EXPLORING STATISTICAL CLASSIFICATION, GIS ANALYSIS AND MAPPING OF HERBIVORE BEHAVIOURS USING ACCELEROMETERS AND HIGH ACCURACY GPS

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1 Abstract

Electronic sensors equipped with accelerometers have the potential to remotely monitor and record herbivore behaviours. In the UK, sheep are a significant consumer in both managed pasture and upland ecosystems. The ability to automatically collect behavioural data could help inform research into ecosystem functioning and animal welfare. This study evaluated the placement of accelerometers and the ability of data generated to automatically classify four behaviours in sheep; grazing, standing (non grazing), lying head up and lying head down. An application of this method was used to analyse and map data in a GIS and investigate if sheep show a preference for areas with higher fructan levels in grass. Three sheep were fitted with two accelerometers each. One attached to a head halter and one centrally located across the withers by means of a dog harness. Training data were collected and discriminant function analysis was used to develop a model that could predict future unobserved behaviours. Correct classification rates of 95.2%, 91.0% and 91.8% were achieved for each sheep. In the fructan study, although no preference was detected, the study did demonstrate that data from accelerometers can be used to generate behavioural distribution maps. The use of accelerometers is a suitable method for classifying a range of behaviours in sheep.

2 Acknowledgements

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3 Objectives

Explore the ability of discriminant function analysis to classify sheep behaviour from accelerometer data.

Combine GPS and accelerometer data to investigate if sheep exhibit a preference for higher levels of fructan.

4 Contents

5 Introduction

The UK has a population of 22.9 million sheep (Defra, 2012)and is the largest producer of sheep meat within the European Union(European-Union, 2012). The population is distributed on hill, upland and lowland environments with the greatest density being in upland habitats (Defra, 2006).The grazing habitats of sheep are important carbon stores. Upland habitats account for some of the largest stores of carbon in the UK (Milne and Brown, 1997, Natural.England, 2009).Over the last 10,000 years, UK peatlands have sequestered 5.5 billion tonnes of carbon from the atmosphere (JNCC, 2011).The Climate Change Act (2008) puts in place legally binding targets to reduce the UK’s greenhouse gas emissions by at least 80% by 2050. With large carbon stores in UK uplands, land management and the functioning of these ecosystems can directly affect these targets. The management of grazing herbivores is important as it can potentially impact on ecosystem functioning (Tilman et al., 1997) and biodiversity. The need for research into the management of biodiversity and its importance to ecosystem functions has been highlighted by the Biodiversity Theme Action Plan (BTAP) (Natural.Environment.Research.Council, 2009). The BTAP aims to understand further the role of biodiversity in key ecosystem processes and functions. Further, as part of an adaptation plan for climate change risk and reporting requirements under the Climate Change Act (2008), Natural England (NE) has highlighted how climate change driven threats have direct effects on species and their interactions that threaten the ability to protect species and ecosystems. NE response to these threatsrecognises the need for an ecosystem approach, considering the full range of ecosystem services a healthy natural environment provides to people (Natural.England, 2012). Bardgett and Wardle (2010)discussed the significance of herbivores in relation to above and below ground interactions suggesting more research is needed to understand how herbivores modulate ecosystem responses to climate change and consequently how the management of herbivore populations could be changed to mitigate against climate change effects (Bardgett and Wardle, 2010). Scaling up research to the landscape scale to better understand the effects of herbivores on ecosystem processes, that are well studied at localised spatial scales, and their effect on ecosystem functions at the landscape scale, will contribute to the ecosystem approach needed to help understand and mitigate climate change threats to important grazing habitats (Bardgett and Wardle, 2010). Further, the ability to monitor herbivore behaviours in a spatial context at the landscape scale will also enhance the understanding of the influences of grazing on biodiversity &natural environments and ecosystem processes (Putfarken et al., 2008a, Rutter, 2007).

5.1.1 Difficulties with visual sheep observations and the need to automate

Collection of data on sheep behaviour faces several challenges:

- Visual observations of sheep are time consuming and labour intensive, particularly at the landscape scale. Observations in upland environments are further impeded by the varied terrain and potential wide spatial distribution of the target population. The different visual observation sampling protocols, e.g. scan, focal, or continuous sampling (Altmann, 1974) can be difficult to complete as the focal or selected animals have increased opportunity to move out of sight of an observer.
- The presence of an observer or observers can in itself alter the behaviour (Martin and Bateson, 1993)or free choice foraging behaviours of individuals through the human-animal relationship (HAR), further complicating the assessment of natural behaviours. The presence of one or more observers can elicit fear responses in sheep. On farm management such as shearing, castration, tail docking, vaccination, herding and transportation are known to generate fear responses in sheep (Forkman et al., 2007), thus creating future aversion to humans. However the method used for some treatments can reduce future aversion and flight risk (Hargreaves and Hutson, 1990). Behavioural reactions to human presence can also vary between breeds (Le Neindre et al., 1993). These responses are indicative of the HAR, especially one categorised as negative. Sheep can discriminate between different people and exhibit different levels of fear responses (Boivin et al., 1997), however, observers engaged in scientific data collection are unlikely to have developed the type of HAR that results in reduced fear responses similar to that of stock people.
- Manual observations of animals are also at risk of anthropomorphism, whereby behaviours are interpreted in a subjective manner and influenced by the observers' emotions and intentions (Martin and Bateson, 1993). Further, manual observations can also suffer from negative within and between observer reliability and validity. The practice and experience of observers, frequency of behaviour occurrence, and observer fatigue can all affect how well a category of behaviour is measured and the reliability within and between observers (Martin and Bateson, 1993). Further, definitions of behaviour categories are at risk of changing over time, known as observer drift. This, however can be reduced with clear and unambiguously defined categories or through scoring scales such as used by Kaler et al. (2009).

The difficulties inherent in manual observations could be reduced by using some form of automatic recording of behaviours producing quantitative data. Indeed, interest has been growing for some time in automatic techniques where animal behaviour can be monitored on multiple animals, non-invasively for long periods of time (O'Driscoll et al., 2008).

5.1.2 Accelerometers

Accelerometers have been used in livestock research to automatically detect and classify: step counts (Scaglia et al., 2009, Boland et al., 2011), multi behavioural classification (Moreau et al., 2009, Watanabe et al., 2008, Soltis et al., 2012, Nadimi et al., 2008, Nadimi et al., 2012), and total activity levels comprising different behaviours such as feeding, drinking, walking, grooming, ruminating as well as all conscious and unconscious movements (Giannetto et al., 2010, Bertolucci et al., 2008, Piccione et al., 2008d, Piccione et al., 2008a). In agricultural and livestock environments, several different types of accelerometer have been used in applied research.

Accelerometers are available as ready-made all in one solutions, ready-housed component and electrical component only solutions. Off the shelf animal research solutions have all electronic components ready housed in an end product. The provided software manages the transfer and analysis of data. Different products are able to detect and classify different activity levels and locomotion (e.g., Actiwatch) and step counts (e.g., Icetag). Ready housed raw data accelerometers are supplied with software that will convert the raw data into acceleration and angular displacement measurements. However the software is not capable of analyzing data to classify behavioural modes, activity levels or step counts. Component accelerometers are available and have been used but these require the end user to build and fit them in a suitable housing with adequate power while also providing their own means by which to transfer and analyse raw data.

5.1.3 Ready-made accelerometers

Actiwatch

In the early 2000s, Actiwatch devices were manufactured in tandem by MiniMitter Co. MA, USA and Cambridge Neurotechnology Ltd (CNT), UK. Minimitter licensed the technology from CNT. The Actiwatch-Mini® utilises a piezo-electric accelerometer that is set up to record the integration of the amount, duration and intensity of movement in all directions. The corresponding voltage produced is converted and stored as an activity count in the memory unit of the Actiwatch-Mini®. The maximum sampling frequency is 32 Hz. It is important to stress that due to this improved way of recording activity data there is no need for sensitivity setting as the Actiwatch unit records all movement over 0.05 *g*. (Piccione et al., 2008a). The Actiwatch-Mini has been used to monitor activity levels and locomotion in a variety of livestock animals such as cows (Piccione et al., 2011f), goats (Giannetto et al., 2010, Piccione et al., 2008i, Piccione et al., 2008a), horses (Bertolucci et al., 2008) and sheep (Piccione et al., 2008d, Piccione et al., 2007, Piccione et al., 2010a, Piccione et al., 2010d, Piccione et al., 2011a). The ability to automatically monitor activity levels in livestock has been used to investigate the adaptation of animals to different intensive farming management options. Piccione et al. (2011a) investigated the influence of different housing conditions and feeding schedules on the daily rhythm of total locomotor activity (TLA) in sheep using the Actiwatch-Mini. They concluded that restricting food access to a limited number of hours per day forces a cycle in which the short period of food ingestion alternates with a long interval of fasting, resulting in a precise and defined cycle of feeding-fasting and satiety-hunger. During the rest of the day, TLA was reduced with respect to the period of food availability, with some peak of activity. Even if the TLA is mainly entrained by photoperiod, the amount of activity may be influenced by housing conditions and food availability. Their research showed that monitoring of TLA with the Actiwatch-Mini can be applied to describe the adaptation of animals both to different stabling conditions and feeding schedules, to improve welfare and health of sheep. Piccione et al. (2011f) investigated the influence of different farming conditions on the TLA of cows and how this could be used as a tool to determine management-related differences in activity patterns under real-life conditions. They found that for dairy cattle subjected to farming management, most activity is concentrated in the photophase of the light/dark cycle. The activity was rhythmic, even though the management practise changed according to the productive period, and activity reached its peak in the middle of the photophase. However, activity levels differed according to management conditions and could be influenced by food administration and diet composition, even though the main stimulus to the onset of the TLA is in any case the photoperiod. Giannetto et al. (2010) investigated whether changes in photoperiod and restricted feeding were associated with changes in total daily locomotor activity in goats. Using the Actiwatch-Mini helped to show that goats exhibited a daily rhythm of total locomotor activity, with the highest daily amount of activity during the photophase. With *ad libitum* food access, the primary influence of the TLA was identified as the photic stimulus and with restricted feeding the zeitgeber of TLA was shown to be the restricted food access (non-photic stimuli). Further studies have investigated how photoperiod and restricted feeding affect total daily locomotor activity in sheep.Piccione et al. (2010d) considered the daily rhythms of free radicals and anti-oxidant power in sheep, and the possible influences of daily locomotor activity fluctuation, (Piccione et al., 2010a) showed the circadian rhythm of total activity in sheep and goats kept in stable conditions.

Icetag

The IceTag accelerometer (Ice Robotics Inc, Edinburgh, UK), designed specifically for livestock, monitors and records stepping, standing and lying behaviour. It is a leg-based sensor based around a 3 axis accelerometer that has a sampling rate of 16 Hz, averaging the data to 1 second. The Icetag has been updated several times with the Icetag2 available until 2008. The subsequent model, Icetag3D, made available wireless data transfer. The latest model, IceTag®Sensor maintains the same functionality but in a smaller and lighter housing. The end user does not have access to the raw data from each axis, rather the included software, “IceTagAnalyser” converts the data to present the user with information on stepping, lying and standing behaviour. Although the Icetag does not give data on grazing behaviour, Aharoni et al. (2009) and Scaglia et al. (2009) used a procedure to extract time spent grazing and walking without grazing. They summarised the data into 5-minute intervals. If fewer than 10 steps were taken during that interval, the animal was considered to be standing still; if between 10 and 80 steps were taken, the animal was considered to be grazing; and if more than 80 steps were taken, the animal was considered to be walking without grazing (Scaglia et al., 2009). Using this method (Scaglia et al., 2009) attempted to evaluate the effect of time of supplementation on the behaviour and dry matter intake of beef steers continuously stocked on annual ryegrass. They were able to conclude that supplementation in the afternoon hours reduced the time animals spent grazing when data were analyzed within periods of the day. (Aharoni et al., 2009) sought to compare the grazing behaviour, diet intake, and energy cost of activity of Beefmaster × Simford cross cows and small Baladi cows. With the use of the Icetag, they were able to conclude that Baladi cows were better adapted to harsh conditions than heavy beef cows due to better efficiency of intake utilisation and smaller relative locomotion cost of small stature. In an effort to improve grazing management and better understand foraging strategies of dairy cows under progressive defoliation regimens, Gregorini et al. (2011) investigated the feeding station behaviour of dairy cows during the first grazing session of the day in response to daily restrictions of time at pasture. The Icetags were used to calculate feeding station eating steps and searching steps. The eating step length was calculated using validation data collected over two days by dividing the distance walked while eating between the two points (provided by GPS collars) and the number of steps taken between them (using the IceTags). They concluded that changes in the total number of feeding stations shown during the first grazing session of the day occur in response to restrictions of time at pasture helping to further understand changes in eating and locomotive behaviour in competitive feeding scenarios situations in intense grazing management systems. Generally, studies using the Icetag are not concerned with validation as the provided software interprets the data and presents the end user with information on posture (standing vs. lying), leg movement and the number of steps taken per time unit. However, as Ledgerwood et al. (2010) noted, the use of the recorded number of steps per second to classify walking or standing can provide an inaccurate prediction because cows can move their legs without motion of the body, i.e. without walking, and they can also walk so slowly that no leg activity is recorded for one or more seconds. Ledgerwood et al. (2010) aimed to develop an algorithm for predicting the duration of walking and standing periods based on a moving average of the output from the IceTag device and the step count and lying/standing prediction of the IceTag device was also validated against video recordings. They found that sorting data into steps for walking, and steps for standing will improve the correct step counts and suggested that the IceTag provides data that can be used to estimate the number of steps per time unit and to estimate the frequency and duration of walking and standing with a reasonably high accuracy.

5.1.4 Component accelerometers

Accelerometers are also available as standalone electronic components that require the user to integrate a power source, storage and transfer capabilities in an appropriate housing. This approach allows the researcher to develop a bespoke system that is tailored to specific requirements. However, knowledge of electrical components and the ability to integrate all the separate components into one system is required. Unlike the all in one solutions such as the Actiwatch and Icetag, accelerometer data need to be calibrated and validated against the behaviour, activity or movement of interest. Nadimi et al. (2011) and Nadimi et al. (2012) used a dual axis ADXL202 accelerometer (Analog Devices, Norwood, MA) integrated with a MTS310 sensor board (MEMSIC Inc, Andover, MA). These components were further integrated into a wireless sensor network to facilitate wireless monitoring of sheep behaviours including grazing, lying down, standing and walking. Using a separate component based approach they were able to successfully design and establish a wireless network with integrated energy generation (Nadimi et al., 2011) and enhanced communication reliability (Nadimi et al., 2012) for monitoring sheep behaviours. Martiskainen et al. (2009) used a tri-axial ADXL330 accelerometer (Analog Devices, Norwood, MA) integrated with an 8-bit AD converter to convert accelerometer voltage output to integer values. The accelerometer was powered with four 3.7 V lithium batteries (2.4 Ah each). Data were sent to a pc via a wireless data acquisition network. Using a separate component based approach they were able to develop a method for measuring several behavioural patterns of dairy cows. Cornou and Lundbye-Christensen (2010) housed a tri-axial LIS3L02DS accelerometer (STMicroelectronics, Geneva, Switzerland) with a battery package and Bluetooth transfer capabilities. They successfully used these integrated components on group-housed sows and showed how multivariate models are well suited to categorise activity types.

5.1.5 Housed accelerometers

Unlike component only accelerometers, ready housed accelerometers provide a solution that requires no knowledge of electronic systems design. However, as with component based accelerometers, data need to be calibrated and validated against the behaviour, activity or movement of interest. These accelerometers usually come supplied with software allowing programming of sample rates and data retrieval. Housed accelerometers have been used with a variety of livestock animals to successfully classify behaviours such as feeding, walking, resting and step counts. Soltis et al. (2012) used the X9-2mini accelerometer (Gulf Coast Data Concepts) fitted to collars to determine if data generated by the device could distinguish between four behaviour patterns: feeding, bathing, walking and swaying in captive African elephants. Robert et al. (2009) used a GP1 SENSR tri-axial accelerometer (SENSR, USA) fitted to the lateral aspect of the right rear leg and were able to show that accelerometers can provide an objective, non-invasive measure of activity and standing, walking and lying behaviours in cows. Watanabe et al. (2008) used the G-MEN DR10 tri-axial accelerometer (SRIC, Nagano, Japan) fitted to cows by means of a head halter. Using the raw accelerometer data, they developed a statistical method using discriminant function analysis to automatically classify eating, ruminating and resting activities with a success rate greater than 90%. Moreau et al. (2009) used the HOBO Pendant G tri-axial accelerometer (Onset Computer Corporation, Pocasset, MA, USA) to develop an automated behaviour analysis system for goats' activities at pasture. Using different accelerometer positions on the goats, they investigated if resting, eating and walking could be automatically classified. They were able to show, with robust calibration, automatic detection of goat behaviours was possible. Ringgenberg et al. (2010) also used the HOBO Pendant G tri-axial accelerometer to automatically detect standing, lying laterally and ventrally in sows and also quantify the number of hind limb steps taken by a sow during a feeding episode. Ledgerwood et al. (2010) also used the HOBO Pendant G tri-axial accelerometer to evaluate its accuracy to detect lying on the left side, lying on the right side, total lying time, and number of lying bouts in dairy cattle. Depending on sampling intervals, they were able to successfully detect all aspects of lying behaviour.

5.2 Validation and calibration

The general practice in using accelerometers to classify animal behaviours requires the accelerometer data be used to train or calibrate classifiers or machine learning algorithms that are validated against observations, often video observations, and then used to classify unobserved behaviours from future accelerometer data (Nathan et al., 2012). All in one solution accelerometers such as the Actiwatch and Icetag come with classifiers and algorithms integrated into the supplied software. Component and housed accelerometers require the user to implement a statistical method to classify the raw data into behaviour or activity classes. Classifiers can be considered to be unsupervised or supervised. Unsupervised classification such as cluster analysis develops class structure within the data where classes are not known *a priori*. With supervised classification, however, such as discriminant function analysis, class structure is known *a priori*, and rules and algorithms are developed to allocate new unknown cases to the appropriate classes (Wade, 1999).

5.2.1 Statistical classifiers and behaviour prediction

5.2.2 Discriminant function analysis

Discriminant function analysis (DFA) is a supervised learning multivariate statistical classifier used to predict group membership from a set of predictors (Tabachnick and Fidell, 2007). In DFA, the independent variables are the predictors and the dependent variables are the groups (Poulsen and French, 2004). In order to predict group membership, DFA creates a discriminant function in the form of a linear equation with a combination of the independent variables weighted to maximize the difference between or among the groups categorized by the dependant variable.

DFA has been used previously on accelerometer data. Soltis et al. (2012)used DFA to attempt to separate four behaviour classes in African Elephants. Watanabe et al. (2008) used DFA to discriminate behaviours in cows using separate axes data from an accelerometer. The classification accuracy varied widely dependent on the axes and behaviour in question. Using the *x* axis data, they achieved correct classification in excess of 98%, but only 34% using data from the Y axis.

5.2.3 Classification trees

Decision trees, or classification and regression trees (CART) (Breiman et al., 1984) are a multi-stage method of classification whereby cases are grouped through successive division of the data into increasingly homogeneous groups or nodes (Finch, 2006) to predict the membership of cases in classes of a categorical dependent variables from measurements of one or several predictor variables (Nadimi et al., 2008). Among the advantages of CART analysis is the lack of assumptions making it inherently non-parametric, able to handle ordinal or non ordinal categorical predictors and skewed or multi-model data (Lewis, 2000). Robert et al. (2009) used a classification tree (Insightful Miner, Insightful Corporation, Seattle,WA) to validate against video recording cattle behaviours using an accelerometer. Lying and standing gave excellent agreement with 99.2% and 98.0% respectively whilst walking was significantly lower with 67.8% agreement.

5.2.4 Neural networks

Artificial networks consists of a group of simple processing units (neurons) which communicate through signals sent to each other (Kröse et al., 1996). By adjusting the weights of the connections between the neurons, trained by a training data set, neural networks can perform a given function(Lee et al., 2010): for example, classification of behaviours from accelerometer data. Nadimi et al. (2012), in their development of a wireless sensor network to classify sheep behaviours, used an MLP-based feed forward back propagation neural network with five layers. Each hidden layer contained 10 neurons. Hyperbolic tangent sigmoid transfer functions were used as the activation function of the hidden layers and a linear transfer function was selected for the output layer. The initialization process was performed using the Nguyen–Widrow initialization algorithm (Nadimi et al., 2012). Using this neural network architecture, they were able to successfully discriminate 83.8% of grazing and 83.2% of lying.

5.2.5 Support vector machine

Support vector machine is a supervised learning classification method. It maps pattern vectors to a high dimensional feature space (Webb, 2003) where hyperplanes are formed that best separate and maximize the distance of observations from the separating hyperplane (Nathan et al., 2012). Martiskainen et al. (2009) used multi-class support vector machine classifiers with data from accelerometers placed on cows to classify behaviours. They achieved over 80% accuracy for all behaviour classes combined. However, misclassification was common for standing, lying, and ruminating; 29%, 15%, and 15% of the cases, respectively mostly confused with each other.

5.2.6 K-means classification algorithm

The K-means classifier (MacQueen, 1967) is an unsupervised learning algorithm. This clustering method partitions data into *k* clusters with the aim of minimising the variability within clusters and maximising the variability between clusters (Landau and Everitt, 2004). A case is assigned to a group or cluster with the closest mean. The group means are then recalculated until the within-group sum of squares are no longer reduced by the movement of cases (Webb, 2003). An advantage of K-means is the minimal data preparation and no calibration procedure is required (Schwager et al., 2007) although the user needs to determine *a priori* the number of clusters to be obtained (Fortin and Dale, 2005).

5.3 GPS

Satellite-based systems became available for use during the 1980’s. One of the best known systems, Argos (Hulbert and French, 2001) was used in animal tracking studies. However, measurements using this system were affected by topography and animal movements and as a result, errors of between 0.5 to 1.5 km and occasionally up to 8 km have been reported (Fancy *et al.* 1988). The development and deployment of the Global Positioning System (GPS) for civil use by the US military presented new possibilities for animal tracking and research studies. However, for reasons of national security, the US Department of Defence implemented “selective availability” which reduced the accuracy of the civilian GPS signal to 100m (Rodgers et al., 1996). In May 2000 selective availability was removed resulting in significant improvements to location accuracy (Adrados et al., 2002). However, further precision can be obtained when differential correction is applied to GPS location data. This involves recording errors in the GPS signal at a fixed known location and then applying them as a correction factor either in real time or by post processing the correction factors to the data collected (Rutter, 2007). Other techniques such as the H-Star technology employed in Trimble mapping and survey grade GPS receivers can further improve precision into the sub metre range (Rutter, 2007), Trimble 2005) allowing data collection on patch scale foraging.

Housed accelerometers and GPS offer a potentially reliable, affordable and easy to implement method to atomically classify and map sheep behaviour. However, the use and performance of statistical classifiers needs to be evaluated before wider adoption.

6 Training a statistical classifier for automatic classification of sheep behaviours using accelerometers

6.1 Introduction

Accelerometers have been used to automatically classify animal behaviours without the need for a human observer in close proximity to focal animals (Naylor and Kie, 2004, Watanabe et al., 2008, Soltis et al., 2012, Ledgerwood et al., 2010). When combined with GPS data, spatially aware behaviour classification is possible (Moreau et al., 2009). Accelerometers provide a means to reducing observer bias and overcoming the difficulties of livestock observations in challenging terrain. While accelerometers have been used widely to classify behaviours in cows, e.g. sleep detection (Hokkanen et al 2011), eating duration (Ueda et al 2011) oestrus detection (Fricke et al 2012, Valenza et al 2012) and eating, ruminating and resting (Watanabe et al 2008), little research has been conducted evaluating their performance for classifying sheep behaviour. Biomedical research has used accelerometers extensively with sheep to investigate the response of fetuses to vibration stimuli by attachment of small accelerometers to the foetus skull (Abrams et al., 1997, Petersa et al., 1996), head impact (Anderson et al., 1997, Anderson et al., 2003), shaken baby syndrome (Sandoz et al., 2012), and spinal studies (Keller et al., 2006b, Colloca et al., 2009, Keller et al., 2006a). These approaches, however, use invasive methods of attachment not suitable for livestock experiments or monitoring. Collar attached Actiwatch accelerometers have been used by Piccione et al. (2008d), Piccione et al. (2011a) to detected diurnal rhythms in activity levels (e.g. – feeding, drinking, walking, grooming and ruminating) in sheep. However, the Actiwatch is an all in one off the shelf system, which rather than detecting individual postures associated with specific behaviours, only detects activity levels. Nadimi et al. (2012) and Nadimi et al. (2011) used the ADXL202 accelerometer (Analog Devices, Inc. Norwood, MA) to detect grazing, lying down, standing, walking, mating and drinking in sheep. These accelerometers, however, are supplied as standalone electronic components that require the user to be competent in electrical systems design. Ready housed raw data accelerometers offer a solution that requires no electronic systems design knowledge while providing the potential to classify individual postures associated with behaviours of interest. Moreau et al. (2009) used the Hobo® G Pendant Data Logger accelerometer (Onset, USA) to classify resting, eating and walking in goats. Ringgenberg et al. (2010) used the same accelerometer to detect standing, sitting and lying in sows. Ready housed accelerometers do, however, require the raw data to be calibrated and validated. Machine learning classifiers have been used to classify component and housed accelerometer data. Accelerometer data, annotated with behaviours', usually from video recordings (Soltis et al., 2012, Watanabe et al., 2008, Ledgerwood et al., 2010, Nadimi et al., 2012) are used as training data for machine learning algorithms. No standardised methods exist in the literature with regards to the choice of classifier. Discriminant function analysis (Soltis et al., 2012, Watanabe et al., 2008, Naylor and Kie, 2004), classification trees (Robért, 2010, Robert et al., 2009, Ungar et al., 2011), neural networks (Nadimi et al., 2012), support vector machines (Hokkanen et al., 2011, Martiskainen et al., 2009) and manually developed decision trees (Moreau et al., 2009) have all shown good classification results with different accelerometers and animals. The majority of studies with sheep and accelerometers have used the Actiwatch system and the included software for classification of activity levels (Piccione et al., 2010d, Piccione et al., 2007, Piccione et al., 2011a, Piccione et al., 2008d, Piccione et al., 2010a). To the author’s knowledge, no ready housed accelerometers have been used with sheep, only component based accelerometers which used neural network algorithms for classification (Nadimi et al., 2012). Ready housed accelerometers used with machine learning classifiers may provide a suitable, low cost, easily deployed system to automatically monitor sheep behaviours. Further, when combined with GPS data, behaviour classification could also be spatially aware, helping to show habitat use by sheep and provide a method to investigate how ecosystems respond to herbivore pressures at the landscape scale by generating behaviour distribution data that could inform sampling strategies for environmental data collection. As using ready housed accelerometers do not require the electrical systems design knowledge needed when using component accelerometers, such a system could be more widely adopted. However, validation and calibration needs to be assessed to determine the ability of a ready housed accelerometer to classify sheep behaviour before deployment in the wider environment and accelerometer attachment positions need to be assessed for their contribution to the model.

The aims of this study were to (1) generate multi class training data collected from sheep attached accelerometers (2) use discriminant function analysis to interrogate the training data and assess this analysis capability for classifying sheep behaviours from accelerometer data.

6.2 Methods

Training data were collected during June and July 2011 in a small enclosure of 550m^2 in North West England located in Shotwick, North West England (SJ 33780 71987). The study site presented opportunities for both grazing and browsing with variable terrain in a small area suitable for observations of the animal’s behaviour to be video recorded. Vegetation was a mix of perennial rye grass (*Loliumperenne*) and clover (*Trifoliumrepens*). Scattered apple trees occupy the site which is bordered by hawthorn to the east and south and wooden fencing to the north and west. Three ewes (Table 1) were fitted with a head halter and dog harness one week prior to the study. Sheep had *ad libitum* access to water and the study site prior to, during and after the study period.

Table 1 Body surface area (cm^2) and mass (kg) of the three ewes used in the study. Body surface area calculated using formula as described by Benedict (1934) in Schmidt-Nielsen (1984). Mass was calculated using the formula described by (Benedict, 1934).

Sheep	Body Surface area (cm^2)	Mass (kg)
1	4172.8	74.1
2	2218.8	39.4
3	2266.8	40.2

6.2.1 Accelerometers

Due to their inexpensive cost and small protective waterproof housing (58 x 33 x 23 mm) weighing 18 g, six HOBO Pendant G accelerometer data loggers (Onset Computer Corporation) were used. This accelerometer is a three-channel logger with 8-bit resolution and can record up to approximately 21,800 combined x-, y-, and z-axis acceleration readings or internal logger events (Figure 1) (Onset Computer Corporation 2011).

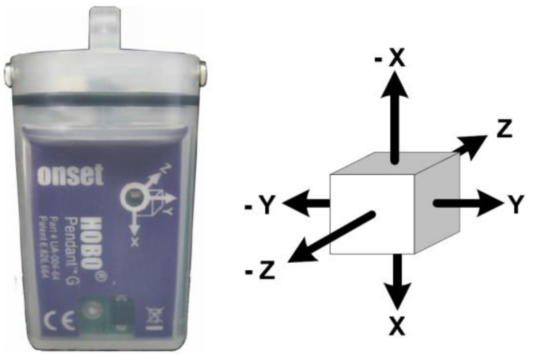


Figure 1 HOBO Pendant G accelerometer data logger X, Y and Z axis of orientation (Onset Computer Corporation 2011).

Two accelerometers were attached to each sheep by two attachment methods. The different attachments were assessed for reliability and the effect of accelerometer location on the predictive capability of the model. A leather head halter allowed the accelerometer to be placed between the frontal bone and the parietal bone (Figure 2) allowing capture of postures and movements of the head, particularly those associated with grazing. A dog harness allowed placement of the accelerometer across the withers (Figure 3). Each attachment type had a small leather pouch attached to allow safe, secure deployment of the accelerometer.

Figure 2 Position of the accelerometer placed between the frontal bone and the parietal bone.

Figure 3 Position of the accelerometer placed across the withers

6.2.2 Behavioural recording and calibration

Training data were annotated with behaviour codes after sheep movements were recorded with a Sony DCR-HC24EMiniDV Handycam®. The camera, mounted on a tripod, was positioned at various locations within the study area dependant on the focal animal position. The internal clock of the camera was synchronised with the internal clock of the computer from which the accelerometers would be activated. This ensured both the camera and accelerometer were synchronized in time to allow accurate annotation of the accelerometer data after behavioural recordings were made. During recording sessions, all sheep were fitted with activated accelerometers via both attachment methods. The aim was to film each individual for four hours during daylight but due to some synchronous accelerometer failures while filming, some recordings were not used. However, video footage containing more than one of the study animals was used to add further annotations to the data. Consequently, the total time filmed and comparable frequencies of behaviours differ amongst the three sheep.

From each accelerometer, data on three axes (x, y and z) for both acceleration (*g*) and angle of tilt (°) were obtained (recording interval = 1 second). This gave up to six variables from a single accelerometer available for analysis. Accelerometer data were downloaded using the Hoboware Pro 3.4.0 software (Onset Computer Corporation). The accelerometer data were exported into an Excel spreadsheet. As well as containing values of acceleration and tilt on three axes, the data also contained the date and time of each one second interval of accelerometer data. The video footage of each sheep was replayed with a time stamp visible on screen. A new column was created in the spreadsheet called behaviour code. This column was manually populated with one of four codes corresponding to one of four behaviour modes (Table 2) as observed during video playback.

Table 2 Number of cases observed in each behaviour group for sheep 1, 2 and 3.

Behaviour	**Group**	**Description**	**Sheep 1**	**Sheep 2**	**Sheep 3**
Standing head down	1	Standing head down while engaged in grazing behaviour	1472	2505	1381
Standing head up	2	Standing head up including walking with head up and vigilance	864	2237	2674
Lying head up	3	Lying head up including vigilance and chewing cud	7681	1781	5433
Lying head down	4	Lying head down including resting	719	3033	945
Total			10736	9558	10433

6.2.3 Statistical analyses

For each individual sheep, discriminant function analysis was performed separately to interrogate respective training data and generate linear discriminant functions. Twelve variables consisting of X, Y and Z acceleration (*g*) and tilt (°) axes were used as predictors of four dependant variables (behavioural groups). A classification table was generated to assess the accuracy of the model to classify sheep behaviours using accelerometers. Univariate and multivariate outliers were identified and removed. Multivariate outliers were identified from Mahalanobis distances. Mahalonobis distances from the groups centroid should follow a χ^2 distribution, and so any individuals with distances above the upper 99.9% quantile of this distribution were declared as outliers. Although the grouped predictors were not normally distributed, z scores greater than 4 were considered univariate outliers (Stevens, 2009).

6.3 Results

Discriminant function analysis using the within-groups matrix was performed using combined head and withers accelerometer data to classify four behaviour groups in three sheep. The within groups method allows cross validation via the "leave one out" jackknifed method. This validation method is useful as bias enters classification if the coefficients used to assign a case to a group are in part derived from that case. Rather than splitting the data in two where a proportion of the data has the group membership hidden from the system, the "leave one out" classification omits data from an individual case when coefficients used to assign that case are computed (Tabachnick and Fidell, 2007).. Twelve variables were used as the independents: Withers X Acceleration (*g*), Withers Y Acceleration (*g*), Withers Z Acceleration (*g*), Withers X Tilt (°), Withers Y Tilt (°), Withers Z Tilt (°), Head X Acceleration (g), Head Y Acceleration (*g*), Head Z Acceleration (*g*), Head X Tilt (°), Head Y Tilt (°), Head Z Tilt (°).

Univariate ANOVA results via the Tests of Equality of Group Means (Appendix 1 Table 9) indicate significant mean differences were observed for all the independent variables on all four behaviour groups for all sheep ($P<0.001$).

Log determinants were not similar for all sheep. Box's M (Appendix 1 Table 10) indicated the assumption of equality of covariance matrices was violated for all sheep ($P<0.001$). A high degree of correlation exists between variables that share the same axis, for example X acceleration and X tilt. Given that tilt variables are derived from accelerometer values, multicollinearity could be an issue. However, SPSS protects the analysis from multicollinearity through checks for tolerance. Withers Y Tilt for sheep 1 failed the tolerance test and was excluded from analysis as reflected in the rank=11 for sheep 1 Box's M output (Appendix 1 Table 10). DFA is sensitive to outliers, both univariate and multivariate. The lack of homogeneity of the covariance matrix could be as a result of outliers in one or more groups (Garson, 2012). Analysis was run again after identifying and deleting univariate and multivariate outliers (Table 3).

Table 3 Number of cases observed in each behaviour group after the removal of univariate and multivariate outliers for sheep 1, 2 and 3. Numbers in brackets are the number of cases removed for each group.

Behaviour	**Group**	**Sheep 1**		**Sheep 2**		**Sheep 3**	
Standing head down	1	1399	(73)	2417	(88)	1321	(60)
Standing head up	2	806	(58)	2135	(102)	2541	(133)
Lying head up	3	7313	(368)	1721	(60)	5207	(226)
Lying head down	4	700	(19)	2899	(134)	910	(35)
Total		10218	(518)	9172	(386)	9979	(454)

Following removal of univariate and multivariate outliers, univariate ANOVA results via the Tests of Equality of Group Means (Appendix 1 Table 11) indicate significant mean differences were observed for all the independent variables on all four behavior groups for all sheep ($P<0.001$).

Although the variability among log determinants was reduced with outliers removed, they were still not similar for all sheep (Appendix 1 Table 12). Box's M indicated the assumption of equality of covariance matrices was violated for all sheep ($P<0.001$). Further, some covariance matrices are singular and the usual procedure will not work. The non-singular groups would be tested against their own pooled within-groups covariance matrix. For these, the log determinants are -20.296 and -20.795 for sheep 1 and 2 respectively. As the assumption of equality of covariance matrices was still violated for all sheep even after the removal of outliers, the analysis was run again based on separate-group covariance matrices with the removal of outliers.

6.3.1 Separate-group covariance matrices with the removal of outliers.

Using separate covariance matrices, classification is based on the separate-group covariance matrices of the functions instead of the pooled within-groups covariance matrix. Cross validation is not available in SPSS using separate covariance matrices and consequently all cases are used the analysis. Further, the rank in the log determinants is equal to the number of discriminant functions in the model. Log determinants were not similar for all sheep (Appendix 1 Table 13). Using the separate groups method does not allow cross validation using the leave one out method. Box's M indicated the assumption of equality of covariance matrices was violated for all sheep ($P<0.001$). Nevertheless, analysis was continued as Box's M can be overly sensitive.

The Wilks' Lambda table shows the "peel off" significance tests of successive discriminant functions. The Wilks' lambda statistic here is the proportion of the total variance in the discriminant scores not explained by differences among groups. Three discriminant functions were calculated for each sheep (Table 4). After the removal of the second and third discriminant functions (2 through 3 and 3) the results were still significantly different for all sheep ($P<0.001$), meaning all functions are carried forwards in the analysis. As an example, for sheep 1, the three discriminant functions had a combined $\Lambda = 0.013$, $\chi^2(30) = 44103.428$, $p< 0.001$. After removal of the first function there was still a strong association between groups and predictors $\Lambda = 0.211$, $\chi^2(18) = 15871.653$, $p< 0.001$. Leaving just the third function, there was still a strong association between groups and predictors $\Lambda = 0.597$, $\chi^2(8) = 5270.159$, $p< 0.001$.

Table 4 Results of the Wilks' Lambda test for all sheep.

Sheep	Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1	1 through 3	.013	44103.428	30	<0.001
	2 through 3	.211	15871.653	18	<0.001
	3	.597	5270.159	8	<0.001
2	1 through 3	.025	33759.956	36	<0.001
	2 through 3	.173	16068.821	22	<0.001
	3	.503	6292.875	10	<0.001
3	1 through 3	.024	37199.471	33	<0.001
	2 through 3	.207	15699.433	20	<0.001
	3	.497	6976.408	9	<0.001

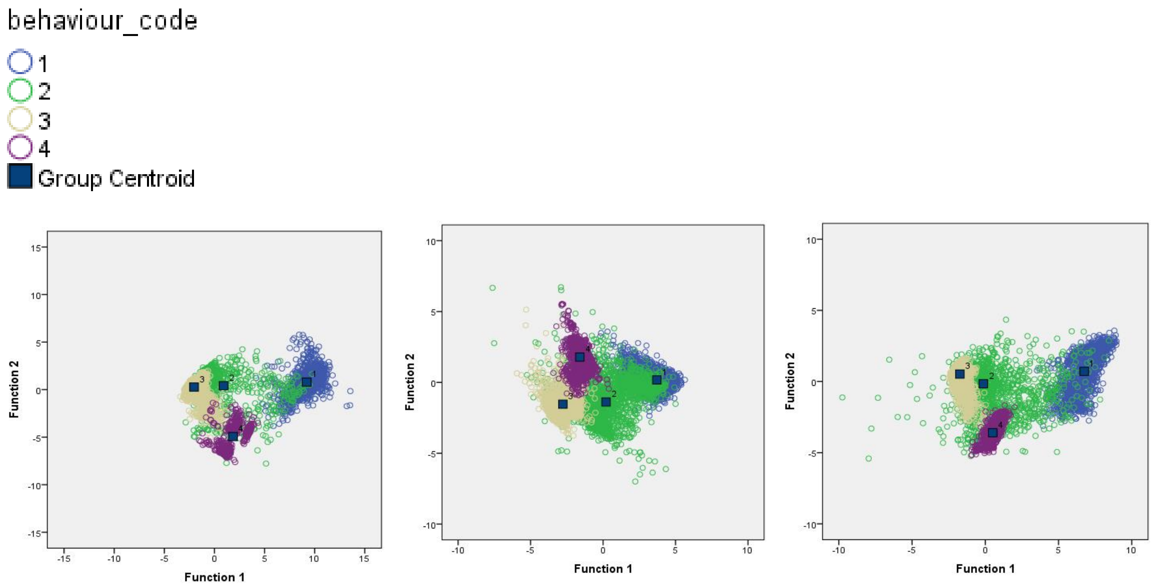
Eigenvalues indicate the proportion of variance explained. Large values suggest a strong function. Large canonical correlations indicate how well a function discriminates. The first discriminant function accounts for 85.6%, 67.1% and 76.0% of the between-group variability for sheep 1, 2 and 3 respectively. Large canonical correlation values also suggest the first function discriminates well for all sheep. Table 5 gives the remaining percentage of variance and associated statistics of each function for each sheep.

Table 5 Eigenvalues, % of variance and canonical correlation of sheep 1, 2 and 3.

Sheep	Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	1	14.881[a]	85.6	85.6	.968
	2	1.825[a]	10.5	96.1	.804
	3	.676[a]	3.9	100.0	.635
2	1	5.894[a]	67.1	67.1	.925
	2	1.906[a]	21.7	88.8	.810
	3	.987[a]	11.2	100.0	.705
3	1	7.640[a]	76.0	76.0	.940
	2	1.399[a]	13.9	89.9	.764
	3	1.013[a]	10.1	100.0	.709

a. First 3 canonical discriminant functions were used in the analysis.

Table 6 & Figure 4 show the first discriminant function separates behaviour 1 from the other behaviour groups well for sheep 1 and 3 but less so for sheep 2. The second discriminant function separates behavior 4 from the other behaviour groups for sheep 1, 2 and 3. However, the second discriminant function has less discriminatory power for the same behaviours in sheep 2. Behaviour 1 occupies a similar space for all sheep, i.e. to the positive side of functions one and two. Behaviour 3 occupies a similar space for all sheep on function one but differs on function 2 for sheep 2 from the other sheep. Behaviour 2 is positioned around the first functions central space for all sheep but differs slightly on the second function for sheep 2. The most obvious difference is the space occupied on the second function for behaviour 4. Although similar for sheep 1 and 3, this group for sheep 2 is positioned on the other side of function 2's dimensional space. The behaviour with the greatest dispersion appears to be behaviour 2, and behaviour 4 the least for all sheep.



Sheep1 Sheep 2 Sheep 3

Figure 4 Combined group plots of the canonical discriminant functions for sheep 1, 2 and 3

Table 6 Functions at Group Centroids for sheep 1, 2 and 3.

Sheep	Behaviour code	Function		
		1	2	3
1	1	9.204	.793	.422
	2	.916	.410	-2.790
	3	-2.039	.276	.227
	4	1.852	-4.937	.001
2	1	3.711	.173	.660
	2	.208	-1.382	-1.502
	3	-2.774	-1.539	1.326
	4	-1.600	1.787	-.231
3	1	6.751	.713	.475
	2	-.130	-.157	-1.716
	3	-1.738	.525	.573
	4	.508	-3.598	.824

The structure matrix of correlations between predictors and discriminant functions (Table 7) suggest the best predictors for distinguishing between standing head down and the other behaviours (first function) is the x axis of each accelerometer placement. The x axis acceleration variable appears to contribute most to this function for all sheep. However, where head x acceleration is the best predictor for sheep 1 and 3, withers x acceleration is the best predictor for sheep 2. Head z tilt contributes the most to function 2 which plays a role in separating lying head down from the other behaviour groups for sheep 1 and 3 but head Y tilt contributes the most to this function for sheep 2.

Table 7 Structure matrix (loading matrix) showing contribution of each variable to each discriminant function. Variables ordered by absolute size of correlation within function. * indicates the largest absolute correlation between each variable and any discriminant function.

Sheep 1				Sheep 2				Sheep 3			
	Function				Function				Function		
	1	2	3		1	2	3		1	2	3
Head X Acceleration	.767*	-.381	.018	Withers X Acceleration	.771*	.133	-.272	Head X Acceleration	.825*	-.339	.229
Head X Tilt (°)	.709*	-.311	.008	Withers X Tilt (°)	.766*	.123	-.240	Head X Tilt (°)	.747*	-.363	.184
Withers X Tilt (°)	.547*	.210	-.067	Head X Acceleration	.649*	.615	.194	Withers X Tilt (°)[b]	.576*	.058	-.513
Withers X Acceleration	.547*	.192	-.114	Head X Tilt (°)	.618*	.610	.157	Withers X Acceleration	.575*	.055	-.512
Withers Z Tilt (°)	.328*	.241	.262	Withers Z Acceleration	.262*	-.200	.205	Head Z Tilt (°)	-.258	.697*	.030
Withers Z Acceleration	.296*	.252	.290	Withers Y Acceleration	.181*	.086	.104	Head Z Acceleration	-.239	.539*	.060
Head Z Tilt (°)	.079	.569*	.491	Withers Y Tilt (°)	.181*	.096	.092	Withers Y Tilt (°)	.057	.387*	.293
Head Z Acceleration	.109	.410	.432*	Head Y Tilt (°)	-.255	.449*	-.151	Withers Y Acceleration	.058	.378*	.313
Withers Y Acceleration	-.096	-.173	.431*	Head Y Acceleration	-.256	.412*	-.134	Withers Z Acceleration	.020	-.280*	-.220
Withers Y Tilt (°)[b]	-.094	-.170	.429*	Head Z Tilt (°)	-.091	.000	.206*	Head Y Acceleration	.066	-.260*	.086
Head Y Tilt (°)[b]	-.034	.120	-.138*	Head Z Acceleration	-.114	.009	.203*	Head Y Tilt (°)	.066	-.256*	.084
Head Y Acceleration	-.038	.117	-.134*	Withers Z Tilt (°)	.125	-.107	.183*	Withers Z Tilt (°)	.047	-.273	-.301*

For sheep 1, of the total usable sample of 10,218 accelerometer readings 9,724 (95.2%) were classified correctly, compared with 5,537 (54%) that would be correctly classified by chance alone. For sheep 2, of the usable 9,172 accelerometer readings, 8,348 (91.0%) were classified correctly, compared with 2,373 (26%) that would be correctly classified by chance alone. For sheep 3, of the total usable 9,979 accelerometer readings, 9,164 (91.8%) were correctly classified, compared with 3,621 (36%) that would be correctly classified by chance alone. Correct classification of behaviour1 was 97.4%, 94.5% and 99.0% for sheep 1, 2 and 3 respectively (Table 8). Behaviour 2 had the highest misclassification rate for all sheep with only 85.2%, 77.9% and 77.3% correctly classified for each sheep respectively (Table 8). For sheep 1 and 3, behaviour3 attracted the most misclassified behaviour2 cases with 7.7% and 17.6% of these cases misclassified as behaviour3 for each sheep respectively (Table 8). For sheep 2, behaviour1 attracted the most misclassified cases with 11.2% of behaviour 2 misclassified as behaviour 1 (Table 8). Behaviour 4 had the highest percentage of correct classifications, 98.0% and 99.8% for sheep 1 and 3 while behaviour3 was the highest for sheep 2 (Table 8).

Table 8 Classification results for sheep 1, 2 and 3 using discriminant function analysis with separate matrices and removal of outliers.

Sheep	Behaviour group		Predicted Group Membership				Total
			1.000	2.000	3.000	4.000	
1	Count	1	1362	37	0	0	1399
		2	50	687	62	7	806
		3	0	303	6989	21	7313
		4	0	14	0	686	700
	%	1	97.4	2.6	0.0	0.0	100.0
		2	6.2	85.2	7.7	.9	100.0
		3	0.0	4.1	95.6	.3	100.0
		4	0.0	2.0	0.0	98.0	100.0
2	Count	1	2284	133	0	0	2417
		2	240	1663	208	24	2135
		3	0	41	1650	30	1721
		4	0	57	91	2751	2899
	%	1	94.5	5.5	0.0	0.0	100.0
		2	11.2	77.9	9.7	1.1	100.0
		3	0.0	2.4	95.9	1.7	100.0
		4	0.0	2.0	3.1	94.9	100.0
3	Count	1	1308	13	0	0	1321
		2	100	1963	448	30	2541
		3	0	220	4985	2	5207
		4	0	2	0	908	910
	%	1	99.0	1.0	0.0	0.0	100.0
		2	3.9	77.3	17.6	1.2	100.0
		3	0.0	4.2	95.7	.0	100.0
		4	0.0	.2	0.0	99.8	100.0

Behaviour 4 had the lowest error rate of all behaviours for all sheep (Figure 5). Behaviour 2 had the highest error rate for all sheep combined (Figure 5). All other behaviours were variable in their error rates between all sheep. Sheep 1 had the lowest error rate and sheep 2 the highest error rate (Figure 5). Behaviour 3 for sheep 3 had the highest individual error rate. Of all the data used in this study, just over 7% were misclassified (Figure 5).

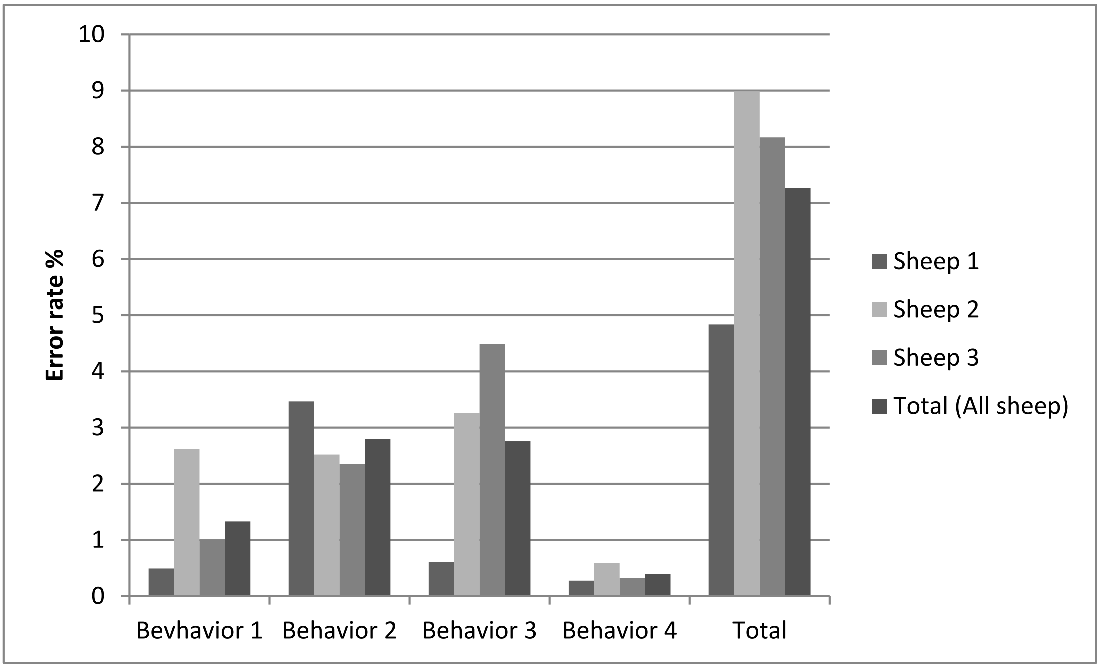


Figure 5 Percentage of cases incorrectly classified from all available training data per individual sheep and the total error rate from all data in the study (29,369 cases). Error rate for each sheep is the total of incorrect cases classified, divided by the total number of cases available for classification multiplied by 100. The total for each sheep is the sum of all cases misclassified for all behaviours divided by the total number of cases available for classification multiplied by 100.

6.4 Discussion

Using discriminant function analysis (DFA) and accelerometers attached to the head and withers of three sheep, a model was developed which accurately classified a number of postures. Three of the postures analysed were correctly classified in over 90% of cases. These high rates suggest accelerometer data, trained and classified with discriminant function analysis could be used to generate large temporal-aware behavioural data. However, care should be taken when using separate covariance matrices as overfitting of the model could occur when not using the cross validation method or splitting training data, for example as a 75%/25 split.

One of the assumptions of DFA is multivariate normality (e.g., normality of each of the independent variables and all their possible linear combinations). DFA is considered robust to failures of normality if violation is caused by skewness rather than outliers and sample sizes are about equal (Tabachnick and Fidell, 2007).The sample sizes for each group in this study were not equal. However, where sample size difference among groups increases, larger overall sample sizes are necessary to assure robustness (Tabachnick and Fidell, 2007). As suggested by Tabachnick and Fidell (2007) robustness is expected with 20 cases in the smallest group if there are only a few predictors (say, five or fewer).

As the number of training data cases in this study were large for all groups, robustness to this assumption was assumed. Box's M indicated that the assumption of equality of covariance matrices was violated, however Box's M can be overly sensitive. DFA can be robust to this violation; however, it should be noted that cases can be over classified into groups with greater dispersion. Inspection of Figure 4 suggests standing head up had greater dispersion across the functions space. Indeed Figure 5 indicates this to be the posture with the greatest error rate when considering all data used in this study. The greatest amount of misclassification into this group was from the lying head up group for sheep one and three and standing head down for sheep two. If standing head down representing grazing is the only behaviour of interest, this misclassification is not of great concern. However if a significant amount of standing head down cases were misclassified as standing head up, then important information that could help generate grazing distribution maps will be lost. The X axis on the head placement contributes most to discriminating between standing head down and the other postures for sheep 1 and 3. The X axis on the withers placement contributes the most for sheep 2. This could be due to movements unique to this individual. Further research should be conducted with a commercial flock to determine which variable contributes most to the discriminating model. The sheep used in the study were different weight and size dimensions. In a commercial flock, the dimensions of the sheep will be more uniform. If it can be shown that one variable (Head X axis) can discriminate successfully between standing head down and other behaviours, this opens up the possibility to extend the data collection period. The limiting factor with the accelerometers used in this study is the memory capacity. However, they can be programmed to only collect data on one axis. If grazing is the main behaviour of interest, only data on the X axis could be collected thus providing a longer data collection time frame.

Consideration needs to be given to defining what accelerometers are recording in behavioural observation studies. Behaviour observations can be categorised as structure, consequence and spatial relation (Martin and Bateson, 1993). Structure describes posture and movement, consequence describes the behavioural effect (eg grazing) and spatial relation describes proximity to environmental features (Morrison et al., 2006). Accelerometers can be considered to be only recording the structure component of behaviour. Careful design of training data collection, the classification model and accelerometer placement, should be applied to ensure a high confidence in the predicted consequence. Regardless of the behaviour or posture of interest, it is important to define the limb movements before any training data is collected. This allows the accelerometer to be placed in the optimal position on the body to record the most extreme movements and positions associated to the structure and consequence of interest, for example, when grazing, the head is in a lowered position. The grazing consequence can be further divided with several discreet unique structural movements of the head resulting from selection and biting to sever herbage from the sword, which often results in a small jolt of the head (Baumont et al., 2006). An accelerometer placed on top of the head, as done so in this study is able to record all structures associated with these consequences. To detect lying behaviours, the accelerometer might be best placed on the leg, thus being best placed to detect the difference in angles between standing and lying and doing so with reduced variables, helping to maximize data collection time. To record urination events, potentially useful in nitrogen deposition studies, the accelerometer could be placed toward the base of the tail, which is raised slightly whilst urinating. This would depend on the placement not interfering with the behaviour.

There is no agreement for standards and methods for calibration, validation and analysis of accelerometer data in sheep behavioural studies. Umstätter et al. (2008) used integrated tilt sensors, similar to accelerometers and set their devices to record every 30 seconds with manual observations used to assign behaviour categories to the datasets. Having initially failed to use discriminant function analysis to discriminate between four behaviours, they reduced the number of classes down to two, active and inactive. Comparison to this study is difficult as they needed to adapt their study to a two class problem. However, they did achieve in excess of 90% correct classification rates. Nadimi et al. (2012) and (Nadimi et al., 2008) used a component accelerometer with one second sampling intervals with video recordings of all sheep to assign behaviours, the same as this study. However, they used neural networks as their classifier and achieved correct classification rates of 84% (grazing), 83% (Lying) and 71% (standing). Their lower classification rates suggest housed accelerometers and discriminant function analysis could discriminate more accurately between behaviours. However their study has the benefit of being able to transmit the accelerometer data wirelessly. The Hobo housed accelerometer does not wirelessly transmit data. Any application of this accelerometer in the future is limited by the need to manually retrieve the recorded data. However, the Hobo accelerometer does not rely on having expertise in electronic systems design, allowing implementation in projects where this knowledge is not present.

The predictive powers of classifying models is dependent on the quality and size of the training dataset (Figueroa et al., 2012, Kalayeh and Landgrebe, 1983). When annotating the training dataset, erroneous classifications could occur due to cases being labeled incorrectly. The quality of the training data could be improved by smoothing the data. One possible method could be to remove *nth* cases at either end of every sequence of behaviours using programming scripts such as Visual Basic or Python. Further, the usefulness of accelerometers is limited by the need to calibrate them to individual subjects (Levineet al. 2001). Obtaining known data sets by observing and videoing individuals with attached accelerometers, followed by annotating the behaviours to the data is time consuming with potential impacts on project costs. Although numerous studies have shown how predictive models can classify animal behaviour from accelerometer data, to the author's knowledge no research into the minimum training sample size required for model accuracy has been conducted. Investigating the minimum number of known behaviour observations required for a discriminant analysis model to accurately predict future unknown behaviours from accelerometer readings could ease the laborious task of transcribing excessive behaviours during the calibration of an accelerometer to an individual sheep. Classifier learning curves could be generated under different conditions to estimate the minimum training data size required for desired performance levels. Further, training data pooled from different sheep could be investigated to assess the classification accuracy when used to classify new individuals. This is likely to need to consider the size and dimensions of the training data sheep and target sheep and any discreet differences in the structure component of behaviours of interest. Further problems could occur when using training data obtained from grazing different sward heights and different angled terrain. Developing equations to offset and account for different sword heights and terrain between the training and un-annotated data may provide a way to use training data obtained from different sward heights and terrain. The attachment methods used in this study provided a stable method of attachment to the body. However, the dog harness, over time, could cause discomfort and abrasion to the sheep. The variables used in the model obtained from this placement did not contribute as much to the model as those obtained from the head halter. It is recommended that the dog harness attachment is not used long term in any study. Other areas of placement could be considered after assessing postures and limb movements associated with any behaviour of interest.

By grazing, sheep remove plant biomass, which can modify the biodiversity and energy balance of grasslands, with resulting feedbacks on net carbon uptake and changes in the influence of climate on land-atmosphere carbon fluxes (Bardgett and Wardle, 2010, Wayne Polley et al., 2008). In order to predict ecosystem carbon balance, understanding how grazing affects CO_2 exchange in grasslands needs to be improved (Wayne Polley et al., 2008). Predictive models need to account for grazing to simulate the dynamics of CO_2 fluxes in grassland ecosystems. However, the potential for grazing to modulate the response of carbon flux to climatic variability needs further investigation (Bardgett and Wardle, 2010). The use of accelerometers, combined with GPS data could help to better understand the effects of grazing at the landscape scale and how ecosystems, under the influence of herbivore pressure, respond to climate change. The data generated could help inform sampling strategies that can account for biotic and abiotic interactions at the landscape scale, which would be difficult to account for at the plot scale. Environmental sensors could also be deployed simultaneously to collect data on abiotic variables, adding further detail to foraging choices and their effects.

The “five freedoms” (Brambell 1965) are a set of universally adopted principles that form the cornerstone of animal welfare legislation and policy in the UK. While some of these freedoms can be readily observed in individual animals, wider flock observations especially in extensive systems can be difficult. Accelerometers have the potential to automatically detect behaviours and body postures that can be used in welfare assessment. As far as can be determined, there are not many studies that have used accelerometers with sheep to automatically detect behaviours that could be used in welfare assessment. Piccione et al. (2008) and Piccione et al. (2011) detected diurnal rhythms in activity levels (eg – feeding, drinking, walking, grooming and ruminating) using accelerometers attached using collars to sheep. These studies however used the actiwatch system, that rather than detecting individual postures associated with specific behaviours, only detect activity levels using the Actiwatch Activity Analysis software. Accelerometers have been used with other animals however that are capable of detecting behaviours associated with body postures such as sleep detection in calfs (Hokkanen et al 2011), eating duration in cows (Ueda et al 2011) estrus detection in cows (Fricke et al 2012, Valenza et al 2012) and eating, ruminating and resting in cows (Watanabe et al 2008). In order for automatic classification of behaviours to be useful for welfare assessment, the recording method needs to be cheap, not be too time consuming and the classified behaviours be relevant to animal welfare rather than simply their ability to be automatically detected (Rusheb et al 2012). Further, real time analysis of the data needs to be in place to alert farmers to welfare issues. Although this study did not have this capability, it has shown that accelerometers have the potential, through posture recognition, to inform farmers of any welfare issues, subject to timely analysis of the data.

Using DFA to classify sheep behaviours from accelerometer data has been shown to perform well for a range of behaviours and postures. Some assumptions of DFA were violated but were considered robust given the data used in this study. Data collection periods could be extended if movements and postures of interest are defined and data on selective axes is collected. However, further research is needed to assess classification accuracy using reduced axis on commercial flocks where the size and dimension of sheep are more uniform than used in this study. Accelerometers have been defined as capable of recognizing the structure component of behaviour observations. Wireless transmission of data would be beneficial. Although the accelerometers used in this study required manual data recovery, they do allow for easy deployment where electronic systems design knowledge is not present. Future research should investigate if smoothing training data improves classification accuracy. Classifier learning curves should be generated to inform of the minimum amount of training data for the model to classify adequately to ease the laborious task of calibration for individual sheep. Using pooled training data to avoid the need for individual calibration should be investigated to assess classification accuracy. Algorithms could be developed as off-sets to take into account training data acquired from different sized sheep and different sword heights. Care needs to be taken with attachment methods to avoid discomfort to sheep. Accelerometers could help to improve the understanding of how grazing at the landscape scale affects ecosystem function responses to climate change. Subject to prompt analysis of data, accelerometers could help with the detection of welfare related issues in sheep.

7 Fructan levels in grass and grazing by sheep

7.1 Introduction

There is growing interest in perennial ryegrass cultivars, developed to have elevated water soluble carbohydrate levels, to improve livestock production systems (Edwards et al., 2007, Turner et al., 2006a, Marley et al., 2007). Sheep show a preference for herbage with higher water soluble carbohydrates (Ciavarella et al., 2000, Allsop et al., 2009, Mayland and Shewmaker, 1999, Ciavarella et al., 1998). Further, increasing dietary carbohydrates such as fructans in sheep diets can improve protein metabolism, reduce ammonia excretions and energy loss and promote increased weight gain (Biggs and Hancock, 1998, Evans et al., 2011, Parsons et al., 2012).

Experiments investigating grazing preference of sheep predominantly take place in highly controlled environments or plots (Ciavarella et al., 2000, Marley et al., 2007, Evans et al., 2011). However, the metabolism of fructans is affected by a number of environmental variables such as irradiance, photoperiod, diurnal regulation, temperature, water availability, nutrient supply, timing of flowering, pests, diseases, and interactions between such abiotic and biotic factors (Turner et al., 2006b). To develop research on the grazing preference of sheep for high fructan content in grasses, experiments need to take into account the fructan accumulating performance of grasses within wider landscape conditions where environmental variables and fructan accumulations can be variable. However, it is difficult to set up experimental pasture plots that take into account all these environmental variables and their interactions. The use of real world landscapes and environments provides an ideal canvas to account for the different environmental conditions and their interactions. However, this increases the difficulty of observing animals to assess their spatial grazing distributions.

GPS has been used in previous studies that investigate the distribution of grazing livestock. However, assumptions regarding movement velocity need to be implemented for the GPS data to infer grazing locations (Putfarken et al., 2008b, Diaz Falu et al., Schlecht et al., 2004, Bertiller and Ares, 2008). The combination of data from extra sensors such as jaw sensors (Rutter et al., 1997, Matsui, 1994) and accelerometers (Moreau et al., 2009, Guo et al., 2009) and GPS data has helped improve behavioural predictions and generate grazing livestock spatial distribution maps.

Accelerometers offer a potentially reliable and affordable method for generating spatial grazing data. They have been used with sheep to detect diurnal rhythms in activity levels (Piccione et al., 2008d, Piccione et al., 2011a). However these products are off-the-shelf solutions that are not capable of distinguishing between different body movements. Nadimi et al. (2012) and Nadimi et al. (2011) used component accelerometers to detect

grazing, lying down, standing, walking, mating and drinking in sheep. However these accelerometers require specialist knowledge of electronic design to integrate them into a system for use with livestock. Ready-housed raw data accelerometers; combined with GPS data could provide an affordable, easy to implement solution for generating spatial grazing data at the landscape scale.
The aims of this study were to evaluate in a field experiment the implementation and performance of a ready-housed raw data accelerometer combined with GPS data to investigate if sheep exhibited a preference for higher levels of fructan in fresh pasture and to examine potential improvements to this approach.

7.2 Methods

7.2.1 Study site

The study site (Figure 6), located in Shotwick, North West England (SJ 33780 71987) is a small 850m^2 herbaceous pasture dominated by perennial ryegrass and clover. Two months before the experiment was conducted, access by the sheep was restricted, the pasture was mown and vegetation around the perimeter was cut back to ensure grazing was the only feeding method available.

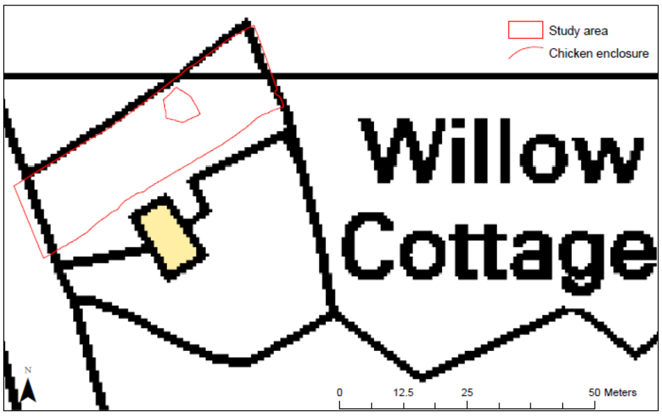


Figure 6 study site located in Shotwick, North West England (SJ 33780 71987).

7.2.2 Sheep

The same three sheep used in section two of this thesis were used as study animals. In the month leading up to the study, each sheep was alternatively fitted with the equipment to allow them to become accustomed to the attachments. Data were collected during four time periods. All sheep were placed in a holding pen for two hours prior to release into the grazing paddock where they were all able to graze freely until the end of each grazing bout. The grazing bout was considered to be finished when the focal animal exhibited no grazing behaviour and was either waiting to exit the trial area into the main site or was ruminating.

7.2.3 Recording equipment

Each sheep was fitted with a Trimble GEO XH GPS unit and a Hobo Pendant G accelerometer. The GPS receiver was securely attached by a body harness and weather proof box (Figure 7). The accelerometer was fixed in a leather pouch attached to a head halter that allowed the accelerometer to be placed between the frontal and parietal bones (Figure 7). The GPS unit and accelerometer had their time synchronised to allow the data to be joined together via a common time attribute during analysis. In order to allow the GPS position to be as close as possible to the biting point of the sheep, an external L1 antenna was fitted to the head of the sheep via a fixing apparatus attached to the head halter (Figure 7). Using this method, when the head was in the down grazing position the antenna was vertically above the location of the mouth.

Figure 7 GPS receiver, accelerometer and external L1 antenna in situ on sheep 1.

7.2.4 Data collection and analysis

The accelerometer data were run through a classification model using discriminant function analysis with previously validated training data in SPSS 15. GPS data were post-processed in Trimble Pathfinder 4.20 using Rinex files obtained via the Trimble VRS Now service. This allowed post processing to be completed immediately upon data retrieval rather than waiting for the delayed availability of Rinex files via the free Ordnance Survey service. The post processed corrected GPS data and accelerometer data were then imported and joined in Arcmap 9.3. When the accelerometer data were run through the classification model, the probability of the predicted behaviour was calculated. When the GPS data were post processed the horizontal precision of each individual position was calculated. Using rule-based decisions, a high confidence grazing layer was created where the predicted behaviour probability was =>0.95 and the GPS horizontal precision was =<0.2m. If the availability of 0.2m horizontal precision positions was low, the precision threshold was increased by 0.1m until a satisfactory number of positions were available. The study site was divided into 0.5m quadrats in Arcmap GIS (Figure 8) where summary data of grazing positions with the desired horizontal precision were appended.

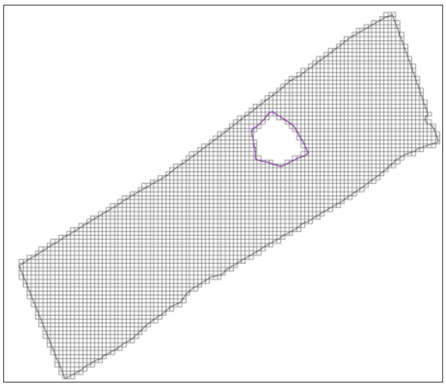


Figure 8 Study site divided into 0.5m quadrats. The inner polygon is a fenced chicken enclosure.

The three highest grazed quadrats were selected as the highest grazed sample locations. The three lowest grazed sample locations were randomly selected from quadrats with a grazing count of one. Coordinates for the three highest and lowest grazed quadrats were transferred to a Trimble Geo XH GPS and located using real time differential correction via the cellular network.

7.2.5 Fructan analysis

Three replicates of grass samples, cut approximately 2.5cm above the ground were collected from each quadrat and stored immediately on dry ice in Ziploc® bags. Samples were then transferred to a -25^{o} C freezer for storage to await analysis of fructan content. A 0.8 – 1 g frozen grass sample was dried at 60^{o} C overnight. Samples were cooled in a desiccator with $CuSO_4$ crystals. 0.2 g dried grass sample was then placed in 100 ml distilled deionised water in a 250 ml flat bottomed flask. These were then placed on shaker at 250 rpm for an hour then 1 ml supernatant was placed in 12 ml anthrone reagent in a 50 ml Ehrlen-Meyer flat bottom flask and incubated for 3 min on a hotplate at 80^{o} C. Optical density of this solution was read in a spectrophotometer at 620 nm, after 2 minutes cooling.
mg ml fructose was calculated against fructose standards exposed to the same procedure. Fructose standards 0, 2.5, 5, 7.5, 10, 12.5, 15 mg ml in 100 ml total volume. 3 minutes was deemed an optimal incubation period, after trialing periods of 2-8 minutes. This agrees with the methods of (Yemm and Willis, 1954), and ensured that polymers of fructan were hydrolysed to fructose. Anthrone reagent is 0.5 g anthrone powder, 340 ml water and 660 ml concentrated sulphuric acid and was kept at 4^{O} C until needed.

7.3 Results

The combined accelerometer and GPS data suggest sheep 1 and 2 utilised the north east section of the study area during all their observation periods (Figure 9, Figure 10, Figure 17, Figure 18). Sheep 3 exhibited a similar pattern for the first two periods but also grazed the south west of the study area during its final two observation periods (Figure 11, Figure

19). Grazing in all sheep exhibits a clustered spatial pattern with connectivity through linear grazing tracks connecting the clustered areas. While sheep 3 showed some clustered grazing events, these are not as densely populated as for the other two sheep. Further, observation two for sheep 3 exhibits a random grazing pattern.

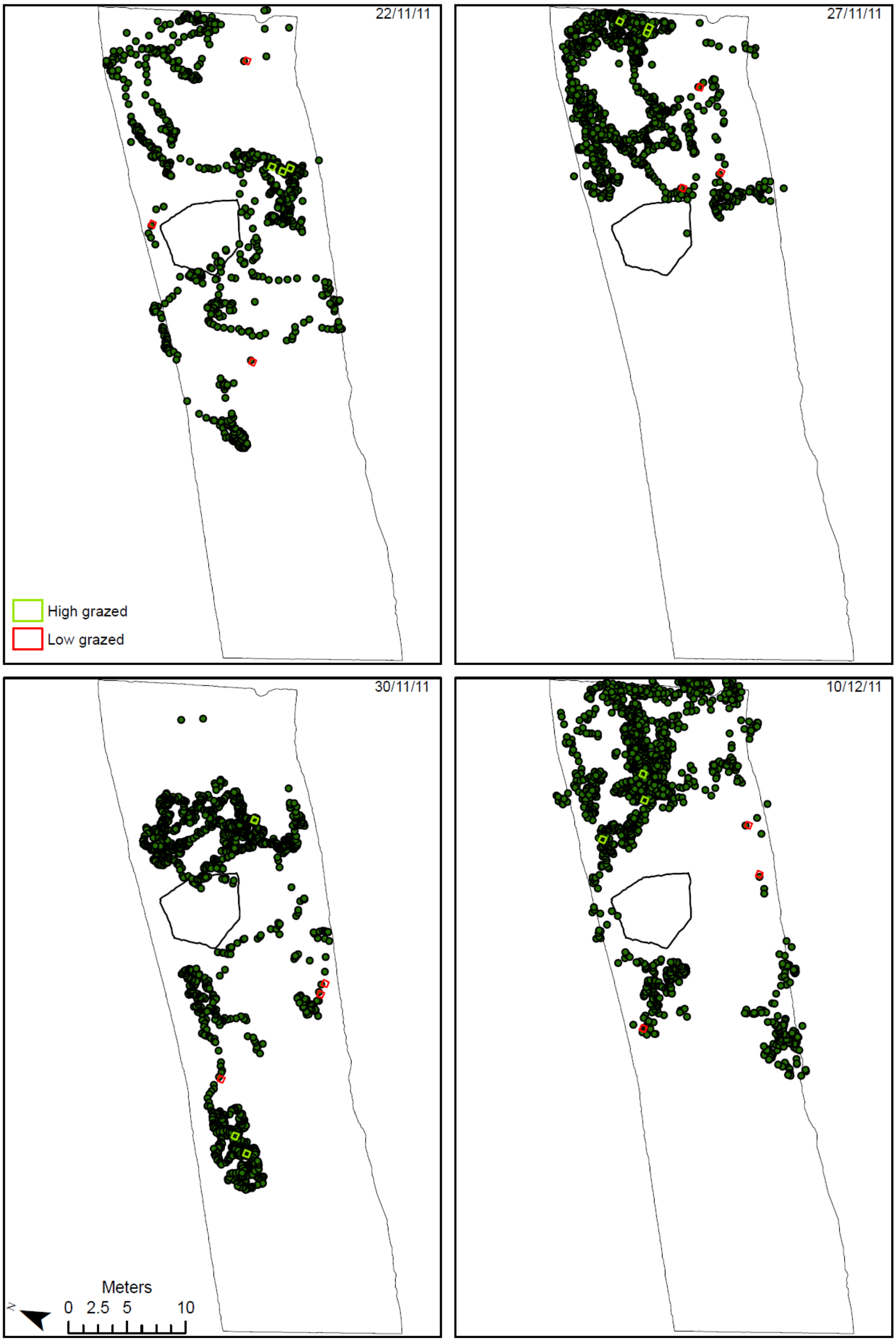


Figure 9 All predicted head down GPS positions for sheep one before removal of cases matching the rule base criteria and the location of the three highest and lowest grazed quadrats.

Figure 10 All predicted head down GPS positions for sheep two before removal of cases matching the rule base criteria and the location of the three highest and lowest grazed quadrats.

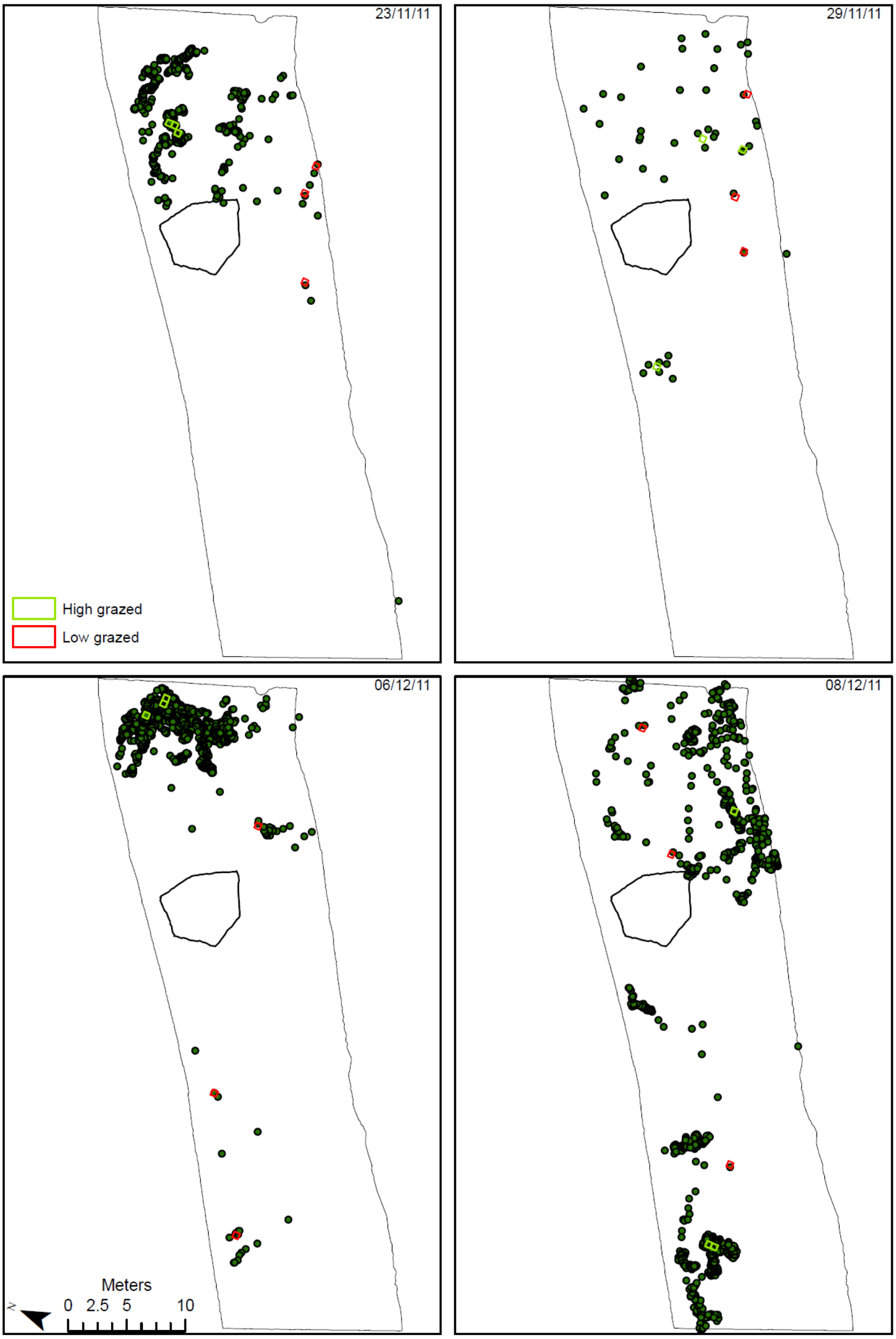


Figure 11 All predicted head down GPS positions for sheep three before removal of cases matching the rule base criteria and the location of the three highest and lowest grazed quadrats.

Observation periods lasted between 31 minutes and 1 hour (Table 14). Grazing was the most frequently predicted posture in nine of the twelve observation periods (Figure 12). Sheep three on two occasions had standing head up as the highest predicted posture.

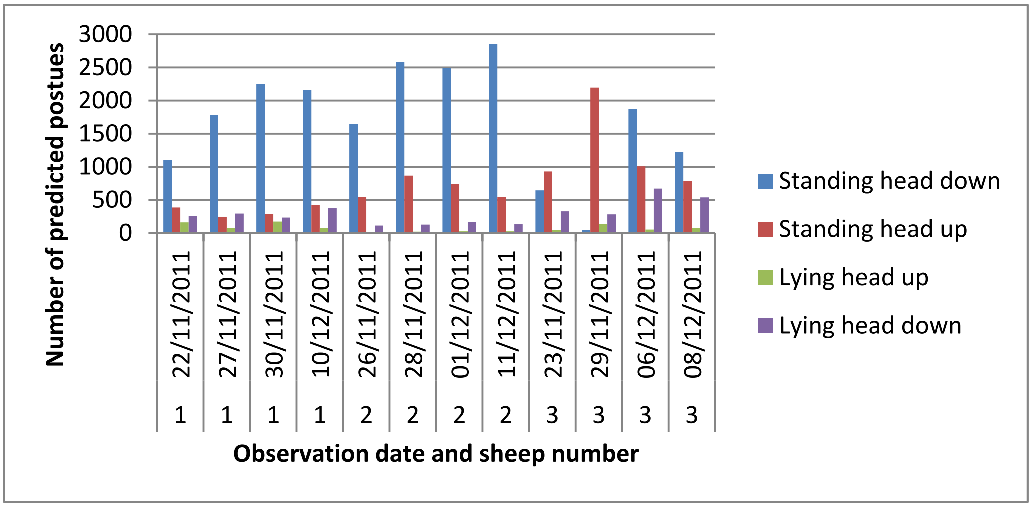


Figure 12 Number of GPS positions classified into one of four postures before removal of positions through a selective rule-base procedure.

A rule-base criterion was applied to the classified grazing accelerometer data. Any cases with a probability <0.95 for this predicted behaviour were removed. Between 1% and 3% of cases were removed for sheep 1, between 7% and 9% for sheep 2 and between 11% and 43% for sheep 3 (Figure 13). Further rule-base criteria were applied to ensure only highly accurate (< 0.4 m) GPS positions remained. Application of this criterion removed a greater number of cases than the accelerometer rule base. With both rule base criteria applied, sheep 1 had between 58% and 70% of cases removed, sheep 2 between 46% and 83% removed and sheep 3 between 43% and 90% of cases removed (Figure 13).

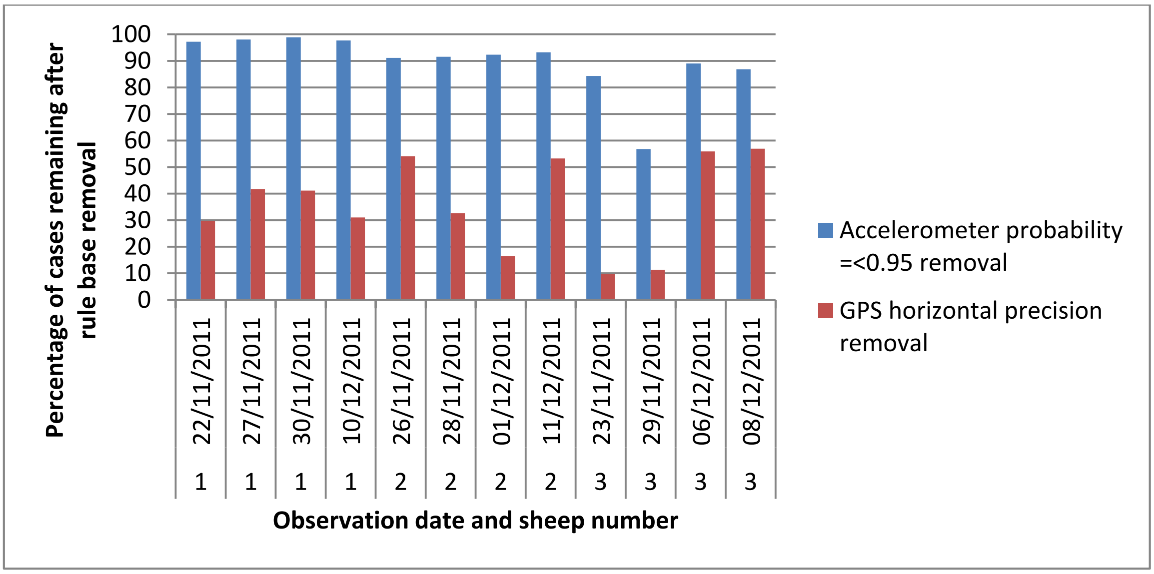


Figure 13 Percentage of standing head down positions remaining after removal of positions where the horizontal precision was =>0.3m for all dates except 30/11/2011 =>0.2m and the 11/12/2011 and 29/11/2011 =>0.4m.

Following removal of cases through the rule base, GIS analysis provided a count of standing head down positions in each quadrat. The number of standing head down positions in the three highest grazed quadrats ranged from 8 – 53 (Figure 14) with an average of 27.

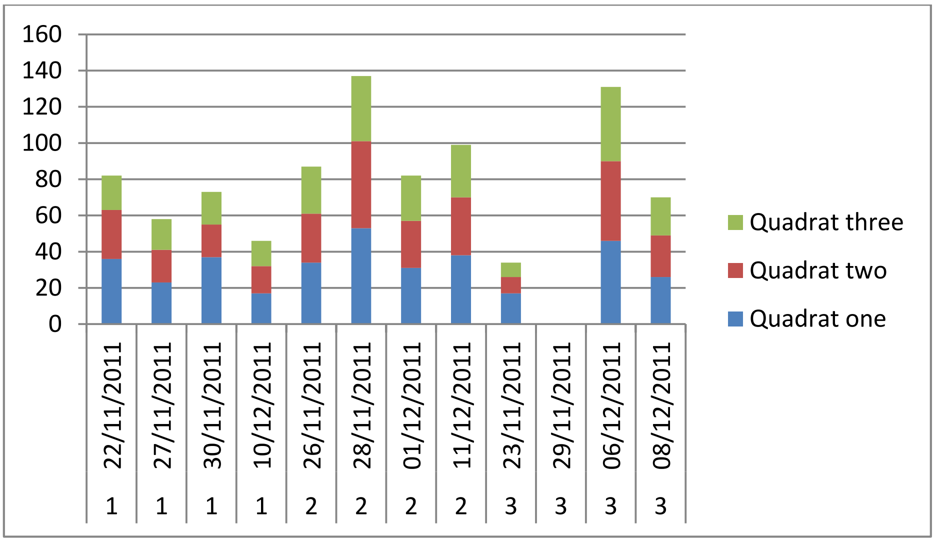


Figure 14 Number of predicted head down GPS positions in the three quadrats with the highest count of this behaviour after removal of cases through the rule base criteria. Quadrat one has the highest, quadrat three has the lowest number of positions.

Fructan levels showed an increasing trend between the first and last observation periods (Figure 15). For all sheep, the high grazed quadrats showed higher median fructan levels than low grazed quadrats (Figure 16). Because of a lack of normality, (Shapiro-Wilk, low grazed W_{36}=0.916 p=0.010 and high grazed W_{33}=0.913 p=0.012), the non-parametric Mann-Whitney U test was the most appropriate test even though it required a slightly different formulation of null hypotheses because some sources of sampling error could not be incorporated into the analysis. Observations were within-quadrat means rather than raw observations. Sample sizes were n=36 (low grazed) and n=33 (high grazed). No significant difference was found in the levels of fructan between low grazed and high grazed quadrats (U=763.00, p=0.195).

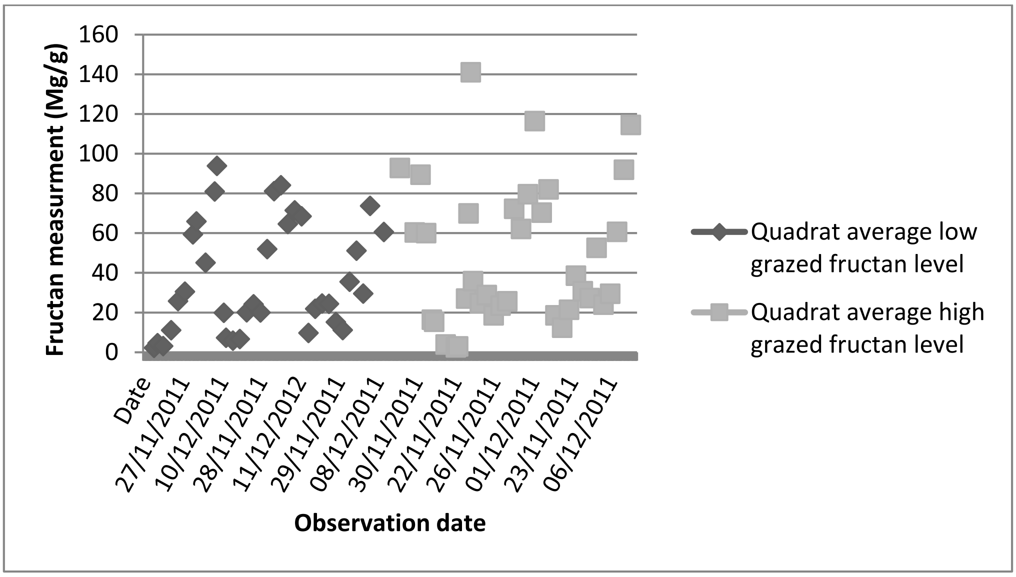


Figure 15 Level of fructan content (Mg/g) from individual grass samples averaged at the individual quadrat level

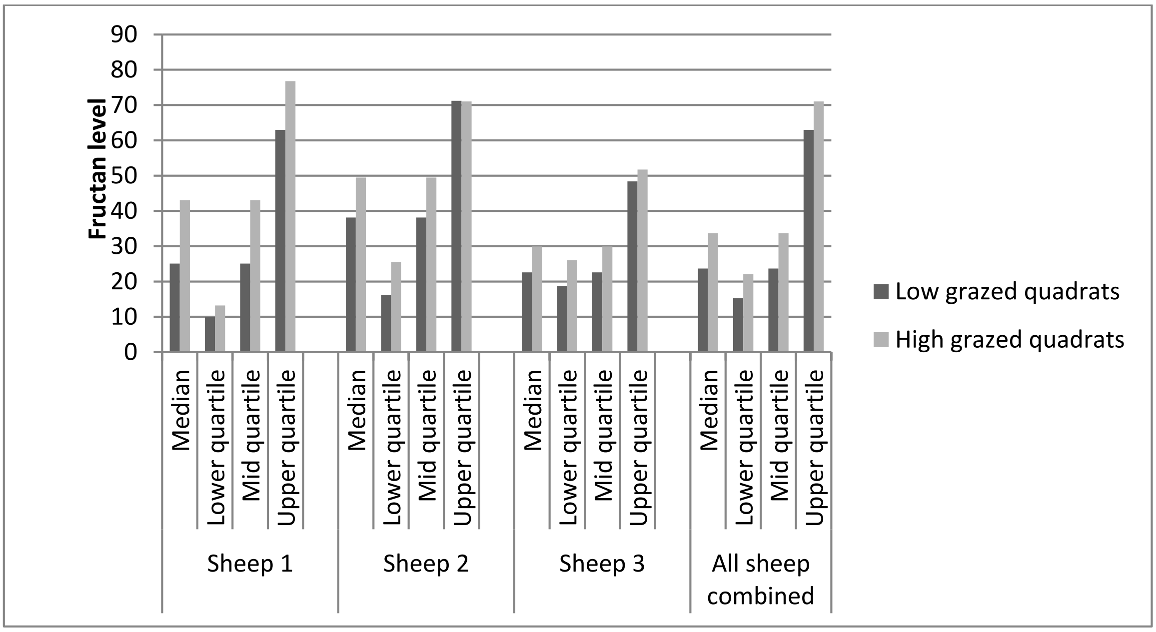


Figure 16 Median, lower, middle and upper quartiles of fructan levels for each sheep and all sheep combined across all their individual observation periods.

7.4 Discussion

This study has shown that ready housed accelerometers combined with GPS can allow reconstructions of grazing locations of sheep. However, no grazing preferences for higher fructan levels were detected in this study. Many factors such as smell, taste, texture, palatability and digestibility are known to influence diet selection. It is difficult to alter or account for one of these in isolation, especially in the field (Ciavarella et al., 1998). This study focused on fructan concentration and did not account for any of these variables. Ideally, these factors should be considered in future to allow any preference for higher fructan levels to be isolated. The distribution of animals is the result of internal and external interactions, available nutrients, forage quality, weather conditions, and environmental terrain (Anderson, 2010). When sheep are grazing, they are known to exhibit close spatial proximity and keep other individual sheep within their visual field (Fisher and Matthews, 2001). Bond et al. (1967) suggested such behaviour could produce an important variable in grazing studies. The existence of this behavioural trait will influence foraging choices meaning the focal animal is not solely selecting on the basis of fructan levels. Also influencing the distribution of the sheep in this study is the location of the only entry point in to the study area, in the far north eastern corner of the site, which was likely also to influence the grazing locations. To counter this effect, a randomly selected location should have been used as a point where the sheep were herded ready for the start of each observation period. At the larger landscape scale, however, this becomes of less concern because the sheep could freely roam.

The accelerometer classification model performed well for all sheep. However, after removing cases with a correct classification probability less than 0.95, the classification model for sheep three performed less favourably, particular for the second observation period where only 44 standing head down positions were recorded. Sheep three could have not adapted to the equipment in time for the study and therefore did not freely graze during the study period. Within the GPS rule base criteria, the requirement of removing any cases with a horizontal precision greater than 0.4 m caused a substantial number of recorded positions to be removed, resulting in the loss of a considerable amount of spatial information. Features in grazing areas such as trees can negatively impact GPS performance (Agouridis et al., 2004). The only entry and exit point to the study area had a large tree located close by, and the entry exit point also likely influenced the foraging locations of the animals to be in close proximity to this area of the site. The number of cases removed through the accelerometer rule base is fewer and more consistent than removal though the GPS rule base. Atmospheric effects and physical obstacles can be present that can affect GPS accuracy. In comparison, the accuracy of behaviour classification through the accelerometer model has fewer factors that can affect correct classification. These include accuracy of training data and difference in slope angles of the terrain used during collection of the training data. Any future study, particularly at the small plot scale should consider such features and attempt to prevent any grazing occurring within a proximity to physical barriers to the sky that could negatively affect GPS quality, and at the landscape scale variability in terrain should be considered when generating a predictive behavioural classification model.

The method of data collection used in this study collected grass samples for analysis after the grazing event. Although collected within close spatial proximity to the grazing location, the fact remains that the sampling protocol resulted in analysis of grass that was remaining after grazing. Although this study found no preference for high levels of fructan, the method of automating behavioural observations could provide a means of recording animal behaviour at the landscape scale. However, the method of determining any intake preference needs to be sufficiently robust to maintain statistical power and determine in sufficient time the intake rates and sugar accumulation levels. Little research exists investigating sheep preference for high fructan grass intake or describing methods for such investigations. Burns et al. (2001) found that fructan content influenced sheep intake of *Festuca arundinacea Schreb.* hay harvested in summer but no research has been conducted in relation to fructan influence on fresh pasture intake. More research exists showing the influence of water soluble carbohydrates (WSC) and non-structural carbohydrates on intake preference. Previous studies investigating grazing preference of sugars in grass have detected preferences for elevated sugar levels using a variety of methods. Jones and Roberts (1991) found that cultivars of perennial ryegrass high in WSC content were more palatable to sheep than cultivars with moderate contents of WSC. However, this research used small (4 m x 3 m) plots sown with each cultivar and the remaining herbage in these plots was measured after each observation period, eliminating the need to generate behavioural distribution data to inform sampling locations. However, at the landscape scale where fructan and WSC accumulation is affected by a greater variety of uncontrolled biotic and abiotic factors, this method of measuring grazing preference becomes impractical. Ciavarella et al. (1998) used shaded and unshaded plots and faecal examination of synthetic alkanes sprayed onto the plots to show a preference by sheep for higher WSC forage. However, this is not a feasible method when attempting to examine preferences at the landscape scale as the alkanes cannot be sprayed across such a large area.

Although no grazing preference was detected for higher levels of fructan, this study has shown that ready housed accelerometers combined with GPS can generate grazing distribution data of sheep. However, at the small plot scale, landscape features such as trees can impact on GPS accuracy resulting in the loss of spatial distribution data. behavioural traits affecting the distribution of sheep need to be considered and accounted for when investigating reasons behind grazing locations such as a preference for high fructan grasses. The experimental design also needs to ensure sufficient statistical power exists to prevent any potential significant findings being missed.

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8.1 Appendix

Table 9 Tests of Equality of Group Means on all independent variables for Sheep 1, 2 & 3.

	Sheep 1					Sheep 2					Sheep 3				
	Wilks' Lambda	F	df1	df2	Sig.	Wilks' Lambda	F	df1	df2	Sig.	Wilks' Lambda	F	df1	df2	Sig.
Withers X Acceleration (g)	0.194	14868.3	3	10732	0.000	0.269	8668.53	3	9552	0.000	0.329	7099.09	3	10429	0.000
Withers Y Acceleration (g)	0.761	1126.19	3	10732	0.000	0.85	560.88	3	9552	0.000	0.818	771.717	3	10429	0.000
Withers Z Acceleration (g)	0.446	4437.42	3	10732	0.000	0.818	710.628	3	9552	0.000	0.913	331.686	3	10429	0.000
Withers X Tilt (°)	0.196	14662.1	3	10732	0.000	0.276	8346.53	3	9552	0.000	0.326	7188.97	3	10429	0.000
Withers Y Tilt (°)	0.761	1124.59	3	10732	0.000	0.845	582.323	3	9552	0.000	0.8	870.068	3	10429	0.000
Withers Z Tilt (°)	0.416	5019.42	3	10732	0.000	0.914	300.548	3	9552	0.000	0.848	620.996	3	10429	0.000
Head X Acceleration (g)	0.14	22031	3	10732	0.000	0.257	9183.81	3	9552	0.000	0.215	12722.3	3	10429	0.000
Head Y Acceleration (g)	0.952	180.697	3	10732	0.000	0.62	1953.62	3	9552	0.000	0.912	335.346	3	10429	0.000
Head Z Acceleration (g)	0.669	1771.68	3	10732	0.000	0.919	280.57	3	9552	0.000	0.638	1972.24	3	10429	0.000
Head X Tilt (°)	0.154	19673.4	3	10732	0.000	0.273	8490.45	3	9552	0.000	0.229	11725.9	3	10429	0.000
Head Y Tilt (°)	0.955	168.644	3	10732	0.000	0.611	2028.59	3	9552	0.000	0.911	339.083	3	10429	0.000
Head Z Tilt (°)	0.618	2210.93	3	10732	0.000	0.929	241.631	3	9552	0.000	0.539	2973.92	3	10429	0.000

Table 10 Box's Test of Equality of Covariance Matrices Log determinants

	Sheep 1		Sheep 2		Sheep 3
behaviour_code	Rank	Log Determinant	Rank	Log Determinant	Log Determinant
1	11	-12.759	12	-23.017	-22.643
2	11	-17.994	12	-5.69	1.046
3	11	-36.316	12	-26.539	-34.477
4	11	-53.858	12	-43.004	-48.773
Pooled within-groups	11	-19.422	12	-13.792	-9.603

Table 11Tests of Equality of Group Means on all independent variables after the removal of univariate and multivariate outliers for Sheep 1, 2 & 3.

	Sheep 1					Sheep 2					Sheep 3				
	Wilks' Lambda	F	df1	df2	Sig.	Wilks' Lambda	F	df1	df2	Sig.	Wilks' Lambda	F	df1	df2	Sig.
Withers X Acceleration (g)	.181	15399.68	3	10214	0.000	.217	11039.12	3	9168	0.000	.263	9307.74	3	9975	0.000
Withers Y Acceleration (g)	.758	1084.84	3	10214	0.000	.821	667.98	3	9168	0.000	.755	1077.82	3	9975	0.000
Withers Z Acceleration (g)	.404	5020.34	3	10214	0.000	.657	1594.81	3	9168	0.000	.861	537.98	3	9975	0.000
Withers X Tilt (°)	.181	15428.15	3	10214	0.000	.220	10834.94	3	9168	0.000	.266	9197.37	3	9975	0.000
Withers Y Tilt (°)	.758	1088.42	3	10214	0.000	.821	668.13	3	9168	0.000	.756	1070.93	3	9975	0.000
Withers Z Tilt (°)	.364	5960.86	3	10214	0.000	.872	448.22	3	9168	0.000	.824	709.43	3	9975	0.000
Head X Acceleration (g)	.100	30720.90	3	10214	0.000	.236	9890.17	3	9168	0.000	.156	18010.98	3	9975	0.000
Head Y Acceleration (g)	.944	200.66	3	10214	0.000	.579	2222.71	3	9168	0.000	.881	449.45	3	9975	0.000
Head Z Acceleration (g)	.622	2070.68	3	10214	0.000	.895	357.54	3	9168	0.000	.542	2809.68	3	9975	0.000
Head X Tilt (°)	.116	26072.30	3	10214	0.000	.251	9115.16	3	9168	0.000	.182	14908.84	3	9975	0.000
Head Y Tilt (°)	.947	191.91	3	10214	0.000	.559	2411.39	3	9168	0.000	.884	436.46	3	9975	0.000
Head Z Tilt (°)	.541	2884.48	3	10214	0.000	.916	279.38	3	9168	0.000	.457	3953.68	3	9975	0.000

Table 12 Box's Test of Equality of Covariance Matrices Log determinants after removal of univariate and multivariate outliers for sheep 1, 2 and 3

	Sheep 1		Sheep 2		Sheep 3	
behaviour_code	Rank	Log Determinant	Rank	Log Determinant	Rank	Log Determinant
1	10	-16.104	12	-29.851	11	-26.355
2	10	-21.729	12	-18.447	11	-14.761
3	10	-37.024	12	-34.002	11	-35.646
4	9	.[a]	11	.[a]	11	-45.873
Pooled within-groups	10	-20.320	12	-23.241	11	-20.955

Table 13Box's test of equality of covariance matrices of canonical discriminant Functions log determinants for sheep 1, 2 and 3.

		Sheep 1	Sheep 2	Sheep 3
behaviour_code	Rank	Log Determinant	Log Determinant	Log Determinant
1	3	.610	-2.107	.198
2	3	4.121	2.301	2.613
3	3	-3.283	-1.272	-4.740
4	3	-1.095	-3.985	-4.778
(identity matrix)	3	0.000	0.000	0.000

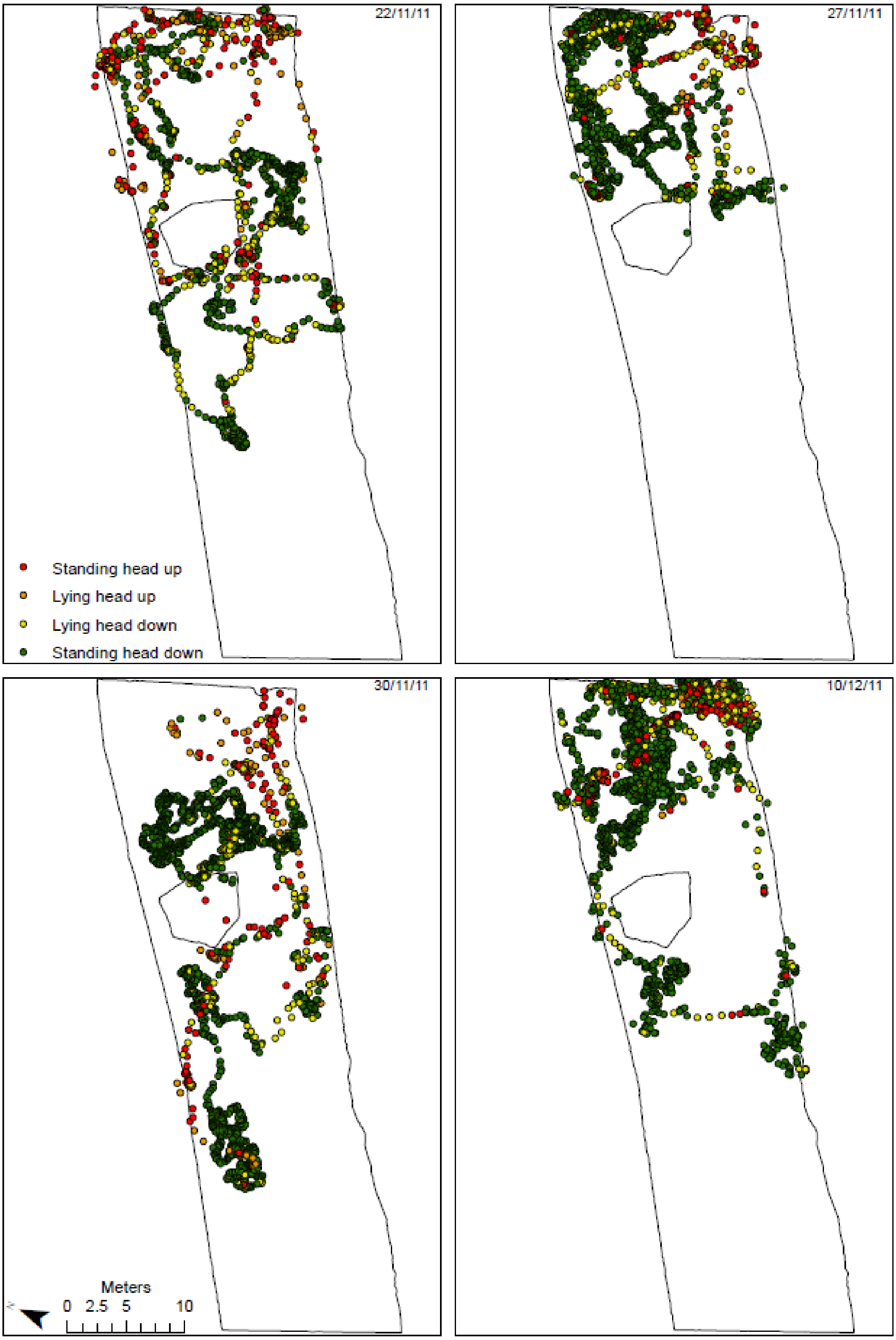

Figure 17 GPS positions and all predicted behaviours for sheep one for all observation periods.

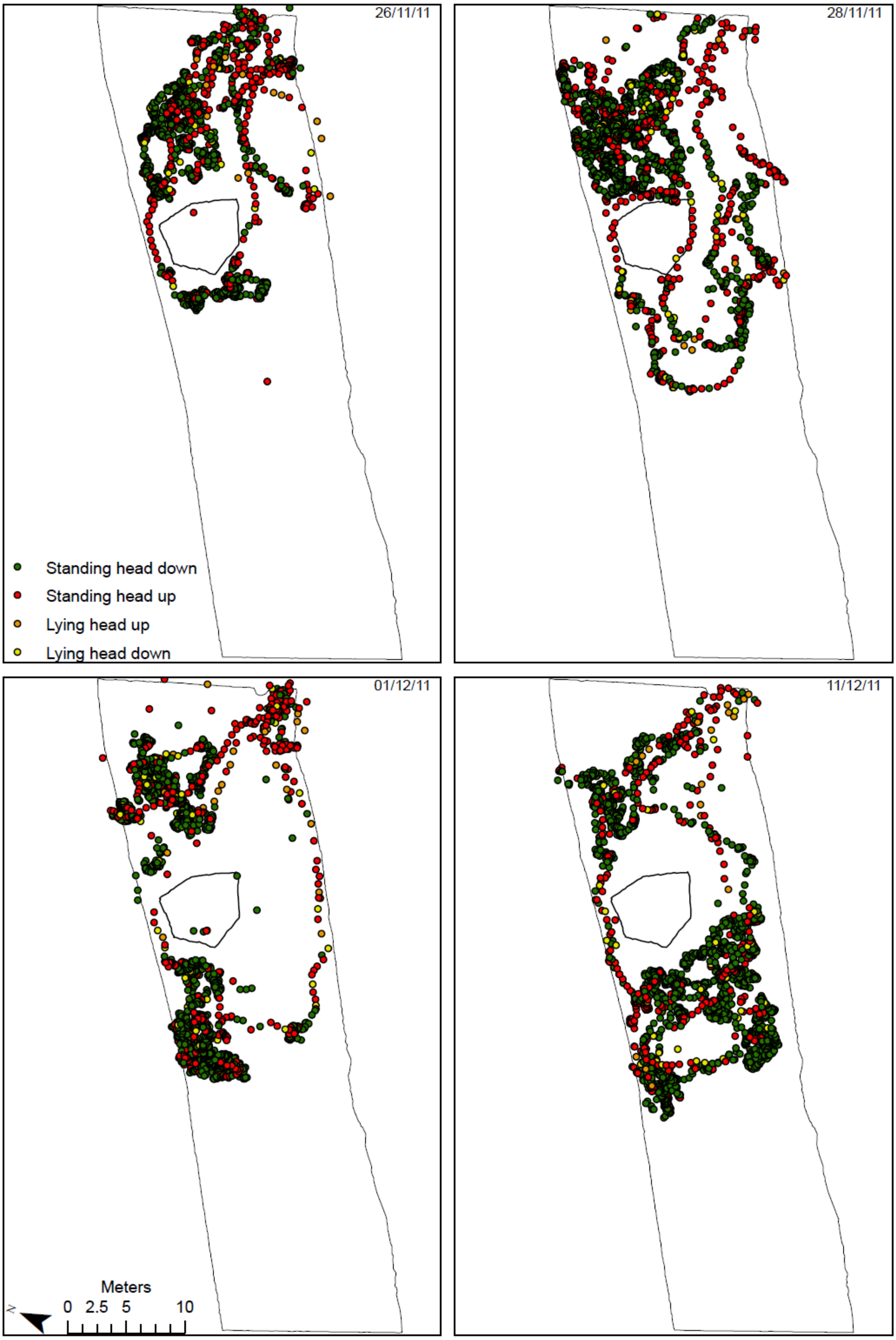

Figure 18 GPS positions and all predicted behaviours for sheep two for all observation periods.

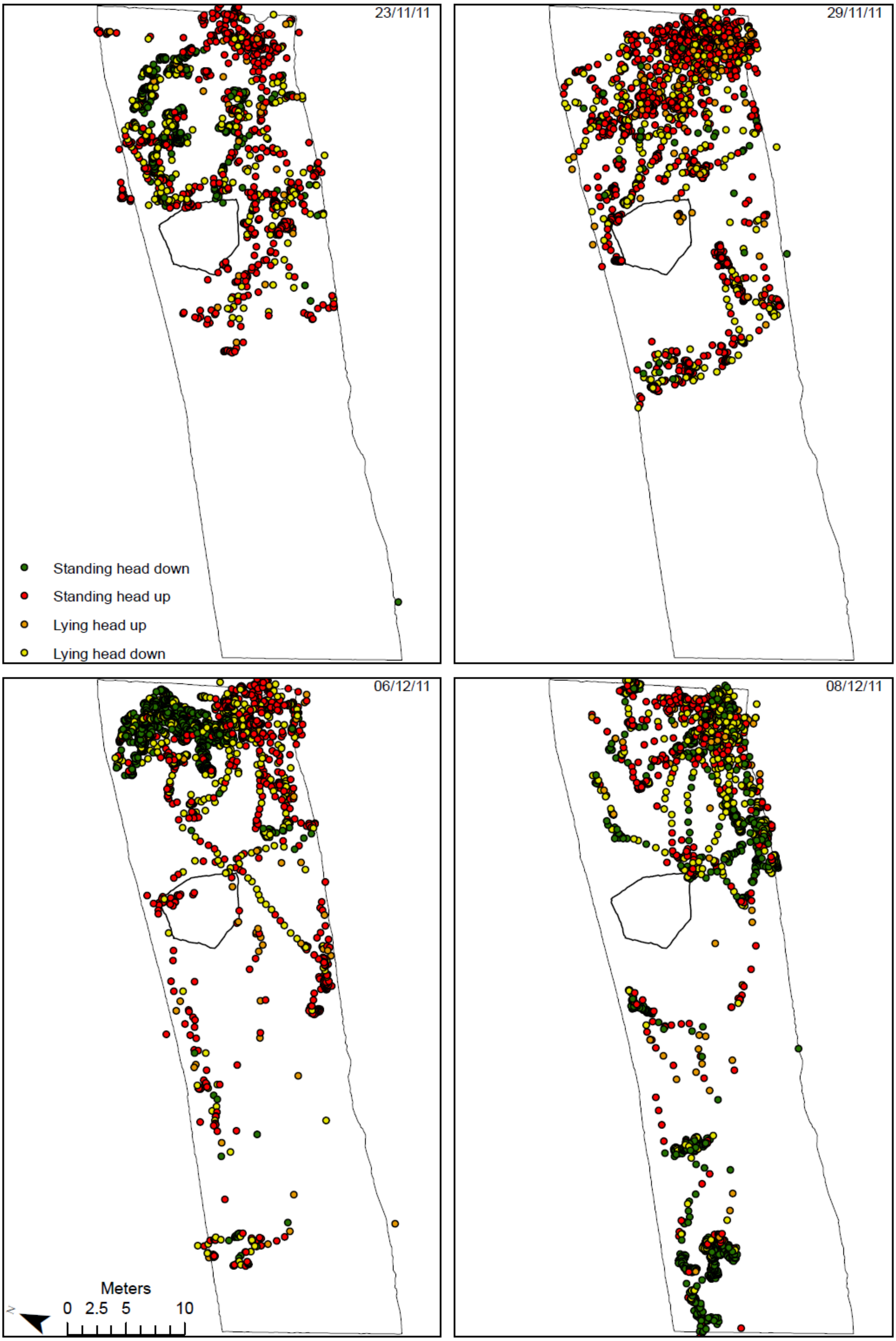

Figure 19 GPS positions and all predicted behaviours for sheep three for all observation periods.

Table 14 Date, duration and data counts for each observation period.

Sheep	1	1	1	1	2	2	2	2	3	3	3	3
Date	22/11/2011	27/11/2011	30/11/2011	10/12/2011	26/11/2011	28/11/2011	01/12/2011	11/12/2011	23/11/2011	29/11/2011	06/12/2011	08/12/2011
Time into paddock	12:15:07	11:58:20	12:04:16	12:12:00	11:41:31	12:03:05	12:12:37	11:11:47	12:16:11	12:00:21	11:47:36	10:12:02
Time out of paddock	12:46:53	12:38:17	12:55:07	13:03:05	12:38:11	13:04:49	13:10:15	12:11:10	12:49:37	12:55:43	12:48:47	10:56:17
Duraion	0:31:46	0:39:57	0:50:51	0:51:05	0:56:40	1:01:44	0:57:38	0:59:23	0:33:26	0:55:22	1:01:11	0:44:15
Standing head down	1102	1780	2252	2158	1644	2579	2490	2856	643	44	1874	1224
Standing head up	384	244	283	422	540	865	741	539	930	2196	1007	784
Lying head up	160	74	173	76	17	19	24	24	45	136	52	76
Lying head down	258	294	232	372	111	126	165	131	328	280	670	538
Total	1904	2392	2940	3028	2312	3589	3420	3550	1946	2656	3603	2622
Total after selecting only cases > 0.95 accelerometer model probabilty	1071	1745	2227	2108	1498	2361	2299	2663	542	25	1668	1063
Total after selecting cases < 20cm horizontal accuracy and accel			926									
Total after selecting cases < 30cm horizontal accuracy and accel	328	743		670	889	843	412	342	62	0	1047	697
Total after selecting cases < 40cm horizontal accuracy and accel								1521		5		
Total after selecting cases < 50cm horizontal accuracy and accel										7		
Quadrat one	36	23	37	17	34	53	31	38	17		46	26
Quadrat two	27	18	18	15	27	48	26	32	9		44	23
Quadrat three	19	17	18	14	26	36	25	29	8		41	21