriate model to further our investigation into the daily behaviours of a healthy commercial flock. To accomplish this, I will investigate the most appropriate algorithm for the data collected in our trial. This will be achieved by following the guidance provided by Fogarty, E.S. et al., (2020a) by evaluating three areas: window setting, model type and behaviour type:
1) **Window setting:** This is the minimum duration of time that behaviours will be segmented in to training data and predicted behaviours and crucial for the effectiveness of an algorithm; the overall goal is to reduce potential misclassification by choosing the optimum length. The time segment needs to contain only a single behaviour for its duration, as data containing possible behavioural variability, or the inclusion of transitioning behaviours may ‘dilute’

the signals that are attempting to be identified (Chen, K.Y. & Bassett, D.R., 2005; Fogarty, E.S. et al., 2020a; Fogarty, E.S. et al., 2020b; Walton, E. et al., 2018). As concluded by Fogarty, E.S. et al., (2020a) the most appropriate window setting for behaviour detection has not yet been explicitly defined and due to the higher volume of shorter observation windows in the data collated from our trial, it was decided that our window settings mimicked that of Walton, E. et al., (2018) comparing; 3, 5 and 7 seconds.

2) **Modelling:** Choosing the most effective machine learning algorithm was completed by exploring five classification models using the 'caret' package in R as detailed below (Kuhn, 2022; R Core Team, 2020):

- Linear Discriminate Analysis (LDA) condenses the data attributes by enhancing the variance between classes and at the same time decreases the variation within the class (Nathan, R. et al., 2012).
- Classification and Regression Trees (CART) are a popular and simple predictive model when decision rules such as yes/no questions are required. In contrast to alternative algorithms predictive performance can be poor, as they are prone to overfitting (Fogarty, E.S. et al., 2020a).
- The K Nearest Neighbour (KNN) algorithm referred to as a 'lazy learner', is one of the simplest forms of machine learning algorithm, it works by classifying data based on the distance from *k* neighbouring observations (Zhang, S., 2020).
- Support Vector Machines (SVM) use a distinct kernel function to construct a hyperplane to separate observations, maximising the distance between data points (Martiskainen, P. et al., 2009; Nathan, R. et al., 2012).
- Random Forests (RF) use a similar process to CART, albeit they offer increased accuracy as multiple classification trees are created, it is because of this that RFs are referred to as an 'ensemble classifier' (Nathan, R. et al., 2012).

3) **Behaviours:** In a previously published study in the assessment of models to classify sheep behaviour, Fogarty, E.S. et al., (2020a) concluded that explicit behaviour identification may be a disadvantage to model efficacy, due in part to both the requirement of a definitive range of 'taught' behaviours that may not be pertinent to the performed behaviour and because the more data there is to process, the greater the computational intensity. This was demonstrated in their results; the ethogram to classify grazing, lying, standing, and walking, achieved

>70% accuracy and in contrast, classification of active or inactive behaviours achieved >90% accuracy. Models that are used to predict between two opposing states suggestibly have greater accuracy levels due to the reduced complexity of the model. Following the findings by Fogarty, E.S. et al., (2020a), in this study the author opted to split ethograms in to postural and activity classes and in each ethogram select two opposing behaviour or postural states to boost model performance. Additionally, an ethogram to classify head orientation was investigated, as neck orientation may provide a greater level of insight, to complement the postural and activity classes:

- Detection of Head Position - Neck orientation (Neck up or neck down)
- Detection of Body posture - Standing or Lying
- Detection of Activity – Active or Inactive – (Grazing = Active, Resting = Inactive)

2.0 Materials and methods

2.1 Data Collection

A trial was conducted on a small holding in Southwest England in the county of Somerset. 10 grass kept commercially reared ewes of comparable parity, age (Table 1) and body condition were selected for observation by the author and fitted with purpose made accelerometer collars.

Sheep	Age	Body Condition Score	Parity
1	5	4.5	3
2	5	4.5	3
3	5	4	3
4	5	4.5	3
5	4	4	2
6	3	4	1
7	5	5	3
8	3	3.5	1
9	3	4	1
10	3	4	1
Mean	**4**	**4**	**2**

Table 1: Flock Data, age body condition score and parity.

The ewes had worn the collars in previous studies and were handled regularly, they were accepting of the collar and did not show any indicators of stress during the handling process. Furthermore, ewes were free to roam in their normal field boundary, making up a total of 20 acres. There was not a purpose made shelter for the livestock, however the farm boundary consisted of large trees to provide natural relief from harsh conditions, with access to three troughs.

The tri-axial accelerometer GENEactiv unit was used due to its robust design, the unit is both waterproof and light weight (16g without straps). The battery life was not limiting and capable of lasting for up to a month depending on the recording frequency, accuracy has been recorded to be improved with higher recordings frequencies, as the study was over a short time period the recording frequency was set at 50hz (ActivInsights Ltd, 2015; Walton, E. et al., 2018). The GENEactiv unit was fitted to a Shearwell bell collar with Velcro and insulation tape (Figure 1). The Shearwell bell collar was used as it is designed to be worn in a commercial setting by sheep. Collars were deployed on the afternoon of 29th August 2018, as mentioned, these ewes are desensitised to handling and the wearing of collars and did not demonstrate any obvious signs of distress. Following deployment of tags, ewes were immediately returned to their field. Data collection started on the morning of the 31st August (Day 1). Collars were removed on the evening of 2nd September 2018 (Day 3). Accelerometer data was then downloaded using the GeneActiv software package.

Figure 1: Ewe wearing Shearwell Bell collar fitted with a GENEactiv accelerometer unit.

2.2 Behavioural Observations and Video Annotation

For ease at the time of handling the ewes were numbered with stock spray on both sides. Due to the remote access of some areas of the farm, it was decided that the observer would monitor sheep in an adjacent field, if viewing was obstructed the alternative was to be in the same field monitoring from a minimum of 20 meters away, so as to not to impact natural behaviours. Behaviours were recorded manually on day 1 and day 2 from 08:00am to 11:00am and on day 3 from 13:00pm to 16:00pm, the alteration in time on day 3 was due to a large amount of resting time taking place in the mornings during the observation window. The manual observations were collected at the most granular level, for example all behaviours were captured, such as drinking, itching, head shaking, head butting etc. For the purpose of this chapter these behaviours were later grouped as per the ethograms used in this study. Due to the nature of the free roaming ewes that spread across multiple fields capturing manual observations by the author was difficult, to mitigate against this a web camera was placed on fence lines and attached to the authors laptop. The purpose of the video recording was to validate the video behaviours against the 'live' manual observations. It became apparent that sheep can change behaviour extremely quickly and thus there was potential for behavioural changes of several individuals to be missed whilst annotating others. For this reason, the video annotations were considered to be superior to the 'live' manual observations.

Approximately 10 hours of human observation and video recordings took place creating 100 sheep hours of data (before cleaning). The manual observations and multiple videos were annotated to the second and later scrutinised by the author to create an ethogram of categorical behaviour. In order to classify videos more efficiently a video player was developed, using a standard windows MediaElement component (Figure 2), videos files were broken up into shorter blocks which reduced the sensitivity of the scroll bar. The second bar and set position were used to create an ethogram from the videos by the author. All visible activities were collated with start time and end time, unseen or unrecognised behaviours were labelled as ‘unknown’ and later discarded. Despite no signs of lameness prior to the study, one ewe became visibly lame during the trial and was subsequently removed from the trial and the data discarded.

Figure 2: Screen shot of the purpose made video player used to scrutinise video recordings of the trial flock.

2.3 Ethogram Development

For the purpose of this study, ethograms were grouped based on a hierarchy of the individual physiological and behavioural states, two behaviours for each algorithm were used in order to reduce algorithm complexity. Specific behaviours: activity, eating and resting, performed outside of their “normal” range are debated to be predictors for disease detection in cattle (Eckelkamp, E. A., 2019; Edwards, J. L. & Tozer, P. R., 2004, Liboreiro, D. N. et al., 2015, Stangferro. et al., 2016). Furthermore, Barwick, J. et al (2018a) suggested that the combination of posture and the level of activity is the primary measure for determining an individual ewe’s health and welfare status (Barwick, J. et al., 2018a; Fogarty, E.S. et al. , 2020a; Moreau, M. et al. , 2009; Weary, D. et al., 2009). All behaviours were collected, the granularity of the data was documented to future proof the trial and offer the author an opportunity to perform a deeper dive on the data if needed at a later date. It is worth noting that as with the study produced by Fogarty, E.S. et al., (2020a), walking was one of the harder behaviours to record in volume and for the purposes of the study and our investigation, walking was best to be included in activity and omitted in isolation.

- Ethogram 1 - Head Position – Head up or head down
- Ethogram 2 – Posture – Standing or Lying
- Ethogram 3 – Activity – Resting or grazing

As mentioned previously where a ewe remained hidden from view by the observer or camera and in the rare case that there was a discrepancy between live manual observations and video observations for the same time period, these events were classified as ‘unknown’ and were deleted as part of the data cleaning process, which inevitably reduced the sample size. Two ewes had to be removed from the study, one due to lameness (as previously mentioned) and the other due to the low volume of known recordings. The latter seemed to remain out of view in almost all videos and masked by other ewes when being observed, all be it marginal she was the youngest of the group and it seemed like an obvious evasive action to being watched.

2.4 Data Processing

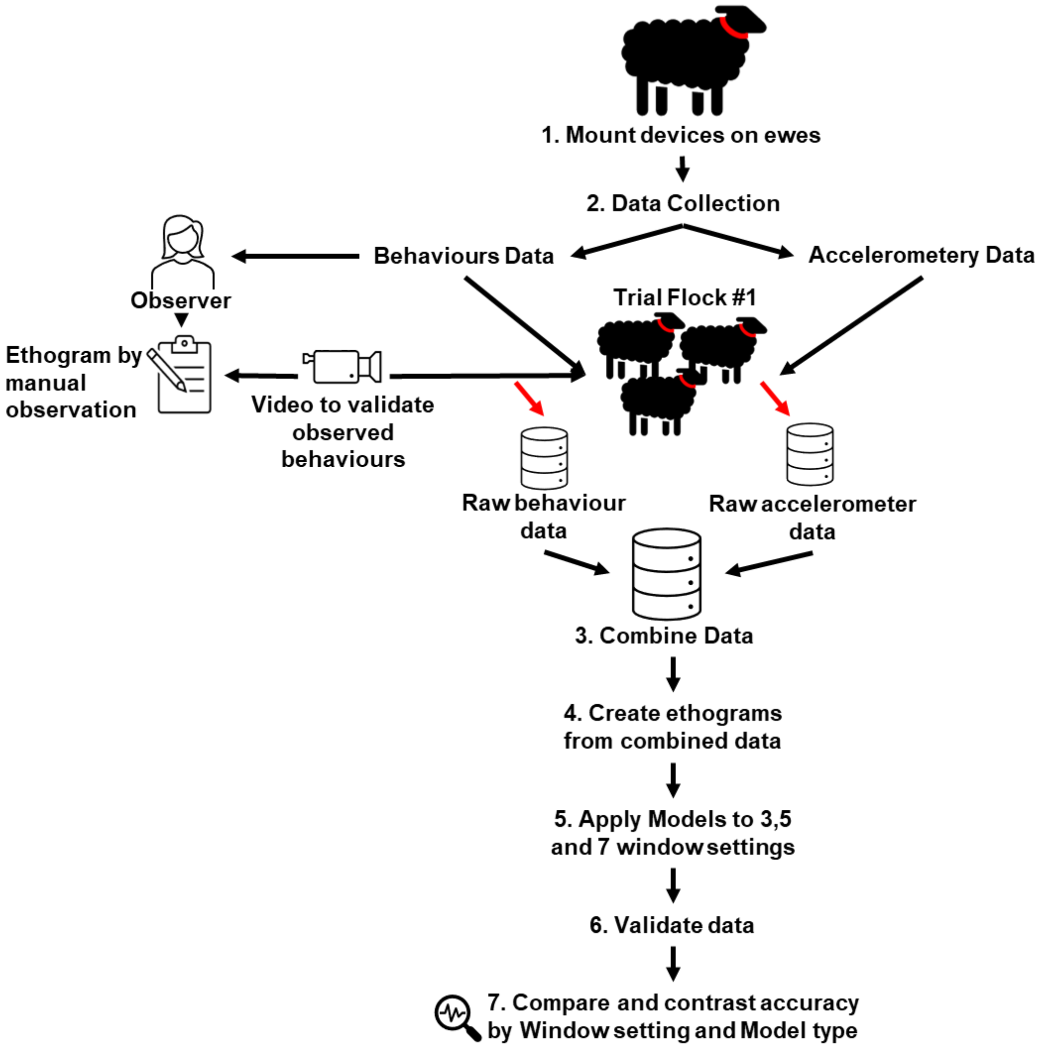

Figure 3: Methods Diagram

2.4.1 Behaviour Data

Video annotations were collated into a master file, with each row containing, Sheep ID, the corresponding behaviour class and the min, max and total duration values of each behaviour segment. Furthermore, each row line included the name of the raw accelerometer binary file. Three window settings were selected for comparison: 3, 5 and 7 seconds. The dataset was produced 3 times, one for each window setting. A column was added to each sheet, to contain the 'Number of epochs' (duration/epoch) within each behaviour segment, any activities under the duration of the chosen epoch setting were excluded, however segments over 1 epoch in length were rounded up.

2.4.2 Accelerometer Data

The raw data that is stored in each GeneActiv device was collated, the columns include; mean of X, Y and Z axis, sheepID and timestamp. For each time window a set of seven feature characteristics were created by a change point analysis, developed by GeneActiv using the GeneAClassify and the changepoint package, were calculated using R (R Core Team, 2020) and defined as follows; UpDownMean; the mean position of the neck position, UpDownMedian; the median position of the neck position, UpDownVar; variance position of the neck position, UpDownSD; the standard deviation of the neck position, UpDownMAD; Mean absolute deviation of neck position, UpDownSkew; skewness of the neck position and MAGSA Mean Acceleration of the neck position(ActivInsights, 2020; Campbell. et al., 2021; Chen, et al,. 2000).

2.4.3 Combined behaviour Data Output

The three behaviour sets, one for each window setting (2.4.1) were used to align with the analysed accelerometery data (2.4.2) using the time stamps of the observed behaviour. The output of this process was a further three datasets containing: the seven calculated feature values (2.4.2), sheep ID, time and date and the corresponding qualitative behaviour class (2.4.1).

2.5 Classification and Predictive Model

Model development was conducted in R (R Core Team, 2020) using the ‘caret’ package (Kuhn, 2022). The caret package was used to create and compare five supervised machine learning models, used for the classification of each ethogram (LDA, CART, KNN, SVM and RF). As demonstrated in previous research, some machine learning models may outperform others at predicting specific behaviours. It was therefore essential to compare a range of models (Fogarty, E.S. et al., 2020a). As with the study produced by Walton, E. et al., (2018) and Fogarty, E.S. et al., (2020a) all models were tested by splitting the full dataset into a training and test set. Model development was made up of the training set at 70% of the original dataset and the remaining 30% was used to validate the models.

2.6 Validation

Model and Classifiers were conducted in R using the ‘caret’ package (Kuhn, 2022) and augmented by using a 10-fold cross validation (Zhang, H. et al. , 2015), this meant that the dataset was divided into ten equal subsets at random. At each iteration, nine subsets were used to build the model while the remaining subset was used for prediction. In conclusion, the final measurement was the average accuracy of all ten iterations (Zhang, H. et al., 2015). Although not essential for the RF, it was decided that all the features should be normalised. This is so that features with a larger range of values will not have an undue influence on the prediction of the behavioural classes, this is because many classifiers and models calculate Euclidean distance using the variance between two data points. The simplest method of normalising is ‘min-max scaling’, the formula for a min-max of [0, 1] is generally given as:

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)'}$$

where x is an original value and x' is the normalised value (Borkin, D. et al., 2019).

From the 10-fold cross validation a confusion matrix was calculated using the ‘MLMetrics’ package in R (Yan, 2016). In order to provide a comprehensive review of the performance of the classification for each, model, ethogram and window size, key performance measures, such as; overall accuracy, kappa, precision, sensitivity and specificity are calculated, using the following equations (F.A.P. Alvarenga, I., 2016; Barwick, J. et al., 2018a; Fogarty, E.S. et al. , 2020a; Yan, 2016):

Overall accuracy = $\frac{(true\ positives + true\ negatives)}{(true\ postives + true\ negatives + false\ positives + false\ negatives)}$

Precision = $\frac{true\ positives}{(true\ postives + false\ positives)}$

Sensitivity =$\frac{true\ positives}{(true\ postives + false\ negatives)}$

Specificity =$\frac{true\ negatives}{(true\ negatives + false\ Positives)}$

F.A.P. Alvarenga, I., (2016) defines the equation definitions as;

- True positive = volume of correctly identified behaviours.
- False negative = volume where the behaviour of interest was misclassified as an alternative behaviour.
- False positive = volume where the behaviour of interest was incorrectly classified as not being observed.
- True negative = volume of correctly classified behavioural states as not being observed.

The Kappa value output from the various models provides a value ranging between 0.00 = 'poor' to 1.00 = 'almost perfect', by comparing the observed accuracy with a predicted accuracy, (F.A.P. Alvarenga, I., 2016; Fogarty, E.S. et al., 2020a; Landis, J.R. & Koch, G.G., 1977).

3.0 Results

3.1 Ethogram One: Head Position – Head up or head down

For ethogram one, the proportion of epoch observations are much higher for head down (80%) unsurprising due to the volume or resting by all ewes during the observation window over the initial two trial days. A summary of the total number of epochs collected for each behaviour are in Table 2.

Table 2: Count of epoch observations by animal and behaviour.

	Ethogram 1 - Head Position (Primary) – Head up or head down						Ethogram 2 - Posture (Secondary) – Standing or Lying						Ethogram 3 - Activity (3rd Tier) – Resting or grazing					
	Head Up			Head Down			Standing			Lying			Grazing			Resting		
Sheep ID	**3**	**5**	**7**	**3**	**5**	**7**	**3**	**5**	**7**	**3**	**5**	**7**	**3**	**5**	**7**	**3**	**5**	**7**
1	761	456	327	1713	1044	733	1717	1037	747	1026	615	440	72	44	31	947	570	409
2	1120	675	489	2024	1230	897	799	483	352	3068	1843	1316	317	193	141	2514	1512	1082
3	892	543	383	1481	895	646	434	264	187	2138	1281	916	n/a	n/a	n/a	1898	1141	818
4	1137	688	490	847	512	365	1947	1173	844	787	473	337	69	41	28	366	219	157
5	203	124	83	2650	1600	1147	1212	729	526	3013	1810	1292	785	472	334	2547	1532	1096
6	312	185	136	3505	2107	1503	1196	720	517	3096	1857	1326	692	415	296	3088	1856	1330
7	248	146	99	2816	1692	1213	2141	1290	926	2064	1240	886	865	520	371	1614	971	693
10	113	68	48	3792	2279	1632	1061	639	458	3262	1957	1398	905	544	390	3254	1958	1399
Total	**4786**	**2885**	**2055**	**18828**	**11359**	**8136**	**10507**	**6335**	**4557**	**18454**	**11076**	**7911**	**3705**	**2229**	**1591**	**16228**	**9759**	**6984**

The results for Ethogram one: Head Position for each of the models and window size is in Table 2. The highest performing algorithm was the SVM using a 5 s epoch, with accuracy recorded at 91.7%. The LDA was the lowest performing model across all window settings.

Table 3: Accuracy, kappa, precision, sensitivity, and specificity values for ML prediction of Ethogram 1 at 3, 5 and 7s epochs. Bold indicates the highest accuracy by epoch group.

		Ethogram 1 - Head Position– Head up or head down				
epoch	**ML**	**Accuracy**	**Kappa**	**Precision**	**Sensitivity**	**Specificity**
3s	**LDA**	89.8%	0.7	91.1%	96.6%	62.8%
	CART	91.1%	0.7	93.1%	95.9%	72.1%
	KNN	91.3%	0.7	93.3%	95.9%	73.0%
	SVM	91.1%	0.7	92.7%	96.5%	69.9%
	RF	**91.4%**	0.7	93.6%	95.8%	74.2%
5s	**LDA**	90.4%	0.7	91.6%	96.8%	65.2%
	CART	91.5%	0.7	93.1%	96.5%	71.7%
	KNN	91.4%	0.7	93.3%	96.0%	73.0%
	SVM	**91.7%**	0.7	92.7%	97.2%	69.9%
	RF	91.6%	0.7	93.6%	96.1%	73.9%
7s	**LDA**	90.3%	0.7	91.8%	96.4%	65.9%
	CART	91.3%	0.7	92.9%	96.6%	70.5%
	KNN	**91.5%**	0.7	93.7%	95.7%	74.6%
	SVM	**91.5%**	0.7	92.7%	97.1%	69.6%
	RF	**91.5%**	0.7	93.9%	95.6%	75.5%

Model descriptions: Linear Discriminate Analysis (LDA), Classification and Regression Trees (CART), K Nearest Neighbour (KNN), Support Vector Machines (SVM) and Random Forest (RF). Max values for each model are in bold. The model recording the highest accuracy are highlighted in green.

3.2 Ethogram Two: Posture – Standing or Lying

The proportion of available data for Ethogram Two, was 36% standing and 64% lying down, these proportions parallel the percentages of the 30 second window setting in the trial completed by Fogarty, E.S. et al., (2020a). The results for the machine learning algorithms for Ethogram 2; standing or lying are in Table 3. The highest performing algorithm was the random forest using a 7s epoch, accuracy was recorded at 91.0% with a 0.8 kappa value. The random forest was the highest accuracy across all window settings.

Table 4: Accuracy, kappa, precision, sensitivity, and specificity values for ML prediction of Ethogram 2 at 3, 5 and 7s epochs. Bold indicates the highest accuracy by epoch group.

		Ethogram 2 - Posture – Standing or Lying				
epoch	**ML**	**Accuracy**	**Kappa**	**Precision**	**Sensitivity**	**Specificity**
3s	**LDA**	83.5%	0.6	81.0%	96.9%	60.1%
	CART	87.9%	0.7	86.0%	96.8%	72.2%
	KNN	89.6%	0.8	89.7%	94.6%	80.9%
	SVM	88.8%	0.8	88.1%	95.4%	77.3%
	RF	**90.5%**	0.8	90.7%	94.8%	83.0%
5s	**LDA**	84.1%	0.6	81.7%	96.8%	61.9%
	CART	88.5%	0.7	87.2%	96.1%	75.4%
	KNN	89.8%	0.8	90.0%	94.4%	81.7%
	SVM	89.6%	0.8	89.2%	95.1%	79.9%
	RF	**90.7%**	0.8	91.0%	94.7%	83.6%
7s	**LDA**	84.6%	0.6	81.9%	97.1%	62.8%
	CART	89.0%	0.8	87.4%	96.7%	75.8%
	KNN	90.3%	0.8	90.5%	94.6%	82.7%
	SVM	90.0%	0.8	89.6%	95.3%	80.7%
	RF	**91.0%**	0.8	91.3%	95.0%	84.2%

Model descriptions: Linear Discriminate Analysis (LDA), Classification and Regression Trees (CART), K Nearest Neighbour (KNN), Support Vector Machines (SVM) and Random Forest (RF). Max values for each model are in bold. The model recording the highest accuracy are highlighted in green.

3.3 Ethogram Three: Activity – Resting or grazing

As with Ethogram one, due to the higher volume of resting behaviours during the observations window, the proportion of resting behaviours was significantly higher than grazing behaviours, 81% and 19% respectively for all window settings, this made an unbalanced ethogram. The results of the model comparison for Ethogram three; grazing or resting are in Table 4. The highest performing algorithm was the random forest using a 7s epoch, with accuracy recorded at 99.3%. The random forest was the highest accuracy across all window settings.

Table 5: Accuracy, kappa, precision, sensitivity, and specificity values for ML prediction of Ethogram 3 at 3, 5 and 7s epochs. Bold indicates the highest accuracy by epoch group.

		Ethogram 3 - Activity – Resting or grazing				
epoch	**ML**	**Accuracy**	**Kappa**	**Precision**	**Sensitivity**	**Specificity**
3s	**LDA**	97.3%	0.6	99.1%	98.1%	69.7%
	CART	98.1%	0.6	98.9%	99.2%	61.5%
	KNN	98.6%	0.7	99.0%	99.5%	66.2%
	SVM	98.5%	0.7	98.8%	99.7%	58.2%
	RF	**98.8%**	0.8	99.2%	99.5%	74.7%
5s	**LDA**	98.2%	0.9	93.9%	96.8%	98.6%
	CART	98.1%	0.9	98.7%	91.0%	99.7%
	KNN	**99.1%**	1.0	97.5%	97.9%	99.4%
	SVM	98.7%	1.0	98.2%	95.0%	99.6%
	RF	**99.1%**	1.0	98.2%	97.1%	99.6%
7s	**LDA**	98.8%	1.0	95.9%	97.5%	99.0%
	CART	98.6%	1.0	97.8%	94.7%	99.5%
	KNN	99.1%	1.0	97.8%	97.7%	99.5%
	SVM	99.0%	1.0	98.5%	96.0%	99.7%
	RF	**99.3%**	1.0	98.4%	97.9%	99.6%

Model descriptions: Linear Discriminate Analysis (LDA), Classification and Regression Trees (CART), K Nearest Neighbour (KNN), Support Vector Machines (SVM) and Random Forest (RF). Max values for each model are in bold. The model recording the highest accuracy are highlighted in green.

4.0 Discussion

Accelerometer technology has been evidently successful at recording behaviour measurements in sheep over recent years. As a result, there has been a clear motivation to research tools that can be used in a commercial setting and thus an increase in sheep studies have been published using ear-borne accelerometers. In previous livestock trials the neck has been one of the most common deployment locations (Barwick et al., 2018b; Fogarty. E.S. et al,.2020a; Martiskainen et al., 2009). Ear tags are commonly worn in the industry, therefore this is undoubtedly more commercially acceptable (Barwick, et al., 2018b; Fogarty et al,.2020). However, research is still in the initial phase with this application method and ear tag placement still has its disadvantages. Barwick, J. et al., (2018a) highlighted that as the ear is small and less rigid and as a consequence less stable, there is higher degree of movement compared with a collar worn device. From experience in the field, ear-flicking is common for sheep, not always due to flies and this may be detrimental to a model. Collars are considered impractical in a commercial environment due to the ability for the sensor to freely move around the neck of the animal, which may potentially limit the number of recordable behaviours and influence classification results as researched by Barwick, J. et al., (2018b). However, several studies have achieved high levels of accuracy using this placement method. Therefore, a neck mounted unit was sufficient for our study, as at this stage the outcome of this research is not to create a commercial farm tool.

In this chapter the author successfully classified a variety of behavioural states with varying accuracy, obtained from a flock of ten ewes that throughout the trial continued to be kept in a commercial setting. Activity detection (Ethogram 3 – Table 4) exceeded >97.3% on all window settings and machine learning algorithms, ranging with a maximum accuracy of 99.3%. Sensitivity and specificity were recorded at similar volumes, with the exception of specificity for 3s window which had a much lower range of 58.2% and 74.7%. Fogarty, E.S. et al., (2020a) achieved an accuracy of 98.1% using the CART and 30s window, this was also achieved by the CART in our study with a shorter window setting of 5 seconds, despite the differing device locations and the recording speeds.

In parallel to the study produced by Walton, E. et al., (2018), the LDA at a 3 second window had the lowest accuracy for all window settings, across all ethograms. The highest accuracy by window setting was the 7s window with the RF model, except for head movement (Ethogram 1 – Table 2), that had a marginally better result by the SVM, with a 0.2 percent point higher accuracy with a 5 second window, however the specificity was point 5.7 lower than the RF and therefore the 7s RF is optimum across all ethograms. The ability to differentiate standing and lying posture (Ethogram 2 – Table 3) ranged from a minimum accuracy of 83.5%, by the LDA 3s window to the maximum accuracy of 91.0% by the RF with a 7s window, the best result in Fogarty, E.S. et al., (2020a) study was 90.6% for the same ethogram using a CART and 30 second window setting, the lower window settings did not achieve similar accuracy, though in contrast, we did not include walking data which may have increased our model accuracy, although it is worth noting that the proportions of observations were more balanced in the trial by Fogarty, E.S. et al., (2020a).

In the current trial, not all sheep performed all behaviours at the same volumes, which had led to a disparity in the contrasting behaviours of the ethograms and therefore care needs to be taken when interpreting the results (Table 1). As a result, ethogram 3 had the lowest volume of observations of all three ethograms, along with resting behaviours (80% higher than activity behaviours). Though it is suggested by the author that the unbalanced datasets may not be detrimental to the study as the distinction between low levels of movement, and therefore lower movement signals, compared with active behaviours thus higher movement signals may mitigate against this. In agreement with this theory, Martiskainen, P. et al., (2009) stated that most sensors are better suited when limited to recording only 1-2 behaviours, it is worth noting that every effort was made to exclude transitional behaviours, which may have also supported in the performance of classifications. There is an understandable desire to classify as many behaviours as possible, yet it would be difficult to create a model with this level of granularity, due to volume of data required to train the algorithm, this may be only detrimental to a model designed to predict specific behavioural states such as on set of parturition (Barwick, J. et al., 2018b; Fogarty, E.S. et al., 2020a). In agreement with Fogarty, E.S. et al., (2020a) it is difficult to obtain high volumes of training data when manually recording behaviours in a commercial setting.

As a result of summarising the primary research, further opportunities to advance the study are attainable. These findings may result in enabling the development of a farm tool that provides various alerts as seen in the cattle industry. It is suggested by the author that utilising this innovative research may provide knowledge that is fundamental to the future of the sheep industry and UK agricultural by enabling key stakeholders in the sheep sector to review the health and welfare benchmark, drive policy and implement strategies to boost production without adverse impacts on sheep wellbeing at the farm level.

Although the ethograms in this study are simple, approaching the behavioural states in a yes or no method, will provide sufficient and useful information to later develop into actionable warning signs, similarly to that of the farm alerts studied by Eckelkamp E.A & Bewley, J.M., (2020), that were generated based on an individual cow's decrease of ≥30% in activity, lying, and eating time compared with each cow's 10 day moving mean. The ethograms could be considered a checklist of questions about the physiological state of the sheep. Is your head up or down? Are you standing or lying? Are you grazing or resting? By studying the duration of these activities, we hope to develop a benchmark for the activity of a healthy ewe, as follows; if the animal has been standing for a duration outside of the normal range, perhaps this is because lying down causes discomfort, which may highlight the onset of mastitis. If the animal is lying more and grazing less, perhaps this animal is lame or suffering from a metabolic disorder. A clear secondary objective would be to gage a greater understanding of the behaviours that underpin the performance of sheep, to include behavioural changes caused by the farm environment and changing climate, such as seasonal weather variation that may cause behaviour fluctuations in sheep that are not as a result of health and welfare status caused by disease or injury.

These variables need to be considered when developing algorithms for commercial application, as they may impact the efficacy of a viable farm tool, specifically tools designed to provide disease alerts. The model and classifiers and their overall ability to predict onset behaviours is the more challenging aspect of this research and its biggest limitation to market, it is suggested by the author that without fully understanding healthy behavioural expression and whether climate and environment modifies daily activity, it could result in wrongfully interpreting ‘normal’ behavioural changes (Barwick, J. et al., 2017; Barwick, J. et al., 2018a; Barwick, J. et al., 2018b; Fogarty, E.S. et al. , 2020a; Fogarty, E.S. et al. , 2020; Martiskainen, P. et al., 2009; Walton, E. et al., 2018; Umstätter, C. et al., 2008).

5.0 Conclusion

The author was able to successfully record the behaviours of sheep in an extensive environment using a tri-axial accelerometer and later evaluate the most appropriate machine learning algorithm to complement the data collected in our trial by investigating three key areas: window setting, model type and ethogram, following the suggestions of Fogarty, E.S. et al., (2020a). As with the study produced by Walton, E. et al., (2018), window setting 7 was able to achieve the highest accuracy, or in the example of ethogram 1, a marginally lower accuracy to achieve a much higher specificity (Table 2). These findings will enable us to take this research to new depths and begin to record and evaluate the behaviours of unsupervised commercial ewes with ease. Before we can confirm that a farm tool is viable using behaviour by proxy, research needs to be undertaken to understand the impacts of the numerous environmental influences such as farm system and climate that may impact sheep behaviour. In order to mitigate against these external factors, the author suggests these areas are obvious next steps to expand on this research.

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Chapter 3 Using Accelerometer Technology and a Random Forest Algorithm to Predict the Behaviours of Unsupervised Sheep and Explore the Effects of Temperature and Rainfall on Daily Behaviour Durations

1.0 Introduction

In recent years there has been a global rise in interest in animal husbandry by consumers and animal welfare groups that has subsequently led to growing pressures to boost the 'quality of life experienced by animals', particularly livestock that are managed by humans for agricultural production, this ethical concern is termed 'welfare'. Historically the farm environment has been dictated by production goals and therefore may not be ideal from a welfare perspective, this in turn has boosted consumers to favour free-range, grass-fed animals associated with organic and extensive farming practices (Averós, X. et al., 2014; Duncan, I. & Fraser, D, 1997; Dwyer, CM & Lawrence, AB, 2005; DEFRA, 2018; Grant, E.P. et al., 2018; Hargreaves, A.L. & Hutson, G.D., 1990; Hansen, B. G. & Osteras, O, 2019). Welfare is a complex and intangible concept as it is the combination of; health and disease, behaviour, husbandry and management, thus both the qualitative and quantitative facets of the animals' condition of life (Duncan, I. & Fraser, D, 1997; Brambell, F. W. R, 1965).

There has been great emphasis on providing conditions that allow livestock to behave as naturally as possible, specifically in the cattle and sheep industry. Behaviour although a condition of welfare, is also considered to have the capacity to provide a useful indication of the physiological state of livestock and therefore suggestively provides an insight of the animals' overall welfare status (Barwick, J. et al., 2020; Centoducati, P. et al., 2015; Frost, A. et al., 1997; Gougoulis, A. et al., 2010; Phythian, C. et al, 2013). It is proposed that behavioural change caused by unfavourable conditions could be effectively demonstrated in daily activity, however the viability of assessing welfare and the preferences of individual grazing animals in a commercial environment is problematic, most notably in sheep that spend much of their production calendar at grass. Currently there is a lack of understanding of how sheep respond and adapt to changes in a commercial environment, which presents a novel area of research (Etim, N.N. et al., 2013; Piirsalu, P. et al., 2020).

Utilising farm tools both wearable and closed-circuit television (CCTV) has been widely adopted in the dairy industry, it is less labour intensive and offers various monitoring classifications, for instance; to detect a lame herd member, oestrus, pain and heat stress. Exploiting the aforementioned technology in addition to traditional farming practices is commonly referred to as precision management and has aided farmers to maximise welfare and production, (Barwick, J. et al., 2018a; Barwick, J. et al., 2018b; Barwick, J. et al., 2020; Fogarty, E.S. et al., 2020a; Fogarty, E.S. et al., 2020b; Smith, D. et al., 2016). It has been deemed essential for British farming to encourage the adoption of new technologies in order be competitive in the post-Brexit marketplace. Though, technology, such as CCTV, is largely inefficient and not feasible in many commercial settings most notably in the sheep sector. The United Kingdom (UK) host approximately 90 breeds and crossbreeds of sheep, all of which spend a large proportion of the year grazing. The UK landscape is made up of varying regional terrains and as a result CCTV could be impractical, arguably the traditional practice of monitoring sheep by human observation is both labour intensive and subjective. (Learmount, J. et al., 2018; Living Countryside, 1999; NSA, 2020b; Royal Duchy College, 2018). Evidently throughout certain times of the farm calendar, handling ewes could be difficult, for instance when lambs are at foot and it may not be practical to disturb them. In addition, it may be difficult to make observational assessments of ill health, specifically if clinical signs of disease are not yet showing and therefore some health and welfare issues may go unnoticed, this supports the use of wearable tools (Barwick, J. et al., 2018a; Gougoulis, A. et al., 2010; Learmount, J. et al., 2018).

Sheep synchronise behaviours with other flock members and are gregarious, thus naturally living in groups. It is suggested that group cohesions and synchronisation are formed primarily by sight. Sheep have a field of vision of approximately 290° and therefore can monitor flock mates with subtle head movements. Group cohesion aids individual sheep to mask signs of compromised health and pain, which despite years of domestication pertains to an inherent anti-predator response, as a result sheep are phlegmatic in their behavioural expression. The position of their eyes, their ability to see in low light and the sensitivity of their hearing (10db) provides enough evidence to support that they have evolved as victims of predatory animals and a clear rationale to investigate novel approaches of observing sheep (Adamczyk, K. et al., 2015; Baskin, L.M, 1974; Barwick, J. et al., 2018a; Barwick, J. et al., 2018b; Estevez, I. et al., 2007; Gougoulis, A. et al., 2010; Jarman, P.J., 1974; Learmount, J. et al., 2018; Piirsalu, P. et al., 2020; Rook, A.J. & Penning, P.D., 1991).

Wearable tools, as adopted in the cattle industry that could allow for continuous and autonomous monitoring of sheep with limited human interaction, could enable collation of qualitative and quantitative commercial behaviour data from the varying farm systems and breeds types. Behaviour data of commercially reared flocks has been largely unsubstantiated, however could provide valid information on flock performance (Barwick, J. et al., 2018a; Barwick, J. et al., 2018b; Barwick, J. et al., 2020; Fogarty, E.S. et al., 2020a; Fogarty, E.S. et al., 2020b; Gougoulis, A. et al., 2010; Moreau, M. et al., 2009; Phythian, C.J. et al., 2016; Smith, D. et al., 2016). Collating this data has huge benefits at the sector level, providing a greater understanding of production and environmental impacts, identifying disease threats, as well as allowing for full traceability of lamb from farm to fork. This could support farmers to offer a superior quality of welfare, which could contribute towards future welfare standards and inform refreshed policy implementation in the UK (DEFRA, 2018; Fogarty, E.S. et al., 2020a; Gougoulis, A. et al., 2010; Paterson MP, R. H. O, 2017; Piirsalu, P. et al., 2020; Phythian, C.J. et al., 2016).

As with the development of these tools for the dairy industry research needs to be undertaken to link observed behaviours to management knowledge. For example, a decrease in gregarious activity, feeding and ruminating are indicators of a dairy cow suffering illness (Smith, D. et al., 2016; Fogarty, E.S. et al., 2020b). The predominant activity in a ‘sheep day’ is grazing and is said to persist for substantial periods of time, less dominant behaviours that equally make up a large proportion of a sheep day include, resting and walking. Thus, it is suggested that peaks and troughs in durations of these activities could be linked to pain and suffering (Eckelkamp E.A & Bewley, J.M., 2020). For example, it was found that a decrease in activity combined with an increase in posture change, was associated with the onset of parturition in Merino ewes (Fogarty, E.S. et al., 2020b). However, there are many environmental factors that may influence production behaviours and therefore care needs to be taken when identifying behavioural changes and attributing them to specific traits. For instance, it was observed that both in dairy cows and goats suffering heat stress there was an increase in time spent standing (Fogarty, E.S. et al., 2020b; Gougoulis, A. et al., 2010; Rook, A.J. & Penning, P.D., 1991). Furthermore, cattle behaviour was found to be influenced by exposure to winter weather, such as cold weather correlating to a decrease in feeding durations and wet conditions influencing both time spent lying and a decrease in feed volumes (Schütz, K. E. et al., 2010). Various research has suggested that both behavioural and postural expression differed when sheep had faced extremes of cold and hot weather compared with flock members that had variable fleece lengths, in agreement with this it was observed in trails that newly shorn flock member behaviours were more obvious in the avoidance of higher temperatures and were more inclined to source shelter at night or in extreme weather (Etim, N.N. et al., 2013; Ferguson, D. M. et al., 2017; Lihou, K. & Wall, R, 2019; Piirsalu, P. et al., 2020; Webster, M.E.D. & Johnson, K.G., 1968). In agreement with this sheep have been observed to be reluctant to move or unable to if suffering from hyperthermia because of being both wet and cold, as well as actively source shade on hot days, when exposed to direct radiation. Adverse weather conditions not only impact productivity, nonetheless has been observed to cause catastrophic losses such as mortality in young sheep stock as a result of the combination of cold weather, rainfall and winds leading to hypothermia (Erickson, 2018; Ferguson, D. M. et al., 2017; Etim, N.N. et al., 2013; Piirsalu, P. et al., 2020).

Despite the rise in popularity of implementing accelerometer technology to improve production in the sheep sector, inferences on the effects climate has on behaviour on commercial livestock is limited, yet vital in order to understand if behaviour could negatively impact the efficacy of the models applied to precision management tools. Therefore, in order to investigate this the tri-axial accelerometer along with the random forest model used to predict behaviours in the previous study (chapter 2) will be utilised on an unsupervised commercial flock of sheep and draw insights on the effects of temperature, rainfall and their interaction as well as investigating whether these variables exclusively and collectively influence behaviour, as observed in other studies by manual observation. In this study the following questions were asked:

(1) Is it possibly to predict behaviours of sheep from an unsupervised dataset, to infer what effects daily climatic variation has on the durations of key production activities?

(2) Does rainfall and temperature influence behaviour/postural durations (Grazing, Lying, Head up (non- grazing, non-resting postural state)?

(3) Are there consistent individual differences in daily behaviour durations?

Based on sheep naturally choosing to synchronous behaviours, as one of their many antipredator characteristics (Adamczyk, K. et al., 2015; Gougoulis, A. et al., 2010), we predicted that individual behaviour would be repeatable across the flock, irrespective of the influence of weather variability. Based on the above-mentioned findings in previous research we predicted temperature would not significantly influence behaviours with the exception of extreme temperature changes. Though, rainfall would influence behaviours, by a reduction in grazing time and an increase in lying time (Erickson, 2018; Ferguson, D. M. et al., 2017; Gougoulis, A. et al., 2010; Jarman, P.J., 1974; Learmount, J. et al., 2018; Piirsalu, P. et al., 2020; Schütz, K. E. et al., 2010).

2.0 Materials and methods

2.1 Data Collection

Accelerometer data was collected at frequency of 10 Hz, which allowed for effective battery life up to 40 days (ActivInsights Ltd, 2015). The GENEActiv accelerometer unit was mounted on to a Shearwell Bell collar, a collar specifically designed for livestock (Figure 1). Twenty commercial welsh mule ewes were selected, this was to mitigate against any issues with loss of hardware and also due in part to the deployment being undertaken at a time when there was heightened risk of liver fluke and lameness, due to adverse weather conditions (DEFRA, 2018). The ewes were all 4 years old, with equal parity and body condition score. The trial was located on a small holding in

Milverton, Somerset, UK. There was a window in the farm calendar, once ewes had recovered post weaning and prior to flushing ready for tupping and this was utilised for the trial. Data was recorded from August 19th – September 15th, 2017, as in the previous study (Chapter 2), the ewes had worn the bell collars and accelerometers in previous studies and did not show any signs of distress during or after deployment.

Figure 1: Ewe wearing Shearwell Bell collar fitted with a GENEactiv accelerometer unit

The ewes had freedom to roam 20 acres of pasture with access to two water troughs. The field boundary was stock fenced, with trees and hedges providing natural shelter from adverse weather conditions. The ewes were farmed as normal and checked twice a day by the farmer, other than a public right of way in the field, the sheep had limited human interaction. Sheep were on a grass diet with access to mineral buckets. During the trial one ewe lost her device, which was not ever found, another ewe was treated for lameness and therefore subsequently treated and removed from the trial and finally one unit appeared to have stopped working after day three of the trial and for this reason was also excluded (reason unknown). Irrespective of the exclusion of three units, there was a total of >10,000 hours of sheep data obtained from 17 ewes over the 25 uninterrupted days (excluding, day of deployment and removal). As well as the behaviour data collection, weather data; daily total rainfall (mm) and daily mean temperature (c) were provided by the met office and retrieved from Huntsham weather station (15km from test site) for the duration of the trial (Table 1) so that we could our research questions as set out previously.

2.2 Weather data

Daily average Temperature

During the 25 days of the study the max temperature, 18.9 degrees Celsius, was recorded on the 28th August. The minimum temperature 10.7 degrees Celsius, was recorded on the 14th September. The average temperature between the 20th August -14th September was 14.6 degrees Celsius. (Table 1)

Daily Rainfall (mm)

The max millimetres of rainfall during the trial was recorded at 12.3mm on the 3rd September, there were 10 dry days during the trial, as well as three days that did not exceed 1mm (Table 1). The longest period of consecutive days of rain was recorded between the 7th - 14th September, the average daily rainfall for this period of 8 days was 5mm.

Table 1: Met office data, mean daily temperature (c) and rainfall (mm) recorded using the weather station at Huntsham (15km from trial site)

Date	Daily Mean Temperature (0900-0900) (C)	Daily Total Rainfall (0900-0900)(mm)
20/08/2017	12.4	11.4
21/08/2017	18.5	n/a
22/08/2017	17.4	n/a
23/08/2017	16.6	0.2
24/08/2017	15.6	n/a
25/08/2017	14.9	n/a
26/08/2017	16.3	n/a
27/08/2017	18.4	n/a
28/08/2017	18.9	n/a
29/08/2017	16.8	3.2
30/08/2017	14.0	n/a
31/08/2017	13.4	2.2
01/09/2017	14.0	n/a
02/09/2017	13.6	7.7
03/09/2017	13.5	12.3
04/09/2017	15.7	1
05/09/2017	16.3	0.8
06/09/2017	14.0	n/a
07/09/2017	13.9	6.9
08/09/2017	14.4	4.9
09/09/2017	12.2	5.5
10/09/2017	12.1	2.3
11/09/2017	12.1	8.2
12/09/2017	12.5	3.5
13/09/2017	12.4	5.6
14/09/2017	10.7	3.2

2.3 Behaviour Classification, Predictive Model and Validation

This study utilises the development and validation of the random forest (RF) model that was produced and tested in trial one (chapter 2). In order to validate the model in trial one (chapter 2) behaviours were recorded manually by a single observer both in the field and with the use of video recordings to produce three ethograms designed to record the different behavioural and postural states of sheep, to include; ethogram 1: head position, ethogram 2: posture and ethogram 3: activity (Table 2). These behaviours, also referred to as categorical variables, were then combined with accelerometer data and later used to create and train the predictive model using the R ‘caret’ package (Campbell. et al., 2021).

Table 2: Total volume of epoch observations by ethogram collated for trial 1 to create the training data used to produce the random forest

	Ethogram 1 - Head Position (Primary) – Head up or head down						Ethogram 2 - Posture (Secondary) – Standing or Lying						Ethogram 3 - Activity (3rd Tier) – Resting or grazing					
	Head Up			Head Down			Standing			Lying			Grazing			Resting		
Sheep ID	**3**	**5**	**7**	**3**	**5**	**7**	**3**	**5**	**7**	**3**	**5**	**7**	**3**	**5**	**7**	**3**	**5**	**7**
1	761	456	327	1713	1044	733	1717	1037	747	1026	615	440	72	44	31	947	570	409
2	1120	675	489	2024	1230	897	799	483	352	3068	1843	1316	317	193	141	2514	1512	1082
3	892	543	383	1481	895	646	434	264	187	2138	1281	916	n/a	n/a	n/a	1898	1141	818
4	1137	688	490	847	512	365	1947	1173	844	787	473	337	69	41	28	366	219	157
5	203	124	83	2650	1600	1147	1212	729	526	3013	1810	1292	785	472	334	2547	1532	1096
6	312	185	136	3505	2107	1503	1196	720	517	3096	1857	1326	692	415	296	3088	1856	1330
7	248	146	99	2816	1692	1213	2141	1290	926	2064	1240	886	865	520	371	1614	971	693
10	113	68	48	3792	2279	1632	1061	639	458	3262	1957	1398	905	544	390	3254	1958	1399
Total	**4786**	**2885**	**2055**	**18828**	**11359**	**8136**	**10507**	**6335**	**4557**	**18454**	**11076**	**7911**	**3705**	**2229**	**1591**	**16228**	**9759**	**6984**

Recording speeds in trial one (chapter 2) were recorded at 50hz, in order to have more confidence in battery longevity for the trial undertaken in this chapter (chapter 3) a frequency of 10hz was used, as a result the training data generated in trial one (chapter 2) had to be rerun and down-sampled. It is worth noting that the frequency did marginally alter the overall accuracy (Table 3), as observed in the study by Walton, E. et al., (2018), which concluded that despite the benefits of recording at a lower frequency to maximise battery life, accuracy increased the higher frequency. Before applying the model to the unsupervised dataset generated in this trial, the overall accuracy was tested as per the previous study (chapter 2), by splitting the down-sampled trial one (chapter 2) data into a training and test set 70:30, per each ethogram and validated using a 10-fold cross validation and was then applied to the unsupervised dataset.

2.4 Data Processing – Unsupervised Model Output

In addition to the data processing as per trial one (chapter 2), an additional dataset for the unsupervised data was created in the same format as the original training data. This included Sheep ID, date, sample time, min, max, total duration and window setting. In trial one (chapter 2) it was concluded that a 7 second window was optimum to achieve the best results and therefore the unsupervised data was split in to 7 second segments. For each time window a set of seven feature characteristics were calculated using R. The output of this process was a dataset containing 25 days of unsupervised data of the 17 sheep in the format; sheep ID, Time and Date along with the features; UpDownMean, UpDownMedian, UpDownVar, UpDownSD, UpDownMAD, UpDownSkew and MAGSA (Campbell. et al., 2021). This dataset was then ready to be applied to the three RF models, one for each ethogram (as previously described).

The predicted output consisted of adding a column to the existing unsupervised data, populated with the RFs predicted behaviour, for each 7 second time segment. The data table generated had; SheepID, Time, Date, the seven calculated features and a predicted behaviours column. The data was then aggregated by SheepID, date, predicted behaviours and sum of duration in seconds. The output of this provided the predicted daily duration and percentage of grazing, resting and postural behaviours of the unsupervised sheep (Table 8-19).

2.5 Statistical Analysis

All descriptive statistics were performed using R, version 3.6.3 (R Core Team, 2020). In order assess of the overall effect of temperature, rainfall and their effect on the aforementioned behaviour classes a linear mixed-effects model (LMM) fitted with the function 'lmer' from the package 'lme4' estimated using REML was undertaken (Bates, D. et al., 2015)**.** Daily Mean Temperature and Daily Rainfall (mm) will be scaled, their individual and combined effects were specified as fixed factors in the model while, Sheep ID and Date are to be included as random effects (formula: list(~1 | ID, ~1 | Date)).

In order to ascertain, whether daily durations of grazing, lying, head up are repeatable among the flock and comparable day-to-day, the author computed repeatability (R), by producing a repeatability estimation using the LMM method, this is a vital indicator of computing the proximity of measurement results to the true value, using values from non-repeatable (0) to repeatable (1) (Nakagawa, S. & Schielzeth, H., 2010). This was performed in R (R Core Team, 2020). using the 'rpt' function in the package 'rptR'. rptR calculated 95% confidence intervals (CIs) via parametric bootstrapping procedures (N=1000) (Stoffel, M.A. et al., 2017).

3.0 Results

3.1 Random Forest Accuracy and Kappa after down sampling training data

In the previous study (chapter 2) recording frequency was 50hz, however, to conserve battery life a recording frequency of 10hz was used for this study (chapter 3). The change in frequency decreased both the accuracy and kappa values marginally across all ethograms (table 3). Ethogram 2 (Posture) was most influenced by this change with accurate posture predictions reducing by >2.4 percent point and although minimal a difference of 0.05 was calculated for Kappa values. These results are not detrimental, as accuracy exceeds >88.6% for all ethograms. However, it is worth noting for future studies, that the impact on accuracy by reducing the recording frequency is not consistent across all behavioural or postural states.

Table 3: Recording frequency and its effect on accuracy and kappa results. Tri-axial accelerometer recorded at a frequency of 50hz in trial 1 and was down sampled to 10hz for trial 2.

Random Forest Overall Accuracy (7 Second Window)		Trial 1: 50hz	Trial 2: 10hz	Difference
Ethogram 1: Head Position (head up/head down)	Accuracy	91.5%	90.4%	-1.15
	Kappa	0.7	0.7	-0.04
Ethogram: 2 Posture (Standing/Lying)	Accuracy	91.0%	88.6%	-2.43
	Kappa	0.8	0.8	-0.05
Ethogram 3: Activity (grazing/resting)	Accuracy	99.3%	98.6%	-0.76
	Kappa	1.0	1.0	-0.03

3.2 Proportion of time spent performing chosen behaviour classes based on Random Forest Output:

3.2.1 Ethogram One: Head Position – Head up or head down

Over the whole trial period ewes on average spent 51% of their time with their head down and 49% with their head up. The minimum duration for head down orientation was recorded by Sheep 15 on the 10th September, it was predicted that for ethogram one, the ewe spent 31% of that day with her head down. This date recorded minimum durations for 8 of the 17 ewes. The highest proportion of time with a head down orientation was 74%, recorded by Sheep 17 on the 23rd August. The highest whole flock average was on August 26th with a prediction of 57% of their time with their head down. (Table 8-9, 14-15)

3.2.2 Ethogram Two: Posture – Standing or Lying

Between the trial date range average postural position, the whole flock was proportionally higher for lying than standing, 56% and 44% respectively. The minimum time spent lying was by sheep 17 on the 3rd September, proportionally the ewe spent 38% of the day lying. September 3rd also resulted in the minimum duration by a whole flock average, in addition 6 ewes similarly shared this as their individual minimum duration of lying activity. Maximum lying duration was recorded by Sheep 15 on the 10th September, results predict she spent 78% of her postural state lying and 22% of the day standing. The average flock max lying duration was recorded on the 1st September, making up at 62% of the overall duration. On the 27th August, six ewes shared the same maximum lying time and thus minimum standing time (Table 10-11, 16-17).

3.2.3 Ethogram Three: Activity – Resting or grazing

The activity model recorded the highest level of accuracy >98% (Table 3), the model predicted that based on the flock average for the trial duration, resting made up more of the day than grazing, 67% and 33% respectively. Minimum proportion of grazing was recorded on the 20th August by Sheep 16 at only 12.6%, this date was the minimum duration for 6 ewes. Based on the whole flock average it was the minimum duration by day 27%. Sheep 2 recorded the maximum duration for grazing activity per day, making up 48% of the 3rd September. Additionally, the 3rd September recorded the whole flock maximum making up 36% of the day, 5 individuals shared this date as their individual maximum grazing day (Table 12-13, 18-19).

3.3 The Average Grazing Time Spent by Each Ewe in Each Rainfall Group for the Duration of the Trial

For the whole period, three rainfall groups were investigated; No rain, one – five mm and greater than 6mm, to explore the effect rain on had on the average proportion of time spent grazing by individual level (Fig.2). 65% of the flock grazed comparably more on days that exceeded 6mm of rainfall vs days with no rainfall and 88% grazed more on days that were between 1-5mm of rainfall as apposed to days with no rainfall. For the period of the trial only one ewe spent proportionally more time grazing on days that had no rainfall.

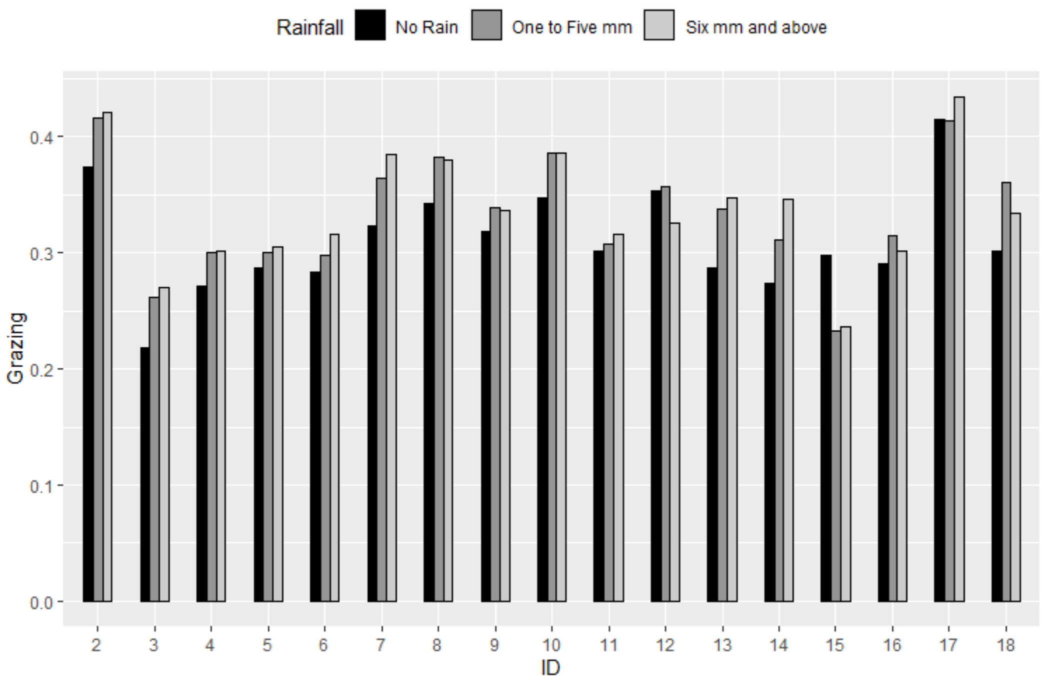

Figure 2: Average Time spent Grazing by Rainfall Group and Sheep ID

4.0 Statistical Analysis

4.1 Linear Mixed Model (estimated using REML)

The linear mixed model (LMM), estimated using REML and nloptwrap optimizer included ID and Date as random effects (formula: list(~1 | ID, ~1 | Date)) and temperature, rainfall and the combination of temperature and rainfall as fixed effects. The response variable consists of the proportion of time spent each day in one of three behavioural states, using the UpDownMean feature of the respective ethogram behaviour data: active behaviour (grazing), postural state (lying) and neck orientation (head up), along with a combination of all these behavioural states

4.2 Grazing

LMM to predict Grazing responses to the effects of temperature and rainfall (formula: Grazing ~ Temp * Rainfall). The model's total explanatory power is substantial (conditional R2 = 0.70) and the part related to the fixed effects alone (marginal R2) is of 0.08. Within this model, the effect of temperature, rainfall and the interaction of Rainfall and Temperature on the response to grazing behaviour is significantly positive, $p < .05$, $p < .001$ and $p < .001$ respectively (Table 4).

Table 4: Linear mixed model fit by REML – Testing the effect of climate on the response to grazing behaviour

Fixed effect	Estimate	*Std. Error*	*df*	*t value*	*P*
(Intercept)	0.343	0.012	22.99	27.7	**< 0.001**
Temp	0.015	0.007	22.00	2.24	**0.04**
Rainfall	0.032	0.008	22.00	3.99	**< 0.001**
Temp:Rainfall	0.029	0.007	22.00	4.20	**< 0.001**

Table consists of all variables tested in the LMM. Random effects for Date and ID were included in the model. Significant P value are in bold.

4.3 Lying

LMM to predict Lying responses to the effects of temperature and rainfall (formula: Lying ~ Temp * Rainfall). The model's total explanatory power is substantial (conditional R2 = 0.76) and the part related to the fixed effects alone (marginal R2) is of 0.02. Within the model the effect of Temperature is non-significantly negative, p 0.740, similarly the effect of Rainfall is also non-significantly negative p 0.135. The interaction effect of Rainfall and Temperature on the response to lying is non-significantly positive p0.372. (Table 5).

Table 5: Linear mixed model fit by REML – Testing the effect of climate on the response to a lying behavioural state

Fixed effect	Estimate	*Std. Error*	*df*	*t value*	*P*
(Intercept)	0.559	0.015	23.24	37.9	**< 0.00**
Temp	-0.003	0.008	22.00	-0.33	0.743
Rainfall	-0.014	0.009	22.00	-1.49	0.149
Temp:Rainfall	-0.007	0.008	22.00	0.89	0.382

Table consists of all variables tested in the LMM. Random effects for Date and ID were included in the model. Significant P value are in bold.

4.4 Head up

LMM to predict head up responses to the effects of temperature and rainfall (formula: `head up` ~ Temp * Rainfall). The model's total explanatory power is substantial (conditional R2 = 0.76) and the part related to the fixed effects alone (marginal R2) is of 0.07. Head up postural state responses to the effect of temperature is non-significantly negative p0.291. Both Rainfall and the interaction effect of Rainfall and Temp on a head up response were non-significantly positive, p = 0.3 and p = 0.8 respectively (Table 6).

Table 6: Linear mixed model fit by REML – Testing the effect of climate on the response to a head up postural state

Fixed effect	Estimate	*Std. Error*	*df*	*t value*	*P*
(Intercept)	0.489	0.015	25.07	33.4	**< 0.00**
Temp	-0.009	0.009	22.00	-1.06	0.303
Rainfall	0.011	0.010	22.00	1.07	0.298
Temp:Rainfall	0.003	0.009	22.00	0.29	0.775

Table consists of all variables tested in the LMM. Random effects for Date and ID were included in the model. Significant P value are in bold.

4.5 Repeatability

Individual sheep showed moderate to high repeatability in all behavioural measures (range 0.60 – 0.67, Table 4), with lying recorded to be the most repeatable. In contrast, day-to-day repeatability was low ranging from 0.08 - 0.11 (Table 20-22).

Table 7: Individual Behaviour Repeatability estimation.

Behaviour Class	R	95% Confidence Interval
Grazing	0.596	0.394-0.733
Lying	0.665	0.446-0.788
Head up	0.635	0.419-0.766

5.0 Discussion

The primary goal was to determine whether it was possible to continuously record and later successfully predict the behaviours of a commercial flock of sheep. Despite the frequency variation marginally impacting results, efficacy of the model accuracy on all ethograms was high and therefore successfully able to predict the behaviours of a commercial flock.

Previous research has suggested that the predominant daily activity of sheep is grazing, with grazing episodes suggested to last for long time periods, thus naturally inferring that resting and walking are less dominant behaviours (Eckelkamp E.A & Bewley, J.M., 2020), however the results from this study indicate that the activity of grazing made up less of the daily activity of sheep at both an individual and flock level. On average, the flock's daily proportion of grazing vs resting was 33% and 67% respectively (Table 19). This finding suggests that resting behaviour is arguably more dominant than grazing. The maximum recorded proportion of grazing by an individual was 48% and therefore continued to remain their less dominant daily activity. Results for posture also compliment these findings, with lying making up a higher proportion of the day vs standing by individual and at the flock level, 56% and 44% respectively (Table 18), indicating that ewes spend much more of their time lying/resting. These findings do demonstrate a contrast in results from previous studies, in this study we used continuous monitoring of ewes in a commercial setting, which differs from previous research that often used sheep in a research environment and monitored by human observation over shorter trial periods, this demonstrates the impacts the many variables, to include and not limited to; grazing type, farm system and breed type that could impact behaviours. However the results suggest that peaks and troughs in durations of these activities by individuals and at flock level could be attributed to changes in ewe health and welfare, as we were able to clearly identify outliers such as demonstrated on the 20th August by Sheep 16 with grazing making up 12.6% of their daily activity.

It would be essential however to understand what was considered a normal range in each setting for each breed and individual before inferring health issues using behaviour by proxy, as suggested by Fogarty, E.S. et al., (2020a) behaviour data needs to be collated and shared to understand the wider impacts of breed type and farm environment on the efficacy of these models. A tool to support farmers cannot simply be created by a 'one size fits all' approach (Eckelkamp E.A & Bewley, J.M., 2020). There have been numerous findings in sheep research to suggest that both behavioural and postural expressions fluctuated in extremes of cold and hot weather, most notably in trails with newly shorn sheep, behaviours observed included standing and a reluctancy to move in both wet and cold conditions (Etim, N.N. et al., 2013; Ferguson, D. M. et al., 2017; Lihou, K. & Wall, R, 2019; Piirsalu, P. et al., 2020; Webster, M.E.D. & Johnson, K.G., 1968).

Behaviours were modulated when suffering heat stress with an increase in standing postures and reduction in less active behaviours in both cattle and goats. Furthermore, cattle reduced feed intake in cold weather and spend more time lying in wet conditions findings as documented in previous sheep research (Fogarty, E.S. et al., 2020b; Gougoulis, A. et al., 2010; Rook, A.J. & Penning, P.D., 1991; Schütz, K. E. et al., 2010). As a result, we expected there to be proportionally lower grazing behaviours and higher lying behaviours on rainy days vs non rainy days. We did not expect temperature to cause huge behavioural variations, unless temperature fluctuated excessively (Erickson, 2018; Ferguson, D. M. et al., 2017; Gougoulis, A. et al., 2010; Jarman, P.J., 1974; Learmount, J. et al., 2018; Piirsalu, P. et al., 2020; Schütz, K. E. et al., 2010).

As hypothesised temperature did not have a significant influence on any of the behaviours in the study. In contrast, grazing behaviour was positively influenced by rainfall, with the exception of one ewe, the flock grazed proportionality more on rainy days as opposed to non-rainy days. For the majority of the flock, results indicate proportion of grazing activity was higher on days with >6mm of rainfall (Figure 2). Grazing was not influenced by temperature but was positively influenced by both rainfall and the combination of temperature and rainfall, therefore arguably the result may be skewed for the latter. These results do infer that rain, or a combination of wet and cold climates do impact sheep behaviour but not necessarily negatively, as grazing was positively influenced by rain. There is further research that needs to be undertaken to understand what caused the positive influence of rain on grazing activities. It is suggested that a trial over a longer trial period, in various locations and ideally with different breeds should be undertaken to understand if the results are comparable with this trial in all cases. Over the trial period, the temperature fluctuated by 8.2 degrees, therefore in agreement with previous research, we can assume that only extreme temperature changes elicit a change in behaviour.

In this study, we also set out to determine whether synchronous behaviours are consistent across the flock and repeatable day to day, irrespective of the influence of weather variability. In support of the research flock behaviours were repeatable and unimpacted by climate. Lying was found to be the most dominant synchronous behaviour, this is not unexpected as the primary purpose to synchronise behaviours is as an antipredator response and therefore sheep that are suffering from ill health are more likely to be less active (Adamczyk, K. et al., 2015; Estevez, I. et al., 2007; Gougoulis, A. et al., 2010). However, surprisingly, daily activity was not repeatable, with repeatability less than <0.11 (Table 20-22). Results indicate the flock will remain cohesive but modulate their behaviour to their environment each day. There are many unknown variables that could cause this for example a further complication is that due to their innate desire to synchronise behaviours, flock hierarchy could be influencing the entire flock (Piirsalu, P. et al., 2020), this theory is largely undocumented. What is clear is that variable such as; the environment, whether farm system, husbandry, climate or otherwise have a daily impact on ewe behaviour.

6.0 Conclusion

In conclusion we were able to use the behaviour data to investigate the influences of climate on three behaviour classes, head orientation, posture, and activity, in this study there were no extreme weather fluctuations however it is clear that rain at low volumes can modify behaviour, results indicate that grazing behaviours were positively influenced by rainfall. We have also demonstrated that a flock will adapt daily to their environment in a commercial setting. It was proposed by Piirsalu, P. et al., (2020) that individual preference of sheep do not directly suggest improvements in their welfare, however as one of the five freedom is the freedom to express natural behaviours, preference has been overlooked as an aspect of welfare (Brambell, F. W. R, 1965; Gougoulis, A. et al., 2010; Piirsalu, P. et al., 2020). The preference of sheep to avoid extreme conditions or options within their environment, may offer valuable information, by identifying unsuitable conditions when adopting changes to farm systems, as well as important information when creating models that use behaviour for prediction of pain and suffering (Brambell, F. W. R, 1965; Gougoulis, A. et al., 2010; Piirsalu, P. et al., 2020). It would be essential to investigate the relationships between environment and behaviour further, in order to know more about the daily impacts of commercially reared sheep to better understand the influence this has on their overall welfare status.

7.0 References

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8.0 Appendix

Table 8: Ethogram 1: Table of predicted <u>head up</u> position duration by sheep, by day. In addition to whole flock average, mix and max head up duration.

Date	ID2	ID3	ID4	ID5	ID6	ID7	ID8	ID9	ID10	ID11	ID12	ID13	ID14	ID15	ID16	ID17	ID18	Whole Flock Average	Whole Flock MIN	Whole Flock MAX
20/08/2017	47418	52031	52941	45185	43876	38969	46809	47012	34153	50330	45759	45493	47159	51758	49420	27328	52633	45781	27328	52941
21/08/2017	47530	38339	47488	40474	36204	38738	38479	45276	35525	45178	41104	38192	40677	43687	40824	22540	46186	40379	22540	47530
22/08/2017	50554	39928	43694	42329	40159	40313	41790	35847	36624	47138	40369	44114	44093	47943	42588	22967	44065	41442	22967	50554
23/08/2017	46921	38822	41790	38738	42917	38577	41027	43848	34881	41608	37359	43743	41258	46291	37681	22428	48699	40388	22428	48699
24/08/2017	43239	41279	44079	40215	37366	37499	35714	35553	34118	41692	40628	41447	43708	48860	40264	28126	46032	39989	28126	48860
25/08/2017	44261	40334	39865	40782	42126	36036	39704	38808	34993	42154	40677	42546	39508	47446	40649	34951	44702	40561	34951	47446
26/08/2017	40516	32669	38850	37786	34727	32809	37569	44023	31955	38668	35287	39732	40978	44016	36995	29267	41090	37467	29267	44023
27/08/2017	46109	38598	47768	37443	37072	33551	39242	36134	31892	43253	42217	45710	41986	49182	38486	32592	44261	40323	31892	49182
28/08/2017	45073	33943	41062	38633	31486	31094	32606	37170	33250	41755	37408	40838	38605	49056	35665	33957	39669	37722	31094	49056
29/08/2017	44604	39109	47733	40810	41706	43533	37170	39515	40572	41202	44289	43309	44086	53613	44156	34552	47061	42766	34552	53613
30/08/2017	42273	39599	44191	41895	40124	39396	39536	38563	37275	44415	41545	42091	44534	50708	43813	36211	45570	41867	36211	50708
31/08/2017	45493	38724	44856	44807	43708	36862	42868	37940	37205	45178	39627	46830	45528	49497	43323	34398	47516	42609	34398	49497
01/09/2017	47824	38976	43386	43610	40474	35462	37009	40390	37863	45143	42567	45444	44163	52136	43253	33495	47285	42264	33495	52136
02/09/2017	38262	37653	39739	37261	34573	31850	33488	39368	35035	41601	40096	45535	42301	49427	36372	30828	40362	38456	30828	49427
03/09/2017	42637	54635	51394	46172	47061	41986	46655	44744	35539	51583	48034	46144	47866	55888	47726	33117	52710	46699	33117	55888
04/09/2017	42357	35987	41153	44695	41083	36659	41279	39116	30849	45213	35875	42819	45493	53067	41755	29043	46585	40766	29043	53067
05/09/2017	42819	42357	41188	42945	42644	36624	38829	42112	41566	45563	40089	44975	43540	57211	47502	36694	46144	43106	36624	57211
06/09/2017	44646	36561	42119	45633	39396	37730	40761	41888	39984	47684	41923	47810	44849	54943	43120	34153	47404	42977	34153	54943
07/09/2017	41482	42434	44471	49756	41979	41020	43078	41566	40383	43092	40957	45388	42567	57463	43792	35014	46655	43594	35014	57463
08/09/2017	44730	41482	39732	51135	41741	36162	41580	39648	35742	47012	42315	40138	41111	54824	48069	28469	43533	42201	28469	54824
09/09/2017	43225	43911	42175	47817	42392	31087	40103	40306	33509	45843	41181	39039	41566	58807	42791	33215	43687	41803	31087	58807
10/09/2017	46823	46403	53879	50477	49658	40621	48797	47488	41804	52759	45934	45619	51198	59311	51506	32823	47978	47828	32823	59311
11/09/2017	45626	41398	47502	48594	50505	35294	46795	44548	37135	45815	47355	43764	41909	55174	49756	26313	43918	44200	26313	55174
12/09/2017	43736	37415	45465	47390	43043	36575	43267	41930	33481	45129	44086	43785	38640	51765	45171	29610	43344	41990	29610	51765
13/09/2017	43834	42805	50995	47292	46494	40019	41433	42105	37212	47341	45787	43897	44156	53130	43946	25193	44961	43565	25193	53130
14/09/2017	46200	43778	49203	48762	47138	38647	40887	40271	35707	43624	45199	38850	45815	54985	46193	28665	41034	43233	28665	54985

Table 9: Ethogram 1: Table of predicted <u>head down</u> position duration by sheep, by day. In addition to whole flock average, mix and max <u>head down</u> duration.

Date	ID2	ID3	ID4	ID5	ID6	ID7	ID8	ID9	ID10	ID11	ID12	ID13	ID14	ID15	ID16	ID17	ID18	Whole Flock Average	Whole Flock MIN	Whole Flock MAX
20/08/2017	38976	34363	33453	41209	42518	47425	39585	39382	52241	36064	40635	40901	39235	34636	36974	59066	33761	40613	33453	59066
21/08/2017	38864	48055	38906	45920	50190	47656	47915	41118	50869	41216	45290	48202	45717	42707	45570	63854	40208	46015	38864	63854
22/08/2017	35840	46466	42700	44065	46235	46081	44604	50547	49770	39256	46025	42280	42301	38451	43806	63427	42329	44952	35840	63427
23/08/2017	39473	47572	44604	47656	43477	47817	45367	42546	51513	44786	49035	42651	45136	40103	48713	63966	37695	46006	37695	63966
24/08/2017	43155	45115	42315	46179	49028	48895	50680	50841	52276	44702	45766	44947	42686	37534	46130	58268	40362	46405	37534	58268
25/08/2017	42133	46060	46529	45612	44268	50358	46690	47586	51401	44240	45717	43848	46886	38948	45745	51443	41692	45833	38948	51443
26/08/2017	45878	53725	47544	48608	51667	53585	48825	42371	54439	47726	51107	46662	45416	42378	49399	57127	45304	48927	42371	57127
27/08/2017	40285	47796	38626	48951	49322	52843	47152	50260	54502	43141	44177	40684	44408	37212	47908	53802	42133	46071	37212	54502
28/08/2017	41321	52451	45332	47761	54908	55300	53788	49224	53144	44639	48986	45556	47789	37338	50729	52437	46725	48672	37338	55300
29/08/2017	41790	47285	38661	45584	44688	42861	49224	46879	45822	45192	42105	43085	42308	32781	42238	51842	39333	43628	32781	51842
30/08/2017	44121	46795	42203	44499	46270	46998	46858	47831	49119	41979	44849	44303	41860	35686	42581	50183	40824	44527	35686	50183
31/08/2017	40901	47670	41538	41587	42686	49532	43526	48454	49189	41216	46767	39564	40866	36897	43071	51996	38878	43785	36897	51996
01/09/2017	38570	47418	43008	42784	45920	50932	49385	46004	48531	41251	43827	40950	42231	34258	43141	52899	39109	44130	34258	52899
02/09/2017	48132	48741	46655	49133	51821	54544	52906	47026	51359	44793	46298	40859	44093	36967	50022	55566	46032	47938	36967	55566
03/09/2017	43757	31759	35000	40222	39333	44408	39739	41650	50855	34811	38360	40250	38528	30506	38668	53277	33684	39695	30506	53277
04/09/2017	44037	50407	45241	41699	45311	49735	45115	47278	55545	41181	50519	43575	40901	33327	44639	57351	39809	45628	33327	57351
05/09/2017	43575	44037	45206	43449	43750	49770	47565	44282	44828	40831	46305	41419	42854	29183	38892	49700	40250	43288	29183	49770
06/09/2017	41748	49833	44275	40761	46998	48664	45633	44506	46410	38710	44471	38584	41545	31451	43274	52241	38990	43417	31451	52241
07/09/2017	44912	43960	41923	36638	44415	45374	43316	44828	46011	43302	45437	41006	43827	28931	42602	51380	39739	42800	28931	51380
08/09/2017	41664	44912	46662	35259	44653	50232	44814	46746	50652	39382	44079	46256	45283	31570	38325	57925	42861	44193	31570	57925
09/09/2017	43169	42483	44219	38577	44002	55307	46291	46088	52885	40551	45213	47355	44828	27587	43603	53179	42707	44591	27587	55307
10/09/2017	39571	39991	32515	35917	36736	45773	37597	38906	44590	33635	40460	40775	35196	27083	34888	53571	38416	38566	27083	53571
11/09/2017	40768	44996	38892	37800	35889	51100	39599	41846	49259	40579	39039	42630	44485	31220	36638	60081	42476	42194	31220	60081
12/09/2017	42658	48979	40929	39004	43351	49819	43127	44464	52913	41265	42308	42609	47754	34629	41223	56784	43050	44404	34629	56784
13/09/2017	42560	43589	35399	39102	39900	46375	44961	44289	49182	39053	40607	42497	42238	33264	42448	61201	41433	42829	33264	61201
14/09/2017	40194	42616	37191	37632	39256	47747	45507	46123	50687	42770	41195	47544	40579	31409	40201	57729	45360	43161	31409	57729

Table 10: Ethogram 2: Table of predicted <u>standing</u> position duration by sheep, by day. In addition to whole flock average, mix and max <u>standing</u> duration

Date	ID2	ID3	ID4	ID5	ID6	ID7	ID8	ID9	ID10	ID11	ID12	ID13	ID14	ID15	ID16	ID17	ID18	Whole Flock Average	Whole Flock MIN	Whole Flock MAX
20/08/2017	37793	32438	32858	36316	39774	42819	40040	36617	42315	34468	30191	40768	36862	36449	28805	49707	35084	37253	28805	49707
21/08/2017	37478	33796	35798	31689	36071	38661	37954	40992	41405	34167	40117	37870	33698	39032	32683	45703	41601	37571	31689	45703
22/08/2017	36645	37163	34195	33138	36456	37275	40635	43876	41321	36729	42462	36246	35098	40418	32410	50960	42665	38688	32410	50960
23/08/2017	40047	31612	35336	35532	34832	40089	36624	43708	42476	37401	43610	38850	33768	39116	36785	47096	43015	38817	31612	47096
24/08/2017	42721	27083	32900	34125	36638	39830	38108	42756	42952	36029	41727	36211	30926	33425	34727	46578	39137	37404	27083	46578
25/08/2017	42812	23457	32830	35084	31647	42091	37471	41237	39102	34678	39690	35189	32445	29736	35154	44268	36148	36061	23457	44268
26/08/2017	41258	27055	34279	35938	33817	38059	38164	43407	40565	34447	41979	32648	33439	35623	34440	47950	35952	37001	27055	47950
27/08/2017	41370	27398	29484	32235	29974	35938	35987	35665	36694	31388	36162	29365	30807	29393	31262	41489	32263	33346	27398	41489
28/08/2017	40593	25200	33887	37429	34748	40201	36764	36232	38682	35952	41230	31780	31661	31584	36701	49126	38297	36475	25200	49126
29/08/2017	40166	28644	33180	35182	32221	37219	41454	42063	40971	35546	35805	39116	33222	29568	34482	43260	37415	36442	28644	43260
30/08/2017	43701	30513	36575	39466	39382	44751	42924	42980	44926	35630	43925	39466	40852	35616	38570	49392	39858	40502	30513	49392
31/08/2017	41783	27251	32697	33950	31080	40047	40313	38808	41083	33152	40992	31934	32816	30226	35399	49749	37415	36394	27251	49749
01/09/2017	38353	25130	28784	30884	30751	39431	36589	37387	36596	33005	33565	32039	30023	26341	30870	39851	33502	33124	25130	39851
02/09/2017	45346	23849	36911	35749	35616	43694	40446	39494	41573	37100	41412	35259	36351	30380	37625	49063	38388	38133	23849	49063
03/09/2017	44583	33663	37681	40152	42322	45836	42238	44135	48741	38052	41041	43722	39711	29967	38549	53263	35070	41102	29967	53263
04/09/2017	44065	26460	34797	34769	33159	49273	43876	44758	48426	34790	48335	40943	40439	28266	38269	50036	41811	40145	26460	50036
05/09/2017	41237	30569	34055	32844	33810	41699	38528	43085	41629	29498	38577	35357	36624	24955	32858	45752	37156	36367	24955	45752
06/09/2017	41867	27902	35588	31773	30688	43673	40803	41671	43750	32431	37849	34951	37107	24374	34048	52570	39032	37063	24374	52570
07/09/2017	43722	29008	35175	26173	34622	45493	37884	43897	40530	35287	38318	37044	38031	20944	37835	45787	39536	37017	20944	45787
08/09/2017	43008	30940	36638	29848	37800	44569	39683	43897	46830	36463	41587	42077	38528	25928	36120	46914	42427	39015	25928	46914
09/09/2017	42462	34461	34139	34559	36890	47880	42518	43400	45836	34314	36477	40446	43036	22232	37219	50575	40509	39233	22232	50575
10/09/2017	37821	35574	31633	33530	35665	45626	36267	40677	41468	31794	38157	39690	33026	18767	34139	52500	38129	36733	18767	52500
11/09/2017	38339	39739	36442	34251	32011	46074	38234	42315	45234	39571	38955	41097	42966	24773	34636	50799	38997	39084	24773	50799
12/09/2017	43904	36995	35385	33936	39396	46361	39739	42525	44534	35280	36694	38493	40166	26327	36974	48503	41685	39229	26327	48503
13/09/2017	41405	37849	34888	33397	35938	45220	41657	46571	40964	37464	38437	37688	39858	27629	38199	52164	41370	39453	27629	52164
14/09/2017	39417	33341	36442	32592	37247	43638	44380	43715	47075	38906	40712	41601	36197	29267	35847	51919	45787	39887	29267	51919

Table 11: Ethogram 2: Table of predicted <u>lying</u> position duration by sheep, by day. In addition to whole flock average, mix and max <u>lying</u> duration

Date	ID2	ID3	ID4	ID5	ID6	ID7	ID8	ID9	ID10	ID11	ID12	ID13	ID14	ID15	ID16	ID17	ID18	Whole Flock Average	Whole Flock MIN	Whole Flock MAX
20/08/2017	48601	53956	53536	50078	46620	43575	46354	49777	44079	51926	56203	45626	49532	49945	57589	36687	51310	49141	36687	57589
21/08/2017	48916	52598	50596	54705	50323	47733	48440	45402	44989	52227	46277	48524	52696	47362	53711	40691	44793	48823	40691	54705
22/08/2017	49749	49231	52199	53256	49938	49119	45759	42518	45073	49665	43932	50148	51296	45976	53984	35434	43729	47706	35434	53984
23/08/2017	46347	54782	51058	50862	51562	46305	49770	42686	43918	48993	42784	47544	52626	47278	49609	39298	43379	47577	39298	54782
24/08/2017	43673	59311	53494	52269	49756	46564	48286	43638	43442	50365	44667	50183	55468	52969	51667	39816	47257	48990	39816	59311
25/08/2017	43582	62937	53564	51310	54747	44303	48923	45157	47292	51716	46704	51205	53949	56658	51240	42126	50246	50333	42126	62937
26/08/2017	45136	59339	52115	50456	52577	48335	48230	42987	45829	51947	44415	53746	52955	50771	51954	38444	50442	49393	38444	59339
27/08/2017	45024	58996	56910	54159	56420	50456	50407	50729	49700	55006	50232	57029	55587	57001	55132	44905	54131	53048	44905	58996
28/08/2017	45801	61194	52507	48965	51646	46193	49630	50162	47712	50442	45164	54614	54733	54810	49693	37268	48097	49919	37268	61194
29/08/2017	46228	57750	53214	51212	54173	49175	44940	44331	45423	50848	50589	47278	53172	56826	51912	43134	48979	49952	43134	57750
30/08/2017	42693	55881	49819	46928	47012	41643	43470	43414	41468	50764	42469	46928	45542	50778	47824	37002	46536	45892	37002	55881
31/08/2017	44611	59143	53697	52444	55314	46347	46081	47586	45311	53242	45402	54460	53578	56168	50995	36645	48979	50000	36645	59143
01/09/2017	48041	61264	57610	55510	55643	46963	49805	49007	49798	53389	52829	54355	56371	60053	55524	46543	52892	53270	46543	61264
02/09/2017	41048	62545	49483	50645	50778	42700	45948	46900	44821	49294	44982	51135	50043	56014	48769	37331	48006	48261	37331	62545
03/09/2017	41811	52731	48713	46242	44072	40558	44156	42259	37653	48342	45353	42672	46683	56427	47845	33131	51324	45292	33131	56427
04/09/2017	42329	59934	51597	51625	53235	37121	42518	41636	37968	51604	38059	45451	45955	58128	48125	36358	44583	46249	36358	59934
05/09/2017	45157	55825	52339	53550	52584	44695	47866	43309	44765	56896	47817	51037	49770	61439	53536	40642	49238	50027	40642	61439
06/09/2017	44527	58492	50806	54621	55706	42721	45591	44723	42644	53963	48545	51443	49287	62020	52346	33824	47362	49331	33824	62020
07/09/2017	42672	57386	51219	60221	51772	40901	48510	42497	45864	51107	48076	49350	48363	65450	48559	40607	46858	49377	40607	65450
08/09/2017	43386	55454	49756	56546	48594	41825	46711	42497	39564	49931	44807	44317	47866	60466	50274	39480	43967	47379	39480	60466
09/09/2017	43932	51933	52255	51835	49504	38514	43876	42994	40558	52080	49917	45948	43358	64162	49175	35819	45885	47161	35819	64162
10/09/2017	48573	50820	54761	52864	50729	40768	50127	45717	44926	54600	48237	46704	53368	67627	52255	33894	48265	49661	33894	67627
11/09/2017	48055	46655	49952	52143	54383	40320	48160	44079	41160	46823	47439	45297	43428	61621	51758	35595	47397	47310	35595	61621
12/09/2017	42490	49399	51009	52458	46998	40033	46655	43869	41860	51114	49700	47901	46228	60067	49420	37891	44709	47165	37891	60067
13/09/2017	44989	48545	51506	52997	50456	41174	44737	39823	45430	48930	47957	48706	46536	58765	48195	34230	45024	46941	34230	58765
14/09/2017	46977	53053	49952	53802	49147	42756	42014	42679	39319	47488	45682	44793	50197	57127	50547	34475	40607	46507	34475	57127

Table 12: Ethogram 3: Table of predicted <u>grazing</u> behaviour duration by sheep, by day. In addition to whole flock average, mix and max <u>grazing</u> duration.

Date	ID2	ID3	ID4	ID5	ID6	ID7	ID8	ID9	ID10	ID11	ID12	ID13	ID14	ID15	ID16	ID17	ID18	Whole Flock Average	Whole Flock MIN	Whole Flock MAX
20/08/2017	27020	18340	15561	21084	26530	27167	27545	18774	29379	19327	16632	26775	26565	26873	10920	35364	18893	23103	10920	35364
21/08/2017	26180	21196	20671	20552	25536	25249	27594	23065	29218	23142	27342	24339	23338	30534	18298	33817	26390	25086	18298	33817
22/08/2017	27846	22876	22659	20524	27286	23065	30884	31346	28931	26691	32179	26138	23317	32956	21854	39291	28686	27443	20524	39291
23/08/2017	29939	20363	23793	23226	25039	26803	25767	27615	29799	27321	32753	25025	23100	29988	26369	35588	26908	27023	20363	35588
24/08/2017	32872	16618	21980	23324	25172	26355	28973	27902	30107	25991	29631	25438	20391	25025	23961	36498	25501	26220	16618	36498
25/08/2017	34566	14560	23142	25753	21140	28686	27895	27363	28791	25802	31080	24913	23030	21840	27104	34811	23373	26109	14560	34811
26/08/2017	33019	18900	25025	27300	23737	27622	28938	28385	28931	26705	32536	23863	23114	27650	26992	38395	24269	27375	18900	38395
27/08/2017	32438	17570	21140	23807	21910	25991	28112	24535	27034	23471	28819	21798	21371	22162	24738	34013	22365	24781	17570	34013
28/08/2017	33474	18060	24794	28609	27104	29428	30009	26481	29729	27111	33047	22988	22799	25508	29582	37464	27251	27849	18060	37464
29/08/2017	32942	20552	25438	28812	25102	26012	33446	30569	30891	27076	28805	28917	25480	23177	27384	34146	26271	27942	20552	34146
30/08/2017	37296	21007	26663	31416	29477	32242	34160	31696	34993	27062	34678	29890	29645	29176	28357	36239	28091	30711	21007	37296
31/08/2017	35728	19376	23296	25669	21994	29148	32277	28035	29855	26096	31948	22498	23653	24108	26460	38332	26817	27370	19376	38332
01/09/2017	31542	16576	19628	23478	21861	29288	29946	26572	28700	25536	24759	22120	22848	20405	23709	29904	23114	24705	16576	31542
02/09/2017	39116	17696	29771	30919	29995	36442	35763	31605	33173	30597	33628	27930	27111	24766	30863	38395	30744	31089	17696	39116
03/09/2017	41356	21357	26299	32872	30926	34027	34174	30016	36946	25746	30513	32641	29736	24283	27657	40502	25109	30833	21357	41356
04/09/2017	36491	18333	25151	25823	22120	36617	34363	28903	36918	26229	34244	29890	27041	20384	29022	36463	31451	29379	18333	36918
05/09/2017	35959	21987	26768	26978	25060	32200	31668	29099	31689	24374	27664	27601	27426	19551	25039	32046	29785	27935	19551	35959
06/09/2017	36239	19152	27650	24528	21000	32473	32879	27825	33586	27083	29078	25781	26964	18137	24773	37541	30219	27936	18137	37541
07/09/2017	39571	20790	27657	19992	26222	32193	31703	31598	31346	28350	31283	28910	30086	12817	29288	32767	32641	28660	12817	39571
08/09/2017	38346	21644	28000	21994	27888	30828	32704	30569	35805	27321	33250	33222	29785	19509	27223	34118	33656	29757	19509	38346
09/09/2017	36218	25361	26103	25053	26775	37800	35420	30646	34825	25718	27916	30058	31094	14798	27671	37324	30485	29604	14798	37800
10/09/2017	35014	26243	25151	27440	27510	31780	29834	28700	33243	24458	31962	31577	24948	11585	26999	37471	31381	28547	11585	37471
11/09/2017	34776	30772	30310	27587	23940	33761	31311	30191	35189	32718	28987	34167	35007	17220	26138	38283	31451	30695	17220	38283
12/09/2017	38773	28091	28203	24941	30849	34818	32060	29309	33684	28763	27209	28966	31654	18270	28693	35336	34398	30236	18270	38773
13/09/2017	36379	28917	26180	27083	26369	30863	33782	30814	32214	28840	28133	29141	29904	21854	29428	39711	32599	30130	21854	39711
14/09/2017	33852	24605	25074	25585	25543	30107	38010	29246	34643	28350	31255	30282	25200	23975	26803	37961	35322	29754	23975	38010

Table 13: Ethogram 3: Table of predicted <u>resting</u> behaviour duration by sheep, by day. In addition to whole flock average, mix and max <u>resting</u> duration.

Date	ID2	ID3	ID4	ID5	ID6	ID7	ID8	ID9	ID10	ID11	ID12	ID13	ID14	ID15	ID16	ID17	ID18	Whole Flock Average	Whole Flock MIN	Whole Flock MAX
20/08/2017	59374	68054	70833	65310	59864	59227	58849	67620	57015	67067	69762	59619	59829	59521	75474	51030	67501	63291	51030	75474
21/08/2017	60214	65198	65723	65842	60858	61145	58800	63329	57176	63252	59052	62055	63056	55860	68096	52577	60004	61308	52577	68096
22/08/2017	58548	63518	63735	65870	59108	63329	55510	55048	57463	59703	54215	60256	63077	53438	64540	47103	57708	58951	47103	65870
23/08/2017	56455	66031	62601	63168	61355	59591	60627	58779	56595	59073	53641	61369	63294	56406	60025	50806	59486	59371	50806	66031
24/08/2017	53522	69776	64414	63070	61222	60039	57421	58492	56287	60403	56763	60956	66003	61369	62433	49896	60893	60174	49896	69776
25/08/2017	51828	71834	63252	60641	65254	57708	58499	59031	57603	60592	55314	61481	63364	64554	59290	51583	63021	60285	51583	71834
26/08/2017	53375	67494	61369	59094	62657	58772	57456	58009	57463	59689	53858	62531	63280	58744	59402	47999	62125	59019	47999	67494
27/08/2017	53956	68824	65254	62587	64484	60403	58282	61859	59360	62923	57575	64596	65023	64232	61656	52381	64029	61613	52381	68824
28/08/2017	52920	68334	61600	57785	59290	56966	56385	59913	56665	59283	53347	63406	63595	60886	56812	48930	59143	58545	48930	68334
29/08/2017	53452	65842	60956	57582	61292	60382	52948	55825	55503	59318	57589	57477	60914	63217	59010	52248	60123	58452	52248	65842
30/08/2017	49098	65387	59731	54978	56917	54152	52234	54698	51401	59332	51716	56504	56749	57218	58037	50155	58303	55683	49098	65387
31/08/2017	50666	67018	63098	60725	64400	57246	54117	58359	56539	60298	54446	63896	62741	62286	59934	48062	59577	59024	48062	67018
01/09/2017	54852	69818	66766	62916	64533	57106	56448	59822	57694	60858	61635	64274	63546	65989	62685	56490	63280	61689	54852	69818
02/09/2017	47278	68698	56623	55475	56399	49952	50631	54789	53221	55797	52766	58464	59283	61628	55531	47999	55650	55305	47278	68698
03/09/2017	45038	65037	60095	53522	55468	52367	52220	56378	49448	60648	55881	53753	56658	62111	58737	45892	61285	55561	45038	65037
04/09/2017	49903	68061	61243	60571	64274	49777	52031	57491	49476	60165	52150	56504	59353	66010	57372	49931	54943	57015	49476	68061
05/09/2017	50435	64407	59626	59416	61334	54194	54726	57295	54705	62020	58730	58793	58968	66843	61355	54348	56609	58459	50435	66843
06/09/2017	50155	67242	58744	61866	65394	53921	53515	58569	52808	59311	57316	60613	59430	68257	61621	48853	56175	58458	48853	68257
07/09/2017	46823	65604	58737	66402	60172	54201	54691	54796	55048	58044	55111	57484	56308	73577	57106	53627	53753	57734	46823	73577
08/09/2017	48048	64750	58394	64400	58506	55566	53690	55825	50589	59073	53144	53172	56609	66885	59171	52276	52738	56637	48048	66885
09/09/2017	50176	61033	60291	61341	59619	48594	50974	55748	51569	60676	58478	56336	55300	71596	58723	49070	55909	56790	48594	71596
10/09/2017	51380	60151	61243	58954	58884	54614	56560	57694	53151	61936	54432	54817	61446	74809	59395	48923	55013	57847	48923	74809
11/09/2017	51618	55622	56084	58807	62454	52633	55083	56203	51205	53676	57407	52227	51387	69174	60256	48111	54943	55699	48111	69174
12/09/2017	47621	58303	58191	61453	55545	51576	54334	57085	52710	57631	59185	57428	54740	68124	57701	51058	51996	56158	47621	68124
13/09/2017	50015	57477	60214	59311	60025	55531	52612	55580	54180	57554	58261	57253	56490	64540	56966	46683	53795	56264	46683	64540
14/09/2017	52542	61789	61320	60809	60851	56287	48384	57148	51751	58044	55139	56112	61194	62419	59591	48433	51072	56640	48384	62419

Table 14: Ethogram 1: Table of predicted <u>head up</u> position percentage by sheep, by day.

Date	ID2	ID3	ID4	ID5	ID6	ID7	ID8	ID9	ID10	ID11	ID12	ID13	ID14	ID15	ID16	ID17	ID18
20/08/2017	55%	60%	61%	52%	51%	45%	54%	54%	40%	58%	53%	53%	55%	60%	57%	32%	61%
21/08/2017	55%	44%	55%	47%	42%	45%	45%	52%	41%	52%	48%	44%	47%	51%	47%	26%	53%
22/08/2017	59%	46%	51%	49%	46%	47%	48%	41%	42%	55%	47%	51%	51%	55%	49%	27%	51%
23/08/2017	54%	45%	48%	45%	50%	45%	47%	51%	40%	48%	43%	51%	48%	54%	44%	26%	56%
24/08/2017	50%	48%	51%	47%	43%	43%	41%	41%	39%	48%	47%	48%	51%	57%	47%	33%	53%
25/08/2017	51%	47%	46%	47%	49%	42%	46%	45%	41%	49%	47%	49%	46%	55%	47%	40%	52%
26/08/2017	47%	38%	45%	44%	40%	38%	43%	51%	37%	45%	41%	46%	47%	51%	43%	34%	48%
27/08/2017	53%	45%	55%	43%	43%	39%	45%	42%	37%	50%	49%	53%	49%	57%	45%	38%	51%
28/08/2017	52%	39%	48%	45%	36%	36%	38%	43%	38%	48%	43%	47%	45%	57%	41%	39%	46%
29/08/2017	52%	45%	55%	47%	48%	50%	43%	46%	47%	48%	51%	50%	51%	62%	51%	40%	54%
30/08/2017	49%	46%	51%	48%	46%	46%	46%	45%	43%	51%	48%	49%	52%	59%	51%	42%	53%
31/08/2017	53%	45%	52%	52%	51%	43%	50%	44%	43%	52%	46%	54%	53%	57%	50%	40%	55%
01/09/2017	55%	45%	50%	50%	47%	41%	43%	47%	44%	52%	49%	53%	51%	60%	50%	39%	55%
02/09/2017	44%	44%	46%	43%	40%	37%	39%	46%	41%	48%	46%	53%	49%	57%	42%	36%	47%
03/09/2017	49%	63%	59%	53%	54%	49%	54%	52%	41%	60%	56%	53%	55%	65%	55%	38%	61%
04/09/2017	49%	42%	48%	52%	48%	42%	48%	45%	36%	52%	42%	50%	53%	61%	48%	34%	54%
05/09/2017	50%	49%	48%	50%	49%	42%	45%	49%	48%	53%	46%	52%	50%	66%	55%	42%	53%
06/09/2017	52%	42%	49%	53%	46%	44%	47%	48%	46%	55%	49%	55%	52%	64%	50%	40%	55%
07/09/2017	48%	49%	51%	58%	49%	47%	50%	48%	47%	50%	47%	53%	49%	67%	51%	41%	54%
08/09/2017	52%	48%	46%	59%	48%	42%	48%	46%	41%	54%	49%	46%	48%	63%	56%	33%	50%
09/09/2017	50%	51%	49%	55%	49%	36%	46%	47%	39%	53%	48%	45%	48%	68%	50%	38%	51%
10/09/2017	54%	54%	62%	58%	57%	47%	56%	55%	48%	61%	53%	53%	59%	69%	60%	38%	56%
11/09/2017	53%	48%	55%	56%	58%	41%	54%	52%	43%	53%	55%	51%	49%	64%	58%	30%	51%
12/09/2017	51%	43%	53%	55%	50%	42%	50%	49%	39%	52%	51%	51%	45%	60%	52%	34%	50%
13/09/2017	51%	50%	59%	55%	54%	46%	48%	49%	43%	55%	53%	51%	51%	61%	51%	29%	52%
14/09/2017	53%	51%	57%	56%	55%	45%	47%	47%	41%	50%	52%	45%	53%	64%	53%	33%	47%

Table 15: Ethogram 1: Table of predicted <u>head down</u> position percentage by sheep, by day.

Date	ID2	ID3	ID4	ID5	ID6	ID7	ID8	ID9	ID10	ID11	ID12	ID13	ID14	ID15	ID16	ID17	ID18
20/08/2017	45%	40%	39%	48%	49%	55%	46%	46%	60%	42%	47%	47%	45%	40%	43%	68%	39%
21/08/2017	45%	56%	45%	53%	58%	55%	55%	48%	59%	48%	52%	56%	53%	49%	53%	74%	47%
22/08/2017	41%	54%	49%	51%	54%	53%	52%	59%	58%	45%	53%	49%	49%	45%	51%	73%	49%
23/08/2017	46%	55%	52%	55%	50%	55%	53%	49%	60%	52%	57%	49%	52%	46%	56%	74%	44%
24/08/2017	50%	52%	49%	53%	57%	57%	59%	59%	61%	52%	53%	52%	49%	43%	53%	67%	47%
25/08/2017	49%	53%	54%	53%	51%	58%	54%	55%	59%	51%	53%	51%	54%	45%	53%	60%	48%
26/08/2017	53%	62%	55%	56%	60%	62%	57%	49%	63%	55%	59%	54%	53%	49%	57%	66%	52%
27/08/2017	47%	55%	45%	57%	57%	61%	55%	58%	63%	50%	51%	47%	51%	43%	55%	62%	49%
28/08/2017	48%	61%	52%	55%	64%	64%	62%	57%	62%	52%	57%	53%	55%	43%	59%	61%	54%
29/08/2017	48%	55%	45%	53%	52%	50%	57%	54%	53%	52%	49%	50%	49%	38%	49%	60%	46%
30/08/2017	51%	54%	49%	52%	54%	54%	54%	55%	57%	49%	52%	51%	48%	41%	49%	58%	47%
31/08/2017	47%	55%	48%	48%	49%	57%	50%	56%	57%	48%	54%	46%	47%	43%	50%	60%	45%
01/09/2017	45%	55%	50%	50%	53%	59%	57%	53%	56%	48%	51%	47%	49%	40%	50%	61%	45%
02/09/2017	56%	56%	54%	57%	60%	63%	61%	54%	59%	52%	54%	47%	51%	43%	58%	64%	53%
03/09/2017	51%	37%	41%	47%	46%	51%	46%	48%	59%	40%	44%	47%	45%	35%	45%	62%	39%
04/09/2017	51%	58%	52%	48%	52%	58%	52%	55%	64%	48%	58%	50%	47%	39%	52%	66%	46%
05/09/2017	50%	51%	52%	50%	51%	58%	55%	51%	52%	47%	54%	48%	50%	34%	45%	58%	47%
06/09/2017	48%	58%	51%	47%	54%	56%	53%	52%	54%	45%	51%	45%	48%	36%	50%	60%	45%
07/09/2017	52%	51%	49%	42%	51%	53%	50%	52%	53%	50%	53%	47%	51%	33%	49%	59%	46%
08/09/2017	48%	52%	54%	41%	52%	58%	52%	54%	59%	46%	51%	54%	52%	37%	44%	67%	50%
09/09/2017	50%	49%	51%	45%	51%	64%	54%	53%	61%	47%	52%	55%	52%	32%	50%	62%	49%
10/09/2017	46%	46%	38%	42%	43%	53%	44%	45%	52%	39%	47%	47%	41%	31%	40%	62%	44%
11/09/2017	47%	52%	45%	44%	42%	59%	46%	48%	57%	47%	45%	49%	51%	36%	42%	70%	49%
12/09/2017	49%	57%	47%	45%	50%	58%	50%	51%	61%	48%	49%	49%	55%	40%	48%	66%	50%
13/09/2017	49%	50%	41%	45%	46%	54%	52%	51%	57%	45%	47%	49%	49%	39%	49%	71%	48%
14/09/2017	47%	49%	43%	44%	45%	55%	53%	53%	59%	50%	48%	55%	47%	36%	47%	67%	53%

Table 16: Ethogram 2: Table of predicted <u>standing</u> position percentage by sheep, by day

Date	ID2	ID3	ID4	ID5	ID6	ID7	ID8	ID9	ID10	ID11	ID12	ID13	ID14	ID15	ID16	ID17	ID18
20/08/2017	44%	38%	38%	42%	46%	50%	46%	42%	49%	40%	35%	47%	43%	42%	33%	58%	41%
21/08/2017	43%	39%	41%	37%	42%	45%	44%	47%	48%	40%	46%	44%	39%	45%	38%	53%	48%
22/08/2017	42%	43%	40%	38%	42%	43%	47%	51%	48%	43%	49%	42%	41%	47%	38%	59%	49%
23/08/2017	46%	37%	41%	41%	40%	46%	42%	51%	49%	43%	50%	45%	39%	45%	43%	55%	50%
24/08/2017	49%	31%	38%	39%	42%	46%	44%	49%	50%	42%	48%	42%	36%	39%	40%	54%	45%
25/08/2017	50%	27%	38%	41%	37%	49%	43%	48%	45%	40%	46%	41%	38%	34%	41%	51%	42%
26/08/2017	48%	31%	40%	42%	39%	44%	44%	50%	47%	40%	49%	38%	39%	41%	40%	56%	42%
27/08/2017	48%	32%	34%	37%	35%	42%	42%	41%	42%	36%	42%	34%	36%	34%	36%	48%	37%
28/08/2017	47%	29%	39%	43%	40%	47%	43%	42%	45%	42%	48%	37%	37%	37%	42%	57%	44%
29/08/2017	46%	33%	38%	41%	37%	43%	48%	49%	47%	41%	41%	45%	38%	34%	40%	50%	43%
30/08/2017	51%	35%	42%	46%	46%	52%	50%	50%	52%	41%	51%	46%	47%	41%	45%	57%	46%
31/08/2017	48%	32%	38%	39%	36%	46%	47%	45%	48%	38%	47%	37%	38%	35%	41%	58%	43%
01/09/2017	44%	29%	33%	36%	36%	46%	42%	43%	42%	38%	39%	37%	35%	30%	36%	46%	39%
02/09/2017	52%	28%	43%	41%	41%	51%	47%	46%	48%	43%	48%	41%	42%	35%	44%	57%	44%
03/09/2017	52%	39%	44%	46%	49%	53%	49%	51%	56%	44%	48%	51%	46%	35%	45%	62%	41%
04/09/2017	51%	31%	40%	40%	38%	57%	51%	52%	56%	40%	56%	47%	47%	33%	44%	58%	48%
05/09/2017	48%	35%	39%	38%	39%	48%	45%	50%	48%	34%	45%	41%	42%	29%	38%	53%	43%
06/09/2017	48%	32%	41%	37%	36%	51%	47%	48%	51%	38%	44%	40%	43%	28%	39%	61%	45%
07/09/2017	51%	34%	41%	30%	40%	53%	44%	51%	47%	41%	44%	43%	44%	24%	44%	53%	46%
08/09/2017	50%	36%	42%	35%	44%	52%	46%	51%	54%	42%	48%	49%	45%	30%	42%	54%	49%
09/09/2017	49%	40%	40%	40%	43%	55%	49%	50%	53%	40%	42%	47%	50%	26%	43%	59%	47%
10/09/2017	44%	41%	37%	39%	41%	53%	42%	47%	48%	37%	44%	46%	38%	22%	40%	61%	44%
11/09/2017	44%	46%	42%	40%	37%	53%	44%	49%	52%	46%	45%	48%	50%	29%	40%	59%	45%
12/09/2017	51%	43%	41%	39%	46%	54%	46%	49%	52%	41%	42%	45%	46%	30%	43%	56%	48%
13/09/2017	48%	44%	40%	39%	42%	52%	48%	54%	47%	43%	44%	44%	46%	32%	44%	60%	48%
14/09/2017	46%	39%	42%	38%	43%	51%	51%	51%	54%	45%	47%	48%	42%	34%	41%	60%	53%

Table 17: Ethogram 2: Table of predicted lying position percentage by sheep, by day

Date	ID2	ID3	ID4	ID5	ID6	ID7	ID8	ID9	ID10	ID11	ID12	ID13	ID14	ID15	ID16	ID17	ID18
20/08/2017	56%	62%	62%	58%	54%	50%	54%	58%	51%	60%	65%	53%	57%	58%	67%	42%	59%
21/08/2017	57%	61%	59%	63%	58%	55%	56%	53%	52%	60%	54%	56%	61%	55%	62%	47%	52%
22/08/2017	58%	57%	60%	62%	58%	57%	53%	49%	52%	57%	51%	58%	59%	53%	62%	41%	51%
23/08/2017	54%	63%	59%	59%	60%	54%	58%	49%	51%	57%	50%	55%	61%	55%	57%	45%	50%
24/08/2017	51%	69%	62%	61%	58%	54%	56%	51%	50%	58%	52%	58%	64%	61%	60%	46%	55%
25/08/2017	50%	73%	62%	59%	63%	51%	57%	52%	55%	60%	54%	59%	62%	66%	59%	49%	58%
26/08/2017	52%	69%	60%	58%	61%	56%	56%	50%	53%	60%	51%	62%	61%	59%	60%	44%	58%
27/08/2017	52%	68%	66%	63%	65%	58%	58%	59%	58%	64%	58%	66%	64%	66%	64%	52%	63%
28/08/2017	53%	71%	61%	57%	60%	53%	57%	58%	55%	58%	52%	63%	63%	63%	58%	43%	56%
29/08/2017	54%	67%	62%	59%	63%	57%	52%	51%	53%	59%	59%	55%	62%	66%	60%	50%	57%
30/08/2017	49%	65%	58%	54%	54%	48%	50%	50%	48%	59%	49%	54%	53%	59%	55%	43%	54%
31/08/2017	52%	68%	62%	61%	64%	54%	53%	55%	52%	62%	53%	63%	62%	65%	59%	42%	57%
01/09/2017	56%	71%	67%	64%	64%	54%	58%	57%	58%	62%	61%	63%	65%	70%	64%	54%	61%
02/09/2017	48%	72%	57%	59%	59%	49%	53%	54%	52%	57%	52%	59%	58%	65%	56%	43%	56%
03/09/2017	48%	61%	56%	54%	51%	47%	51%	49%	44%	56%	52%	49%	54%	65%	55%	38%	59%
04/09/2017	49%	69%	60%	60%	62%	43%	49%	48%	44%	60%	44%	53%	53%	67%	56%	42%	52%
05/09/2017	52%	65%	61%	62%	61%	52%	55%	50%	52%	66%	55%	59%	58%	71%	62%	47%	57%
06/09/2017	52%	68%	59%	63%	64%	49%	53%	52%	49%	62%	56%	60%	57%	72%	61%	39%	55%
07/09/2017	49%	66%	59%	70%	60%	47%	56%	49%	53%	59%	56%	57%	56%	76%	56%	47%	54%
08/09/2017	50%	64%	58%	65%	56%	48%	54%	49%	46%	58%	52%	51%	55%	70%	58%	46%	51%
09/09/2017	51%	60%	60%	60%	57%	45%	51%	50%	47%	60%	58%	53%	50%	74%	57%	41%	53%
10/09/2017	56%	59%	63%	61%	59%	47%	58%	53%	52%	63%	56%	54%	62%	78%	60%	39%	56%
11/09/2017	56%	54%	58%	60%	63%	47%	56%	51%	48%	54%	55%	52%	50%	71%	60%	41%	55%
12/09/2017	49%	57%	59%	61%	54%	46%	54%	51%	48%	59%	58%	55%	54%	70%	57%	44%	52%
13/09/2017	52%	56%	60%	61%	58%	48%	52%	46%	53%	57%	56%	56%	54%	68%	56%	40%	52%
14/09/2017	54%	61%	58%	62%	57%	49%	49%	49%	46%	55%	53%	52%	58%	66%	59%	40%	47%

Table 18: Ethogram 3: Table of predicted grazing behaviour percentage by sheep, by day

Date	ID2	ID3	ID4	ID5	ID6	ID7	ID8	ID9	ID10	ID11	ID12	ID13	ID14	ID15	ID16	ID17	ID18
20/08/2017	31%	21%	18%	24%	31%	31%	32%	22%	34%	22%	19%	31%	31%	31%	13%	41%	22%
21/08/2017	30%	25%	24%	24%	30%	29%	32%	27%	34%	27%	32%	28%	27%	35%	21%	39%	31%
22/08/2017	32%	26%	26%	24%	32%	27%	36%	36%	33%	31%	37%	30%	27%	38%	25%	45%	33%
23/08/2017	35%	24%	28%	27%	29%	31%	30%	32%	34%	32%	38%	29%	27%	35%	31%	41%	31%
24/08/2017	38%	19%	25%	27%	29%	31%	34%	32%	35%	30%	34%	29%	24%	29%	28%	42%	30%
25/08/2017	40%	17%	27%	30%	24%	33%	32%	32%	33%	30%	36%	29%	27%	25%	31%	40%	27%
26/08/2017	38%	22%	29%	32%	27%	32%	33%	33%	33%	31%	38%	28%	27%	32%	31%	44%	28%
27/08/2017	38%	20%	24%	28%	25%	30%	33%	28%	31%	27%	33%	25%	25%	26%	29%	39%	26%
28/08/2017	39%	21%	29%	33%	31%	34%	35%	31%	34%	31%	38%	27%	26%	30%	34%	43%	32%
29/08/2017	38%	24%	29%	33%	29%	30%	39%	35%	36%	31%	33%	33%	29%	27%	32%	40%	30%
30/08/2017	43%	24%	31%	36%	34%	37%	40%	37%	41%	31%	40%	35%	34%	34%	33%	42%	33%
31/08/2017	41%	22%	27%	30%	25%	34%	37%	32%	35%	30%	37%	26%	27%	28%	31%	44%	31%
01/09/2017	37%	19%	23%	27%	25%	34%	35%	31%	33%	30%	29%	26%	26%	24%	27%	35%	27%
02/09/2017	45%	20%	34%	36%	35%	42%	41%	37%	38%	35%	39%	32%	31%	29%	36%	44%	36%
03/09/2017	48%	25%	30%	38%	36%	39%	40%	35%	43%	30%	35%	38%	34%	28%	32%	47%	29%
04/09/2017	42%	21%	29%	30%	26%	42%	40%	33%	43%	30%	40%	35%	31%	24%	34%	42%	36%
05/09/2017	42%	25%	31%	31%	29%	37%	37%	34%	37%	28%	32%	32%	32%	23%	29%	37%	34%
06/09/2017	42%	22%	32%	28%	24%	38%	38%	32%	39%	31%	34%	30%	31%	21%	29%	43%	35%
07/09/2017	46%	24%	32%	23%	30%	37%	37%	37%	36%	33%	36%	33%	35%	15%	34%	38%	38%
08/09/2017	44%	25%	32%	25%	32%	36%	38%	35%	41%	32%	38%	38%	34%	23%	32%	39%	39%
09/09/2017	42%	29%	30%	29%	31%	44%	41%	35%	40%	30%	32%	35%	36%	17%	32%	43%	35%
10/09/2017	41%	30%	29%	32%	32%	37%	35%	33%	38%	28%	37%	37%	29%	13%	31%	43%	36%
11/09/2017	40%	36%	35%	32%	28%	39%	36%	35%	41%	38%	34%	40%	41%	20%	30%	44%	36%
12/09/2017	45%	33%	33%	29%	36%	40%	37%	34%	39%	33%	31%	34%	37%	21%	33%	41%	40%
13/09/2017	42%	33%	30%	31%	31%	36%	39%	36%	37%	33%	33%	34%	35%	25%	34%	46%	38%
14/09/2017	39%	28%	29%	30%	30%	35%	44%	34%	40%	33%	36%	35%	29%	28%	31%	44%	41%

Table 19: Ethogram 3: Table of predicted <u>resting</u> behaviour percentage by sheep, by day.

Date	ID2	ID3	ID4	ID5	ID6	ID7	ID8	ID9	ID10	ID11	ID12	ID13	ID14	ID15	ID16	ID17	ID18
20/08/2017	69%	79%	82%	76%	69%	69%	68%	78%	66%	78%	81%	69%	69%	69%	87%	59%	78%
21/08/2017	70%	75%	76%	76%	70%	71%	68%	73%	66%	73%	68%	72%	73%	65%	79%	61%	69%
22/08/2017	68%	74%	74%	76%	68%	73%	64%	64%	67%	69%	63%	70%	73%	62%	75%	55%	67%
23/08/2017	65%	76%	72%	73%	71%	69%	70%	68%	66%	68%	62%	71%	73%	65%	69%	59%	69%
24/08/2017	62%	81%	75%	73%	71%	69%	66%	68%	65%	70%	66%	71%	76%	71%	72%	58%	70%
25/08/2017	60%	83%	73%	70%	76%	67%	68%	68%	67%	70%	64%	71%	73%	75%	69%	60%	73%
26/08/2017	62%	78%	71%	68%	73%	68%	67%	67%	67%	69%	62%	72%	73%	68%	69%	56%	72%
27/08/2017	62%	80%	76%	72%	75%	70%	67%	72%	69%	73%	67%	75%	75%	74%	71%	61%	74%
28/08/2017	61%	79%	71%	67%	69%	66%	65%	69%	66%	69%	62%	73%	74%	70%	66%	57%	68%
29/08/2017	62%	76%	71%	67%	71%	70%	61%	65%	64%	69%	67%	67%	71%	73%	68%	60%	70%
30/08/2017	57%	76%	69%	64%	66%	63%	60%	63%	59%	69%	60%	65%	66%	66%	67%	58%	67%
31/08/2017	59%	78%	73%	70%	75%	66%	63%	68%	65%	70%	63%	74%	73%	72%	69%	56%	69%
01/09/2017	63%	81%	77%	73%	75%	66%	65%	69%	67%	70%	71%	74%	74%	76%	73%	65%	73%
02/09/2017	55%	80%	66%	64%	65%	58%	59%	63%	62%	65%	61%	68%	69%	71%	64%	56%	64%
03/09/2017	52%	75%	70%	62%	64%	61%	60%	65%	57%	70%	65%	62%	66%	72%	68%	53%	71%
04/09/2017	58%	79%	71%	70%	74%	58%	60%	67%	57%	70%	60%	65%	69%	76%	66%	58%	64%
05/09/2017	58%	75%	69%	69%	71%	63%	63%	66%	63%	72%	68%	68%	68%	77%	71%	63%	66%
06/09/2017	58%	78%	68%	72%	76%	62%	62%	68%	61%	69%	66%	70%	69%	79%	71%	57%	65%
07/09/2017	54%	76%	68%	77%	70%	63%	63%	63%	64%	67%	64%	67%	65%	85%	66%	62%	62%
08/09/2017	56%	75%	68%	75%	68%	64%	62%	65%	59%	68%	62%	62%	66%	77%	68%	61%	61%
09/09/2017	58%	71%	70%	71%	69%	56%	59%	65%	60%	70%	68%	65%	64%	83%	68%	57%	65%
10/09/2017	59%	70%	71%	68%	68%	63%	65%	67%	62%	72%	63%	63%	71%	87%	69%	57%	64%
11/09/2017	60%	64%	65%	68%	72%	61%	64%	65%	59%	62%	66%	60%	59%	80%	70%	56%	64%
12/09/2017	55%	67%	67%	71%	64%	60%	63%	66%	61%	67%	69%	66%	63%	79%	67%	59%	60%
13/09/2017	58%	67%	70%	69%	69%	64%	61%	64%	63%	67%	67%	66%	65%	75%	66%	54%	62%
14/09/2017	61%	72%	71%	70%	70%	65%	56%	66%	60%	67%	64%	65%	71%	72%	69%	56%	59%

Table 20: Repeatability LMM method - Grazing.

```
Repeatability estimation using the lmm method
Call = rpt(formula = Grazing ~ Temp * Rainfall + (1 | Date) + (1 | ID),
grname = c("Date", "ID"), data = Behaviour_long, datatype = "Gaussian",
nboot = 1000, npermut = 0)

Data: 442 observations
----------------------------------------
Date (26 groups)

Repeatability estimation overview:
```

R	SE	2.50%	97.50%
0.076	0.0314	0.0294	0.156

```
Bootstrapping and Permutation test:
```

	N	Mean	Median	2.50%	97.50%
boot	1000	0.0782	0.0751	0.0294	0.156

```
Likelihood ratio test:
logLik full model = 797.5074
logLik red. model = 775.6809
D  = 43.7, df = 1, P = 1.96e-11
----------------------------------------

ID (17 groups)

Repeatability estimation overview:
```

R	SE	2.50%	97.50%	P_permut	LRT_P
0.596	0.0886	0.394	0.733	NA	0

```
Bootstrapping and Permutation test:
```

	N	Mean	Median	2.50%	97.50%
boot	1000	0.584	0.595	0.394	0.733

```
Likelihood ratio test:
logLik full model = 797.5074
logLik red. model = 613.139
D  = 369, df = 1, P = 1.76e-82

-----------------------------------
```

Table 21: Repeatability LMM method - Lying.

```
Repeatability estimation using the lmm method
Call = rpt(formula = Lying ~ Temp*Rainfall + (1 | Date) + (1 | ID), grname
= c("Date", "ID"), data = Behaviour_long, datatype = "Gaussian", nboot =
1000, npermut = 0)

Data: 442 observations
----------------------------------------
Date (26 groups)

Repeatability estimation overview:
```

R	SE	2.50%	97.50%
0.0913	0.038	0.039	0.185

```
Bootstrapping and Permutation test:
```

	N	Mean	Median	2.50%	97.50%
boot	1000	0.0963	0.0907	0.039	0.185

```
Likelihood ratio test:
logLik full model = 803.2484
logLik red. model = 764.6387
D  = 77.2, df = 1, P = 7.65e-19
----------------------------------------

ID (17 groups)

Repeatability estimation overview:
```

R	SE	2.50%	97.50%
0.665	0.0869	0.446	0.788

```
Bootstrapping and Permutation test:
```

	N	Mean	Median	2.50%	97.50%
boot	1000	0.646	0.655	0.446	0.788

```
Likelihood ratio test:
logLik full model = 803.2484
logLik red. model = 563.3441
D  = 480, df = 1, P = 1.18e-106

-----------------------------------
```

Table 22: Repeatability LMM method – Head up.

```
Call = rpt(formula = `head up` ~ Temp*Rainfall + (1 |
Date) + (1 | ID), grname = c("Date", "ID"), data =
Behaviour_long, datatype = "Gaussian", nboot = 1000,
npermut = 0)

Data: 442 observations
----------------------------------------
Date (26 groups)

Repeatability estimation overview:
```

R	SE	2.50%	97.50%
0.113	0.0446	0.0462	0.219

```
Bootstrapping and Permutation test:
```

	N	Mean	Median	2.50%	97.50%
boot	1000	0.118	0.113	0.0462	0.219

```
Likelihood ratio test:
logLik full model = 797.7259
logLik red. model = 751.1691
D  = 93.1, df = 1, P = 2.47e-22
----------------------------------------

ID (17 groups)

Repeatability estimation overview:
```

R	SE	2.50%	97.50%
0.635	0.0905	0.419	0.766

```
Bootstrapping and Permutation test:
```

	N	Mean	Median	2.50%	97.50%
boot	1000	0.617	0.628	0.419	0.766

```
Likelihood ratio test:
logLik full model = 797.7259
logLik red. model = 570.0113
D  = 455, df = 1, P = 2.37e-101
```

Table 23: Linear Mixed Model Analysis fit by REML Grazing.

```
Linear mixed model fit by REML. t-tests use Satterthwaite's method
['lmerModLmerTest']
Formula: Grazing ~ zTemp * zRainfall + (1 | ID) + (1 | Date)
   Data: Behaviour_long


REML criterion at convergence: -1602.5


Scaled residuals:
    Min      1Q  Median      3Q     Max

-3.9454 -0.5227  0.0184  0.5676  3.8083
```

Random effects:

Groups	Name	Variance	Std.Dev.
Date	(Intercept)	0.0002658	0.0163
ID	(Intercept)	0.002085	0.04566
Residual	Residual	0.0011479	0.03388

Number of obs: 442, groups: Date, 26; ID, 17

Fixed effects:

	Estimate	Std. Error	df	t value	Pr(>|t|)
(Intercept)	0.34286	0.012384	22.987266	27.685	< 0.001 ***
zTemp	0.01525	0.006802	22.00007	2.242	0.04 *
zRainfall	0.03155	0.007911	22.00007	3.988	< 0.001 ***
zTemp:zRainfall	0.02885	0.006877	22.00007	4.195	< 0.001 ***

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Correlation of Fixed Effects:

	(Intr)	zTemp	zRainfall
zTemp	0.254		
zRainfall	0.279	0.845	
zTmp:zRnfll	0.342	0.743	0.818

Table 24: Linear Mixed Model Analysis fit by REML Lying.

```
Linear mixed model fit by REML. t-tests use Satterthwaite's method
['lmerModLmerTest']
Formula: Lying ~ zTemp * zRainfall + (1 | ID) + (1 | Date)
   Data: Behaviour_long

REML criterion at convergence: -1614

Scaled residuals:
    Min      1Q  Median      3Q     Max
-3.5239 -0.5500 -0.0546  0.5714  3.5590
```

Random effects:

Groups	Name	Variance	Std.Dev.
Date	(Intercept)	0.0004053	0.02013
ID	(Intercept)	0.0029541	0.05435
Residual	Residual	0.0010798	0.03286

Number of obs: 442, groups: Date, 26; ID, 17

Fixed effects:

	Estimate	Std. Error	df	t value	Pr(>|t|)
(Intercept)	0.55855	0.01473	23.243788	37.918	< 0.00 ***
zTemp	-0.0027	0.008067	22.000015	-0.332	0.743
zRainfall	-0.014	0.009382	22.000015	-1.494	0.149
zTemp:zRainfall	-0.0073	0.008156	22.000015	0.893	0.382

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Correlation of Fixed Effects:

	(Intr)	zTemp	zRainfall
zTemp	0.253		
zRainfall	0.279	0.845	
zTmp:zRnfll	0.342	0.743	0.818

Table 25: Linear Mixed Model Analysis fit by REML Head up.

```
Linear mixed model fit by REML. t-tests use Satterthwaite's method
['lmerModLmerTest']
Formula: `head up` ~ zTemp * zRainfall + (1 | ID) + (1 | Date)
   Data: Behaviour_long


REML criterion at convergence: -1602.9


Scaled residuals:
    Min      1Q  Median      3Q     Max
-2.4577 -0.6373 -0.0231  0.6447  3.3026
```

Random effects:

Groups	Name	Variance	Std.Dev.
Date	(Intercept)	0.0004909	0.02216
ID	(Intercept)	0.0027692	0.05262
Residual	Residual	0.0011025	0.0332

Number of obs: 442, groups: Date, 26; ID, 17

Fixed effects:

	Estimate	Std. Error	df	t value	Pr(>|t|)
(Intercept)	0.4886	0.014633	25.068845	33.391	< 0.00 ***
zTemp	-0.0093	0.008783	22.000023	-1.056	0.303
zRainfall	0.0109	0.010214	22.000023	1.067	0.298
zTemp:zRainfall	0.00257	0.008880	22.000023	0.289	0.775

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Correlation of Fixed Effects:

	(Intr)	zTemp	zRainfall
zTemp	0.277		
zRainfall	0.305	0.845	
zTmp:zRnfll	0.373	0.743	0.818

Chapter 4 General Conclusion

1.0 Introduction

This chapter will conclude the study of assessing methods to improve our understanding of the health and welfare status of sheep and the influences of their immediate environment by summarising the key research findings in relation to the thesis aims and questions. It will also review the limitations of the study and propose opportunities for future research. The future of agriculture offers many challenges such as; climate change, population growth and disease threats that present risks for the UK sheep industry, however arguably the author suggest that challenges can also be considered an opportunity to improve (Averós, X. et al., 2014; Duncan, I. & Fraser, D, 1997; Dwyer, CM & Lawrence, AB, 2005; DEFRA, 2018; Grant, E.P. et al., 2018; Hargreaves, A.L. & Hutson, G.D., 1990; Hansen, B. G. & Osteras, O, 2019). It has become clear that as the farm environment has been dictated by production goals, they may not be ideal from a welfare perspective and this presents an opportunity to understand how UK flocks are influenced by their immediate environment by utilising novel approaches to improve welfare.

The key objective of this study was to establish the best technique, gained from novel approaches, to classify sheep behaviour of an unsupervised commercial flock. Based on the lack of literature and therefore gap in knowledge across the industry of how sheep respond and adapt to changes in a commercial environment, there was opportunity to utilise behaviour data and investigate this novel research area (Etim, N.N. et al., 2013; Piirsalu, P. et al., 2020). Results indicated that the predominant daily activity of sheep behaviour was resting, conflicting with research produced previously that has inferred resting as the least dominant behaviours (Hinch, 2017). There are discrepancies in the natural behavioural expressions across the 2000 breeds, that could be the cause of the conflicting results, however this would need to be researched further (Barwick, J. et al., 2018a; Fogarty, E.S. et al., 2020a; Hinch, G. N, 2017). Nevertheless, these findings do confirm that movement, physiology and behaviour of commercial animals can be used to assist in achieving performance goals. The author suggests this research supports the use of technological advances utilising behavioural data as an aid to improve welfare, performance and productivity. Progressing this research further to gain a daily activity benchmark is considered to create a superior quality of husbandry. Furthermore, as data can be collected, stored and shared, there is an opportunity to utilise this to improve traceability 'from farm to fork'. This also a requirement of the new domestic agricultural policy (DEFRA, 2018).

Unlike many trials that have been published in more recent years, the author was solely responsible for the data collection, from both the application of the collars on the ewes in both trials, as well as the observations and video annotations. The author later created the ethogram and investigated the most appropriate model to support in predicting the behaviour data of sheep in a commercial setting and later used this model to analyse the predicted behavioural responses to the effects of rain and temperature variation of an unsupervised flock (Figure 1: Methods Diagram). It is felt by the author that one person at each step removed the potential for bias in the data set and enabled a greater understanding of the potential influences of the environment. In addition, the author worked for many years as a shepherd and therefore has benefitted from industry knowledge and for this reason advocates the use of technology in understanding the behaviours of sheep to improve their welfare.

A secondary aim was to investigate whether rainfall and temperature influence behaviour/postural durations (Grazing, Lying, Head up (non- grazing, non-resting postural state). Based on a review of the available research, it was suggested that temperature would not significantly influence behaviours with the exception of extreme temperature changes, however rainfall would influence behaviours, by a reduction in grazing time and an increase in lying time (Erickson, 2018; Ferguson, D. M. et al., 2017; Gougoulis, A. et al., 2010; Jarman, P.J., 1974; Learmount, J. et al., 2018; Piirsalu, P. et al., 2020; Schütz, K. E. et al., 2010). As hypothesised temperature did not have a significant influence on any of the behaviours in the study. In contrast, despite suggesting that rainfall would increase lying durations the results infer that rain positively influenced sheep behaviour by increasing grazing durations, the flock grazed proportionality more on rainier days as opposed to non-rainy days.

Furthermore, based on a natural drive to synchronise behaviours, due to an inherent antipredator response (Adamczyk, K. et al., 2015; Gougoulis, A. et al., 2010), it was predicted that individual sheep behaviour would be repeatable across the flock, irrespective of the influence of weather variability. Results indicate flock behaviours were repeatable and unimpacted by climate and the flock did remain cohesive. Yet results demonstrated that the whole flock would alter their behaviour to their environment day-to-day. Findings also suggest that lying was the most dominant synchronous behaviour.

2.0 Study Limitations

2.1 Data Collection

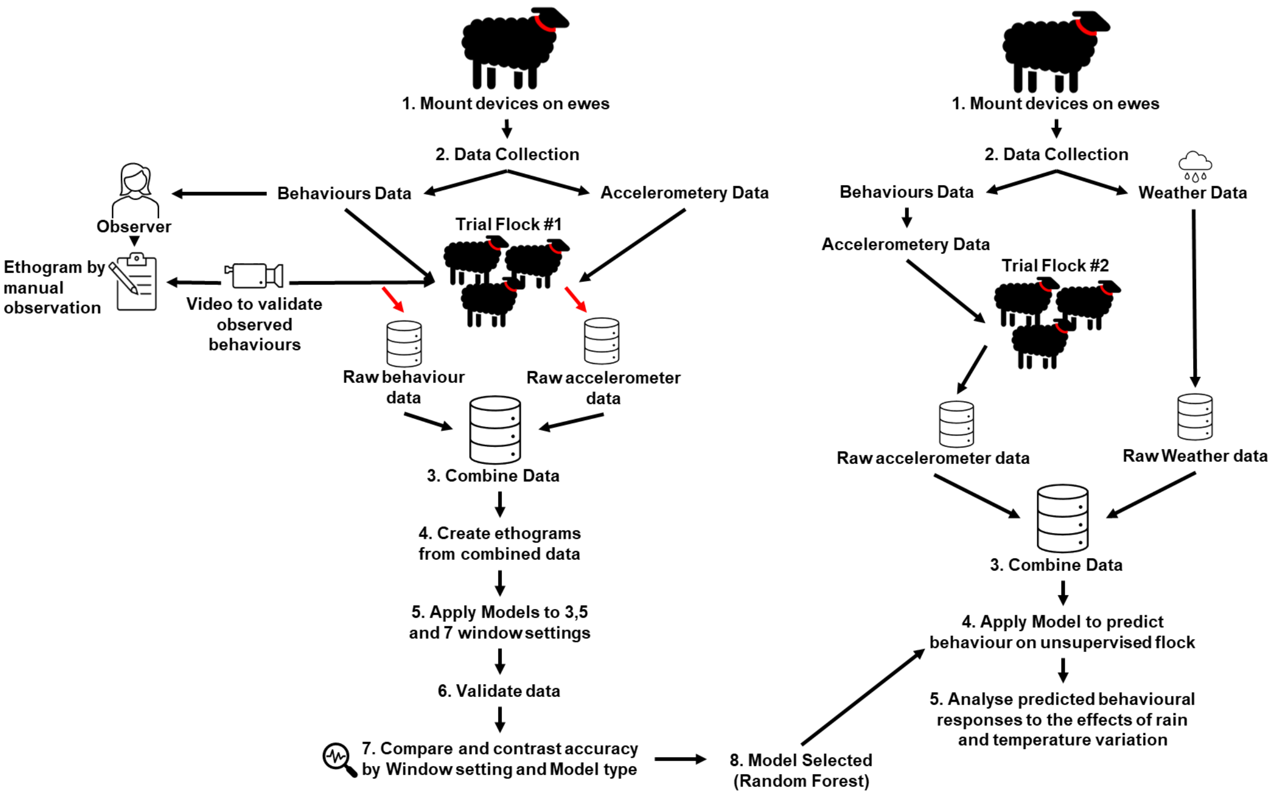

Figure 1: Methods Diagram

2.1.1 Observations

As previously realised in a trial completing similar research, capturing behaviour data of commercial ewes is problematic. Due in part to the nature of the commercial environment whereby ewes roam multiple or large fields (Fogarty, E.S. et al., 2020a). To mitigate against this, ewes could have been confined to one smaller field. However, it was essential to complete the data collection in a commercial setting, with limited human interruption so as to not impact natural behaviours. The importance of this became clear during in-field behaviour data collection, whereby the inherent antipredator behaviour of sheep was evident and as a result the data for one ewe had to be discarded, as she made a concerted effort to avoid the author during the observation windows (Adamczyk, K. et al., 2015; Baskin, L.M, 1974; Barwick, J. et al., 2018a; Barwick, J. et al., 2018b; Estevez, I. et al., 2007; Gougoulis, A. et al., 2010; Jarman, P.J., 1974; Learmount, J. et al., 2018; Piirsalu, P. et al., 2020; Rook, A.J. & Penning, P.D., 1991).

The author categorised all behaviours to reduce incidence of observer bias, as the traditional practices of human observation are subjective. Yet, this created a challenge; annotating behaviour events, with only one person data collecting, inevitably led to some missed behavioural changes. This issue was alleviated by the addition of video recordings, an in-field webcam was used as opposed to closed circuit television (CCTV), as this was not feasible in a commercial setting due to the location, for both access to power and field visibility. Gaining a clear view of the whole flock has been evidenced in previous research to be difficult in a commercial environment (Learmount, J. et al., 2018; Living Countryside, 1999; NSA, 2020b; Royal Duchy College, 2018). Webcams were able to record behaviours that were missed during annotations, all unseen or unrecognised behaviours were labelled as ‘unknown’ and later discarded as part of the data cleaning process, which inevitably reduced the sample size.

Monitoring ewes prior to the trial would have also been pertinent to the study, as the observation window had to be changed on the third day, due to the large amount of resting activity performed in the earlier hours of the day. Gaining a clearer understanding the time of day when each of the required behaviour classes were at their highest, would have enabled a more balanced dataset.

2.1.2 GENEActiv Unit

The GENEActiv accelerometer unit was mounted on to a Shearwell Bell collar, this collar was specifically designed for commercial livestock. However, one ewes managed to rub of the mounted device and subsequently was not found, to mitigate against this, the author suggests that it would best to source a collar with an integrated accelerometer unit or have this made. Furthermore, one unit stopped working with reasons unknown, it may have been possible to increase the number of animals recorded to mitigate against any short comings with technology, however in future research it may be possible with advances in technology to move to live data collection without the need to remove collars, so that these issues may be realised at the start of the trial as opposed to the end.

2.1.3 Recording Frequency and battery longevity

Recording frequency improved accuracy however impacted battery life, as detected by Walton, E. et al., (2018). In the initial study the trial period did not exceed 5 days, so to ensure the optimal accuracy the recording frequency was set to 50hz. However, in trial two the battery needed to last for up to a month and to ensure continuous recording for the trial period the frequency was reduced to 10hz. In addition, the training data for the model had to be down sampled and rerun. As a result, the original model accuracy was marginally impacted. The author suggests that this could have been avoided, as it was inevitable that future research would have led to recording behaviours in trials over longer time periods and therefore in order to future proof the model the recording frequency could have been initially created at 10hz.

2.2 Dataset

2.2.1 Activity volumes

Due to adverse weather conditions prior to deployment, there was a heightened risk of liver fluke and lameness (DEFRA, 2018). To mitigate against this, ewes received a thorough lameness check and were selected, based on age, parity, and condition score. Despite this, in both trials there was an incidence of lameness, one ewe in each trail had to treated, yet subsequently removed from the trials and their data excluded. To alleviate the impact of units loss or absence due to ill health, twenty ewes were selected for the study in trial two.

The volume of sheep could have been increased to ensure a more robust sample size, flock size and technology permitting.

As observed by Fogarty, E.S. et al., (2020a), specific activities were harder to record at the same volumes as others, in both their study and ours, walking was one of the harder behaviours to record in volume. This was less detrimental in this study as the ethogram called for less definitive behaviour collection and walking was grouped in activity and omitted in isolation. However, care needs to be taken when interpreting the results. Not all sheep performed all behaviours at the same volumes. which led to a disparity in the contrasting behaviours. Due in part to the observation window limiting behavioural variety as mentioned previously, there was a higher volume of resting behaviours recorded, as evident in the proportion of resting and grazing behaviours recorded, 81% and 19% respectively, this resulted in unbalanced datasets. However, the author suggests that the unbalanced dataset may not be detrimental to this study as movement signals will alter significantly between active and non-active behaviours.

2.2.2 Weather Data

Based on previous research, it was expected that temperature would not cause notable behavioural variations, unless temperature fluctuated excessively (Erickson, 2018; Ferguson, D. M. et al., 2017; Gougoulis, A. et al., 2010; Jarman, P.J., 1974; Learmount, J. et al., 2018; Piirsalu, P. et al., 2020; Schütz, K. E. et al., 2010). Over the trial period, the temperature fluctuated by only 8.2 degrees, therefore we were unable to confirm or deny these claims. In addition, Erickson (2018) has suggested that the ‘wind chill’ factor can double heat loss of sheep and can lead to hypothermia, therefore the addition of wind speed, as well as rainfall, temperature and their durations would have been highly beneficial. This could be investigated by running the trial over a longer time period or by investigating optimum times of the year in order to capture behaviour when adverse weather conditions are probable. The other clear benefit to this trial would have been weather data by the hour, so that we could have seen if the weather conditions modified the activities at the point in time. R. A. Champion (1994) reported that rain in excess of 1mm per hour during a ‘peak eating time’ reduced the time spent grazing and thus modified the grazing pattern. Our data suggests that sheep spend a higher proportion of their time grazing on rainier days, however the detail to explain whether this was during or after a specific rain event is something that cannot be reported.

3.0 Key findings

The secondary aim of this study was to explore the influences of weather conditions on the behaviour/posture of commercially farmed sheep. This was investigated by using time spent in each activity as the numerator, divided by the total minutes in the day (denominator), the sum of which provides the proportion of time by each activity on each day. The results indicate two key findings, these findings demonstrate a conflicting result when compared to previous studies:

1. The predominant activity of the commercial sheep recorded in this study were resting behaviours.
2. There was a higher duration of grazing on days with greater volumes of rain.

3.1 Dominate Activity

It is suggested by Hinch (2017) that the dominant behaviour of sheep in their natural environment is feed gathering. It is unclear as to whether this is suggesting that ‘feed gathering’ is solely the act of grazing and therefore inferring that grazing is the dominant activity of ‘all’ sheep. It would be important to understand whether ‘feed gathering’ is inclusive of ‘ranging behaviours’, conceivably what is being referred to as ‘harvesting mode’ in the same paper, whereby the sheep are walking/standing with their heads on the ground as though grazing but not actually eating (as observed during trial 1 by the author). If Hinch (2017) is suggesting that grazing is the dominant activity of ‘all’ sheep, I would dispute this based on the results from this study. On average, the flock’s daily proportion of grazing versus resting activity was 33% and 67% respectively, this suggests that the dominant behaviour of the flock was resting behaviour.

The results suggest that sheep display a repeatable pattern of daily resting and grazing behaviours, as also reported by R.A. Champion (1994). Therefore, this demonstrates that as the dominant activity was resting behaviours for the whole trial period, its unlikely that proportions of time spent resting was because of an immediate change to their environment. Lying/resting was the dominant behaviour/posture for this breed, on this farm, during the date range the ewes were recorded. Arguably, the trial was completed late summer, early autumn and the changing season may have influenced the behavioural patterns of the ewes.

There is evidence to suggest that sheep are highly motivated to avoid high temperatures (Hinch, 2017). In addition, cold stress thresholds in sheep have not been widely documented (Piirsalu, P. et al. 2020). Compared to cattle and other livestock species, sheep are better adapted to cold temperatures, as their fleece provides natural insulation to extreme weather (Erickson, 2018; Piirsalu, P. et al. 2020). Despite this, Erickson (2018) suggest that sheep are motivated to seek shelter and huddle together in cold, wet and windy conditions to conserve heat. Therefore, we can infer from this, that grazing is not going to be the dominant behaviour if the weather is poor. It would be interesting to understand whether the volumes of activity alter throughout the seasons, perhaps we had higher proportions of lying activity due to seasonality and therefore this may alter at different times of year. Piirsalu, P. et al. (2020) reported that sheep are more motivated to be outdoors rather than indoors when offered shelter, even in temperatures as low as −20 ◦C. Despite the ewe’s preference to be outside it may result in a reduction of grazing time that we, until now, may have been unaware of. In addition to weather conditions, Hinch (2017) suggests factors such as; vegetation and soil type, typography of the land, as well as the sheep breed, will all influence foraging behaviour and these combined, highlights the difficultly of defining what ‘normal’ sheep behaviour is. The author feels that as a result of this finding, it is not practical in any sheep behaviour study to suggest that the conclusions are true of ‘all’ sheep, a ‘one-size fits all’ approach cannot be applied here and therefore we need to move away from high-level species-specific behaviour traits. Sheep are a complex and highly adaptable species.

3.2 The Influence of Rain on the Time Spent Grazing

The results from trial 2 indicated that there was a higher duration of grazing on days with greater volumes of rain. The author is unsure as to whether this relationship has been documented, however in previous research there has been evidence to suggest a significant decline in grazing, if rain fell in a period in which the eating activity was normally high (R.A. Champion, 1994). Hinch (2017) suggests that the majority of herbivores used in farming generally have a main ‘meal’ around sunrise. R.A. Champion, (1994) also reported that when eating activity was usually low, feeding patterns remained unaffected by rainfall (R.A. Champion, 1994). In contrast, Hinch (2017) suggests its less specific and following the main meal at sunrise, subsequent feeding patterns are largely dependent on both, feed availability and weather condition. In agreement Schütz, K. E. et al. (2010), reported a marked decline in lying time, feed intake and skin temperature in response to wet conditions in dairy cattle. This is also evidenced by Erickson (2018) that advises that sheep may be unable to move when wet and cold.

It would be crucial to consider what caused this positive influence of rain on grazing activities, to gain a greater understanding of the preferences of sheep and impacts of their immediate environment. Results indicated that the flock will remain cohesive but modulate their behaviour to their environment each day, this was also reported by R.A. Champion (1994) with results suggesting that sheep will modify their normal grazing pattern to compensate for any disruptions. This outcome compliments the results in the study of trial two, perhaps the ewes spend a longer proportion of time grazing on days it rained to compensate for periods of time they were unable to eat in sufficient volumes (R.A. Champion.,1994).

As the flock was unsupervised, we do not have a daily narrative as to what may have influenced the daily changes such as hourly weather data and bite rates, in addition to many unknown variables that can be investigated in this area to improve our understanding of the environmental influences that modify sheep behaviour and in hindsight, it would have been useful to have some narrative to confirm some of these assumptions. As suggested by Fogarty, E.S. et al., (2020a) and as previously stated under the heading of 3.1, these behavioural studies should be reproduced for all commercial breeds and farm types to be collated and shared to understand the wider impacts the environment has on the efficacy of future behaviour models. It would be essential to research this further, with farm, breed, environment, and seasonality all taken into account.

4.0 Further Research Directions

Lessons learned following data collection and processing, has led the author to suggest that further development to improve the current model, by ensuring data set balance as well as expanding the model to include a variety of breeds, should be actioned for future research, in addition to increasing the overall sample size of training data by extending trial lengths and increasing the volume of sheep. Furthermore, selecting a commercial environment that use smaller field rotations that can be accessible from buildings so that CCTV can be used should be considered. Detailed weather data would offer a clear benefit to this trial and would have enabled a superior analysis of the key findings. Additionally, despite the many positives of having one person responsible for the whole process, from data collection to manipulation, an increase in observer numbers to offer greater support by enabling added data collection and reducing missed behavioural events would be highly beneficial to the efficacy of the model. Although, it would be essential to have an agreed behaviour classification format to mitigate against observer bias.

A further research area that has been presented is examining the data outputs from trial two, to comprehend the daily activity of sheep and what this means from a production perspective. It was possible to identify outliers in an individual's daily activity, as demonstrated on the 20th August by Sheep 16, whereby grazing attributed to 12.6% of their daily activity, this was 17.0 percent point lower than her average grazing activity and it is clear that this would be essential information, as it suggests that it is feasible to understand what is considered a healthy range. As a result of summarising this research, we present further opportunities to enable the development of a farm tool that provides various alerts as seen in the cattle industry (Eckelkamp E.A and Bewley, J.M., 2020). The next stage to meet this requirement would be to link observed behaviours to management knowledge.

5.0 Conclusion

Overall, the research demonstrates that accelerometers were able to offer a non-invasive measure capable of capturing the behavioural activities of commercial sheep. The random forest model produced in the initial trials, was the most appropriate model to classify sheep behaviour and later provided insight into the daily activity of the flock. The linear mixed model was able to determine that temperature did not influence behaviours and inferred that rainfall positively increased grazing durations, this novel finding requires further research to evaluate this relationship. The author has outlined the importance and potential risks associated with drawing conclusions from specific studies and assuming they are true of ‘all’ sheep behaviour, as identified with the contrasts in dominant activities in this and previous trials. In addition, assessing the daily activity of the flock may lead to identifying performance information that can complement production goals and further enhance our understanding of commercial sheep behaviour and the influences of their immediate environment.

6.0 References

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7.0 Appendix

Figure 2: Grazing - Bootstap repeatabilities with Confidence interval.

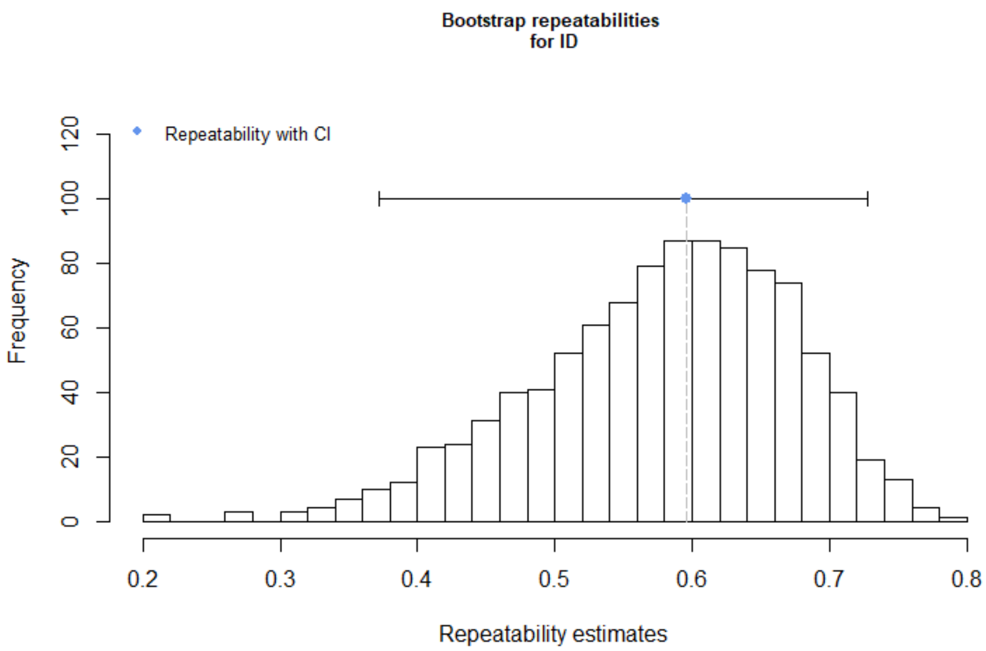

Figure 3: Lying - Bootstap repeatabilities with Confidence interval.

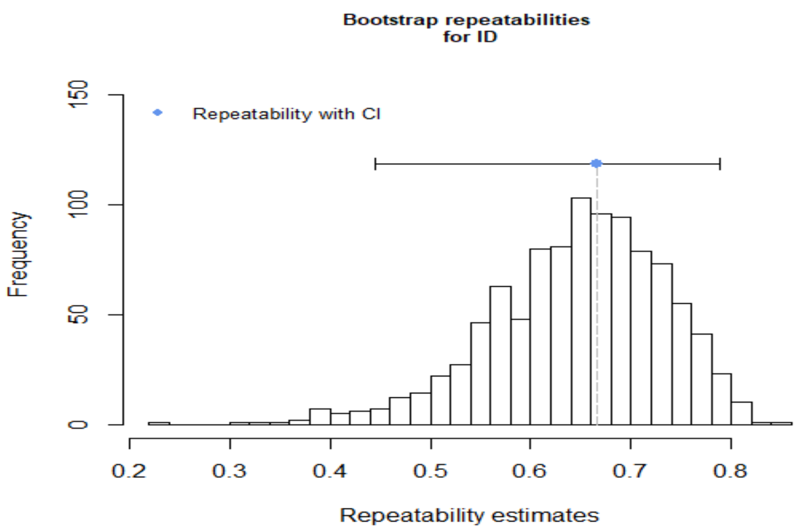

Figure 4: Head up - Bootstap repeatabilities with Confidence interval.

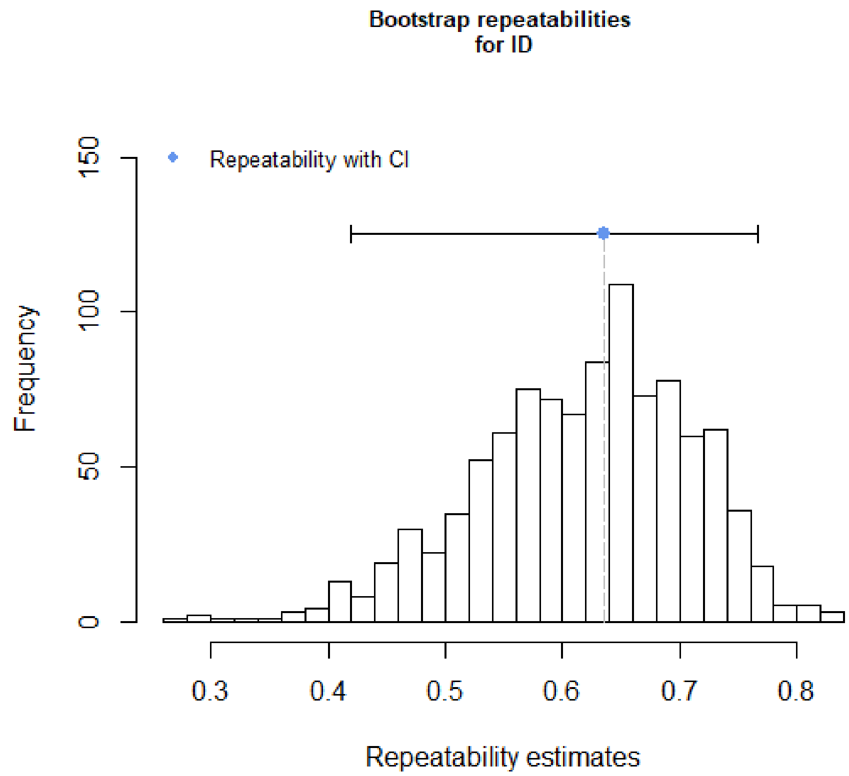

Figure 5: Grazing Average by Temperature Group by ID

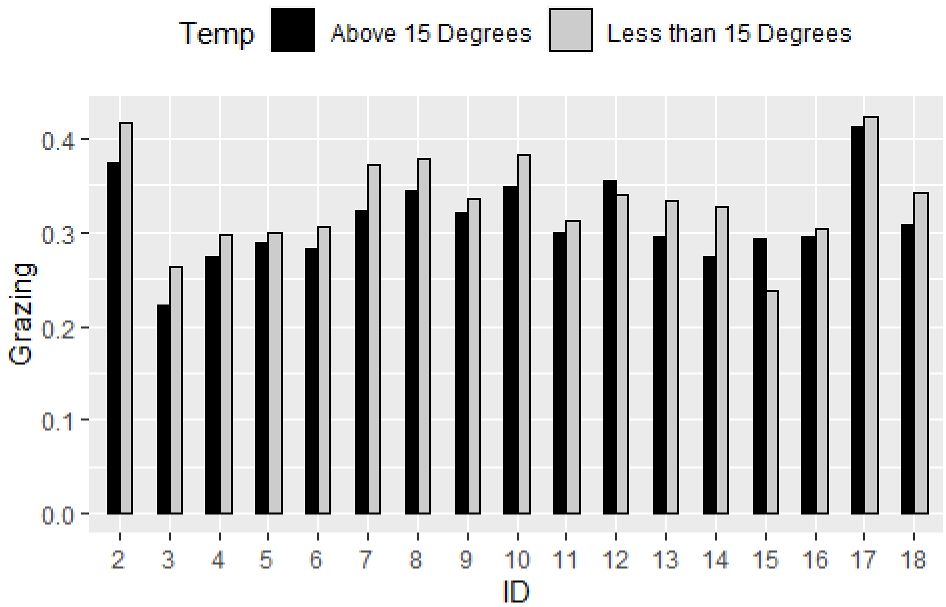

Figure 6: Grazing Average by Temperature Group by Date

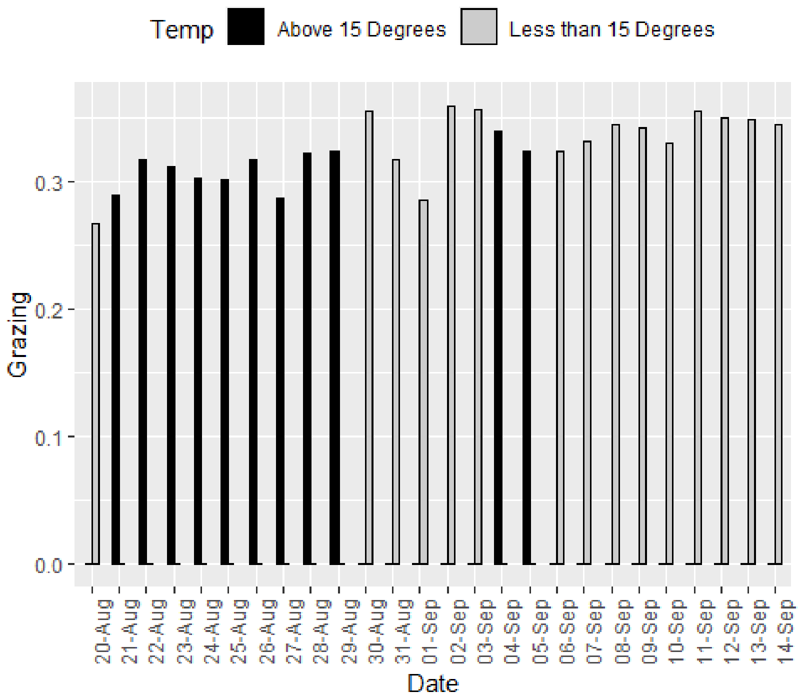

Figure 7: Grazing Average by Rainfall Group by Date

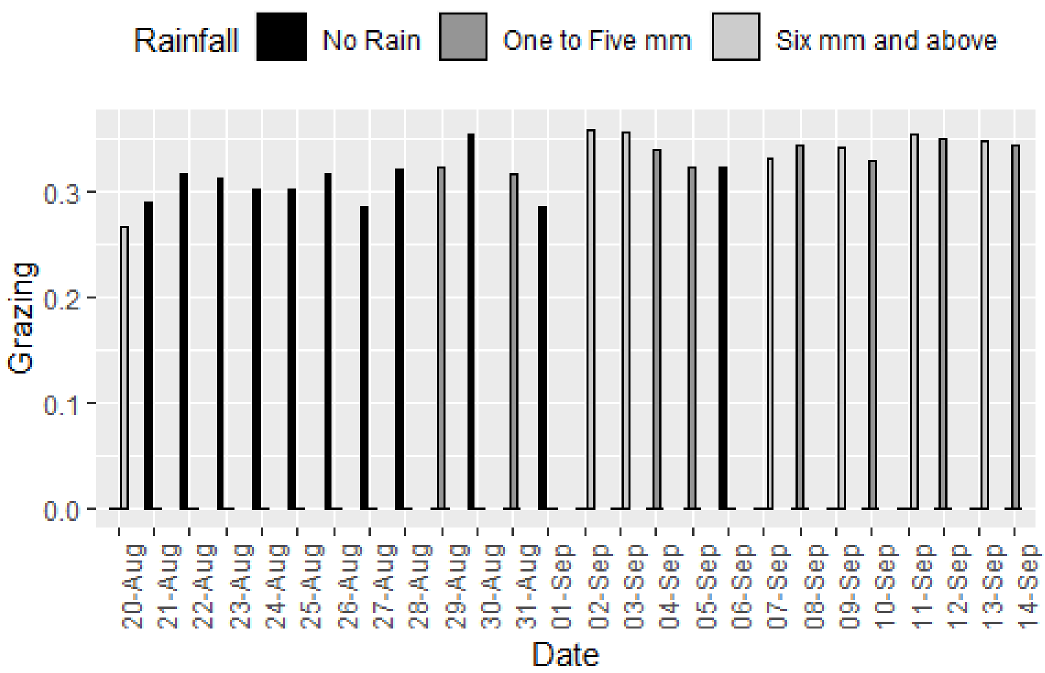

Figure 8: Temperature and Rainfall with Grazing Average

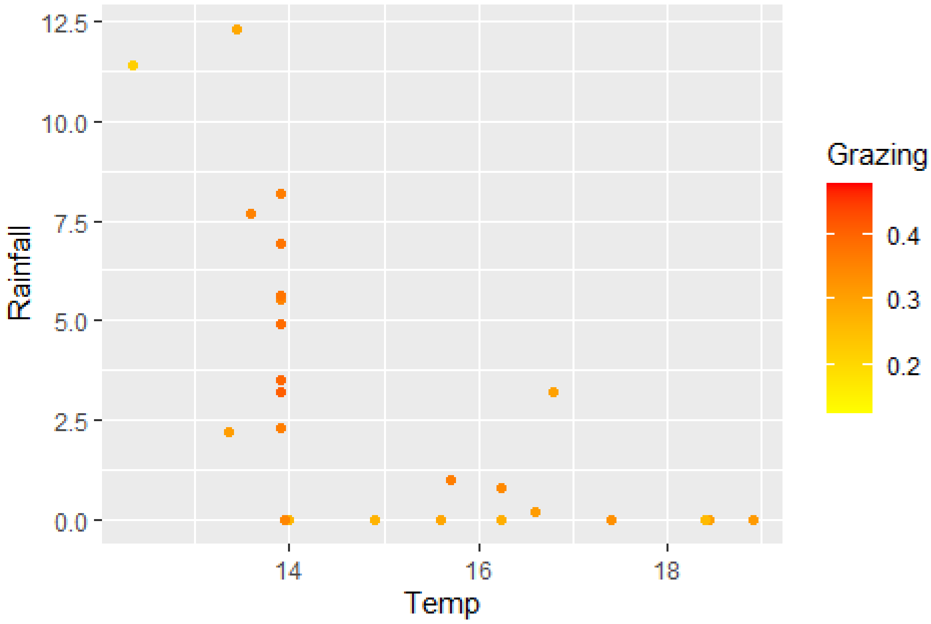

Figure 9: Temperature and Rainfall with Lying Average

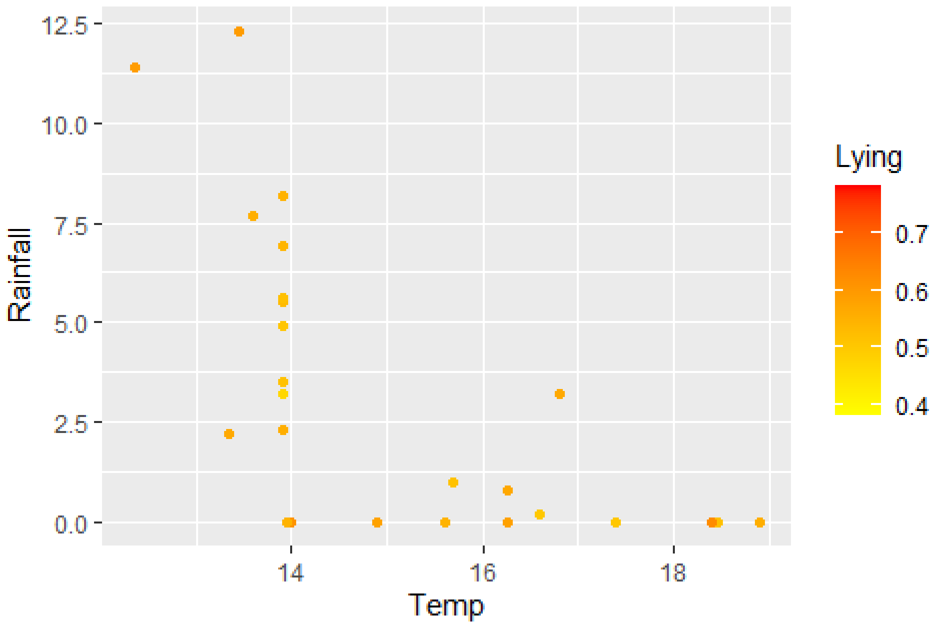

Figure 10: Temperature and Rainfall with Head up Average

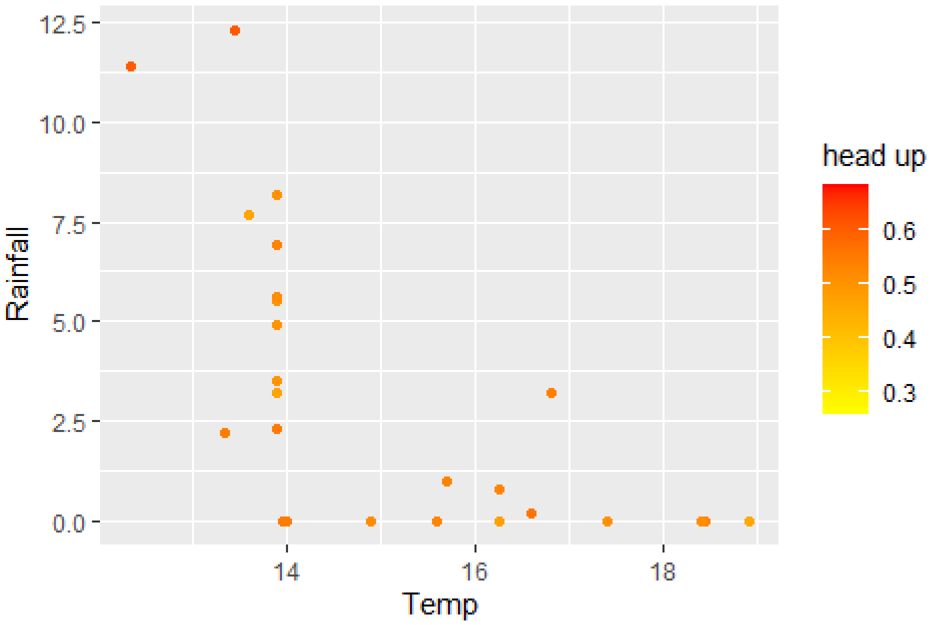

Figure 11: Daily Mean Temperature and Daily Rainfall mm ggplot denistiy plot

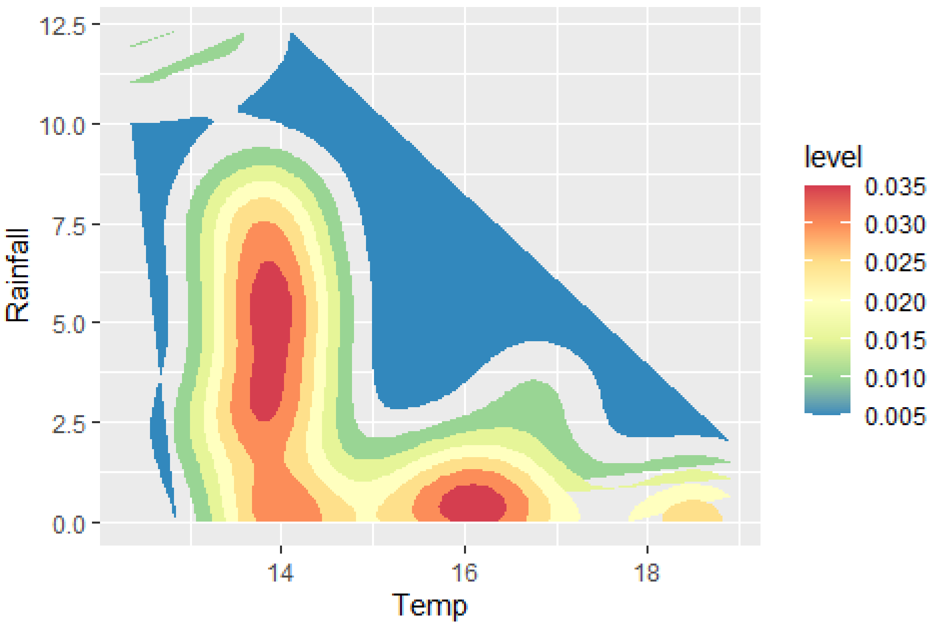

Figure 12: Daily Mean Temperature and Date with ggplot density plot

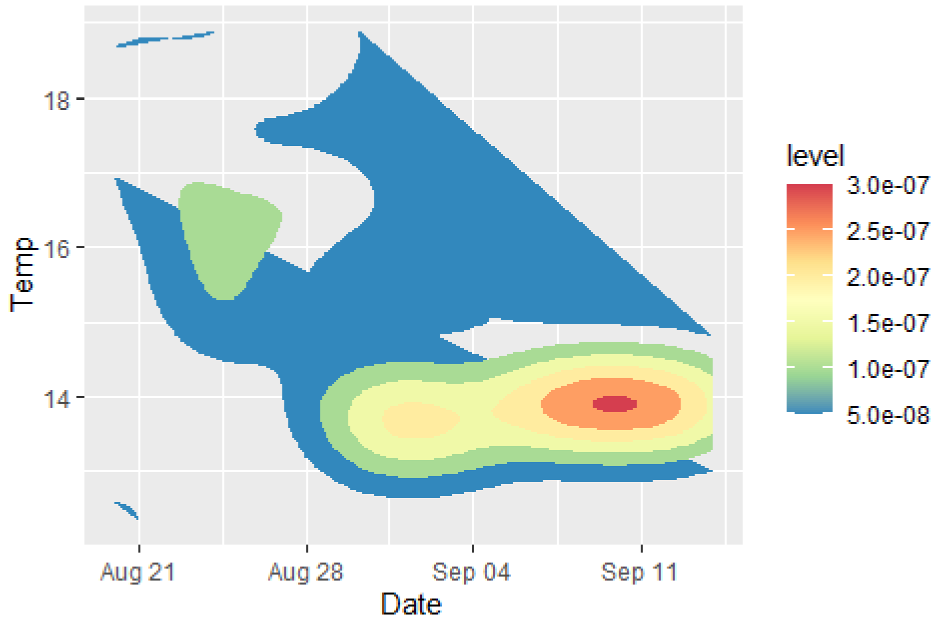

Figure 13: Rainfall (Daily mm) and Date with ggplot density plot

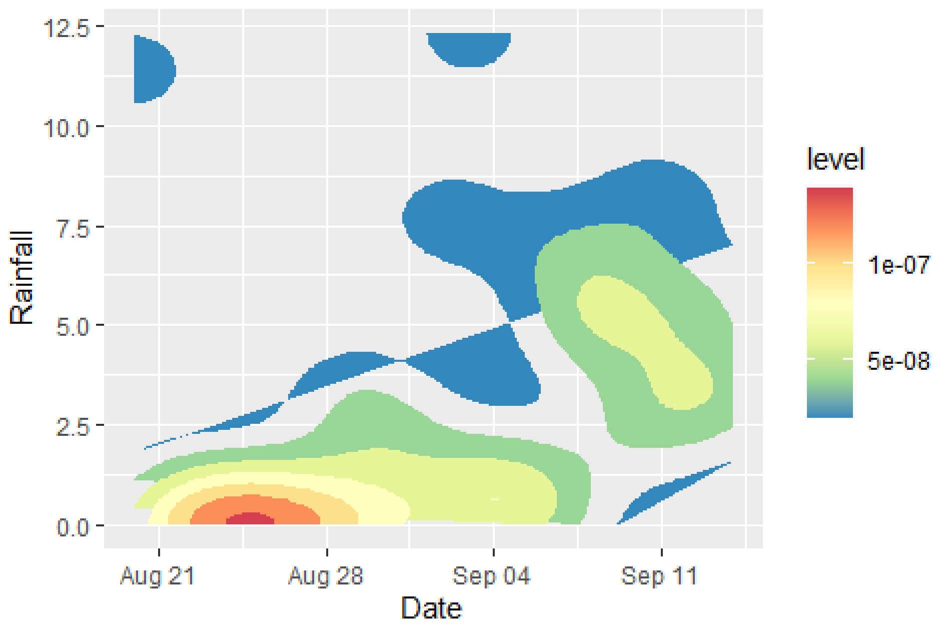

Figure 14: Ethogram 1, duration of head up and head down with temperature and rainfall on the second y-axis

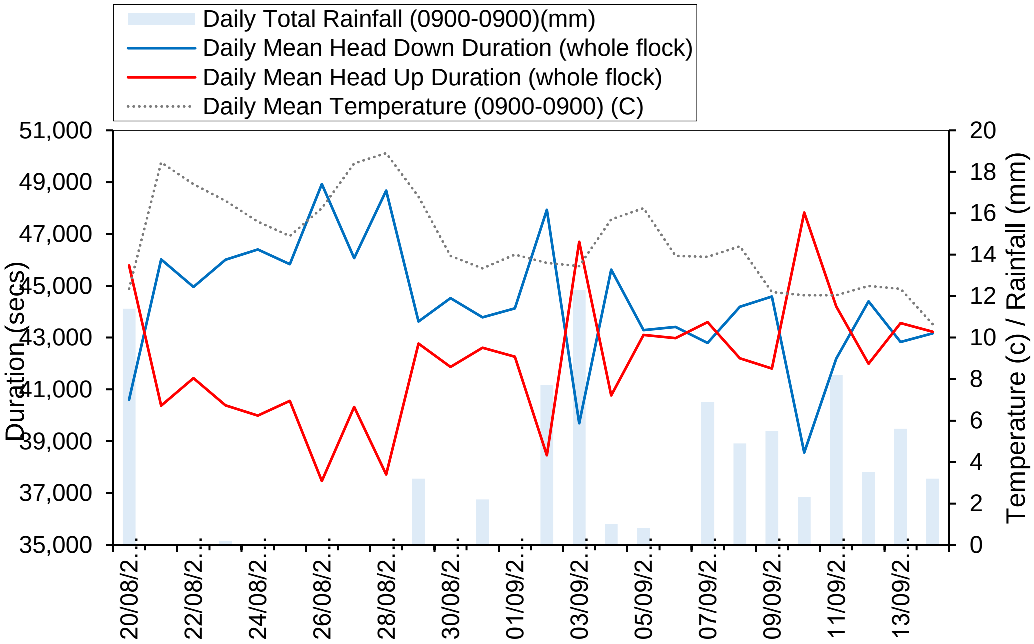

Figure 15: Ethogram 2, duration of lying and standing with temperature and rainfall on the second y-axis

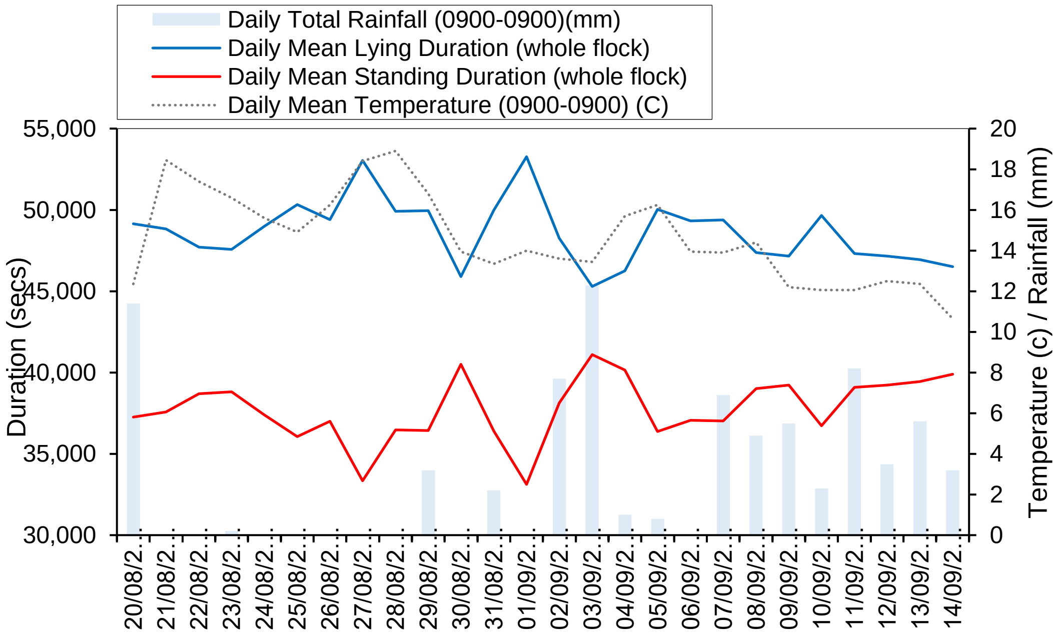

Figure 16: Ethogram 3, duration of grazing and resting with temperature and rainfall on the second y-axis