Investigation of Bluetooth Low Energy (BLE) as a precision livestock farming tool in grazing sheep systems

Aimee May Walker

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School of Biodiversity, One Health and Veterinary Medicine
College of Medical, Veterinary and Life Sciences
University of Glasgow

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Abstract

The livestock industry has seen substantial growth in the development and availability of technologies and tools in recent decades. These precision livestock farming (PLF) technologies can be employed by farmers to monitor an array of behavioural, physiological, and environmental variables to assist in production and welfare management. Benefits of employing such tools have been demonstrated within intensive farming systems, such as pig and poultry, and for dairy cattle, where PLF tools have seen the greatest adoption. However, the uptake of tools for species considered to have a lower economic value, such as domestic sheep (*Ovis aries*), has been slower, especially in grazing systems where fewer technologies have been developed, validated, and made commercially available. The incorporation of PLF tools within grazing systems can be more complex given the potential scale of farms, flock sizes, and dispersion of animals over wide areas, which can create challenges in transmitting information. Given the fairly small physical size of sheep compared to cattle, there is also a requirement for devices to be robust, lightweight, and cost-effective.

Bluetooth low energy (BLE) is a rapidly growing technology which has expanded across multiple sectors in recent years, predominantly for location and proximity monitoring. As a low-cost, low-power device, with long-battery life, and suitable for use in outdoor conditions, it offers promising potential as PLF tool in sheep grazing systems. Whilst animals in extensive systems are generally considered to have more behavioural freedom than those in intensive systems, they are exposed to greater environmental challenges. The ability to monitor animal location, proximity and relationships over time could provide useful information for both production and welfare aspects of sheep management. However, the signal strength of BLE devices can be noisy, and further information is needed to understand the relationship between signal strength and distance within an outdoor environment to assess the ability of BLE to act as on-sheep monitoring tool.

A prototype BLE system was developed for the thesis, consisting of a purpose-built device with BLE reader, trialled alongside three types of commercially available BLE beacons. The main aims of the thesis were (1) to characterise the relationship

between BLE signal strength and distance, and to assess the range of BLE in outdoor systems, (2) to assess the application of BLE for sheep localisation in grazing systems, and (3) to investigate the capability of BLE to be utilised as a monitoring tool to detect sheep contact patterns and relationships, and changes over time - which may indicate a potential welfare or management problem.

Calibration studies of the three beacon types were conducted within a field environment to explore how signal strength changed with distance and whether this was affected by device height and thus animal behaviour. From these calibrations, distance prediction equations based on signal strength were developed. The potential impact of sheep bodies on the signal strength and operating range was assessed for two of the beacon types by conducting calibrations under both a clear and blocked line-of-sight. Across all beacon types, signal strength declined with increasing beacon distance from a reader, with reduced ranges at lower reader and beacon heights. An on-sheep study, with corresponding observer data, demonstrated that animal behaviour, thus posture and height of the BLE device from the ground also impacted on both the beacon's probability of being reported and its signal strength. This showed that operating ranges and translation of signal strength into a distance is then highly dependent upon the behaviours displayed by sheep during a recording interval.

BLE was also trialled as a means of localisation within a grazing system. A static multilateration approach was tested in a paddock (approximately 5 440 m2) using six BLE readers, followed by an on-sheep validation in the localisation of a weaned lamb, fitted with both a BLE beacon and separate global navigation satellite system (GNSS) device, within a larger paddock (1.4 ha), surrounded by nine BLE readers. In the static approach, the multilateration method produced a mean localisation error of 22.02 m, with the on-sheep validation producing similar mean localisation errors – 19.00 m using a midpoint method, and 23.77 m using the multilateration method. Whilst the studies demonstrated the technical feasibility of localising sheep in an outdoor system using BLE, it also highlighted that interpretation of signal strength into distance can be unpredictable, particularly in relation to animal behaviour and movement. Based on the range of BLE devices tested, a high number of static readers would also be required to adequately cover a grazing system. Substantial development in BLE range and accuracy would then be required for any viable commercial application of such a system.

Finally, an on-sheep study examined the use of the BLE system as a monitoring tool, conducted during the high activity period of lambing and early lactation. Lamb mortality and poor ewe-lamb relationships remain a top welfare and economic concern, with high numbers of lamb losses occurring between birth and weaning. Using the purpose-built device as an on-animal device worn by ewes (also fitted with a BLE beacon) alongside BLE beacons on lambs, ewe-ewe and ewe-lamb relationships were assessed across pre- to post-lambing phases, and in relation to lamb age over a six-week period. The BLE system successfully detected and demonstrated expected patterns in ewe and lamb relationships. The numbers of ewe-ewe contacts reported within a 5-minute duty cycle was found to decline between pre-lambing to lambing, and lambing to post-lambing, suggestive of segregation at parturition. The pattern in the number of daily ewe-lamb contacts changed across increasing lamb ages. Whilst initially reporting a high number of contacts, this gradually declined until approximately 14 days old, a period during which lambs typically begin to spend more time within peer groups. The number of contacts was also assessed in relation to ewe lameness, with the BLE system indicating a reduction in contacts with neighbouring ewes, and an increase in contacts with their own lambs. As lame ewes are more inactive, then it may be easier for lambs to remain in closer proximity.

To conclude, the investigations within this thesis trialled a BLE system for the purposes of animal monitoring within a sheep grazing system. Calibration studies identified challenges in the detection of BLE signals and translation into distance, which can be affected by device height, animal behaviour and orientation. The potential operating ranges and extent to which signal strength can provide useful information may then limit BLE application in some scenarios as this will be highly affected by animal behaviour. However, the BLE system did demonstrated potential in identifying contact patterns and relationships amongst ewes and lambs, which could be used to monitor and identify both positive ewe-lamb relationships, as well as potential issues if ewe-lamb contacts deviated from an expected range based on the lambs age and breed. Adding BLE to a suite of sensors and data streams could potentially enhance and complement findings from this thesis.

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Author's Declaration

I declare that, except where explicit reference is made to the contribution of others, that this dissertation is the result of my own work and has not been submitted for any other degree at the University of Glasgow or any other institution.

Aimee May Walker
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Definitions/Abbreviations

BCS	Body condition score
BLE	Bluetooth low energy
CV	Coefficient of variation
dBm	Decibels per milliwatt
EID	Electronic identification
PHY	Physical
GAM	Generalised additive model
GAP	Generic access profile
GLM	Generalised linear model
GNSS	Global navigation satellite system
GPS	Global positioning system
GSM	Global system for mobile communications
GUI	Graphical user interface
h	Hours
ha	Hectares
HCI	Host controller interface
hdop	Horizontal dilution of precision
HF	High frequency
IMS	Integrated management systems
IMU	Inertial monitoring unit
IoT	Internet of Things
IP	Ingress protection
ISM	Industrial, scientific and medical
IR	Infrared
kg	Kilograms
L	Litre
LF	Low frequency
LL	Link layer
LoRa	Long range
LoRaWAN	Long range wide area network
LPWA	Low power wide area
M.A.S.L.	Meters above sea level
MB	Megabyte

MEM	Mixed effects model
m	Meters
mm	Millimetres
min	Minutes
ms	Milliseconds
PLF	Precision livestock farming
RFID	Radio frequency identification
RMS	Root mean square
RSSI	Received signal strength indicator
s	Seconds
SD	Standard deviation
SME	Starvation-mismothering-exposure
Tx	Transmission
TTN	The Things Network
UAV	Unmanned aerial vehicle
UHF	Ultra-high frequency
ULP	Ultra-low power
UUID	Universally unique identifier
UWB	Ultra-wideband
VF	Virtual fencing
Wi-Fi	Wireless fidelity
WISP	Wearable integrated sensor platform
WOW	Walk-over-weigher
WSN	Wireless sensor network

Chapter 1 General Introduction

Modern livestock production is a complex situation, where in addition to achieving a decent economic return, farmers must manage animal health and welfare, product quality and food safety, whilst also minimising the environmental impact (Frost, 2003; Berckmans, 2014). In addition, the demand for animal products has increased, whilst the number of farmers producing livestock has declined, resulting in fewer but larger farms holding increasing numbers of livestock (Berckmans, 2014; Andonovic et al., 2018). Simultaneously, the availability of skilled labour within this industry has declined (Halachmi et al., 2019; Waterhouse et al, 2019). Consequently, farmers often have less time to spend on individual monitoring, making it more challenging to manage animals and their welfare as effectively. Thus, to remain sustainable, whilst meeting technical, economic, and regulatory demands, there is an increased incentive for livestock farmers to adopt automated systems which can assist in monitoring and managing the production process (Wathes, 2007). Indeed, in recent decades there has been substantial development in the advancement of precision livestock farming (PLF) technologies (Aquilani et al., 2022), and tools providing real-time or near real-time monitoring are becoming increasingly available. However, whilst a range of technologies have now been developed and incorporated into more intensive farming systems, such as pig and poultry, and for the dairy sector (Buller, 2020; Aquilani et al., 2022), the development and application of tools in more extensive systems, and for species considered to have a lower economic value, such as sheep and goats, has been much slower (Bahlo et al, 2019). There is therefore a gap in knowledge on the application of such technologies within extensive systems of these species (Silva et al., 2022).

This chapter aims to provide an overview on the existing literature on PLF technologies and their implementation within different livestock systems and discuss some of the challenges associated with applying PLF in grazing sheep systems. The chapter will also discuss the main welfare challenges in sheep systems, and the potential areas in which PLF technologies could assist in improving management and welfare, as well as the overall aims of the thesis.

1.1 Precision livestock farming

PLF can be defined as the use of technologies and process engineering principles to automatically monitor animals over time and space, to model and manage animal production, health, and welfare (Wathes, 2009; Van Hertem et al., 2017). Whilst definitions vary within literature, PLF is generally considered to encompass the use of single, or multiple tools within an integrated system (Aquilani et al., 2022), where the aim is to monitor livestock at the smallest manageable production unit, through continuous direct monitoring of an output or outputs (Wathes, 2009). Whilst then implementing PLF at a basic level would allow for management at the pen, herd or flock level, the real benefit of PLF is that animals could be monitored at the individual level – known as the “per animal approach” (Halachmi & Guarino, 2016), hence allowing farmers to make more informed and targeted management decisions.

The term ‘precision livestock farming’ or ‘PLF’ is most widely used within literature to describe the application of technologies within livestock systems (and is therefore the term used throughout this thesis); however, the term was not coined until 2004 (Berckmans, 2004), and other terms such as ‘integrated management systems (IMS)’ and ‘Smart Farming’ have also been utilised (Werkheiser, 2018). Research into the use of information and communication technologies within livestock production began to increase from the early 1990’s (Norton et al., 2019), however, the first widely adopted application of PLF can be considered to have occurred within the 1970’s, with the introduction of the electronic milk meter for dairy cows (Halachmi & Guarino, 2016). Since this time, the PLF sector has grown rapidly (Aquilani et al., 2022), and applications of PLF technologies have expanded across livestock sectors. However, the development of these tools has remained greatest within intensive farming systems, particularly indoors, where conditions and access to facilities make application and transmission of information easier to implement (Aquilani et al., 2022).

1.1.2 Types of PLF technologies

A wide range of PLF technologies and tools have been developed to suit a variety of purposes, and for different livestock systems. These technologies can be both animal-based; measuring a physical, physiological or behavioural aspect, or non-animal based; monitoring the environment or conditions in which animals are kept, to monitor management aspects (such as feeding, milking, and bedding), or to monitor physical or behavioural indicators in the animals themselves (Herlin et al., 2021). An overview of some of the main PLF tools is provided in Table 1.1.

Animal-based sensors (often referred to as wearables) can be attached to the animal externally, typically in the form of an ear tag, collar, or leg strap, or internally, as a bolus or implant. Non-animal sensors are typically located within the animals vicinity, or at specific locations relating to the management practice or activity being measured (Herlin et al., 2021).

Table 1.1 Examples of precision livestock farming (PLF) tools.

Technology Type	Precision Livestock Farming (PLF) tool	References
Electronic identification (EID)	Radio frequency identification (RFID)	Cappai et al. (2018) Morgan-Davies et al. (2018)
	Biometric identification	Shojaeipour et al. (2021)
Management Tools	Auto drafter	Morgan-Davies et al. (2018)
	EID enabled Weigh crate	Morgan-Davies et al. (2018)
	Walk-over-weigher (WOW)	González-García et al. (2018)
	Virtual fencing (VF)	Staahltoft et al. (2023) Confessore et al (2021)
	Automated milking system / Milking robot	Ji et al (2022) Zanchi et al (2025)
	Automated grass measurement system	Castro Muñoz et al. (2021)
Location	Global navigation satellite system (GNSS) tracker	Thomas et al. (2008) Taylor et al. (2011)
	Radar	Gygax et al. (2007)
	Bluetooth low energy (BLE)	Trogh et al., 2017 Maroto-Molina et al. (2019) Maxa et al., 2023
	Unmanned aerial vehicles (UAVs) / Drones	Nyholm (2020) Vucic and Axell (2022)
Social Interactions	Contact / proximity loggers	Triguero-Ocaña et al. (2019) Ozella et al. (2020)
	Bluetooth low energy (BLE)	Sohi et al. (2017) Paganoni et al. (2021)
Motion sensors / Activity	Accelerometer	Barwick et al. (2018) Fogarty et al. (2020) Price et al. (2022)

	Inertial monitoring unit (IMU)	Achour et al. (2019) Liu et al. (2023)
	Pitch and roll sensor	Umstätter et al. (2008)
	Inclinometer	Voß et al. (2021)
	Mercury tilt switches	Rutter et al. (1997)
	Pedometers	López-Gatius et al. (2005)
	Jaw and bite sensors	Rutter et al. (1997)
Physiological sensors	Temperature sensors	Atkins et al. (2018) Fuchs et al. (2019)
	Heart rate monitors	Munro et al. (2017) Reefmann et al., 2009
	Oxygen sensor	Salzer et al. (2022)
	Respiration sensor	Atkins et al. (2018) Reefmann et al., 2009
	Oestrus detectors	Alhamada et al., (2017)
	Urine sensors	Betteridge et al. (2010)
Environmental sensors	Weather station	Alexy and Horváth (2022)
	Soil moisture	Plauborg et al. (2005)
	Barn / shed environment (e.g. temperature, humidity, ventilation, light)	Atkins et al. (2018) Chen and Chen (2019)
Camera	Camera / video (image analysis, computer vision, machine learning)	Samperio et al. (2021) Molina et al. (2023)
Sound analysis	Microphone / sound sensor	Ferrari et al. (2008) Galli et al. (2011)

1.1.2.1 Electronic identification

As the target goal of PLF is individual animal management, electronic identification (EID) of animals is a crucial component towards this objective. EID systems not only allow for independent animal identification, but for associated information (e.g. management, breeding, health information) to be stored and carried with animals throughout their life (Vaintrub et al., 2021; Finzel et al., 2023). The development of identification systems began in the 1960s, with passive EID systems beginning to be trialled on farms in the 1970s (Rossing, 1999). Passive EID operates using an EID tag which is assigned to an animal and read by an active reader. The tags do not have a battery, but instead contain a copper coil which is charged during data transmission with a reader (Vaintrub et al., 2021).

Radio-frequency identification (RFID) works by transmitting radio waves (containing the identity of an animal) from an RFID tag to an RFID reader (Moubayed et al., 2012). RFID can be passive - requiring energy from the reader to charge and respond to it, semi-active - where the RFID tag contains a battery, but is active only when a radio signal is received from the reader, and active - where the tag can continuously transmit a signal (Moubayed et al., 2012). RFID also operates on different radio frequency levels - classified into three groups: low frequency (LF), high frequency (HF), and ultra-high frequency (UHF), which will influence the distance over which tags and readers can transmit information (Vaintrub et al., 2021). Whilst active tags may operate within a range of 20—100 m, passive tags typically have a range of 3 m or less (Tzanidakis et al., 2023). EID tags are most commonly applied to animals in the form of an ear tag, however, other methods such as a ruminal bolus or injectable sub-cutaneous electronic identification are also available (Vaintrub et al., 2021).

Biometric identification systems have also been proposed (although not widely deployed), whereby a unique, lifetime identity is associated with an animal based on a unique trait or identifier, such as muzzle / nose pattern, iris pattern, facial image, or DNA profile (Awad, 2016). However, there are challenges surrounding biometric identification accuracy, particularly arising from inefficient image capturing (Awad, 2016).

1.1.2.2 Management tools

Management tools can be considered any device or technology which can assist farmers in data collation and management, or management tasks such as managing and maximising pasture productivity (i.e. by adjusting stocking densities and time spent in specific locations), improving grazing efficiency, reducing costs associated with fencing and animal movement, and reducing manual labour (Vaintrub et al, 2021). Information collection on a large range of animal parameters can be difficult to collate and maintain, thus the development of sensor and computer technology to implement automated data collection systems is perhaps one of the most useful PLF tools (Banhazi and Black, 2009). Information regarding animal performance, labour input, environmental performance and other essential criteria (i.e. flock / herd registry, tracking yield, breeding and genetics) could then be stored and processed (Banhazi and Black, 2009; Vaintrub et al, 2021).

Stationary management tools include devices such as automatic drafters, walk-over-weighers (WOWs), and weigh crates. Automatic drafters typically operate alongside EID tags and antenna / readers and use a selective gate for animal management (e.g. feeding control). Walk-over-weighers (WOWs) use a weighing platform within a one-way corridor (leading to a stimulant) and an EID reader to identify and record data for individual animals, whilst weigh crates allow each individual animal to be weighed standing still by passing through a corridor (with manually operated door), whereby identities are read via either a handheld RFID reader or fixed antenna (Vaintrub et al., 2021). Similarly, mating detection systems for reproductive management (such as the electronic Alpha Detector (Alpha D) in sheep) also use EID, whereby rams are fitted with a harness containing an active EID reader which detects and records ewe EID tags, allowing farmers to monitor mating frequency and the number of ewes mated (Alhamada et al., 2017).

Virtual fencing (VF) systems have been developed as an alternative grazing management tool, whereby animals are managed and contained via electronic boundaries (Tzanidakis et al., 2023). Using this system, animals are fitted with a collar containing Global navigation satellite systems (GNSS), audio signal reproduction and a battery powered (or battery and solar powered) device which can deliver an electric shock (Tzanidakis et al., 2023). Animals are directed and retained in chosen areas by applying an audible and / or electrical stimulus when approaching the electronic boundary (Aquilani. et al, 2022). Whilst the system does not completely negate the need for physical barriers (e.g. security for roads, property rights) it can be applied as a means of guiding and moving animals based on pasture availability and management requirements (Vaintrub et al., 2021). There has been significant research into this type of technology, primarily for cattle, but also for sheep and goats. Several products have been commercially available such as Agersens / eShepherd, BoviGuard, Halter, Monil, NoFence, and Vence (Vaintrub et al., 2021; Aquilani. et al, 2022). However, factors such as device cost and battery performance, along with available infrastructure and network coverage have hindered uptake and implementation. There have also been some welfare concerns regarding the repeated need for stimuli observed in some individuals, and the effects of prolonged exposure to electric shocks (Vaintrub et al., 2021; Aquilani. et al, 2022). Other types of pasture management systems include tools for automated grass measurement, e.g. Grasshopper, which is integrated with GNSS to provide real-time grass height measurements using sonic transmission (Vaintrub et al., 2021).

Other types of management systems include devices such as automatic milking systems and automatic feed systems. Automatic milking systems are one of the earliest examples of PLF technology, with milking robots first being trialled in experimental farms in 1986 and applied within a commercial dairy farming in 1992 (John et al. 2016). Automatic milking systems have been widely adopted within the dairy industry, and advancements in the technology means that milking systems can now be applied not only in indoor systems, but also in pasture based systems, as well as allowing animals to choose when to be milked across the 24 hr period (Monteiro et al., 2021). Electronic milk meters and flow indicators can monitor the milk flow and volume of each individual animal, as well as analyse milk samples to assess animal health (Simitzis et al., 2022). Today many milking robot systems also assess factors such as milk yield, colour, composition (i.e. percentages of lactose, fat and protein), blood percentage, and somatic cell count. This can provide information regarding yield and productivity, but also on animal health and disease detection (e.g. mastitis). Precision feeding systems may be conducted at an individual level through dedicated single animal feeders, or at more of a group level; whereby animals are assigned groups based on yield / weight, and sorted using automatic drafting systems (Vaintrub et al., 2021). Individual automated feeding systems can record the animals ID, time and date of feeding, feeding duration, and weight of feed consumed, whilst recent developments in automated feeding systems can also tailor the amount and composition of feed to ensure nutrient specifications are met (Monteiro et al., 2021). Feed management systems have been implemented within several sectors, but most notably within poultry systems, such as the implementation of the Flockman system, which can allow farmers to monitor feed intake and adjust based on projected growth trajectories. In addition, this system can also assess the effects of environmental factors on growth and health (Neethirajan, 2017).

1.1.2.3 Animal location

Location or positioning systems include a variety of devices by which animals can be located, or tracked to monitor their movements, both in outdoor grazing systems and within buildings in intensive systems (Halachmi et al., 2019). Animal position may be classed not just as a specific location, but also positioning within references to known points or resources. Continuous monitoring of animal location can provide information regarding animal behaviour, health, spatial and resource use, and social interactions (Gygax et al., 2007). The basis of most indoor positioning systems are wearable on-animal devices (i.e. a tag) which transmit a signal, and multiple stationary readers (located throughout the study area) which can detect and report these signals. Examples of these systems include radar, ultra-wideband (UWB), low frequency positioning (eg. NEDAP and Smartbow), RFID, and Bluetooth (Halachmi et al., 2019; Herlin et al., 2021).

Radar systems, such as that by Gygax et al. (2007) use a battery operated transponder which transmits a radar signal (attached to animals via a neck collar), and multiple base stations at fixed points within a barn which report these signals. This system can provide coordinates on the x, y, and z-axis (thus also indicating animal posture), however, the accuracy on the z-axis is reported to be affected by base station height and orientation to the animal. In addition, barn equipment, in particular metal obstacles, such as partitions and feed racks can also interfere on the signal (Gygax et al., 2007). UWB localisation similarly uses animal tags and stationary receivers. Animal location within a barn or indoor system is calculated based on the arrival time of a UWB tags radio signal to multiple time-synchronised receivers (Ren et al., 2021; Benaissa et al., 2023). However, within larger indoor systems a high number of receiving devices may be required to provide adequate coverage, whilst Benaissa et al. (2023) report a device lifespan of approximately 4-6 months.

Whilst initially developed as a means of identification, RFID has also been applied as a positioning technology (Herlin et al., 2021). Animals are fitted with a form of RFID tag, whilst antennas or readers are located throughout the study area, thus the animal is 'seen' and reported by the reader when within a given operating range (Bonneau et al., 2020). However, RFID is considered to have a poor spatial accuracy given the typically short range of devices, and therefore more applicable as a means of monitoring location in terms of presence / absence within a particular area or zone, or to monitor visits to a water or feeding point (Bonneau et al., 2020). Similar drawbacks across these technologies include the high number of receivers often required for accurate localisation, which in larger indoor systems could be substantial, as well as issues regarding signal range, and environment / obstacle interference on signals.

GNSS devices are geospatial positioning tools which can estimate locations based on triangulation with at least three orbiting satellites (Fogarty et al., 2015). GNSS devices can use one or multiple satellite systems such as Global Positioning System (GPS – US), GLONASS (Russia), and Galileo (EU). Distances to each satellite are calculated based on the time taken for a satellites transmitted electromagnetic wave to be received by the GNSS device (Kaplan, 2017). GNSS is one of the most extensively research tools within wildlife and livestock monitoring, and many GNSS based tools are commercially available, especially for cattle. Some examples of these systems include mOOvement, Herddogg, and The CowManger System (dos Reis et al., 2021).

Other forms of animal localisation include acoustic tags (most commonly employed in fisheries), whereby animal position is calculated by triangulating tags from multiple receivers (Bonneau et al., 2020). Whilst more recently, computer vision has been proposed and tested as a non-invasive method of location monitoring, However, the camera type, environment, lighting, and animal distance from the camera have been found to influence the accuracy of detection (Bonneau et al., 2020).

An emerging promising technology is Bluetooth or Bluetooth low energy (BLE) which has begun to be explored over the last few years due to the relatively low-cost, long-battery life and ability to communicate data wirelessly. BLE has been proposed and trialled as a means of animal location based on path loss of a transmitted radio signal (Nikodem, 2021). Trials within indoor barn systems and small outdoor paddock systems have utilised multiple fixed receivers, with BLE tags (which transmit a signal) fitted on animals. Animal position is then calculated based on the received signal strength at the fixed receivers. Some studies have also proposed and tested the use of combined technologies within grazing systems, whereby a proportion of animals are fitted with BLE tags, whilst others within the flock or herd are fitted with both a BLE receiver and GNSS (Maroto-Molina et al., 2019). In addition, BLE has also been investigated as a form of proximity monitoring (Sohi et al., 2017; Waterhouse et al., 2019; Paganoni et al., 2021) to monitor social interactions or resource use.

Proximity loggers work by recording the date, time and length of an interaction with another individual (Handcock et al., 2009). In this instance location is given relative to other individuals within the monitored population, as opposed to a definitive location. Monitoring animal interactions can provide useful information on population and group dynamics, mating events, and disease transmission (Handcock et al., 2009).

1.1.2.4 Motion sensors / activity

Motion and activity sensors include devices which measure a change in body or body-part position, or animal motion and acceleration (Fogarty et al., 2019). An early example of a motion sensor is a mercury tilt switch, which is a dichotomous switch consisting of a mercury bead and two connecting leads contained within a sealed glass chamber. Specific behaviours associated with a change in orientation (e.g. head lowering during feeding) were identified through the opening and closing of the circuit based on the rotation of the sensor and mercury bead (Whitford and Klimley, 2019). However, the last experiments utilising mercury tilt sensors were conducted in the 1990s, with other types of sensor (e.g. accelerometers) becoming more popular (Fogarty et al., 2018). Devices such as inclinometers also measure tilt or the angle of a slope or elevation and have been applied to monitor activities such tail raising in cattle, which may be associated with calving (Voß et al., 2021), e.g. the commercially available Moocall.

Pedometers measure the number of steps taken by an animal and thus can estimate the daily distance travelled (Neethirajan and Kemp, 2021). In addition to general activity and patterns, pedometers have also been used for identification of specific events – particularly oestrus in cattle (Wathes et al., 2008; Tekin et al., 2021). However, whilst commercial pedometers can calculate lying time, step count, and activity on the sensor, only summaries are typically transmitted to farm software (Halachmi et al., 2019).

Accelerometers are electromechanical devices which measure accelerating forces, whereby the velocity and orientation of movement are calculated based on the voltage generated on microscopic crystals within the sensor (Chapa et al., 2020). Accelerometers are mounted within wearable on-animal devices, typically attached to the foot, neck, head, or ear, thus allowing animal movement to be measured in terms of speed and direction (Vaintrub et al., 2021). In terms of monitoring livestock behaviour, accelerometers are considered one of the most promising PLF technologies (Benjamin and Yik, 2019). Over the last decade, tri-axial accelerometers, which measure movement on an x, y, and z-axis (by measuring the earths gravitational pull in relation to the degree by which the device is tilted (Benjamin and Yik, 2019)), and thus also allow for animal posture to be measured, have been widely studied (Fogarty et al., 2018). Applications of accelerometers include detection of parturition, detection of lameness, monitoring grazing behaviour, energy expenditure, and monitoring changes in activity patterns. Whilst not yet widely commercially available for other sectors, there are several sensors within the cattle industry which utilise accelerometers, such as IceTag, RumiWatch, MooMonitor, CowManager Sensor, and Heatime HR LD system, (Herlin et al., 2021; Neethirajan and Kemp, 2021).

As an extension of this approach studies have also investigated the application of inertial measurement units (IMUs) as a means of activity and behaviour monitoring. IMUs consist of a 3-axis accelerometer, alongside a 3-axis gyroscope, and 3-axis magnetometer, and can therefore measure linear and angular accelerations, which can be used to estimate an animal's trajectory (Achour et al., 2019). Studies involving IMUs have largely centred around developing behavioural classification models (Andriamandroso et al., 2017; Achour et al., 2019; Liu et al., 2023; Peng et al., 2024), for application of gait analysis in cattle (Fischer et al., 2022), and to monitor grazing behaviour in sheep (Guo et al., 2018).

1.1.2.5 Physiological sensors

Physiological sensors are devices which can measure heart rate, body temperature, rumen pH, bodily fluids (such as blood or urine), or even changes in production output (e.g. milk yield, egg production) (Nielsen, 2022). Radio telemetric thermal sensors can transmit information regarding body temperature, and are available as rectal probes, microprocessor controlled temperature loggers, or as ruminal boluses (Kasawan et al., 2024). Continual monitoring would allow for identification of temperature changes, which may be indicative of illness, disease or inflammation, or be utilised for detection of events such as oestrus (Kasawan et al., 2024). Other devices such as wearable sweat analysers are electromechanical devices which can measure sodium and lactate levels or monitor sweat levels as indication of stress, whilst rumen or reticulum boluses can measure multiple parameters such as temperature, pH, and rumen activity

(Kasawan et al., 2024). Some commercially available options (e.g. eBolus) are also able to transmit this data wirelessly, allowing real-time monitoring.

1.1.2.6 Environmental sensors

The environment in which animals are kept can significantly affect animal health, welfare and productivity (Fournel et al., 2017; Lovarelli et al., 2020). The majority of environmental sensors used in PLF systems to date are typically associated with indoor systems to manage conditions within animal housing facilities (Potter and Oloyede, 2023); particularly for the dairy cattle sector, and for pigs and poultry. Examples of indoor environmental sensors include temperature, ventilation, and climate control systems (which can help prevent heat and cold stress), humidity and air quality sensors (which can help monitor and prevent respiratory issues and diseases); including specific devices to monitor dust, and ammonia, oxygen, and carbon dioxide concentrations (Rowe et al., 2019; Lovarelli et al., 2020; Potter and Oloyede, 2023). There are also a number of devices to monitor water supply quality;including temperature, pH, phosphate and nitrate concentrations (Kaur et al., 2023), as well as other environmental factors such as vibration and radiation (Rowe et al., 2019). These types of environmental sensors have largely been developed and incorporated into poultry management, such as the commercially available ChickenBoy; to monitor gases and air quality (Buller et al., 2020), whilst more recent studies have investigated the use of electronic noses and air analysis to monitor poultry health and identification of enteric diseases (Halachmi et al., 2019). However, as highlighted by Fournel et al. (2017) the animals' environment also consists of physiological and behavioural factors, such as the degree of crowding, spatial distribution, and social interactions, which may be monitored by other types of PLF tools (i.e. cameras and image analysis). Such environmental sensors may also be employed within other aspects of the livestock industry, including transportation and abattoirs.

Within outdoor systems, environmental sensors include weather stations (including real-time or automatic weather stations) which can provide information on multiple climatic parameters such as rainfall, temperature, humidity, solar exposure, wind speed, cloud cover and atmospheric pressure (Nyamuryekung'e, 2024). Other individual environmental sensors revolve around soil quality;

including temperature (e.g. digital thermometers), moisture (e.g. resistive and capacitive sensors), pH (pH soil sensors), and soil nutrient and structure (e.g. portable X-ray fluorescence spectrometers and near infrared spectrometers), as well as temperature and humidity sensors, atmospheric pressure sensors, rain gauge or sensors, and anemometers to measure wind (Brick et al., 2023). Remote sensing applications such as drones and satellite imagery / weather satellite can also be used to map and monitor climatic conditions, grassland and grazing attributes, and can also be integrated with predictive models (Mbuthia et al., 2022; Nyamuryekung'e, 2024)

1.1.2.7 Cameras

Cameras are a non-invasive tool which can monitor a range of animal-related factors, such as individual identification through image analysis and machine learning, to monitor animal weight, water, and feed intake, to detect potential health issues such as lameness through gait analysis, to measure pain (Neethirajan and Kemp, 2021) such as the grimace scale in pigs (Viscardi et al., 2017), as a means of animal localisation (Bonneau et al., 2020), and to monitor distribution and activity; such as the eYenamic system for poultry (Buller et al., 2020). Various types of cameras and image analysis have been developed, largely for indoor systems where they can be easily installed, but also within grazing systems.

Thermal cameras use infrared (IR) radiating energy to provide heat-based images (thermograms) to measure body temperature. Thermal imaging can therefore monitor and detect changes in body temperature and may be applied as a means of climate control (e.g. in poultry houses - Halachmi et al., 2019), detecting heat stress, oestrus, infection or inflammation (e.g. hoof lesions), and mastitis (Caja et al., 2020). Other proposed applications of thermal cameras include combined use with unmanned ariel vehicles (UAVs) to located separated or injured animals in more extensive systems (e.g. to locate lost lambs) (Caja et al., 2020). 3D cameras have been employed as a means of body condition scoring (BCS), to measure feed intake (Halachmi et al., 2019), and to successfully detect lameness in cattle (Lovarelli et al., 2020). Multi-spectral images from satellites have also been used within extensive grazing systems to assess changes in pasture and rangeland condition, biomass, and growth rate (Handcock et al., 2009).

1.1.2.8 Sound analysis

Sound analysis is a non-invasive method of continuous animal monitoring, whereby microphones or sound sensors are mounted within animal housing (Norton et al., 2019). Sound analysers are one of the few PLF technologies which have been primarily developed and studied as a means of monitoring animal health and welfare, particularly within the pig and poultry sectors (Norton et al., 2019). Within the pig industry, cough sound analysis has been successfully used to distinguish between healthy and sick pigs, such as detection of respiratory diseases to provide an early warning system to farmers (Ferrari et al., 2008; Neethirajan, 2017; Norton et al., 2019). Some commercial options such as SoundTalks are available in this area (SoundTalks, 2022). Vocalisations have also been classified to identify specific behaviours such as playing, as well as signs of stress and / or pain, such as scream detection (Ferrari et al., 2008; Neethirajan, 2017; Norton et al., 2019). More recently there has also been increased interest and research of vocalisation analysis within the poultry sector, such as to monitor thermal comfort and environmental factors on chick health (Neethirajan, 2017), in relation to growth and feed uptake (Aydin et al., 2014), to monitor social separation, and for the detection of disease and other welfare issues such as feather pecking (Norton et al., 2019). On-animal microphones and sound analysers have also been applied in the monitoring of behavioural aspects, particularly surrounding grazing. Acoustic biotelemetry has been applied to investigate jaw activity and ingestive behaviour in both cattle and sheep (Galli et al., 2011), whilst rumination microphones have been used to detect cud chewing in cows (Neethirajan, 2017).

1.1.3 Application of PLF in sheep grazing systems

Whilst being less developed than other livestock sectors, there has been growing interest in the application of sensors and other wearable technologies within sheep research since the late 1990s (Neethirajan, 2017; Fogarty et al., 2018). The application of PLF tools within sheep research has previously been reviewed by Fogarty et al. (2018), in extensive sheep systems by Silva et al. (2022), and in extensive dairy sheep farming by Vaintrub et al. (2021). PLF tools employed within research settings have primarily centred around GNSS devices (with almost 50 % of studies reviewed by Fogarty et al. (2018) utilising GNSS), as well as motion sensors (in particular tri-axial accelerometers), or a combination of both (Fogarty et al., 2018; Vaintrub et al., 2021). Alternatively, studies have also investigated applications of physiological sensors (such as heart rate monitors, oestrus detectors, temperature sensors, urine sensors, and oxygen and respiration sensors), with a smaller number of studies investigating jaw and bite sensors, and contact loggers (Fogarty et al., 2018). Primary research purposes of PLF tools have been to categorize and quantify animal behaviour, to investigate feeding patterns and feed intake, to monitor animal position and flock movement, or to validate sensors (Fogarty et al., 2018; Vaintrub et al., 2021).

In terms of PLF application within the sheep sector itself, there is typically a poor uptake of tools and technologies, although this does vary by country, production system, and economic return (Morgan-Davies et al., 2024). Where technologies are in place, they typically relate to production and management, such as weigh-crates, milk meters, EID stick readers, and flock management systems (Morgan-Davies et al., 2024). EID is perhaps one of the tools with the greatest uptake, having become mandatory for sheep and goats in the EU in 2004 (Cappai et al., 2018; Morgan-Davies et al., 2018), and will become mandatory in Australia as of January 2025 (Australian Government, 2024). However, uptake in other areas (e.g. western US and New Zealand) where EID is not mandatory has been poorer (Finzel et al., 2023). EID systems could significantly aid farmers decision making regarding animal management and health by allowing identification of poorly / or well performing individuals, or to identify specific traits (Finzel et al., 2023), as well as assisting in traceability and disease control (Banhazi et al., 2012). However, EID is perhaps most beneficial when applied alongside other management tools such as automatic drafters and weigh scales (Vaintrub et al., 2021). These tools utilise EID records for sorting and selection and could therefore also act to reduce manual labour associated with animal selection, as this tends to be one of the most labour-intensive activities. The use of these combined technologies also allows for a targeted management approach as demonstrated by Morgan-Davies et al. (2018) to provide targeted winter feeding and selective worming treatment. The study highlighted potential benefits of a PLF approach within extensive systems not only to improve welfare, but also to improve labour efficiency, anthelmintic control, and economic resilience. However, whilst extensively tested, stationary management tools such as automatic drafters are not yet in widespread use (Vaintrub et al, 2021), or in the case of walk-over-weighers (WOW) not yet commercially available (Morgan-Davies et al., 2024) despite promising results.

Wearable on-animal sensors have been applied in research settings to investigate a range of behavioural and physiological factors within grazing sheep systems. GNSS devices have been the most extensively utilised device within sheep research, for applications such as monitoring grazing areas in hill sheep (Rutter et al., 1997), to investigate sheep grazing patterns, distribution, and use of water points in relation to weather conditions (Thomas et al., 2008), as a means of assessing shelter-seeking and paddock utilisation in merino ewes (Taylor et al., 2011), as well as to identify parturition and to assess lamb weaning weights in relation to ewe movement and activity (Johnson et al., 2022). In addition, GNSS has also been employed with flock / pasture management systems such as virtual fencing. Whilst less numerous than devices offered within the cattle sector, commercial GNSS devices for sheep include Digitanimal GPS sheep tracker, and NoFence (Vaintrub et al., 2021; Digitanimal, 2024).

Within experimental settings accelerometers have been used for behavioural classification of ewes and lambs to register movement patterns linked with specified behaviours such as resting, grazing, moving, and running or playing (Giovanetti et al., 2017; Vaintrub et al., 2021; Price et al., 2022). Recent sheep research has also examined the ability of accelerometers to detect specific events or states, such as to identify behavioural changes associated with parturition (Fogarty et al., 2020), to identify abnormal gait patterns and detection of lameness (Barwick et al., 2018), to assess activity and behavioural changes in parasitised sheep (Ikurior et al., 2020), to detect urination events (Lush et al., 2018), to detect mating behaviour in rams (Mozo et al., 2019), and to monitor lamb suckling events (Kuźnicka and Gburzyński, 2017). Whilst many of these research studies have demonstrated promising classification of behaviours and high success in detecting events, commercial options employing such systems are not generally available within the sheep industry.

Physiological sensors could provide insight into the animals health and welfare, and response to environmental conditions over time. Studies have investigated the use of devices such as heart monitors, respiration belts, and wearable body surface humidity and temperature loggers to investigate emotional reactions in sheep in response to both positive and negative stimuli (Reefmann et al., 2009). Heart rate and body temperature sensors in the form of implantable sensors have also been investigated and validated – showing changes in heart rate and temperature in relation to diurnal and seasonal patterns (Fuchs et al., 2019). However, implantable sensors would require surgery and thus are not a viable commercial option. However, other forms of temperature sensors could be particularly beneficial for monitoring factors such as heat stress, illness and disease. Other applications of wearable sensors include automatic oestrus detection to assist farmers in reproductive management (Alhamada et al., 2017).

There is therefore lots of potential in how PLF technologies could be adopted into the management of small ruminants. However, in considering how these tools could act to improve welfare and animal management it is important to consider how the issues in grazing systems may differ from more intensive farming.

1.1.4 Challenges to implementing PLF in extensive systems

Where PLF technologies are available for implementation within sheep systems, uptake is still typically poor. Boothby and White (2021) cite the main barrier to adoption as the high initial investment cost of implementing devices or systems, along with upkeep costs, and a lack of subsidies to support implementation. Lack of integration between systems and a lack of support after technology uptake, as well as connectivity issues also play a role. There also tends to be a general reluctance towards adoption in some instances due to negative experiences reported by other adopters, and the level of investment and training required to implement some technologies (Boothby and White, 2021). In comparison with intensive production systems, there are also additional challenges for the development and incorporation of PLF tools within extensive systems (Bahlo et al., 2019).

1.1.4.1 Data transmission

Whilst intensive farming systems typically have more infrastructure in place which can support the integration of PLF systems and allow for data transmission from the facilities in which livestock are kept (Tedeschi et al., 2021), data transmission within extensive systems is often more complex (Maroto-Molina et al., 2019), particularly where the aim is to provide real-time monitoring. The scale of farms, and often high livestock numbers means that animals can be dispersed over wide, and often remote areas (Bahlo et al., 2019), hence data may need to be transmitted over large distances, in areas where electricity and internet networks are often absent (Castagnolo et al., 2023) and transmission is typically limited. In addition, data transmission may be further confounded by the environmental conditions, as factors such as the type of terrain, slope and vegetation cover have all been reported to limit and / or interfere with the use of positioning systems and wireless communications (Bahlo et al., 2019), whilst in many cases communication via copper wire and wi-fi (wireless fidelity) based systems do not work within extensive systems (Waterhouse et al., 2019). Options such as the Global System for Mobile Communications (GSM) have provided opportunity for more frequent update and transfer of information, however, GSM can have inconsistent coverage within rural areas and may not be an energy efficient means of monitoring livestock under extensive conditions (Maroto-Molina et al., 2019; Castagnolo et al., 2023). However, the introduction of the Internet of Things (IoT) and low power wide area (LPWA) networks has enhanced connectivity for the development of sensors and smart devices within extensive systems, being more energy efficient and relatively inexpensive (Maroto-Molina et al., 2019). LPWA technologies such as Sigfox, LoRa (long range), and NB-IoT and Ingenu can provide long-range communication, with reported coverage ranges of 30-50 km (SIGFOX), 10-15 km (LoRa) and ~15km (Ingenu) within rural areas (Centenaro et al., 2016). In addition, a single gateway can receive data from thousands of sensors (Waterhouse et al., 2019) hence few reception devices would be required to provide transmission over large areas.

1.1.4.2 Energy and battery life

Within extensive systems, devices will typically need to have a long battery life and low energy consumption to be a viable long-term monitoring solution (Aquilani, et al., 2022). There may then need to be a trade-off between the range over which data can be transmitted and the power requirements to maximise device life (Bahlo et al., 2019). Where there are many wireless sensor networks (WSNs) operating, high network traffic could result in signal collisions and lead to a faster energy depletion because of data retransmission (Anisi et al., 2015). Whilst LPWA technologies offer great potential for the development of PLF within extensive systems, there may still be some limitations depending on number of devices, frequency of broadcasting, and the size of data packets. As there is typically a lower level of input and frequency of handling in extensive systems, there is further requirements to maximise the operational life of devices and minimise the frequency at which maintenance is required (Bahlo et al., 2019), particularly for wearable on-animal devices.

1.1.4.3 Environmental conditions

In addition to the potential impacts of animals themselves on sensors or other PLF tools, devices implemented in extensive systems need to be able to withstand variable climate and weather conditions and are more prone to physical damage and interference (Aqeel-Ur-Rehman et al., 2014). To protect electronic components, devices therefore need to be robust and with a high fault tolerance (Bahlo et al., 2019), as factors such as continuous exposure to high or low temperatures may reduce the battery life or capacity of wireless sensor nodes (Park et al., 2005).

1.2 Sheep production, management and welfare

The sheep or domestic sheep (*Ovis aries*) industry is an important farming sector, contributing to major products such as meat, wool / hair, milk, and skins (Morris, 2009). There is an estimated world population of ~1 000 million sheep, with the most prominent sheep farming areas occurring in Europe, Asia, Australia, New Zealand, and South America (Morris, 2017). Within temperate regions sheep are primarily kept for meat production (Morris, 2009), whilst dairy sheep production is largely in sub-tropical temperate areas of Asia, Europe, and Africa (Pulina et al., 2018).

There are three major management systems used for sheep production: extensive (for wool and meat), intensive (typically dairy), and traditional pastoralism (Morris, 2017). The type of system in place will vary according to both country and product, however, extensive management systems are the most common within sheep producing countries (Kilgour et al., 2008). Extensive management systems can include both lowland farming systems; with relatively small flocks grazing in fenced enclosures, and rangeland management systems; with large flocks on unfenced pastures (Kilgour et al., 2008). However, extensive management systems are typically characterised by animals which are managed outdoors year-round, relying on pasture feeding (often on poorer quality grassland), and with limited monitoring and human interaction (Munoz et al., 2019).

Sheep in extensive systems are often believed to have a higher welfare than those in intensive systems (Goddard et al., 2006), as they are kept in more 'natural' conditions with greater behavioural freedom and opportunities to control their movement (Dwyer and Lawrence, 2008; Munoz et al., 2019). However, sheep in extensive systems are exposed to greater environmental challenges (Dwyer and Lawrence, 2008). Exposure to extreme conditions, combined with other challenges such poor nutrition and body condition, predation risk, and lack of shelter are not only issues in themselves but may lead to chronic stress.

The lack of regular inspection within more extensive sheep grazing systems may also lead to chronic or untreated disease and / or injury, as issues may go undetected for variable lengths of time (Goddard et al., 2006). Common issues resulting from reduced human interaction are often related to obstetric difficulties and issues around lambing, as well as lameness, flystrike and parasitic infection (Dwyer & Lawrence, 2008). Some of these challenges may cause significant pain and / or stress, or in more extreme cases be fatal. Furthermore, the infrequent or reduced human contact may result in additional stress for sheep during handling, transportation, and slaughter than those subject to greater levels of interaction (Goddard et al., 2006).

Within extensive sheep systems nutrition remains an important factor in ewe and lamb mortality due to the often low nutritional value and quantity of available grazing (Morris, 2017). As pregnancy occurs during winter grazing, often a period of undernutrition, this can impact on ewe health and productivity (Morgan-Davies et al., 2008), and the levels of lamb mortality observed. Undernourishment has been found to influence the expression of both maternal and neonate behaviours expressed at parturition which may subsequently lead to poor bond development and an increased likelihood of ewes deserting lambs (Dwyer et al., 2003).

Indeed, the top welfare challenges identified in extensive sheep systems in Australia include ewe and lamb mortality, poor nutrition, intestinal parasites, flystrike, mastitis, and the provision of water and shelter (Munoz et al., 2019). Whilst specific welfare challenges will vary between countries, relating to the production, scale and environment (Munoz et al., 2019), similar welfare issues have also been identified within European countries. Within the TechCare project (of which this thesis was part) the top welfare challenges reported by stakeholders from nine sheep-producing countries related to nutritional issues (under / malnutrition), health issues – in particular lameness, gastrointestinal parasites, ectoparasites, and mastitis, as well as poor maternal relationships, mortality and reproductive disorders (Morgan-Davies et al., 2024).

1.3 Potential applications of PLF to address sheep management and welfare challenges

Across livestock sectors the development and application of PLF technologies have focused on tools and integrated information systems to monitor and improve animal productivity and health (Buller et al., 2020). However, more recently there has been a shift to incorporate other aspects of animal welfare which could be monitored by PLF technologies. In addition, given the environmental, structural, and technological challenges associated with more extensive systems such as for sheep and goats, PLF technologies applied in grazing systems to date have tended to be at the group or flock level, rather than individual level (Buller et al., 2020). As discussed previously, many of the PLF tools which have been examined within sheep research are also not commercially available. However, research studies have demonstrated the potential of various PLF tools to detect and monitor aspects of animal behaviour, physiology, location, movement, and interactions, which could assist in the management and welfare management of sheep grazing systems, by identifying individual animals requiring some form of action.

Within grazing sheep systems infectious diseases and lameness are common management and welfare concerns (Morrone et al., 2022; Silva et al., 2022). Technologies which can help farmers detect and therefore treat animals at an early stage would therefore act to improve welfare and help minimise economic losses on farms (Morrone et al., 2022). Proposed benefits of activity monitoring, particularly accelerometers or IMUs, include identification and alert of parturition, which may help in early detection of dystocia and in reducing lamb mortality (Silva et al., 2022). Monitoring feeding and drinking behaviours such as grazing and ruminating would provide insight into animal nutrition and gastrointestinal health, which is a main concern within the sheep industry. However, many of these tools are still within the development and or validation stages for small ruminants (Schillings et al., 2021).

Changes in animal behaviour or deviation from usual activity patterns and interactions are perhaps some of the most indicative measures of animal health and welfare (Kasawan et al., 2024). Sensors which can monitor animal location, movements and activity in real-time could then act as a potential early warning of a health or welfare issue (Rutter, 2014). In addition, proximity and location monitoring provides information on spatial and resource use – such as feed and water points, or use of shelters, as well as flock interactions which could be used to monitor disease transmission. One of the most promising technologies in terms of localisation and proximity monitoring, across a multitude of industries, is BLE. The development of BLE into an energy efficient, low data rate technology makes it particularly suitable for use within IoT applications (Jeon et al., 2018). Since the aim of PLF is individual animal monitoring in real-time, BLE as a relatively low-cost, low weight device which can transmit and communicate information in real-time, warrants further investigation for application in extensive sheep systems.

1.3.1 Applications of BLE

Since the introduction of BLE there has been a growing development and incorporation of the technology across multiple sectors, such as for asset tracking, contact tracing, health monitoring, and to provide proximity-based services or marketing (Spachos and Plataniotis, 2020; Yang et al., 2020).

1.3.1.1 Asset tracking & supply chain monitoring

One of the main applications to date has been for asset tracking, both for personal belongings (e.g. luggage, bikes, and keys), pets, and within commercial settings such as for industrial asset tracking, inventory management within warehouses, and for healthcare asset management (Pinto, 2023). This could include tracking of equipment or parts, tools, and personnel (Krishnan & Mendoza Santos, 2021). In addition to providing asset location, proposed benefits comprise more efficient allocation of resources, error reduction, loss prevention, improved maintenance and servicing, and cost reduction in terms of time, labour, and asset loss / replacement (Pinto, 2023). There has also been significant investment into this area, with the development of Apple Inc's AirTags, Samsung SmartTag's, Tile and other similar applications (Jang et al., 2024).

1.3.1.2 Health monitoring

Within the healthcare industry BLE has been applied as a means of contact tracing, most notably through mobile contact tracing apps during the COVID-19 pandemic (Etzlinger et al., 2021), and, in some studies, using wearable BLE devices and BLE beacons within hospital and care home settings (Thompson et al., 2023; Zhang et al., 2023). However, BLE has also been proposed for other health monitoring purposes, such as detection of wandering behaviour in dementia patients (Kolakowski et al., 2019), and as a means of monitoring health and well-being, and detection of emergency situations for residents within care homes and active and assisted living (KolaKowski et al., 2020).

1.3.1.3 Proximity based services and marketing

Within the retail sector, BLE can be utilized as a means of both proximity marketing to highlight offers and discounts to customers, as well as offering opportunity to monitor and manage store flow, layout and identification of popular products. Similarly, within the tourism and entertainment industry BLE can be used as a means of providing self-guided tours, providing point of interest information, or for networking and directions during events and within smart museums (Spachos and Plataniotis, 2020).

1.3.2 Applications of BLE in animal monitoring

BLE has also expanded into applications within wildlife and livestock monitoring, largely by providing a means by which information collected via other sensors and devices can be transmitted. Studies incorporating BLE for this purpose range from activity monitoring in crabs and turtles (Kaidarova, et al., 2018), acoustic monitoring in birds (Magno et al., 2020), wireless blood pressure monitoring in rats (Uemura et al., 2004), and data capture of electric signals in captive harbour seals (Kim et al., 2021). Indeed, within the livestock industry several commercially available tools and management systems (e.g. livestock RFID readers and weigh creates) employ BLE as a means of data communication and connectivity.

The use of BLE as a monitoring tool in and of itself is however in the early stages of development, but in comparison with “store-on-board” proximity loggers, offers the potential for real-time monitoring. Within the livestock industry, most applications of BLE to date have occurred within indoor barn environments, and largely for the monitoring and localisation of dairy cows (Tøgersen et al., 2010; Trogh et al., 2017; Bloch and Pastell, 2020; Nikodem, 2021; Maxa et al., 2023, Szyc et al., 2023). These studies have typically entailed the use of BLE readers at fixed reference points within a barn, and BLE devices which broadcast a signal assigned to animals via a collar or other form of attachment. Other indoor applications of BLE as a PLF tool have also included activity monitoring and investigation of resting and feeding areas in pigs (Lee et al., 2022).

Within outdoor environments BLE has mainly been applied as a monitoring tool in conjunction with other technologies, typically GNSS, where a proportion of animals in the herd or flock are fitted with a BLE beacon, whilst some individuals are fitted with a GNSS device, which also acts as roving BLE reader for the BLE beacons. Maroto-Molina et al. (2019) utilised a combination of GNSS collars and BLE tags for location monitoring of both sheep and cattle in grazing systems, whilst Vidal-Cardos et al. (2024) employed a combination of GNSS collars and BLE tags to monitor cow-calf relationships in beef cattle. Some commercially available virtual fencing systems (e.g. Nofence), have now also began to incorporate BLE into their monitoring systems. Whilst primarily providing animal location via GNSS, devices can also switch to a BLE based location when animals are located within shelters or barns, thus conserving battery life of the devices (Nordic Semiconductor, 2018). Other proposed methods of animal monitoring and localisation using BLE involve the use of UAVs fitted with a BLE reader and GNSS device. Such a system was investigated in off-animal studies by Mesquita et al., (2023) who tested the use of Apple Inc AirTags alongside a UAV (with mobile phone to read the beacon signals and obtain GNSS locations), and by Nyholm (2020) and Vucic and Axell (2022) who both investigated the application of BLE tags and UAVs as a means of tracking sheep in grazing systems in Norway. Within this system BLE tags were mounted to collars and / or ear tags, which could be read by a BLE receiver on-board a UAV when flying overhead. Estimated field locations were based on the UAVs GNSS position at the time the BLE tag was read.

More specifically within sheep systems, BLE has largely been investigated as a proximity monitoring tool, particularly to measure the ewe-lamb relationship. Both Sohi et al. (2017) and Paganoni et al. (2021) utilised the BLE component of Actigraph GT3X sensors to monitor ewe-lamb interactions for the purpose of determining maternal pedigree. Similarly, Waterhouse et al. (2019) reported a higher number of ewe-lamb contacts and stronger BLE signal strength in related vs unrelated ewe-lamb pairings using a Bluetooth proximity sensor. Commercial options utilizing Bluetooth as an alternative to traditional mothering up and genomic testing have also been developed for commercial use (e.g. Smart Shepherd). The system uses Bluetooth-enabled collars which are worn by ewes and lambs for a minimum period of 48-hours to record ewe and lamb interactions and proximities. The system is reported to have a high level of agreement (98 %)

with DNA based pedigrees, whilst offering a cheaper and less time-consuming method of obtaining dam pedigrees. However, the store-on-board method, does require data to be downloaded from individual devices upon collar removal, as real-time transmission is not currently available.

Whilst several studies and commercially available PLF tools have begun to explore the use of BLE as a monitoring tool within different livestock sectors, the majority have tended to occur in indoor systems where there has typically been a high number of BLE readers covering relatively small areas, or in outdoor systems using BLE to monitor close contacts at relatively short distances. However, BLE devices continue to be developed, and the advertised operating ranges continue to increase, offering greater potential for the application of BLE in outdoor livestock systems. In addition, whilst BLE signal strength and range has been investigated in multiple indoor scenarios, there are fewer studies which have explored BLE range in outdoor systems, especially in the context of on-animal application (Huels et al., 2025; Kirkpatrick et al., 2021). Where this has been investigated it has typically been over short distance ranges. The overarching aim of this thesis was therefore to test and assess the functionality of BLE as potential PLF monitoring tool, within the context of outdoor sheep systems.

1.4 Aims of the thesis

This thesis was part of the TechCare project, funded by EU Horizon 2020. The TechCare project aimed to investigate and develop innovative approaches and business models to monitor and improve welfare management in sheep and goats through precision technologies. The project aimed to identify PLF tools which could monitor and / or manage animal welfare, behaviour, health, or performance, testing some of these tools in situ to evaluate their potential for application in commercial small ruminant systems.

The primary objective of this thesis was to investigate the potential for a BLE system to act as monitoring tool in grazing sheep systems, using a multi-sensor device developed for the project. The primary aims of the thesis were to:

1. Characterise the relationship between BLE signal strength and distance in outdoor systems.
2. Assess the application of BLE for animal localisation, and
3. To investigate the capability of BLE to be utilised as a monitoring tool to detect relationships, and changes to these – which may indicate a potential welfare or management problem, by applying the BLE system as a mean of monitoring ewe and lamb contacts.

Specific aims of the thesis were to:

1. Calibrate devices to assess signal strength and potential operating range of BLE in an outdoor field environment and develop distance prediction equations whereby the distance between devices can be estimated. The calibration also aimed to assess effects of:
    a. device height (Chapters 3 and 4)
    b. line-of-sight (Chapter 4)
2. Investigate the feasibility of utilising BLE as a means of localisation within a sheep grazing system (Chapter 3).
3. Assess the accuracy / sensitivity of the BLE system in reporting expected sheep identities and investigate how this relates to ewe-lamb distance and sheep behaviour (Chapter 5).

4. Investigate the potential of BLE to monitor the ewe-lamb relationship during the lambing and early lactation period (Chapter 6). More specifically to:
    a. Monitor changes in ewe-ewe relationships across the pre- to post-lambing phases.
    b. Detect changes in ewe-lamb relationships based on lamb age, and whether this related to lamb performance in the context of lamb weight change.
    c. Investigate whether BLE could identify differences in ewe-ewe and ewe-lamb contacts between lame and non-lame ewes.

Chapter 2 Development of a protype Bluetooth Low Energy (BLE) system for sheep studies

2.1 Introduction

2.1.1 Bluetooth Low Energy

BLE, also previously known as Bluetooth Smart, Wibree, and Ultra Low Power (ULP) (Townsend, 2014; Gupta, 2016), is a short-range wireless communication technology which operates using radio waves (Yang et al., 2020). Introduced in June 2010 by the Bluetooth Special Interest Group, BLE was developed as part of the ‘Bluetooth 4.0 Core Specification’ with the aim of “designing a radio standard with the lowest possible power consumption, specifically optimized for low cost, low bandwidth, low power, and low complexity” (Townsend, 2014). BLE was initially designed for applications in the growing IoT industry, where the earlier ‘Bluetooth Classic’ (the 1st iteration of Bluetooth) was less efficient. Hence, whilst still having similarities to ‘Bluetooth Classic’ they are distinct protocols, with the BLE protocol focusing on low latency and energy consumption (Yang et al., 2020). To obtain this goal, the basis of BLE is that the radio is turned off as quickly and for as long as possible, by transmitting data in short bursts, and spacing connection intervals as far as possible over a programable interval (between 7.5 ms – 4 s), thus conserving battery life (Townsend, 2014). It is therefore possible for devices utilising the BLE standard to operate for months or years on “coin-cell” or smaller batteries without recharging or replacement (Gupta, 2016).

2.1.1.1 BLE stack protocol

BLE devices operate following the BLE protocol, which is a layered architecture (called a protocol stack) consisting of multiple smaller protocols relating to specific areas of operation and data transmission (Afaneh, 2022). These layers work together to define how BLE devices can communicate and exchange information. There are three main components to the BLE stack; the application, which is the highest layer, contains the user interface and defines the logic on how data sent and received is handled, whilst the core components, the host and controller, are composed of multiple layers, each with a specific responsibility (Figure 2.1). Information is passed between these layers via the Host Controller Interface (HCI) (Townsend, 2014). The controller (or lower layer) functions are typically applied on a Bluetooth chip, to perform low-level operations such as discovering nearby devices, making connections, and exchanging data packets. The host (or upper layers) then use the low-level processes to conduct more complex tasks such as transferring large chunks of data, by splitting them into smaller sections and reassembling them (Gupta, 2016).

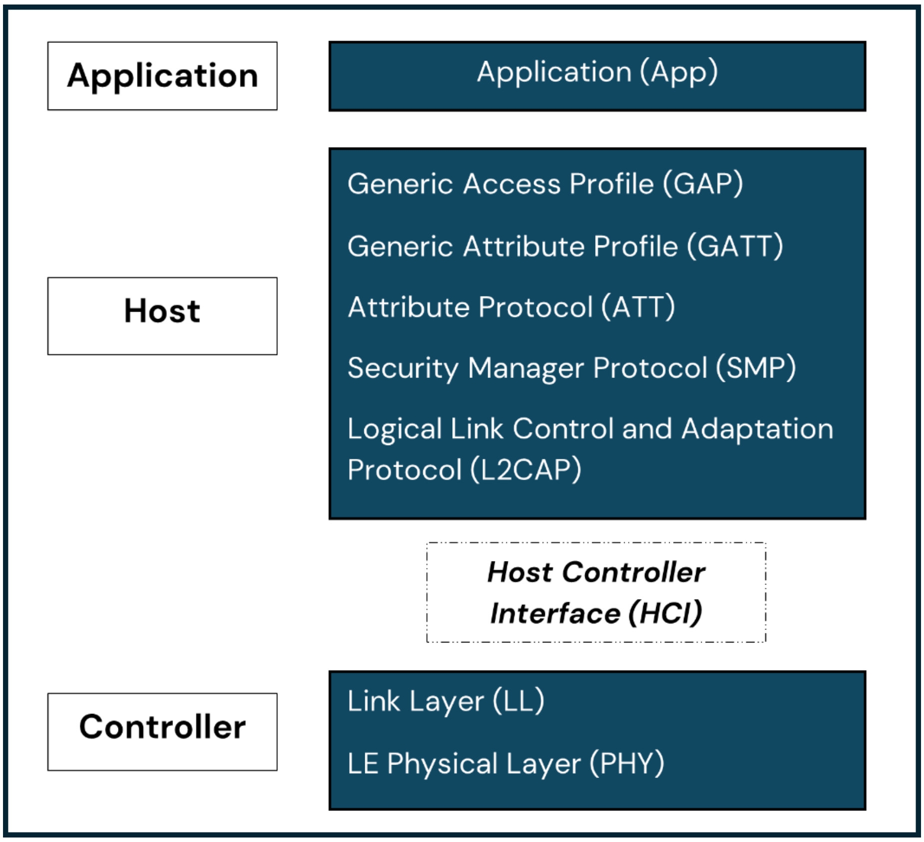

Figure 2.1 Bluetooth Low Energy (BLE) protocol stack - layers defining the operation and transmission of information (adapted from Townsend, 2014).

2.1.1.2 Communication and transmission of data

The role of a BLE device and its interaction with other devices is determined by the Generic Access Profile (GAP) layer (Afaneh, 2020). There are two methods by which BLE devices can communicate data: broadcasting and connections, each requiring two device roles. Broadcasting is a one-way form of communication whereby 'advertising' packets are periodically transmitted from one device (the broadcaster) to a secondary device (an observer or reader), which repeatedly scans preset frequencies for any advertising devices (Townsend, 2014). The main benefits to this type of communication are that in addition to being fast and easy to use, data can be sent to multiple devices at a time. However, as any scanning device (observer) can pick up the advertised data, this may not be a suitable method of transmission for sensitive data. In contrast, communication via "connections" allows for two-way exchange of data packets, via a private and permanent connection. In this instance, a central (master) device, repeatedly scans preset frequencies for 'advertising' packets by a peripheral (slave) device. Once a connection is established the central device dictates the timing of periodical exchange of 'data' packets between devices (Townsend, 2014). However, it should be noted that BLE devices can act as both a central and peripheral device and may be connected to multiple other peripheral and central devices. The additional protocol layers using this method of communication can allow for greater control and organisation of data, and may consume less power than broadcasting, as the timed data exchange can allow the radio to be turned off for longer periods (Townsend, 2014).

The physical transmission of information between BLE devices is controlled by the physical (PHY) layer. The radio uses the 2.4 GHz Industrial, Scientific, and Medical (ISM) radio band, also used by Bluetooth Classic and Wi-Fi (Townsend, 2014; Mäkelä and Lindskogen, 2018). This band is divided into 40 radio frequency channels between 2400 – 2483.5 MHz, each separated by 2 MHz (Afaneh, 2018). Three channels (37, 38, and 39) act as the primary advertising channels; used for broadcasting, discovery, and initiation of connections between devices. To minimise interference between advertising channels, they are spread across the radio frequency band, at 2402, 2426, and 2480 MHz for channels 37-39 respectively (Townsend, 2014; Mäkelä and Lindskogen, 2018). The other 37 channels, classed as data channels, are used for secondary advertising and transmission of data following connection between devices (Mäkelä and Lindskogen, 2018). As the ISM radio band is shared with other protocols (i.e. Bluetooth Classic, Wi-Fi, Zigbee) the BLE standard implements a 'frequency hopping spread spectrum' technique. Using this method, the radio of connected devices will 'hop' between the 37 data channels for each connection event, with the value of the 'hop' communicated at the initiation of the connection (Townsend, 2014). This minimises congestion on a single channel, thereby reducing the potential for information to be lost due to collision of data packets (Mäkelä and Lindskogen, 2018).

The link layer (LL) controls the operational state of the radio (based on the device role outlined by the GAP layer) and determines which actions can be performed. There are seven states in which the radio can operate: standby, advertising, scanning, initiating, connection, synchronisation, and isochronous broadcasting

(Hlapisi, 2023). The focus here will be on the five main states (Mäkelä and Lindskogen, 2018):

- Standby: the device is in idle or sleep mode – not sending or receiving information (packets). In this state the radio is powered off, hence the device requires very little power.
- Advertising: The device sends ‘advertising’ packets and may also listen for and respond to requests from other devices.
- Scanning: The device is listening for ‘advertising’ packets being broadcast by any devices within range and may respond to them.
- Initiating: The device attempts to establish a connection with another BLE device - the device initiating the connection is referred to as the initiator.
- Connection: The radio is connected with another BLE device under one of two roles - the initiator from the initiating state will act as the central (master) device, with the second device operating as the peripheral (slave).

The possible states of a given device depend upon the type of connection and the device role (Afaneh, 2022), as outlined in Figure 2.2.

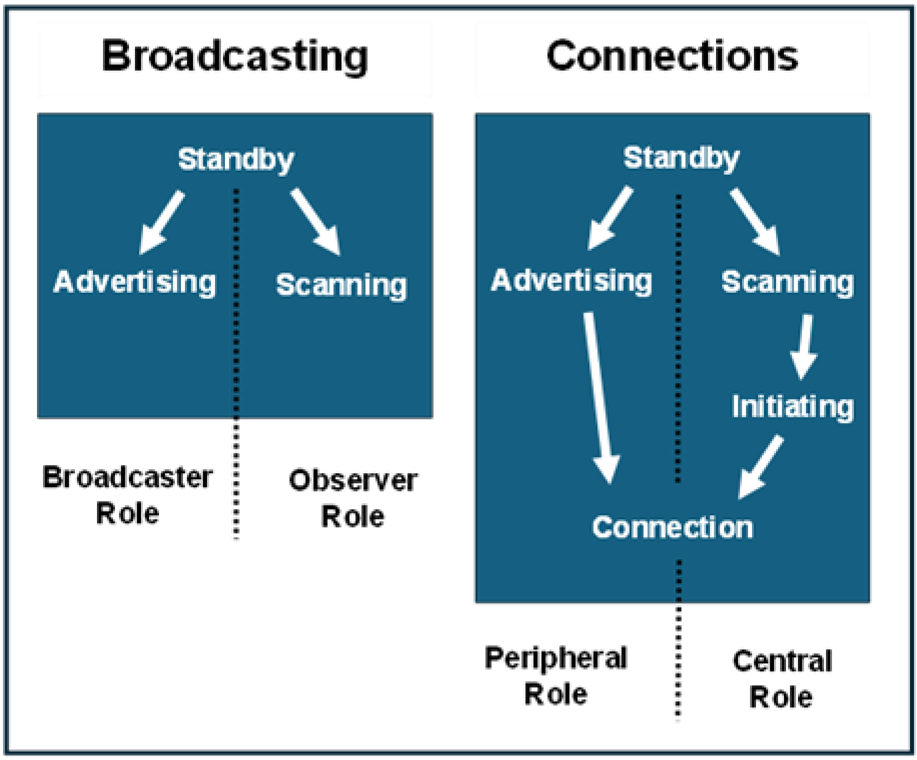

Figure 2.2 Radio states based on the method of communication and device role (adapted from Afaneh, 2022).

2.1.1.3 BLE range and signal strength

The operating range over which BLE devices can communicate is dependent on several factors, such as the operating environment, line-of-sight, antenna design, quality of the transmitter and receiver, the enclosure, and device orientation (Townsend, 2014). Advertising devices typically have a configurable transmission (TX) power, which can be used to increase the strength of the signal transmitted. Usually this is across a short programable range of -30 to 0 decibels per milliwatt (dBm) but will be dependent upon the specific device and manufacturer. However, a higher TX power will reduce the battery life of the device, hence there is often a trade-off between battery life and device range (Townsend, 2014). In addition, the signal strength reported may still be limited by the receiving antenna.

2.2 Design of a multi-sensor device

As part of the overarching TechCare project, a multi-sensor device was commissioned from CENSIS: Scotland's Innovation Centre for sensing, imaging and Internet of Things (IoT) technologies. The device, named a WISP (wearable integrated sensor platform), consisted of an enclosure ~ 12×8×5 cm and weighing 333 g (Figure 2.3), which contained three sensors: a BLE reader, GNSS receiver, and accelerometer, as well as a long range wide area network (LoRaWAN) communication module (which transmits data using a wireless modulation technique), and an 8 megabyte (MB) flash memory drive. All three sensors were programmed to record and report data on a 5-minute duty cycle, both in real-time (where LoRa gateway coverage was available), and to the on-board flash drive. The sensors were split over a primary and secondary micro board, allowing some sensors to stay in a low power mode until required to take some form of action, and thus conserve energy. Space was also included within the WISP enclosure for an optional BLE beacon to be included, depending upon the purpose of application.

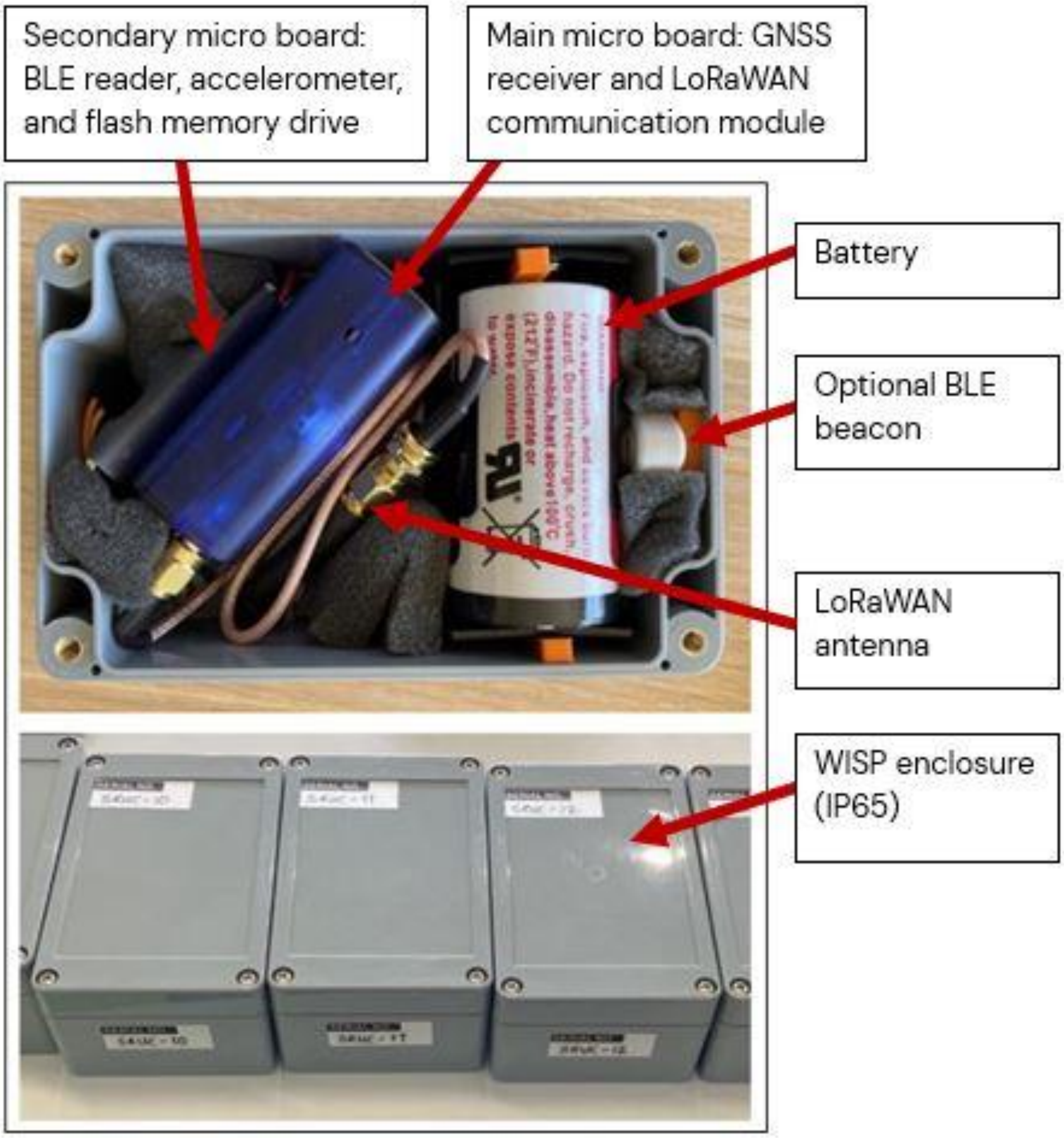

Figure 2.3 Wearable integrated sensor platform (WISP), containing a Bluetooth Low Energy (BLE) reader, global navigation satellite system (GNSS) receiver, and accelerometer (~ 12x8x5 cm, 333 g).

2.2.1 WISP enclosure

The electronic components of the WISP were contained in an enclosure with an ingress protection (IP) rating of 65. The IP rating is a standardised measure of an enclosure's resistance to accidental contact or foreign objects (ingress of dust) – 1st digit, and protection against liquids – 2nd digit (International Electrotechnical Commission, 2024). The resistance to contact / foreign objects is rated from 0 (no protection) to 6 (no ingress of dust), hence the WISP enclosure, with a ranking of 6, is classed as "dust-tight" (International Electrotechnical Commission, 2024). The resistance of an enclosure to liquids is ranked from 0 (no protection) to 9 (no harmful effects from water projected at high pressure and high temperature). With a rating of 5, the WISP is classed as "protected against water jets" (International Electrotechnical Commission, 2024), hence, whilst not protected from water immersion, the WISP enclosure was considered waterproof and suitable for outdoor application.

2.2.2 Sensors

2.2.2.1 GNSS receiver

The GNSS receiver was programmed to operate for the first three minutes of each duty cycle. WISPs were multi-constellation enabled (GALILEO, GLONASS, GPS), and were programmed to report a valid fix once a minimum of 4 satellites were tracked. At the end of every duty cycle, a rolling average filter was applied (to minimum of 10 valid fixes) to generate a single GNSS location for each duty cycle.

2.2.2.2 Accelerometer

The tri-axial accelerometer remained active for the full duty cycle, and operated by calculating the root mean square (RMS) of acceleration across all three (x, y, z) axes every 30 s. At the end of the duty cycle the highest RMS recorded was reported, hence a single motion index number corresponding to the largest RMS of acceleration in a 30 s interval was reported per duty cycle.

2.2.2.3 BLE reader

The BLE reader within the WISP (an Observer) was designed to operate alongside commercial BLE beacons (a Broadcaster) (Figure 2.4). The BLE components of the system operated most simply as a beacon which transmitted (referred to as “advertising”) a unique ID, and readers which received and reported these ID’s along with the beacon’s received signal strength indicator (RSSI), reported as negative values in units of decibels per milliwatt (dBm). The BLE reader within the WISP (operating on BLE 4.2) was programmed to report the identity and RSSI of the 16 beacons with the highest average RSSI within each duty cycle. Readers operated by scanning for 30 s then idling for 30 seconds (s). During each scanning window the RSSI of any beacon seen was added to that of any previous adverts. At the end of each duty cycle beacons were sorted and reported based on their average RSSI (e.g., Total Power (sum of beacon RSSI) / No. of adverts (No. of times beacon seen by the reader)), where the beacon reported at beacon rank 1 exhibited the highest average RSSI for that duty cycle and the beacon at the highest reported rank (up to 16) the lowest average RSSI.

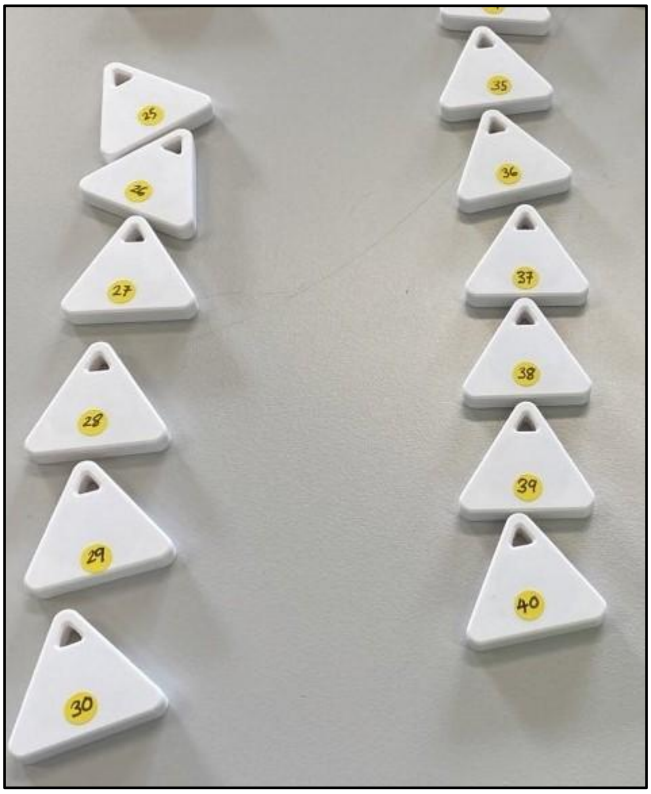

Figure 2.4 Example of a commercial Bluetooth low energy (BLE) beacon - Beacon Type 1 (Shenzhen Feasycom Technology Co., Ltd).

2.2.3 BLE beacons

Due to beacon availability and development, three types of commercially available BLE beacons were trialled alongside the WISP. Beacon Type 1 was used within the first WISP-beacon calibration and localisation studies (Chapter 3), whilst Beacon Types 2 and 3 were used in further calibration studies (Chapter 4), and in the on-sheep ewe-lamb studies (Chapters 5 and 6). Each of these beacons operated on a different version of BLE and thus had different publicised maximum BLE advertising ranges (Table 2.1). Regardless of the beacon type, each beacon used in the project was programmed with a 4-digit beacon identity prior to use, using the "FeasyBeacon" app (Shenzhen Feasycom Technology Co., Ltd), which would be reported by the BLE reader within the WISP. These identities were assigned based on the last 4 digits of each beacon's universally unique identifier (UUID). For consistency across beacon types and studies, all beacons were set to an advertising interval of 1285 milliseconds (ms), and a TX power of 0 dBm.

Table 2.1 Beacon characteristics and settings.

	Beacon Type 1	**Beacon Type 2**	**Beacon Type 3**
Beacon Name	FSC-BP103	FSC-BP108B	FSC-BP108N
Manufacturer	FeasyBeacon	FeasyBeacon	FeasyBeacon
BLE version	5.0	5.1	5.2
Chipset	TI CC2640R2F	Renesas / Dialog DA14531	Nordic nRF52832
Size	37.8×33.8×7.9 mm	48×37×7.8 mm	48×37×7.8 mm
Net weight	6.4 g	15 g	14 g
IP	IP40	IP67	IP67
Operating temperature range	-20 to +60°C	-20 to +60°C	-20 to +60°C
Estimated battery life (Based on default settings: advertising interval 1300 ms, TX power 0 dBm)	1 year	6 years	2 years
Power supply (battery type)	CR2032	CR3032	CR3032
Antenna type	PCB Coil antenna	PCB serpentine antenna	Ceramic antenna
Default advertising interval	1300 ms	1300 ms	1300 ms
Programable advertising range	0 to 10000 ms	0 to 10000 ms	0 to 10000 ms
Default TX power	0 dBm	0 dBm	0 dBm
Programable TX power range	-23 to +5 dBm	-19.5 to +2.5 dBm	-40 to +4 dBm
RSSI range	0 to ~127 dBm	0 to ~127 dBm	0 to ~127 dBm
Maximum advertising distance	130 m	400 m (open area)	500 m (open area)

* Data obtained from manufacturers data sheets: Beacon Type 1 (Shenzhen Feasycom Technology Co., Ltd, a), Beacon Type 2 (Shenzhen Feasycom Technology Co., Ltd, b), and Beacon Type 3 (Shenzhen Feasycom Technology Co., Ltd, c).

2.2.4 Data reporting

2.2.4.1 Flash memory drive

WISPs recorded and stored data from each duty cycle to the on-board flash memory drive (Figure 2.5). Data was retrieved from individual WISPs via a data logger app (a frozen python app - using wxWidgets for the graphical user interfaces (GUI) elements), using a micro USB to USB cable, which exported and downloaded any stored data as a .csv file.

2.2.4.2 LoRa

Where LoRa gateway coverage was available, WISPs also transmitted data in near real-time via its LoRaWAN communication module. For each duty cycle, the gateway would receive a data packet from the WISP, which was uploaded firstly to The Things Network (TTN), an open-source network for LoRa. From here, data was forwarded through a cloud-based middleware and a decoder, where the data was translated and pushed to the final application server, in this case ArcGIS, to be stored and downloaded as a .csv file (Figure 2.5).

2.2.4.3 Data output per duty cycle

The .csv files contained one row of data per duty cycle, which included:

- A message ID
- WISP device ID (via LoRa only)
- Timestamp (corresponding to the time the data was stored to the flash memory drive / or sent via LoRa)
- Battery voltage
- GNSS:
  - Latitude (degrees)
  - Longitude (degrees)
  - Altitude (metres above sea level – MAMSL)
  - Number of satellites seen
  - Horizontal dilution of precision (hdop) – a measure of the GNSS accuracy on the horizontal plane.
- Accelerometer:
  - Motion index number
- BLE reader:
  - Beacon ID: 4 digit beacon identity (of up to 16 BLE beacons)
  - RSSI value (corresponding to each Beacon ID)

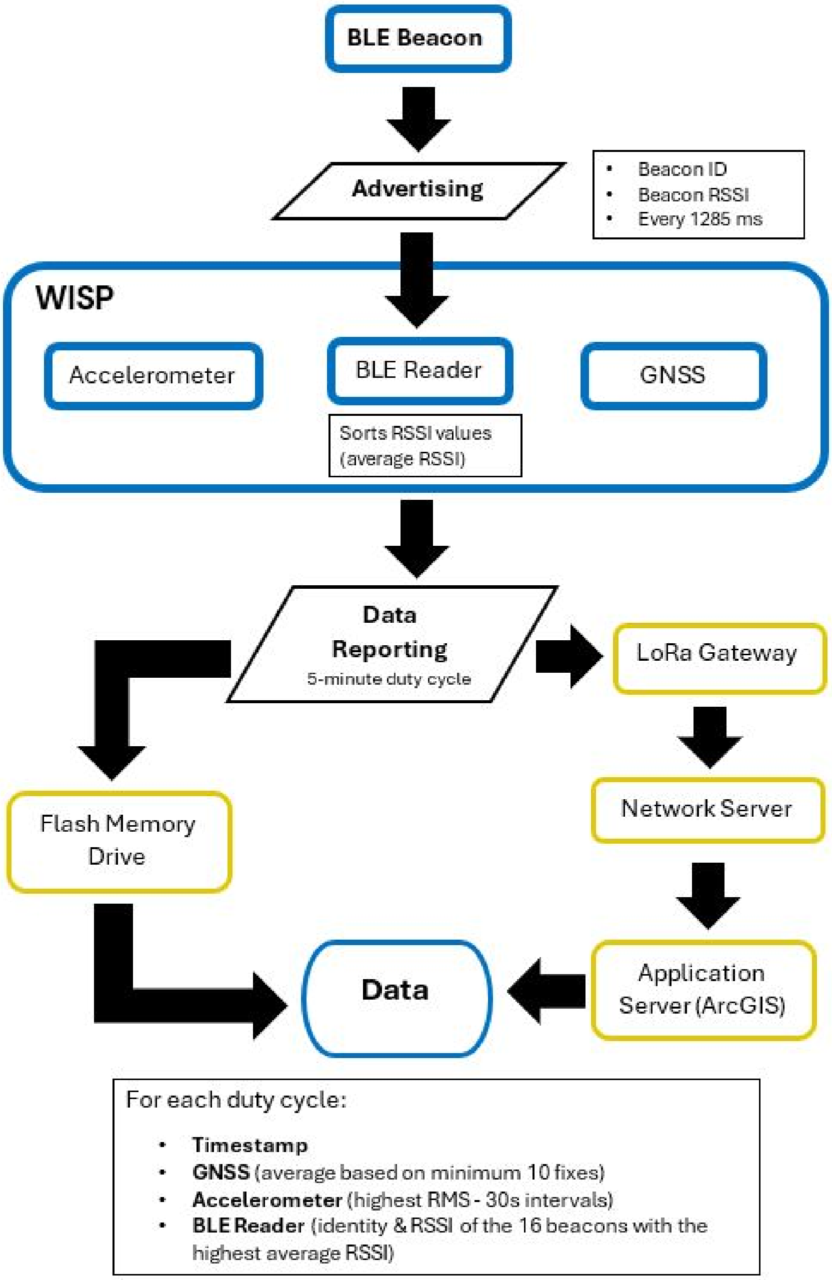

Figure 2.5 Illustration of the system and process of data transmission between the Bluetooth Low Energy (BLE) beacons, wearable integrated sensor platforms (WISPs) and raw data files.

2.2.5 Application and attachment of devices

2.2.5.1 WISP attachment

WISPs were designed for use both as a static BLE reader and wearable on-animal device (for adult sheep):

1. Static BLE reader (Chapters 3 and 4):
   WISPs were placed inside a plastic zip-lock bag and secured to a cane / wooden fence post / plastic electric fence post at the desired height from the ground using waterproof duct tape (Figure 2.6).

2. Wearable on-animal device – ewes only (Chapters 5 and 6):
   WISPs were placed inside a plastic zip-lock bag and secured with waterproof duct tape; on which the WISP's ID was recorded in marker pen. WISPs were then attached to adjustable neck collars made of wide polypropylene webbing and plastic buckle attachment, with a backing layer onto which WISPs were fixed by cable ties. As some chafing was noted during the first phase of on-sheep studies, WISPs were additionally padded with a layer of foam, secured with waterproof duct tape, during all further on-sheep phases (Figures 2.7 and 2.8).

2.2.5.2 BLE beacon application

The BLE beacons were also applied in both off-sheep calibration and on-sheep studies, where they were attached using one of the following methods:

1. Off-sheep calibration (Chapters 3 and 4):
   During device calibration studies, where beacons were tested at static positions, they were either wrapped in cellophane or placed within a zip-lock bag and duct-taped to a plastic electric fence posts at the desired height (Figure 2.9).

2. Contained with the WISP – ewes only (Chapters 5 and 6):
   Where WISPs were used as an on-animal device, a BLE beacon was also placed within the WISP enclosure (Figures 2.3 and 2.8).

3. String - ewes only (Chapters 5 and 6):
   Where ewes were assigned a beacon, but not a WISP, beacons were attached simply with sting secured around the neck (Figure 2.10).

4. Collar 1 - weaned lambs (Chapter 3):
   BLE beacons were contained within an adjustable elasticated polyester running belt (within a zipped pocket), fitted around the lambs' neck as a collar (Figure 2.11).

5. Collar 2 - lambs aged 1 to 45 days old (Chapters 5 and 6):
   Expandable elasticated neckbands with a Velcro closure were handsewn for the study. The beacons were contained within a small pouch at the front of the collar (worn underneath the lambs neck) to which a small cable tie with the beacons 4-digit ID was attached (Figure 2.12).

Figure 2.6 Set-up and attachment of a wearable integrated sensor platform (WISP) as a static Bluetooth Low Energy (BLE) reader.

Figure 2.7 Collar design and attachment of the wearable integrated sensor platform (WISP) as a wearable on-animal device.

Figure 2.8 Attachment of a wearable integrated sensor platform (WISP) on ewe as a wearable on-animal device.

Figure 2.9 Set-up and attachment of Bluetooth Low Energy (BLE) beacon in static off-sheep calibration.

Figure 2.10 Attachment of Bluetooth Low Energy (BLE) beacon to ewe via string.

Figure 2.11 Attachment of Bluetooth Low Energy (BLE) beacon using collar type 1.

Figure 2.12 Attachment of Bluetooth Low Energy (BLE) beacon using collar type 2.

Chapter 3 Application of Bluetooth Low Energy (BLE) for proximity and location monitoring in grazing sheep

The studies present in this chapter have been published in **animal**, "**Development of a novel Bluetooth Low Energy device for proximity and location monitoring in grazing sheep**", Vol 18 (9), September 2024, 101276; available online 25th July 2024. Provided in Appendix A.

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A.M. Walker [a, b], N.N. Jonsson [b], A. Waterhouse [a], H. McDougall [c], F. Kenyon [c], A. McLaren [a], C. Morgan-Davies [a].

[a] Hill and Mountain Research Centre, Scotland's Rural College (SRUC), Kirkton, Crianlarich, FK20 8RU, UK

[b] School of Biodiversity, One Health and Veterinary Medicine, University of Glasgow, 464 Bearsden Road, Bearsden, Glasgow, G61 1QH, UK

[c] Disease Control, Moredun Research Institute, Pentlands Science Park, Penicuik, EH26 0PZ, UK

Corresponding author: Aimee Walker.

3.1 Introduction

Monitoring animal location and proximity can provide useful information regarding landscape and resource use, social contacts, and animal performance and behaviour (Maroto-Molina et al., 2019). Over time this can also provide information on animal activity, which can be a useful indicator of health and welfare status (Liu et al., 2018; Nikodem, 2021). However, many of the technologies available tend to be impractical for use within grazing systems. Given the low value of individual animals and the often large flock sizes, the cost of PLF tools will be a factor in the uptake and use of such technologies within small ruminant sectors (Umstätter et al., 2008; Maroto-Molina et al., 2019). The introduction of IoT and LPWA networks has enhanced connectivity options, and along with advancements in technology such as BLE, presents opportunities for development of real-time monitoring within extensive systems. Whilst GNSS has been one of the most employed sensors within sheep research (Fogarty et al., 2018), BLE could offer a less power-intensive means of monitoring both novel animal proximity and animal location. Several studies have already begun to explore the use of BLE within livestock monitoring (Maroto-Molina et al., 2019; Lee et al., 2022, Maxa et al., 2023), both in combination with other technologies, as a means of localisation within indoor systems (Tøgersen et al, 2010; Bloch and Pastell, 2020; Szyc et al, 2023), and within sheep systems to investigate the ewe-lamb relationship (Sohi et al., 2017; Waterhouse et al., 2019; Paganoni et al., 2021).

However, BLE signal strength is known to be a noisy measure of proximity (Lovett et al., 2020), and whilst there have been several studies exploring BLE signal strength and range within indoor environments, there have been fewer in outdoor systems (Luciani and Davis, 2013; Mathew et al., 2017). Hence further information is required to ascertain how BLE devices would perform within a field setting. There were two main aims to this study, the first being the characterisation of the relationship between BLE signal strength and distance in an outdoor environment, using the purpose-built WISP alongside a BLE beacon. The second aim was to assess the use of BLE for the location of grazing sheep. Localisation was trialled in a field environment, firstly in a static beacon localisation study, and then an on-sheep validation, where a weaned lamb was fitted with a BLE beacon.

3.2 Material and methods

The studies within this chapter were conducted using WISPs alongside Type 1 BLE beacons, the characteristics of which are detailed in Chapter 2. The calibration and static localisation studies were conducted off-sheep and not subject to ethical approval. The on-sheep validation study used data obtained from a larger pilot study conducted under the scope of the overarching TechCare project. Ethical approval for this study was obtained through the Moredun Research Institute's Animal Welfare and Ethical Review Body (ref: E20/21).

3.2.1 Calibration study

3.2.1.1 Study design

The WISPs and BLE beacons were calibrated within a field environment to evaluate the relationship between a beacon's reported RSSI and its distance from a BLE reader (within a WISP), to assess the BLE signal range, and to develop a prediction equation whereby beacon distance from a WISP could be estimated based on its reported RSSI (Figure 3.1). Five WISPs were attached to a plastic electric-fence post located at a central point within the field. Eight beacons attached to posts were rotationally located at log intervals at distances of 1–128 m from WISPs, measured using a measuring wheel (Voche, Surveyors metric folding distance measuring wheel). Beacons were located at each of these measured distances for 29-minutes to allow opportunity for WISPs to obtain five possible RSSI readings per distance for each WISP-beacon pair. To determine whether WISP or beacon height impacted the likelihood of a beacon being received by the reader, or the RSSI values reported, both device types were tested at multiple heights. Beacons were tested at heights of 0.3 m (representing approximate ewe lying or lamb height) and 0.7 m (representing approximate ewe standing height), whilst WISPs were tested at 0.3, 0.7 and 2 m (Figure 3.2).

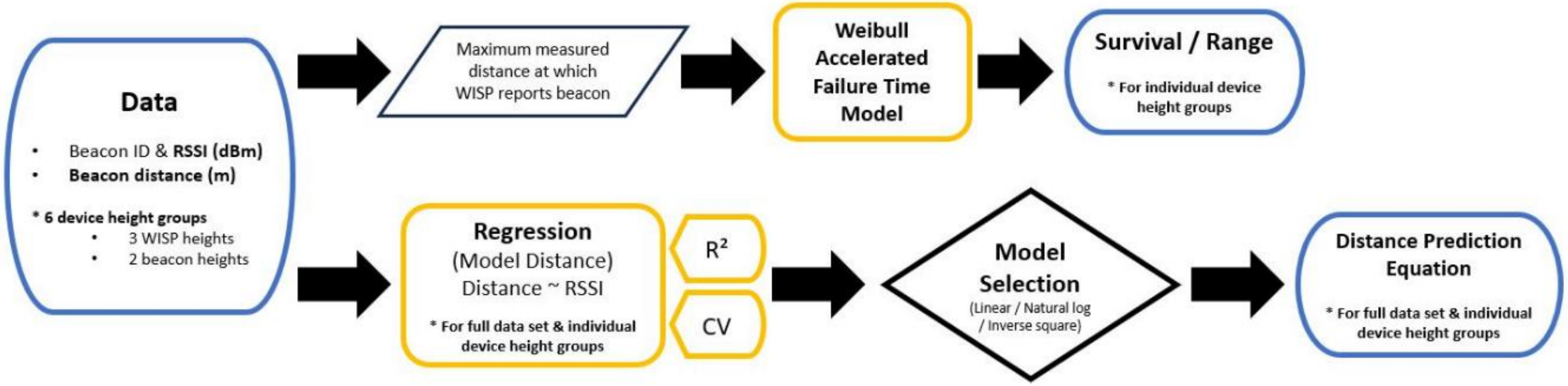


Figure 3.1 Flow diagram indicating the process of analysis for the off-sheep calibration study.

Abbreviations: RSSI = received signal strength indicator; WISP = wearable integrated sensor platform.

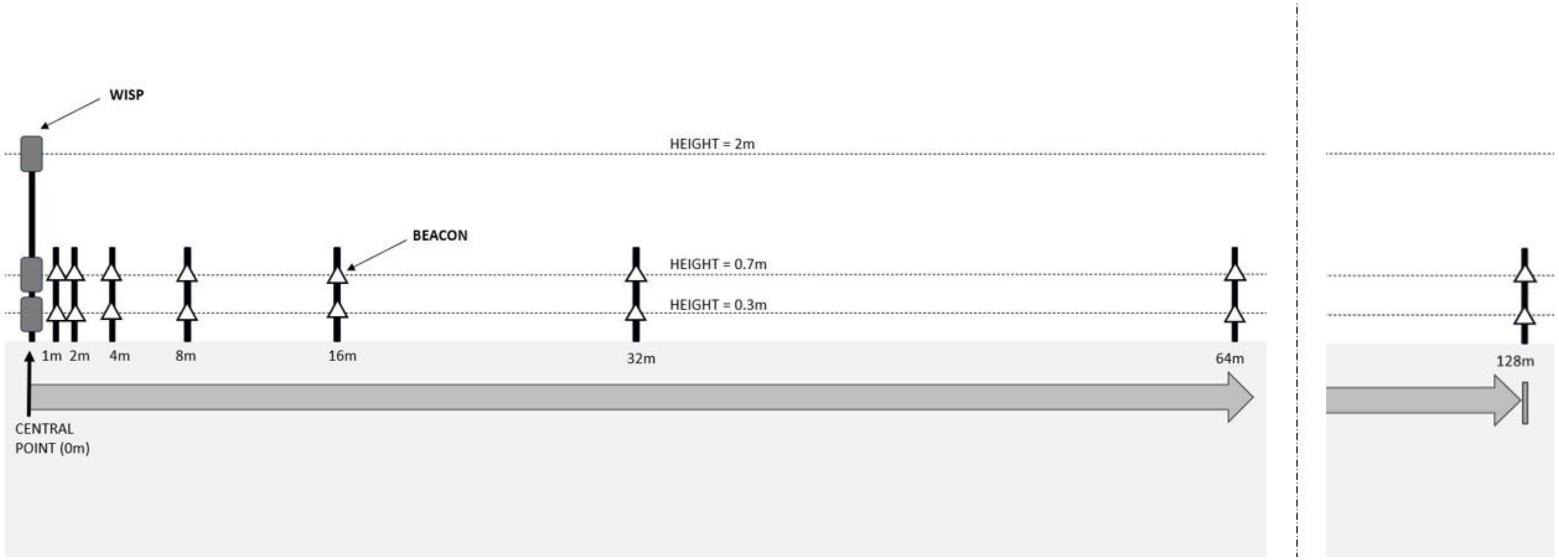


Figure 3.2 Configuration of the off-sheep calibration study, showing the device heights and distances examined, where Bluetooth Low Energy (BLE) beacons were tested at log distances of 1 – 128 m from wearable integrated sensor platforms (WISPs).

3.2.1.2 Range of devices

The maximum measured distance at which a beacon's signal was reported by a WISP was used to assess the BLE range at different WISP and beacon heights. As the precise distance at which a beacon's signal could no longer be reported by a WISP occurred at an unknown distance between two actual measured distances, the calibration data from each individual WISP-beacon height group was structured as interval-censored data sets, whereby for each WISP-beacon pairing the lower bound was the greatest measured distance at which the beacon was reported by the WISP, and the upper bound the subsequent measured distance, from which point the WISP failed to report the beacon. The "survreg" and "surv" functions from the survival package in R (version 3.5-5; Therneau, 2023) were applied to the data set to fit a Weibull accelerated failure time model. This model was considered to encompass the features required to describe the signal strength and is often employed to model reliability and survival. The "predict" function (version 4.2.2; R Core Team, 2022) was then applied to generate survival curves of the probability of a beacon being reported with increasing distance from the WISP for each of the WISP and beacon height combinations.

3.2.1.3 Development of the distance prediction model

A distance prediction equation was developed from the RSSI values obtained at each measured distance during the calibration by applying the "lm" function in R (version 4.2.2; R Core Team, 2022) to fit a regression. This was conducted for three models: linear, natural log, and inverse square, applied to both the full data set collectively, and for each individual WISP-beacon height group. The inverse function from the regression (generated for each group) was then applied along with the "predict" function to generate predicted distances for given RSSI values of -45 to -90 dBm. The three models were assessed based on their CV and R^2 results to select the most appropriate prediction equation for the WISP-beacon heights used within each study stage.

3.2.2 Static beacon localisation study

3.2.2.1 Study design

A localisation study was conducted on static beacons within an ~60 x 90 m area to determine whether beacons could be located based on their RSSI from multiple WISPs. The objectives of this study were to assess the error associated with the RSSI and distance prediction equation, and to test a multilateration approach as a means of localisation, the process for which is outlined in Figure 3.3. Six WISPs (numbered 1 – 6) were attached to fence posts at a height of 0.7 m; two located along the width of the paddocks (~60 m) at the 15 and 45 m mark, whilst four WISPs were located along a partial length of the outer fence line at distances of approximately 30, 50, 70, and 90 m. This resulted in an average WISP-WISP distance of 50.75 m. Sixteen beacons (labelled Beacon A – P) were attached to posts (0.7 m height) and laid out in a grid-like array within the paddock (Figure 3.4). As WISPs could report a maximum of 16 unique beacon identities within a duty cycle, there was no risk of competition between beacons for recording by any of the WISPs. WISPs and beacons were located at their designated position for a 2-hour period to provide a possible 24 RSSI readings per WISP-beacon pair. Locations of each WISP were based on the mean (of 17-24) GNSS coordinates from the on-board GNSS receiver, recorded during the data capture window. There was a mean difference of 1.02 – 3.03 m between single and mean WISP-GNSS coordinates of individual WISPs. GNSS locations for the beacons were obtained using the Android app “GPS Logger” (version 3.2.1, Basic Air Data). A separate study was conducted to assess the error associated with this app using 2 mobile phones to obtain 12 GNSS coordinates per phone for 2 locations. There was a mean difference of 0.93 m (SD = 0.57) between individual and mean coordinates for Phone 1 (used within the static beacon study), and 1.73 m (SD = 1.13) for Phone 2. Coordinates obtained by each phone had a mean difference of 2.14 m.

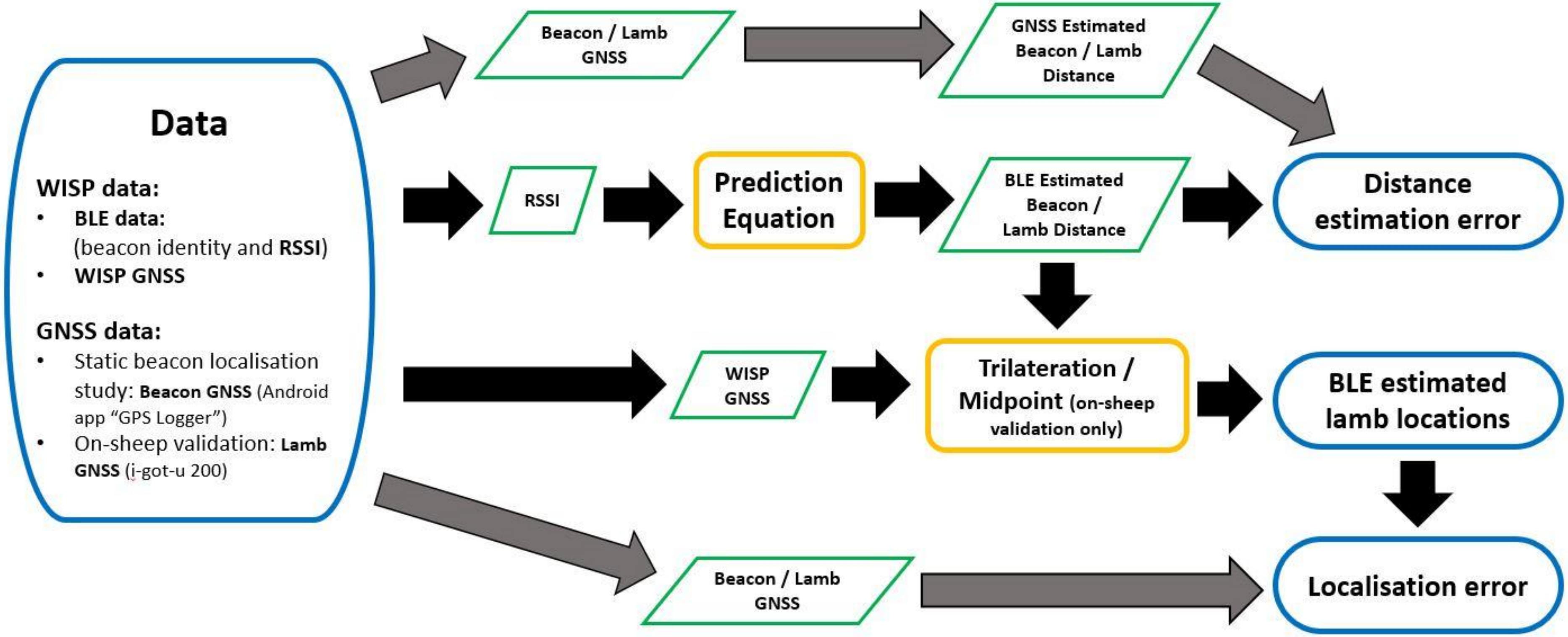


Figure 3.3 Flow diagram indicating the process of analysis for beacon and lamb localisation, as conducted in the static beacon localisation and on-sheep validation studies.

Abbreviations: BLE = Bluetooth low energy; GNSS = global navigation satellite systems; RSSI = received signal strength indicator.

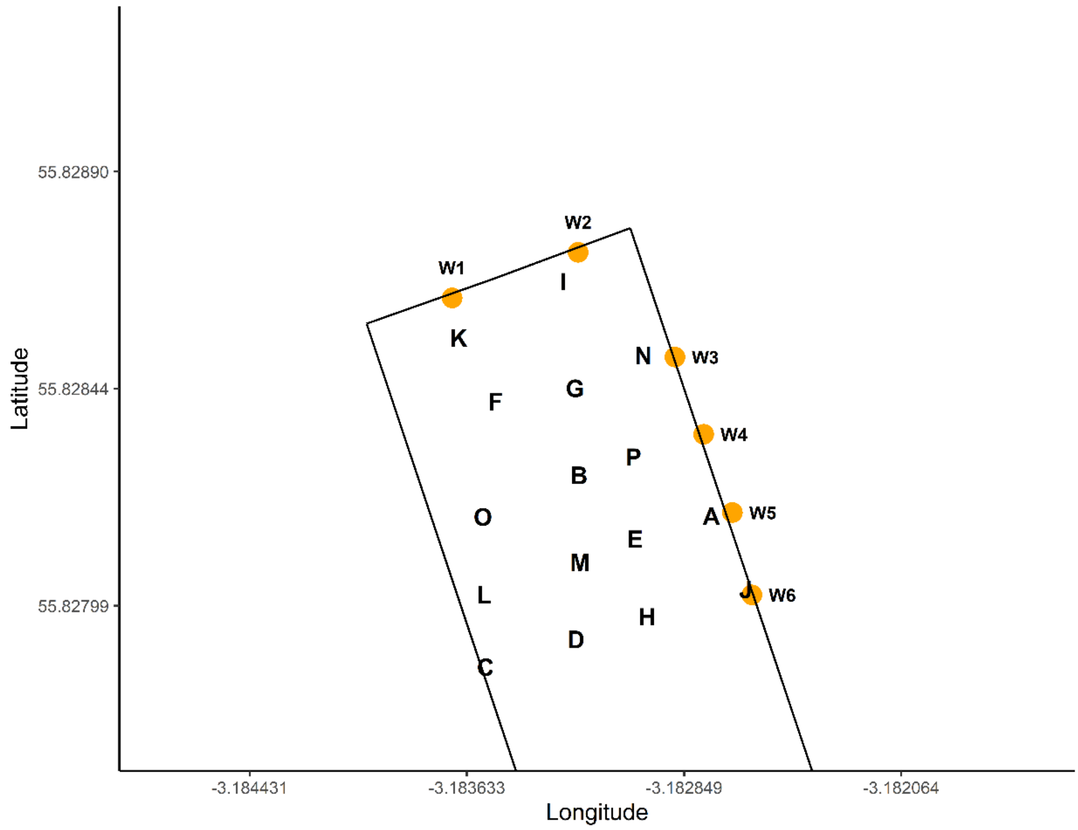


Figure 3.4 Off-sheep static beacon localisation study layout.

The 16 beacon global navigation satellite system (GNSS) locations labelled A-P. Mean GNSS locations of wearable integrated sensor platforms (WISPs), labelled W1-6, along the paddock fence lines.

3.2.2.2 Statistical analysis

Flash drive data (selected as the most complete data set) from each WISP was downloaded and combined, and the relevant 2-hour window of data selected for analysis. Data was reviewed to determine which WISPs had reported which beacons and compare variation in RSSI over time. Distances between each of the six WISPs (using mean GNSS coordinates), and between each WISP and beacon were calculated using the “disthaversine” function from the “geosphere” package in R (Version 1.5-18; Hijmans, 2022). BLE based WISP-beacon distances (for each possible WISP-beacon pairing) were calculated by applying the RSSI of each beacon reading obtained to the distance prediction equation and then calculating the overall mean across time for each WISP-beacon pair. These were then compared with the WISP-GNSS based distance estimates. To then calculate beacon locations, GNSS coordinates of WISPs were first converted from longitude and latitude

(WGS84 / EPSG: 4 326) to that of the British National Grid (EPSG: 27 700) using the "st_transform" function from the "sf" package in R (Version 1.0-14; Pebesma and Bivand, 2023). Final estimated beacon locations were calculated using a multilateration approach (Zhou et al., 2012; Luomala and Hakala, 2022) described below. Field boundaries for the study area were calculated based on the GNSS coordinates of corner and mid-paddock fence posts.

Multilateration localisation method: Applying the multilateration approach, the beacon's predicted distance was plotted as the radius of a circle around the reporting WISP, given by:

Equation 3.1

$$\text{Predicted distance}^2 = (\text{x} - \text{WISP longitude})^2 + (\text{y} - \text{WISP latitude})^2$$

Where beacons were reported by multiple WISPs, the intersection of the resulting circles was solved to generate potential beacon locations, using:

Equation 3.2

$$Beacon\ x\ coordinate_{1,2} = \frac{(a+c)}{2} + \frac{\left((c-a)(r_0{}^2 - r_1{}^2)\right)}{2D^2} \pm 2\frac{(b-d)}{D^2}\partial$$

$$Beacon\ y\ coordinate_{1,2} = \frac{(b+d)}{2} + \frac{((d-b)(r_0{}^2 - r_1{}^2))}{2D^2} \mp 2\frac{(a-c)}{D^2}\partial$$

$$and\ \partial = \frac{1}{4}\sqrt{(D+r_0+r_1)(D+r_0-r_1)(D-r_0+r_1)}(-D+r_0+r_1)$$

where: a = 1st WISP longitude; b = 1st WISP latitude; c = 2nd WISP longitude; d = 2nd WISP latitude; D = distance between 1st and 2nd WISP; r_0 = beacon predicted distance from WISP 1; r_1 = beacon predicted distance from WISP 2; and ∂ = area of a triangle with edge lengths r_0, r_1, and D.

These points were filtered to remove those which fell outside the paddock boundary. The final estimated beacon location was calculated as the mean of the potential beacon locations falling within the paddock boundary, and the resulting coordinates were compared with the beacons GNSS based location. An example of the multilateration process for one of the beacons (Beacon E) is shown in Figure 3.5.

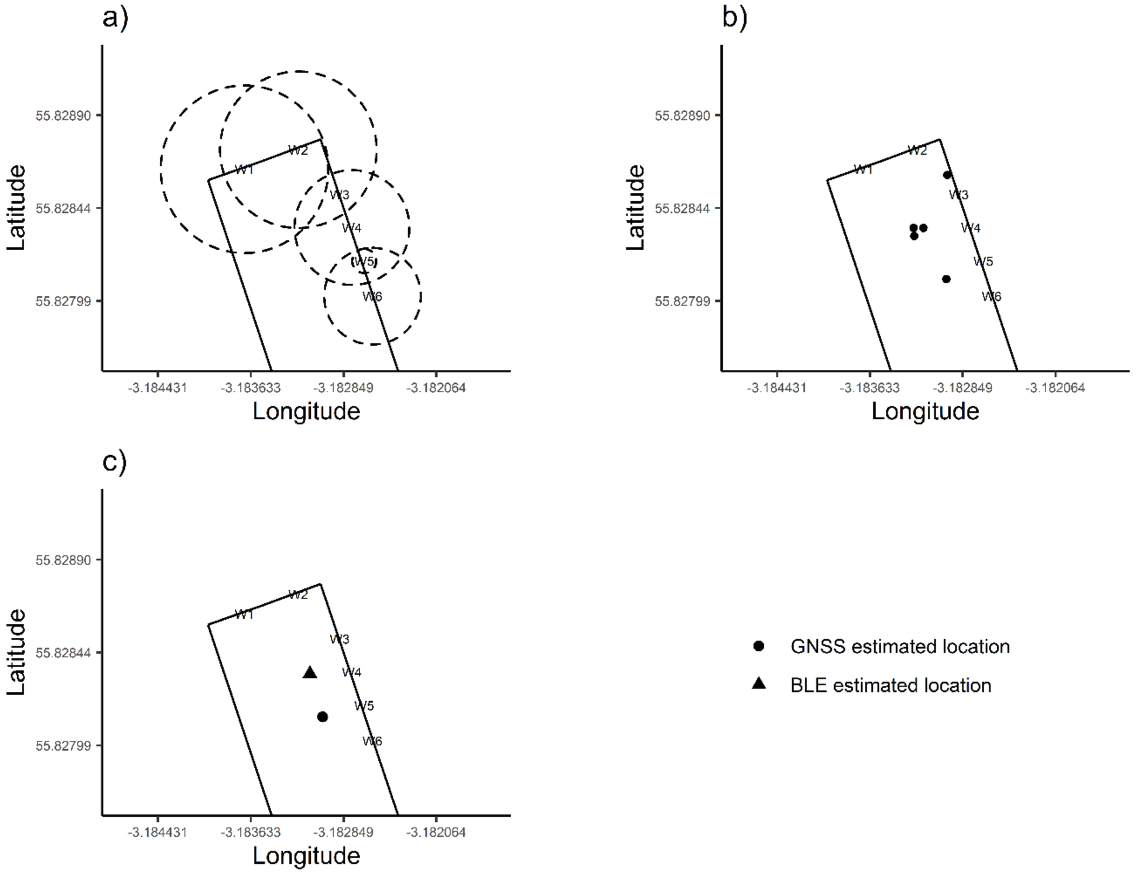


Figure 3.5 Example of the multilateration localisation method used within the static beacon localisation study and on-sheep validation.

a) displays the predicted distances of beacon E, plotted as the radius of a circle from each wearable integrated sensor platform (WISP), denoted by W1-6, which reported the beacon.

b) shows the estimated beacon locations - points where the circles intersected and which fell within the field boundary.

c) shows the final Bluetooth Low Energy (BLE) estimated beacon location - the mean of points calculated in b, in comparison with the corresponding global navigation satellite systems (GNSS) estimated location.

3.2.3 On-sheep validation

3.2.3.1 Study design

Localisation and proximity distance using BLE was then validated in an on-sheep scenario, where 24 weaned lambs (Texel x Mule) were fitted with collars containing a BLE beacon (Collar 1 – Chapter 2), 12 of which also had separate GNSS devices (i-gotU 200 or i-gotU 600, Mobile Action Technology). Lambs were all released into two adjoining paddocks (~1.4 ha) with connecting open gateway, which were surrounded by nine WISPs (Figure 3.6). The WISPs were located at a height of 2 m, attached to canes along the fence line. Four WISPs were staggered along the length of both outer fence lines (~240 m), whilst one was located at the open gateway between paddocks (indicated by W5 within Figure 3.6).

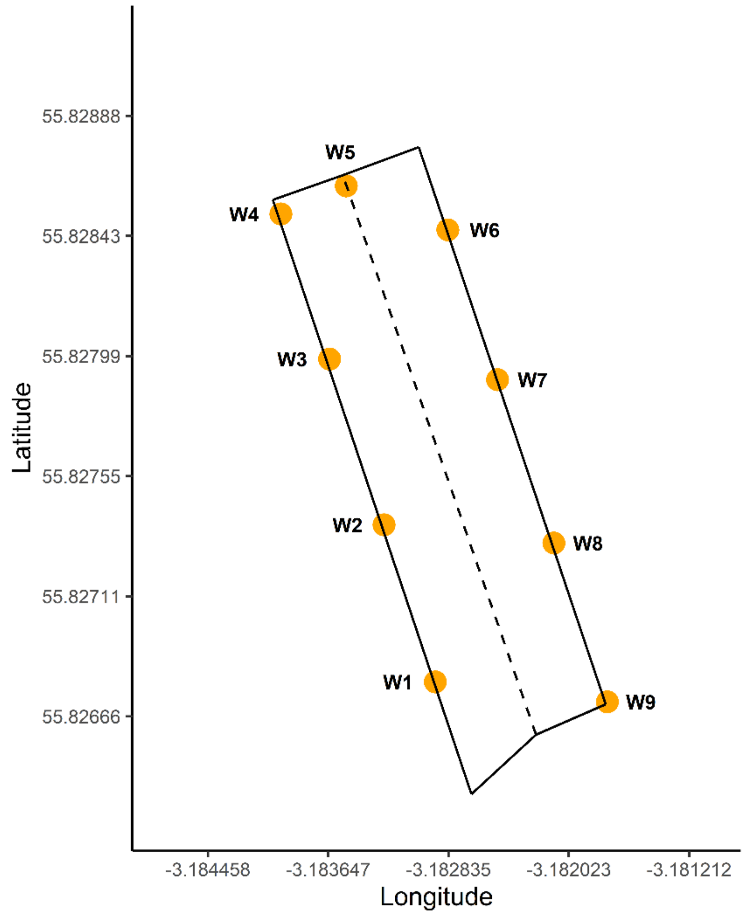


Figure 3.6 Layout of the on-sheep validation showing the configuration of the two adjacent paddocks.

Labels W1-9 indicated the mean global navigation satellite systems (GNSS) location of the nine wearable integrated sensor platforms (WISPs) located along the surrounding fence lines.

3.2.3.2 Statistical analysis

The analysis presented here examines a sample of data (24 h) from one lamb, wearing both a BLE beacon and i-gotU 200, as a validation of the developed distance prediction equation for both proximity monitoring and illustration of the use of BLE as a means of localisation in an on-animal scenario. As the most complete data set, WISP data was gathered from WISP flash drives for the selected day (8 September 2021) and combined into a single .csv file. For each data point, the reported RSSI was applied to the prediction equation to estimate the beacons, and hence lamb's distance from the reporting WISP.

Similarly, the lamb's GNSS data was downloaded from the i-got-u and filtered using a similar approach to Hromada et al. (2023), where locations with outlying altitude data (< 210 m and > 240 m) were removed from the data set (~1%). A new variable, "movement", was derived: lambs were classed as being stationary or moving depending upon whether lamb coordinates remained consistent – moving 0 m (stationary), or there was a change in GNSS coordinates (moving) between the timestamp of interest and the preceding 5-minutes. Similarly, a variable "distance travelled" was calculated using the "disthaversine" function from the "geosphere" package in R (Version 1.5-18; Hijmans, 2022) to calculate the total distance travelled between the corresponding GNSS coordinates for the reporting timestamp and each of the coordinates over the preceding 5-minutes. A "distance travelled group" was assigned based on the "distance travelled", where 0 m = none, > 0-10 m = very low, 10-20 m = low, 20-40 m = mid, and > 40 m = high. GNSS coordinates were then transformed from longitude and latitude to British National Grid as described previously.

The timestamps of both the WISP (BLE) and i-got-u (GNSS) data sets were then rounded to the nearest minute and joined based on the rounded time. To estimate lamb locations, data was grouped to find occasions where multiple WISPs reported the lamb's beacon within any independent 5-minute interval (i.e. 00:00:00-00:04:59, 00:01:00–00:05:59) over the course of the day, giving a total possible 1436 intervals. As all WISPs operated on independent time intervals, grouped data included instances where WISP reporting periods overlapped from between 1-5 minutes. Where independent intervals resulted in the same groupings of WISPs with the same reporting timestamp, any duplicates were removed. Overall "movement" and "distance travelled group" categorisations were therefore assigned for each interval – where movement was assigned if listed for any of the reporting WISPs, and the highest "distance travelled group" from any of the reporting WISPs assigned overall.

Two BLE localisation methods were then evaluated to calculate lamb locations for each possible 5-minute interval. For each time interval, a single new BLE timestamp was generated by calculating the mean timestamp of all reporting WISPs. Similarly, a new GNSS timestamp and coordinates were calculated by finding the mean of the GNSS data points within the corresponding interval. The first localisation method followed the multilateration approach described previously (Figure 3.3). However, in this instance intersecting points which fell outside the field boundary were not filtered out, and the final estimated lamb location was based on all potential locations generated.

Midpoint localisation method: The second localisation approach was based on calculating the midpoint (mean) between estimated coordinates on the straight-line distance between reporting WISP pairs. This was conducted for every possible WISP pairing within the time interval. Initial beacon coordinates were calculated from each WISP within a pair by plotting the predicted distance along the straight line between the two respective WISPs; calculated as follows:

Equation 3.3

$$beacon\ x\ coordinate_1\ = x1\ + \left(\left(\frac{d1}{D}\right) \times (x2\ - x1)\right)$$

$$Beacon\ y\ coordinate_1\ = y1\ \left(\left(\frac{d1}{D}\right) \times (y2\ - y1)\right)$$

$$Beacon\ x\ coordinate_2\ = x2\ + \left(\left(\frac{d2}{D}\right)\ \times (x1\ - x2)\right)$$

$$Beacon\ y\ coordinate_2\ = y2\ + \left(\left(\frac{d2}{D}\right) \times (y1\ - y2)\right)$$

where: x1 = 1st WISP longitude; y1 = 1st WISP latitude; x2 = 2nd WISP longitude; y2 = 2nd WISP latitude; d1 = beacon predicted distance from WISP 1; d2 = beacon predicted distance from WISP 2; and D = distance between 1st and 2nd WISP.

For that pairing, the estimated beacon location was taken as the mean of these two points along the WISP-WISP distance. The final lamb location for each time interval was calculated by finding the mean of the estimated locations from all pairings of the reporting WISPs. To examine opportunities to scale up, lamb trajectories were generated from both BLE localisation methods and compared with that of the original GNSS locations reporting every 1 min. Trajectories were produced using the “ltraj” function in the adehabitatLT package in R (version 0.3.27; Calenge et al., 2023) both for the full 24-hour study period and per hour.

3.3 Results

3.3.1 Calibration study

The relationship between WISP-beacon distance and RSSI was examined firstly as one data set, regardless of WISP or beacon height. Although there was an overall decline in RSSI with increasing beacon distance, there was a wide range in the RSSI values reported per distance and these values also overlapped between distances (Figure 3.7). However, individual WISP-beacon pairs produced similar RSSI values across repetitions, typically reporting a consistent RSSI or varying by 1-2 dBm. Apart from three instances out of 1 463 data points, where there was a difference of 8, 9, and 16 dBm (all at distances of 1 and 2 m) pairings varied by no more than 5 dBm. Where beacons were reported by a WISP, they were generally reported in all five repetitions, particularly at shorter distances of 1-16 m, whilst at distances of 32 and 64 m there were more instances of the beacon only being reported during some repetitions.

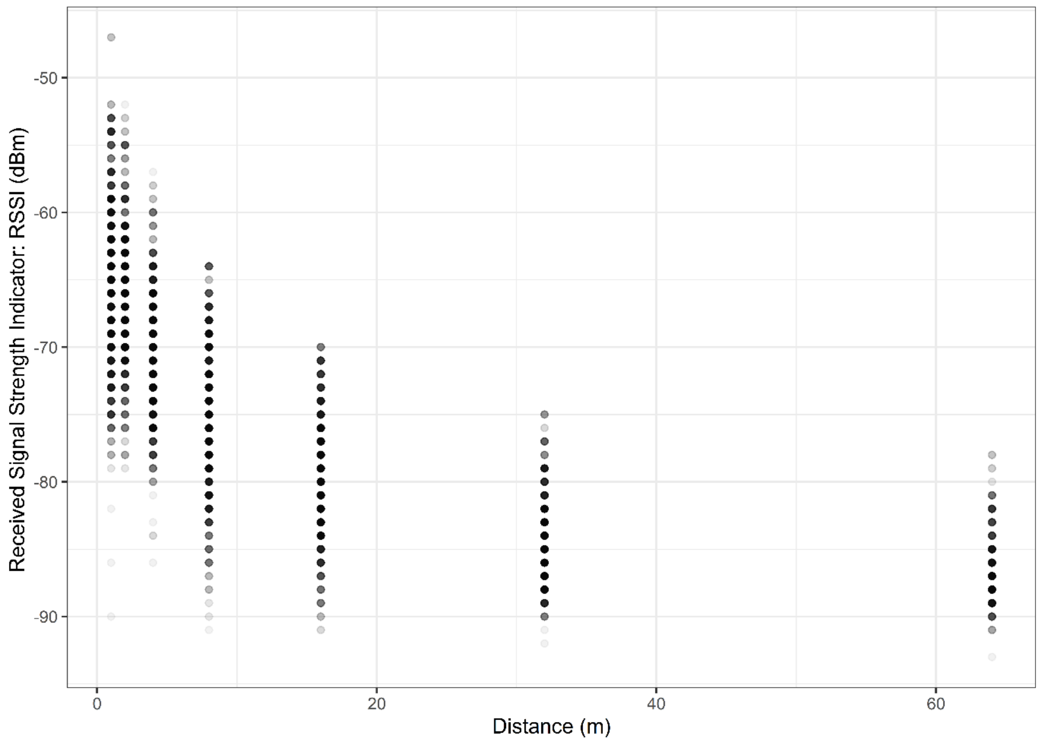


Figure 3.7 Beacon received signal strength indicator (RSSI) values reported by wearable integrated sensor platforms (WISPs) at measured beacon distances at log intervals from 1-64 m, based on combined device height data from the off-sheep calibration study.

3.3.1.1 Range of devices

The proportion of beacons reported per distance differed between WISP-beacon height groups (Figure 3.8). At 16 m all groups reported ≥ 92.5% of beacons, however by 32 m this had fallen to 18.5% where both devices were at a height of 0.3 m. The total number of beacon readings per WISP and beacon for each distance is summarised in Tables 3.1 and 3.2.

Two Weibull accelerated failure time models were compared; the first model assessing the impact of WISP and beacon height only, and the second model assessing the impact of WISP and beacon height, as well as their interaction. A likelihood ratio test indicated that the second model provided a better fit, with a higher log-likelihood value (-1182.1) than the first model (-1187.5), X^2 (2) = 10.752, p = 0.004626), hence the second (interaction) model was selected for use. The Weibull accelerated failure time model indicated that the BLE signal range differed according to the height at which the WISPs and beacons were located. WISP and beacon heights were both found to be significant factors within the model (Table 3.3), with higher device heights resulting in a longer signal range. The interaction between WISP and beacon heights was also found to be significant at a WISP height of 2 m and beacon height of 0.7 m. The probability of a beacon being reported declined at much shorter distances when both devices were located at a height of 0.3 m, declining to a 0 % probability at distances beyond ~ 60 m. In comparison, WISPs at a height of 2 m and beacon height of 0.7 m had > 80% probability of reporting beacons beyond 60 m, reaching a ~ 0 % probability by ~ 120 m (Figure 3.9). Setting a 95 % probability threshold the WISP-beacon range would therefore be between ~ 8 to 44 m depending upon both the WISP and beacon heights, whilst a 75 % probability threshold would give a range of ~ 17 to 66 m.

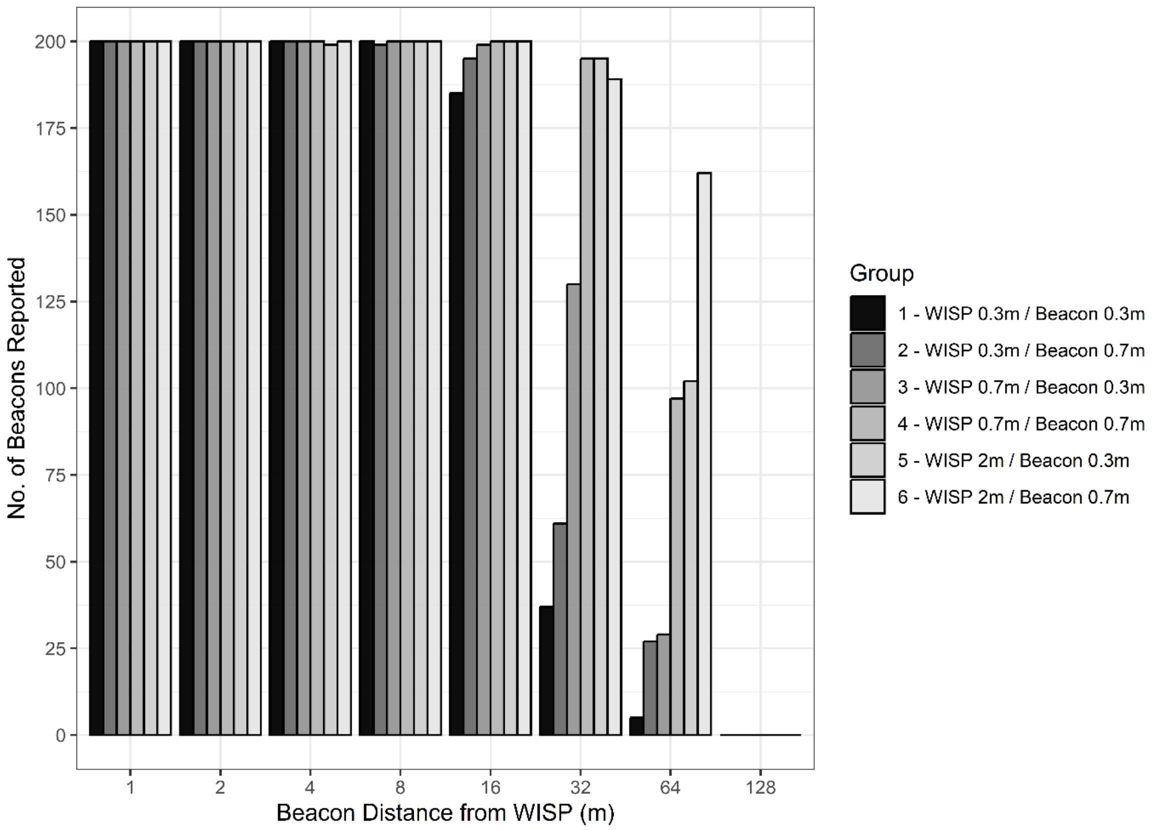


Figure 3.8 Total number of beacons reported per distance by the wearable integrated sensor platforms (WISPs) during the off-sheep calibration study.

This is shown for each WISP-beacon height group, where WISPs were tested at heights of 0.3, 0.7, and 2 m, and beacons were tested at heights of 0.3 and 0.7 m.

Table 3.1 Off-sheep calibration study summary: total beacon readings reported per individual wearable integrated sensor platform (WISP).

	WISP ID				
Distance	1	2	3	4	5
1	240 (100%)	240 (100%)	240 (100%)	240 (100%)	240 (100%)
2	240 (100%)	240 (100%)	240 (100%)	240 (100%)	240 (100%)
4	240 (100%)	240 (100%)	240 (100%)	240 (100%)	239 (99.6%)
8	240 (100%)	240 (100%)	240 (100%)	240 (100%)	239 (99.6%)
16	236 (98.3%)	234 (97.5%)	240 (100%)	239 (99.6%)	230 (95.8%)
32	232 (96.7%)	148 (61.7%)	141 (58.8%)	130 (54.2%)	156 (65%)
64	158 (65.8%)	71 (29.6%)	33 (13.8%)	70 (29.2%)	90 (37.5%)
128	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)
Total no. beacon readings	1586 (82.6%)	1413 (73.6%)	1374 (71.6%)	1399 (72.9%)	1434 (74.7%)

Table 3.2 Off-sheep calibration study summary: total beacon readings reported per individual beacon.

	Beacon ID							
Distance	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
1	150 100 %	150 100 %	150 100 %	150 100 %	150 100 %	150 100 %	150 100 %	150 100 %
2	150 100 %	150 100 %	150 100 %	150 100 %	150 100 %	150 100 %	150 100 %	150 100 %
4	150 100 %	150 100 %	150 100 %	150 100 %	150 100 %	150 100 %	150 100 %	149 99.3 %
8	150 100 %	150 100 %	150 100 %	150 100 %	150 100 %	150 100 %	150 100 %	149 99.3%
16	150 100 %	150 100 %	150 100 %	150 100 %	150 100 %	150 100 %	150 100 %	129 86 %
32	105 70 %	100 67 %	92 61.3 %	105 70 %	101 67 %	88 59 %	123 82 %	93 62 %
64	50 33 %	46 31 %	49 32.7 %	63 42 %	45 30.0 %	49 33 %	92 61 %	28 19 %
128	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)
Total no. beacon readings	905 75 %	896 75 %	891 74 %	918 77 %	896 75 %	887 74 %	965 80 %	848 71 %

Table 3.3 Summary of the Weibull accelerated failure time model of beacon distance to failure of being reported, based on wearable integrated sensor platform (WISP) and beacon height during the off-sheep calibration study.

Parameter	Value	SE	z	p-value
Intercept[1]	3.4234	0.0288	118.84	$<2 \times 10^{-16}$
WISP height				
0.3 m	Reference WISP height			
0.7 m	0.4677	0.0409	11.45	$<2 \times 10^{-16}$
2 m	0.8669	0.0430	20.15	$<2 \times 10^{-16}$
Beacon height				
0.3 m	Reference beacon height			
0.7 m	0.3039	0.0403	7.55	4.4×10^{-14}
WISP height × Beacon height				
WISP 0.3 m × Beacon 0.3 m	Reference WISP × Beacon height			
WISP 0.7 m × Beacon 0.7 m	0.0769	0.0592	1.30	0.194
WISP 2 m × Beacon 0.7 m	-0.1235	0.0596	-2.07	0.038
Log (scale)[2]	-1.0414	0.0262	-39.76	$<2 \times 10^{-16}$

[1] Intercept as given by the survreg function is the log of the standard parameterisation of the Weibull distribution scale parameter.

[2] Log (scale) as given by the survreg function is the natural log of the scale parameter (Scale = 0.353, x2 = 662.06 (5), p = 7.8 x 10-141), where scale is the reciprocal of the standard parameterisation of the Weibull distribution shape (hence shape = 1/0.353 = 2.83).

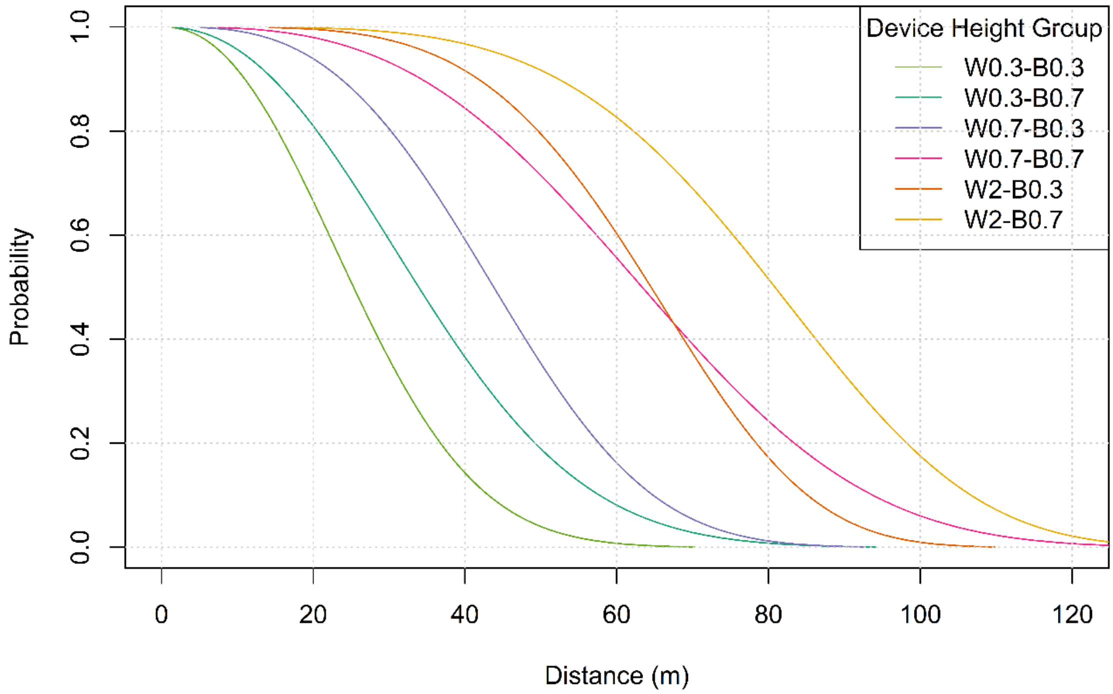


Figure 3.9 Bluetooth Low Energy (BLE) signal survival curves generated from the off-sheep calibration study.

Where the y-axis indicates the probability of a beacon signal being reported by a wearable integrated sensor platform (WISP) beyond that distance. W0.3-B0.3 indicates a WISP and beacon height of 0.3 m, W0.3-B0.7 a WISP height of 0.3 m and beacon height of 0.7 m, W0.7-B0.3 a WISP height of 0.7 m and beacon height of 0.3 m, W0.7-B0.7 a WISP and beacon height of 0.7 m, W2-B0.3 a WISP height of 2 m and beacon height of 0.3 m, and W2-B0.7 a WISP height of 2 m and beacon height of 0.7 m.

3.3.1.2 Development of the distance prediction model

Three prediction models (linear, natural log, and inverse square) were then applied to the obtained RSSI values for both the full calibration study data set and individually for each WISP-beacon height group. Comparison of the models, with the resulting SDs, CVs, and upper and lower confidence intervals of mean predicted distances, for each measured distance is provided within Appendix B, along with each model's adjusted R^2. Of the three models tested, the natural log model resulted in the highest adjusted R^2 values across all WISP and beacon height combinations and was selected for use in the distance prediction equation. As the BLE range and proportion of beacons reported varied with WISP and beacon height, the prediction equations applied within the static beacon localisation study and on-sheep validation corresponded to the WISP and beacon heights used in each scenario. We therefore report on two distance prediction equations, the first applies to the static beacon localisation study, and is based on a WISP and beacon height of 0.7 m (equation 3.4), and the second prediction equation is based on a WISP height of 2 m and combined beacon heights of 0.3 and 0.7 m (to equate to sheep both lying and standing) which was applied to the on-sheep validation (equation 3.5). For prediction equation 1, the regression resulted in a distance prediction equation of:

Equation 3.4

$$Predicted\ distance\ =\ e^{-7.468966\ -(0.126271\ \times RSSI)}$$

(adjusted R^2 = 0.7517, F (1, 1 290) = 3 910, p < 0.0001).

Whilst for prediction equation 2, the regression gave a distance prediction equation of:

Equation 3.5

$$Predicted\ distance =\ e^{-9.501993\ -(0.151980\ \times RSSI)}$$

(adjusted R^2 = 0.695, F (1, 2 645) = p < 0.0001).

The prediction equations generated for each of the WISP-beacon height groups, and the relationship between RSSI and distance are shown in Figure 3.10. All prediction equations resulted in similar distance estimations for RSSI values of approximately -45 to -75 dBm, covering an estimated distance range of ~0–8 m, after which point the prediction equations began to diverge in their estimations. At lower RSSI values of -80 to -90 dBm there was much greater variation in the distances estimated by the different prediction equations, and a greater change in distance estimation between RSSI values where WISPs and beacons were located at higher heights. For example, at a WISP and beacon height of 0.3 m a change in RSSI from -89 to -90 resulted in a difference in distance estimation of 2.24 m, whilst at a WISP height of 2 m and beacon height of 0.7 m there was a difference of 11.45 m. In terms of the on-sheep validation, this means that a lower RSSI value is likely to be reported by lambs lying down vs standing at the same distance.

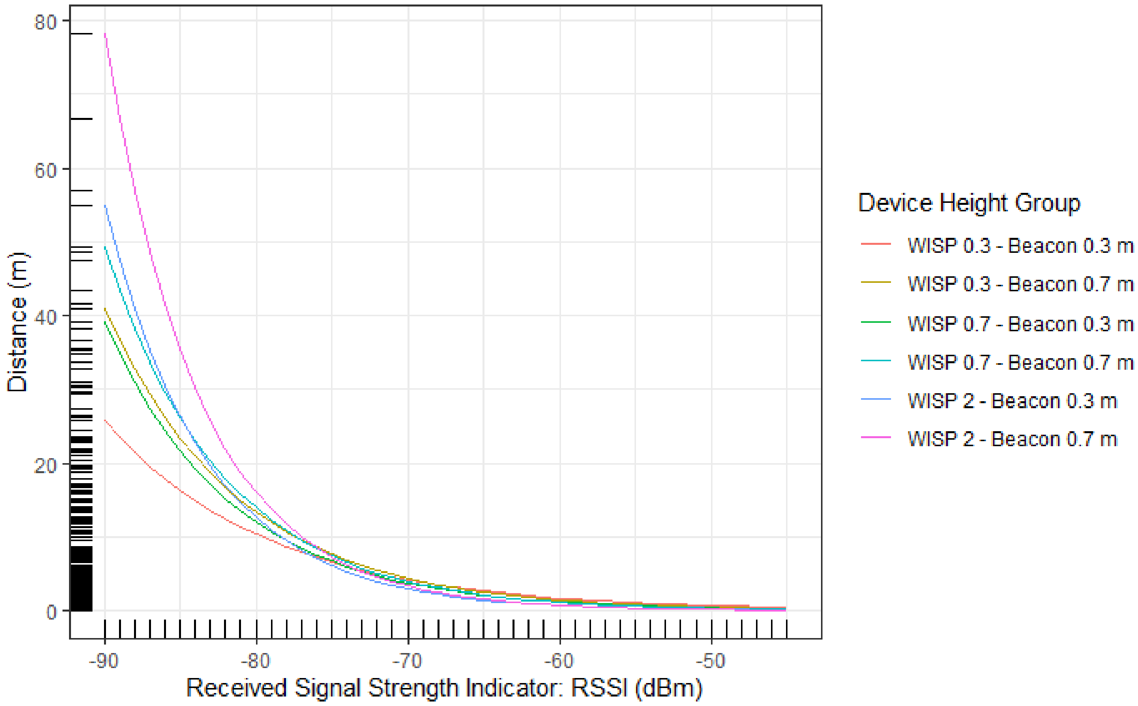


Figure 3.10 Comparison of the off-sheep calibration regression lines.

Where estimated beacon distances were calculated from received signal strength indicator (RSSI) for each of the wearable integrated sensor platform (WISP)-beacon height group prediction equations. WISPs were tested at heights of 0.3, 0.7, and 2 m, and beacons were tested at heights of 0.3 and 0.7 m.

3.3.2 Static beacon localisation study

3.3.2.1 Received signal strength indicator and distance prediction equation

During the static beacon study, WISPs reported a large proportion of messages via LoRa, 141 of a possible 144 messages (98 %), however flash drive data was selected for analysis being the most complete data set. Fifteen of the 16 beacons were reported by at least one WISP during the study period, with individual WISPs reporting between 6 - 13 beacons, thus generating at least one RSSI reading for 54 of 96 possible WISP-beacon pairings (56 %). The total number of beacons reported per WISP, and corresponding number of RSSI readings is summarised in Table 3.4. WISP-beacon distances ranged from 1.93 to 97.77 m, and whilst RSSI readings were reported for 38 of the 44 WISP-beacon pairings (86 %) located < 63 m apart, RSSI readings were obtained for only 16 of 52 WISP-beacon pairings (31 %) when > 63 m apart. However, this was the distance at which the Weibull survival analysis estimated a 50 % probability of a beacon being reported beyond.

Table 3.4 Total number of received signal strength indicator (RSSI) readings (out of 24) for each wearable integrated sensor platform (WISP)-beacon pairing during the off-sheep static beacon localisation study.

	WISP ID						
Beacon ID	**1**	**2**	**3**	**4**	**5**	**6**	**Total no. of WISPs Reporting**
A	--	14	--	24	23	--	3
B	8	14	21	23	23		5
C	--	--	--	--	--	--	0
D	1	--	--	--	23	1	3
E	9	22	--	24	23	24	5
F	24	4	24	24	--	--	4
G	24	22	24	24	--	--	4
H	1	2	--	1	23	24	5
I	24	22	24	--	--	--	3
J	--	--	--	--	23	24	2
K	24	22	24	--	--	--	3
L	24	--	--	--	--	--	1
M	24	--	--	--	23	24	3
N	24	22	24	24	1	--	5
O	24	--	--	1	--	--	2
P	24	22	24	24	23	8	6
Total no. of beacons reported	13	10	7	9	9	6	54

Where multiple RSSI readings for a WISP-beacon pair were obtained across the 2-hour data collection period, reported RSSI values had a maximum difference of 6 dBm and mean difference of 2.21 dBm. Estimated beacon distances from WISPs were calculated by applying the reported RSSI values to equation 3.4, as this used the 0.7 m height settings. The final estimated beacon distance was classed as the mean predicted distance generated from all RSSI values for that pairing (Figure 3.11). Overall, there was a mean underestimation of 12.13 m (SD = 15.97) by the prediction equation in comparison with the WISP-GNSS estimated beacon distances. Of the 54 WISP-beacon pairings for which a distance was obtained, 21 beacons (39 %) were estimated to within 10 m of the GNSS distance, and 41 beacons (76 %) to within 20 m. The largest differences between GNSS and BLE distance estimations occurred at distances over 64 m, which was beyond that of the calibration data, and the 50 % probability of being reported.

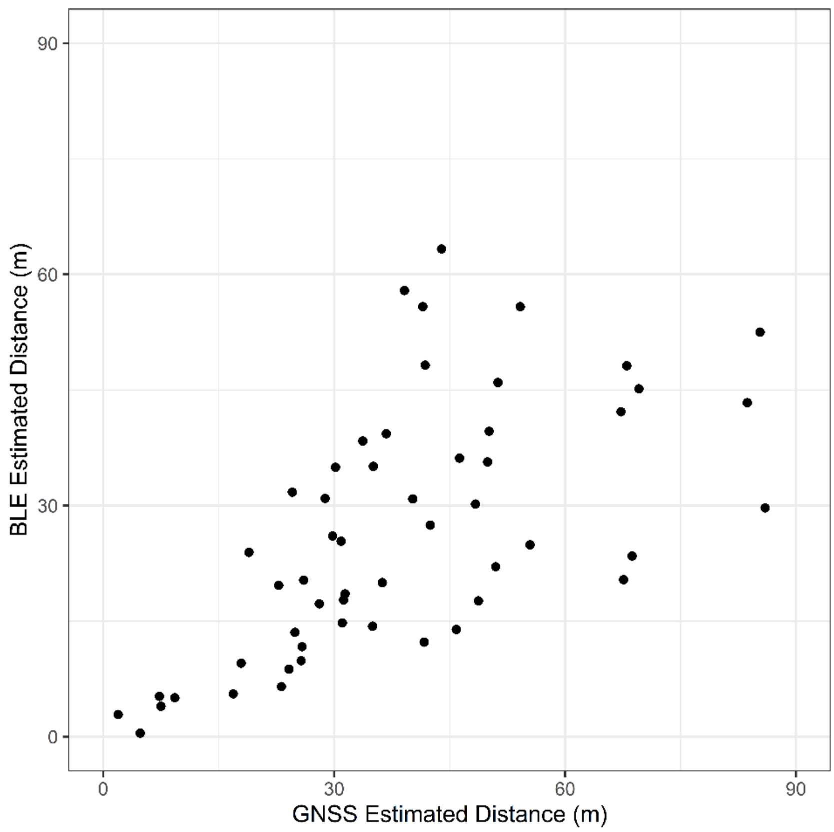


Figure 3.11 Comparison of the estimated distances between each wearable integrated sensor platform (WISP) and beacon in the off-sheep static beacon localisation study.

Calculated using Bluetooth Low Energy (BLE) - based on the mean received signal strength indicator (RSSI) and applying prediction equation 1, vs distances calculated based on global navigation satellite systems (GNSS).

3.3.2.2 Localisation: static beacons

Applying the predicted distances to the multilateration method (with a minimum of two intersecting WISPs reporting a given beacon) allowed locations for 11 of the 16 beacons to be generated (Table 3.5). The localisation error was classed as the distance between final estimated beacon locations and their respective GNSS coordinates. The error ranged from 5.34 – 37.34 m, with a mean distance of 22.02 m (SD = 9.77). Where beacons were unable to be located using the multilateration approach, this was either the result of not being reported by the required number of WISPs (Beacons C and L), or the predicted distances resulted in circles which did not intersect (Beacons D, I, J).

Table 3.5 Summary of the off-sheep static beacon localisation study, indicating the number of wearable integrated sensor platforms (WISPs) reporting each beacon, and the associated localisation error.

Beacon ID	No. of reporting WISPs	No. of intersecting WISP pairs	Beacon localisation error (m)
A	3	1	28.11
B	5	8	5.34
C	0	--	--
D	3	0	--
E	5	4	24.13
F	4	3	32.42
G	4	2	11.57
H	5	6	37.34
I	3	0	--
J	2	0	--
K	3	1	23.83
L	1	--	--
M	3	1	22.77
N	5	3	14.00
O	2	1	28.89
P	6	4	13.81

3.3.3 On-sheep validation

3.3.3.1 Received signal strength indicator and distance prediction equation

Of the 24 lambs within the study, data from a single lamb ("most average" lamb) was selected as a proof of concept and illustration of the system. The lamb selected for analysis had a total beacon count of 323 of a possible 2 592 messages (12.46 %) reported for the chosen study day. This was considered typical with beacon counts obtained for other lambs, which ranged from 197 – 454, with an overall mean beacon count of 280 (based on all 24 lambs) and mean beacon count of 314 based on the 12 lambs for which GNSS data was obtained. This averaged at 1.12 WISP readers reporting the selected lamb's beacon in each 5-minute interval, however, distribution in time and space was very varied. Individual WISPs reported between 17 (5.90 %) and 64 (22.22 %) RSSI readings, of a maximum 288. This was not unexpected as the paddock was ~236 m in length, which was beyond the WISP-beacon range, and therefore not possible for every WISP to report on every occasion. However, the staggering of WISPs around the paddock resulted in a maximum distance of 73 m between WISPs along each paddock length, and 77 m between WISPs located on the opposite fence line. The maximum distance of a lamb's beacon from at least one WISP at any given time would therefore be ~39 m, a distance at which the Weibull accelerated failure time model indicated that > 90 % of beacons would be reported beyond.

In comparison with the WISP-beacon mean GNSS estimated distances, the corresponding BLE predicted distances resulted in an error ranging from an underestimation of 104.22 m to an overestimation of 70.72 m, and mean underestimation of 1.59 m (SD = 18.52) (Figure 3.12). Overall, equation 3.5 underestimated beacon distance, however mean errors by individual WISPs varied from an underestimation of 9.09 m to an overestimation of 7.69 m. Instances where the lamb was considered stationary resulted in a mean underestimation of 0.40 m (SD = 17.72) and moving points in a mean underestimation of 2.80 m (SD = 19.23); t (1 638.9) = -2.64, p = 0.008. A one-way ANOVA also found a difference in prediction error between "distance travelled group", (F (4, 1 651) = 16.24, p = 4.74 × 10-13), with Tukey's HSD post hoc tests indicating a higher prediction error in “low” vs “high” levels of movement (p = 0.043) and “low” vs “mid” levels of movement (p = 0.093).

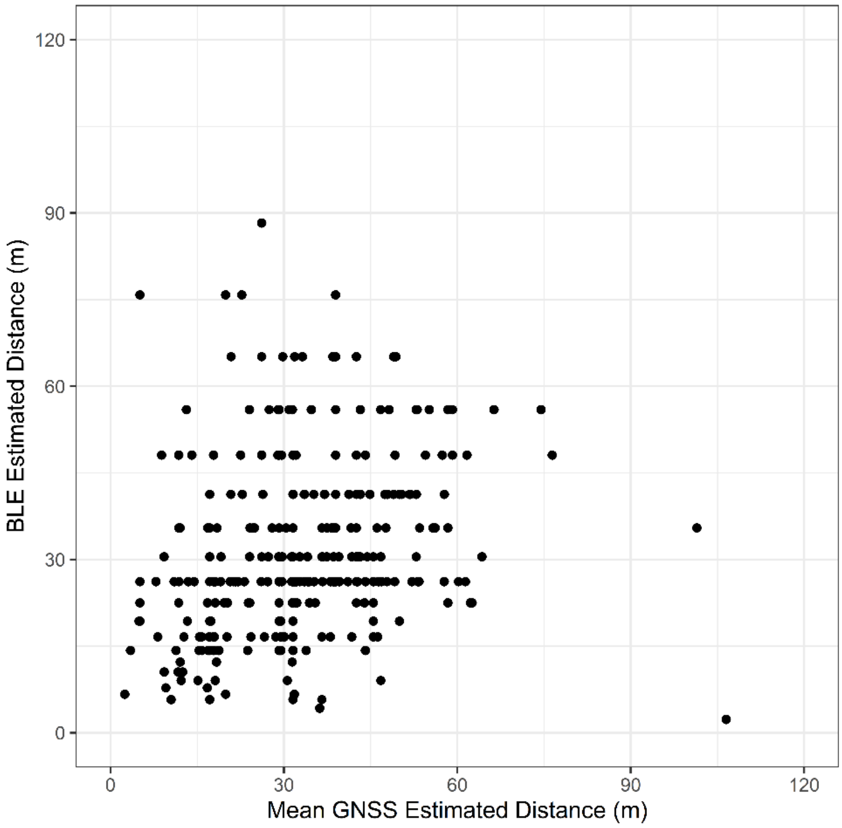


Figure 3.12 Comparison of estimated distances between wearable integrated sensor platforms (WISPs) and the lamb (beacon) during the on-sheep validation.

Calculated using Bluetooth Low Energy (BLE) – by applying prediction equation 2, vs distances calculated based on global navigation satellite systems (GNSS).

3.3.3.2 Localisation: on-sheep

The lamb’s beacon was reported by a maximum of 4 of 9 WISPs during any given independent 5-minute interval (i.e. 00:00:00-00:04:59, 00:01:00-00:05:59). In most cases the lamb was reported by a single WISP, whilst reported by two or more WISPs in 26 % of intervals (Table 3.6). There were also periods during which the lamb was not observed by any WISP, the longest of which was a period of 1 h 8 min. Both localisation methods were then applied and filtered to ensure unique groupings of reporting WISPs across intervals. The midpoint method generated a greater number of lamb locations, primarily where there were just two reporting WISPs (Table 3.7).

Table 3.6 Summary of the on-sheep validation, indicating the number of wearable integrated sensor platforms (WISPs) reporting the lamb's beacon within any independent 5-minute interval.

No. of reporting WISPs	No. of intervals	% of intervals
0	277	19.29
1	788	54.87
2	276	19.22
3	64	4.45
4	31	2.16
Total no. of Intervals for day	1436	100

Table 3.7 Summary of the number of lamb locations generated within the on-sheep validation, by localisation method. Abbreviations: WISPs = wearable integrated sensor platforms.

	No. of lamb locations generated	
No. of reporting WISPs	Multilateration Method	Midpoint Method
2	69	111
3	27	30
4	9	9
Total no. of locations	105	150

When the resulting lamb locations were compared with the lamb's mean GNSS coordinates for the corresponding interval, the distance between locations (the localisation error), ranged from 1.39 – 74.67 m using the multilateration method, and 0.87 – 71.58 m using the midpoint method (Figure 3.13). The multilateration method resulted in a slightly higher localisation error with a mean of 23.77 m (SD = 12.49), whilst the midpoint method resulted in a mean of 19.00 m (SD = 11.00); t (205.38) = 3.15, p = .002. There was also a greater proportion of locations estimated to within 10 and 20 m of the GNSS location using the midpoint method, with 26 of 150 locations (17.33 %) within 10 m and 89 of 150 locations (59.33 %) within 20 m. In comparison, the multilateration method estimated 9 of 105 locations (8.57 %) to within 10 m, and 44 of 105 locations (41.90 %) to within 20 m. The midpoint method appeared to generate similar mean localisation errors for both 2, 3, and 4 reporting WISPs, of 19.20, 18.05, and 19.76 m, respectively. Mean localisation errors appeared marginally higher with an increased number of reporting WISPs for the multilateration method, with mean localisation errors of 22.55, 25.42, and 28.19 m. However, due to the low number of observations where there were 4 reporting WISPs, this was not analysed further.

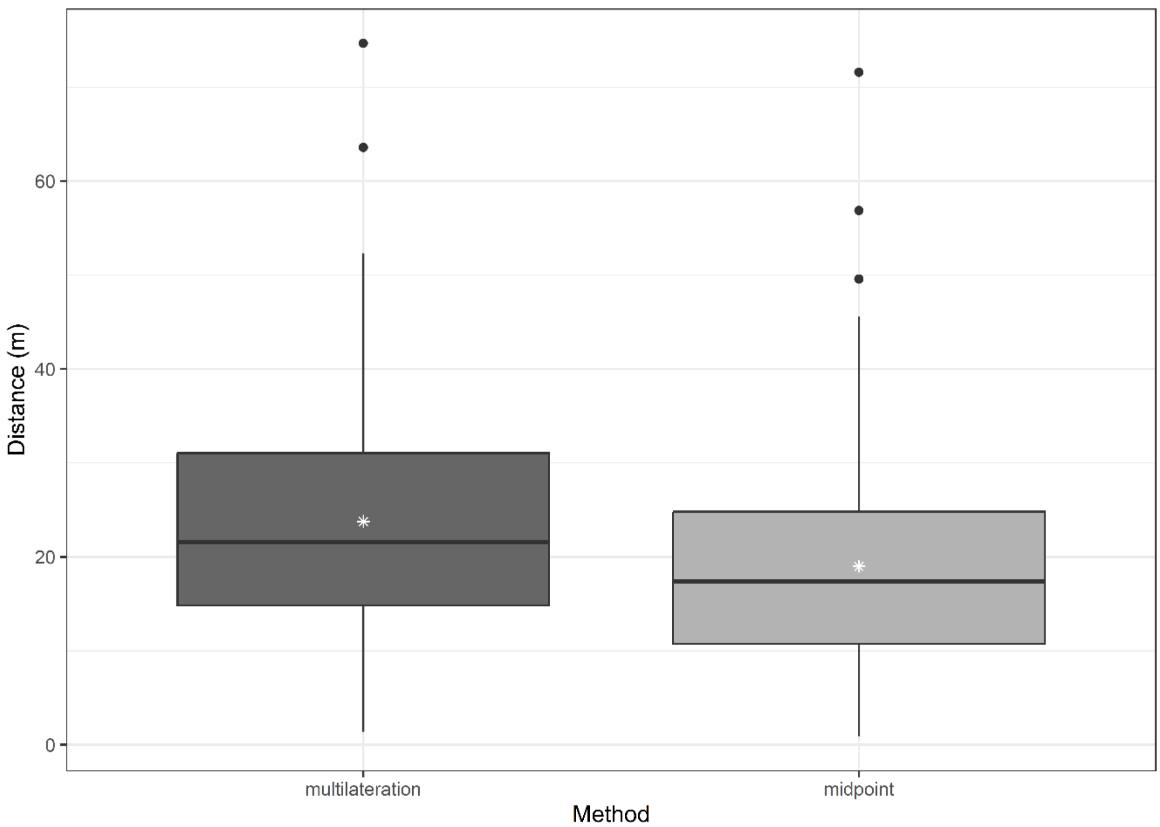


Figure 3.13 Comparison of distance between Bluetooth Low Energy (BLE) estimated lamb locations and corresponding mean global navigation satellite systems (GNSS) lamb locations (the localisation error) for both localisation methods.

Star indicates the mean localisation error.

A two-way ANOVA showed no statistically significant interaction between the localisation method and movement variable - lamb moving vs stationary (F (1, 251) = 0.90, P = 0.34), however simple main effects analysis indicated that both localisation method (p = 0.001) and movement (p = 0.043) had an effect on the localisation error. There was very little difference in mean localisation error however between moving and stationary points within both localisation methods. The multilateration method resulted in a mean localisation error of 21.01 m (SD = 12.02) for stationary and 25.68 m (SD = 12.54) for moving points; t (92.876) = 1.92, p = 0.058, whilst the midpoint method resulted in slightly lower mean localisation errors of 17.90 (SD = 10.16) for stationary points and 19.72 (SD = 11.51) for moving points; t (134.6) = 1.01, p = 0.31. Thus, regardless of the localisation method, the error was always greater when the lamb was moving as opposed to stationary, and similarly the error was greater using the multilateration method regardless of whether the lamb was moving or stationary. However, the effect of lamb movement on the error does not appear to be dependent on the localisation method or vice versa.

When compared based on the lamb's "distance travelled group", instances where the lamb had a very low level of movement resulted in the highest mean localisation errors, using both the multilateration and midpoint methods (Figure 3.14). A one-way ANOVA indicated that there was a difference in localisation error between "distance travelled group" within both the multilateration (F (4, 100) = 2.70, p = 0.035) and midpoint methods (F (4, 145) = 2.86, p = 0.026). Tukey's HSD post hoc tests found that for the multilateration method the mean localisation error was higher in instances where the lamb had a "very low" level of movement compared with both "mid" (p = 0.097) and "none" (p = 0.037). Whilst for the midpoint method there was a higher mean localisation error for "very low" compared with a "mid" level of movement (p = 0.065).

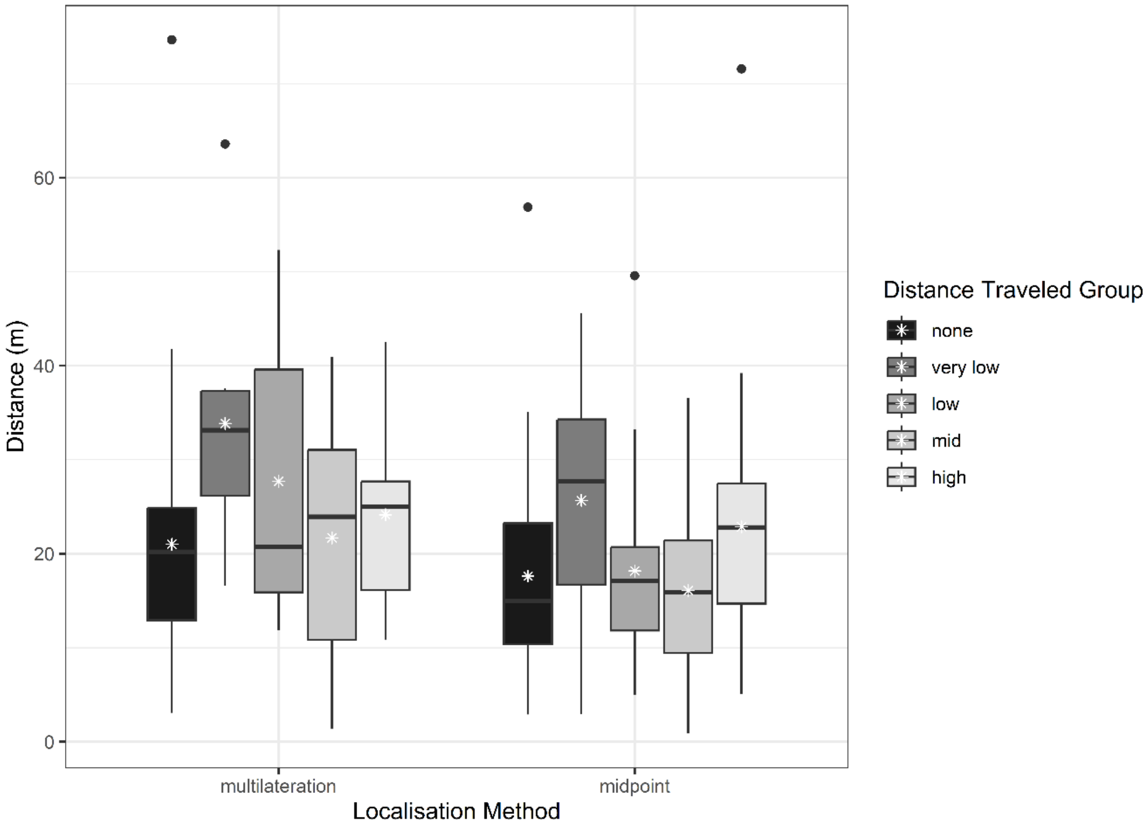


Figure 3.14 Comparison of distance between Bluetooth Low Energy (BLE) generated lamb locations and mean global navigation satellite systems (GNSS) lamb locations by the distance travelled group.

Star indicates the mean distance (m).

3.3.3.3 Lamb trajectories

Given the low total number of lamb locations generated by both localisation methods, the trajectories produced from the BLE were based on much fewer data points than the full GNSS data. When split into hourly trajectories there were six hours for which the multilateration method, and three hours for which the midpoint method failed to produce a single location. During hours in which trajectories were generated, these were based on a maximum of 14 (multilateration) and 16 (midpoint) locations. The GNSS was set to report every 1-minute, however, some locations were given more frequently, and as a result hourly trajectories contained between 58 and 71 lamb locations. An example trajectory from 0100 h - 0200 h is displayed in Figure 3.15; chosen as this period contained the greatest number of data points from both BLE localisation methods, as well as 59 GNSS locations. Whilst having similar start and end points for the hour, the trajectories generated by both BLE methods show greater movement patterns and changes in direction than displayed by the GNSS trajectory, which indicated that lamb travelled ~40 m during this period. This pattern was similarly observed across hourly trajectories, including those where the GNSS indicated that the lamb was stationary throughout.

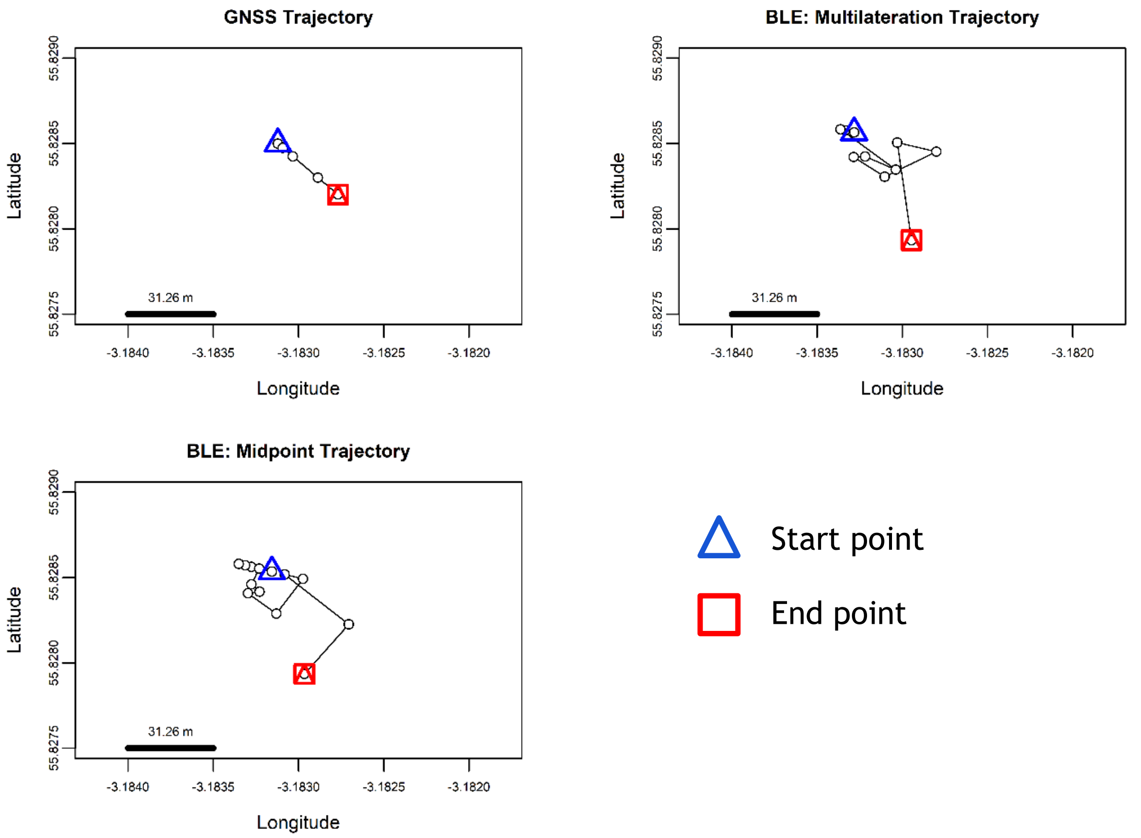


Figure 3.15 Lamb trajectories from 0100 h – 02:00 h comparing the full global navigation satellite systems (GNSS) data for the hour with Bluetooth Low Energy (BLE) trajectories using the multilateration and midpoint localisation methods.

3.4 Discussion

3.4.1 Received signal strength indicator: distance, device height, and range

One of the aims of this study was to characterise RSSI in terms of beacon distance from the BLE reader within the WISP and investigate the potential range and limitations of the BLE devices in an outdoor environment. As observed from the overall pattern of the calibration study, there is a natural decrease in the strength of a radio wave over distance, known as the path loss (Nyholm, 2020). This trend of RSSI declining with increasing beacon distance from the WISP was observed across all WISP-beacon height groups. However, within each of the measured distances there was a large range in the RSSI values reported, and these values would often overlap between distances. RSSI is known to be a noisy measure of proximity, and this overlap in RSSI values being reported across a range of distances has also been found within a barn system (Nikodem, 2021) and other indoor environments (Vanheel et al., 2011). However, whilst there was a large overall range per distance, there was in-fact very little variation in signal strength of individual WISP-beacon pairings across repetitions, with most pairings differing by 2 dBm or less. This was the case across distances, although at 32 m and 64 m, there were fewer overall instances of beacons being reported, and more occasions where beacons were reported by WISPs during only some repetitions. The ranges in RSSI per distance, even within WISP-beacon height groups, therefore, indicate that a proportion of the variation observed is a result of the specific devices used, and differences arising between individual WISP and beacon pairings. This was particularly evident at a WISP and beacon height of 0.3 m, where only one of the five WISPs reported beacons at distances of 32 and 64 m. As a result, this could make standardising a distance prediction equation for a large number of devices more challenging.

As indicated by the Weibull accelerated failure time model (Figure 3.9), depending on the threshold set as an acceptable proportion of beacons being reported, the functional range of the BLE devices will be reduced at lower WISP and beacon heights. Triguero-Ocaña et al. (2019) similarly found a decreased probability of devices being received with increasing distance (up to 20 m) in proximity loggers, and a decreased signal strength when devices were located at a height of 0 m compared to 1 m. The presence of vegetation was also found to decrease the signal strength, with a greater impact at further distances. Whilst conducted across much shorter distances of 2 m, Kirkpatrick et al. (2021) also report an increased device range in proximity loggers when the receiving devices were located at a higher height, and that mean RSSI values were lower in long grass compared to cut grass, indicating that vegetation was also likely influencing the signal strength.

The operating range of BLE devices and the signal strength reported will be influenced by the transmission power as well as the transmitting and receiving antennas design and location (Townsend et al., 2014), all of which will differ to some degree between individual beacons and WISPs. The operating environment of the devices will also impact on the signal strength (Townsend et al., 2014), and obstacles located between the transmitter and receiver, may result in absorption, reflection or scattering of the signal (Goldsmith, 2005). This could act to alter the reported RSSI from that if there had been a clear line of sight between devices, or in some cases prevent the beacon from being reported. These factors make the translation of RSSI values into a corresponding distance challenging in an outdoor environment, where obstacles within the field (i.e., fences, water troughs, and vegetation), as well as the field topography, weather conditions, and the animals themselves all have the potential to interfere with the signal. When using the BLE beacons on sheep, the placement of the beacons, as well as their behaviour, posture, and orientation to the reporting WISP at a given time could therefore influence both the likelihood of the beacon being received by the reader, and on the RSSI value which is reported. Instances where the lamb is lying down, or grazing (and the beacon is in a lowered position) are therefore likely to have a reduce probability of being reported, in comparison with a lamb standing or actively walking with head and neck erect at the same distance, particularly as that distance increases.

3.4.2 Distance prediction equations

As both WISP and beacon height was found to influence the potential range of the BLE signal, multiple distance prediction equations were developed from the calibration data to correspond to the WISP and beacon heights used within each of the studies, rather than applying one single equation. Equation 3.4, used within the static study, had an overall tendency to underestimate the WISP-beacon distance, with a mean underestimation of 12.13 m. However, the prediction equation was able to estimate 76 % of the beacons to within 20 m of the WISP-GNSS estimated beacon distance, and 39 % to within 10 m. Beacons located at distances over 60 m resulted in the largest underestimations compared with WISP-GNSS distances and tended to have multiple beacons located between them and the reporting WISP. At these greater distances, variations in RSSI had potential to have a greater impact on the predicted distance. Small changes in RSSI resulting in large changes in distance estimation have been found within other radio frequency transceivers (Mukhopadhyay et al., 2015). However, some of the differences observed between the predicted and WISP-GNSS estimated distances will also include error associated with both the WISPs GNSS receiver and the GPS logger app used to obtain the beacon coordinates. Typically, GNSS systems are considered accurate in a range of 5 – 30 m (Maroto-Molina et al., 2019). Within this study, the WISPs had a grand mean error of 1.69 m between individual and mean GNSS coordinates, whilst the GPS logger app had a mean difference of 0.93 m, both of which will contribute to some of the variation between estimations.

The on-sheep validation presented different challenges in terms of estimating the beacon's and therefore the lamb's distance from any given WISP, given the potential distance which a lamb could move over the recording period. Johnson et al. (2021) reports an average of 3.4 km (± 0.89) travelled by sheep over the course of the day, resulting in a mean of 11.81 m within a 5-minute period. Within the study the lamb under observation was found to travel a maximum estimated distance of 81.24 m and mean of 9.50 m during a 5-minute interval. When compared with the mean GNSS location for the corresponding interval, equation 3.5 resulted in a close mean underestimation of 1.59 m, however, there were also some extreme values produced where the estimated distance differed from the WISP-GNSS distance by as much as 104 m. Despite some of these larger errors, a large proportion of the lamb's beacon readings were estimated to within 20 m of the WISP-GNSS estimated distance (254 of 332 – 77 %), and 156 (47 %) to within 10 m. Whilst the prediction equation resulted in a slightly closer mean distance estimation for stationary compared with moving points, instances where the lamb had travelled furthest over the interval did not produce the largest errors. Instead, instances where the lamb was classed as having a "very low" level of movement resulted in the greatest differences between the predicted and mean WISP-GNSS distance for the interval.

Some of the error observed between these estimates may be due to the configuration of the WISPs and the way in which they operate. The WISPs report a single figure, the mean RSSI, for a 5-minute interval, however, during this time the lamb could move beyond the range of the reporting WISP, even if only moving a short distance. In addition, the lamb's behaviour and posture may also change over the interval and could be within the WISPs range when standing, but not if lying down. These estimations also do not consider the presence of other sheep or obstacles which may impact on the signal strength over the course of the reporting interval, which may act to prevent the focal lamb's beacon being received by the WISP, or to reduce the signal strength reported. As the readers scan on a 30 s on / 30 s off, the mean RSSI value reported could also be based on readings from as little as a 30 s period when the lamb was within range, resulting in a higher than expected RSSI and therefore a closer distance estimation by the prediction equation. This is a potential limitation of the system, where in the current configuration a lamb's beacon reported only once, but with a high RSSI could be reported over a lamb with multiple readings but lower average RSSI. Whilst we found very few instances in this study where all 16 beacon positions for a WISP were filled (16 of 2585 – 0.62 %), and so few opportunities for this to have occurred, this could be a larger issue where a greater number of sheep are present. In such instances, sheep consistently located towards the edge of a WISPs range, and therefore with a lower average RSSI may be missed by WISPs. As the lamb's behaviour and posture for a given interval was unknown, equation 3.5 was developed based on combined calibration data from a WISP height of 2 m and beacon heights of both 0.3 and 0.7 m. However, individual prediction equations (Figure 3.10) developed for each beacon height indicate that as the RSSI value decreases there is a greater difference in distance estimates, with a beacon height of 0.3 m producing a shorter distance than those located at 0.7 m. Lamb behaviour and posture are therefore likely to have a greater impact on the prediction equation when located further from the reporting WISP. The GNSS locations used to estimate the beacon distances are themselves also subject to error. Duncan et al. (2013) reported a mean error of 19.6 m ± 30.9 m and a circular error of 10.8 m using the i-gotU GT-600, which will also contribute to the differences observed between GNSS and BLE estimated beacon distances.

Distance estimation errors based on RSSI will vary depending upon the devices used, the conditions in which they are applied, and the methods used to translate RSSI to distance. Previous studies have reported very low mean distance estimation errors of 0.41 m (Thaljaoui et al., 2015) and 0.98 m (Adewumi et al., 2013) in an indoor environment, and 0.88 m in an outdoor environment (Adewumi et al., 2013). However, these studies tested RSSI across smaller distance ranges of between 0.25 – 3.5 m (Thaljaoui et al., 2015) and 1 – 10 m (Adewumi et al., 2013). Whilst variability in RSSI between WISP-beacon pairs, combined with effects of lamb movement on contact success and number of RSSI readings reported during each window resulted in a level of noise within the estimated distance from the prediction equation, an average mean underestimation of 1.59 m within the context of the ~1.4 ha paddock is relatively small.

3.4.3 Localisation

The static beacon localisation study aimed to locate beacons within an ~5 400 m^2 area based on data obtained over a 2-hour period. Using the multilateration approach, locations were generated for 11 of the 16 beacons, all of which were estimated to within 37.34 m of their estimated GNSS location, resulting in a mean difference of 22.02 m. The beacon with the largest localisation error, Beacon H, was the beacon which had both the greatest over and underestimation by the prediction equation. This resulted in circles intersecting at different areas within the paddock, hence the mean estimated location was much further from that of the GNSS. In comparison, Beacon B was reported by the same number of WISPs (five), however, four of these WISPs all intersected at very similar points, with a larger underestimation from just one WISP, therefore resulting in a closer mean estimate, with a localisation error of 5.34 m. Highlighted during the static beacon study was that the multilateration method was reliant on RSSI values generating predicted distances which produced intersecting circles, where under ideal circumstances the method would generate a cluster of points which intersected at the same (or close to the same) position. However, whilst occurring for some beacons, this was not in the case in all instances, and hence the mean of estimated points was instead applied to generate the final estimated location. Nonetheless, in some instances beacons were not able to be located despite having been reported by multiple WISPs, as no circles intersected.

The on-sheep validation therefore investigated both the multilateration and a midpoint localisation method, which did not require distance estimations to intersect. However, both methods still required a minimum of two WISPs reporting within an overlapping 5-minute interval to estimate the lamb's location. Given the length of the paddocks (~236 m) it was expected that each individual WISP would not report on every occasion, as there would be times when the lamb was beyond a WISPs range, particularly those located at either end of the paddocks. The lamb's beacon was most frequently reported by only a single WISP during any given 5-minute interval, giving an indication of proximity to the reporting WISP but not a definitive location. However, over time, this could still give an indication of the lamb's activity throughout the paddock. There were also periods during which the lamb was not reported by any WISP, the longest of which was between 1120 h and 1228 h, when the corresponding GNSS suggests that the lamb was stationary. If lying down, this would reduce the chance of the lamb's beacon being reported and more likely that the lamb was beyond the effective range of any WISP, as the beacon would be located closer to the ground.

A total of 105 locations were generated for the lamb over the course of the day using the multilateration method, whilst 150 locations were generated using the midpoint method. Although, similar localisation errors were generated by both methods, there was a slightly lower mean error using the midpoint method, and a greater proportion of locations were estimated to within 10 m of the GNSS. Instances where the lamb was classed as having a "low" level of movement resulted in the highest mean localisation error, however, there was no significant difference in mean localisation error between most of the "distance travelled group” classifications. The distance travelled was calculated based on the lamb’s GNSS locations reporting every minute, and so was subject to error from the i-gotU. In addition, the classification was based on the highest level of movement from any WISP, however as WISPs reported on independent intervals the proportion of the 5-minute interval for which each WISP reported could vary from between 1 to 5 minutes. Some of the errors arising in the localisation are therefore likely a result of the configuration of the WISP reporting intervals, where the movement classification and distance travelled may have differed between each of the reporting WISPs. Particularly using the multilateration method, the length of the overlapping period and difference in the distance travelled between recording periods of WISPs could impact on whether distance prediction estimates generated overlapping circles.

The study investigated the range of BLE devices in an outdoor system, and the feasibility of applying BLE technology as a means of animal proximity and location monitoring within outdoor livestock systems and highlights some potential challenges for on-animal application. The calibration of the WISPs and beacons suggests that the species, their height and behaviour, as well as the beacon placement, and the environment of intended application will need to be taken into account when considering the effective BLE range within that particular scenario. In addition, variation in animal posture and the potential distance and speed at which they might travel over a recording interval will affect the likelihood of being reported, and the possible interpretation of BLE signal strength into distance. Whilst static BLE readers could offer a means of monitoring livestock proximity within range of known points within extensive systems, animal localisation, given the BLE ranges observed, would require many BLE readers. Hence a combination of BLE beacons and on-sheep roving readers, equipped with GNSS, may be more plausible. However, improvements in BLE range and accuracy would be required for practical application. In terms of real-time monitoring, whilst almost all data was transmitted during the static localisation study, data acquisition within extensive systems can be variable, with previous studies utilising LoRaWAN reporting data acquisition in the ranges of 46 % (McIntosh et al., 2023) to 82 % (Ojo et al., 2022), hence data loss and its potential effect on the interpretation of results will also need to be considered. However, depending upon the intended purpose of monitoring, the time frame for a recording period will alter, and it may also not be necessary for animals to be recorded on every occasion. This poses several questions, namely: what proportion of beacon loss is acceptable in terms of livestock monitoring, and does this alter depending on purpose? And how close do proximity and localisation estimates need to be? - particularly in more extensive sheep systems where a lower degree of resolution may be acceptable given the potential scale of farms.

3.5 Conclusion

The study reports on the calibration of BLE devices within outdoor systems, where BLE signal strength was found to decline with increasing beacon distance from a reader. As the height at which both the reader and beacon were located had an impact on the survival of BLE signals, when applied on-sheep, the functional BLE range will therefore be influenced by animal behaviour and posture. As proof of concept, the study then utilised developed distance prediction equations from RSSI values for the localisation of grazing sheep. Whilst not yet too practical given the range and number of readers (WISPs) which may be required in more extensive settings, this study demonstrates that the application of BLE as fixed readers for animal monitoring and localisation is possible. Continued advances in the range of BLE devices, along with opportunity for data to be received in real-time through developments in IoT technologies makes BLE a potential tool for future development in this sector.

Chapter 4 WISP-Beacon Calibration and investigation of shadowing effects

4.1 Introduction

As a type of wireless radio communication, BLE is subject to the same challenges as other wireless communication systems. Where there is a clear line-of-sight between a transmitter and receiver the reported signal strength will differ according to the distance between devices due to path loss. Path loss is the reduction in power density of an electromagnetic wave as it propagates through space (Tetcos LLP, 2024). This may or may not include differences in RSSI arising from antenna gains. However, whilst the transmission of a radio wave travelling in a clear line-of-sight would allow for a constant RSSI for a given distance, the environment and terrain in outdoor systems will impact on the signal reported (Tetcos LLP, 2024). Signal interference can impact on the interpretation of signal strength, thus translation into an estimated distance can be challenging. In most wireless communications a transmitted signal will usually travel to a receiver via multiple paths - known as multipath propagation (Lee, 1997), because of scattering, reflection, refraction, or diffraction of the transmitted electromagnetic wave (Speidel, 2021). This can occur when a transmitted signal hits objects within the surrounding environment, including buildings, hills, vegetation, rain, snow, or other objects (Speidel, 2021). Hence even in instances where there is a clear line-of-sight between transmitters and receivers, multipath propagation is likely to still occur.

Signal fading is the term used to describe the fluctuation in the amplitude of a radio signal over time and / or distance (Younis, 2018) caused by multipath propagation. The interference on the transmitted signal can result in multiple versions of a given signal being received, but with varying amplitudes, phases, angles and times of arrival (Lee, 1997). These signals may combine at the receiver constructively or destructively, causing the signal strength to vary for different points in space (Lee, 1997). Delay spread is the term given to the wider time width of a transmitted signal arriving at a receiver (i.e. the difference in arrival time between the first and last versions of a transmitted signal) arising from the different signal paths taken (Lee, 1997). Doppler spread refers to the increase or decrease in signal path length due to motion between the receiver and transmitter. This can shift the frequency of the electromagnetic wave received, which will be either positive or negative, as transmitters and receivers move towards or away from one another respectively (Lee, 1997).

In some circumstances multiple versions of a signal will then be received, but the ‘first version’ will be that arising from the clear line-of-sight pathway. However, shadowing can occur when obstacles between a transmitter and receiver are positioned such that there is no clear line-of-sight, hence all received versions of a transmitted signal have undergone scattering, reflection, refraction, or diffraction. As radio signals travel at different speeds through air as opposed to objects such as walls, human or sheep bodies (Flueratoru et al., 2021) there may be more significant effects on the reported RSSI. Thus, in an outdoor sheep system, the weather conditions, environment (e.g. vegetation, field / paddock layout and topography, field features – walls, fences etc.), and flock size may all impact on the BLE signal. Another potential issue in systems where there are multiple broadcasting devices is packet collisions, whereby signals are transmitted from two or more broadcasting devices at the same time, and on the same channel, resulting in a loss of information of the collided data (Ghamari et al., 2018). The chances of this occurring will increase as the density of broadcasting devices increases (Ng et al., 2020).

This series of calibration studies aimed to assess the BLE signal range between the WISPs and Beacon Types 2 and 3, to characterise the relationship between RSSI and distance in an outdoor environment. This calibration was then used to develop a distance prediction equation for each beacon type, whereby a beacons distance from a WISP could be estimated based on its RSSI. As the device height was found to impact on the BLE signal of Beacon Type 1 (Chapter 3), the calibration also aimed to assess whether WISP and / or beacon height impacted on the likelihood of a beacon being reported by a WISP and the RSSI values given, and thus in an on-sheep scenario whether the assignment of a beacon to a ewe or lamb, and their behaviour could impact on the signal strength. The study further aimed to assess the impact of shadowing on the BLE signal, in particular whether a sheep's body itself could impact on the signal. This was assessed by conducting the calibration firstly where there was a clear line of sight between WISPs and beacons, followed by a "shadowing" study where the line of sight between devices was blocked.

4.2 Material and methods

Following the calibration of Beacon Type 1 and localisation studies (Chapter 3), two new beacon types – Beacon Types 2 and 3 were trialled alongside the WISPs. As described in Chapter 2, these beacons were publicised as having a greater BLE operating range than that of Beacon Type 1, with distance ranges of 400 m and 500 m (in open areas) for Beacon Types 2 and 3 respectively. The beacons were programmed following the process described in Chapter 2, with the WISP-beacon system also operating and reporting in the same manner.

4.2.1 Standard (clear line-of-sight) calibration

4.2.1.1 Study design

A calibration study was conducted to assess and compare the WISP-beacon range of the Type 2 and 3 beacons within a field environment, and to evaluate the relationship between a beacon's reported RSSI and its distance from a WISP. The study was conducted within a field of permanent pasture (~1.73 ha) at SRUC's Hill and Mountain Research Centre at Crianlarich, within a relatively flat section along the lower length of the field (Figure 4.1) to minimise any potential impacts of topography on the BLE signal.

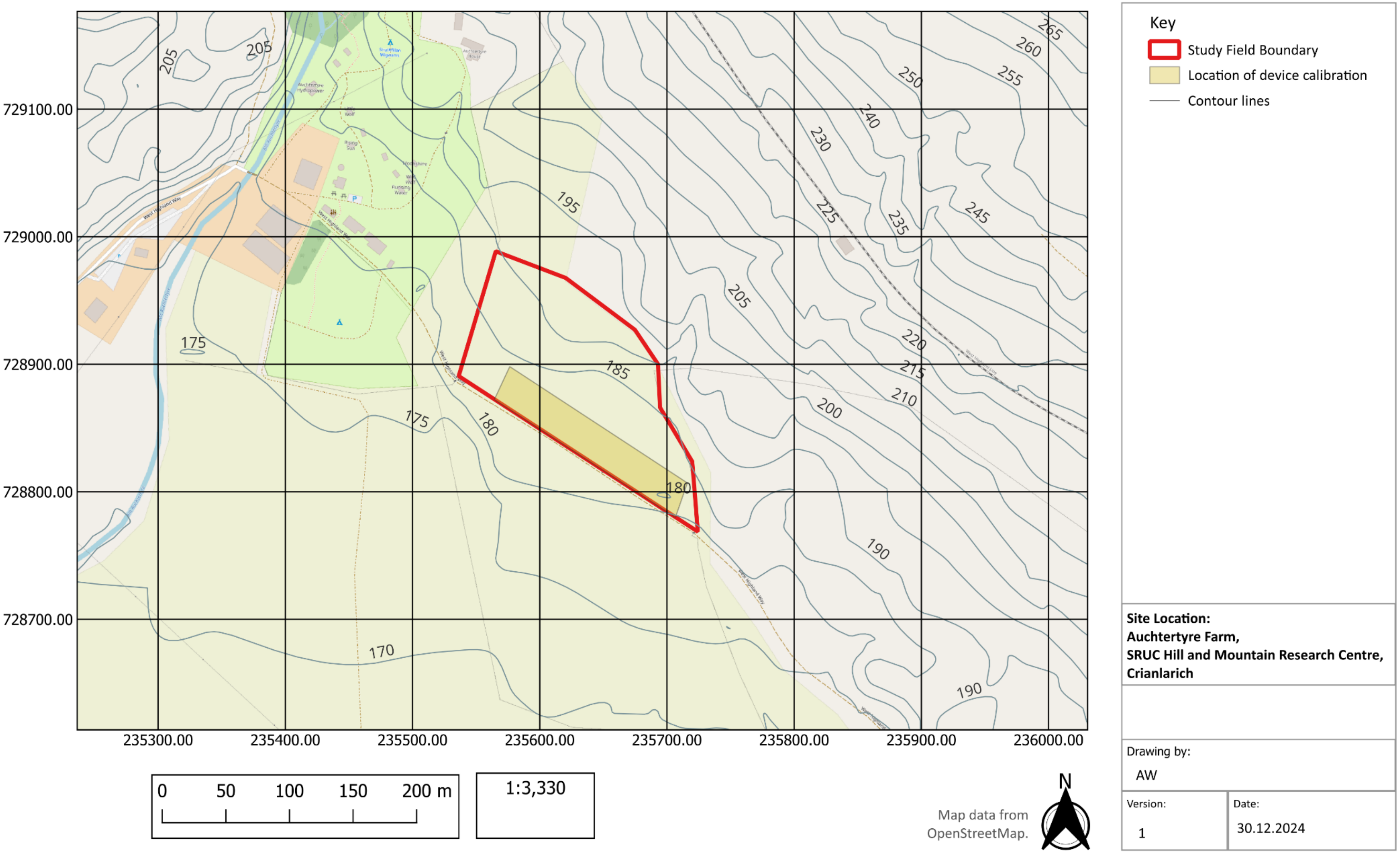


Figure 4.1 Field location of the calibration study - SRUC's Hill and Mountain Research Centre.

The calibration was conducted using six WISPs and eight of each beacon type, following the same protocol as described for the calibration of Beacon Type 1 (Chapter 3). However, due to the drop of in RSSI readings observed between 64 and 128 m when using a log scale for Beacon Type 1, the WISP-beacon distances in this instance were 0, 1, 2, 5, 10, 20, 30, 50, 70, 90, and 110 m, as it was expected that the use of shorter distance increments would provide a clearer indication of the WISP-beacon signal range. WISPs and beacons were also tested at heights of 0.3 m (representing approximate ewe lying or lamb standing height) and 0.7 m (representing approximate ewe standing height) only. Prior to the start of the study, and at various points throughout, the FeasyBeacon app was used to verify that the 16 beacons were 'on' and 'advertising'. The date, start, and end times of when beacons were located at each of the measured distances were manually recorded, to later select the relevant data points from each of the WISPs.

4.2.1.2 Data handling

Of the six WISPs used in this calibration, three experienced battery loss prior to the end of the study, and hence only partial data was available. The calibration of the devices is therefore based on data from the three WISPs which recorded over the full study duration. Whilst data was recorded both to the flash drive and sent via LoRa, the data analysis was conducted using that of the individual WISP flash drives, being the most complete data set. Data was downloaded from each WISP using a "Data Logger" app (Chapter 2). The date and times of when beacons were located at each of the measured distances were used to manually pull out the relevant data points from each individual WISP file, to create a final full .csv file containing the data for both beacon types (which included the beacon type, distance, WISP ID, WISP height, beacon ID, beacon height, repetition – from 1-5, and RSSI value). All statistical analysis was then conducted in R (R Core Team, 2022).

4.2.1.3 Statistical analysis

An initial assessment of the WISP-beacon range and effect of the device heights was conducted by examining the proportion of beacon readings reported per measured distance for each of the beacon types, WISP and beacon heights, and device identities – visualised using “ggplot2” (Wickham, 2016). To conduct a survival analysis of the WISP-beacon BLE signal, a new column “Status” was assigned to indicate whether (for each individual observation) the event of interest “BLE signal death” (ie. failure of a WISP to report an RSSI value for the beacon) had occurred - assigned a value of “1”, or not occurred (ie. WISP reported an RSSI value for the beacon) – assigned a value of “0”. Measured WISP-beacon distances of “0 m” were then converted to a value of “0.01 m” to allow a Weibull accelerated failure time model to be fitted to the data and to generate survival curves. This followed the same protocol as described for the Type 1 Beacons (Chapter 3).

The relationship between RSSI and distance was examined based on the range and mean RSSI values obtained per measured distance for each of the beacon types, device heights and identities. The RSSI values obtained at each of the measured distances were then utilised to develop a prediction equation for each of the beacon types, whereby the WISP-beacon distance could be estimated based on the RSSI value reported. A natural log model was then fitted to the data (chosen as the natural log model provided the best fit for the Type 1 Beacons – Chapter 3) by applying the “lm” function in R (version 4.2.2; R Core Team, 2022) to fit a regression. Following the protocol used for the Type 1 Beacons (Chapter 3) this was conducted for the full data set collectively (regardless of WISP and beacon height) and for each WISP-beacon height combination individually. The inverse function of the regression was then applied to the “predict” function to generate predicted distances for given RSSI values of -100 to -10 dBm.

4.2.2 Shadowing (blocked line-of-sight) calibration

4.2.1.1 Study design

An additional calibration was then conducted to examine the potential effects of shadowing, whereby there was an obstruction between the BLE transmitter (beacon) and receiver (WISP), to determine if and how this might impact on the likelihood of a beacon's signal being received, and / or on the RSSI value reported. For comparison with the line-of-sight calibration conducted in study 1, the same six WISP and 16 beacon identities were used. The set up of devices followed the protocol outlined in Study 1, however, in this instance, to simulate the effects of the WISP-beacon signal being blocked by a ewe's or lamb's body, two adjoining 4-pint milk cartons (totalling 4.55 L) filled with water were placed on top of a crate in front of the beacon to block the signal pathway to the WISP. The milk cartons were of the same size and shape, and both filled to the same marker line, to ensure content volume was as consistent as possible. The same crate and milk cartons (38 x 20 x 36.5 cm) were utilised across the study, placed approximately 10 cm from the beacon under test (hence individual milk cartons were located approximately 10 and 20 cm respectively in front of the beacon) (Figure 4.2). This was conducted for only one device height combination - WISP height 0.7 m and beacon height 0.3 m, replicating approximate ewe and lamb standing heights, and only for measured distances of 1, 2, 5, 10, 20, and 30 m. For each measured distance, beacons were left in position for a minimum of 14 minutes to obtain a possible two RSSI readings for each WISP-beacon pairing, and the date, start, and end times recorded to later allow the relevant data points to be selected for each WISP.

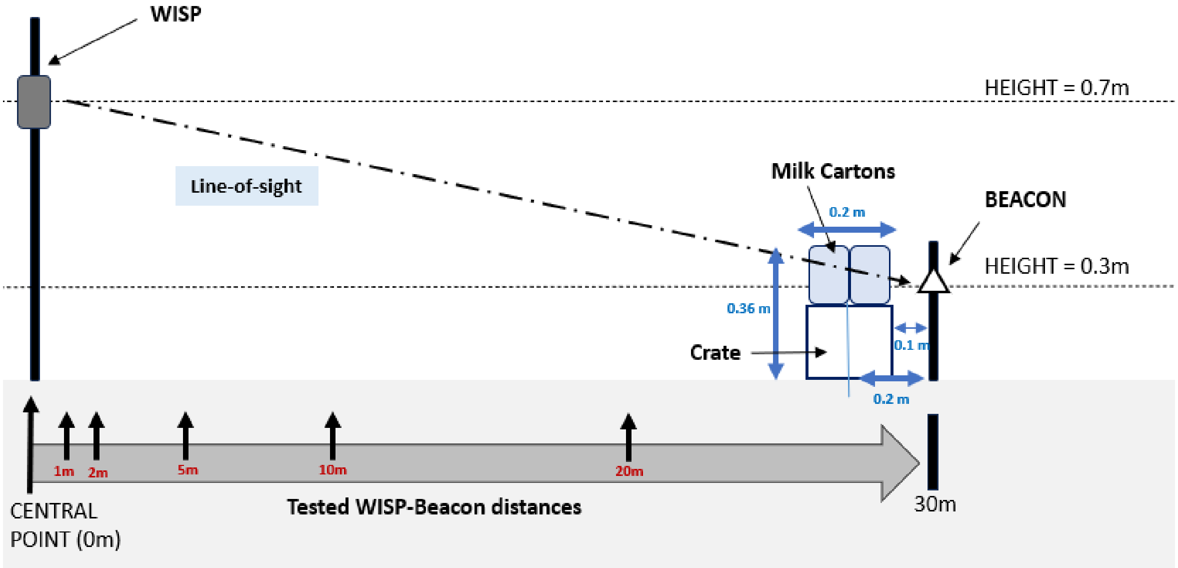


Figure 4.2 Set-up and layout of shadowing (blocked line-of-sight) calibration.

4.2.1.2 Data handling

As the field work for Studies 1 and 2 was conducted successively, data for the study was available from three WISPs only (the same identities as that of Study 1). Flash drive data from each of the three reporting WISPs was downloaded via the "Data Logger" app (Chapter 2). The relevant data points for when each beacon was located at each measured distance were manually selected to create a final full .csv file containing the information from all three WISPs. All further analysis was then conducted in R (R Core Team, 2022).

4.2.1.3 Statistical analysis

Initial analysis investigating the proportion of beacon readings reported and survival analysis of the BLE signal was conducted following the methods described in Study 1. For comparison between the blocked and clear line-of-sight calibrations, data from Study 1 was filtered to select a subset of data (WISP height 0.7 m and beacon height 0.3 m – for measured distances of 1- 30 m only) corresponding to the device heights and distances used within Study 2. The data sets were then merged, with a new variable “Calibration Type” derived. For each beacon type, a regression model; using the “lm” function in R (version 4.2.2; R Core Team, 2022), was generated to assess the effect of log(distance), the calibration type, and their interaction on the reported signal strength (RSSI) of a beacon. The regression models were then visualized using the visreg package in R (version 2.7.0; Breheny & Burchett, 2017).

4.3 Results

4.3.1 Study 1: clear line-of-sight calibration

4.3.1.1 Proportion of RSSI values reported

A total of 6 228 RSSI readings (58.98%) were obtained across the study from a total possible 10 560, had an RSSI been reported for every WISP-beacon pairing at every measured distance. However, beacon readings were not expected to be obtained on every occasion, as a drop off in beacon readings was anticipated to occur as the WISP-beacon distance increased and reached the limit of the BLE signal range between devices. A greater proportion of RSSI readings were obtained for Beacon Type 2 as opposed to Beacon Type 3, both overall and by individual WISPs (Table 4.1), with WISP ID 1 reporting a greater proportion of readings for both beacon types (63.69%). The total number of possible RSSI readings reported for individual beacons varied from 60-69% for Beacon Type 2, and between 58-67% for Beacon Type 3 (Table 4.2) - except for Beacon 3.7, for which no RSSI values were obtained. WISP ID 1 reported the greatest proportion of RSSI readings for both beacon types, the only exception being Beacon 2.6, for which WISP ID 1 reported the fewest RSSI readings. In some cases, there was a difference of as much as 20% between the proportion of possible RSSI readings reported by individual WISPs for the same beacon ID (e.g. Beacon 3.8).

Table 4.1 Number of beacon readings reported (and percentage of total possible) by wearable integrated sensor platform (WISP) ID and beacon type.

WISP ID	Beacon Type 2 (of 1760)	Beacon Type 3 (of 1760)	Total (of 3520)
1	1219 (69.26%)	1042 (59.20%)	2261 (63.69%)
2	1101 (62.56%)	912 (51.82%)	2013 (57.19%)
3	1051 (59.72%)	903 (51.31%)	1954 (55.51%)
Total (of 5280)	3371 (63.84%)	2857 (54.11%)	6228 (58.98%) (of10560)

Table 4.2 Number of beacon readings reported (and percentage of total possible) by wearable integrated sensor platform (WISP) and beacon ID.

Beacon ID	WISP ID 1 (of 220)	WISP ID 2 (of 220)	WISP ID 3 (of 220)	Total (of 660)
Type 2 Beacons				
2.1	154 (70.00%)	137 (62.27%)	129 (58.64%)	420 (63.64%)
2.2	149 (67.73%)	135 (61.36%)	129 (58.64%)	413 (62.58%)
2.3	155 (70.45%)	132 (60.00%)	126 (57.27%)	413 (62.58%)
2.4	165 (75.00%)	145 (65.91%)	145 (65.91%)	455 (68.94%)
2.5	142 (64.55%)	131 (59.55%)	127 (57.73%)	400 (60.61%)
2.6	138 (62.73%)	147 (66.82%)	141 (64.09%)	426 (64.55%)
2.7	169 (76.82%)	141 (64.09%)	129 (58.64%)	439 (66.52%)
2.8	147 (66.82%)	133 (60.45%)	125 (56.82%)	405 (61.36%)
Type 3 Beacons				
3.1	161 (73.18%)	134 (60.91%)	147 (66.82%)	442 (66.97%)
3.2	161 (73.18%)	133 (60.45%)	141 (64.09%)	435 (65.91%)
3.3	156 (70.91%)	127 (57.73%)	121 (55.00%)	404 (61.21%)
3.4	133 (60.45%)	124 (56.36%)	128 (58.18%)	385 (58.33%)
3.5	141 (64.09%)	131 (59.55%)	123 (55.91%)	395 (59.85%)
3.6	130 (59.09%)	127 (57.73%)	127 (57.73%)	384 (58.18%)
3.7	0 (0.00 %)	0 (0.00 %)	0 (0.00 %)	0 (0.00 %)
3.8	160 (72.73%)	136 (61.82%)	116 (52.73%)	412 (62.42%)

The proportion of beacons reported per distance differed according to both the beacon type, and the height at which the WISP and beacon were located (Figure 4.3). Beacon Type 2 reported at least 75 % of possible RSSI readings across all device height groups at distances of 0-10 m, however, the proportion of readings reported declined to less than 25 % by a distance of 30 m when WISPs were located at a height of 0.3 m, and by a distance of 50 m when WISPs were at 0.7 m and beacons at 0.3 m. In contrast, where both WISPs and beacons were at a height of 0.7 m, more than 50 % of possible RSSI readings were still reported at a distance of 90 m, falling to 27 % at the maximum measured distance of 110 m. Within the Type 3 beacon, there was a reduced proportion of RSSI readings at earlier distances in comparison with the Type 2 beacon, due to the failure of one of the beacons to be reported during the study. Despite this, more than 70 % of possible RSSI readings were still obtained at distances up to 20 m across all device height groups. However, by 30 m the proportion of RSSI readings reported fell to between 66 – 68 % when WISPs were at a height of 0.7 m, and to between 33 – 48 % at a WISP height of 0.3 m. By 50 m less than 33 % of possible RSSI readings were reported within any device height group, and whilst RSSI readings were still obtained at 110 m for a combined WISP and beacon height of 0.7 m, only 15 % of possible RSSI readings were reported.

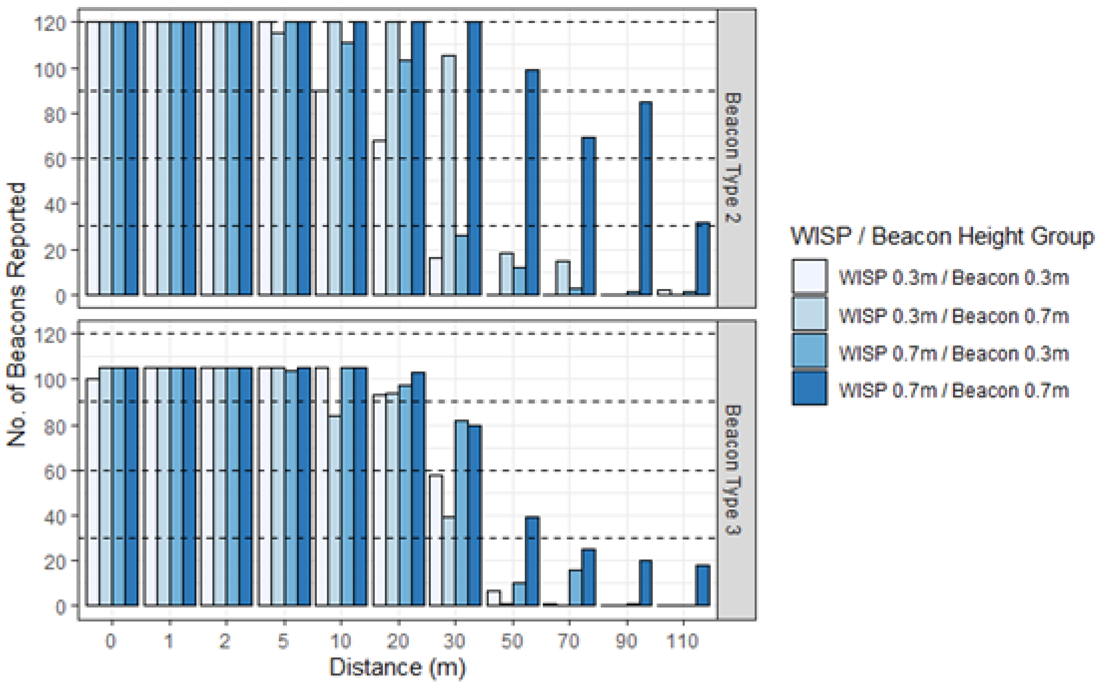


Figure 4.3 Proportion of possible beacon readings obtained per measured distance.

The proportion of RSSI readings reported per distance also varied depending upon the identity of the reporting WISP (Figure 4.4). Within Beacon Type 2, WISP ID 1 reported readings at greater distances than that of other WISPs when devices were at mixed heights, being responsible for all RSSI values reported at distances greater than 30 m when WISPs were at a height of 0.3 m and beacons at 0.7 m, and at distances greater than 20 m when WISPs were at a height of 0.7 m and beacons at 0.3 m. WISP ID 1 similarly reported a greater proportion of beacons at longer WISP-beacon distances for Beacon Type 3, when both WISPs and beacons were located at a height of 0.7 m. There was also some variation in the proportion of RSSI readings obtained for individual WISP-beacon pairings, particularly at greater distances (Figure 4.5). Within both beacon types, when a beacon was reported at shorter distances, readings tended to be reported for all five repetitions of that WISP-beacon pairing. However, as the WISP-beacon distance increased, there were more instances of readings being reported for only some repetitions.

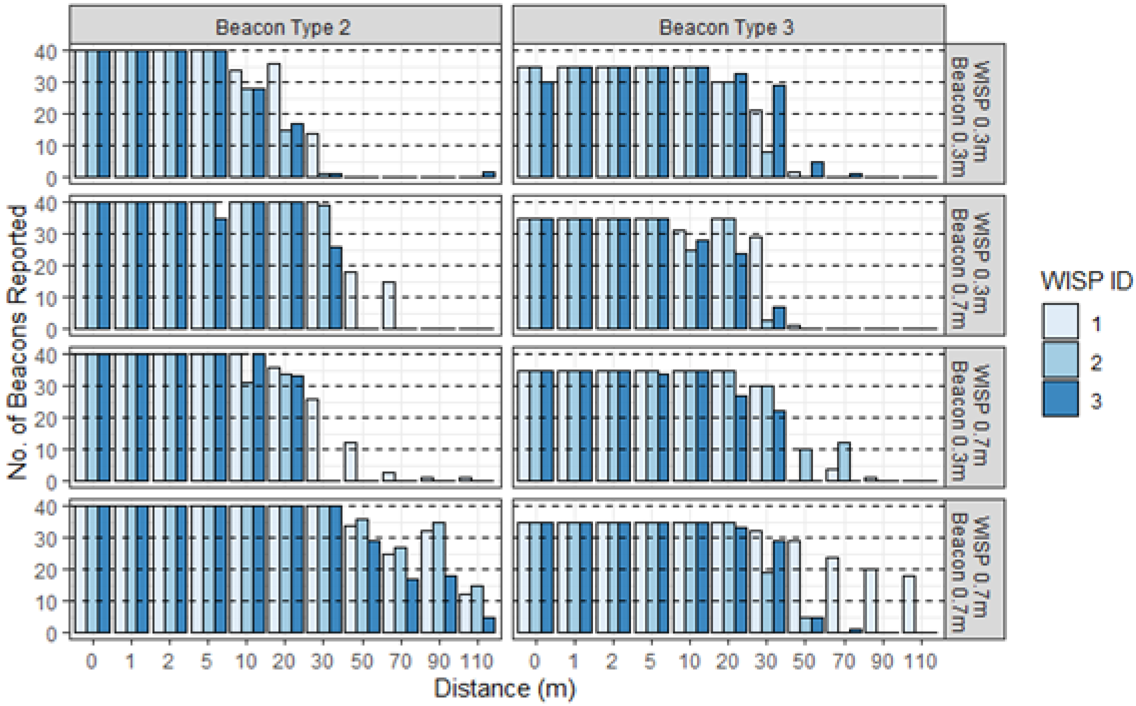


Figure 4.4 Proportion of possible beacon readings obtained per measured distance by wearable integrated sensor platform (WISP) ID.

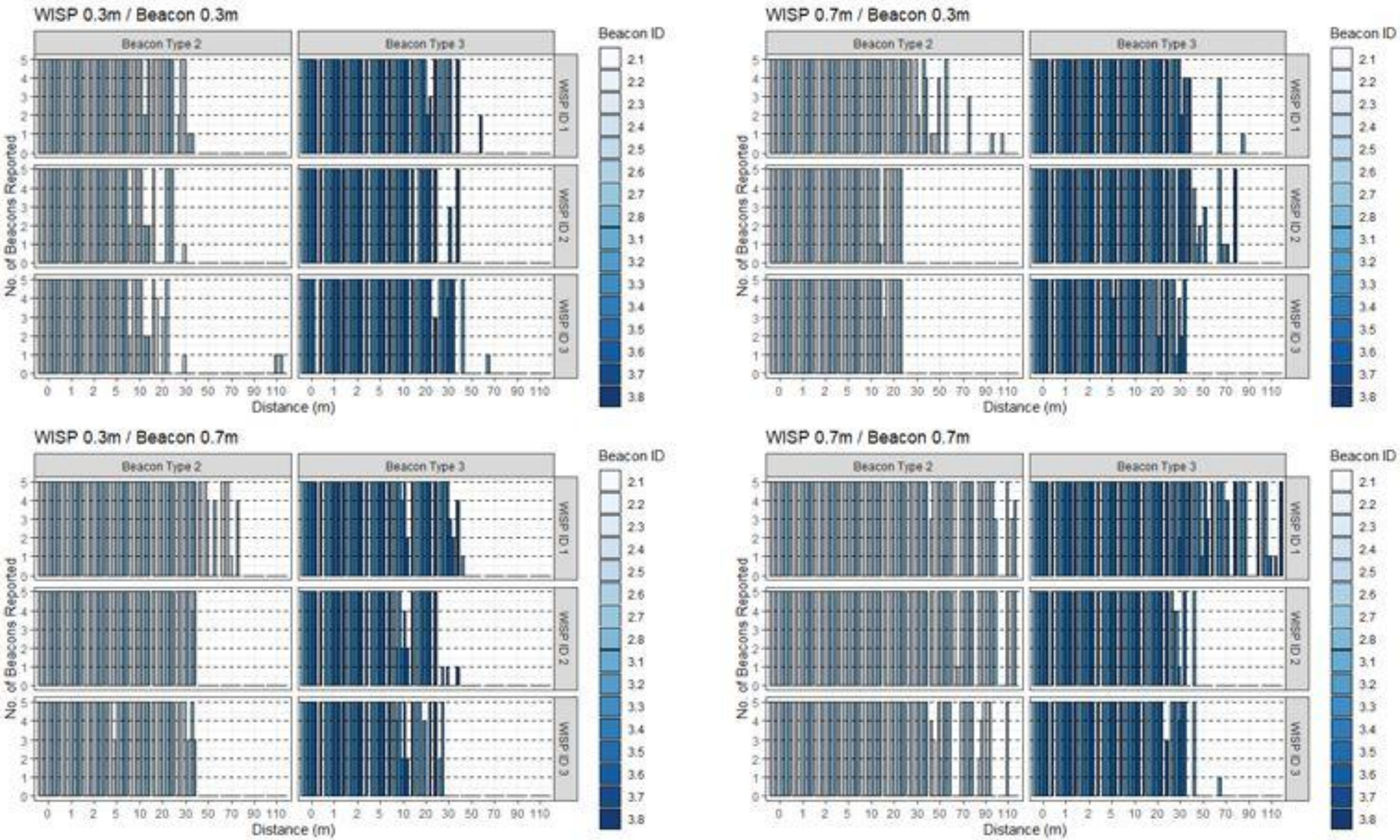


Figure 4.5 Proportion of possible beacon readings obtained per measured distance for each wearable integrated sensor (WISP)-beacon pairing, for each WISP/beacon height group.

4.3.1.2 Range of devices - BLE signal survival

The Weibull accelerated failure time models generated for each of the beacon types indicated that the probability of a beacon's BLE signal being received and reported by a WISP declined with increasing WISP-beacon distance, and differed according to the height at which WISPs and beacons were located (Figures 4.6 and 4.7). Within both beacon types, the probability of a beacon signal being reported declined at shorter distances when both WISPs and beacons were at a height 0.3 m, whilst the greatest distance ranges in signal survival occurred when both devices were at a height of 0.7 m. Instances, where devices were at mixed heights resulted in very similar curves regardless of whether it was the WISP or beacon at 0.3 or 0.7 m. Whilst the curves generated for each of the device height combinations were similar for both beacon types, the 75 % and 50 % survival probability thresholds were reached at shorter distances for Beacon Type 3. Based on a 75 % probability threshold, the BLE WISP-beacon signal range of the Type 2 Beacons would be between ~39 – 50 m depending on the device heights, whilst the range of the Type 3 beacons would be between ~34 – 47.5 m. However, if reduced to a 50 % probability threshold the BLE signal ranges increased to between ~62 – 81 m for Type 2 Beacons, and ~55 – 77 m for Type 3 Beacons. The beacon types were found to be a significant factor within the model, with Beacon Type 3 having a reduced signal range (Table 4.3). The height at which both the WISP and beacon were located were also found to be significant factors within the model, with the higher device heights of 0.7 m resulting in a longer distance range. Likewise, the interaction between WISP and beacon height was significant at combined WISP and beacon heights of 0.7 m.

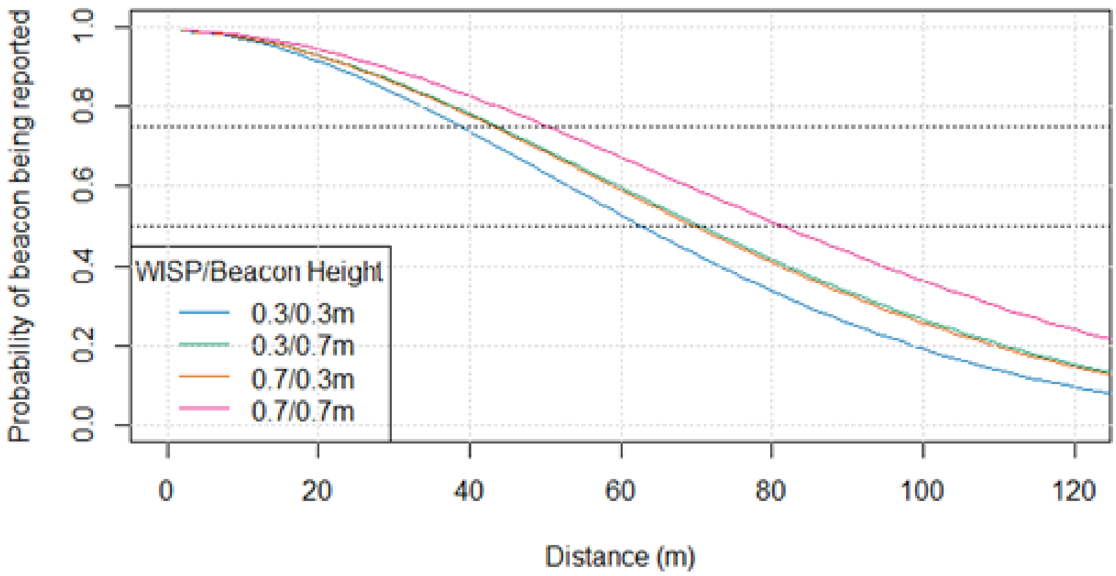


Figure 4.6 Weibull survival curves for Beacon Type 2, based on wearable integrated sensor platform (WISP) and beacon height.

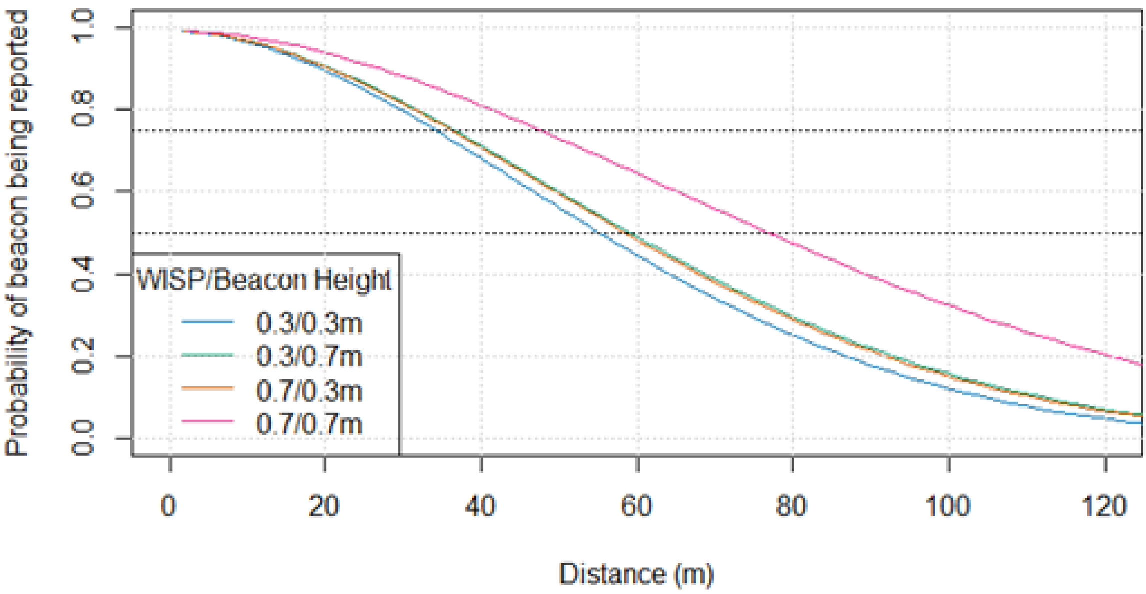


Figure 4.7 Weibull survival curves for Beacon Type 3, based on wearable integrated sensor platform (WISP) and beacon height.

Table 4.3 Summary of the Weibull accelerated failure time model.

Parameter	Value	SE	z	p-value
Intercept[1]	4.3501	0.0175	248.57	$<2 \times 10^{-16}$
Beacon Type				
2	Reference Beacon Type			
3	-01281	0.0165	-7.76	8.7×10^{-15}
WISP height				
0.3 m	Reference WISP height			
0.7 m	0.0573	0.0216	2.65	0.0081
Beacon height				
0.3 m	Reference beacon height			
0.7 m	0.0684	0.0218	3.14	0.0017
WISP Height x Beacon Height				
0.3 x 0.3	Reference WISP and beacon height			
0.7 x 0.7	0.2052	0.0337	6.09	1.1×10^{-9}
Log (scale)[2]	-0.6211	0.0121	-51.43	$<2 \times 10^{-16}$

[1] Intercept as given by the survreg function is the log of the standard parameterisation of the Weibull distribution scale parameter.

[2] Log (scale) as given by the survreg function is the natural log of the scale parameter (Scale = 0.537, X^2 = 265.73 (4), p = 2.7 x 10^{-56}), where scale is the reciprocal of the standard parameterisation of the Weibull distribution shape (hence shape = 1/0.537 = 1.86).

4.3.1.3 Relationship between RSSI and WISP-beacon distance

The relationship between RSSI and WISP-beacon distance was investigated firstly as a full data set for each beacon type, regardless of WISP and beacon height. Overall RSSI values for Beacon Type 2 ranged from -92 to -16 dBm, whilst values for Beacon Type 3 ranged from -92 to -20 dBm. Both beacon types displayed similar patterns of declining RSSI as the WISP-beacon distance increased, with similar ranges in RSSI values per measured distance (Figures 4.8 and 4.9). RSSI values at a single measured distance differed by as much as 47 and 45 dBm for Type 2 and 3 beacons respectively, with large ranges in RSSI values (of between 22 – 47 dBm) observed for WISP-beacon distances of 0 – 30 m, and shorter RSSI ranges (of between 4 – 15 dBm) at longer WISP-beacon distances of 50 – 110 m. The RSSI values reported at each measured distance also overlapped, and particularly at longer WISP-beacon distances, very similar mean RSSI values were reported for measured WISP-beacon distances of 50 - 110 m for Beacon Type 2, and 30 - 110 m for Beacon Type 3 (Table 4.4).

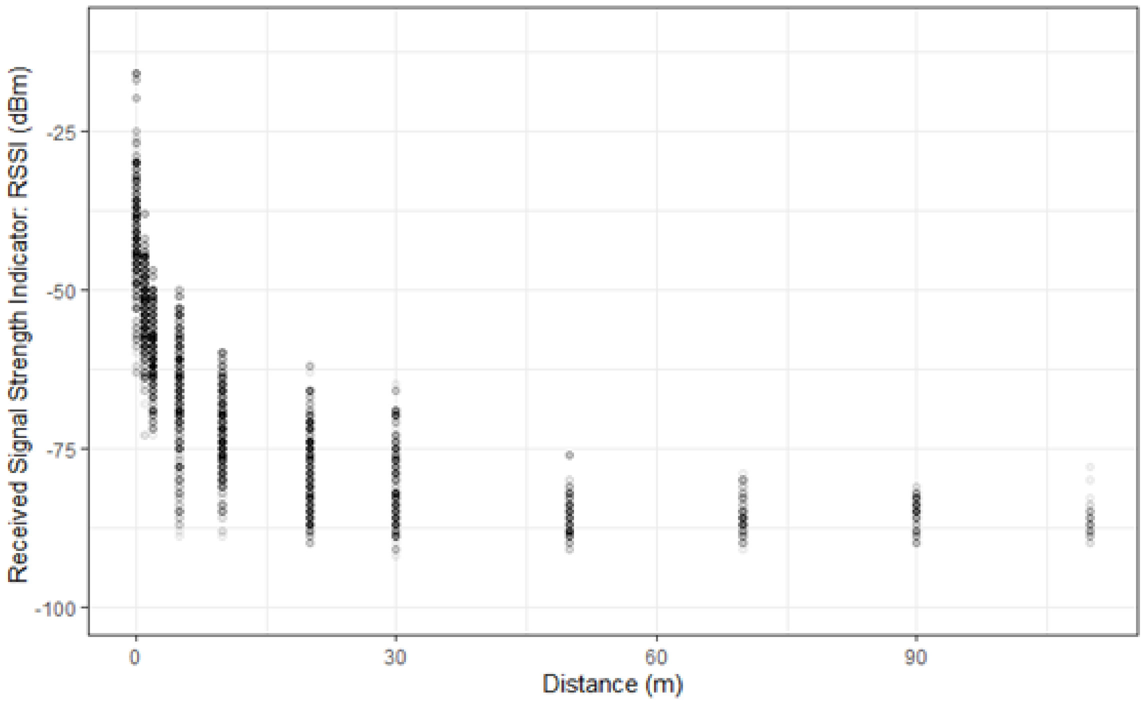


Figure 4.8 Received signal strength (RSSI) values reported per distance for Beacon Type 2.

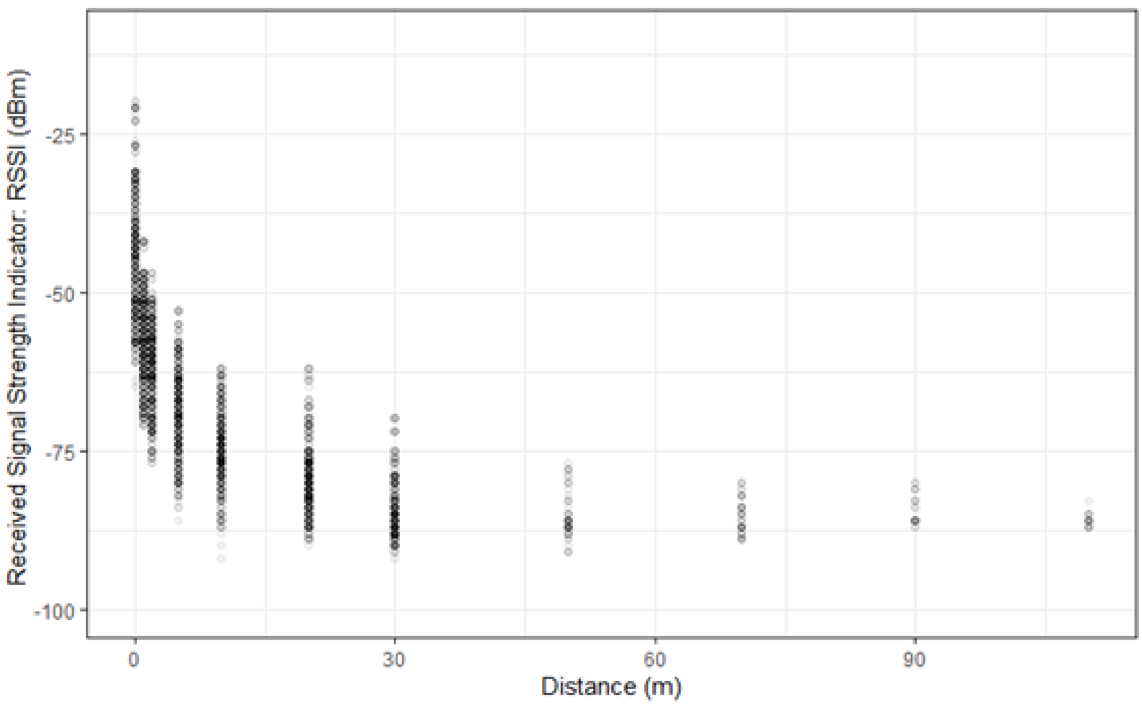


Figure 4.9 Received signal strength (RSSI) values reported per distance for Beacon Type 3.

Table 4.4 Summary of RSSI values reported per distance.

Distance	Mean RSSI	Minimum RSSI	Maximum RSSI	RSSI Range	RSSI 1st Quantile	RSSI 3rd Quantile
Beacon Type 2						
0	-40.68	-63	-16	47	-46	-36
1	-52.90	-73	-38	35	-57	-49
2	-59.49	-73	-47	26	-63	-56
5	-66.18	-89	-50	39	-71	-61
10	-72.44	-89	-60	29	-76	-68
20	-78.15	-90	-62	28	-84	-74
30	-80.27	-92	-65	27	-85	-75
50	-85.47	-91	-76	15	-88	-84
70	-85.57	-91	-79	12	-87	-84
90	-85.20	-90	-81	9	-86	-84
110	-86.37	-90	-78	12	-88	-85
Beacon Type 3						
0	-44.20	-65	-20	45	-52	-38
1	-57.72	-71	-42	29	-62	-53
2	-61.98	-77	-47	30	-67	-57
5	-68.93	-86	-53	33	-74	-64
10	-74.68	-92	-62	30	-78	-72
20	-79.37	-90	-62	28	-83	-77
30	-84.07	-92	-70	22	-87	-82
50	-85.16	-91	-77	14	-87	-83
70	-85.21	-89	-80	9	-87	-84
90	-84.19	-87	-80	7	-86	-83
110	-85.89	-87	-83	4	-86.75	-85.25

The relationship between RSSI and distance was then examined when data was grouped based on WISP and beacon height (Figures 4.10 and 4.11). Within all height groups, for both beacon types, there were larger ranges in RSSI at shorter distances, and much smaller ranges in RSSI as the distance increased – however this was likely due to the smaller overall number of observations obtained at longer distances. For Type 2 beacons, there was a gradual decline in RSSI between 0 to ~30 m within height groups where either device was located at 0.3 m. Within the combined 0.7 m WISP and beacon height group there was an initial decline in RSSI values between 0 and 1 m, and then a steady decline in RSSI, with values plateauing at distances of 50 – 110 m. This pattern was similarly observed for the Type 3 beacons, however, RSSI values began to plateau at an earlier distance of ~30 m.

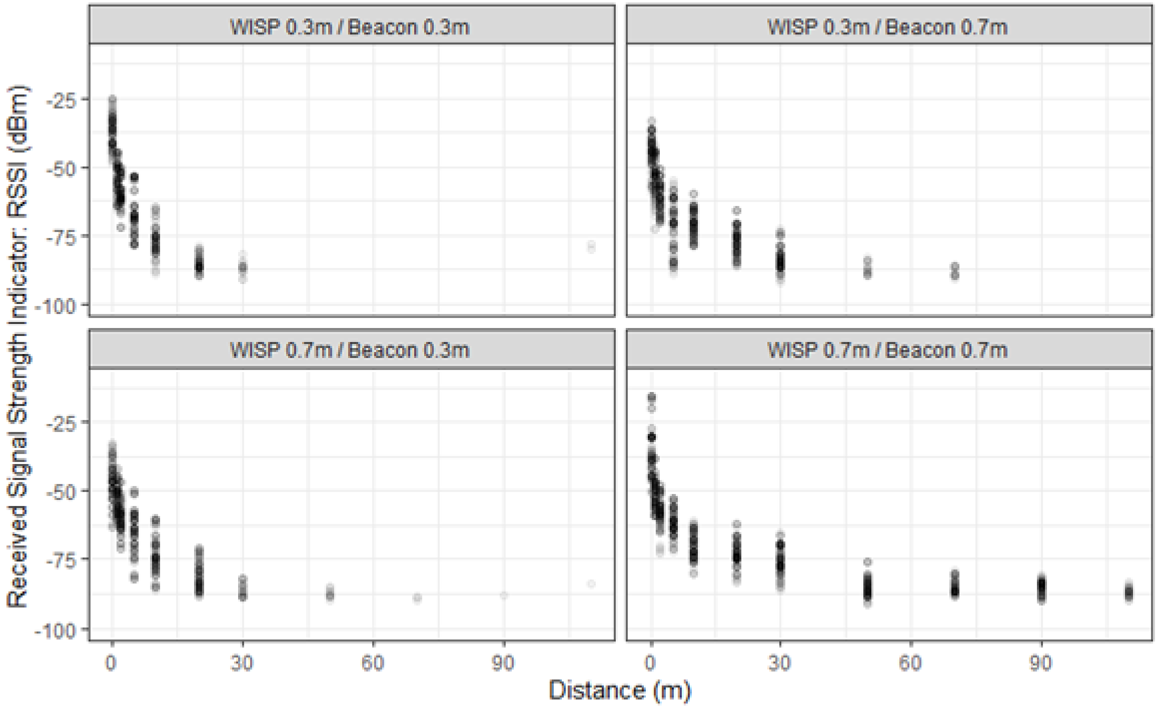


Figure 4.10 Received signal strength indicator (RSSI) values reported per distance for Beacon Type 2, for each WISP and beacon height group.

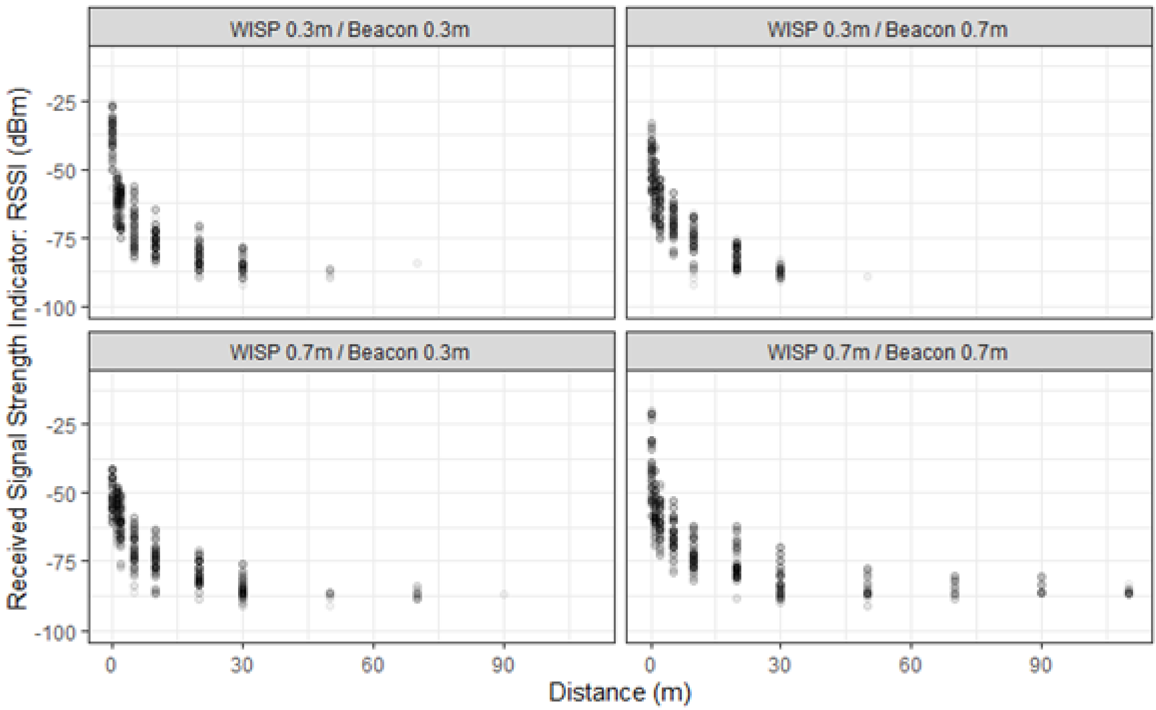


Figure 4.11 Received signal strength indicator (RSSI) values reported per distance for Beacon Type 3, for each WISP and beacon height group.

Whilst large ranges in RSSI values were then reported per distance within each height group, RSSI values of individual WISP-beacon pairings tended to have little variation. Within Beacon Type 2, individual WISP-beacon pairings typically produced similar RSSI values across all five repetitions at each distance, with 65 % of instances resulting in either a consistent RSSI or varying by only 1 dBm. This resulted in a mean difference in RSSI of 2.04 dBm. However, there were also some extreme instances where individual pairings varied up to a maximum of 30 dBm, the seven greatest of which all occurred at a WISP-beacon distance of 5 m. Similarly, within Beacon Type 3, RSSI values per WISP-beacon pairing had a mean difference of 1.93 dBm between repetitions, with 61 % of instances resulting in a consistent RSSI or difference of 1 dBm. The maximum difference in RSSI was 23 dBm, with the three greatest differences occurring at a WISP-beacon distance of 10 m.

A MEM indicated that for both beacon types, the distance between a WISP and beacon, and the height combination of both devices, had an effect on RSSI (Tables 4.5 And 4.6). For both beacon types, a higher random intercept variance resulted from the WISP ID as opposed to the Beacon ID, whilst a higher random intercept variance was generated for both WISP and beacon ID (and their interaction) for the Type 3 beacon in comparison with the Type 2 beacon. This suggests that at 0 m there is a greater difference in RSSI values between specific WISP-beacon pairings for Type 3 beacons. The intraclass correlation coefficient (ICC) was also greater in the Type 3 beacons, suggesting that WISP ID and Beacon ID explain a greater proportion of the variance within that data set. However, in both instances the ICC was relatively low suggesting that RSSI values based on WISP ID, beacon ID, or the WISP-beacon pairing were only moderately different from the variation within each WISP or beacon ID, or WISP-beacon pairing.

Table 4.5 Summary of mixed effects model (MEM) output for RSSI based on WISP-beacon distance and height group for Beacon Type 2.

Parameter	Lamb Daily Weight Gain		
	Estimate	**CI**	**p-value**
Intercept	-58.517014	-60.96 – -56.07	< 0.001
Distance	-0.520897	-0.54 – -0.50	< 0.001
WISP-Beacon Height Group:			
WISP 0.3m : Beacon 0.3m	Reference ewe breed		
WISP 0.3m : Beacon 0.3m	-2.173650	-3.32 – -1.02	< 0.001
WISP 0.3m : Beacon 0.3m	-1.354415	-2.54 – -0.17	0.025
WISP 0.3m : Beacon 0.3m	5.115090	3.97 – 6.26	< 0.001
Random effects			
[1]σ^2	126.32		
[2]$\tau 00_{\text{WISP ID X Beacon ID}}$	0.51		
[2]$\tau 00_{\text{WISP ID}}$	3.07		
[2]$\tau 00_{\text{Beacon ID}}$	2.53		
[3] ICC	0.05		
[4] $N_{\text{WISP ID}}$	3		
[4] $N_{\text{Beacon ID}}$	8		
Observations	3371		
[5] **Marginal R^2**	0.469		
[6] **Conditional R^2**	0.493		

[1] Residual variance: the variability unexplained by the model parameters (fixed effects).
[2] Random intercept variance: between group variance.
[3] Intraclass correlation coefficient: quantifies the proportion of variance explained by WISP and Beacon ID.
[4] Total number of observations.
[5] Variance explained by fixed effects.
[6] Variance explained by fixed and random effects.

Table 4.6 Summary of mixed effects model (MEM) output for RSSI based on WISP-beacon distance and height group for Beacon Type 3.

Parameter	Lamb Daily Weight Gain		
	Estimate	**CI**	**p-value**
Intercept	-61.696421	-64.88 – -58.52	< 0.001
Distance	-0.600654	-0.63 – -0.58	< 0.001
WISP-Beacon Height Group:			
WISP 0.3m : Beacon 0.3m	Reference ewe breed		
WISP 0.3m : Beacon 0.3m	-0.877469	-2.02 – -0.27	0.134
WISP 0.3m : Beacon 0.3m	-0.220515	-0.89 – -1.33	0.697
WISP 0.3m : Beacon 0.3m	4.944716	3.84 – 6.04	< 0.001
Random effects			
[1]σ^2	112.24		
[2]$\tau_{00\ \mathrm{WISP\ ID\ X\ Beacon\ ID}}$	1.97		
[2]$\tau_{00\ \mathrm{WISP\ ID}}$	5.35		
[2]$\tau_{00\ \mathrm{Beacon\ ID}}$	4.03		
[3] ICC	0.09		
[4] $N_{\mathrm{WISP\ ID}}$	3		
[4] $N_{\mathrm{Beacon\ ID}}$	7		
Observations	2857		
[5] Marginal R^2	0.440		
[6] Conditional R^2	0.491		

[1] Residual variance: the variability unexplained by the model parameters (fixed effects).
[2] Random intercept variance: between group variance.
[3] Intraclass correlation coefficient: quantifies the proportion of variance explained by WISP and Beacon ID.
[4] Total number of observations.
[5] Variance explained by fixed effects.
[6] Variance explained by fixed and random effects.

4.3.1.4 Development of distance prediction models

Following the same protocol as that of Beacon Type 1 (Chapter 3), a natural log model was applied to the obtained RSSI values from each of the measured distances, both for the full data set and each of the device height groups of both beacon types. A comparison of the resulting SDs, CVs, upper and lower confidence intervals, and adjusted R^2 values of mean predicted distances, for each measured distance is provided in Appendix C. Within both beacon types, the resulting distance estimations for given RSSI values in the range of -100 to -10 dBm differed according to the height at which both the WISP and beacon were located (Figures 4.12 and 4.13). Across all beacon types and devices heights, RSSI values in the range of approximately -60 to -10 dBm resulted in distance estimations of less than 1 m (a large range in RSSI). As the RSSI declined the curves generated from each of the device height combinations began to differ, and by -100 dBm the distance estimations between the height combinations differed by as much as 518 m (for Beacon Type 2). As RSSI values decreased, and particularly at values of -90 to -100 dBm, a small change of just 1 dBm resulted in fairly large changes in distance estimation, with RSSI values at the lower end of the scale generating predicted distances beyond that of any actual measured distance within the calibration study.

As this combination of WISPs and BLE beacons were planned for use in on-sheep studies, where their behaviour, and thus WISP and beacon height would be variable, the final distance prediction equations utilised in all further studies (for each beacon type) were based upon the calibration of all combined WISP and beacon heights (indicated in red within Figures 4.12 and 4.13). Two distance prediction equations were therefore developed, with the regression for Beacon Type 2 giving a distance prediction equation of:

Equation 4.1

$$\text{Predicted Distance} = \mathrm{e}^{-8.546723 - (0.147242 \times \text{RSSI})}$$

And the regression for Beacon Type 3 giving a distance prediction equation of:

Equation 4.2

$$\text{Predicted Distance} = \mathrm{e}^{-9.365093 - (0.153242 \times \text{RSSI})}$$

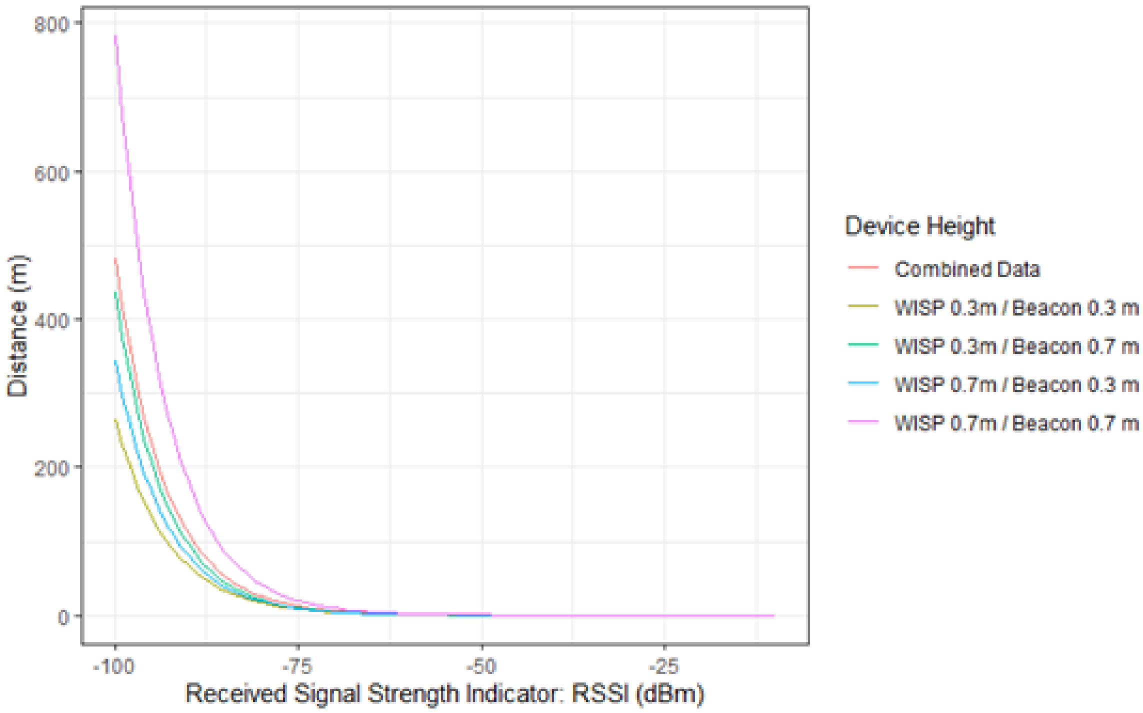


Figure 4.12 Predicted wearable integrated sensor platform (WISP)-beacon distances based on device heights, using the natural log model for Beacon Type 2.

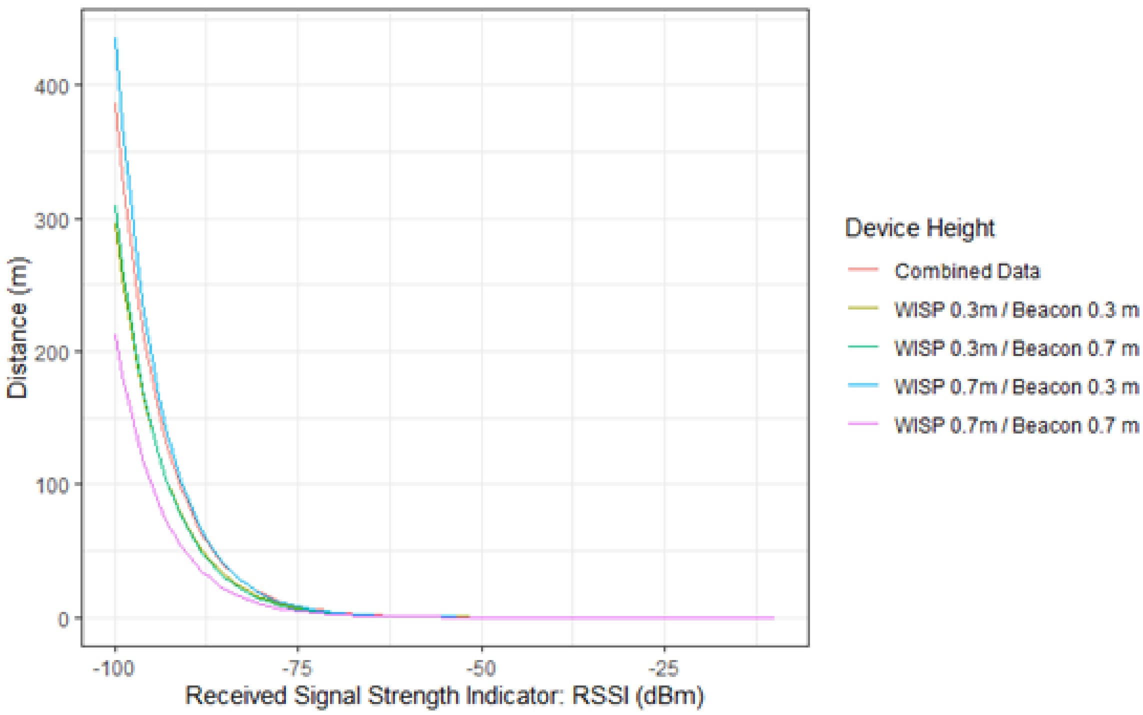


Figure 4.13 Predicted wearable integrated sensor platform (WISP)-beacon distances based on device heights, using the natural log model for Beacon Type 3.

4.3.2 Study 2: blocked line-of-sight calibration

4.3.2.1 Proportion of RSSI values reported.

A total of 509 (88 %) RSSI readings were obtained from a total possible 576 readings, had an RSSI been reported for all possible WISP-beacon pairings. A greater proportion of readings were reported for the Type 2 as opposed to the Type 3 beacons, with WISP ID 1 being responsible for the greatest proportion of overall RSSI readings, and WISP ID 3 the fewest (Table 4.7). The overall proportion of RSSI readings for individual beacons varied from 94-100 % for the Type 2 beacons, and 0-100 % for the Type 3 beacons (Table 4.8), with greater variation in the proportion of readings reported by WISP ID 3. As observed within Study 1, Beacon 3.7 (Type 3 beacon) failed to be reported by any WISP at any point in the study.

Table 4.7 Number of beacon readings reported (and percentage of total possible) by wearable integrated sensor platform (WISP) ID and beacon type.

WISP ID	**Beacon Type 2** (of 96)	**Beacon Type 3** (of 96)	**Total** (of 192)
1	96 (100%)	82 (85.42%)	178 (92.71%)
2	96 (100%)	74 (77.08%)	170 (88.54%)
3	92 (95.83%)	69 (71.88%)	161 (83.85%)
Total (of 288)	284 (98.61%)	225 (78.13%)	509 (88.37%) (of 576)

Table 4.8 Number of beacon readings reported (and percentage of total possible) by wearable integrated sensor platform (WISP) and beacon ID.

Beacon ID	WISP ID 1 (of 12)	WISP ID 2 (of 12)	WISP ID 3 (of 12)	Total (of 36)
Type 2 Beacons				
2.1	12 (100%)	12 (100%)	10 (83.33%)	34 (94.44%)
2.2	12 (100%)	12 (100%)	11 (91.67%)	35 (97.22%)
2.3	12 (100%)	12 (100%)	12 (100%)	36 (100%)
2.4	12 (100%)	12 (100%)	11 (91.67%)	35 (97.22%)
2.5	12 (100%)	12 (100%)	12 (100%)	36 (100%)
2.6	12 (100%)	12 (100%)	12 (100%)	36 (100%)
2.7	12 (100%)	12 (100%)	12 (100%)	36 (100%)
2.8	12 (100%)	12 (100%)	12 (100%)	36 (100%)
Type 3 Beacons				
3.1	12 (100%)	12 (100%)	12 (100%)	36 (100%)
3.2	10 (83.33%)	10 (83.33%)	8 (66.67%)	28 (77.78%)
3.3	12 (100%)	10 (83.33%)	9 (75.00%)	31 (86.11%)
3.4	12 (100%)	10 (83.33%)	10 (83.33%)	32 (88.89%)
3.5	12 (100%)	10 (83.33%)	9 (75.00%)	31 (86.11%)
3.6	12 (100%)	10 (83.33%)	10 (83.33%)	32 (88.89%)
3.7	0 (0%)	0 (0%)	0 (0%)	0 (0%)
3.8	12 (100%)	12 (100%)	11 (91.67%)	35 (97.22%)

Within this shadowing calibration, the Type 2 beacon reported all possible RSSI readings at distances of 1-20 m, falling to 92 % at the 30 m mark. This was a greater proportion than that observed during the standard calibration (Study 1), where the proportion of RSSI readings began to decline at 10 m (Figure 4.14). Within the Type 3 Beacon, all possible RSSI readings (apart from Beacon 3.7) were reported at distances of 1-5 m, after which point the proportion of RSSI readings began to decline, falling to 54 % at 30 m. This was a slightly earlier and greater decline than that observed within the standard calibration (Study 1) of the Type 3 beacon.

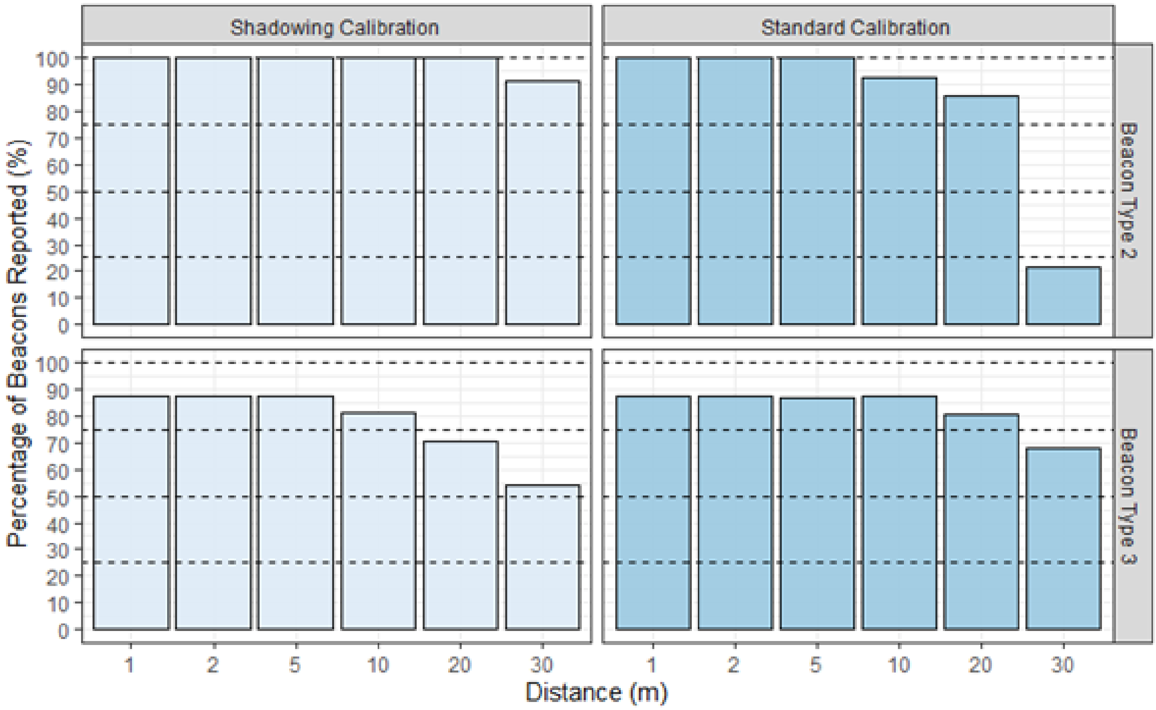


Figure 4.14 Percentage of beacon readings reported per beacon type for each measured distance during the shadowing effects vs standard calibration.

Where: shadowing = total possible 48 beacons per distance, and standard = total possible 120 beacons per distance.

The proportion of RSSI readings reported for the Type 2 beacon was found to decline at a shorter WISP-beacon distance during the standard as opposed to the shadowing calibration. Whilst WISP IDs 2 and 3 failed to generate any RSSI readings at the 30m mark during the standard calibration of beacon type 2, both WISPs reported 75% or greater during the shadowing calibration (Figure 4.15). Beacon Type 3 displayed a similar pattern across both the standard and shadowing calibrations, however, there was a slightly greater decline in the proportion of RSSI readings reported by WISPs 2 and 3 at distances of 10-30m (Figure 4.16).

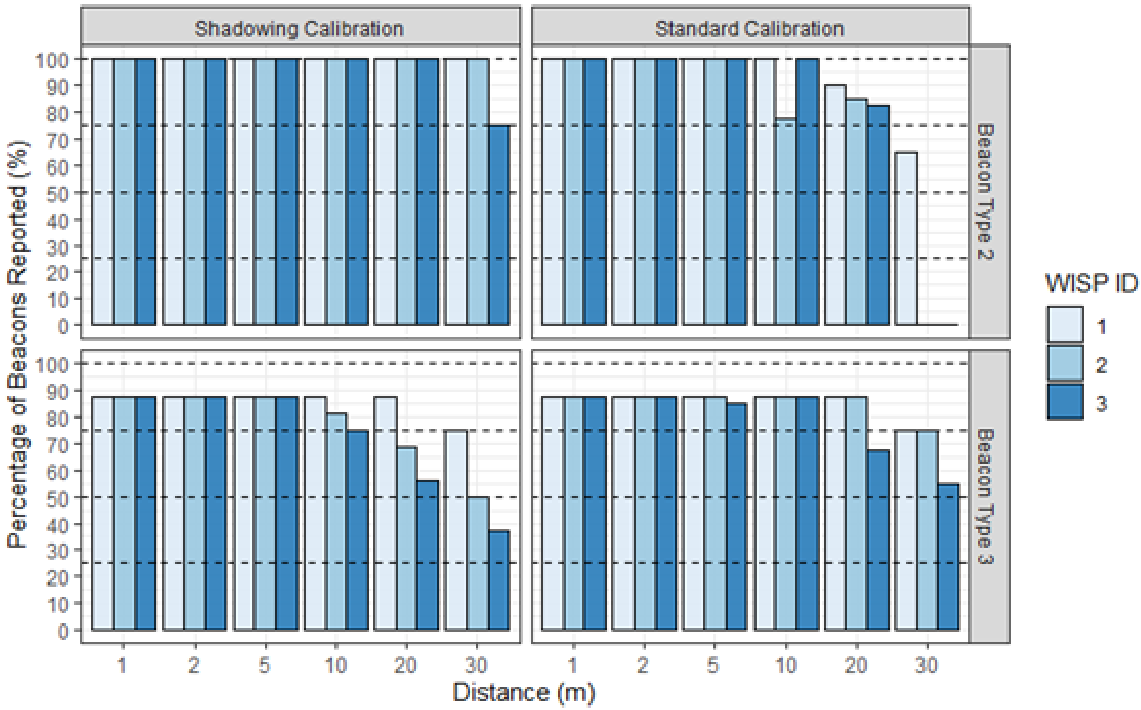


Figure 4.15 Percentage of beacon readings reported per beacon type for each measured distance and wearable integrated sensor platform (WISP) ID during the shadowing effects vs standard calibration.

Where: shadowing = total possible of 16 beacons per distance, and standard = total possible 40 beacons per distance.

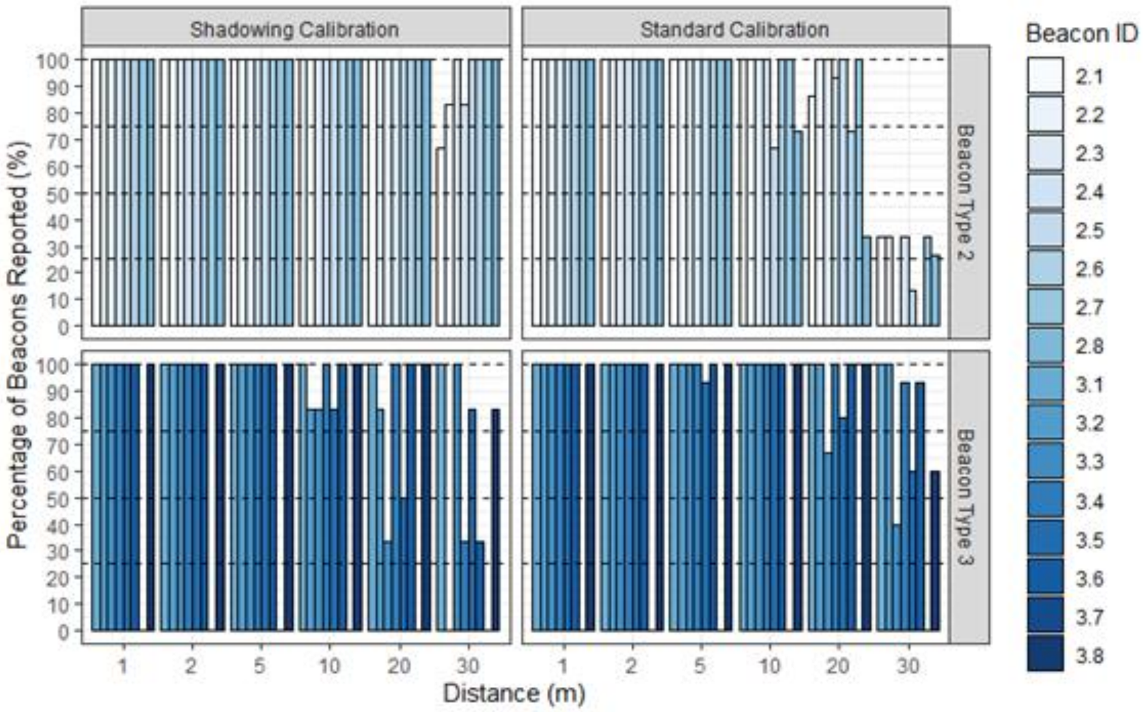


Figure 4.16 Percentage of beacon readings reported per beacon type for each measured distance and Beacon ID during the shadowing effects vs standard calibration.

Where: shadowing = total possible 16 beacons per distance, and standard = total possible 40 beacons per distance.

4.3.2.2 Range of devices - BLE signal survival

The Weibull accelerated failure time model generated very similar survival curves for both beacon types under standard calibration (Study 1) conditions, reaching a 75 % probability threshold at ~ 19.5 m (Figure 4.17). However, whilst there was a reduced BLE distance range for the Type 3 beacon under shadowing conditions, which reached a 75 % probability threshold at ~17 m, the Type 2 beacon displayed an increased BLE distance range, with a probability of ~ 94 % at the maximum measured distance of 30 m. The beacon type, calibration type and their interaction (for Type 3 beacons under standard calibration conditions) were all found to be significant factors within the model (Table 4.9).

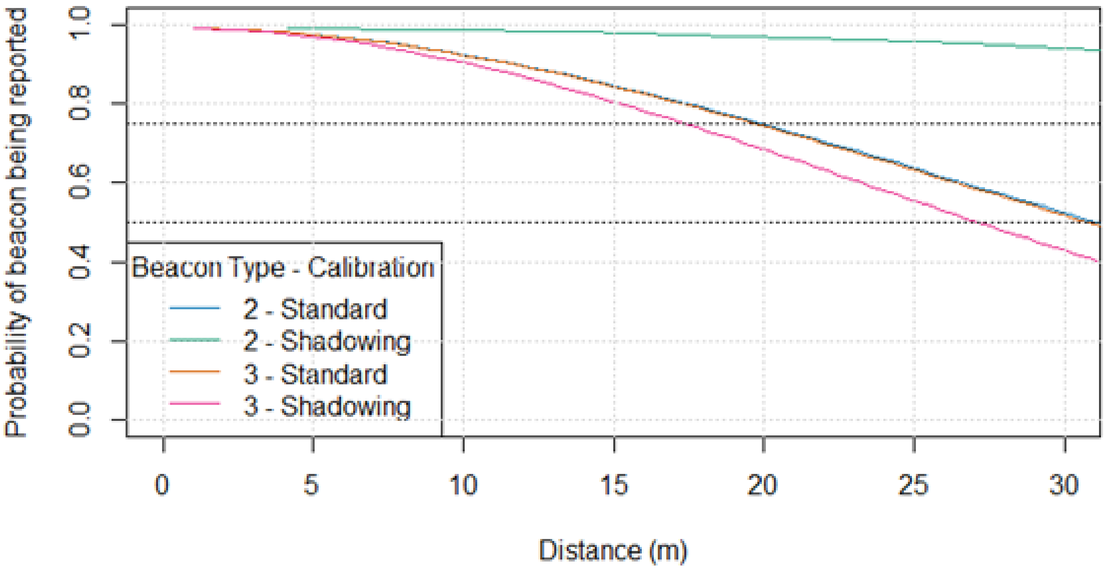


Figure 4.17 Weibull survival curves based on Beacon Type and Calibration Type (for a wearable integrated sensor platform (WISP) height of 0.7 m and beacon height of 0.3 m).

Table 4.9 Summary of the Weibull accelerated failure time model.

Parameter	Value	SE	z	p-value
Intercept[1]	4.8740	0.2610	18.67	$<2 \times 10^{-16}$
Calibration Type				
Standard	Reference Calibration Type			
Shadowing	-1.2416	0.2599	-4.78	1.8×10^{-6}
Beacon Type				
2	Reference Beacon Type			
3	-1.3775	0.2648	-5.20	2×10^{-7}
Calibration Type x Beacon Type				
Standard × 2	Reference Calibration and Beacon Type			
Shadowing × 3	1.3692	0.2724	5.03	5×10^{-7}
Log (scale)[2]	-0.6938	0.0443	-15.65	$<2 \times 10^{-16}$

[1] Intercept as given by the survreg function is the log of the standard parameterisation of the Weibull distribution scale parameter.

[2] Log (scale) as given by the survreg function is the natural log of the scale parameter (Scale = 0.5, X^2 = 70.19 (3), p = 3.9×10^{-15}), where scale is the reciprocal of the standard parameterisation of the Weibull distribution shape (hence shape = 1/0.5 = 2).

4.3.2.3 Effects of blocked line-of-sight (shadowing) on reported RSSI values

Regressions generated for both Beacon Type 2 (Table 4.10) and Beacon Type 3 (Table 4.11) found that both log(distance) (m), the calibration type, and the interaction of log(distance) (m) and calibration type, were significant factors. Hence the effects of shadowing / blocked line of sight on the reported signal strength (RSSI) is dependent on the distance between the WISP and beacon. Within Beacon Type 2 the mean RSSI at a distance of 0 m, under standard conditions is -52.43 dBm, with a unit change in log(distance) (m) resulting a decrease of 9.25 dBm. At a distance of 0 m the RSSI is 6.05 dBm lower under shadowing as opposed to standard conditions. The difference in RSSI between calibration types (blocked vs clear line-of-sight) changes by 2.30 dBm for every unit change in log(distance) (m). A similar trend was also observed for Beacon Type 3, where under standard conditions the mean RSSI at a distance of 0 m was -55.45 dBm, with a decline of 8.29 dBm for every unit change in log(distance) (m). At a distance of 0 m the RSSI was 9.95 dBm lower for the shadowing compared with the standard calibration, whilst the RSSI between calibration types changed by 3.17 dBm for every unit change in log(distance) (m).

Across both beacon and calibration types, the range in RSSI values tended be greater at shorter WISP-beacon distances, with a reduced range in RSSI reported at greater distances of 20 and 30 m. Mean RSSI values at each measured distance differed by a maximum of 6 dBm between the shadowing and standard calibrations for Beacon Type 2, and 11 dBm for Beacon Type 3. Across both beacon types, the blocked line-of-sight (shadowing calibration) resulted in a weaker BLE signal being reported, particularly at shorter WISP-beacon distances of 1-5 m. However, as the WISP-beacon distance increased the blocked line-of-sight had less of an impact on the RSSI reported (Figure 4.18).

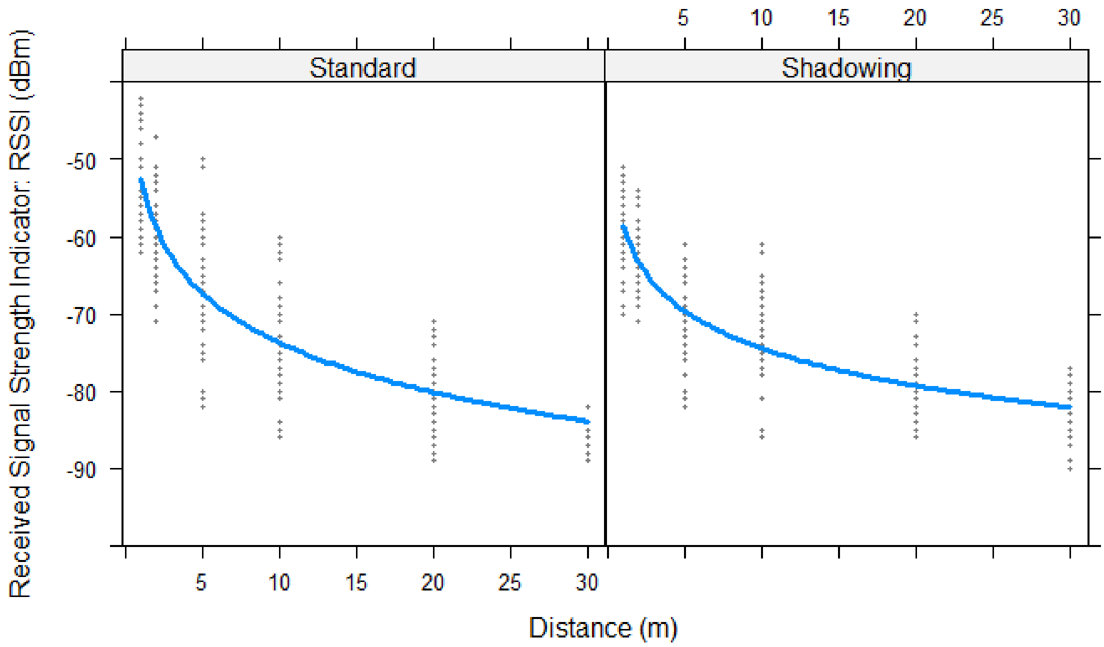
Table 4.10 Summary of regression model for Beacon Type 2.

Parameter	Estimate	SE	t-value	p-value
Intercept	-52.4323	0.4001	-131.045	$<2 \times 10^{-16}$
Log (distance) m	-9.2451	0.2098	-44.065	$<2 \times 10^{-16}$
Calibration Type				
Standard	Reference Calibration and Beacon Type			
Shadowing	-6.0465	0.7334	-8.245	5.99×10^{-16}
Distance x Calibration Type				
0 m x Standard	Reference Distance and Calibration Type			
Distance x Shadowing	2.3003	0.3521	6,533	1.09×10^{-10}
Adjusted R^2	0.7502			
F statistic	884.8			
DF	3 and 880			
p-value	$2,2 \times 10^{-16}$			

Table 4.11 Summary of regression model for Beacon Type 3.

Parameter	Estimate	SE	t-value	p-value
Intercept	-55.4502	0.3910	-141.824	$<2 \times 10^{-16}$
Log (distance) m	-8.2867	0.1842	-45.000	$<2 \times 10^{-16}$
Calibration Type				
Standard	Reference Calibration and Beacon Type			
Shadowing	-9.9504	0.7347	-13.543	$<2 \times 10^{-16}$
Distance x Calibration Type				
0 m x Standard	Reference Distance and Calibration Type			
Distance x Shadowing	3.1702	0.3555	8.918	$<2 \times 10^{-16}$
Adjusted R^2	0.7444			
F statistic	798.9			
DF	3 and 819			
p-value	$2{,}2 \times 10^{-16}$			

a)



b)

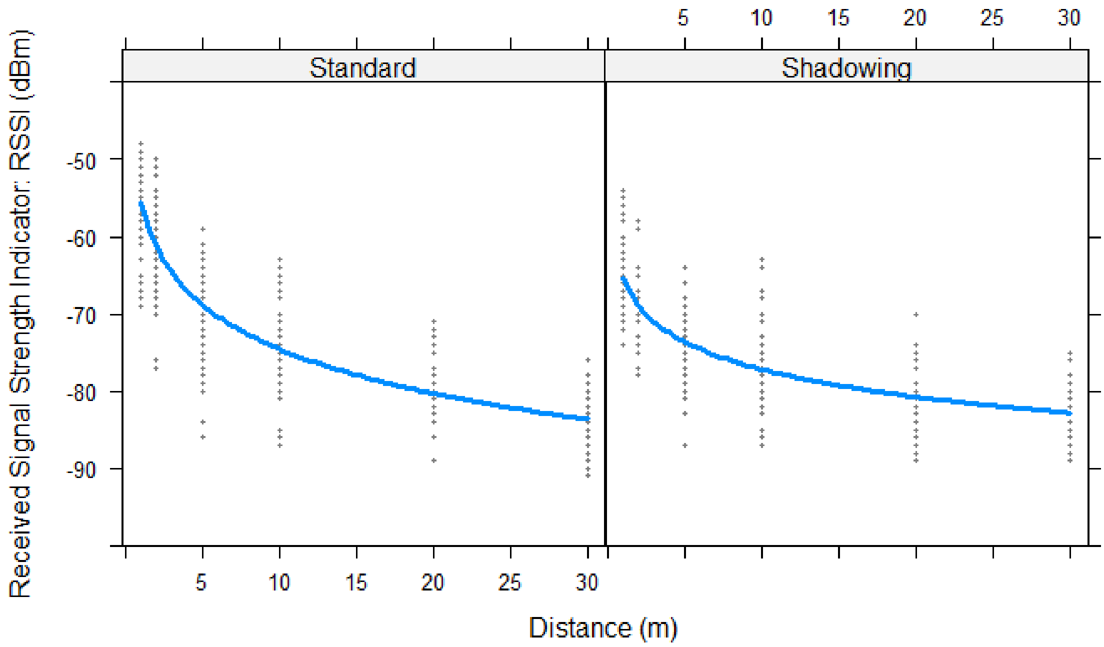


Figure 4.18 Comparison of regression lines under shadowing (blocked line of sight) and standard (clear line of sight) conditions, for a) Beacon Type 2, and b) Beacon Type 3.

4.4 Discussion

4.4.1 WISP-beacon BLE range

As observed within the calibration of the Type 1 beacon (Chapter 3) the height at which WISPs and beacons (Beacon Types 2 and 3) were located impacted on both the probability of a beacon being reported and the RSSI values reported per distance. Given the previous calibration (Chapter 3), a level of variation between device heights was expected and has been reported in multiple BLE studies (Triguero-Ocaña et al., 2019; Kirkpatrick et al., 2021; Zou et al., 2024). Factors affecting RSSI and BLE positioning within indoor systems have also reported variations in RSSI in relation to receiver height, and orientation of both the receiving and transmitting devices (Mamun et al., 2019). A level of variation around a mean value would therefore be expected at each distance. However, the WISP ID, beacon ID, and the specific pairing of WISP-beacon IDs also impacted on the proportion of beacons reported at each distance, with some devices (e.g. WISP ID 1) appearing to have a greater BLE operating range in terms of either transmitting or receiving data packets. As demonstrated across the standard and shadowing calibrations, this variation appeared to be consistent - with particular device IDs (e.g. WISP ID 1) being responsible for a greater number of readings and higher RSSI values across both studies. Similar device variations between different BLE pairings were also reported by Bloch and Pastell (2020) within a barn environment. The specific WISP-beacon pairing could then influence both the BLE operating range and RSSI value reported at each distance. If this is variation is consistent, then it would be technically feasible for device ID to be considered within interpretation of RSSI values. However, this would be highly impractical for wide scale application.

Whilst Beacon Types 2 and 3 were described within the manufacturers data sheets as having operating ranges of 400 (Shenzhen Feasycom Technology Co., Ltd, b) and 500 m (Shenzhen Feasycom Technology Co., Ltd, c) respectively (within an open environment), under the field conditions in which they were tested the effective ranges of the BLE beacons with the WISP were found to be much shorter (< 100 m). The survival curves generated from the Weibull distributions indicate that beyond 81 m for Type 2 and 77 m for Type 3 beacons there was only a 50 % chance that beacons would be reported at distances greater than this. However, given that in most applications a higher probability threshold of at least 75 % would likely be required, the BLE ranges of the WISP-beacon system could be considered to fall within 30-50 m depending upon the device heights. Whilst this is a greater range than that of the Type 1 beacon, the increase was not as great as expected.

There are multiple potential reasons for the BLE ranges observed. Firstly, the large BLE ranges reported within newer BLE versions are typically only observed in large open environments with a clear line-of-sight between transmitter and receiver (Jeon et al., 2018). However, the maximum theoretical distance is typically based only on RSSI values without consideration to the environmental conditions and based on transmitters operating at the maximum TX power (Jeon et al., 2018). As TX power will influence the battery life of devices, the study here used the default of 0 dBm rather than the maximum possible for each of the beacon types. In addition, whilst this study aimed to conduct the experiments within as flat an area as possible, the nature of the environment and distance covered (up to 110 m) means that there will be some variation in ground height across the study area which may contribute to variations in signal strength reported across distances. In most circumstances, rather than just a single direct line-of-sight path existing, rather variations of the signal will also be received via ground reflected propagation pathways (Rappaport, 2024). As these signals are reflected, the wavelengths may be altered in relation to the height and angle of the transmitting device (Rappaport, 2024). Hence, even in conditions where there is a clear line-of-sight, in practice, unavoidable environmental factors will result in a faster rate of signal decay than would be theoretically expected (Jeon et al., 2018). Furthermore, whilst the beacons (operating on BLE 5.1 and 5.2 respectively) have an increased broadcasting range, one of the main limiting factors to the tested system is that the BLE receiver within the WISP is operating on BLE 4.2. Whilst newer versions of BLE are backwards compatible with BLE 4.2 there may be limitations to the receivers range and reception.

It was also noted that whilst WISP-beacon parings typically resulted in an RSSI value being reported during all repetitions at shorter measured distances, as the distance increased more beacons tended to be reported during only some repetitions. Packet collisions can occur when two or more beacons transmit a signal on the same channel at the same time, resulting in the receiver being unable to correctly decode some or all transmitted data packets. These collisions can then result in slow or incomplete discoveries depending upon the discovery time, advertisement frequency, scan duration, and scan frequency (Molina et al., 2021). Whilst packet collisions may be responsible for some beacons failing to be reported, this would require collisions to occur during all scanning windows over the 5-minute duty cycle. Given that this variability across repetitions tended to occur alongside an overall reduction in the proportion of beacons reported, it would suggest that this variability is associated with WISP-beacon pairings approaching the limit over which their BLE range can communicate – either due to distance or environmental factors acting to block or reduce the signal strength.

4.4.2 RSSI and distance estimation

The advertising channel and corresponding frequency over which a signal is transmitted can result in variable RSSI values being reported for devices operating at the same distance and under the same conditions. Flueratoru et al. (2021) reported variations of 5 dBm in BLE devices tested at 2 m in indoor environments, whilst Powar et al. (2017) similarly found variations of up to 15 dBm between advertising channels in BLE beacons tested in an indoor system. The study by Powar et al. (2017) also demonstrated that although some fluctuation still exists when devices broadcast on a single channel, there is less variation than when devices advertise by transitioning through all advertisement channels. As the BLE specification does not currently provide a means of recording and reporting the broadcasting channel over which a data packet has been sent (Powar et al., 2017) fluctuation in RSSI around a mean should be expected to occur at each distance. This study did find that within both beacon types a range of RSSI values were reported at each distance, but that the variability in RSSI decreased as the WISP-beacon distance increased - this may be in part due to the fewer observations obtained at greater distances as WISP-beacon pairings fell out of BLE range.

Whilst mean RSSI values initially declined with increasing WISP-beacon distance the RSSI values plateaued at ~50 m, varying by only a few dBm after this distance.

Hence whilst the prediction model may be useful as indicator of approximate distance, the generated equation shows that a unit change in RSSI translates to a greater change in distance (m) as RSSI values decline. There is therefore a very large RSSI range (approximately -20 to -60 dBm) over which there is little change in distance, but all indicating a very close WISP-beacon proximity. Similarly, whilst the equation could theoretically estimate distances > 100 m, from approximately 50-110 m RSSI values appeared to fluctuate around approximately -85 dBm, whilst the greatest observed value within the study was -92 dBm. Hence, by a certain distance within this system (30-50 m depending on device height), the BLE operates such that a beacon's signal is either reported or not, but that the RSSI value contributes little to interpretation of an actual distance, other than being greater than ~50 m. The use of the equation to interpret distance would therefore appear to be most useful within an RSSI range of approximately -60 to -90 dBm. However, the variability amongst devices, combined with variability from the environment in which devices are being applied, could make widescale standardisation of range and distance translation difficult. Interpretation of RSSI into distance ranges, or a "very close" to "far" distance categorisation may be more realistic within some applications.

4.4.3 Impact of shadowing / blocked line-of-sight

Within on-sheep applications the probability of a BLE signal being reported is likely to be further confounded by the presence of other sheep. Within the Type 3 beacon, the shadowing study acted to reduce the survival curve of the BLE signal, indicating a range of ~17 m at a 75 % probability threshold, and ~27 m at a 50 % probability threshold. However, the shadowing did not act to reduce the signal survival of the Type 2 beacon. With the exception of 10 m, the placement of an obstacle between the beacon and WISP also altered the mean signal strength reported when compared to values during the standard calibration. RSSI is known to vary as a result of obstacles which can attenuate the radio signal, however, the alteration observed will depend on the size, location (i.e. the position of the obstacle in relation to both the transmitter and receiver), type of material, and thickness of the obstacle (Szyc et al., 2023). Previous studies have demonstrated the effects of BLE signals travelling through a human body, which can absorb part of the signal leading to a greater rate of decay (Della Rosa et al., 2012). The study by Della Rosa et al. (2012), found that RSSI reduced by up to 15 dBm at 3 m when blocked by a human body, whilst variations of up to 30 dBm were reported by Mamun et al. (2019) in a similar study. This study also reports that the extent of fluctuation in RSSI related to the angle / position of the human body in relation to the transmitting and receiving devices. The level to which attenuation occurs is also different between tissue types. Christoe et al. (2021) report varying degrees of signal depletion when travelling through water, meat and fat. Hence the animals body composition, size (ewe and lamb), and orientation to the receiving and transmitting antennas could influence the RSSI reported.

4.4.4 Implications for application on-sheep

As a gregarious species, instances will then arise where multiple sheep bodies may be within very close proximity when applying BLE as a wearable on-animal device. This could act to block or alter signals between the individual with the reporting WISP and the animal of interest with the broadcasting beacon. Furthermore, the behaviour (and thus beacon height) of both individuals, as well as the animals body position and orientation of the device relative to one another will likely impact on the BLE signal. This could be particularly relevant for some behaviours such as suckling, or instances where both animals are lying. Given the reduced BLE range at lower device heights, ewe-lamb contacts would be expected to have a shorter range than ewe-ewe contacts. However, as the WISP reports the average RSSI of a 5-minute duty cycle, a substantial number of signals would have to be blocked or reduced to prevent a beacon being reported. However, it is more likely that the interpretation of animal distances will be affected. Even when applied within the same system, weather conditions (e.g. rain, snow), humidity, and temperature could influence the RSSI values reported (Szyc et al., 2023). Whilst the developed prediction equations within this study may then be indicative of an approximate WISP-beacon distance within this particular setting, the variability amongst devices, combined with variability from the environment in which devices are being applied, could then make widescale standardisation of range and distance translation difficult as RSSI values are dependent on conditions at specific points in both space and time.

4.4.4 Limitations

A limitation of the “shadowing” / blocked line of sight study, is that only a single obstacle was tested, and only at single set distance from the beacon. Whilst the study then demonstrated that the signal strength and likelihood of a beacon being reported was impacted by the presence of an obstacle, further studies would be required to examine the extent to which sheep bodies impacted the BLE signal, and potential factors (such as number of sheep, orientation, distance between WISP and beacon, and body size) which may influence this. The study was also limited by the number of WISPs for which data was obtained. Due to battery failure, the study compared only three WISPs, however, the data indicates a strong WISP ID effect, and further studies should therefore include a greater number of WISPs to assess the overall trend and effects of WISP-beacon interactions on the reported BLE signal.

Thes studies also demonstrated potential issues with the BLE technology and the transmission of the signal between devices. Within both the standard and shadowing calibration study, Beacon 3.7 was not reported by any WISP at any point within the study. However, the beacon was operating and functioning when checked using the “FeasyBeacon” app. As it was therefore unclear whether there was a connection issue between all tested WISPs and this particular beacon, or all devices were functioning correctly, but the beacon simply failed to be reported, the decision was made to include the beacon within the analysis.

4.5 Conclusion

The calibration studies of the Type 2 and 3 beacons further demonstrated variability in signal strength arising from specific device IDs and combinations of WISP-beacon pairings. This could make a standardised distance translation more complex. The survival curves generated also reinforced that the effects of height, as observed within the calibration of the Type 1 beacon (Chapter 3) were not related to a specific beacon type, but rather associated with line of-sight and BLE range across BLE specifications. The RSSI values reported also indicated that signal strength was likely to be a poor indicator of distance changes beyond approximately 50 m. In addition, the blocked line-of-sight study suggests that where sheep are located between the BLE beacon and WISP, beacons may be less likely to be reported (particularly the Type 3 beacon). Where signals are reported, these will be weaker than where there is a clear line-of-sight, especially at close distances of 1-10 m. This may then have implications for on-sheep studies, where sheep in close proximity appear further away based on RSSI values.

Chapter 5 Application of Bluetooth Low Energy (BLE) to monitor the ewe-lamb relationship during the early lactation period: Methodology and focal ewe-lamb analysis.

5.1 Introduction

Previous studies applying BLE within sheep monitoring have explored the use of the technology to detect very close contacts, such as use of resources – i.e. to quantify drinking habits (Abecia et al., 2024), within location monitoring of grazing flocks – e.g. using a combination of GNSS collars and BLE beacons (Maroto-Molina et al., 2019), or utilising BLE readers on-board UAVs to detect beacons on sheep (Vucic and Axell, 2022). Several studies have also applied BLE within the context of proximity monitoring of ewe-lamb contacts, primarily as a means of determining maternal pedigree – determined based on the number of BLE signals received between ewe-lamb pairings (Sohi et al., 2017; Waterhouse et al., 2019; Paganoni et al., 2021). These studies have demonstrated differences in contact duration and distances between related and non-related ewes and lambs, and the ability of BLE to successfully match lambs with their dams. The estimated BLE distances assessed within these studies have been within ranges of 0 - 24 m (Sohi et al., 2017) and 1 - 15 m (Paganoni et al., 2021), however, more recent versions of BLE could allow for monitoring over greater distance ranges. This then presents an opportunity to monitor not just the number of contacts but could provide insight into changes in spatial proximity of relationships over time.

Within gregarious species, such as sheep, social factors can have an important influence on behaviour (Hinch, 2017). Associations between ewes and lambs, and between conspecifics, can influence group sizes, home ranges, and spatial distributions, which will be further influenced by the environmental conditions and size of area in which the flock is kept (Hinch, 2017). During the lambing and post-lambing period the relationship and spatial distance between ewes and ewe-lamb pairs changes over time according to lamb age / time since lambing, but also across daily diurnal activity patterns (Galeana et al., 2007; Arnold & Grassia, 1985). Within the study by Sohi et al. (2017) the number of ewe-lamb contacts was found to differ between light and dark periods, with higher contacts occurring at night – a period during which flocks would not typically be inspected. Being able to remotely and continuously monitor sheep interactions could then provide a wealth of information in relation to flock dynamics and establishing typical ewe-lamb patterns, which could allow for identification of potential issues when these patterns deviate.

BLE offers a potential solution by which this information could be monitored within grazing sheep systems, particularly within the context of ewe-lamb monitoring, as the light weight of BLE beacons (~6 - 15 g according to beacon type) present a device suitable for use on lambs. However, whilst signal strength of BLE typically declines with increasing separation distance between devices (as observed within the calibration studies – Chapter 4), the application of the BLE system as an on-sheep proximity monitoring tool does present additional challenges for the transmission and detection of beacon signals. The combined movement of sheep, and direction and speed at which they travel towards or apart from one another, will likely have implications on the transmitted beacon signal being received (Lee, 1997), and the strength of the signal reported. Given that device height can also impact BLE range (Triguero-Ocaña et al., 2019; Kirkpatrick et al., 2021), signals may be further confounded by the behaviour and postural changes (impacting on the height-distance relationship between transmitting and receiving devices on the respective sheep of interest) across individual and consecutive duty cycles. To then assess the functionality of BLE as a proximity monitoring tool within sheep grazing systems, the WISP and BLE beacons were trialled within an on-sheep study during the high activity period of pre-lambing and early lactation. This chapter details the data collection and methodology of the ewe-lamb study design and presents the data analysis and results relating to a subset of the data during which focal observations were conducted. The statistical analysis and results obtained for the full ewe-lamb study are discussed within Chapter 6.

The primary aim of the focal observations was to assess how the BLE devices performed when both the WISPs and beacons were on sheep. Contacts between observed ewe-lamb groups (ewes with twin lambs) were assessed to examine if sheep behaviour influenced the likelihood of a beacon being reported, and / or the reported RSSI and thus distance estimation. The study therefore consisted of several smaller aims:

1. To examine the overall proportion of expected focal ewe and focal lamb beacons reported.
2. To assess whether a beacon being reported was affected by ewe and lamb behaviour, and ewe-lamb distance.
3. To examine how BLE signal strength and the developed distance prediction equation for the type 3 beacon (Chapter 4) related to ewe-lamb distances estimated by an observer and assess if this was affected by ewe and lamb behaviour.
4. To examine the consistency of focal lamb beacons being reported by their dam over time.

5.2 Material and methods

All procedures and experimental protocols were approved by SRUC's Animal Experiment Committee (SHE AE 10-2022 – approved 13th April 2022).

5.2.1. Study dates and location

The ewe-lamb study was conducted over a six-week period from the 20th April to 2nd June 2022 at Auchtertyre Farm (SRUC's Hill and Mountain Research Centre) near Crianlarich, in the West Highlands of Scotland. The study flock was kept within two adjoining fields of ~3 ha of permanent pasture – the lower field being the location for all calibration studies (Chapters 3 and 4). The upper field was ~1.07 ha, and the lower field ~1.73 ha, which were connected via an open gate (Figure 5.1). A single water trough was located in the southwest corner of the lower field.

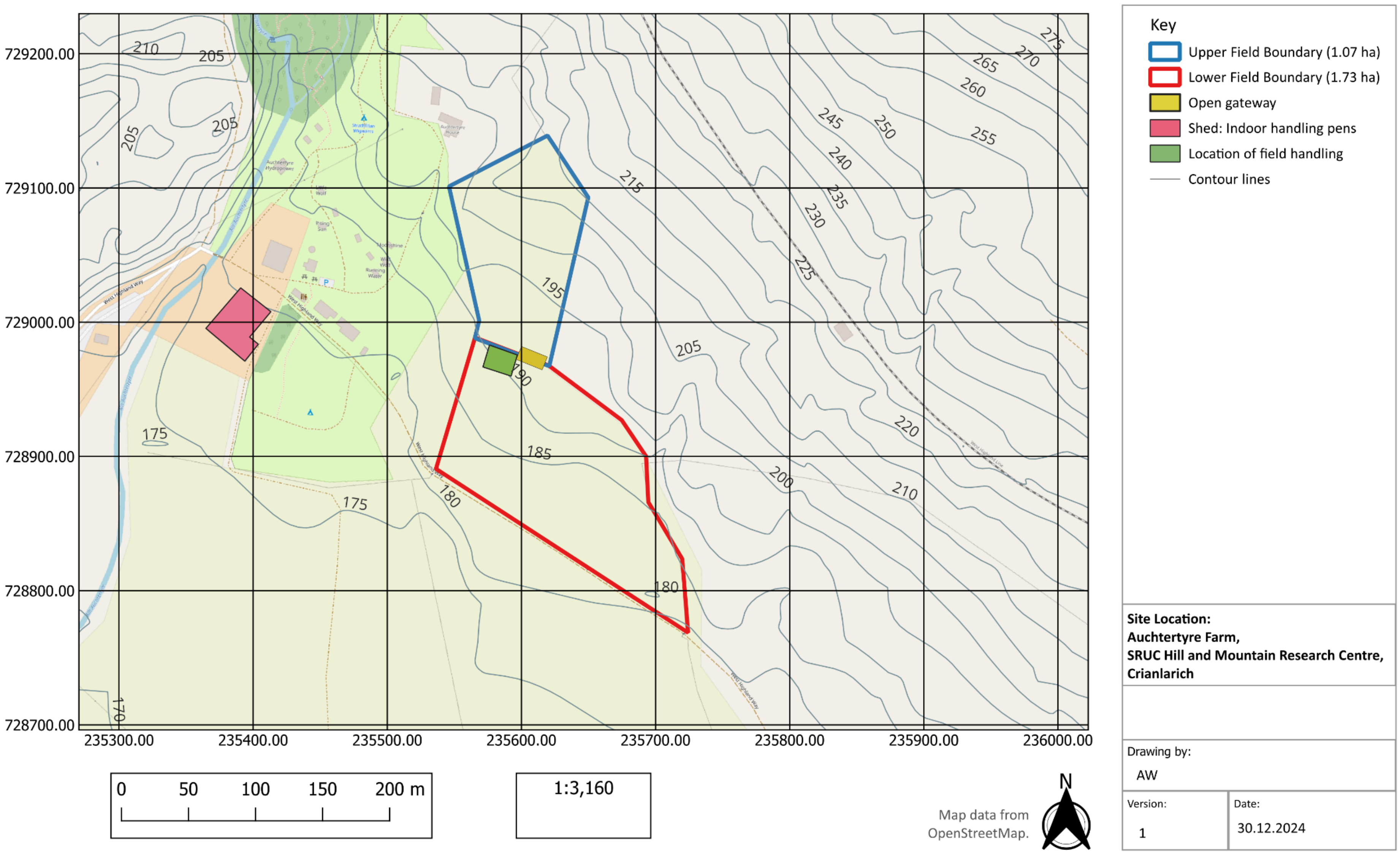


Figure 5.1 Location of ewe-lamb study fields and indoor handling shed.

5.2.2. Animals and study phases

The study flock consisted of 38 ewes (25 Lleyn and 13 Scottish Blackface) and their lambs. Whilst the study aimed to follow twin-bearing ewes, 26 ewes had twin lambs, three had single lambs, six had triplets, and three did not lamb. The study therefore included 73 lambs, alongside one fostered-on lamb, for a total of 74 lambs. In addition, to typical daily checks by farm shepherds, farm technicians conducted checks on the study flock twice-daily (morning / afternoon) during the first four weeks, reducing to once daily during weeks five and six (as most ewes had lambed).

The study was conducted over three phases (Table 5.1). WISPs and beacons were fitted on-sheep for a period of 9 - 15 days, followed by a rest period of three / four days to allow the batteries to be replaced and the data to be downloaded from the WISPs. As five of the ewes (Group 2) lambed on or within 2 d prior to the study start date, these ewes and their lambs were fitted with devices at a slightly later start date during Phase 1 than the other 33 ewes within the flock (Group 1). Ewes were supplemented with hay during Phase 1, whilst the whole study flock was temporarily moved to nearby pasture between Phases 2 and 3 to allow the grass to recover.

Table 5.1 Study phase dates and durations.

Phase	Start Date	End Date	Duration
1 – Group 1	20/04/22	02/05/22	14 d
1 – Group 2	22/04/22	02/05/22	12 d
2	06/05/22	20/05/22	15 d
3	24/05/22	02/06/22	10 d

5.2.3. Devices and device assignment

The study used a combination of WISPs as wearable on-animal devices on ewes (containing a Type 2 Beacon – Chapter 2), alongside Type 2 and 3 beacons fitted to ewes via string or to lambs via collar type 2 (containing a Type 3 Beacon - Chapter 2). Assignment of beacon types to ewes and lambs was based on available numbers of each beacon type. The system operated as previously described in Chapter 2.

At the initial study start date, Group 1 was gathered within the Shed (indoor handling pens) at Auchtertyre Farm (Figure 5.1). Ewes were fitted with either a WISP (containing a BLE beacon) or BLE beacon only and spray-painted on both flanks with a study number (1 - 33); recorded against their farm tag ID, to allow for visual identification at a distance. As there were a limited number of WISPs (23), four WISPs were held back to be assigned to ewes within Group 2. This was to ensure ewe-lamb data during the 1st week after lambing was captured. Ewes within Group 1 were then randomly assigned one of the remaining 19 WISPs or a BLE beacon only (14). Group 2 was gathered within a pen in the study field (Figure 5.1) two days later, where they were also assigned a device and spray painted with a study number (34 - 38). During Phases 2 and 3, all ewes were assigned devices on the same date during a gathering within the shed. However, there was a reduction in the number of WISPs available (16) due to use within the wider TechCare project. In addition, as some ewes experienced chaffing from the WISP collars (eight ewes in total across the study), they were subsequently assigned a Beacon only in following phases, with adjustments made to the WISP design (Chapter 2). Of the ewes which did not experience chaffing or had previously been assigned a BLE beacon only, the allocation of devices during Phases 2 and 3 was based on whether the ewe had lambed, age of lamb(s), and breed of ewe.

During Phase 1, the 10 lambs which had been born prior to the start of the study were assigned their collar alongside their dams during the in-field gathering of Group 2. All other lambs were assigned their neckband at the time of standard tagging and recording, which would occur within 24 h of birth. At this point the ewe's ID, lamb's ID and their assigned BLE beacon number were recorded, and lambs were spray-painted with their dam's study number on each side of the body.

For twin lambs, the second lamb was additionally spray-painted with a dot on its back. Of the ewes which lambed triplets, either the entire group was removed from the study, or only two lambs remained within the study (one lamb fostered-off) hence there was no requirement for a third spray marking type. After initial BLE beacon assignment at tagging and recording, new beacon IDs were allocated (based on neckband size) when the flock was gathered and handled within the shed at the start of each study phase.

5.2.3. Animal removal from study

Throughout the study period seven ewes and their lambs were temporarily removed from the study to indoor pens within the shed. In these instances, devices (where already assigned) were removed, before being refitted on the same animals prior to re-joining the study. In addition, several animals were permanently removed from the study, resulting in a total of 33 ewes and 53 lambs by the end of the study period. Reasons for removals are outlined in Table 5.2.

Table 5.2 Animals removed during the study period.

	Ewe / Lamb	No. of Animals	Reason for Removal
Temporary Removal	Ewe	1	Prolapse
		1	Mastitis
		1	Ewe not enough milk
		4	Small / weak lamb
	Lamb	2	Prolapse
		1	Mastitis
		2	Ewe not enough milk
		6	Small / weak lamb
Permanent Removal	Ewe	4	Lambed triplets – moved indoors with all lambs
		1	Died following lambing
	Lamb	12	Triplet lamb – moved indoors with dam
		5	Moved to indoor pen – orphan lamb / lamb removed from ewe
		3	Died at lambing / prior to recording and tagging
		1	Missing during Phase 2 – suspected to have been taken by a fox

5.2.4. Collection of animal data

5.2.4.1 Ewe data

All ewes were assessed prior to the start of the study and at the end of the study to obtain a body condition score (BCS) and weight in kilograms (kg). These were obtained by Auchtertyre Farm technicians during in-shed handling, following the protocols outlined within the TechCare Meat Sheep Welfare Assessment Measures (TechCare, 2023) - provided within Appendix D. BCS was measured on a scale of 1 to 5, in 0.25 increments, using methods by Russell et al. (1968), whilst weights were obtained using an EID weigh crate (0.1 kg error). Starting BCS and weights were obtained for ewes in Group 1 on the study start date (20th April), whilst for Group 2 information was taken from an earlier assessment on 21st March 2022. Study end weights were obtained at device removal of Phase 3 on 2nd June 2022.

5.2.4.2 Lamb data

Lamb birth weights (kg) were recorded by a farm technician using a manual scale (Figure 5.2) at the time of standard tagging and recording. Study end weights and BCS for lambs followed the same protocol as outlined for ewes, obtained on 2nd June 2022.

Figure 5.2 Weighing of a lamb at recording and tagging.

5.2.4.1 Ewe condition / welfare data

Sheep condition data, hereby referred to as "welfare data" was also collected during pre-study (21st March 2022) and end-of-study (2nd June 2022) handling, at in-shed gathering events (collected by farm technicians), as well as during six weekly in-field welfare assessments (conducted every Friday). The selected measures (Table 5.3) respectively followed the handled and in-field protocols outlined in the TechCare project (TechCare, 2023) – provided in Appendix D.

Table 5.3 Summary of sheep condition (welfare) data collected.

Welfare measure	Score Range	Conducted during:	
		in-shed	in-field
Ewe-lamb distance (m) – related to maternal behaviour	Recorded in (estimated) 1 m increments from 1-50 m, after which lambs were classed as >50 m		X
Lameness (gait) scoring	0-3	X	X
DAG score (extent of faecal deposition on the fleece) – related to gastrointestinal parasites / nutrition	0-4	X	X
Fleece condition (fleece loss / irritation – itching or scratching) – related to ectoparasites and/or myiasis (flystrike) / nutrition	0 / 1 (binary scoring)	X	X
Respiratory problems	0 / 1 (binary scoring)	X	
Dental loss	0-2	X	

5.2.5. Focal observations

Focal observations were carried out three days per week, with a total of 56 observations across the three study phases. Focal observations were conducted on ewe-lamb groups (dam with twin lambs only), with the aim of obtaining data (from the focal ewes WISP) across a range of lamb ages and for both ewe breeds. On a given day, the focal groups selected for observation were therefore based on the focal ewe having a WISP, the ewe breed, and lamb age. Whilst groups selected were initially based on the order in which they were spotted within the field, observations therefore became progressively more targeted towards groups where data for specific lamb ages and ewe breeds were lacking.

Once a focal group was selected, the ewe and both lambs were observed for a 20-minute period. The date, an observation ID, observation start time, and each animals spray-marked ID was recorded (e.g. ewe = E1, lamb 1 (no dot) = L1, lamb 2 (with dot) = L1D). At 1-minute intervals the following information was recorded under each lamb ID:

- Ewe's behaviour (from a pre-defined list – Table 5.4).
- Lamb's behaviour (from a pre-defined list – Table 5.4).
- Estimated ewe-lamb distance in metres (m) – using field features and distance between fence posts (~2 m) as reference.
- Whether the lamb was within the ewes nearest 15 neighbours (and therefore expected to be reported if within the BLE distance range) – defined as YES / NO / UNSURE. This was an estimation based on the observers assessment – being easier to ascertain during some behaviours, at closer distances, and when fewer sheep were within proximity.
- Where possible, an expected beacon rank position (2-16) relating to the order in which beacons were expected to be reported by the focal ewes' WISP (the strongest signal being reported first) was also recorded. For instance, if the lamb was consistently the closest animal to the focal ewe, then the expected rank position was 2 – as the ewes own ID was expected at Rank 1. Given the movement of ewes and lambs across a duty cycle, this was only recorded in some instances (typically where ewes and lambs were in very close proximity and there was little or no movement).

Table 5.4 Ethogram of ewe and lamb behaviours during focal observation.

Behaviour	Ewe / Lamb	Description of behaviour
Grazing[1]	Ewe & Lamb	Grazing with head down or chewing with head up, either standing still or moving.
Lying[1]	Ewe & Lamb	In a lying posture whilst idle or inactive - a recumbent position with minor head movements.
Playing[2,3]	Lamb only	Including superfluous activity such as running, jumping or frolicking in a co-ordinated manner (with no apparent purpose), object play, or social play - interacting with another lamb or lambs.
Scratching[4]	Ewe & Lamb	Rubbing body against objects, scratching body with hind leg or stretching whole or part of the body.
Standing[1]	Ewe & Lamb	Static standing with minor limb and head movements, whilst idle or inactive. Head may be up or down.
Suckling[5]	Lamb only	Places head under ewe - in contact with udder for more than 5 s.
Walking[1]	Ewe & Lamb	Minimum of 2 progressive steps forward, backwards or sideways.
Not Observed	Lamb only	Lamb not seen within vicinity of ewe – not located using binocular search.

Behavioural definitions based on: [1] Barwick et al., 2018, [2] Dwyer, 2003, [3] Randle, 1993, [4] Chapagain et al., 2014, [5] Pickup and Dwyer, 2011.

During the observations animals were observed from a distance, using binoculars, when necessary, to minimise disturbance. If the focal ewe was particularly active, they were followed at a distance to maintain a view of all three individuals (where possible). If one of the lambs was unable to be located at a given 1 min interval it was recorded as not observed. If at the end of the study the lamb was still not observed a search was conducted within the field to locate the lamb. On occasions where lambs were positioned such (i.e. lying) that lamb twin identity (dot / no dot) could not be determined, information was recorded under two columns, and lambs were approached at the end of the observation period to confirm identities of each. All observational data was recorded on paper and transcribed into a single .csv file.

5.2.6. Statistical analysis of focal observation data

5.2.6.1 Data collation

As there was no LoRa gateway operating during Phase 1 of the study, data analysis was conducted using flash drive data downloaded from each individual WISP. Data from individual flash drives was manually filtered to select data rows corresponding to relevant time periods of focal observations only. This data was then merged into one single .csv file containing data for all focal observations – with new variables “Observation ID”, “WISP ID”, and “Total no. of beacons reported” generated. In one instance (observation 40) where flash drive data was unavailable, but LoRa data could be obtained, the relevant information was similarly selected from the LoRa .csv file. All further analysis was conducted in R version 2.4.4 (R Core Team, 2020). The data was lengthened by converting the .csv file from reporting 16 beacons per row, to a single beacon per row, and assigning a new variable “Beacon rank” based on the position (out of 16) at which the beacon was reported. All rows where no beacon was reported were removed from the data set to create a final “working data set”.

The observational data set was initially edited within excel. Data was grouped into intervals corresponding to the duty cycle of the focal ewes WISP (i.e. five 1-minute observations per duty cycle). Using the WISPs reporting timestamp, the data was transformed into a single row per lamb for each duty cycle, with the following variables:

- Timestamp (based on the focal ewes WISP).
- Observation ID.
- WISP ID.
- Focal ewe ID (i.e. E1).
- Focal lamb ID (i.e. L1 or L1D).
- Lamb age (days) at observation.
- The ewe behaviour recorded at each 1-minute observation (i.e. Ewe behaviour 1/2/3/4/5).
- The lamb behaviour recorded at each 1-minute observation (i.e. Lamb behaviour 1/2/3/4/5).
- The observer estimated ewe-lamb distance at each 1-minute observation.
- Whether the focal lamb was within the ewes nearest 15 neighbours (defined as Yes / No).
- The expected beacon rank of the focal lamb

Three new variables were then generated to summarise ewe and lamb data for each duty cycle. A “Mean Observer Estimated Ewe-Lamb Distance”, “Overall Ewe Behaviour” and “Overall Lamb Behaviour” were categorised based on all five 1-minute observations. If a single behaviour was recorded at all observations (i.e. five observations of lying) then this behaviour was given as the overall behaviour. However, where two or more behaviours were recorded, the overall classifications were:

- Inactive (where observations consisted of a mix of lying and standing).
- Active (where for the ewe: observations consisted of a mix of grazing and walking, and for lambs: grazing, walking, playing, and suckling).
- Mixed (where both inactive and active behaviours were recorded).

5.2.6.2 Initial summary of data

Initial summarisation of the data was conducted using the “dplyr” package in R (Version 1.1.2; Wickham et al., 2023).

5.2.6.3 Analysis of focal ewe beacons

The “working data set” was filtered to find rows in which a focal ewes’ WISP reported its own beacon only. The proportion of beacons reported was summarised using the “dplyr” package in R (Version 1.1.2; Wickham et al., 2023). Data was further grouped and summarised based on the “WISP ID” (and thus WISP-beacon pairing), to assess for variation amongst device identities.

The distance prediction equation for the Type 2 beacons (equation 4.1 - Chapter 4) was applied to the obtained RSSI values for each data row to generate a new variable “BLE Estimated Distance”. A summary of the overall signal strength, and per WISP ID, was generated via the “dplyr” package in R (Version 1.1.2; Wickham et al., 2023). A Kruskal-Wallis and Dunn’s test was conducted to assess whether there was a difference in signal strength between individual WISP-beacon pairings. Within the “working data set” a new variable was generated to specify whether a reported beacon was a ewe’s own beacon or that or a neighbouring sheep. A comparison of RSSI values between a ewe’s own beacon (located within the WISP), and that of neighbouring sheep, was visualised using ggplot2 (Version 3.5.1; Wickham, 2016).

Using the subset of data relating to reports of a ewe’s own beacon only, data was grouped by “Observation ID” and summarised to obtain the number of possible duty cycles per observation (either 3 or 4 duty cycles depending upon the reporting timestamp of the focal ewes’ WISP), and the number of duty cycle in which the ewe’s own beacon was reported.

5.2.6.4 Analysis of focal lamb beacons

The “working data set” was filtered to include rows relating to a ewe reporting its own lambs only. This subset of data was then merged with the observational data set, and a new variable “Beacon Reported” (Yes / No) was generated. Instances where a lamb had not been fully observable for a full duty cycle, or the observer had been unable to determine whether the lamb was one of the focal ewes nearest 15 neighbours, or not, were removed.

A “Distance Group” variable was generated based on the mean observer estimated ewe-lamb distances reported – with classifications of “0-1 m”, “1-2 m”, “2-5 m”, “5-10 m”, “10-20 m”, and “> 20 m”. The proportion of beacons reported within each of these categories was summarised using the “dplyr” package in R (Version 1.1.2; Wickham et al., 2023). The proportion of beacons reported was then assessed in relation to combined “Overall Ewe behaviour” and “Overall Lamb Behaviour” by grouping and summarising the data via the “dplyr” package in R (Version 1.1.2; Wickham et al., 2023). Combined ewe and lamb behaviours for which there were 18 or more observations were then summarised to assess the proportion of beacons reported within each of the “Distance Group” categories.

Comparison of signal strength in relation to the mean observer estimated ewe-lamb distances was visualised using ggplot2 (Version 3.5.1; Wickham, 2016). The distance prediction equation for the Type 3 beacons (equation 4.2 - Chapter 4) was applied to the obtained RSSI values for each data row to generate a new variable “BLE Estimated Distance”. BLE estimated distances were also visualised in relation to the mean observer estimated ewe-lamb distances using ggplot2 (Version 3.5.1; Wickham, 2016). For each of the selected “Combined ewe and lamb behaviours” the signal strength and “BLE Estimated Distance” were similarly visualised using ggplot2 (Version 3.5.1; Wickham, 2016). The “lm” function in R (version 4.2.2; R Core Team, 2022) was then applied to calculate the gradient of the regression line within each behaviour category.

Data was then grouped by “Observation ID” and “Focal Lamb ID” to summarise:

- the number of duty cycles per observation for which data was obtained.
- the number of potential duty cycles in which a lamb could be reported (i.e. the focal lamb was observed to be within the ewe’s nearest 15 neighbours and had a maximum mean observer estimated distance of 42 m across all corresponding duty cycles of the observation period).
- The number of duty cycles in which the focal lamb beacon was reported by the focal ewes’ WISP.

Instances where data was not available for all duty cycles were filtered out, and the remaining data was summarised using the “dplyr” package (Version 1.1.2; Wickham et al., 2023) to compare the number of times a focal lamb’s beacon was reported across consecutive duty cycles (of either 3 or 4 duty cycles depending upon the reporting timestamp of the focal ewes' WISP).

5.3 Results: Ewe-lamb focal observations

5.3.1 Summary of data obtained

BLE data was obtained for 53 of 56 focal observations, due to battery failure in the other three instances. As observations were conducted on twin lambs, data was available relating to 106 individual ewe-lamb focal observations (Table 5.5). Due to the rotation of WISPs between ewes (per study Phase) data was collected from 19 different WISP IDs – with 1-7 observations per WISP.

Table 5.5 Summary of Bluetooth Low Energy (BLE) data obtained for focal observations.

	Ewe Breed		Total
	Lleyn Ewes	Scottish Blackface	
Total no. of focal observations	39	14	53
Total individual ewe-lamb observations	78	28	106
Total no. of unique groups	15	5	20
No. of observations per unique focal group	1-5	2-4	1-5
Age range of lambs (days)	1-34	2-24	1-34

Due to the differing 5-minute duty cycles of each WISP, data from most observations (44 of 53 – 83%) related to a 15-minute observation period – i.e. 3 corresponding timestamps. However, for 9 observations (17 %) timestamps reported such that there were 4 corresponding timestamps – covering the full 20-minute observation. Data was therefore obtained from a total of 168 unique duty cycles.

5.3.1.1 Overall proportion of beacons reported

Of the possible 2 688 beacons that could have been reported (168 duty cycles x 16 beacons per duty cycle), 1 800 (66.96 %) were reported. WISPs always reported a minimum of two beacons, indicating that there was always at least one sheep within BLE range, as it was expected that each ewe's own beacon would be reported at the 1st beacon rank (i.e. its own beacon was closest and thus should have the strongest signal). A minimum of eight beacons, and thus at least seven neighbouring sheep were reported in 125 duty cycles (74 %), whilst 16 beacons were reported in 43 duty cycles (26 %).

5.3.2 Reporting of focal ewe "own" beacons

5.3.2.1 Proportion of beacons reported

Of the 168 duty cycles, a ewe's own beacon was reported in 141 duty cycles (84 %), but failed to be reported in 27 duty cycles. Except for one instance (where a total of 3 beacons were reported), all cases where a ewe's own beacon failed to be reported occurred in duty cycles for which the maximum of 16 beacons were reported by the ewe's WISP. In all instances where a beacon was reported, this was always at the 1st beacon rank, and thus had the strongest signal of any beacon reported in that duty cycle. As WISPs were reallocated at each study phase, there were 39 different WISP-ewe pairings, of which 17 (44 %) resulted in the ewes own beacon failing to be reported at least once during the observation period. On average, WISPs reported their own beacon in 81% of instances, however, the proportion of own beacon reports varied depending on individual WISP ID (Table 5.6) – although there were few data points for some WISPs.

Table 5.6 Summary of "own beacon" reports by wearable integrated sensor platform (WISP) ID.

WISP ID	Total possible “Own beacon” readings	“Own beacon” readings reported
2	3	2 (67%)
4	3	1 (33%)
6	3	2 (67%)
10	6	6 (100%)
11	22	16 (73%)
12	4	4 (100%)
13	6	4 (67%)
14	10	10 (100%)
15	12	9 (75%)
17	3	2 (67%)
18	6	6 (100%)
19	12	12 (100%)
20	6	4 (67%)
21	13	11 (85%)
22	6	4 (67%)
23	11	11 (100%)
24	16	15 (94%)
27	10	10 (100%)
29	16	12 (75%)

5.3.2.2 Signal strength of focal ewe beacons

Overall RSSI values reported for focal ewe beacons ranged from -50 to -14 dBm (range of 36 dBm). However, individual WISP-beacon pairings resulted in ranges of 0 – 12 dBm, and mean range of 3.53 dBm (Figure 5.3) A Kruskal-Wallis test indicated that there was a difference in reported RSSI values of a WISP's own beacon depending upon the WISP-beacon pairing, X^2 (df =18, n=19) = 130.73, p = 2.2×10^{-16}. Post hoc comparisons using Dunn's test (with a Bonferroni correction for multiple tests) found differences between some but not all WISP-beacon pairings.

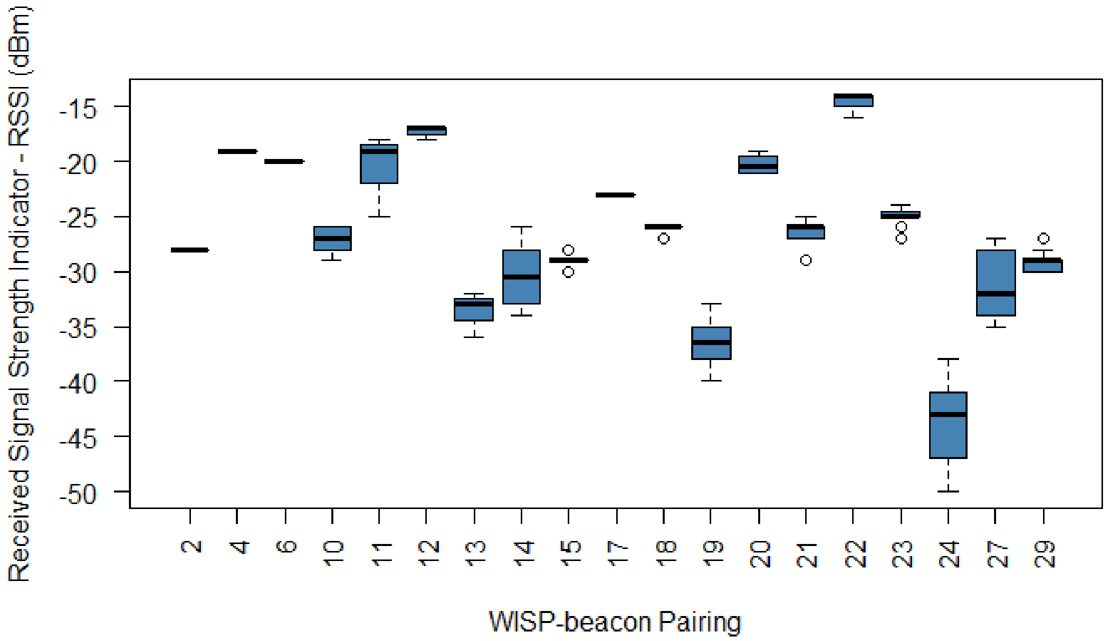


Figure 5.3 Comparison of signal strength reported for a wearable integrated sensor's (WISP's) "own beacon" by WISP-beacon pairing.

However, whilst there was some variation between device pairings, RSSI values of a focal ewe's own beacons were higher than those reported for any neighbouring sheep, which had a mean RSSI of -80.45 dBm and ranged from -92 to -34 dBm (Figure 5.4). There were only 5 of 1637 RSSI readings (0.31 %) from neighbouring sheep which fell within the same signal strength range as a ewe's own beacon. Three of these instances were by the same WISP (WISP ID 29), and in all 5 instances the neighbouring sheep reported was a focal lamb, where in at least one of the five 1-minute observations for the duty cycle the observed ewe-lamb distance was 0 m (ewe and lamb in-contact).

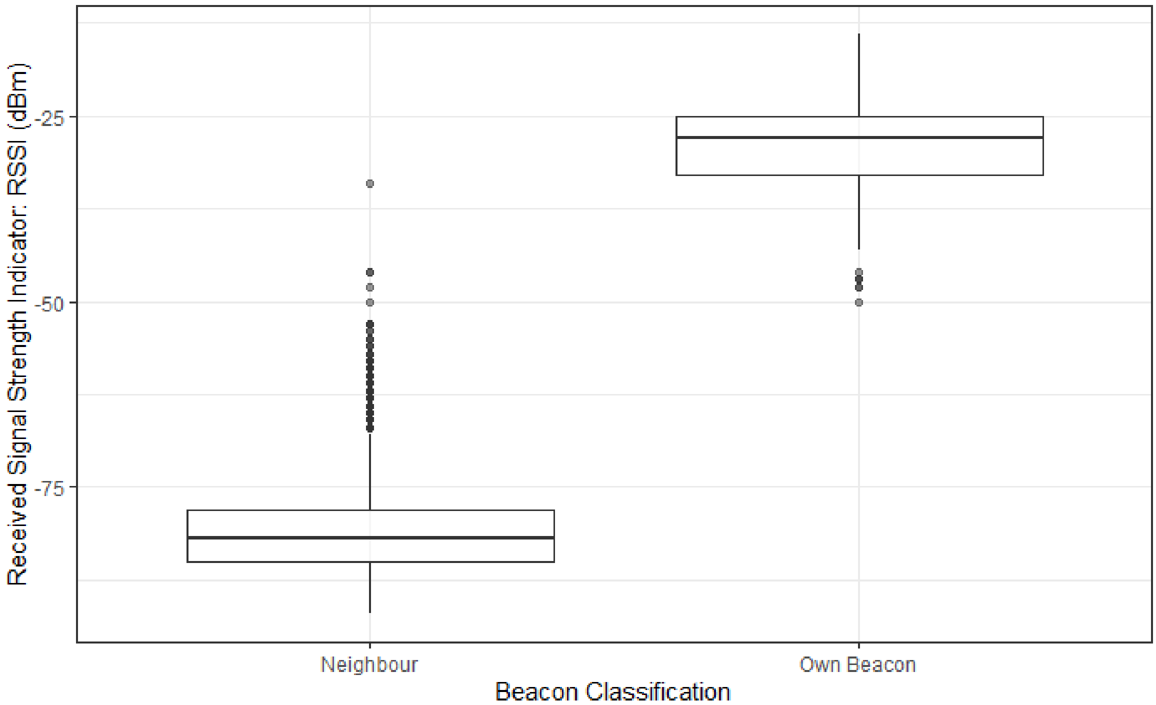


Figure 5.4 Comparison of reported signal strength of a focal ewes own vs neighbouring sheep beacon.

Distance estimates of ewes' own beacons - Type 2 beacons (equation 4.1 - Chapter 4), ranged from 0.02 – 0.82 m, with a mean predicted distance of 0.14 m. When examined based on WISP-beacon pairing, mean predicted distances of "own beacons" ranged from 0.03 to 0.23 m for all except one WISP - WISP ID 24, which had a higher mean predicted distance of 0.48 m.

5.3.2.3 Reporting of beacons over time

The ewe's own beacon was reported across the entire observational period (15 or 20 min depending on whether 3 or 4 duty cycles of data were obtained) in 36 of the 52 (69 %) observations for which data was obtained. Whilst in 16 observations beacons were missed during some duty cycles, there were no instances where the ewe's own beacon was not reported at least once during an observation period (Table 5.7).

Table 5.7 Summary of ewe "own beacon" reports per observation period.

No. of duty cycles for which data was reported	Data obtained for:	
	3 duty cycles (15 min)	4 duty cycles (20 min)
0	0 (0%)	0 (0%)
1	5 (11.63%)	1 (11.11%)
2	8 (18.60%)	1 (11.11%)
3	30 (69.77%)	1 (11.11%)
4	NA	6 (66.67%)
Total duty cycles	43	9

5.3.3 Reporting of focal lamb beacons

5.3.3.1 Proportion of beacons reported

A total of 282 data points (individual lamb duty cycles) remained after filtering. Of these observations, there were 266 instances (94 %) where the lamb was considered to have been within the ewe's nearest 15 neighbours for the full duty cycle and thus, distance dependent (in relation to the BLE range), expected to be reported by the focal ewe's WISP. In the other 16 instances, lambs were observed for the full duty cycle, but at least 15 other sheep were observed to be located between the focal lamb and ewe, and it was therefore expected that these beacons would be reported, rather than that of the focal lamb.

Lambs considered to have been within the focal ewes nearest 15 neighbours, had mean observer estimated distances of 0 – 42 m. These observed distances were considered to be within a reasonable BLE distance range given that the 75 % probability threshold for Type 3 beacons (Chapter 4) was between ~34 – 47.5 m, depending on device height. Lambs considered to be beyond the ewes nearest 15 neighbours also had greater mean observer estimated distances of 42 – 60 m, and thus a reduced probability of being reported. However, a relatively high proportion of lamb beacons were not reported by the focal ewes' WISP even at close distance ranges (Table 5.8). In addition, there were three instances where a focal lamb's beacon was reported when at least 15 other sheep were located between the lamb and focal ewe – including the lamb located at the furthest mean observed distance of 60 m. In all three cases, the "Overall Ewe Behaviour" was categorised as "Grazing", however the "Overall Lamb Behaviour" varied, being either "Lying" (43.4 m), "Playing" (60 m), or "Active" (48 m).

Table 5.8 Reporting of focal lamb beacons in comparison with observer estimated ewe-lamb distances.

Mean observer estimated ewe-lamb distance (m)	No. of data points	Lamb reported	Lamb Not reported
Lamb within focal ewes nearest 15 neighbours:			
0 - 1	77	47 (61 %)	30 (39 %)
1.01 - 2	46	23 (50 %)	23 (50 %)
2.01 -5	46	31 (67 %)	15 (33 %)
5.01 - 10	0	NA	NA
10.01 - 20	44	32 (73 %)	12 (27 %)
20.01 - 42	53	31 (58 %)	22 (42 %)
Lamb beyond focal ewes nearest 15 neighbours:			
42.01 -60	16	3 (19 %)	13 (81 %)
Total	282	167 (59 %)	115 (41 %)

5.3.3.2 Effect of ewe and lamb behaviour on proportion of beacons reported

Of the 266 observations where a focal lamb was considered to have been within the focal ewe's nearest 15 neighbours, the lamb's beacon was reported in 164 instances (62 %). A matrix of the number of observations and number of focal lamb beacons reported, per combined "Overall Ewe Behaviour" and "Overall Lamb Behaviour" is provided in Table 5.9. Ewes were categorised as having five possible overall behaviours, whilst lambs had seven possible categorisations. Whilst for some ewe behaviours the lamb behaviour was variable (i.e. for ewe "Mixed" behaviour, lamb behaviours were recorded in all seven categorises), others appeared to be linked (i.e. when the ewe was "Lying" the lamb was also "Lying" in 91 % of observations).

Given the low number of observations within some ewe-lamb behaviour classifications, the combined effect of distance and sheep behaviour on the proportion of beacons reported was examined for five behaviour classification groups - those with a minimum total of 18 observations (Table 5.10). Some behaviour classifications occurred more frequently at shorter (i.e. ewe lying / lamb lying), or longer (i.e. ewe grazing /lamb lying) distances, whilst others occurred across a range of observer estimated ewe-lamb distances. Within each distance range the proportion of beacons reported differed according to the behaviour classification, in some cases by as much as a 75 %.

Table 5.9 Proportion of focal lamb beacons reported within a duty cycle per ewe-lamb behaviour classification.

Overall Ewe Behaviour	Overall Lamb Behaviour							Total Observations
	Lying	Standing	Walking	Grazing	Inactive	Active	Mixed	
Lying	43 35 (81%)	0	0	0	0	0	4 4 (100%)	47 39 (83%)
Grazing	27 14 (52%)	18 9 (50%)	2 1 (50%)	10 6 (60%)	4 1 (25%)	10 6 (60%)	66 46 (70%)	137 83 (61%)
Inactive	1 0 (0%)	0	0	0	2 1 (50%)	0	3 1 (33%)	6 2 (33%)
Active	2 2 (100%)	0	3 0 (0%)	0	0	2 0 (0%)	16 11 (69%)	23 13 (57%)
Mixed	9 5 (56%)	4 1 (25%)	1 0 (0%)	2 2 (100%)	2 0 (0%)	3 2 (67%)	32 17 (53%)	53 27 (51%)
Total Observations	82 56 (68%)	22 10 (45%)	6 1 (17%)	12 8 (67%)	8 2 (25%)	15 8 (53%)	121 79 (65%)	266 164 (62%)

*Total number of observations in black (i.e. possible no. of focal lamb beacons which could be reported within category), total number (%) of focal lamb beacons reported in blue.

Table 5.10 Proportion of focal lamb beacons reported within a duty cycle based on ewe-lamb behaviour classification and observer estimated distance groups.

Mean observer estimated ewe-lamb distance (m)	Ewe / Lamb Behaviour Classification				
	Ewe Lying / Lamb Lying	**Ewe Grazing / Lamb Lying**	**Ewe Grazing / Lamb Standing**	**Ewe Grazing / Lamb Mixed**	**Ewe Mixed / Lamb Mixed**
0 - 1	26 25 (96%)	1 1 (100%)	NA	NA	17 7 (41%)
1.01 - 2	8 6 (75%)	NA	5 1 (20%)	11 6 (55%)	6 4 (67%)
2.01 -5	2 2 (100%)	2 1 (50%)	5 2 (40%)	17 14 (82%)	2 1 (50%)
5.01 - 10	NA	NA	NA	NA	NA
10.01 - 20	7 2 (29%)	10 6 (60%)	NA	16 15 (94%)	6 5 (83%)
20.01 - 42	NA	14 6 (43%)	8 6 (75%)	16 10 (63%)	1 0 (0%)
Total	43 35 (81%)	27 14 (52%)	18 8 (50%)	66 46 (70%)	32 17 (53%)

*Total number of observations in black (i.e. possible no. of focal lamb beacons which could be reported within category), total number (%) of focal lamb beacons reported in blue.

5.3.3.3 Signal strength of focal lamb beacons

Of the 167 focal lamb beacons reported, RSSI values ranged from -88 to -34 dBm. When applying the BLE prediction equation for Type 3 beacons (equation 4.2 - Chapter 4) this translated to estimated ewe-lamb distances within the range of 0.17 – 33.56 m. A comparison of the mean observer estimated distance in relation to the obtained RSSI values and corresponding BLE distance estimates is shown in Figure 5.5. There was a wide spread in RSSI values obtained at shorter mean observer estimated distances, with a tendency for the prediction equation to overestimate ewe-lamb distance. At greater mean observer estimated distances the prediction equation underpredicted ewe-lamb distance, however, there were much fewer observations at these distances. In addition, the three greatest mean observer estimate distances related to the lamb beacons which were beyond the focal ewes nearest 15 neighbours, and hence not expected to have been reported. The reporting of these beacons therefore represented instances in which the beacon of at least one sheep located closer to the focal ewe failed to be detected by the WISP or produced a lower RSSI than that of the focal lamb.

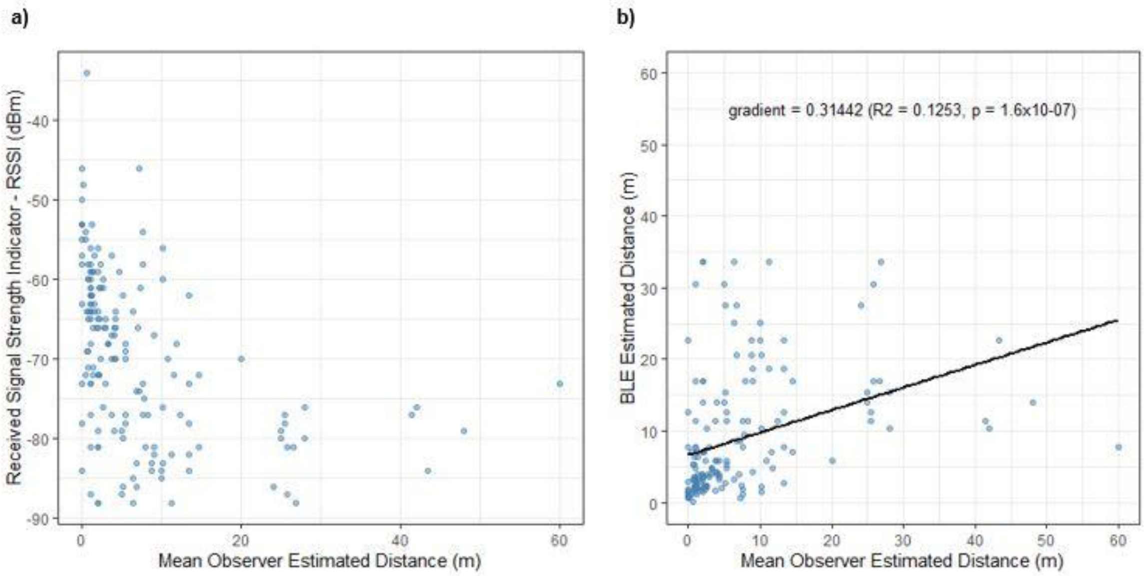


Figure 5.5 Comparison of a) reported signal strength indicator (RSSI) of focal lamb beacons, and b) Bluetooth Low Energy (BLE) estimated ewe-lamb distances, in relation to observer based ewe-lamb distance estimations.

5.3.3.4 Effect of ewe and lamb behaviour on signal strength

The RSSI and distance prediction equations were then assessed in relation to combined ewe and lamb behaviour, using data from the same five ewe and lamb behaviour classifications outlined in section 5.3.3. The large spread in RSSI values was particularly evident when both ewes and lambs were "Lying", especially as all values occurred within a close proximity range (Figure 5.6). In comparison, RSSI values when the ewe was "Grazing" and the lamb was "Standing" were less variable. In addition, there was a more evident decline in RSSI as the mean observer estimated distance increased.

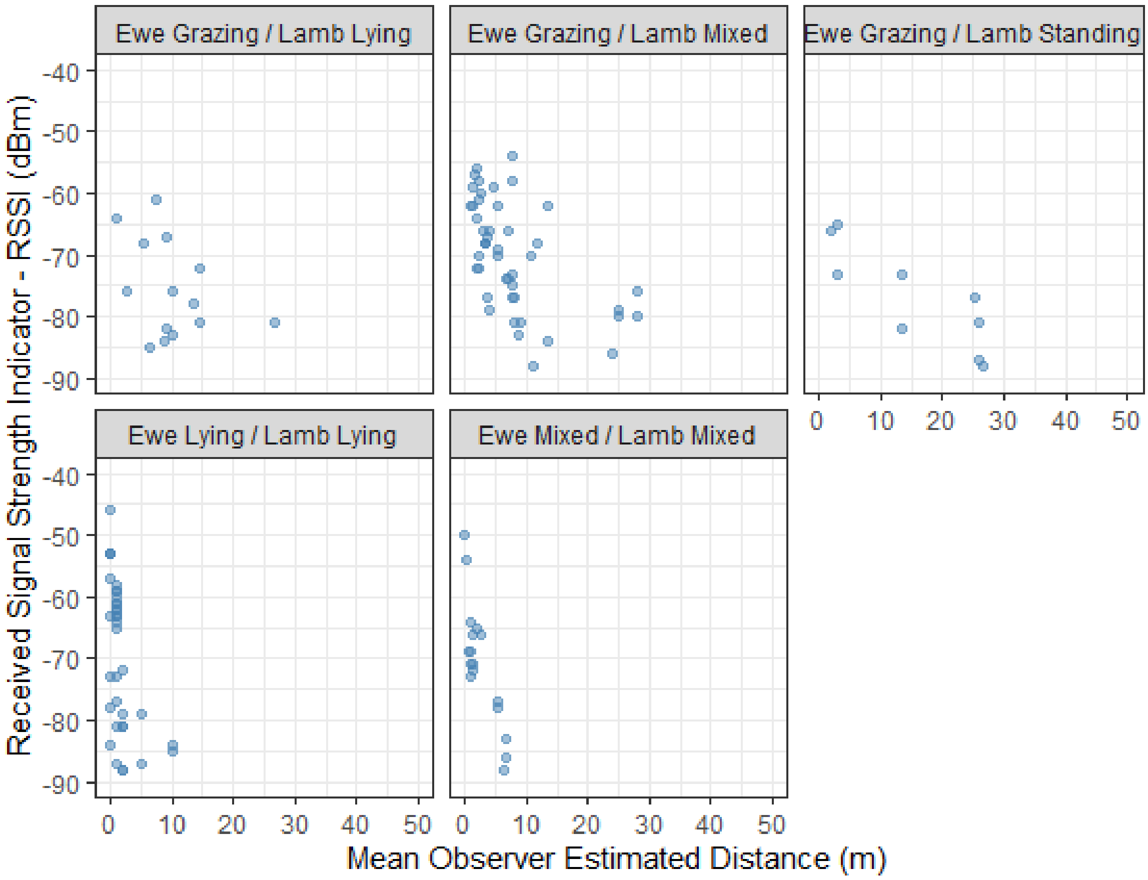


Figure 5.6 Relationship between reported beacon signal strength indicator (RSSI) of a focal lamb's beacon and observer estimated ewe-lamb distances for different ewe-lamb behaviour classifications over a 5-minute duty cycle.

The resulting slopes of the BLE estimated distance in relation to the mean observer estimated distance differed between each of the behaviour categories (Table 5.11). Within both “Ewe Lying / Lamb Lying” and “Ewe Mixed / Lamb Mixed” the resulting slopes were particularly steep with the BLE tending to overestimate the ewe-lamb distance, however, mean observer estimated distances did not exceed 10 m in these instances (Figure 5.7). In all cases where the ewe was classed as “Grazing” the slopes were not as steep, however there was still large variations in BLE estimated distance, with a tendency to underpredict at larger mean observer estimated distances.

Table 5.11 Linear regression of Bluetooth Low Energy (BLE) vs observer estimated ewe-lamb distances for different ewe and lamb behaviour classifications.

Behaviour Classification	No. of Observations	Regression line slope
Ewe Grazing / Lamb Lying	14	0.3459 (R^2 = 0.003816, p = 0.3258)
Ewe Grazing / Lamb Mixed	46	0.5622 (R^2 = 0.2954, p = 5.663 x 10^{-05})
Ewe Grazing / Lamb Standing	8	0.7885 (R^2 = 0.5495, p = 0.01349)
Ewe Lying / Lamb Lying	35	2.2651 (R^2 = 0.2388, p = 0.001703)
Ewe Mixed / Lamb Mixed	17	3.274 (R^2 = 0.7399, p = 5.793 x 10^{-06})

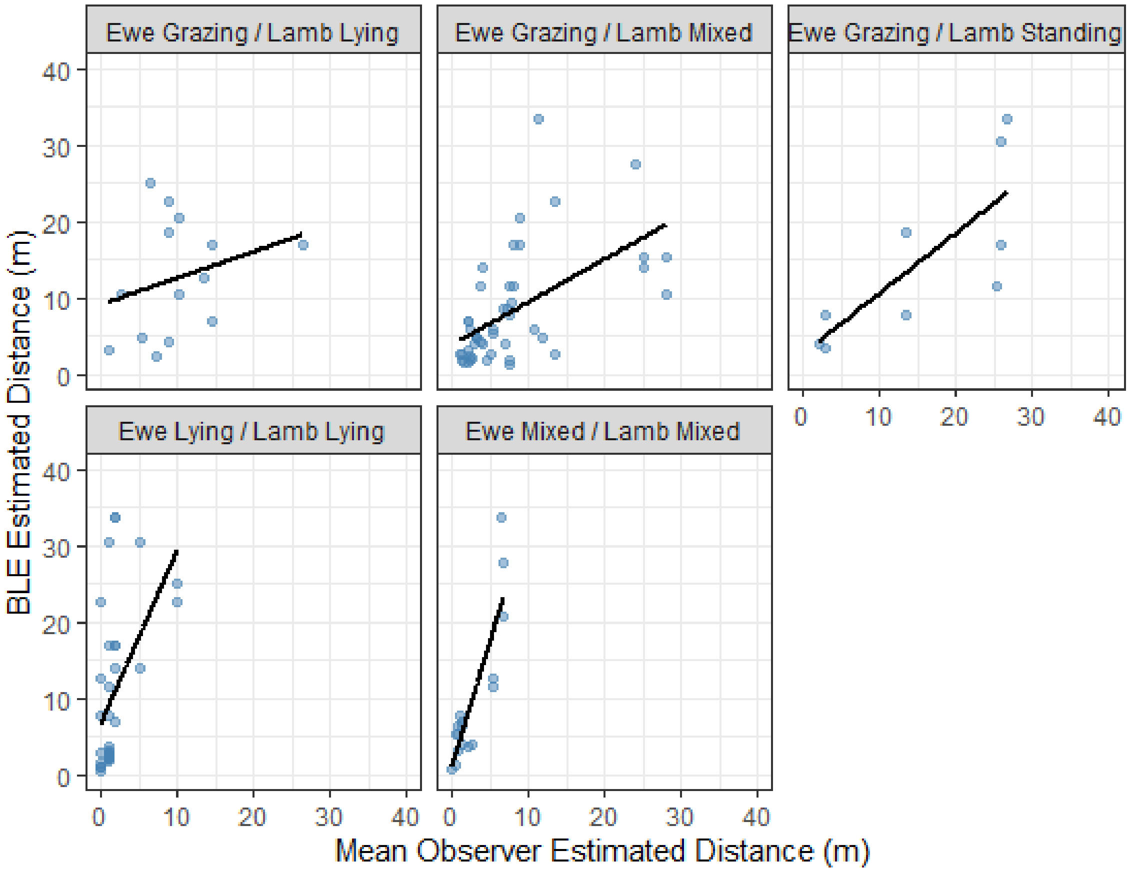


Figure 5.7 Comparison of Bluetooth Low Energy (BLE) estimated, and observer estimated ewe-lamb distances (m) for different ewe-lamb behaviour classifications over a 5-minute duty cycle.

5.3.3.5 Reporting of beacons over time

Of the 106 individual ewe-lamb focal observations for which data was obtained, there were 81 in which the focal lamb had potential to be reported across the entire observational period (15 or 20 min depending on whether 3 or 4 duty cycles of data were obtained). In 12 of the 81 observations (15 %) the focal lamb's beacon failed to be reported across the entire interval. However, in most cases the beacon was reported in at least one duty cycle across a 15 or 20-minute period (Table 5.12).

Table 5.12 Summary of focal lamb beacon reports per observation period.

No. of duty cycles for which data was reported	Data obtained for:	
	3 duty cycles (15 min)	4 duty cycles (20 min)
0	8 (12.31 %)	4 (25.00 %)
1	15 (23.08 %)	2 (12.50 %)
2	21 (32.31 %)	2 (12.50 %)
3	21 (32.31 %)	1 (6.25 %)
4	NA	7 (43.75 %)
Total duty cycles	65	16

In the 8 instances where the beacon failed to be reported in all duty cycles, all "Overall Ewe Behaviour" classifications were observed except for "Inactive", whilst all seven possible "Overall Lamb Behaviours" were observed. Hence, the consecutive failure to report the beacon did not appear to be the result of a specific ewe, lamb, or combined ewe-lamb behaviour. In addition, the mean observed ewe-lamb distance differed between duty cycles of the observation period, in all except one instance – with observer estimated ewe-lamb distances ranging from 0 – 30 m.

5.4 Discussion

Across the focal observation study, at least one neighbouring sheep's beacon was reported in every duty cycle for which data was obtained, and in most cases (74 %) a minimum of seven neighbouring sheep were reported. Within this small flock scenario, the BLE range would therefore appear sufficient in terms of spatial distance between individuals or groups, that occurrence of contacts could be monitored over time. However, applications in larger scale systems may be dependent on the scale over which the flock could disperse and gregariousness of the flock, which can differ between sheep breeds (Hinch, 2017).

Whilst a relatively high proportion of a focal ewes' own beacons were reported, they were expected to have been reported within every duty cycle given that the beacon was located within the WISP, and thus within a few cm of the BLE reader. The failure of ewes' "own beacons" to be reported occurred across multiple WISP-beacon pairings. However, within an observation period (15 or 20 min) a ewe's "own beacon" was always reported in at least one instance, suggesting the issue was related to a temporary interference of the signal. Given that failures mostly occurred when 16 beacons were reported (and thus 15 neighbouring sheep, or more, were within the focal ewe's proximity) – a potential reason for these failures may be related to the higher signal traffic. Large numbers of advertising devices operating within range of a BLE receiver can lead to increased signal collisions and are more likely to occur with increasing transmission frequency and short advertisement intervals (Shan et al., 2017; Tipparaju, 2021). Alternatively, this could indicate an issue with very close proximity between a beacon and reader – however, this was not observed within the calibration studies.

The ewe-lamb distances estimated by the observer were considered to be within a reasonable range over which the BLE could operate based on the device calibrations (Chapter 4). However, it should be noted that the observer estimated ewe-lamb distances will also have a level of error. It was also expected that some beacons may be missed at longer ewe-lamb separation distances as devices reached the edge of their operating range. The proportion of beacons reported was found to vary between distance group classifications, however, the highest proportion of beacons being reported occurred within a range of 10-20 m, whilst a high proportion of beacons failed to be reported at very close observer estimated ewe-lamb distances (as much as 50% at 1-2 m). A study by Huels et al. (2025) which tested BLE proximity loggers in grassland at 0-2 m, also observed a reduction in the number of data points between 0 and 1.5 m, but an increase again at 2 m. Studies investigating the effects of the human body on BLE signals report a large decay in RSSI signals because of absorption due to the high water percentage (Deng et al., 2018). In addition, the orientation of a person's body and placement between the transmitting and receiving device by impact on how signals are affected (Mamun et al., 2019). It would then be expected that sheep bodies would similarly act upon the transmitted BLE signals, and at closer proximities the shadowing effects may be greater, particularly if sheep are positioned in such a way that the line-of-sight is blocked by both the ewe and lamb. One aspect which differed from the calibration is the layer of foam padding surrounding the WISP, which would also contribute to a level of signal interference.

The relationship between distance and the likelihood of a beacon being reported was also associated with the combined ewe and lamb behaviour, and the influence of behaviour on the separation distance between the focal ewe and lamb. For instance, if the ewe was "Lying" then the lamb was also most frequently recorded as "Lying", and this combined behaviour combination was most frequently observed at relatively close ewe-lamb observer estimated distances. In comparison, when the ewe was "Grazing", the lamb's behaviour was more variable, and there were more observations at greater ewe-lamb observer estimated distances. The displayed behaviours and separation distances at which they were expressed, in turn had implications on the signal strength and the relationship between RSSI and distance. Behaviour classifications of "Ewe Lying / Lamb Lying" and "Ewe Mixed / Lamb Mixed" both had particularly steep gradients, resulting from the rapid decline in RSSI over a short observer estimated distance. In addition, particularly, where both individuals were "Lying" there was a high variability in RSSI values. This may be associated with the posture of the animal and the reduced device heights, which as observed within the calibration study, acted to reduce the range over which BLE could effectively operate. In many instances where both individuals were observed "Lying", lambs were positioned with their body next to that of the ewe - with the collar and beacon facing away from the ewe's body, whilst the ewe's WISP was positioned underneath their neck.

In both cases, the devices were also within or close to vegetation. There are then many factors within this context which could contribute to multipath propagation and shadowing, and thus a reduction in signal strength. For other behaviour classifications where the lamb was in an upright posture during at least some duty cycles (e.g. “Standing”, “Mixed”) beacons were reported at greater observer estimated distances and the resulting slopes of the regression were closer to one. However, there was still a tendency for the reported RSSI to result in an overestimation of ewe-lamb distance as observer estimated distance increased. The variability in RSSI across observer estimated distances was also observed (to varying degrees) across behaviour classifications.

5.5 Conclusion

The application of the BLE system to monitor contacts in relation to distance would then appear to be heavily dependent upon the behaviours displayed by both the individual with the transmitting device and the receiving device. The behaviours displayed during a given duty cycle, as well the number of other sheep within proximity, their orientation towards one another, and the broadcasting time of the devices, will all play a role in determining whether a beacon is “seen” and reported by a WISP, and on the signal strength. Interpretation of RSSI into a distance is then complicated by these factors, and for some behaviour classifications would appear to be a poor predictor of distance. For other behaviour classifications BLE based distance estimates are more indicative of observed distances, but still contain a level of variability. Hence depending upon the application, the use of BLE for proximity monitoring may be better suited towards presence /absence. The study demonstrated that whilst beacons would periodically be missed in relation to the above factors, a high number of interactions would still be detected over the course of a day. In terms of monitoring the ewe-lamb relationship, single missed observations and reappearance of the lamb within subsequent intervals would still provide insight into the relationship.

Chapter 6 Analysis of ewe-ewe and ewe-lamb relationships during the lambing and early lactation period using Bluetooth Low Energy (BLE)

6.1 Introduction

The lambing and early lactation period is a stage during which sheep are likely to be more vulnerable to welfare and environmental challenges, with potential to have ongoing implications on animal productivity and welfare (Dwyer and Lawrence, 2005; Fogarty et al., 2021). It is also a period of high activity and evolving dynamics, thus presenting an ideal period in which to investigate the application of Bluetooth Low Energy (BLE) as a monitoring tool in grazing sheep.

Within extensive systems, the often harsh and variable environments, along with less frequent supervision, can result in issues going undetected (Dwyer and Lawrence, 2005). Lamb mortality is a welfare and economic concern (Dwyer and Lawrence, 1998), impacting on farming productivity and profitability. In addition, poor maternal relationships were cited by stakeholders within the TechCare project as one of the main welfare concerns (Morgan-Davies et al., 2024). Within extensive systems a high number of lamb losses can occur between birth and weaning, estimated at approximately 15 % (Temple and Manteca, 2020). Most losses occur during the first three days, with perinatal mortality accounting for between 80-90 % of pre-weaning mortality (Everett-Hincks and Dodds, 2008). A considerable proportion of these losses can be attributed to the Starvation-Mismothering-Exposure (SME) complex, which is more commonly observed in twin or multiple lambs (Haughey, 1991). Lamb performance and survival is dependent on multiple interlinked factors including lamb birth weight, litter size, sex, birth ease, weather conditions at lambing, environment and lambing site characteristics, ewe condition and nutrition during pregnancy, ewe breed and social behaviour, ewe age and parity, and the development of the ewe-lamb bond (Lockwood, 2018). In many extensive systems predation will also contribute to lamb survival which may be influenced not only by predator density, but by maternal behaviour and response to predation – such as flocking behaviours which can differ between breeds (Dwyer, 2009).

Ewe behaviour prior to, during, and after lambing can also have a significant effect on lamb survival (Dwyer and Lawrence, 1998). Early attachment behaviours which promote ewe-lamb recognition encourage exclusive attachment with the lamb and can impact on the quality of subsequent care such as maternal vigilance, frequent sucking interactions, and maintaining a close spatial proximity, which may have implications in later lamb life and lamb survival (Dwyer, 2014). Whilst lamb birth weight is considered the primary factor contributing to lamb survival (Paganoni et al., 2014), optimal birth weights will vary according to the ewe breed, age and size (Hinch and Brien, 2014). In addition, lamb survival and growth rates are typically poorer in primiparous compared with multiparous ewes (Paganoni et al., 2014). Several factors may contribute towards this lower survival, such as lower lamb birth weights, higher rates of dystocia, and longer delivery periods, which in turn may lead to a poorer ewe-lamb bond being established. The ewe-lamb relationship can also change significantly between birth and weaning. Whilst the ewe-lamb bond is considered to remain strong for between 90-100 days, there is a gradual increase in mean ewe-lamb distance (Galeana et al., 2007). Typically, lambs will stay close to their mother during the first weeks, but separation distance will gradually increase until around four weeks of age when lambs spend more time within peer groups (Arnold & Grassia, 1985).

Within extensive systems, human-animal contacts can be infrequent and seasonal (Temple and Manteca, 2020), and sheep will often lamb unsupervised (Waterhouse, 1996). Neonatal survival has been identified as an area of welfare concern, however the provision of shepherding during this period could be considerably valuable (Goddard et al., 2006). The availability and recruitment of skilled labour can however make this challenging, and also represents the highest costs associated with sheep systems (Goddard et al., 2006). Depending upon the type of system, the flock size, scale of dispersal and the availability of labour, the frequency of inspection may then be limited. This can make human intervention during parturition difficult, whilst issues arising post-lambing may go unidentified for a period of time (Goddard et al., 2006; Temple and Manteca, 2020). The development of devices or tools which could allow farmers to monitor ewe-lamb relationships and identify potential issues in real-time could then be particularly beneficial both from a management and welfare perspective (Temple and Manteca, 2020).

The primary objective of this study was to assess the functionality of BLE as a proximity monitoring tool, by determining whether BLE could detect trends and patterns in ewe-ewe and ewe-lamb relationships over the pre-lambing and early lactation period. There were three main goals within this:

1. To investigate the ewe-ewe relationship: whether ewe-ewe contacts and signal strength differed with the lambing stage (pre- / during / post-) of the reporting ewe, and whether this differed between breeds, and between primiparous and multiparous ewes.
2. To investigate the ewe-lamb relationship: to determine if and how the number of BLE contacts and signal strength changed with lamb age, and how this relationship compared based on ewe breed, status (primiparous vs multiparous), and between twin lambs.
3. To investigate welfare and production issues: whether BLE could detect differences in counts and signal strength based on production and / or welfare measures - firstly, investigating the effects of ewe lameness on the number of ewe and lamb contacts reported, and secondly by investigating whether ewe-lamb contacts corresponded to lamb weight change.

6.2 Material and methods

This chapter utilises the full BLE data set obtained from the six-week ewe-lamb study, along with the animal and in-field welfare data, as described in the material and methods section of Chapter 5.

6.2.1 Data collation

The collation of data sets and all further analysis was conducted in R version 2.4.4 (R Core Team, 2020). For each study phase, flash drive data from each individual WISP was combined into a single .csv file, with new variables "WISP ID" and "Study phase" assigned. The data was then lengthened by converting the .csv file from reporting 16 beacons per row, to a single beacon per row, and assigning a new variable "Beacon rank order" based on the position (out of 16) at which the beacon was reported. All rows where no beacon was reported were removed from the data set. Separate "Date" and "Time" variables were then generated from the "Timestamp" variable, before combining data from all three phases into one large working .csv file.

Several new variables were then generated using the "dplyr" package in R (Version 1.1.2; Wickham et al., 2018):

- WISP Animal ID: visual spray-marked ID of the ewe assigned to the reporting WISP.
- WISP Animal breed: breed of the ewe assigned to the reporting WISP.
- Beacon animal ID: visual spray-marked ID of the ewe / lamb assigned to the beacon being reported by the WISP.
- Beacon animal breed: breed of the ewe / lamb assigned to the beacon being reported by the WISP.
- Ewe status: classification of the ewe assigned to the reporting WISP – classed as either "Primiparous" (1^{st} lambing) or "Multiparous" (ewe previously lambed).
- Lambing status: classification of the ewe assigned to the reporting WISP's lambing stage, defined as either "pre-lambing", "lambing", or "post-

lambing”. Where “lambing” encompassed a 3-day period from the day prior to the day following the date on which lambing was noted / presumed, and pre- and post-lambing included all data prior to / after this phase.

These were generated by joining the data set with separate .csv files containing the assignment of WISPs and beacons during each phase; joined based on the date, WISP or Beacon ID, and date of lambing.

Weather data including daily precipitation (mm), minimum, maximum and mean temperature (°C) were obtained for the study period from the Met Office: Kirkton (Tyndrum No. 3) Met Office weather station (grid ref. NN 35949 28385; 170 m.a.s.l.). It should be noted that daily measurements were here reported from 09:00 to 09:00 the following day. For the purposes of the study, daily measurements were considered to be for the single date on which the measurement began and thus merged with the lambing data set (using this date) accordingly.

6.2.2 Data analysis ewe-ewe relationships

Ewes that did not lamb (three ewes) or who were permanently removed from the study following lambing (four ewes) were not included in any further analysis.

The reporting of ewe beacons was summarised using the “dplyr” package in R (Version 1.1.2; Wickham et al., 2023), with counts and RSSI values visualised using “ggplot2” package (Version 3.5.1; Wickham, 2016). Differences between the reporting of “own” and “neighbouring ewe” beacons were tested using Welch’s t-test. Analysis of the effects of lambing status and other potential factors (ewe breed and ewe status) on the number of ewe-ewe contacts and RSSI values were conducted using a mixed-effects model (MEM), using the “lme4” package in R (Version 1.1-35.5; Bates et al., 2015), with Gaussian distribution, whereby the ewe ID was included as a random effect.

6.2.3 Data analysis ewe-lamb relationships

Analysis of ewe-lamb relationships focused on contacts between a dam and own lambs only. The data set was therefore filtered to include instances of a lamb beacon being reported by its dam only. Where fewer than three days' worth of data was available for a ewe-lamb pairing, this data was excluded from further analysis. Data relating to single lamb (one instance), or where data was only available for one twin lamb of a ewe-lamb group, were also removed.

The relationship between ewe-lamb contacts and lamb age was visualised using ggplot2 (Version 3.5.1; Wickham, 2016). Analysis of the effects of lamb age, and additional factors (ewe breed, ewe status, and lamb birth weight) on the number of ewe-lamb beacon readings reported per day was conducted using a mixed-effects model (MEM), using the "lme4" package in R (Version 1.1-35.5; Bates et al., 2015), with Gaussian distribution, where Ewe ID, Lamb ID, and the interaction of Ewe ID and Lamb age were included as a random effect. Two MEM models were then generated; the first including a linear term for lamb age, the second including a polynomial term for lamb age using the "poly" function from R base (version 4.2.2; R Core Team, 2022). An ANOVA was then conducted to compare and select the most appropriate model. The model output was displayed visually using the "ggeffects" package (version 2.2.1; Lüdecke, 2018).

6.2.4 Analysis of ewe-ewe and ewe-lamb relationships in relation to production and welfare measures

Whilst weekly in-field welfare measures included lameness, fleece and dag scores, only lameness will be discussed further, as several observations of both lame and non-lame ewes were recorded.

6.2.4.1 Effects of ewe lameness on ewe-ewe contacts

The effects of ewe lameness on ewe-ewe contacts used a subset of the data from the "neighbouring ewe" data set in section 6.2.2. Data was selected from the 21st

April – 30th May (a total of 30 study days, where devices were on animals). Data was summarised using the “dplyr” package in R (Version 1.1.2; Wickham et al., 2018) to generate a new variable “mean no. of neighbours reported” per day, per ewe ID. A lamb age variable was then generated based on lambing date, whereby day 0 related to the day of lambing, and pre-lambing days were represented by a negative number. As lameness scores were recorded every Friday, a variable “lameness status” was assigned based on study day for a weeklong period running from the Tuesday prior to the day of lameness assessment, to the Monday after the day of lameness assessment (under the assumption that changes in lameness status occurred approximately halfway between each assessment. The effect of lameness on the mean number of ewe-ewe contacts in relation to lamb age was then assessed using a mixed-effects model (MEM), using the “lme4” package in R (Version 1.1-35.5; Bates et al., 2015), whereby ewe ID was a random effect.

6.2.4.2 Effects of ewe lameness on ewe-lamb contacts

The effects of ewe lameness on ewe-lamb contacts were similarly conducted on a six day subset of the “ewe-lamb” data set described in section 6.2.3 using the same process as described above.

6.2.4.3 Effects of ewe-lamb contacts on lamb daily weight gain

Using the ewe-lamb data set from section 6.2.3, the “dplyr” package in R (Version 1.1.2; Wickham et al., 2023) was used to summarise the mean daily number of ewe-lamb contacts per ewe-lamb pair. The daily weight gain for each lamb was calculated based on the weight change (kg) between a lamb’s birth weight (obtained within 24 hours of birth) and weight at the study end. A MEM, using the “lme4” package in R (Version 1.1-35.5; Bates et al., 2015) was used to assess the effects of mean ewe-lamb contacts on lamb daily weight gain. This also considered the effects of ewe breed (Lleyn or Scottish Blackface) and ewe status (primiparous or multiparous), as well as ewe ID (as a random effect).

6.3 Results

From the filtered data set a total of 1 284 271 individual BLE beacon readings were obtained across 128 819 duty cycles, based on data from 32 ewes: 22 Lleyn and 10 Scottish Blackface. As the number of WISPs available and the assignment of WISPs to ewes differed across study phases, the number of data points obtained varied between individual ewes (Table 6.1). Weather data from the study period is summarised in Table 6.2.

Table 6.1 Summary of data obtained per ewe.

	Minimum	Maximum	Mean
Days of data obtained	3.00	28.00	14.44
Mean no. of duty cycles reported per day	229.80	288.00	276.08
Total number of duty cycles in which data was reported	864.00	7890.00	4025.59
Total proportion of possible duty cycles in which data was reported	79.72%	100.00%	95.82%
Total number of BLE beacon readings reported	8290.00	89671.00	41441.34
Mean number of BLE beacons reported per duty cycle	7.08	13.38	9.88
Mean RSSI (dBm)	-72.36	-79.09	-75.95
Total range in RSSI (dBm)	60.00	82.00	72.88

All ewes reported between 1-16 beacons within a duty cycle, with beacons reported at all 16 possible slots in 25 093 of 128 819 duty cycles (19.48 %). Lleyn ewes reported a higher overall mean of 10.33 beacons per duty cycle (SD = 4.71), in comparison with Scottish Blackface ewes, which reported a mean of 9.28 beacons per duty cycle (SD = 4.70); t (89 418) = 37.958, p < 0.001 (Welch's t-test).

Table 6.2 Summary of weather data over study period.

	Min	Max	Mean
Precipitation (mm)	0.00	40.40	5.68
Mean daily temp °C	6.15	12.60	10.02
Total dry days	15		
Total rain days	17		

*Data obtained from: Met Office Automatic weather data - Kirkton (Tyndrum No.3) Met Office weather station: grid ref. NN 35949 28385, 170 m.a.s.l.

6.3.1 Analysis of ewe-ewe relationships pre-, during, and post-lambing

Of the 32 ewes for which data was obtained, 28 ewes produced lambs and remained within the study for the full six-week duration. Further ewe-ewe analysis will therefore focus on these 28 ewes.

6.3.1.1 Summary of ewe beacons reported

A total of 663 205 BLE readings of beacons assigned to ewes were obtained over the course of the study, from 121 006 unique WISP duty cycles. Of these readings, 100 450 (15.15 %) related to a ewe reporting its own beacon (contained within its assigned WISP). Whilst ewes' reported their own beacon in most instances, there were some duty cycles in which they were not reported (Table 6.3). When a ewe's WISP did report its own beacon, RSSI values were typically much higher (thus the signal was stronger) than those reported for neighbouring ewe beacons (Figure 6.1).

Table 6.3 Summary of ewe beacons reported per duty cycle.

Beacon Type Reported	No. of duty cycles (of 121 006)	Proportion of duty cycles (%)
"Own" beacon only	8 533	7.05
Neighbouring ewe beacons only	20 556	16.99
"Own" beacon + neighbouring ewe beacons	91 917	75.96

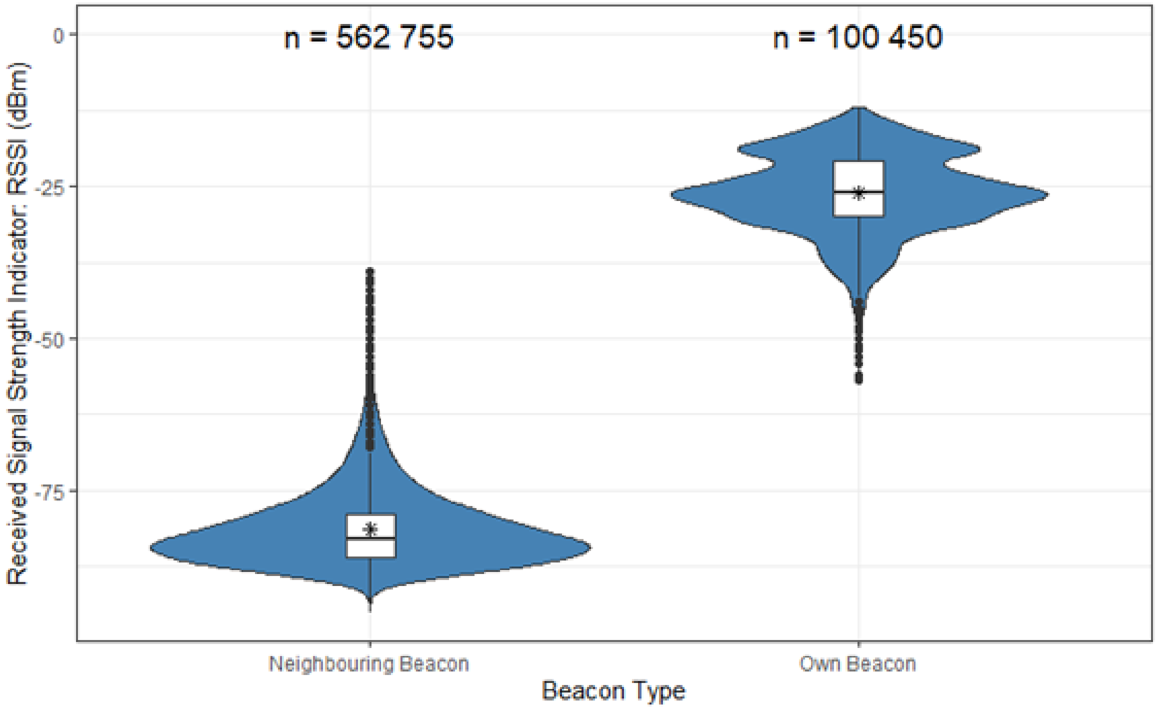


Figure 6.1 Comparison of received signal strength indicator (RSSI) values reported for a ewes own beacon and that of a neighbouring ewe beacon.

The mean is indicated by the star, whilst the boxplot indicates the median, 1st and 3rd quartiles.

From the 112 473 duty cycles during which neighbouring ewe beacons were reported, a total of 562 755 individual ewe-ewe BLE readings were obtained, based on WISP data from 28 ewes (20 Lleyn and 8 Scottish Blackface). An overall mean of 5.00 neighbouring ewes were reported per duty cycle, however, the Lleyns ewes reported a greater mean of 5.17 (SD = 3.02), in comparison to 4.65 (SD = 2.82) for the Scottish Blackface ewes; t (73 449) = 28.127, $p < 0.001$ (Welch's t-test). The mean number of neighbouring ewes reported also differed based on ewe status, with multiparous ewes reporting a greater mean of 5.14 (SD = 3.00) neighbouring ewe beacons, in comparison to primiparous ewes, which reported a mean of 4.77 (SD = 2.89) neighbouring ewe beacons per duty cycle; t (90 629) = 20.905, $p < 0.001$ (Welch's t-test).

6.3.1.2 Ewe-ewe contacts based on lambing status

A summary of available data on ewe-ewe contacts, based on the reporting ewes lambing status is given in Table 6.4.

Table 6.4 Summary of neighbouring ewe beacons reported based on lambing status of the reporting ewe.

	Lambing Status		
	Pre-Lambing	**Lambing**	**Post-Lambing**
No. reporting sheep	14	12	25
Min no. duty cycles per ewe	153	165	253
Max no. duty cycles per ewe	3080	857	6587
Mean no. duty cycles per ewe	1408.43	564.50	3439.24
Min average no. of neighbouring ewes reported per ewe	4.94	2.97	3.53
Max average no. of neighbouring ewes reported per ewe	8.70	8.72	7.45
Mean average no. of neighbouring ewes reported per ewe	6.74	5.67	4.73
Mean average RSSI (dBm) per ewe	-80.54	-81.20	-81.57

The mean number of ewe-ewe contacts reported per ewe differed according to the lambing phase (Figure 6.2). All except two ewes (E25 and E7, both Lleyn) reported a greater number of ewe-ewe contacts per duty cycle during pre-lambing compared with lambing and post-lambing. A MEM, where the ewe ID was a random effect, indicated that there was a reduction in the number of ewe-ewe contacts between pre-lambing to lambing, and post-lambing, and that the number of ewe-ewe contacts differed according to the ewe breed (Table 6.5). Within both breeds the mean number of ewe-ewe contacts declined from pre-lambing to lambing, and lambing to post-lambing, however, the mean number of contacts was also lower in Scottish Blackface compared within Lleyn ewes across all three phases (Figure 6.3).

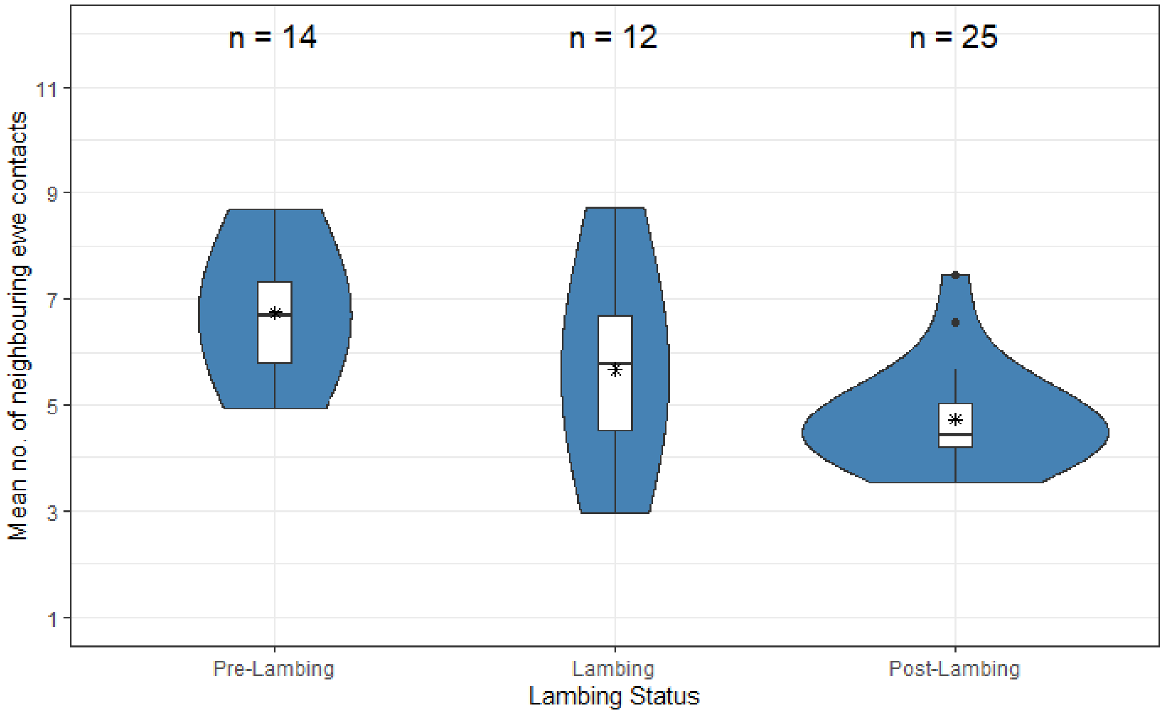


Figure 6.2 Mean number of ewe-ewe contacts reported per ewe, based on lambing status.

The mean is indicated by the star, whilst the boxplot indicates the median, 1st and 3rd quartiles.

Table 6.5 Summary of mixed effects model (MEM) output for number of ewe-ewe contacts based on lambing phase.

Parameter	Average no. ewe-ewe contacts		
	Estimate	**CI**	**p-value**
Intercept	6.7616	6.18 – 7.34	< 0.001
Lambing status:			
Pre-lambing	Reference lambing status		
Lambing	-1.1965	-1.85 – -0.54	0.001
Post-lambing	-2.0412	-2.64 – -1.44	< 0.001
Ewe breed:			
Lleyn	Reference ewe breed		
Scottish Blackface	-0.8637	-1.71 – -0.02	0.045
Random effects			
[1] σ^2	0.65		
[2] $\tau_{00\ \text{Ewe ID}}$	0.54		
[3] ICC	0.45		
[4] $N_{\text{Ewe ID}}$	28		
Observations	51		
[5] **Marginal R^2**	0.430		
[6] **Conditional R^2**	0.688		

[1] Residual variance: the variability unexplained by the model parameters (fixed effects).
[2] Random intercept variance: between group variance.
[3] Intraclass correlation coefficient: quantifies the proportion of variance explained by Ewe ID.
[4] Total number of observations.
[5] Variance explained by fixed effects.
[6] Variance explained by fixed and random effects.

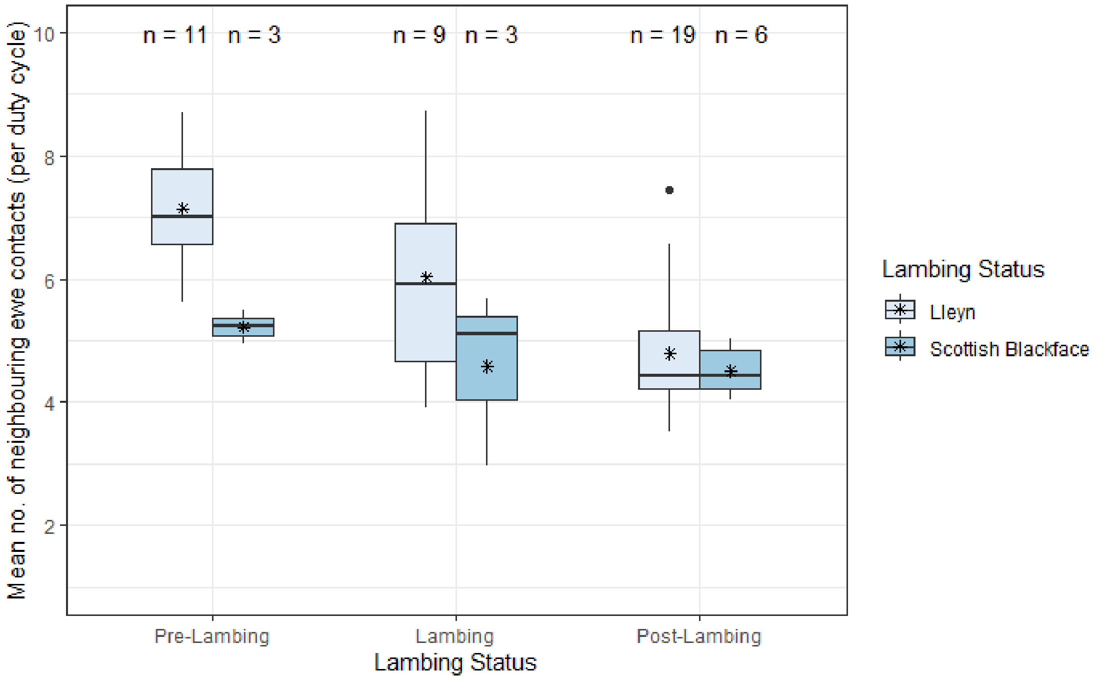


Figure 6.3 Mean number of ewe-ewe contacts reported per ewe, according to lambing status and breed.

The mean is indicated by the star, whilst the boxplot indicates the median, 1st and 3rd quartiles.

The mean RSSI values reported for neighbouring ewes similarly declined across lambing stages (Figure 6.4). A MEM, where the ewe ID was a random effect, indicated that there was a small but significant reduction in the mean RSSI between pre-lambing to lambing, and post-lambing, (Table 6.6). Applying the developed distance prediction equations (Chapter 4) to the mean RSSI values results in an overall increase in mean ewe-ewe distance of 4.50 m (from 27.44 to 31.94 m) across the three lambing status phases using the Type 2 beacon, and 3.36 m (from 19.63 to 22.99 m) using the Type 3 beacon.

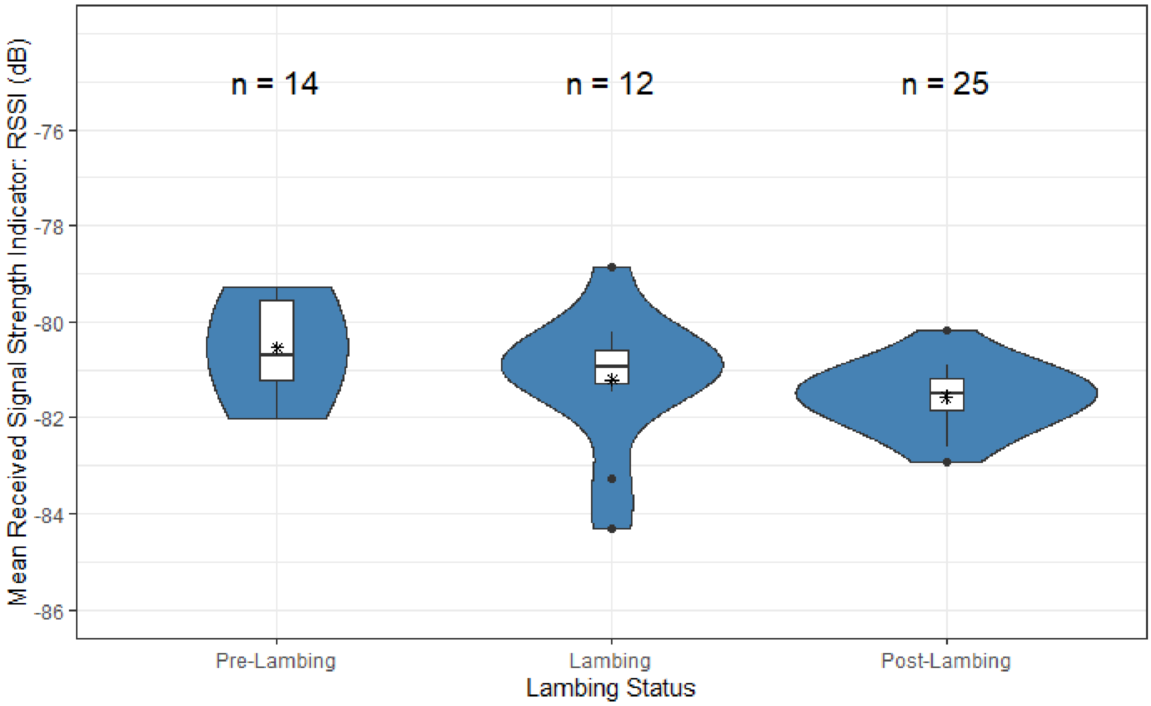


Figure 6.4 Mean RSSI of neighbouring ewes, according to lambing status.

The mean is indicated by the star, whilst the boxplot indicates the median, 1st and 3rd quartiles.

Table 6.6 Summary of mixed effects model (MEM) output of mean neighbouring ewe RSSI in relation to lambing phase.

Parameter	Average no. ewe-ewe contacts		
	Estimate	**CI**	**p-value**
Intercept	-80.5183	-80.98 – -80.06	< 0.001
Lambing status:			
Pre-lambing	Reference lambing status		
Lambing	-0.7327	-1.28 – -0.18	0.010
Post-lambing	-1.0010	-1.49 – -0.51	< 0.001
Random effects			
[1] σ^2	0.45		
[2] $\tau_{00\ \text{Ewe ID}}$	0.37		
[3] ICC	0.45		
[4] $N_{\text{Ewe ID}}$	28		
Observations	51		
[5] Marginal R^2	0.181		
[6] Conditional R^2	0.553		

[1] Residual variance: the variability unexplained by the model parameters (fixed effects).
[2] Random intercept variance: between group variance.
[3] Intraclass correlation coefficient: quantifies the proportion of variance explained by Ewe ID.
[4] Total number of observations.
[5] Variance explained by fixed effects.
[6] Variance explained by fixed and random effects.

6.3.2 Analysis of ewe-lamb relationships

Data relating to 21 ewes and their twin lambs was yielded from the filtered data set. As WISPs were reallocated to ewes between study phases, the number of days data and lamb ages for which data was obtained differed between ewe-lamb pairings. A summary of the data obtained is given in Table 6.7.

Table 6.7 Summary of ewe-lamb data obtained.

	Total	Lleyn	Scottish Blackface
Total No. of ewes with available data	21	15	6
Total no. lambs / ewe-lamb pairings	42	30 *15 sets of twins	12 *6 sets of twins
Total beacon readings obtained	97483	61810	35673
Min no. of days data per ewe-lamb pair	3	3	8
Max no. of days data per ewe-lamb pair	26	24	26
Mean no. of days data per ewe-lamb pair	14.05	13.20	16.17
Lamb-age range	1-44 days	1-39 days	1-44 days
No. multiparous ewes	13	10	3
No. primiparous ewes	8	5	3

6.3.2.1 Relationship between ewe-lamb contacts and lamb age

The total number of ewe-lamb contacts per day differed according to the lamb's age. The number of ewe-lamb contacts per day was typically high at young lamb ages (1-4 days old) with a steady decline in contacts until ~14 days old. The mean number of contacts per day then ranged from 133-167 contacts per day, before increasing again at approximately 24 days old (Figure 6.5). The mean signal strength was similarly the highest (strongest) when lambs were 1-3 days old and declined from approximately -67 dBm to -71 dBm from 1-15 days old. Between lamb ages of 16-44, mean RSSI values fluctuated between approximately -71 to -68 dBm (Figure 6.6). When translated into an estimated distance using the overall Beacon Type 3 prediction equation (equation 4.2, Chapter 4) ewe-lamb distances ranged from 0.002 – 154.42 m. However, for 93 934 of the 97 483 beacon readings obtained (96.36%) estimated ewe-lamb distances were less than 50 m, and in 86 957 of 97 483 instances (89.20 %) less than 30 m. This resulted in an overall mean ewe-lamb estimated distance of 10.79 m, whilst mean estimated distances per lamb age ranged from approximately 6-14 m.

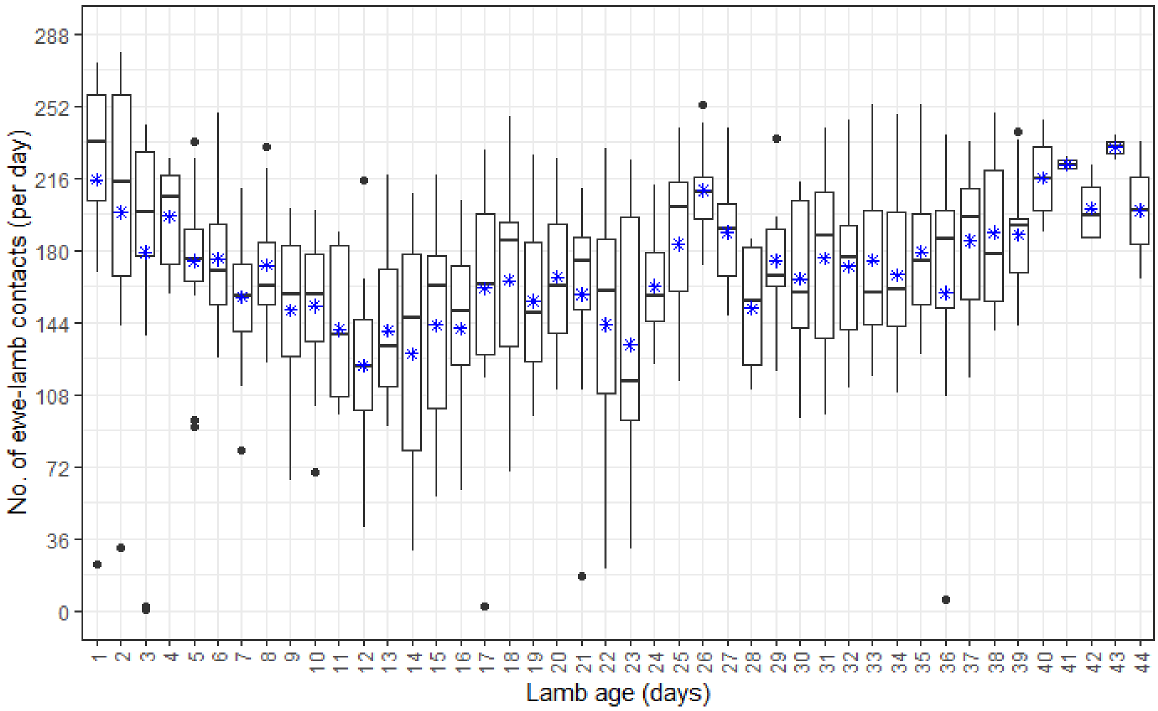


Figure 6.5 Daily number of ewe-lamb contacts (of a maximum 288) in relation to lamb age (based on 2-25 ewe-lamb pairings per lamb age).

The mean is indicated by the star, whilst the boxplot indicates the median, 1st and 3rd quartiles.

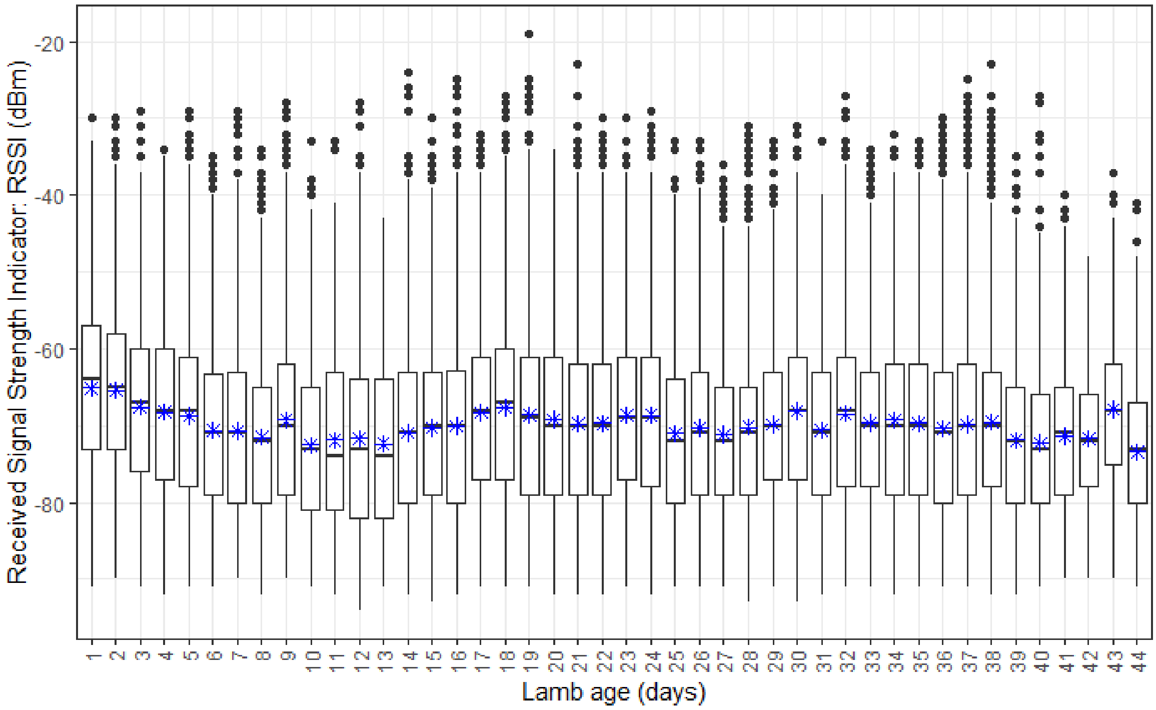


Figure 6.6 Received signal strength indicator (RSSI) values reported for contacts with a ewe's own lamb, based on lamb age.

The mean is indicated by the star, whilst the boxplot indicates the median, 1st and 3rd quartiles.

The relationship between the number of ewe-lamb contacts per day was modelled over lamb age (days) in relation to ewe breed and parity, as well as lamb birth weight (kg). A comparison of a two mixed effects models (MEMs) indicated that a polynomial regression for lamb age provided a better fit than a linear regression for lamb age (p = 8.462 x 10-8) and was selected for use. The model indicated that the interaction of lamb age, ewe breed, ewe status, and lamb birth weight all influenced the daily number of ewe-lamb contacts (Table 6.8). Model predictions for the number of daily ewe-lamb contacts across increasing lamb age (days), for both ewe breeds and parities in relation to three selected lamb birth weights (2.5, 3.5, and 4.5 kg), are presented in Figure 6.7.

Table 6.8 Summary of mixed effects model (MEM) output for number of ewe-lamb contacts per day.

Parameter	Daily no. ewe-lamb contacts		
	Estimate	**CI**	**p-value**
Intercept	140.3372	28.13 – 252.54	**0.014**
Lamb age [1st degree]	-645.0925	-2293.98 – 1003.80	0.443
Lamb age [2nd degree]	-415.1309	-2355.38 – 1525.11	0.674
Lamb birth weight (kg)	6.7630	-23.95 – 37.47	0.665
Ewe breed:			
Lleyn	Reference ewe breed		
Scottish Blackface	27.5259	-175.72 – 230.77	0.790
Ewe status:			
Primiparous	Reference ewe status		
Multiparous	-69.3549	-234.85 – 96.14	0.411
Lamb age [1st degree] x Lamb birth weight (kg)	192.7753	-259.05 – 644.60	0.402
Lamb age [2nd degree] x Lamb birth weight (kg)	254.5868	-294.52 – 803.69	0.363
Lamb age [1st degree] x Ewe breed (Scottish Blackface)	-647.1743	-2568.48 – 1274.13	0.508
Lamb age [2nd degree] x Ewe breed (Scottish Blackface)	2092.3854	-23.37 – 4208.14	0.053
Lamb age [1st degree] x Ewe status (Multiparous)	2456.9942	527.22 – 4386.76	**0.013**
Lamb age [2nd degree] x Ewe status (Multiparous)	906.2142	-1297.82 – 3110.25	0.420
Lamb birth weight (kg) x Ewe breed (Scottish Blackface)	-2.6211	-56.14 – 50.90	0.923
Lamb birth weight (kg) x Ewe status (Multiparous)	12.7217	-30.08 – 55.53	0.560

Ewe breed (Scottish Blackface) x Ewe status (Multiparous)	179.9007	-144.01 – 503.81	0.276
Lamb age [1st degree] x Lamb birth weight (kg) x Ewe breed (Scottish Blackface)	124.0200	-385.41 – 633.45	0.633
Lamb age [2nd degree] x Lamb birth weight (kg) x Ewe breed (Scottish Blackface)	-559.7412	-1146.11 – 26.63	0.061
Lamb age [1st degree] x Lamb birth weight (kg) x Ewe status (Multiparous)	-633.3671	-1147.83 - -118.90	**0.016**
Lamb age [2nd degree] x Lamb birth weight (kg) x Ewe status (Multiparous)	-323.6149	-926.21 – 278.98	0.292
Lamb age [1st degree] x Ewe breed (Scottish Blackface) x Ewe status (Multiparous)	-2082.2161	-4647.80 – 483.36	0.111
Lamb age [2nd degree] x Ewe breed (Scottish Blackface) x Ewe status (Multiparous)	-3408.1007	-6108.06 - -708.15	**0.013**
Lamb birth weight (kg) x Ewe breed (Scottish Blackface) x Ewe status (Multiparous)	-49.6242	-140.19 – 40.94	0.282
Lamb age [1st degree] x Lamb birth weight (kg) x Ewe breed (Scottish Blackface) x Ewe status (Multiparous)	726.4722	-12.90 – 1465.84	0.054

Lamb age [2nd degree] x Lamb birth weight (kg) x Ewe breed (Scottish Blackface) x Ewe status (Multiparous)	951.6696	168.57 – 1734.78	**0.017**
Random effects			
[1] σ^2	244.12		
[2] τ_{00} Ewe ID x Lamb age	991.72		
[2] τ_{00} Lamb ID: Ewe ID	667.43		
[2] τ_{00} Ewe ID	576.20		
[3] ICC	0.90		
[4] N Lamb ID	42		
[4] N Ewe ID	21		
[4] N Ewe ID x Lamb age	314		
Observations	589		
[5] Marginal R^2	0.212		
[6] Conditional R^2	0.922		

[1] Residual variance: the variability unexplained by the model parameters (fixed effects).
[2] Random intercept variance: between group variance.
[3] Intraclass correlation coefficient: quantifies the proportion of variance explained by Ewe ID.
[4] Total number of observations.
[5] Variance explained by fixed effects.
[6] Variance explained by fixed and random effects.

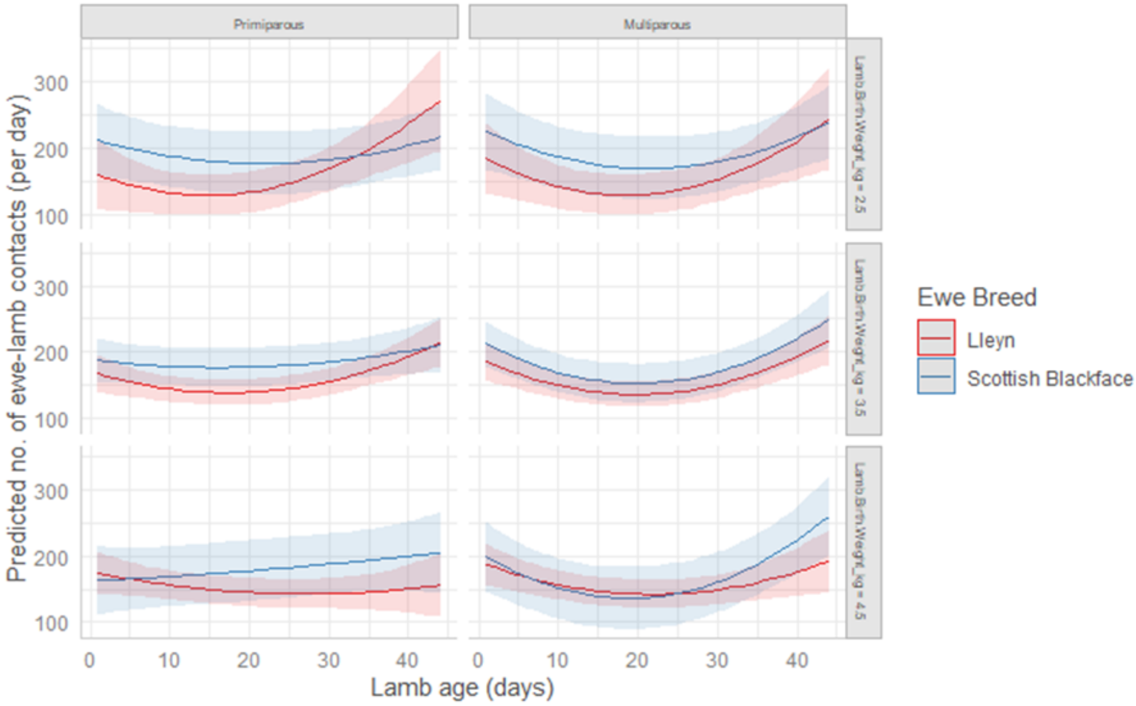


Figure 6.7 Number of daily ewe-lamb contacts per lamb age based on mixed effects model (MEM).

6.3.2.2 Comparison of ewe-lamb contacts between twin lambs

The daily difference in the number of ewe-lamb contacts between twin lambs is summarised in Table 6.9. The number of ewe-lamb contacts per day between a dam and both lambs tended to be similar, with an overall mean difference of 27.33 and median difference of 12.63 contacts. In most ewe-lamb groupings (17 of 21 – 81 %), the mean difference between twins ranged from 7.60 - 17.33 contacts. However, there were two instances where there was a particularly large difference in mean contacts between lambs, for Ewe ID's E12 and E20. This is likely due to very few, or in the case of E20, no beacon readings, being reported for one of the lambs on some days.

The difference in daily ewe-lamb contacts between twins differed according to the ewe breed. There was a greater difference in ewe-lamb contacts between twin lambs of Scottish Blackface ewes, which reported a mean difference of 35.87 contacts (SD = 65.61), in comparison to Lleyn ewes, which reported a mean difference of 17.62 contacts (SD = 24.21); t (106.99) = -2.6239, p = 0.00996 (Welch's t-test). Daily ewe-lamb contacts also differed based on ewe status, with primiparous ewes reporting a mean difference of 31.73 contacts (SD = 60.25) and multiparous ewes reporting a mean difference of 18.20 contacts (SD = 25.16); t (142.78) = -2.2868, p = 0.0237 (Welch's t-test).

Table 6.9 Comparison of daily ewe-lamb contacts between twin lambs.

Ewe ID	Ewe Breed	Ewe Status	No. of days data	Difference in lamb birth weights (kg)	Mean difference in daily ewe-lamb contacts	Min difference in daily ewe-lamb contacts	Max difference in daily ewe-lamb contacts	SD difference in daily ewe-lamb contacts
E2	Lleyn	Primiparous	8	3.0	11.87	0	24	9.23
E4	Lleyn	Multiparous	19	0.6	12.63	2	38	9.39
E5	Lleyn	Primiparous	5	0.2	7.60	0	15	5.77
E6	Lleyn	Multiparous	21	0.4	17.33	0	42	14.91
E9	Lleyn	Primiparous	13	0.1	12.15	2	24	7.45
E12	Lleyn	Multiparous	3	0.2	128.00	1	207	111.07
E14	Scottish Blackface	Multiparous	8	0.3	10.63	2	32	10.86
E16	Lleyn	Multiparous	11	0.6	14.91	4	41	12.64
E17	Lleyn	Primiparous	16	0.2	15.13	0	62	16.29
E20	Scottish Blackface	Primiparous	18	0.5	137.72	2	247	98.53
E21	Scottish Blackface	Primiparous	26	0.7	12.50	2	30	9.61
E22	Lleyn	Multiparous	14	0.5	7.67	0	14	5.61
E23	Lleyn	Multiparous	24	0.2	9.96	1	29	9.22
E28	Lleyn	Multiparous	7	0.2	40.14	16	63	19.06
E29	Lleyn	Multiparous	7	0.4	9.72	1	28	9.11
E31	Lleyn	Multiparous	19	0.4	15.32	1	55	15.39
E34	Lleyn	Primiparous	22	0.5	9.36	0	34	8.95
E35	Lleyn	Multiparous	9	0.5	59.11	45	80	10.73
E36	Scottish Blackface	Multiparous	26	0.3	9.19	0	32	7.63
E37	Scottish Blackface	Multiparous	9	0.4	15.78	2	33	10.58
E38	Scottish Blackface	Primiparous	8	1.4	17.25	2	68	21.14

6.3.3 Analysis of ewe-ewe and ewe-lamb relationships in relation to production and welfare measures

6.3.3.1 Effects of ewe lameness on ewe-ewe contacts

A total of 406 observations were obtained from 28 different ewes; 20 Lleyn and 8 Scottish Blackface, which is summarised in Table 6.10. Nineteen of the 28 ewes were recorded as sound across the full study period, whilst nine were recorded as lame across part the study.

Table 6.10 Summary of data obtained for ewe-ewe contacts relation to ewe lameness.

	Total	Ewe Breed	
		Lleyn	Scottish Blackface
No. unique ewe IDs	28	20	8
Total no. of observations	406	274	132
No. ewes lame (for at least 3 days)	9	5	4
Lamb age range	-15 – 42	-9 – 37	-15 – 42
Min no. of ewes reporting per lamb age	1	1	1
Max no. of ewes reporting per lamb age	14	11	5
Mean no. of ewes reporting per lamb age	7	5.83	2.36

A MEM found that the daily mean number of ewe-ewe contacts was influenced by the interaction of lamb age and ewe breed, and the lameness status of the ewe (Table 6.11). Across both breeds, ewes which were lame tended to display a lower mean number of ewe-ewe contacts in comparison with non-lame ewes at that lamb age. A simplified GAM showing the relationship between the mean number of ewe-ewe contacts across increasing lamb age, and according to ewe lameness status, is presented in Figure 6.8.

Table 6.11 Summary of mixed effects model (MEM) output of daily mean no. of ewe-ewe contacts in relation to lamb age and lameness.

Parameter	Mean no. ewe-ewe contacts		
	Estimate	**CI**	**p-value**
Intercept	6.2344	5.89 – 6.58	< 0.001
Lamb age	-0.0659	-0.08 – -0.06	< 0.001
Lameness Status:			
Not lame	Reference lameness status		
lame	-0.7034	-0.97 – -0.44	< 0.001
Ewe breed:			
Lleyn	Reference lambing status		
Scottish Blackface	-0.8228	-1.46 – -0.19	0.011
Lamb age x Ewe breed (Scottish Blackface)	0.0243	0.01 – 0.04	0.008
Random effects			
[1] σ^2	0.74		
[2] $\tau 00_{\text{Ewe ID}}$	0.46		
[3] ICC	0.38		
[4] $N_{\text{Ewe ID}}$	28		
Observations	406		
[5] Marginal R^2	0.391		
[6] Conditional R^2	0.624		

[1] Residual variance: the variability unexplained by the model parameters (fixed effects).
[2] Random intercept variance: between group variance.
[3] Intraclass correlation coefficient: quantifies the proportion of variance explained by Ewe ID.
[4] Total number of observations.
[5] Variance explained by fixed effects.
[6] Variance explained by fixed and random effects.

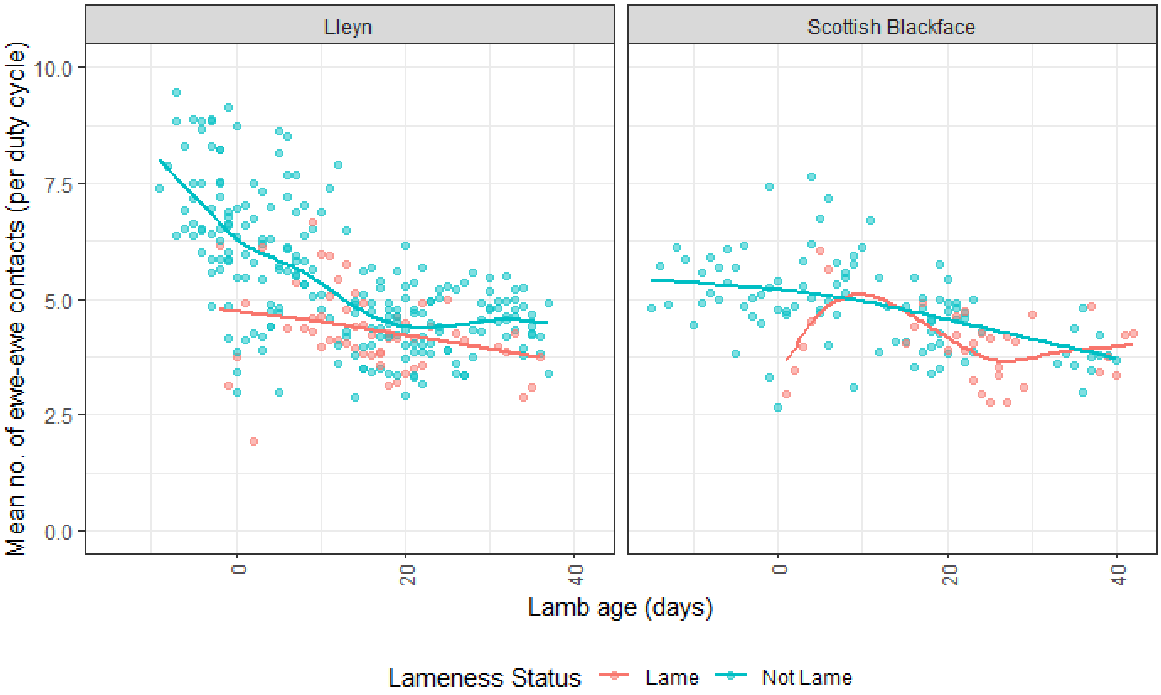


Figure 6.8 Number of daily ewe-ewe contacts per lamb age with fitted Generalised additive model (GAM), in relation to lameness status and ewe breed.

6.3.3.2 Effects of ewe lameness on ewe-lamb contacts

A summary of the subset of data relating to contacts between a ewe and her own lambs in relation to the ewes lameness status is provided in Table 6.12. Data was obtained for lamb ages of 1-42 days old, where a minimum of one ewe, thus two lambs was reported at each lamb age.

Table 6.12 Summary of data obtained for ewe-lamb contacts relation to ewe lameness.

	Total
Total no. ewes	21
Total no. lambs	42
Total no. of observations	546
Lamb age range	1 – 42
Min no. of observations per lamb age	1
Max no. of observations per lamb age	14
Mean no. of observations per lamb age	7
Min no. of lame ewes per lamb age	1
Max no. of lame ewes per lamb age	9
Mean no. of lame ewes per lamb age	3.55

A MEM indicated that the daily mean number of ewe-lamb contacts (where ewe and lamb ID were a random factor) differed in relation to the interaction between lamb age and birth weight, as well as the lameness status of the ewe (Table 6.13). Ewes which were classed as lame tended to report a higher mean number of ewe-lamb contacts per day in comparison with non-lame ewes across the observed lamb age range. A simplified GAM (based on ewe lameness status only) shows the overall relationship between the daily number of ewe-lamb contacts with increasing lamb age (Figure 6.9).

Table 6.13 Summary of mixed effects model (MEM) output of daily mean no. of ewe-lamb contacts in relation to lamb age and lameness.

Parameter	Mean no. ewe-ewe contacts		
	Estimate	**CI**	**p-value**
Intercept	101.4515	46.81 – 156.09	< 0.001
Lamb age	2.3569	0.44 – 4.28	0.016
Lamb birth weight (kg)	13.8230	-0.17 – 27.82	0.053
Lameness Status:			
Not lame	Reference lameness status		
lame	14.7455	4.83 – 24.66	0.004
Lamb age x Lamb birth weight (kg)	-0.5685	-1.08 – -0.06	0.030
Random effects			
[1] σ^2	1459.68		
[2] $\tau 00_{\text{Ewe ID}}$	900.00		
[3] ICC	0.38		
[4] $N_{\text{Ewe ID}}$	21		
Observations	546		
[5] **Marginal R^2**	0.030		
[6] **Conditional R^2**	0.400		

[1] Residual variance: the variability unexplained by the model parameters (fixed effects).
[2] Random intercept variance: between group variance.
[3] Intraclass correlation coefficient: quantifies the proportion of variance explained by Ewe ID.
[4] Total number of observations.
[5] Variance explained by fixed effects.
[6] Variance explained by fixed and random effects.

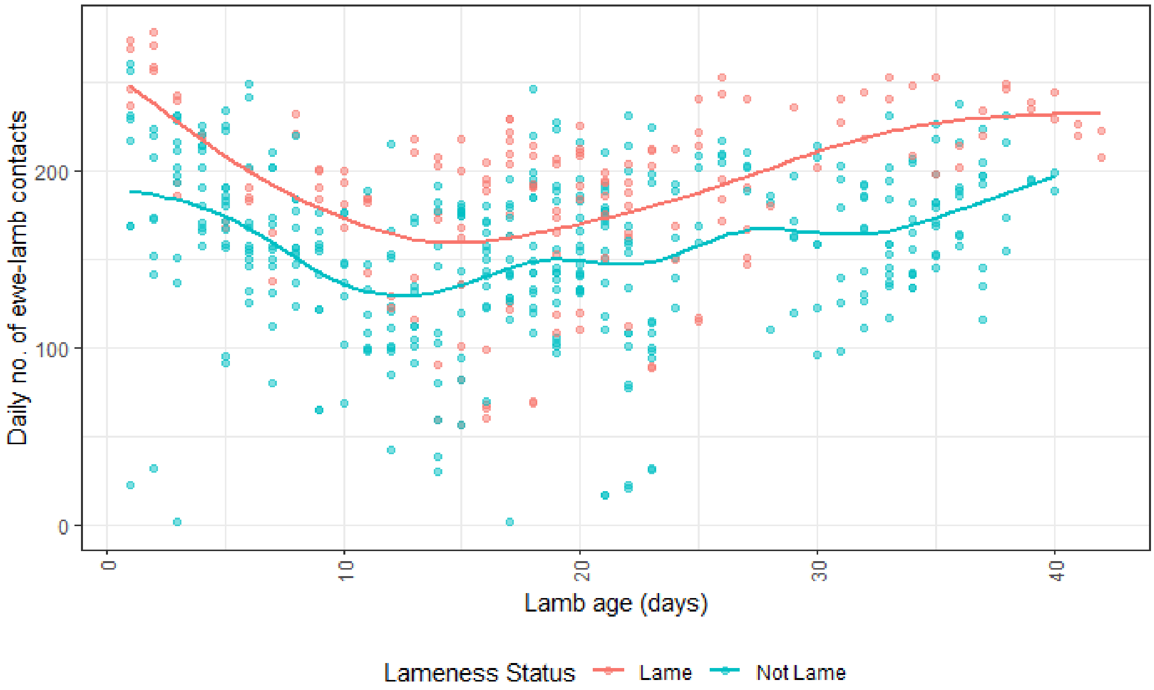


Figure 6.9 Number of daily ewe-lamb contacts per lamb age with fitted Generalised additive model (GAM), in relation to lameness status.

6.3.3.3 Do ewe-lamb contacts relate to lamb weight change?

A MEM indicated that the mean daily number of contacts, and the interaction of ewe breed and status, had an effect on lamb daily weight gain (Table 6.14). However, lamb daily weight gain was typically higher in Lleyn as opposed to Scottish Blackface ewes, with means of 0.26 kg (SD = 0.07) and 0.21 kg (SD = 0.04) respectfully. Lamb daily weight gain was also found to be higher in multiparous ewes, with a mean of 0.28 kg (SD = 0.07), compared with primiparous ewes, with a mean of 0.20 kg (SD = 0.04). The relationship between mean daily number of ewe-lamb contacts and lamb daily weight gain is displayed in Figure 6.10.

Table 6.14 Summary of mixed effects model (MEM) output for number of ewe-lamb contacts per day.

Parameter	Lamb Daily Weight Gain		
	Estimate	**CI**	**p-value**
Intercept	0.1189	0.04 – 0.19	0.003
Mean daily no. of contacts	0.000503	0.00 – 0.00	0.022
Ewe breed:			
Lleyn	Reference ewe breed		
Scottish Blackface	0.0047	-0.06 – -0.07	0.877
Ewe status:			
Primiparous	Reference ewe status		
Multiparous	0.1049	0.06 – -0.15	< 0.001
Ewe breed × Ewe status:			
Lleyn × Primiparous	Reference ewe breed and ewe status		
Scottish Blackface × Multiparous	-0.0963	-0.18 – -0.02	0.021
Random effects			
[1]σ^2	0.0023		
[2]$\tau 00_{\text{Ewe ID}}$	0.0044		
[3] ICC	0.1584		
[4] $N_{\text{Ewe ID}}$	21		
Observations	42		
[5] **Marginal R^2**	0.483		
[6] **Conditional R^2**	0.565		

[1] Residual variance: the variability unexplained by the model parameters (fixed effects).
[2] Random intercept variance: between group variance.
[3] Intraclass correlation coefficient: quantifies the proportion of variance explained by Ewe ID.
[4] Total number of observations.
[5] Variance explained by fixed effects.
[6] Variance explained by fixed and random effects.

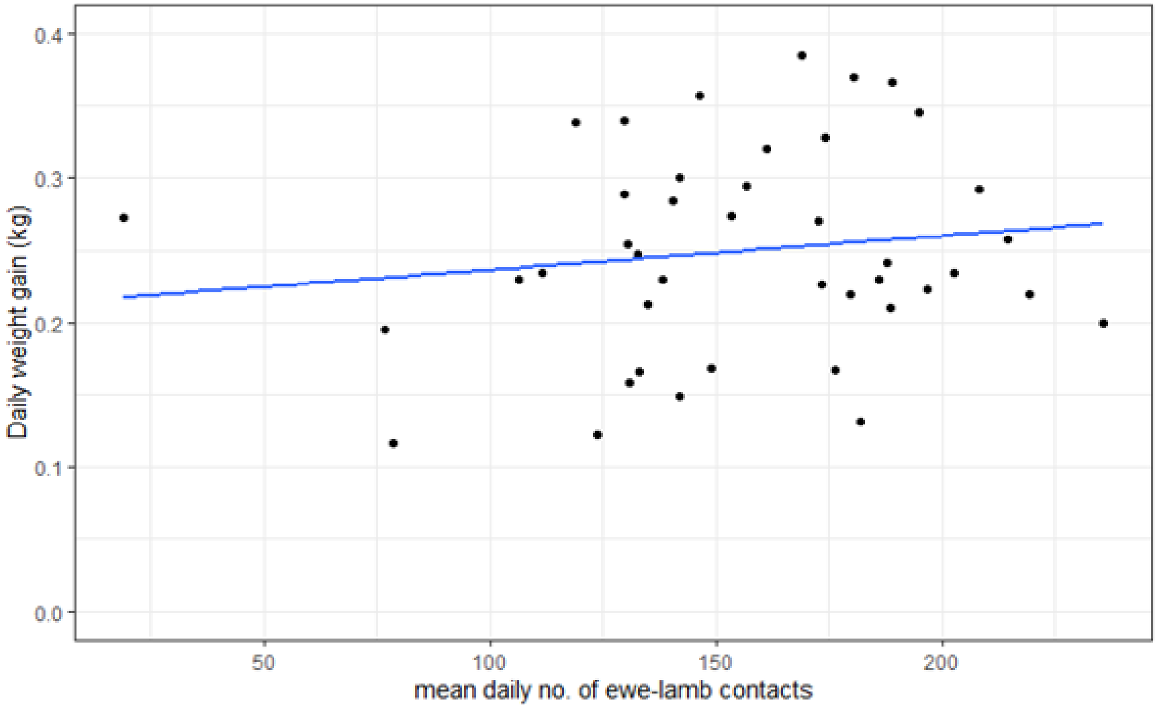


Figure 6.10 Lamb daily weight gain in relation to mean number of daily ewe-lamb contacts.

6.4 Discussion

6.4.1 BLE detection of ewe-ewe contacts and relationship patterns

The WISP-beacon system demonstrated that BLE could detect changes in ewe-ewe contact patterns across the study period. Ewe-ewe contacts declined between the pre-lambing to lambing, and lambing to post-lambing phases. Other PLF sensors, such as accelerometers, have also demonstrated behavioural and postural changes in ewes at parturition (Fogarty et al., 2020). Whilst sheep are usually highly gregarious, ewes will retreat from the flock to give birth and often remain segregated for several hours following parturition (Lindsay et al., 1990). This separation is considered an important factor in contributing to lamb survival, as the absence of other ewes may promote the ewe-lamb bond and lamb recognition of the ewe (Dwyer and Lawrence, 2005). However, the inclination to isolate and length of separation differs between breeds and parities (Dwyer and Lawrence, 2005). This was observed within the study, with Scottish Blackface ewes reporting fewer ewe-ewe contacts than Lleyn ewes, not only during lambing, but across all phases. The continued reduction in ewe-ewe contacts post-lambing, by both breeds, fits with previous sheep contact network studies, where ewe-ewe contacts were reduced when lambs were present within the flock, particularly for ewes with newborn as opposed to almost weaned lambs (Norton et al., 2012).

6.4.2 BLE detection of ewe-lamb contacts and relationship patterns

The WISP-beacon system also illustrated a change in ewe-lamb dynamics with increasing lamb age and time from parturition. The MEM indicated that the number of ewe-lamb contacts reported by the BLE differed according to the interaction of lamb age, lamb birth weight, ewe breed, and ewe parity. However, whilst the interaction of these multiple factors was found to be significant, the plotted predicted values of the number of ewe-lamb contacts per lamb age showed a similar overall trend across breeds and parities, for the three selected lamb birth weights. Although, there was also a typically higher predicted number of ewe-lamb contacts in Scottish Blackface, as opposed to Lleyn, across all groups.

The strongest mean RSSI values for ewe-lamb contacts were recorded at lamb ages of 1-3 days, resulting in a close mean BLE estimated distance of 6.82 m during this period. There was also a high number of ewe-lamb contacts during this period, which is in line with previous studies, as lambs typically remain close to their dam following birth (Arnold and Grassia, 1985). Ewe-lamb pairs have also been reported to remain in close proximity for the first week after birth (Arnold and Grassia, 1985). The RSSI values reported indicated that lambs remained in relatively close proximity throughout the lamb ages observed (1-44 days), with mean BLE estimated distances ranging from approximately 6-14 m depending on lamb age. However, the study did find a decline in the number of contacts between lamb ages of 1-14 days, followed by an increase in contacts again at approximately 24 days old. The period where the lowest number of ewe-lamb contacts were observed (lamb ages 12-23 days) does coincide with the period (aged 2-3 weeks) during which peer contacts and play behaviours have been reported to peak (Sachs and Harris, 1978). This trend was observed within the model for both breeds; however, the curve was more apparent in multiparous ewes. In addition, contacts are dependent on multiple associated factors including ewe nutrition, environmental conditions, the lambing process, and the expression of maternal and neonate behaviours (Dwyer and Lawrence, 1998), thus individual variation would be expected to occur between ewe-lamb pairings.

The litter size can also influence the ewe-lamb relationship, with multiple born lambs often having a lower association with their dam than single-born lambs, but close association with their siblings (Ozella et al., 2022). Multiple born lambs have been observed to spend large proportions of time in close proximity with one another, often developing high levels of synchronisation in activities (Galeana et al., 2007; Abecia et al., 2022). For instance, as lambs get older, ewes may only allow twins to suckle when both lambs are present (Galeana et al., 2007). At the same time, higher levels of separation and maternal abandonment have been reported in twin lambs, with breed and parity both thought to contribute to the incidence of this occurring (Alexander et al., 1983). Within this study, the mean number of contacts between ewes and lambs tended to be comparable for both twins - in most instances differing by less than 20 contacts per day. The similarity in ewe-lamb contacts reported by the BLE, fits with the visual observations

(Chapter 5) and in-field welfare assessments conducted, where twin-lambs were typically observed to be in close proximity (within a few metres of one another).

Whilst there was greater variation in ewe-lamb contacts between twins of Scottish Blackface ewes, this may be a result of the smaller number of Scottish Blackface ewes compared with the Lleyn ewes, and one particularly large difference in ewe E20. However, the BLE system also detected a difference in the number of contacts between twins of primiparous and multiparous ewes, which would suggest ewe-lamb contacts are more variable between twins during the first parity.

The two instances where particularly high variation occurred between twins (ewes E12 and E20), is thought to be a result in this instance of contact issues between the WISP and beacon rather than an indication of ewe-lamb separation, as during all visual observations (Chapter 5) and in-field welfare assessments the pairings were observed within relatively close proximities and comparable ranges with other pairings. Given the effects of sheep behaviour and device height on the likelihood of a WISP reporting a beacon, and impact on signal strength (Chapters 4 and 5), it is likely that there will be instances where lambs are within the vicinity of their dam but are not reported by the ewes WISP. However, the very low counts observed in some cases are suggestive of beacon failure or failure to connect with the WISP, rather than signal interference. There were also a further three instances where a beacon failed to be reported not only by a focal ewe, but by any WISP during a full study phase. As two of these beacons were reported in an earlier phase, this would suggest a failure of the beacon, or loss of battery.

Given the availability of WISPs and assignment across phases, data was not available for all pairings across all lamb ages. Whilst the focus of this study was on investigating whether BLE could detect changes in contact patterns, understanding the individual variation in contacts of healthy ewe-lamb pairings (in relation to breed, parity, and lamb age) would be required to establish an expected contact range before BLE could be applied as a potential alert of a possible issue. Based on the effects of behaviour on the translation of RSSI into distance (Chapter 5), it is unlikely that RSSI estimates would be reliable enough to be utilised, or at the very most would need to be based on broad distance ranges. However, an expected number of contacts per day (within a range), or maximum length of time without contact (dependent on lamb age) could be a feasible option.

6.4.3 Investigation of BLE contacts in relation to production / welfare measures

The WISP-beacon system indicated that ewe-ewe and ewe-lamb contacts were altered in ewes which were lame. Affected ewes reported a reduced number of neighbouring ewes per duty cycle but tended to report a higher number of contacts with their own lambs per day in comparison with ewe-lamb interactions of non-lame ewes. In addition, the mean signal strength of ewe-lamb contacts was greater in lame ewes, suggesting that lambs were typically in closer proximity than lambs of non-lame ewes. Previous sensor-based studies (Lewis et al., 2023) have reported behavioural differences between lame and non-lame ewes, whereby lame ewes displayed a greater proportion of inactive behaviours, as did their lamb(s). The study also found that increased inactivity in ewes and lambs resulted in a greater number of ewe-lamb contacts. Within the focal observations of this study (Chapter 5), ewe and lamb behaviour often appeared to be linked, particularly when "lying", when the ewe-lamb distance was typically < 10 m. Thus, if lameness results in increased periods of inactivity, such as "lying", then increased ewe-lamb contacts would likely be detected by BLE. There could then be potential for BLE contacts to act as an indicator of lameness (or other welfare issue). However, as contacts also differed between breeds, parity, and lamb age, consideration may also need to be given to these factors to determine an appropriate stage for an alert, where the number of contacts deviates from an expected level.

The results of the study also suggest that ewe-lamb contacts could be indicative of lamb daily weight gain, with greater ewe-lamb contacts typically resulting in a greater weight gain. Preweaning performance is considered to be the most important phase of lamb growth, and period during which the largest daily liveweight gains can be achieved (Gascoigne and Lovatt, 2015). Lamb growth and weight gain can be influenced by several variables, including litter size, dam age and parity, sire and dam breed, lamb sex, as well as ewe milk production (influenced by ewe nutrition during pregnancy) and concentration of protein (Gascoigne and Lovatt, 2015; Lima et al., 2019). However, the milk supply provided by the ewe is considered to be the main determinant of lamb growth during the first few weeks (Ewbank, 1967), with milk yield peaking between 2-4 weeks after lambing. Between 4-6 weeks lambs begin to consume forage, and by 8-weeks milk accounts for only a small proportion of their energy intake (Gascoigne and Lovatt, 2015). The higher number of contacts could be associated with increased suckling and thus a potentially greater milk intake, leading to increased growth. A positive correlation between suckling behaviours and milk yield has previously been reported (Hinch, 1989). Higher daily weight gain in lambs has also been associated with lambs and dams spending a greater proportion of time performing inactive behaviours (Price et al., 2022). As observed within Chapter 5, instances where both ewes and lamb were lying typically occurred at short distances ranges, and hence there may be more opportunity for beacons to be detected. The relationship between the number of contacts and growth rates also differed between ewe breeds and parities. Whilst there were a small number of observations within some groups, the data was suggestive that lamb weight gain was greater in multiparous ewes, who had maternal experience.

6.4.4 Conclusion

The WISP-beacon system demonstrated that BLE is capable of detecting patterns and relationships based on the daily count of beacon readings reported. The mean number of neighbouring ewes was found to decline at onset of lambing, and further reduced after lambing, which may be indicative of segregation from the flock at parturition, and display of maternal attachment behaviours. Decreased ewe-ewe contacts and increased ewe-lamb contacts were also associated with lame ewes. In addition, the BLE system demonstrated changes in the number of ewe-lamb contacts in relation to lamb age, with very similar daily counts obtained between twins, who typically display high levels of synchronisation. BLE could then potentially be used to detect when ewe-lamb contacts deviate from an expect range, acting to alert farmers to a potential issue. High contacts between ewes and lambs were also related with a higher daily weight, thus monitoring contacts could also have benefits in terms of production.

Chapter 7 Discussion

This thesis identified BLE as an emerging low-cost, low-energy device, worthy of investigation as a potential PLF tool to assist farmers in production and welfare monitoring within sheep grazing systems. However, BLE has been reported to be a noisy measure of proximity and distance, and information regarding the range and signal strength in grass / vegetative systems is limited (Luciani and Davis, 2013; Mathew et al., 2017), particularly within the context of a field grazing environment. The thesis therefore aimed to investigate the relationship between BLE signal strength and distance within a field environment using a multi-sensor device developed for the project. The thesis then sought to assess the potential of a BLE system for localisation within a sheep grazing environment, and as a proximity monitoring tool to identify changes in relationships (set during the lambing and early lactation period) which could be indicative of a potential issue.

7.1 Main findings

7.1.1 Signal strength and distance

Three types of BLE beacon operating on differing BLE specifications were trialled alongside the developed WISP in off-sheep calibration studies. Whilst range (as described through the survival curves) differed between each beacon type, in all cases, the probability that a beacon reported at a measured distance would still be reported at greater distances declined as the WISP-beacon distance increased. The height at which the transmitting (beacon) and receiving (WISP) device were located also impacted on the probability of a beacon signal being reported, with those at lower heights having a reduced range. The survival curves generated indicated that across all beacon types the 75% threshold was reached by approximately 50 m for the “on-sheep” heights tested (0.3 and 0.7 m). In addition, whilst there was an initial decline in signal strength with increasing distance, the RSSI values reported tended to level off at between 30-50 m. This would suggest that whilst some beacons may be reported beyond this distance, these lower RSSI values could be reported across wide distance ranges, thus whilst confirming presence of a beacon, would not be indicative of a distance from the WISP. The strength of the signal reported was also found to fluctuate within each measured distance, even where there was a clear line-of-sight between devices. Some of this variation was attributed to specific WISPs or beacons, or combinations of WISP-beacon parings producing higher or lower RSSI values.

7.1.2 Impact of sheep behaviour on BLE signal

Perhaps the most important finding of the thesis, however, was the on-sheep focal ewe-lamb study (Chapter 5) which demonstrated that the probability of a beacon being “seen” and reported by a WISP, as well as translation of BLE signal strength into distance was confounded by the behaviour of both animals, as this would influence their orientation, posture, and thus height of the device from the ground. Variability arising from the behaviour of the animal wearing a BLE beacon will have implications on any application of a BLE system, including localisation and proximity. However, implications will be greater where both the BLE reader and beacon are on-sheep, and thus signals being reported are determined by two independent and moving animals. Given these factors, and potential distances which sheep could move toward or apart from one another over a 5-minute duty cycle, the translation of RSSI into distance is then likely to be a poor indicator of actual sheep distance within a grazing system. Although a “close”, “near”, “far” categorisation could provide an indication.

7.1.3 Localisation potential

Within Chapter 3, BLE was trialled as a means of localisation and thus potential proxy for activity monitoring within a sheep grazing system. Within this setup the WISPs were utilised as static BLE readers with known locations to detect and report on beacons assigned to weaned lambs. The study used developed distance prediction equations based on the static calibration work. The resulting individual distances estimated from the BLE for each WISP-beacon pairing during a static beacon localisation study typically underestimated distance when compared with GNSS based estimates. The underestimations at larger WISP-beacon distances (65-

90 m) may in part be due to the calibration study of the Type 1 beacons not obtaining RSSI values within this distance range. However, as observed within the Type 2 and 3 beacon calibrations (Chapter 4), this underestimation may also be reflective of RSSI values plateauing beyond a certain distance, and hence no longer indicative of increasing distance. Whilst the distance prediction equation resulted in a mean underestimation of just 1.59 m in the on-sheep validation, large over (71 m) and underestimations (104 m) were also produced, thus reflecting the wide range in RSSI values obtained for independent GNSS based distances. The number of intervals for which a lamb location could be generated was also limited by the number of WISPs which had reported the beacon, as there were only 26 % of intervals where two or more WISPs reported the beacon during the same period. Whilst 60 % of lamb locations generated via BLE were within 20 m of the GNSS based location, the maximum distance between WISPs was 73 m. As a result of the RSSI fluctuations and translation to distance, trajectories generated, although indicative of the animals movement, produced a “zig zag” pattern. To mitigate for temporal fluctuations in RSSI within a similar BLE localisation study in cattle, Yamanishi et al. (2019) implemented a “long short term memory” localisation technique, a type of recurrent neural network (whereby a location at a given point in time depends on the previous location) which reduced the “zig zag” pattern also exhibited in the cows BLE based trajectory. Data training and machine learning models could then help to improve the accuracy of the BLE location estimations.

7.1.4 BLE as a monitoring tool

The third primary aim of the thesis was to assess whether BLE could act as a monitoring tool to detect changes in relationships and proximity – which may be indicative of a management or welfare issue. This was examined during the lambing and early lactation period given that lamb mortality and poor ewe-lamb relationships are considered one of the main welfare concerns within sheep systems. Whilst the calibration (Chapter 4) and focal ewe-lamb studies (Chapter 5) suggested that RSSI and distance interpretation would be a poor indicator in many instances due to the high variability in signal strength, the use of BLE to monitor the number of ewe-ewe and ewe-lamb contacts (Chapter 6) showed potential as a monitoring tool to explore how relationships changed over time. Based on the field observations conducted throughout the ewe-lamb study and based on literature from previous ewe-lamb studies, several expected differences were detected by the BLE system.

Firstly, the number of ewe-ewe contacts declined based on the lambing stage, which fits with reports of ewe separation at parturition. This was, however, a subtle decrease, and as exact timings of lambing were not known for all sheep within the study, further work would be required to assess the scale at which BLE could detect this separation. Secondly, the BLE system was capable of detecting changes in the ewe-lamb relationship according to lamb age and time from parturition. The pattern in daily ewe-lamb counts observed by the BLE is in keeping with behavioural observations of previous ewe-lamb studies (Arnold and Grassia, 1985; Sachs and Harris, 1978), with high contacts and very close proximity during the first three days, with the number of contacts declining as lambs become more independent, spending time with peers. The number of ewe-lamb contacts was also typically very similar between twin lambs, who often display high levels of synchronization (Galeana et al., 2007). Furthermore, higher contacts between ewes and lambs were also associated with a higher daily weight gain, in relation to breed and parity, potentially due to better maternal care. If typical ewe-lamb patterns were established (e.g. in relation to breed and lamb age) then BLE could potentially offer a means of detecting both good ewe-lamb relationships and identifying any potential issues, where for example, ill or separated lambs result in a deviation from an expected, or population rolling statistic describing number or timing of contacts. Whilst there were no welfare challenges to the lambs monitored by the BLE in this study, the ability to detect contact patterns suggests it could be an interesting avenue for further exploration. Thirdly, when contacts were examined in relation to ewe lameness, it was found that lame ewes reported fewer neighbouring ewe beacons during a duty cycle but reported a higher number of ewe-lamb contacts per day. This is likely due to lame ewes being more inactive, thus spending less time with conspecifics, whilst increasing opportunity for lambs to be in closer proximity.

7.2 Limitations, challenges and future considerations

7.2.1 Technical limitations

A potential limiting factor in the assessment of BLE range and signal strength could have been due to the BLE reader within the WISP operating on BLE 4.2, thus the receiving device may have acted to limit the BLE range of the various beacon types. Beacons operating on more recent BLE specifications could potentially have an enhanced range if also operating alongside readers on a more recent BLE specification.

The duty cycles and thus reporting times of WISPs were staggered to accommodate the transmission of real-time data via LoRa. However, this did present a challenge within the on-sheep localisation study, as each generated location data was based on overlapping 5-minute intervals as opposed to the same 5-minute period. This will have contributed to the variation in distance estimations and contributed to discrepancies in the final BLE estimated location, especially where different levels of movement occurred within each interval. Ideally WISPs would have reported so that duty cycles corresponded to the same intervals, to more accurately assess the time-synchronised location estimates of the BLE.

The ewe-lamb studies (Chapters 5 and 6) were limited by availability and timescales to obtain beacons, thus a mixture of both Type 2 and Type 3 beacons were employed. There were a limited number of WISPs available for application during the study and this also reduced between phases due to use within the wider TechCare project. In addition, some ewes experienced chafing around the neck due to the WISP – which was not experienced during a pilot trial the previous year. To reduce the risk of this occurring again, additional foam padding was applied around the WISP in subsequent phases, which may have caused a level of interference on the beacon signals (a factor not accounted for within the calibration studies). This also reduced the number of ewes within each phase who could potentially be assigned a WISP, as those showing signs of chafing from the previous phase were discounted from WISP application – instead being fitted with a beacon only. This limited the data collected at varying lamb ages and within differing ewe breeds and parities. One lamb within the study also repeatedly escaped from the BLE collar – hence periods of data could not be utilised. Nonetheless, as the WISPs were operating on a 5-minute duty cycle, a substantial amount of data was obtained over the six-week study period.

There were also some technical issues with a small number of beacons, which failed to be reported throughout a study or failed in subsequent phases, despite having been identified on the FeasyBeacon app at the start of the study. Beacons which were not functioning at the end of the study, likely suffered from battery loss or malfunction, however, those still operating at study end suggest potential communication issues with the BLE reader in the WISP.

7.2.3 Welfare implications

The chafing experienced by the ewes within the on-sheep study also highlights that whilst PLF technologies are designed to assist in production and welfare management, the devices themselves may have welfare implications. It is therefore important that devices are validated and assessed to prevent adverse outcomes from any PLF technologies applied (Tuyttens et al., 2022). For use within extensive systems where visual inspections are sometimes limited (thus the area in which PLF tools could be potentially most beneficial), this also raises concerns if devices result in injury or cause distress but go undetected (Herlin et al., 2021). Thus, work to assess the implications of technologies and wearables on health and welfare is also essential. When designing devices especially for commercial application, the type of attachment and placement should then aim to be both suitable and comfortable for long-term term wear by sheep, whilst also optimising the technology. The potential for this problem, and actions taken, were included within the ethical approval process. No animals experienced harms beyond that considered in ethical approval.

7.2.4 Practical limitations

7.2.4.1 Battery life and power

BLE beacons are capable of functioning for several years without requiring a battery swap. However, to be functional within a commercial setting the BLE reader would also be required to have a longer battery life. Within this thesis, the BLE reader was part of prototype multi-sensor device, which included GNSS, thus the battery life was approximately 14 days. However, using only the BLE reader and LoRa for data transmission would increase the length of time over which the device could operate. Although the size, weight, and lifespan are current issues for wearable technologies, it is realistic to expect most of these issues can be overcome in time.

7.2.4.1 Number of WISPs / BLE readers deployed

Whilst the studies in Chapter 3 did demonstrate that localisation using BLE was feasible within a field setting, they also highlighted several challenges. Firstly, the generation of a location requires a beacon to be “seen” and reported by multiple devices within the same period. However, based on distance ranges over which BLE signals were detected and reported within this thesis, a high density of static BLE readers would be required for BLE to sufficiently cover areas in which sheep were grazing. A high number of readers was similarly required within the cattle localisation by Yamanishi et al. (2019). Whilst this high density of readers would be achievable and more easily implemented within indoor systems, it would be impractical in most outdoor systems, particularly more extensive environments where animals could be distributed over large areas.

The study also highlighted that animal behaviour and level of movement over an interval would impact not only on signal strength, and thus distance interpretation, but on whether the animal was detected at all. Periods where the lamb was unable to be located corresponded to instances where the GNSS devices suggested the lamb was stationary, and thus likely lying. This fits with the reduced survival curves generated during the calibration studies when devices were located closer to the ground.

7.2.5 Opportunities and avenues for further investigation

Whilst the thesis highlighted limitations to the use of BLE for localisation in grazing systems when applied as a static reader, BLE could still offer opportunity for localisation within sheep grazing systems by utilising BLE in combination with GNSS. Under this system, most of the flock would be assigned a BLE beacon only, whilst a proportion would be fitted with a GNSS device and BLE receiver. Individuals wearing the BLE receiver would then report on neighbouring sheep beacons detected, and their GNSS location used as a proxy for all sheep identified. Such systems have been demonstrated within grazing livestock by Maroto-Molina et al. (2019) and Vidal-Cardos et al. (2024), and a similar system has been developed for sheep by Norwegian Company “RealTimeID” (RealTimeID, 2025) during the same timeline as this PhD, with commercial launch planned for 2025. However, based on the BLE ranges observed within this thesis, consideration will likely need to be given to the type of flock system, gregariousness of the sheep breed and potential scale of flock distribution, as well as an understanding of sheep subgroups to best select individuals assigned the GNSS / BLE reader devices.

The behaviour of the sheep will also influence the proximity range over which they operate. Given the effects which device height could have on the likelihood of a beacon being reported, further investigation into the effects of combined topography and animal behaviour on BLE signal would be beneficial in understanding how different environments might limit the proximity range over which neighbouring beacons could be detected. This system could then take advantage of both the higher location accuracy of GNSS, and lightweight, low-power BLE beacons, which would be more cost-effective for application in sheep systems. However, whilst the BLE beacons offer a long-battery life, there would still be limitations due to the battery life of the GNSS. Alternatively, the use of UAVs (equipped with GNSS and BLE reader) to read BLE beacons on sheep have been proposed (Nyholm, 2020; Vucic and Axell, 2022). Depending upon the location in which beacons fitted to sheep, UAVs could potentially achieve a better BLE range, due to line-of-sight, and reduced impact of vegetation and proximity of other sheep on the signal strength. However, it would likely be necessary to fly at low heights to maximise the number of beacons read – which could cause a level of distress amongst the flock. An alternative opportunity for BLE localisation would be the use of strategically placed BLE readers to provide information regarding presence / absence within range of specific locations or at resources.

The BLE system did demonstrate potential as a monitoring tool during lambing and to assess the ewe-lamb relationship. Whilst exact lambing times were not known for all sheep within this study, the reduction in neighbouring ewes observed during the “lambing” phase suggests that identification of parturition could be a potential avenue for further investigation of BLE - using accurate lambing times and with in-field observations to confirm separation from other ewes. Although, as discussed by Fogarty et al. (2020) regarding GNSS, BLE would perhaps only provide information on a daily scale, whilst technologies such as accelerometers may provide information on behavioural changes on a finer hourly scale. Expected changes to the ewe-lamb relationship were observed in the number of contacts between ewe-lamb pairs in relation to lamb age, as well as between ewe breeds and parity. As a main area of production loss and welfare concern, the identification of positive ewe-lamb relationship and alerts of potentially poor welfare / issue could be beneficial in both regards, particularly if this was in real-time. Further investigation in this area could help to identify baseline ranges of expected contacts, whilst the inclusion of lamb issues – such as lamb separation, ill health, or other welfare issue, would provide information on how this affected the number of contacts received by the BLE system, and stage at which this was identified.

7.2.5 Further applications / investigation of the WISP system

In addition to the BLE data examined, a large amount of data was available from the other sensors within WISP (GNSS and accelerometer data). Whilst these were not the focus of the thesis, analysis of other sensor types in relation to ewe-lamb monitoring could be investigated in future, using the same visual observations and welfare data. Other potential avenues for exploration of the WISP are summarised in Table 7.1.

Table 7.1 Potential applications and areas of further investigation using the developed Bluetooth low energy (BLE) device.

Technology and data	Application
Accelerometer	1. Detection of events: can gathering events / disturbances / predation (in relevant systems) be detected based on the reported motion index. 2. Animal activity: comparison of daily activity patterns • Relationship to welfare / production measures • Relationship to weather conditions • By factors such as breed, lamb age
BLE	1. Proximity: • Presence / absence • Social networks and contact patterns • Ewe-lamb relationships / dam assignment • Disease transmission 2. Animal localisation / animal activity
GNSS	1. Animal localisation 2. Animal activity / range • Diurnal patterns • Trajectories & distances • Spatial / resource use
LoRa / Flash drive	1. Data transmission: Comparison of data obtained from LoRa vs flash drive – what proportion of real-time data is reported via LoRa? • What proportion could be missed without affecting the interpretation of the data? • Is this affected by weather?

7.3 Conclusion

Bluetooth low energy (BLE) has expanded rapidly across sectors as a localisation and proximity monitoring tool. The low cost of BLE beacons, their light weight, and ability to communicate and allow transmission of data in real-time, are features which make them appealing tools for application within the livestock sector. This thesis assessed how the technology could perform within the context of an outdoor grazing system. Despite factors such as device height, animal behaviour, transmission ranges and environment, as a monitoring tool to examine interactions between individuals, BLE showed promising results in the detection of patterns between contacts in relation to lamb age. This thesis highlighted that BLE could then be avenue for further exploration as a surveillance tool to monitor ewe-lamb relationships. The thesis also highlights the merits of a balance in PLF research and product development / testing of both on-animal work, with tests in non-animal field conditions. Both aspects together provide a good evaluation and understanding of the technology in a sheep grazing environment.

Appendix A Published version of studies presented in Chapter 3

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Development of a novel Bluetooth Low Energy device for proximity and location monitoring in grazing sheep

A.M. Walker [a,b,*], N.N. Jonsson [b], A. Waterhouse [a], H. McDougall [c], F. Kenyon [c], A. McLaren [a], C. Morgan-Davies [a]

[a] Hill and Mountain Research Centre, Scotland's Rural College (SRUC), Kirkton, Crianlarich FK20 8RU, UK
[b] School of Biodiversity, One Health and Veterinary Medicine, University of Glasgow, 464 Bearsden Road, Bearsden, Glasgow G61 1QH, UK
[c] Disease Control, Moredun Research Institute, Pentlands Science Park, Penicuik EH26 0PZ, UK

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ABSTRACT

Monitoring animal location and proximity can provide useful information on behaviour and activity, which can act as a health and welfare indicator. However, tools such as global navigation satellite systems (**GNSS**) can be costly, power–hungry and often heavy, thus not viable for commercial uptake in small ruminant systems. Developments in Bluetooth Low Energy (**BLE**) could offer another option for animal monitoring, however, **BLE** signal strength can be variable, and further information is needed to understand the relationship between signal strength and distance in an outdoor environment and assess factors which might affect its interpretation in on-animal scenarios. A calibration of a purpose-built device containing a BLE reader, alongside commercial BLE beacons, was conducted in a field environment to explore how signal strength changed with distance and investigate whether this was affected by device height, and thus animal behaviour. From this calibration, distance prediction equations were developed whereby beacon distance from a reader could be estimated based on signal strength. BLE as a means of localisation was then trialled, firstly using a multilateration approach to locate 16 static beacons within an ~5 400 m2 section of paddock using 6 BLE readers, followed by an on-sheep validation where two localisation approaches were trialled in the localisation of a weaned lamb within ~1.4 ha of adjoining paddocks, surrounded by nine BLE readers. Validation was conducted using 1 days' worth of data from a lamb fitted with both a BLE beacon and separate GNSS device. The calibration showed a decline in signal strength with increasing beacon distance from a reader, with a reduced range and earlier decline in the proportion of beacons reported at lower reader and beacon heights. The distance prediction equations indicated a mean underestimation of 12.13 m within the static study, and mean underestimation of 1.59 m within the on-sheep validation. In the static beacon localisation study, the multilateration method produced a mean localisation error of 22.02 m, whilst in the on-sheep validation, similar mean localisation errors were produced by both methods – 19.00 m using the midpoint and 23.77 m using the multilateration method. Our studies demonstrate the technical feasibility of localising sheep in an outdoor environment using BLE technology; however, potential commercial application of such a system would require improvements in BLE range and accuracy.

Implications

Animal location and proximity data can provide valuable information on behaviour and activity; however, many of the technologies available are difficult to implement within extensive sheep systems. This study investigated Bluetooth Low–Energy devices, which could act as a less-power–intensive monitoring tool. The study found that the height of both the Bluetooth Low Energy reader and beacon impacted the reported signal strength and proportion of beacons reported. Thus, within an on-sheep system, sheep behaviour and posture could influence the effective Bluetooth Low Energy range, and translation of signal strength into an estimated distance and proximity.

Introduction

Increased demand for animal products from a declining number of farmers producing livestock is resulting in fewer but larger

* Corresponding author.
E-mail address: Aimee.Walker@sruc.ac.uk (A.M. Walker).

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farms holding increasing numbers of livestock (Berckmans, 2014). Consequently, there may be less time for individual monitoring, making it more challenging to manage animals and their welfare as effectively. However, precision livestock farming (**PLF**) technologies have developed substantially in recent decades (Aquilani et al., 2022), and tools providing real-time or near real-time monitoring are becoming increasingly available, allowing farmers to make more informed and targeted decisions whereby animals can be managed at the individual level (Wathes et al., 2008). Whilst a range of PLF tools have been developed and incorporated into more intensive farming systems (Buller et al., 2020; Aquilani et al., 2022), application in more extensive systems, and for species considered to have a lower economic value, such as sheep and goats, has been much slower (Bahlo et al., 2019). Within extensive systems, there are additional challenges in transmitting information, and requirements for devices to withstand variable climate and weather conditions (Bahlo et al., 2019). However, there has been growing interest in exploring the use of sensors and other technologies to assist with animal management in extensive grazing systems (Fogarty et al., 2021).

Monitoring animal location and proximity can provide useful information regarding landscape and resource use, social contacts, and animal behaviour (Maroto-Molina et al., 2019). Over time, this can also provide information on animal activity, which can be a useful indicator of health and welfare status (Liu et al., 2018; Nikodem, 2021). However, many of the technologies available tend to be impractical for use within grazing systems. Given the low value of individual animals and the often large flock sizes, the cost of PLF tools will be a factor in the uptake and use of such technologies within small ruminant sectors (Umstätter et al., 2008; Maroto-Molina et al., 2019). The introduction of the Internet of Things (**IoT**) and low power wide area (**LPWA**) networks has enhanced connectivity options, and along with advancements in technology such as Bluetooth Low Energy (**BLE**), presents opportunities for the development of real-time monitoring within extensive systems. Whilst global navigation satellite systems (**GNSS**) have been one of the most employed sensors within sheep research (Fogarty et al., 2018), BLE could offer a less power-intensive means of monitoring both novel animal proximity and animal location. Several studies have already begun to explore the use of BLE within livestock monitoring (Maroto-Molina et al., 2019; Lee et al., 2022, Maxa et al., 2023), both in combination with other technologies, as a means of localisation within indoor systems (Tøgersen et al, 2010; Bloch and Pastell, 2020; Szyc et al, 2023), and within sheep systems to investigate the ewe-lamb relationship (Waterhouse et al., 2019), particularly as a means of establishing maternal pedigree (Sohi et al., 2017; Paganoni et al., 2021). However, BLE signal strength is known to be a noisy measure of proximity (Lovett et al., 2020), and whilst there have been several studies exploring BLE signal strength and range within indoor environments, there have been few in outdoor systems. There has however been a growing development and application of BLE within other sectors, such as for contact tracing, asset tracking, health monitoring, and to provide proximity-based services or proximity marketing (Spachos and Plataniotis, 2020; Yang et al., 2020), demonstrating potential for this type of technology to be applied within animal monitoring. There were two main aims to this study, the first being the characterisation of the relationship between BLE signal strength and distance in an outdoor environment, using a purpose-built device containing a BLE reader alongside commercial BLE proximity beacons. The second aim was to assess the use of BLE for the location of grazing sheep. Localisation was trialled in a field environment, firstly in a static beacon localisation study, and then an on-sheep validation, where a weaned lamb was fitted with a BLE beacon.

Material and methods

Device design

A multisensor device was developed, commissioned from CENSIS: Scotland's Innovation Centre for sensing, imaging and IoT technologies. This wearable integrated sensor platform device (**WISP**) consisted of an IP65 enclosure containing a BLE reader, GNSS receiver, and accelerometer, as well as a long–range wide area network (**LoRaWAN**) communication module (a category of LPWA technologies, which transmits data using a wireless modulation technique, **LoRa** – referring to long range) and 8 MB flash memory drive (Supplementary Figure S1a). WISPs weighed 333 g and were designed for use as either / both a static BLE reader and wearable on-animal device. Alongside the WISP, commercial BLE 5.0 beacons weighing 14 g (Supplementary Figure S1b) were used throughout the series of studies. These had a reported operating distance of up to 130 m and received signal strength indicator (**RSSI**) range of 0 to ∼−127 dB per milliwatt (**dBm**) (Shenzhen Feasycom Technology Co., Ltd).

The system operated most simply as a beacon which transmitted (called advertising) a unique ID, and BLE readers which received and reported these IDs along with the beacon's RSSI. Beacons were preprogrammed with an identity number and set to an advertising interval of 1 285 ms. The WISPs reported data on a 5-min duty cycle, both in real-time via LoRa (where gateway coverage was available) and to the flash drive. The BLE reader within the WISP (operating on BLE 4.2) was programmed to report the identity and RSSI of 16 beacons with the strongest signal for that duty cycle. These were the 16 beacons with the highest average RSSI, where RSSI values within the range of −35 to −45 dBm were considered high values, and those within the range of −85 to −95 dBm were considered low values. Readers operated by scanning for 30 s then idling for 30 s, where during each scanning window the RSSI of any beacon seen was added to that of any previous adverts. At the end of each duty cycle, beacons were sorted based on their average RSSI (Total Power (sum of beacon RSSI) / No. of adverts (No. of times beacon seen by the reader)), and timestamp, beacon ID and single RSSI values were transmitted by LoRa and saved to the WISP flash drive (Supplementary Figure S2), along with a single WISP GNSS location (based on the average from a minimum of 10 fixes).

Calibration study

Study design

The WISPs and beacons were calibrated within a field environment to evaluate the relationship between a beacon's reported RSSI and its distance from a BLE reader (within a WISP), in order to assess the BLE signal range, and to develop a prediction equation whereby beacon distance from a WISP could be estimated based on its reported RSSI (Fig. 1). Five WISPs were attached to a plastic electric-fence post located at a central point within the field. Eight beacons attached to posts were rotationally located at log intervals at distances of 1 – 128 m from WISPs, measured using a measuring wheel (Voche, Surveyors metric folding distance measuring wheel). Beacons were located at each of these measured distances for 29min to allow opportunity for WISPs to obtain five possible RSSI readings per distance for each WISP-beacon pair. To determine whether WISP or beacon height impacted the likelihood of a beacon being received by the reader, or the RSSI values reported, both device types were tested at multiple heights. Beacons were tested at heights of 0.3 m (representing approximate ewe lying or lamb height) and 0.7 m (representing approximate ewe standing height), whilst WISPs were tested at 0.3, 0.7 and 2 m (Supplementary Figure S3).

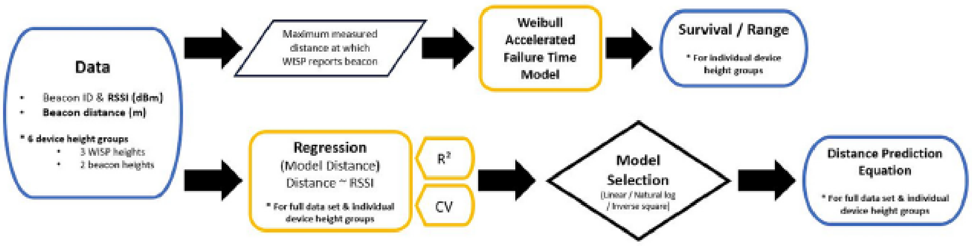

Fig. 1. Flow diagram indicating the process of analysis for the off-sheep calibration study. Abbreviations: RSSI = received signal strength indicator; WISP = wearable integrated sensor platform.

Range of devices

The maximum measured distance at which a beacon's signal was reported by a WISP was used to assess the BLE range at different WISP and beacon heights. As the precise distance at which a beacon's signal could no longer be reported by a WISP occurred at an unknown distance between two actual measured distances, the calibration data from each individual WISP-beacon height group were structured as interval-censored data sets, whereby for each WISP-beacon pairing, the lower bound was the greatest measured distance at which the beacon was reported by the WISP, and the upper bound the subsequent measured distance, from which point the WISP failed to report the beacon. The "survreg" and "surv" functions from the survival package in R (version 3.5–5; Therneau, 2023) were applied to the data set to fit a Weibull accelerated failure time model. This model was considered to encompass the features required to describe the signal strength and is often employed to model reliability and survival. The "predict" function (version 4.2.2; R Core Team, 2022) was then applied to generate survival curves of the *P* of a beacon being reported with increasing distance from the WISP for each of the WISP and beacon height combinations.

Development of the distance prediction model

A distance prediction equation was developed from the RSSI values obtained at each measured distance during the calibration by applying the "lm" function in R (version 4.2.2; R Core Team, 2022) to fit a regression. This was conducted for three models: linear, natural log, and inverse square, applied to both the full data set collectively, and for each individual WISP-beacon height group. The inverse function from the regression (generated for each group) was then applied along with the "predict" function to generate predicted distances for given RSSI values of −45 to −90 dBm. The three models were assessed based on their CV and R2 results to select the most appropriate prediction equation for the WISP-beacon heights used within each study stage.

Static beacon localisation study

Study design

A localisation study was conducted on static beacons within a ~60 × 90 m area to determine whether beacons could be located based on their RSSI from multiple WISPs. The objectives of this study were to assess the error associated with the RSSI and distance prediction equation, and to test a multilateration approach as a means of localisation, the process for which is outlined in Fig. 2. Six WISPs (numbered 1 – 6) were attached to fence posts at a height of 0.7 m; two were located along the width of the paddocks (~60 m) at the 15 and 45 m mark, whilst four WISPs were located along a partial length of the outer fence line at distances of approximately 30, 50, 70, and 90 m. This resulted in an average WISP-WISP distance of 50.75 m. Sixteen beacons (labelled Beacon A – P) were attached to posts (0.7 m height) and laid out in a grid-

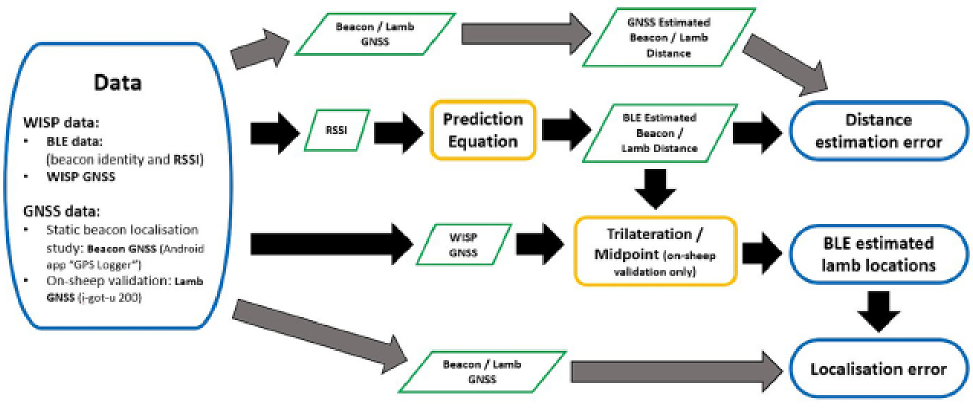

Fig. 2. Flow diagram indicating the process of analysis for beacon and lamb localisation, as conducted in the static beacon localisation and on-sheep validation studies. Abbreviations: BLE = Bluetooth low energy; GNSS = global navigation satellite systems; RSSI = received signal strength indicator; WISP = wearable integrated sensor platform.

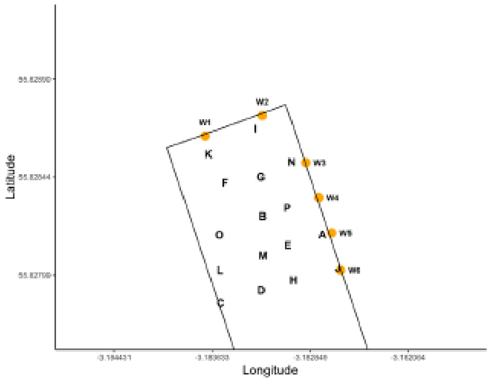

Fig. 3. Off-sheep static beacon localisation study layout, indicating the 16 beacon global navigation satellite systems (GNSS) locations (A-P) within two adjacent paddocks, and the mean GNSS locations of wearable integrated sensor platforms (WISPs), labelled W1-6, along the paddock fence lines.

like array within the paddock (Fig. 3). As WISPs could report a maximum of 16 unique beacon identities within a duty cycle, there was no risk of competition between beacons for recording by any of the WISPs. WISPs and beacons were located at their designated position for a 2-h period to provide a possible 24 RSSI readings per WISP-beacon pair. Locations of each WISP were based on the mean (of 17–24) GNSS coordinates from the on-board GNSS receiver, recorded during the data capture window. There was a mean difference of 1.02 – 3.03 m between single and mean WISP-GNSS coordinates of individual WISPs. Global navigation satellite systems locations for the beacons were obtained using the Android app "GPS Logger" (version 3.2.1, Basic Air Data). A separate study was conducted to assess the error associated with this app using two mobile phones to obtain 12 GNSS coordinates per phone for two locations. There was a mean difference of 0.93 m (SD=0.57) between individual and mean coordinates for Phone 1 (used within the static beacon study), and 1.73 m (SD=1.13) for Phone 2. Coordinates obtained by each phone had a mean difference of 2.14 m.

$$\begin{aligned} Beacon\ x\ coordinate_{1,2} &= \tfrac{(a+c)}{2} + \tfrac{\left((c-a)\left({r_0}^2-{r_1}^2\right)\right)}{2D^2} \pm 2\tfrac{(b-d)}{D^2}\partial \\ Beacon\ y\ coordinate_{1,2} &= \tfrac{(b+d)}{2} + \tfrac{\left((d-b)\left({r_0}^2-{r_1}^2\right)\right)}{2D^2} \mp 2\tfrac{(a-c)}{D^2}\partial \\ and\ \partial &= \tfrac{1}{4}\sqrt{(D+r_0+r_1)(D+r_0-r_1)(D-r_0+r_1)(-D+r_0+r_1)} \end{aligned} \tag{2}$$

where : a = 1st WISP longitude; b = 1st WISP latitude; c = 2nd WISP longitude;
d = 2nd WISP latitude; D = distance between 1st and 2nd WISP;
r0 = beacon predicted distance from WISP 1; r1 = beacon predicted distance from WISP 2;
and ∂ = area of a triangle with edge lengths r0, r1, and D.

Statistical analysis

Flash drive data (selected as the most complete data set) from each WISP was downloaded and combined, and the relevant 2-h window of data was selected for analysis. Data were reviewed to determine which WISPs had reported which beacons and compare variation in RSSI over time. Distances between each of the six WISPs (using mean GNSS coordinates), and between each WISP and beacon were calculated using the "distHaversine" function from the "geosphere" package in R (Version 1.5–18; Hijmans, 2022). BLE–based WISP-beacon distances (for each possible WISP-beacon pairing) were calculated by applying the RSSI of each beacon reading obtained to the distance prediction equation, and then calculating the mean of these estimated distances. These were then compared with the WISP-GNSS–based distance estimates. To then calculate beacon locations, GNSS coordinates of WISPs were first converted from longitude and latitude (WGS84 / EPSG: 4 326) to that of the British National Grid (EPSG: 27 700) using the "st_transform" function from the "sf" package in R (Version 1.0–14; Pebesma and Bivand, 2023). Final estimated beacon locations were calculated using a multilateration approach (Zhou et al., 2012; Luomala and Hakala, 2022) described below. Field boundaries for the study area were calculated based on the GNSS coordinates of corner and mid-paddock fence posts.

Multilateration localisation method: Applying the multilateration approach, the beacon's predicted distance was plotted as the radius of a circle around the reporting WISP, given by:

$$Predicted\ Distance^2 = (x - WISP\ Longitude)^2 + (y - WISP\ Latitude)^2 \tag{1}$$

Where beacons were reported by multiple WISPs, the intersection of the resulting circles was solved to generate potential beacon locations:

These points were filtered to remove those which fell outside the paddock boundary. The final estimated beacon location was calculated as the mean of the potential beacon locations falling within the paddock boundary, and the resulting coordinates were compared with the beacon GNSS–based location. An example of the multilateration process for one of the beacons (Beacon E) is shown in Fig. 4.

On-sheep validation

Study design

Localisation and proximity distance using BLE were then validated in an on-sheep scenario, using data from a larger study where 24 weaned lambs (Texel × Mule) were fitted with collars containing a BLE beacon, 12 of which also had separate GNSS devices (i-gotU 200 or i-gotU 600, Mobile Action Technology). Lambs were all released into two adjoining paddocks (~1.4 ha)

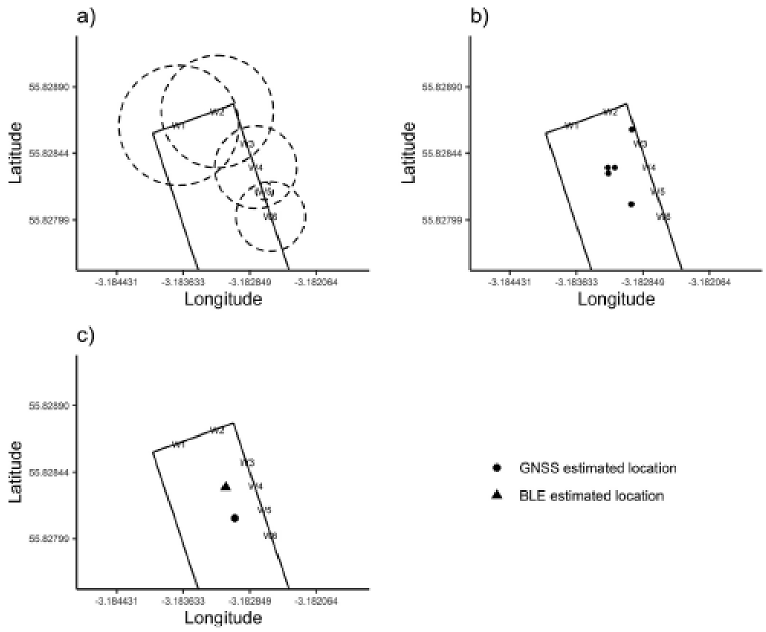

Fig. 4. Example of the multilateration localisation method used within the static beacon localisation study and on-sheep validation, where: a) displays the predicted distances of beacon E, plotted as the radius of a circle from each wearable integrated sensor platform (WISP), denoted by W1-6, which reported the beacon, b) shows the estimated beacon locations – points where the circles intersected and which fell within the field boundary, c) shows the final Bluetooth Low Energy (BLE) estimated beacon location – the mean of points calculated in b, in comparison with the corresponding global navigation satellite systems (GNSS) estimated location.

with connecting open gateway, which were surrounded by nine WISPs (Fig. 5). The WISPs were located at a height of 2 m, attached to canes along the fence line. Four WISPs were staggered along the length of both outer fence lines (~240 m), whilst one was located at the open gateway between paddocks (indicated by W5 within Fig. 5).

Statistical analysis

The analysis presented here examines a sample of data (24 h) from one lamb, wearing both a BLE beacon and i-gotU 200, as a validation of the developed distance prediction equation for both proximity monitoring and illustration of the use of BLE as a means of localisation in an on-animal scenario. As the most complete data set, WISP data were gathered from WISP flash drives for the selected day (8 September 2021) and combined into a single.csv file. For each data point, the reported RSSI was applied to the prediction equation to estimate the beacons, and hence lamb's distance from the reporting WISP.

Similarly, the lamb's GNSS data were downloaded from the i-got-u and filtered using a similar approach to Hromada et al. (2023), where locations with outlying altitude data (<210 m and > 240 m) were removed from the data set (~1%). A new variable, "movement", was derived: lambs were classed as being stationary or moving depending upon whether lamb coordinates remained consistent – moving 0 m (stationary), or there was a change in GNSS coordinates (moving) between the timestamp of interest and the preceding 5 min. Similarly, a variable "distance travelled" was calculated using the "disthaversine" function from the "geosphere" package in R (Version 1.5–18; Hijmans, 2022) to calculate the total distance travelled between the corresponding GNSS coordinates for the reporting timestamp and each of the coordinates over the preceding 5-min. A "distance travelled group" was assigned based on the "distance travelled", where 0 m = none, > 0–10 m = very low, 10–20 m = low, 20–40 m = mid, and > 40 m = high. Global navigation satellite systems coordinates were then transformed from longitude and latitude to British National Grid as described previously.

The timestamps of both the WISP (BLE) and i-got-u (GNSS) data sets were then rounded to the nearest minute and joined based on the rounded time. To estimate lamb locations, data were grouped to find occasions where multiple WISPs reported the lamb's beacon within any independent 5-min interval (i.e. 00:00:00–00:04:59, 00:01:00–00:05:59) over the course of the day, giving a total possible 1 436 intervals. As all WISPs operated on independent time intervals, grouped data included instances where WISP reporting periods overlapped from between 1 and 5 min. Where independent intervals resulted in the same groupings of WISPs with the same reporting timestamp, any duplicates were removed. Overall "movement" and "distance travelled group" categorisations were therefore assigned for each interval – where "moving" was assigned if listed for any of the reporting WISPs, and the highest "distance travelled group" from any of the reporting WISPs assigned overall.

Two BLE localisation methods were then evaluated to calculate lamb locations for each possible 5 min interval. For each time interval, a single new BLE timestamp was generated by calculating the mean timestamp of all reporting WISPs. Similarly, a new GNSS timestamp and coordinates were calculated by finding the mean of the GNSS data points within the corresponding interval. The first

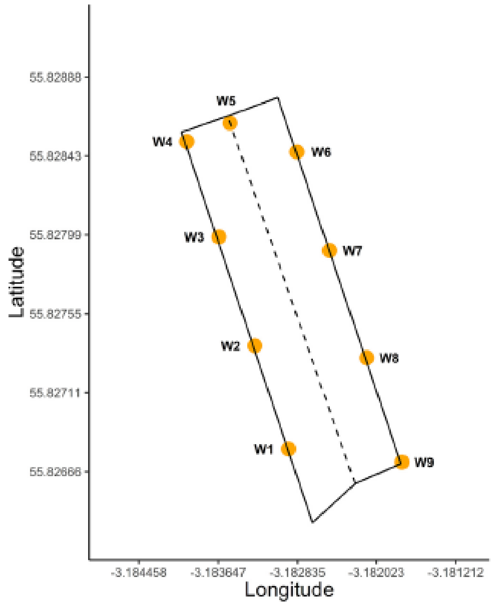

Fig. 5. Layout of the on-sheep validation showing the configuration of the two adjacent paddocks, and the mean global navigation satellite systems (GNSS) location of the 9 wearable integrated sensor platforms (WISPs) located along the surrounding fence lines.

localisation method followed the multilateration approach described previously (Fig. 2). However, in this instance, intersecting points which fell outside the field boundary were not filtered out, and the final estimated lamb location was based on all potential locations generated.

Midpoint localisation method: The second localisation approach was based on calculating the midpoint (mean) between estimated coordinates on the straight-line distance between reporting WISP pairs. This was conducted for every possible WISP pairing within the time interval. Initial beacon coordinates were calculated from each WISP within a pair by plotting the predicted distance along the straight line between the two respective WISPs; calculated as follows:

$$\begin{aligned} \textit{Beacon x coordinate}_1 &= x1 + \left(\left(\tfrac{d1}{D}\right) \times (x2 - x1)\right) \\ \textit{Beacon y coordinate}_1 &= y1 + \left(\left(\tfrac{d1}{D}\right) \times (y2 - y1)\right) \\ &\textit{and} \\ \textit{Beacon x coordinate}_2 &= x2 + \left(\left(\tfrac{d2}{D}\right) \times (x1 - x2)\right) \\ \textit{Beacon y coordinate}_2 &= y2 + \left(\left(\tfrac{d2}{D}\right) \times (y1 - y2)\right) \end{aligned} \quad (3)$$

where :, x1, =, 1st, WISP, longitude; , y1, =, 1st, WISP, latitude; , x2, =, 2nd, WISP, longitude; y2, =, 2nd, WISP, latitude; , d1, =, beacon, predicted, distance, from, WISP, 1; d2, =, beacon, predicted, distance, from, WISP, 2; , D, =, distance, between, 1st, and, 2nd, WISP.

For that pairing, the estimated beacon location was taken as the mean of these two points along the WISP-WISP distance. The final lamb location for each time interval was calculated by finding the mean of the estimated locations from all pairings of the reporting WISPs. To examine opportunities to scale up, lamb trajectories were generated from both BLE localisation methods and compared with that of the original GNSS locations reporting every 1 min. Trajectories were produced using the "ltraj" function in the adehabitatLT package in R (version 0.3.27; Calenge et al., 2023) both for the full 24-h study period and per hour.

Results

Calibration study

The relationship between WISP-beacon distance and RSSI was examined firstly as one data set, regardless of WISP or beacon height. Although there was an overall decline in RSSI with increasing beacon distance, there was a wide range in the RSSI values reported per distance and these values also overlapped between distances (Supplementary Figure S4). However, individual WISP-beacon pairs produced similar RSSI values across repetitions, typically reporting a consistent RSSI or varying by 1–2 dBm. Apart from three instances out of 1 463 data points, where there was a difference of 8, 9, and 16 dBm (all at distances of 1 and 2 m), pairings varied by no more than 5 dBm. Where beacons were reported by a WISP, they were generally reported in all five repetitions, particularly at shorter distances of 1–16 m, whilst at distances of 32 and 64 m, there were more instances of the beacon only being reported during some repetitions.

Range of devices

The proportion of beacons reported per distance differed between WISP-beacon height groups (Supplementary Figure S5). At 16 m, all groups reported $\geq$ 92.5% of beacons, however, by 32 m, this had fallen to 18.5% where both devices were at a height of 0.3 m. The total number of beacon readings per WISP and beacon for each distance is summarised in Tables 1 and 2. The Weibull accelerated failure time model indicated that the BLE signal range differed according to the height at which the WISPs and beacons were located. WISP and beacon heights were both found to be significant factors within the model (Table 3), with higher device heights resulting in a longer signal range. The interaction between WISP and beacon heights was also found to be significant at a WISP height of 2 m and beacon height of 0.7 m. The *P* of a beacon being reported declined at much shorter distances when both devices were located at a height of 0.3 m, declining to a 0% *P* at distances beyond ~60 m. In comparison, WISPs at a height of 2 m and beacon

Table 1
Off-sheep calibration study summary: total beacon readings reported per individual wearable integrated sensor platform (WISP).

Distance	WISP ID 1	2	3	4	5
1	240 (100%)	240 (100%)	240 (100%)	240 (100%)	240 (100%)
2	240 (100%)	240 (100%)	240 (100%)	240 (100%)	240 (100%)
4	240 (100%)	240 (100%)	240 (100%)	240 (100%)	239 (99.6%)
8	240 (100%)	240 (100%)	240 (100%)	240 (100%)	239 (99.6%)
16	236 (98.3%)	234 (97.5%)	240 (100%)	239 (99.6%)	230 (95.8%)
32	232 (96.7%)	148 (61.7%)	141 (58.8%)	130 (54.2%)	156 (65%)
64	158 (65.8%)	71 (29.6%)	33 (13.8%)	70 (29.2%)	90 (37.5%)
128	–	–	–	–	–
Total no. beacon readings	1 586 (82.6%)	1 413 (73.6%)	1 374 (71.6%)	1 399 (72.9%)	1 434 (74.7%)

Table 2
Off-sheep calibration study summary: total beacon readings reported per individual beacon.

Distance	Beacon ID 1	2	3	4	5	6	7	8
1	150 (100%)	150 (100%)	150 (100%)	150 (100%)	150 (100%)	150 (100%)	150 (100%)	150 (100%)
2	150 (100%)	150 (100%)	150 (100%)	150 (100%)	150 (100%)	150 (100%)	150 (100%)	150 (100%)
4	150 (100%)	150 (100%)	150 (100%)	150 (100%)	150 (100%)	150 (100%)	150 (100%)	149 (99.3%)
8	150 (100%)	150 (100%)	150 (100%)	150 (100%)	150 (100%)	150 (100%)	150 (100%)	149 (99.3%)
16	150 (100%)	150 (100%)	150 (100%)	150 (100%)	150 (100%)	150 (100%)	150 (100%)	129 (86%)
32	105 (70%)	100 (66.7%)	92 (61.3%)	105 (70%)	101 (67.3%)	88 (58.6%)	123 (82%)	93 (62%)
64	50 (33.3%)	46 (30.7%)	49 (32.7%)	63 (42%)	45 (30%)	49 (32.7%)	92 (61.3%)	28 (18.7%)
128	–	–	–	–	–	–	–	–
Total no. beacon readings	905 (75.4%)	896 (74.7%)	891 (74.3%)	918 (76.5%)	896 (74.7%)	887 (73.9%)	965 (80.4%)	848 (70.7%)

Table 3
Summary of the Weibull accelerated failure time model of beacon distance to failure of being reported, based on wearable integrated sensor platform (WISP) and beacon height during the off-sheep calibration study.

Parameter	Value	SE	z	*P*-value
Intercept[1]	3.4234	0.0288	118.84	$<2 \times 10^{-16}$
WISP height				
0.3 m	Reference WISP height			
0.7 m	0.4677	0.0409	11.45	$<2 \times 10^{-16}$
2 m	0.8669	0.0430	20.15	$<2 \times 10^{-16}$
Beacon height				
0.3 m	Reference beacon height			
0.7 m	0.3039	0.0403	7.55	4.4×10^{-14}
WISP height × Beacon height				
WISP 0.3 m × Beacon 0.3 m	Reference WISP×Beacon height			
WISP 0.7 m × Beacon 0.7 m	0.0769	0.0592	1.30	0.194
WISP 2 m × Beacon 0.7 m	−0.1235	0.0596	−2.07	0.038
Log (scale)[2]	−1.0414	0.0262	−39.76	$<2 \times 10^{-16}$

[1] Intercept as given by the survreg function is the log of the standard paramaterisation of the weibull distribution scale parameter.
[2] Log (scale) as given by the survreg function is the natural log of the scale parameter (Scale = 0.353, x^2 = 662.06 (5), $P = 7.8 \times 10^{-141}$), where scale is the reciprocal of the standard paramaterisation of the weibull distribution shape (hence shape = 1/0.353 = 2.83).

height of 0.7 m had > 80% *P* of reporting beacons beyond 60 m, reaching a ~0% *P* by ~120 m (Fig. 6). Setting a 95% *P* threshold the WISP-beacon range would therefore be between ~8 and 44 m depending upon both the WISP and beacon heights, whilst a 75% *P* threshold would give a range of ~17–66 m.

Development of the distance prediction model

Three prediction models (linear, natural log, and inverse square) were then applied to the obtained RSSI values for both the full calibration study data set and individually for each WISP-beacon height group. Comparison of the models, with the resulting SDs, CVs, and upper and lower confidence intervals of mean predicted distances, for each measured distance is provided within the Supplementary Materials (Supplementary Table S1), along with each model's adjusted R^2. Of the three models tested, the natural log model resulted in the highest adjusted R2 values across all WISP and beacon height combinations and was selected for use in the distance prediction equation. As the BLE range and proportion of beacons reported varied with WISP and beacon height, the prediction equations applied within the static beacon localisation study and on-sheep validation corresponded to the WISP and beacon heights used in each scenario. We therefore report on two distance prediction equations, the first applies to the static beacon localisation study, and is based on a WISP and beacon height of 0.7 m (prediction Eq. (1), and the second prediction equation is based on a WISP height of 2 m and combined beacon heights of 0.3 and 0.7 m (to equate to sheep both lying and standing) which was applied to the on-sheep validation (prediction Eq. (2). For prediction Eq. (1), the regression resulted in a distance prediction equation of:

$$Predicted\ Distance = e^{-7.468966 - (0.126271 \times RSSI)} \quad (4)$$

(R2 Adjusted = 0.7517, F(1, 1 290) = 3 910, $P < 0.0001$). Whilst for prediction Eq. (2), the regression gave a distance prediction equation of:

$$Predicted\ Distance = e^{-9.501993 - (0.151980 \times RSSI)} \quad (5)$$

(R2 Adjusted = 0.695, F(1, 2 645) = 6 031, $P < 0.0001$).

The prediction equations generated for each of the WISP-beacon height groups, and the relationship between RSSI and distance are shown in Fig. 7. All prediction equations resulted in similar distance estimations for RSSI values of ~ −45 to −75 dBm, covering an estimated distance range of ~0 – 8 m, after which point the prediction equations began to diverge in their estimations. At lower RSSI values of −80 to −90 dBm, there was much greater variation in the distances estimated by the different prediction equations, and a greater change in distance estimation between RSSI values where WISPs and beacons were located at higher heights. For example, at a WISP and beacon height of 0.3 m, a change in RSSI from −89 to −90 resulted in a difference in distance estimation of 2.24 m, whilst at a WISP height of 2 m and beacon height of 0.7 m, there was a difference of 11.45 m. In terms of the on-sheep validation, this means that a lower RSSI value is likely to be reported by lambs lying down vs standing at the same distance.

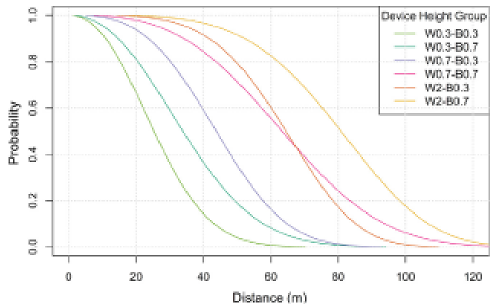

Fig. 6. Bluetooth Low Energy (BLE) signal survival curves generated from the off-sheep calibration study. Where the y-axis indicates the *P* of a beacon signal being reported by a wearable integrated sensor platform (WISP) beyond that distance. W0.3-B0.3 indicates a WISP and beacon height of 0.3 m, W0.3-B0.7 a WISP height of 0.3 m and beacon height of 0.7 m, W0.7-B0.3 a WISP height of 0.7 m and beacon height of 0.3 m, W0.7-B0.7 a WISP and beacon height of 0.7 m, W2-B0.3 a WISP height of 2 m and beacon height of 0.3 m, and W2-B0.7 a WISP height of 2 m and beacon height of 0.7 m.

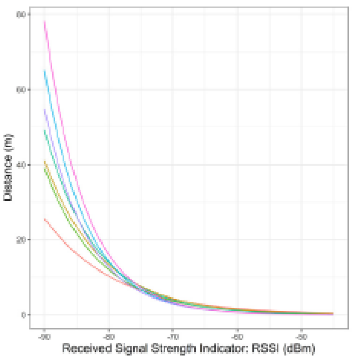

Fig. 7. Comparison of the off-sheep calibration study regression lines of the estimated beacon distances calculated from received signal strength indicator (RSSI) for each of the WISP-beacon height group prediction equations. Where wearable integrated sensor platforms (WISPs) were tested at heights of 0.3, 0.7, and 2 m, and beacons were tested at heights of 0.3 and 0.7 m.

Static beacon localisation study

Received signal strength indicator and distance prediction equation

During the static beacon study, WISPs reported a large proportion of messages via LoRa, 141 of a possible 144 messages (98%), however, flash drive data were selected for analysis being the most complete data set. Fifteen of the 16 beacons were reported by at least one WISP during the study period, with individual WISPs reporting between 6 and 13 beacons, thus generating at least one RSSI reading for 54 of 96 possible WISP-beacon pairings (56%). The total number of beacons reported per WISP and the corresponding number of RSSI readings is summarised in Table 4. WISP-beacon distances ranged from 1.93 to 97.77 m, and whilst RSSI readings were reported for 38 of the 44 WISP-beacon pairings (86%) located <63 m apart, RSSI readings were obtained for only 16 of 52 WISP-beacon pairings (31%) when > 63 m apart. However, this was the distance at which the Weibull survival analysis estimated a 50% *P* of a beacon being reported beyond.

Where multiple RSSI readings for a WISP-beacon pair were obtained across the 2-h data collection period, reported RSSI values had a maximum difference of 6 dBm and a mean difference of 2.21 dBm. Estimated beacon distances from WISPs were calculated by applying the reported RSSI values to prediction Eq. (1), as this used the 0.7 m height settings. The final estimated beacon distance was classed as the mean predicted distance generated from all RSSI values for that pairing (Fig. 8). Overall, there was a mean underestimation of 12.13 m (SD = 15.97) by the prediction equation in comparison with the WISP-GNSS estimated beacon distances. Of the 54 WISP-beacon pairings for which a distance was obtained, 21 beacons (39%) were estimated to be within 10 m of the GNSS distance, and 41 beacons (76%) to be within 20 m. The largest differences between GNSS and BLE distance estimations occurred at distances over 64 m, which was beyond that of the calibration data, and the 50% *P* of being reported.

Localisation: static beacons

Applying the predicted distances to the multilateration method (with a minimum of 2 intersecting WISPs reporting a given beacon) allowed locations for 11 of the 16 beacons to be generated (Table 5). The localisation error was classed as the distance between the final estimated beacon locations and their respective GNSS coordinates. The error ranged from 5.34 to 37.34 m, with a mean distance of 22.02 m (SD = 9.77). Where beacons were unable to be located using the multilateration approach, this was either the result of not being reported by the required number of WISPs (Beacons C and L), or the predicted distances resulted in circles which did not intersect (Beacons D, I, and J).

On-sheep validation

Received signal strength indicator and distance prediction equation

Of the 24 lambs within the study, data from a single lamb were selected as a proof of concept and illustration of the system. The lamb selected for analysis had a total beacon count of 323 of a possible 2 592 messages (12.46%) reported for the chosen study day. This was considered typical with beacon counts obtained for other lambs, which ranged from 197 to 454, with a mean beacon count of

Table 4
Total number of received signal strength indicator (RSSI) readings (out of a maximum possible 24) for each wearable integrated sensor platform (WISP)-beacon pairing during the off-sheep static beacon localisation study.

	WISP ID						
Beacon ID	1	2	3	4	5	6	Total no. of WISPs Reporting
A	–	14	–	24	23	–	3
B	8	14	21	23	23		5
C	–	–	–	–	–	–	0
D	1	–	–	–	23	1	3
E	9	22	–	24	23	24	5
F	24	4	24	24	–	–	4
G	24	22	24	24	–	–	4
H	1	2	–	1	23	24	5
I	24	22	24	–	–	–	3
J	–	–	–	–	23	24	2
K	24	22	24	–	–	–	3
L	24	–	–	–	–	–	1
M	24	–	–	–	23	24	3
N	24	22	24	24	1	–	5
O	24	–	–	1	–	–	2
P	24	22	24	24	23	8	6
Total no. of beacons reported	13	10	7	9	9	6	54

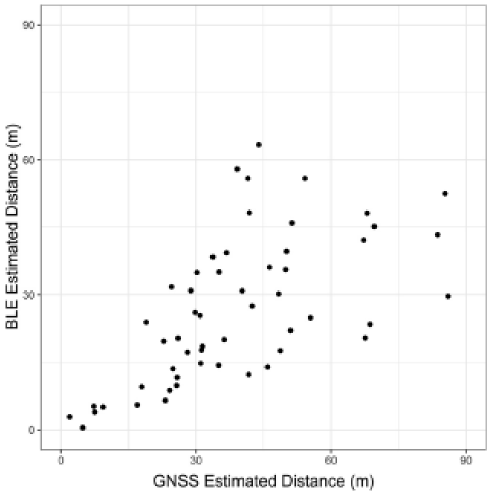

Fig. 8. Comparison of the estimated distances between each wearable integrated sensor platform (WISP) and beacon in the off-sheep static beacon localisation study, calculated using Bluetooth Low Energy (BLE) – based on the mean received signal strength indicator (RSSI) and applying prediction Eq. (1), vs distances calculated based on global navigation satellite systems (GNSS).

280. This averaged at 1.12 WISP readers reporting the selected lamb's beacon in each 5 min interval; however, distribution in time and space was very varied. Individual WISPs reported between 17 (5.90%) and 64 (22.22%) RSSI readings, of a maximum of 288. This was not unexpected as the paddock was ~236 m in length, which was beyond the WISP-beacon range, and therefore not possible for every WISP to report on every occasion. However, the staggering of WISPs around the paddock resulted in a maximum distance of 73 m between WISPs along each paddock length, and 77 m between WISPs located on the opposite fence line. The maximum distance of a lamb's beacon from at least one WISP at any given time would therefore be ~39 m, a distance at which the Weibull accelerated failure time model indicated that > 90% of beacons would be reported beyond.

Table 5
Summary of the off-sheep static beacon localisation study, indicating the number of wearable integrated sensor platforms (WISPs) reporting each beacon, and the associated localisation error.

Beacon ID	No. of reporting WISPs	No. of intersecting WISP pairs	Beacon localisation error (m)
A	3	1	28.11
B	5	8	5.34
C	0	–	–
D	3	0	–
E	5	4	24.13
F	4	3	32.42
G	4	2	11.57
H	5	6	37.34
I	3	0	–
J	2	0	–
K	3	1	23.83
L	1	–	–
M	3	1	22.77
N	5	3	14.00
O	2	1	28.89
P	6	4	13.81

In comparison with the WISP-beacon mean GNSS estimated distances, the corresponding BLE predicted distances resulted in an error ranging from an underestimation of 104.22 m to an overestimation of 70.72 m, and mean underestimation of 1.59 m (SD = 18.52) (Fig. 9). Overall, prediction Eq. (2) underestimated beacon distance; however, mean errors by individual WISPs varied from an underestimation of 9.09 m to an overestimation of 7.69 m. Instances where the lamb was considered stationary resulted in a mean underestimation of 0.40 m (SD = 17.72) and moving points in a mean underestimation of 2.80 m (SD = 19.23); t (1 638.9) = −2.64, P = 0.008. A one-way ANOVA also found a difference in prediction error between "distance travelled group", (F(4, 1 651) = 16.24, $P = 4.74 \times 10^{-13}$), with Tukey's HSD posthoc tests indicating a higher prediction error in "low" vs "high" levels of movement (P = 0.043) and "low" vs "mid" levels of movement (P = 0.093).

Localisation: on-sheep

The lamb's beacon was reported by a maximum of 4 of 9 WISPs during any given independent 5-min interval (i.e. 00:00:00–00:04:59, 00:01:00–00:05:59). In most cases, the lamb was reported by a single WISP, whilst reported by two or more WISPs in 26% of intervals (Table 6). There were also periods during which the lamb was not observed by any WISP, the longest of which was

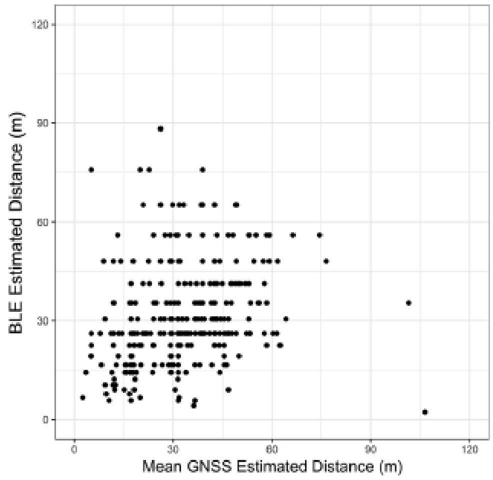

Fig. 9. Comparison of estimated distances between wearable integrated sensor platforms (WISPs) and the lamb (beacon) during the on-sheep validation, calculated using Bluetooth Low Energy (BLE) – by applying prediction Eq. (2), vs distances calculated based on global navigation satellite systems (GNSS).

Table 6
Summary of the on-sheep validation, indicating the number of wearable integrated sensor platforms (WISPs) reporting the lamb's beacon within any independent 5-min interval.

No. of reporting WISPs	No. of intervals	% of intervals
0	277	19.29
1	788	54.87
2	276	19.22
3	64	4.45
4	31	2.16
Total no. of Intervals for day	1 436	100

Table 7
Summary of the number of lamb locations generated within the on-sheep validation, by localisation method. Abbreviations: WISPs = wearable integrated sensor platforms.

	No. of lamb locations generated	
No. of reporting WISPs	Multilateration Method	Midpoint Method
2	69	111
3	27	30
4	9	9
Total no. of locations	105	150

a period of 1 h 8 min. Both localisation methods were then applied and filtered to ensure unique groupings of reporting WISPs across intervals. The midpoint method generated a greater number of lamb locations, primarily where there were just two reporting WISPs (Table 7).

When the resulting lamb locations were compared with the lamb's mean GNSS coordinates for the corresponding interval, the distance between locations (the localisation error) ranged from 1.39 to 74.67 m using the multilateration method, and 0.87 to 71.58 m using the midpoint method (Fig. 10). The multilateration method resulted in a slightly higher localisation error with a mean of 23.77 m (SD = 12.49), whilst the midpoint method resulted in a mean of 19.00 m (SD = 11.00); t (205.38) = 3.15, P = 0.002. There was also a greater proportion of locations estimated to be within

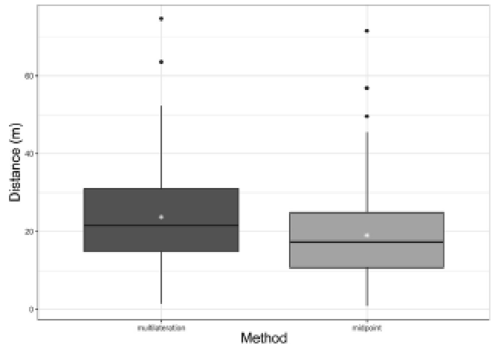

Fig. 10. Comparison of distance between Bluetooth Low Energy (BLE) estimated lamb locations and corresponding mean global navigation satellite systems (GNSS) lamb locations (the localisation error) for both localisation methods. Star indicates the mean localisation error.

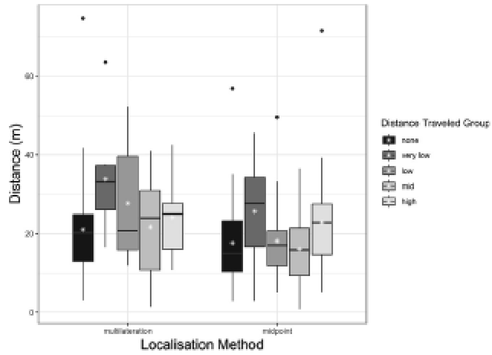

Fig. 11. Comparison of distance between Bluetooth Low Energy (BLE) generated lamb locations and mean global navigation satellite systems (GNSS) lamb locations by the distance travelled group. Star indicates the mean distance (m).

10 and 20 m of the GNSS location using the midpoint method, with 26 of 150 locations (17.33%) within 10 m and 89 of 150 locations (59.33%) within 20 m. In comparison, the multilateration method estimated 9 of 105 locations (8.57%) to be within 10 m, and 44 of 105 locations (41.90%) to be within 20 m. The midpoint method appeared to generate similar mean localisation errors for both 2, 3, and 4 reporting WISPs, of 19.20, 18.05, and 19.76 m, respectively. Mean localisation errors appeared marginally higher with an increased number of reporting WISPs for the multilateration method, with mean localisation errors of 22.55, 25.42, and 28.19 m. However, due to the low number of observations where there were 4 reporting WISPs, this was not analysed further.

A two-way ANOVA showed no statistically significant interaction between the localisation method and movement variable – lamb moving vs stationary (F(1, 251) = 0.90, P = 0.34); however, simple main effects analysis indicated that both localisation method (P = 0.001) and movement (P = 0.043) had an effect on the localisation error. There was very little difference in mean localisation error however between moving and stationary points within both localisation methods. The multilateration method resulted in a mean localisation error of 21.01 m (SD = 12.02) for

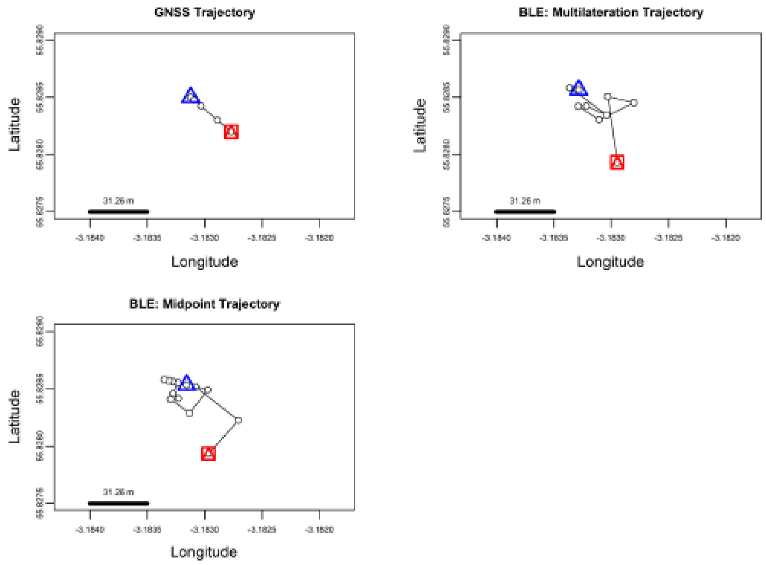

Fig. 12. Lamb trajectories from 0100–0200 h comparing the full global navigation satellite systems (GNSS) data for the hour with Bluetooth Low Energy (BLE) trajectories using the multilateration and midpoint localisation methods.

stationary and 25.68 m (SD = 12.54) for moving points; t (92.876) = 1.92, *P* = 0.058, whilst the midpoint method resulted in slightly lower mean localisation errors of 17.90 (SD = 10.16) for stationary points and 19.72 (SD = 11.51) for moving points; t (134.6) = 1.01, *P* = 0.31. When compared based on the lamb's "distance travelled group", instances where the lamb had a very low level of movement resulted in the highest mean localisation errors, using both the multilateration and midpoint methods (Fig. 11). A one-way ANOVA indicated that there was a difference in localisation error between "distance travelled group" within both the multilateration (F(4, 100) = 2.70, P = 0.035) and midpoint methods (F(4, 145) = 2.86, P = 0.026). Tukey's HSD posthoc tests found that for the multilateration method, the mean localisation error was higher in instances where the lamb had a "very low" level of movement compared with both "mid" (*P* = 0.097) and "none" (*P* = 0.037). Whilst for the midpoint method, there was a higher mean localisation error for "very low" compared with a "mid" level of movement (*P* = 0.065).

Lamb trajectories

Given the low total number of lamb locations generated by both localisation methods, the trajectories produced from the BLE were based on much fewer data points than the full GNSS data. When split into hourly trajectories, there were 6 h for which the multilateration method, and 3 h for which the midpoint method failed to produce a single location. During hours in which trajectories were generated, these were based on a maximum of 14 (multilateration) and 16 (midpoint) locations. The GNSS was set to report every 1 min; however, some locations were given more frequently, and as a result, hourly trajectories contained between 58 and 71 lamb locations. An example trajectory from 0100 to 0200 h is displayed in Fig. 12; chosen as this period contained the greatest number of data points from both BLE localisation methods, as well as 59 GNSS locations. Whilst having similar start and end points for the hour, the trajectories generated by both BLE methods show greater movement patterns and changes in direction than displayed by the GNSS trajectory, which indicated that the lamb travelled ~40 m during this period. This pattern was similarly observed across hourly trajectories, including those where the GNSS indicated that the lamb was stationary throughout.

Discussion

Received signal strength indicator: distance, device height, and range

One of the aims of this study was to characterise RSSI in terms of beacon distance from the BLE reader within the WISP and investigate the potential range and limitations of the BLE devices in an outdoor environment. As observed from the overall pattern of the calibration study, there is a natural decrease in the strength of a radio wave over distance, known as the path loss (Nyholm, 2020). This trend of RSSI declining with increasing beacon distance from the WISP was observed across all WISP-beacon height groups. However, within each of the measured distances, there was a large range in the RSSI values reported, and these values would often overlap between distances. RSSI is known to be a noisy measure of proximity, and this overlap in RSSI values being reported across a range of distances has also been found within a barn system (Nikodem, 2021) and other indoor environments (Vanheel et al., 2011). However, whilst there was a large overall range per distance, there was in-fact very little variation in signal strength of individual WISP-beacon pairings across repetitions, with most pairings differing by 2 dBm or less. This was the case across distances, although at 32 m and 64 m, there were fewer overall instances of beacons being reported, and more occasions where beacons were reported by WISPs during only some repetitions.

The ranges in RSSI per distance, even within WISP-beacon height groups, therefore indicate that a proportion of the variation observed is a result of the specific devices used, and differences arising between individual WISP and beacon pairings. This was particularly evident at a WISP and beacon height of 0.3 m, where only one of the five WISPs reported beacons at distances of 32 and 64 m. As a result, this could make standardising a distance prediction equation for a large number of devices more challenging.

As indicated by the Weibull accelerated failure time model (Fig. 6), depending on the threshold set as an acceptable proportion of beacons being reported, the functional range of the BLE devices will be reduced at lower WISP and beacon heights. Triguero-Ocaña et al. (2019) similarly found a decreased *P* of devices being received with increasing distance (up to 20 m) in proximity loggers, and a decreased signal strength when devices were located at a height of 0 m compared to 1 m. The presence of vegetation was also found to decrease the signal strength, with a greater impact at further distances. Whilst conducted across much shorter distances of 2 m, Kirkpatrick et al. (2021) also report an increased device range in proximity loggers when the receiving devices were located at a higher height, and that mean RSSI values were lower in long grass compared to cut grass, indicating that vegetation was also likely influencing the signal strength.

The operating range of BLE devices and the signal strength reported will be influenced by the transmission power as well as the transmitting and receiving antenna design and location (Townsend et al., 2014), all of which will differ to some degree between individual beacons and WISPs. The operating environment of the devices will also impact the signal strength (Townsend et al., 2014), and obstacles located between the transmitter and receiver, may result in absorption, reflection or scattering of the signal (Goldsmith, 2005). This could act to alter the reported RSSI from that if there had been a clear line of sight between devices, or in some cases prevent the beacon from being reported. These factors make the translation of RSSI values into a corresponding distance challenging in an outdoor environment, where obstacles within the field (i.e., fences, water troughs, and vegetation), as well as the field topography, weather conditions, and the animals themselves all have the potential to interfere with the signal. When using the BLE beacons on sheep, the placement of the beacons, as well as their behaviour, posture, and orientation to the reporting WISP at a given time could therefore influence both the likelihood of the beacon being received by the reader, and on the RSSI value which is reported. Instances where the lamb is lying down, or grazing (and the beacon is in a lowered position) are therefore likely to have a reduced *P* of being reported, in comparison with a lamb standing or actively walking with head and neck erect at the same distance, particularly as that distance increases.

Distance prediction equations

As both WISP and beacon height were found to influence the potential range of the BLE signal, multiple distance prediction equations were developed from the calibration data to correspond to the WISP and beacon heights used within each of the studies, rather than applying one single equation. Prediction Eq. (1), used within the static study, had an overall tendency to underestimate the WISP-beacon distance, with a mean underestimation of 12.13 m. However, the prediction equation was able to estimate 76% of the beacons to be within 20 m of the WISP-GNSS estimated beacon distance, and 39% to be within 10 m. Beacons located at distances over 60 m resulted in the largest underestimations compared with WISP-GNSS distances, and tended to have multiple beacons located between them and the reporting WISP. At these greater distances, variations in RSSI had the potential to have a greater impact on the predicted distance. Small changes in RSSI resulting in large changes in distance estimation have been found within other radio frequency transceivers (Mukhopadhyay et al., 2015). However, some of the differences observed between the predicted and WISP-GNSS estimated distances will also include error associated with both the WISPs GNSS receiver and the GPS logger app used to obtain the beacon coordinates. Typically, GNSS systems are considered accurate in a range of 5 – 30 m (Maroto-Molina et al., 2019). Within this study, the WISPs had a grand mean error of 1.69 m between individual and mean GNSS coordinates, whilst the GPS logger app had a mean difference of 0.93 m, both of which will contribute to some of the variation between estimations.

The on-sheep validation presented different challenges in terms of estimating the beacon's and therefore the lamb's distance from any given WISP, given the potential distance which a lamb could move over the recording period. Johnson et al. (2021) reports an average of 3.4 km (±0.89) travelled by sheep over the course of the day, resulting in a mean of 11.81 m within a 5-min period. Within the study, the lamb under observation was found to travel a maximum estimated distance of 81.24 m and a mean of 9.50 m during a 5-min interval. When compared with the mean GNSS location for the corresponding interval, prediction Eq. (2) resulted in a close mean underestimation of 1.59 m; however, there were also some extreme values produced where the estimated distance differed from the WISP-GNSS distance by as much as 104 m. Despite some of these larger errors, a large proportion of the lamb's beacon readings were estimated to be within 20 m of the WISP-GNSS estimated distance (254 of 332 – 77%), and 156 (47%) to within 10 m. Whilst the prediction equation resulted in a slightly closer mean distance estimation for stationary compared with moving points, instances where the lamb had travelled furthest over the interval did not produce the largest errors. Instead, instances where the lamb was classed as having a "very low" level of movement resulted in the greatest differences between the predicted and mean WISP-GNSS distance for the interval.

Some of the errors observed between these estimates may be due to the configuration of the WISPs and the way in which they operate. The WISPs report a single figure, the mean RSSI, for a 5-min interval, however, during this time, the lamb could move beyond the range of the reporting WISP, even if only moving a short distance. In addition, the lamb's behaviour and posture may also change over the interval and could be within the WISP's range when standing, but not if lying down. These estimations also do not consider the presence of other sheep or obstacles which may impact the signal strength over the course of the reporting interval, which may act to prevent the focal lamb's beacon from being received by the WISP, or to reduce the signal strength reported. As the readers scan on a 30 s on / 30 s off, the mean RSSI value reported could also be based on readings from as little as a 30 s period when the lamb was within range, resulting in a higher than expected RSSI and therefore a closer distance estimation by the prediction equation. This is a potential limitation of the system, where in the current configuration, a lamb's beacon reported only once, but with a high RSSI could be reported over a lamb with multiple readings but a lower average RSSI. Whilst we found very few instances in this study where all 16 beacon positions for a WISP were filled (16 of 2 585 – 0.62%), and so few opportunities for this to have occurred, this could be a larger issue where a greater number of sheep are present. In such instances, sheep are consistently located towards the edge of a WISP range, and therefore with a lower average RSSI may be missed by WISPs. As the lamb's behaviour and posture for a given interval were unknown, prediction Eq. (2) was developed based on combined calibration data from a WISP height of 2 m and beacon heights of both 0.3 and 0.7 m. However, individual prediction equations (Fig. 7) developed for each beacon height indicate that as the RSSI value decreases, there is a greater difference in distance estimates, with a beacon height of 0.3 m producing a shorter distance than those located at 0.7 m. Lamb behaviour and posture are therefore likely to have a greater impact on the prediction equation when located further from the reporting WISP. The GNSS locations used to estimate the beacon distances are themselves also subject to error. Duncan et al. (2013) reported a mean error of 19.6 m ± 30.9 m and a circular error of 10.8 m using the i-gotU GT-600, which will also contribute to the differences observed between GNSS and BLE estimated beacon distances.

Distance estimation errors based on RSSI will vary depending upon the devices used, the conditions in which they are applied, and the methods used to translate RSSI to distance. Previous studies have reported very low mean distance estimation errors of 0.41 m (Thaljaoui et al., 2015) and 0.98 m (Adewumi et al., 2013) in an indoor environment, and 0.88 m in an outdoor environment (Adewumi et al., 2013). However, these studies tested RSSI at small distances ranges between 0.25 – 3.5 m (Thaljaoui et al., 2015) and 1 – 10 m (Adewumi et al., 2013). Whilst variability in RSSI between WISP-beacon pairs, combined with effects of lamb movement on contact success and number of RSSI readings reported during each window resulted in a level of noise within the estimated distance from the prediction equation, an average mean underestimation of 1.59 m within the context of the ~1.4 ha paddock is relatively small.

Localisation

The static beacon localisation study aimed to locate beacons within an ~5 400 m^2 area based on data obtained over a 2-h period. Using the multilateration approach, locations were generated for 11 of the 16 beacons, all of which were estimated to be within 37.34 m of their estimated GNSS location, resulting in a mean difference of 22.02 m. The beacon with the largest localisation error, Beacon H, was the beacon which had both the greatest over and underestimation by the prediction equation. This resulted in circles intersecting at different areas within the paddock, hence, the mean estimated location was much further from that of the GNSS. In comparison, Beacon B was reported by the same number of WISPs (five); however, four of these WISPs all intersected at very similar points, with a larger underestimation from just one WISP, therefore resulting in a closer mean estimate, with a localisation error of 5.34 m. Highlighted during the static beacon study was that the multilateration method was reliant on RSSI values generating predicted distances which produced intersecting circles, where under ideal circumstances the method would generate a cluster of points which intersected at the same (or close to the same) position. However, whilst occurring for some beacons, this was not the case in all instances, and hence, the mean of estimated points was instead applied to generate the final estimated location. Nonetheless, in some instances, beacons were not able to be located despite having been reported by multiple WISPs.

The on-sheep validation therefore investigated both the multilateration and a midpoint localisation method, which did not require distance estimations to intersect. However, both methods still required a minimum of two WISPs reporting within an overlapping 5-min interval to estimate the lamb's location. Given the length of the paddocks (~236 m), it was expected that each individual WISP would not report on every occasion, as there would be times when the lamb was beyond a WISP's BLE range, particularly those located at either end of the paddocks. The lamb's beacon was most frequently reported by only a single WISP during any given 5-min interval, giving an indication of proximity to the reporting WISP but not a definitive location. However, over time, this could still give an indication of the lamb's activity throughout the paddock. There were also periods during which the lamb was not reported by any WISP, the longest of which was between 1120 and 1228 h, when the corresponding GNSS suggests that the lamb was stationary. If lying down, this would reduce the chance of the lamb's beacon being reported and more likely that the lamb was beyond the effective range of any WISP, as the beacon would be located closer to the ground.

A total of 105 locations were generated for the lamb over the course of the day using the multilateration method, whilst 150 locations were generated using the midpoint method. Although similar localisation errors were generated by both methods, there was a slightly lower mean error using the midpoint method, and a greater proportion of locations were estimated to be within 10 m of the GNSS. Instances where the lamb was classed as having a "low" level of movement resulted in the highest mean localisation error; however, there was no significant difference in mean localisation error between most of the "distance travelled group" classifications. The distance travelled was calculated based on the lamb's GNSS locations reporting every minute, and so was subject to error from the i-gotU. In addition, the classification was based on the highest level of movement from any WISP, however as WISPs reported on independent intervals, the proportion of the 5-min interval for which each WISP reported could vary from between 1 and 5 min. Some of the errors arising in the localisation are therefore likely a result of the configuration of the WISP reporting intervals, where the movement classification and distance travelled may have differed between each of the reporting WISPs. Particularly using the multilateration method, the length of the overlapping period and difference in the distance travelled between recording periods of WISPs could impact on whether distance prediction estimates generated overlapping circles.

The study investigated the range of BLE devices in an outdoor system, and the feasibility of applying BLE technology as a means of animal proximity and location monitoring within outdoor livestock systems and highlights some potential challenges for on-animal application. The calibration of the WISPs and beacons suggests that the species, their height and behaviour, as well as the beacon placement, and the environment of the intended application will need to be taken into account when considering the effective BLE range within that particular scenario. In addition, variation in animal posture and the potential distance and speed at which they might travel over a recording interval will affect the likelihood of being reported, and the possible interpretation of BLE signal strength into distance. Whilst static BLE readers could offer a means of monitoring livestock proximity within range of known points within extensive systems, animal localisation, given the BLE ranges observed, would require many BLE readers. Hence, a combination of BLE beacons and on-sheep roving readers, equipped with GNSS, may be more plausible. However, improvements in BLE range and accuracy would be required for practical application. In terms of real-time monitoring, whilst almost all data were transmitted during the static localisation study, data acquisition within extensive systems can be variable, with previous studies utilising LoRaWAN reporting data acquisition in the ranges of 46% (McIntosh et al., 2023) to 82% (Ojo et al., 2022); hence, data loss and its potential effect on the interpretation of results will also need to be considered. However, depending upon the intended purpose of monitoring, the time frame for a recording period will alter, and it may also not be necessary for animals to be recorded on every occasion. This poses several questions, namely: what proportion of beacon loss is acceptable in terms of livestock monitoring, and does this alter depending on purpose? And how close do proximity and localisation estimates need to be? – particularly in more extensive sheep systems where a lower degree of resolution may be acceptable given the potential scale of farms.

Conclusion

The study reports on the calibration of BLE devices within outdoor systems, where BLE signal strength was found to decline with increasing beacon distance from a reader. As the height at which both the reader and beacon were located had an impact on the survival of BLE signals, when applied on-sheep, the functional BLE range will therefore be influenced by animal behaviour and posture. As proof of concept, the study then utilised developed distance prediction equations from RSSI values for the localisation of grazing sheep. Whilst not yet too practical given the range and number of readers (WISPs) which may be required in more extensive settings, this study demonstrates that the application of BLE as fixed readers for animal monitoring and localisation is possible. Continued advances in the range of BLE devices along with the opportunity for data to be received in real-time through developments in IoT technologies makes BLE a potential tool for future development in this sector.

Supplementary material

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Ethics approval

Ethical approval for the farm trial was obtained through the Moredun Research Institute's Animal Welfare and Ethical Review Body (ref: E20/21).

Data and model availability statement

None of the data were deposited in an official repository. Original data are available from the authors upon request.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) did not use any AI and AI-assisted technologies.

Author ORCIDs

Walker, A.M.: https://orcid.org/0000-0002-0738-7768.
Jonsson, N.N.: https://orcid.org/0000-0003-3245-9783.
Waterhouse, A.: https://orcid.org/0000-0003-3666-6077.
Kenyon, F.: https://orcid.org/0000-0002-8073-0382.
McLaren, A.: https://orcid.org/0000-0001-8515-9974.
Morgan-Davies, C.: https://orcid.org/0000-0003-4243-837X.

CRediT authorship contribution statement

A.M. Walker: Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **N.N. Jonsson:** Writing – review & editing, Supervision, Methodology, Formal analysis, Conceptualization. **A. Waterhouse:** Writing – review & editing, Supervision, Resources, Methodology, Investigation, Conceptualization. **H. McDougall:** Methodology, Investigation, Conceptualization. **F. Kenyon:** Writing – review & editing, Supervision, Resources, Methodology, Investigation, Conceptualization. **A. McLaren:** Writing – review & editing, Supervision, Methodology, Conceptualization. **C. Morgan-Davies:** Writing – review & editing, Supervision, Resources, Project administration, Methodology, Funding acquisition, Conceptualization.

Declaration of interest

None.

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Appendix B Prediction model comparison Beacon Type 1 (Chapter 3)

Table B.1 Comparison of the three distance prediction models (linear, natural log, and inverse square) examined for Beacon Type 1 - for both the full off-sheep calibration data set (regardless of device height), and individually for each device height group.

	Comparison of Distance Prediction Models				
	Linear Model				
Distance (m)	SD	CV	L95% CI	U95% CI	Adj R^2
All Combined Device Heights[1]					
1	8.02	782.03	0.57	1.48	
2	6.00	239.91	2.16	2.84	
4	5.79	72.07	7.70	8.35	
8	6.76	45.41	14.51	15.27	
16	5.60	27.27	20.20	20.84	
32	4.32	16.25	26.26	26.86	
64	4.32	14.76	28.83	29.66	0.51
128	--	--	--	--	
WISP 0.3 m / Beacon 0.3 m[2]					
1	3.57	200.06	1.29	2.29	
2	3.67	152.64	1.89	2.92	
4	3.00	57.07	4.83	5.67	
8	2.97	28.22	10.08	10.90	
16	2.37	16.03	14.45	15.14	
32	1.02	5.82	17.24	17.92	
64	3.02	16.65	14.37	21.85	0.56
128	--	--	--	--	
WISP 0.3 m / Beacon 0.7 m[3]					
1	4.91	2043.42	-0.44	0.93	
2	4.84	125.21	3.19	4.54	
4	3.79	52.81	6.64	7.70	
8	5.62	53.04	9.82	11.39	0.51
16	4.74	27.65	16.47	17.81	

32	3.81	16.64	21.91	23.86	
64	2.58	10.10	24.48	26.52	
128	--	--	--	--	
WISP 0.7 m / Beacon 0.3 m[4]					
1	6.22	1159.57	-0.33	1.40	
2	4.31	209.61	1.46	2.65	
4	4.50	52.35	7.97	9.22	
8	5.61	52.35	9.09	10.65	
16	5.08	27.73	17.61	19.03	
32	2.45	9.13	26.37	27.22	
64	2.90	9.79	28.52	30.72	0.63
128	--	--	--	--	
WISP 0.7 m / Beacon 0.7 m[5]					
1	7.53	-308.16	-3.49	-1.39	
2	5.80	167.66	2.65	4.27	
4	5.95	60.70	8.97	10.63	
8	4.23	19.07	21.61	22.79	
16	5.30	28.21	18.05	19.53	
32	4.34	16.19	26.19	27.41	
64	3.23	10.23	30.89	32.19	0.50
128	--	--	--	--	
WISP 2 m / Beacon 0.3 m[6]					
1	7.46	177.19	3.17	5.25	
2	5.57	735.99	-0.02	1.53	
4	7.70	134.27	4.66	6.81	
8	9.35	65.90	12.88	15.49	
16	5.37	22.00	23.65	25.15	
32	5.26	18.32	27.98	29.47	
64	7.28	21.17	32.98	35.84	0.57
128	--	--	--	--	
WISP 2 m / Beacon 0.7 m[7]					
1	10.82	416.64	1.09	4.11	
2	6.82	-1269.58	-1.49	0.41	
4	7.47	86.54	7.59	9.67	0.57
8	6.18	33.60	17.53	19.26	

16	7.584576	33.06	21.88	24.00	
32	6.36	19.18	32.26	34.09	
64	5.83	15.91	35.77	37.58	
128	--	--	--	--	

	Natural Log Model				
Distance (m)	SD	CV	L95% CI	U95% CI	Adj R^2
All Combined Device Heights[1]					
1	2.43	89.33	2.58	2.85	
2	1.63	59.02	2.67	2.85	
4	2.63	57.95	4.39	4.70	
8	6.10	67.96	8.63	9.32	
16	7.62	53.85	13.72	14.59	
32	8.58	36.91	22.66	23.84	
64	8.58	29.45	28.32	29.96	0.69
128	--	--	--	--	
WISP 0.3 m / Beacon 0.3 m[2]					
1	1.04	47.09	2.06	2.35	
2	1.45	58.73	2.26	2.66	
4	1.56	44.42	3.30	3.73	
8	3.44	46.10	6.97	7.93	
16	4.54	34.05	12.68	14.00	
32	2.78	14.62	18.06	19.91	
64	1.02	5.04	19.02	21.56	0.70
128	--	--	--	--	
WISP 0.3 m / Beacon 0.7 m[3]					
1	1.32	62.43	1.93	2.30	
2	2.16	67.89	2.88	3.48	
4	1.76	41.64	3.99	4.48	
8	6.77	94.33	6.23	8.12	
16	7.22	54.22	12.30	14.34	
32	9.83	41.29	21.28	26.32	
64	7.58	25.08	27.22	33.21	0.68
128	--	--	--	--	
WISP 0.7 m / Beacon 0.3 m[4]					
1	1.43	6.93	2.19	2.59	0.72

2	1.20	46.89	2.39	2.73	
4	2.39	48.38	4.61	5.27	
8	3.74	62.69	5.44	6.48	
16	7.70	57.40	12.33	14.48	
32	7.70	22.23	26.99	29.15	
64	6.93	18.94	33.94	39.20	
128	--	--	--	--	
WISP 0.7 m / Beacon 0.7 m[5]					
1	1.48	79.90	1.65	2.06	
2	1.63	57.10	2.63	3.08	
4	2.84	55.65	4.71	5.51	
8	5.67	38.49	13.95	15.53	
16	5.55	49.24	10.50	12.04	
32	8.16	36.41	21.26	23.57	
64	9.18	27.45	31.61	35.31	0.75
128	--	--	--	--	
WISP 2 m / Beacon 0.3 m[6]					
1	2.03	58.31	3.20	3.76	
2	1.17	47.66	2.30	2.62	
4	3.93	93.55	3.65	4.75	
8	8.49	94.79	7.77	10.14	
16	7.68	46.74	15.36	17.51	
32	9.29	40.28	21.75	24.38	
64	10.38	29.51	33.12	37.20	0.68
128	--	--	--	--	
WISP 2 m / Beacon 0.7 m[7]					
1	6.61	169.13	2.99	4.83	
2	1.66	70.90	2.11	2.57	
4	2.58	54.94	4.34	5.06	
8	3.81	40.89	8.79	9.86	
16	8.53	60.66	12.87	15.25	
32	12.53	43.49	27.02	30.61	
64	15.60	42.09	34.65	39.49	0.72
128	--	--	--	--	

Inverse Square Model

Distance (m)	SD	CV	L95% CI	U95% CI	Adj R^2
All Combined Device Heights[1]					
1	0.37	23.19	NaN	NaN	
2	0.27	16.74	1.61	1.65	
4	0.43	22.18	NaN	NaN	
8	1.28	47.58	NaN	NaN	
16	1.74	47.46	NaN	NaN	
32	2.04	40.64	NaN	NaN	
64	2.04	33.53	NaN	NaN	0.33
128	--	--	--	--	
WISP 0.3 m / Beacon 0.3 m[2]					
1	0.22	14.25	1.50	1.56	
2	0.34	21.01	1.55	1.64	
4	0.36	19.90	1.77	1.88	
8	1.14	40.26	NaN	NaN	
16	1.55	36.90	NaN	NaN	
32	NA	NA	NaN	NaN	
64	NA	NA	NaN	NaN	0.33
128	--	--	--	--	
WISP 0.3 m / Beacon 0.7 m[3]					
1	0.27	18.04	1.46	1.54	
2	0.64	36.52	1.68	1.86	
4	0.40	20.51	1.88	1.99	
8	0.60	26.79	NaN	NaN	
16	4.30	95.67	NaN	NaN	
32	0.25	7.77	NaN	NaN	
64	NA	NA	NaN	NaN	0.36
128	--	--	--	--	
WISP 0.7 m / Beacon 0.3 m[4]					
1	0.26	16.34	1.54	1.61	
2	0.20	12.65	1.58	1.64	
4	0.51	25.11	1.98	2.12	
8	1.25	52.50	NaN	NaN	
16	1.16	34.44	NaN	NaN	0.33
32	0.00	0.00	NaN	NaN	

64	NA	NA	NaN	NaN	
128	--	--	--	--	
WISP 0.7 m / Beacon 0.7 m[5]					
1	0.25	17.88	1.37	1.44	
2	0.26	16.66	1.55	1.62	
4	0.59	29.57	1.91	2.08	
8	1.37	36.08	NaN	NaN	
16	0.92	32.07	NaN	NaN	
32	1.75	38.56	NaN	NaN	
64	0.00	0.00	NaN	NaN	0.50
128	--	--	--	--	
WISP 2 m / Beacon 0.3 m[6]					
1	0.27	15.09	1.75	1.82	
2	0.16	9.95	1.63	1.67	
4	0.73	38.31	NaN	NaN	
8	0.80	35.04	NaN	NaN	
16	1.20	33.27	NaN	NaN	
32	1.58	36.40	NaN	NaN	
64	1.57	32.27	NaN	NaN	0.22
128	--	--	--	--	
WISP 2 m / Beacon 0.7 m[7]					
1	0.48	27.55	NaN	NaN	
2	0.23	14.09	1.57	1.63	
4	0.33	17.10	1.87	1.96	
8	0.60	23.35	2.47	2.63	
16	1.09	35.73	NaN	NaN	
32	1.48	34.99	NaN	NaN	
64	1.49	29.63	NaN	NaN	0.28
128	--	--	--	--	

Appendix C Natural log prediction models Beacon Types 2 and 3 (Chapter 4)

Table C.1 Comparison of the natural log prediction models generated for each of the WISP-beacon height groups for Beacon Type 2.

	Natural Log Model – Beacon Type 2				
Distance (m)	SD	CV (%)	L95% CI	U95% CI	Adj R^2
All Combined Device Heights[1]					
0	0.27	164.96	0.14	0.19	
1	0.79	116.74	0.61	0.75	
2	1.51	88.82	1.57	1.84	
5	13.01	170.57	6.45	8.80	
10	12.19	100.25	11.02	13.30	
20	23.98	84.61	26.01	30.66	0.7574
30	29.20	77.49	34.16	41.20	
50	25.54	40.85	58.08	66.98	
70	23.61	37.93	57.22	67.29	
90	21.35	36.92	53.26	62.42	
110	21.24	30.96	61.31	75.91	
WISP 0.3 m / Beacon 0.3 m[2]					
0	0.05	76.92	0.05	0.07	
1	0.54	81.80	0.57	0.76	
2	1.09	81.24	1.14	1.53	
5	3.95	87.89	3.78	5.21	
10	10.36	74.17	11.80	16.13	
20	13.12	34.53	34.82	41.18	0.7896
30	14.76	31.80	38.54	54.26	
50	NA	NA	NaN	NaN	
70	NA	NA	NaN	NaN	
90	NA	NA	NaN	NaN	
110	2.88	19.28	-10.93	40.76	
WISP 0.3 m / Beacon 0.7 m[3]					
0	0.18	124.36	0.12	0.18	0.7289
1	1.03	155.90	0.47	0.85	

2	1.26	76.32	1.42	1.88	
5	18.53	132.90	10.52	17.37	
10	4.49	70.01	5.60	7.23	
20	12.21	70.93	15.01	19.42	
30	23.22	54.69	37.97	46.96	
50	20.60	31.90	54.33	74.82	
70	20.15	26.50	64.87	87.19	
90	NA	NA	NaN	NaN	
110	NA	NA	NaN	NaN	
WISP 0.7 m / Beacon 0.3 m[4]					
0	0.32	129.38	0.19	0.31	
1	0.31	67.80	0.41	0.52	
2	1.08	80.38	1.14	1.53	
5	6.21	141.86	3.26	5.50	
10	10.14	91.85	9.13	12.95	
20	16.13	60.19	23.64	29.95	0.6354
30	16.54	34.87	40.75	54.11	
50	12.61	22.02	49.23	65.25	
70	6.27	8.57	57.58	88.72	
90	NA	NA	NaN	NaN	
110	NA	NA	NaN	NaN	
WISP 0.7 m / Beacon 0.7 m[5]					
0	0.12	111.69	0.09	0.13	
1	0.50	66.95	0.65	0.83	
2	2.31	113.73	1.62	2.45	
5	2.36	70.18	2.94	3.80	
10	8.00	67.33	10.43	13.32	
20	12.22	69.78	15.30	19.72	0.8562
30	19.09	73.31	22.59	29.50	
50	41.24	43.49	86.59	103.04	
70	29.39	32.89	82.30	96.42	
90	34.65	36.99	86.18	101.13	
110	29.27	24.91	106.96	128.07	

Table C.2 Comparison of the natural log prediction models generated for each of the WISP-beacon height groups for Beacon Type 3.

	Natural Log Model – Beacon Type 3				
Distance (m)	SD	CV	L95% CI	U95% CI	Adj R^2
All Combined Device Heights[1]					
0	0.23	130.21	0.15	0.20	
1	0.97	101.65	0.87	1.05	
2	2.04	110.02	1.66	2.05	
5	5.97	109.46	4.88	6.03	
10	11.79	103.33	10.25	12.57	
20	15.21	70.27	20.12	23.16	0.7368
30	21.77	53.37	38.13	43.46	
50	20.95	46.26	39.72	50.84	
70	16.79	38.54	38.34	48.81	
90	11.90	32.66	31.03	41.87	
110	6.53	14.50	41.80	48.29	
WISP 0.3 m / Beacon 0.3 m[2]					
0	0.06	135.87	0.03	0.06	
1	1.03	83.90	1.03	1.42	
2	1.81	94.86	1.56	2.26	
5	5.77	89.11	5.36	7.59	
10	6.41	60.03	9.44	11.92	
20	13.38	59.34	19.79	25.30	0.8583
30	17.22	49.94	29.96	39.01	
50	10.45	21.48	38.99	58.32	
70	NA	NA	NaN	NaN	
90	NA	NA	NaN	NaN	
110	NA	NA	NaN	NaN	
WISP 0.3 m / Beacon 0.7 m[3]					
0	0.21	125.72	0.13	0.21	
1	0.80	98.36	0.66	0.97	
2	1.72	97.05	1.44	2.10	0.6983
5	3.87	99.76	3.13	4.63	
10	14.61	127.11	8.32	14.66	
20	11.76	52.54	19.97	24.78	

30	12.30	27.24	41.17	49.14	
50	NA	NA	NaN	Nan	
70	NA	NA	NaN	NaN	
90	NA	NA	NaN	NaN	
110	NA	NA	NaN	NaN	
WISP 0.7 m / Beacon 0.3 m[4]					
0	0.21	85.14	0.20	0.28	
1	0.59	111.93	0.41	0.64	
2	2.08	146.92	1.01	1.81	
5	7.01	121.16	4.42	7.15	
10	12.05	109.31	8.69	13.36	
20	12.70	67.87	16.15	21.27	0.6615
30	20.79	50.28	36.77	45.91	
50	17.28	29.89	45.44	70.16	
70	14.04	25.80	46.93	61.89	
90	NA	NA	NaN	NaN	
110	NA	NA	NaN	NaN	
WISP 0.7 m / Beacon 0.7 m[5]					
0	0.23	128.87	0.13	0.22	
1	1.12	95.84	0.95	1.38	
2	2.06	100.72	1.65	2.44	
5	4.94	107.76	3.62	5.53	
10	8.00	70.62	9.78	12.88	
20	15.31	81.78	15.73	21.71	0.7697
30	32.31	67.82	40.45	54.82	
50	31.16	52.76	48.96	69.17	
70	25.13	43.84	46.95	67.70	
90	17.41	32.40	45.60	61.90	
110	9.80	14.44	63.02	72.77	

Appendix D TechCare Meat Sheep Welfare Assessment Measures

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