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Measuring grazing behaviour of dairy cows: Validation of sensor technologies and assessing application potential in intensive pasture-based milk production systems

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A DREAM written down with a date, becomes a GOAL

A GOAL broken down into steps becomes a PLAN

A PLAN backed by ACTION

becomes REALITY

Dedicated to

My family

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SUMMARY

Grazing is the natural feed intake behaviour of a cow. However, in the last century, intensive confinement systems with silage feeding and concentrate supplementation have replaced many extensive pasture-based milk production systems. Grazed grass is now acknowledged as the cheapest feed available as a consequence of rising machinery, labour and feeding costs. Thus there is a renewed interest in intensive pasture-based milking systems. In addition, policy objectives, societal expectations and environmental concerns have all supported reconsiderations for pasture-based milk production.

Novel technology to aid measuring and managing grassland and cow grazing behaviour have the potential to facilitate improved performance. Until recently, sensor technologies for dairy farms were mainly developed for measuring feeding behaviour of housed cows. Adapting and calibrating these technologies to grazing context would therefore further support improved pasture-based dairying.

In this thesis, two sensor technologies were validated against visual observation. The RumiWatch noseband sensor (Itin+Hoch, Switzerland) is a high precision technology designed for research applications. It can measure detailed grazing behaviour such as grazing bites, rumination chews, time spent grazing and time spent ruminating. The MooMonitor+ (Dairymaster, Ireland) is the second technology assessed in this thesis. It is a collar based accelerometer and is primarily designed for use on commercial farms. The initial development was for oestrus detection. It can now monitor grazing and rumination times. The results of the studies reported in this thesis revealed that both sensors were highly accurate compared to visual observation.

The implementation of sensor technology on commercial dairy farms is still slow. This is especially true on pasture-based dairy systems. The management of grazing cows is thus largely not supported by technology.

With increasing herd sizes and skilled labour shortages, sensor technology to support grazing management will likely improve some major dairy farm management challenges. A key factor in pasture-based milk production is the correct grass allocation to maximize the grass utilization per cow. Cow behaviour is indicative of the quantity and quality of feed available as well as animal performance, health and welfare. Thus, the measurement of cow grazing behaviour is an important management indicator.

A further study of detailed individual grazing behaviour aimed to identify behavioural indicators of restricted versus sufficient availability of grass. Such objective measurement has potential since currently grass allocation is based on subjective eye measurements and calculations per herd. To identify behavioural indicators, a group of 30 cows in total were allocated a restricted pasture allowance of 60 % of their intake capacity. Their behavioural characteristics were compared to those of 10 cows with pasture allowance of 100 % of their intake capacity. The grazing behaviour and activity of cows was measured using the RumiWatchSystem, consisting of the noseband sensor and pedometer. The results showed that bite frequency was continuously higher for cows with a restricted grass allocation, but also rumination behaviour was affected by the restriction. This study contributes vital information towards developing a decision support tool for automated allocation of grass based on feedback from individual cows rather than herd based measurements.

Further research activities should focus on identification of significant changes in grazing behaviour of cows at individual animal and herd level. This would allow implementation of specific thresholds to be used in decision support tools. After developing and validating the decision support tools, the application of automated solutions for grazing management can improve efficiency and productivity of pasture-based milk production systems.

ZUSAMMENFASSUNG

Im letzten Jahrhundert entwickelten sich Milchproduktionssysteme von einer extensiven Weidehaltung zu einer intensiven Stallhaltung mit silagebasierter Grundfutterration und Zufütterung von Kraftfutter. Das Interesse an der Weidehaltung wächst heutzutage aber wieder, da Weidegras auf Grund von gestiegenen Kosten für Maschinen, Futter sowie Lohnkosten die billigste Futtergrundlage darstellt. Außerdem ist das natürliche Futteraufnahmeverhalten von Kühen das Grasen auf der Weide. Nicht nur ökonomische Gründe begünstigen die Entwicklung der Weidehaltung, sondern auch im Bereich der Verbraucherakzeptanz, Einflüsse auf die Umwelt und politischen Anpassungen birgt die weidebasierte Milchproduktion im Vergleich zur intensiven Stallhaltung Vorteile. Außerdem begünstigt die digitale Revolution mit der Integration von sensorbasierten Technologien für das Betriebsmanagement die mögliche Intensivierung im Bereich weideland-basierter Milchproduktion. Ein effizientes und profitables Betriebsmanagement lässt sich nicht nur durch eine technisierte Unterstützung in der Erfassung des Grasaufwuchses und des Weidemanagements umsetzen, sondern auch durch die Überwachung des tierindividuellen Weideverhaltens.

Ursprünglich wurden die sensorbasierten Technologien zur Erfassung des Fressverhaltens im Stall entwickelt. Jedoch unterscheidet sich das Futteraufnahmeverhalten der Kühe auf der Weide deutlich vom Stall. Deshalb müssen die Technologien an das spezifische Fressverhalten auf der Weide angepasst und kalibriert werden.

In dieser Arbeit werden zwei unterschiedliche Sensoren mit verschiedenen Anwendungspotentialen im Vergleich zu visueller Beobachtung validiert. Der Nasenbandsensor von RumiWatch ist ein höchstpräzises Messinstrument für wissenschaftliche Fragestellungen. Der Sensor kann detaillierte Parameter des Weideverhaltens erfassen, z.B. Fressbisse oder Wiederkauschläge sowie Fress- und Wiederkauzeit.

Der zweite Sensor, der MooMonitor+ (Dairymaster, Irland) beinhaltet eine praxisorientierte Aktivitätsmessung, die ursprünglich zur Brunsterkennung entwickelt wurde. Durch eine Weiterentwicklung der Rohdatenauswertung mittels Algorithmen ist es nun möglich auch Fress- und Wiederkaudauern aufzuzeichnen. Beide Validierungsstudien resultierten in einer hohen Übereinstimmung der automatischen Messung mit der Direktbeobachtung.

Die erfolgreiche Integration von softwareunterstützten Technologien auf der Betriebsebene sollte verbessert werden. Speziell im Bereich der Weidehaltung und des Weidemanagements sind wenig Technologien vorhanden. Steigende Tierzahlen und fehlende Arbeitskräfte könnten den Bedarf nach sensorbasierten Technologien zur Unterstützung des Weidemanagements begünstigen. Ein Hauptfaktor in der weidebasierten Milchproduktion ist die passende Zuteilung von bedarfsgerechter Weidefläche, um die Nutzung der Weide zu maximieren, sowie die Tierleistung zu optimieren. Das Fressverhalten der Kühe stellt hierbei eine wichtige Größe für Tierleistung, Gesundheit sowie Tierwohl dar. Ebenso kann das Weideverhalten die Futterqualität und Futterverfügbarkeit repräsentieren.

Die dritte Studie dieser Arbeit untersuchte deshalb, ob es mögliche Indikatoren im Fressverhalten von Kühen gibt, die eine unzureichende Futterverfügbarkeit aufzeigen. Die Zuteilung der Weidefläche basiert momentan auf subjektiven Erfahrungswerten der Betriebsleiter und wird auf Herdenebene kalkuliert. In einer dritten Studie der Arbeit wurden deshalb zur Bestimmung von spezifischen Verhaltensindikatoren insgesamt 30 Kühe mit 60 % ihres Futterbedarfs gefüttert, während 10 Tiere eine 100-%ige Futterzuteilung zur Verfügung hatten. Dabei wurde das RumiWatchSystem, bestehend aus dem Nasenbandsensor und dem Pedometer zur Verhaltensbeobachtung eingesetzt.

Die Ergebnisse der Studie zeigten, dass sich vor allem die Bissfrequenz durch eine begrenzte Futterverfügbarkeit erhöht sowie das Wiederkauverhalten beeinflusst wurde. Diese Studie stellt einen ersten Entwicklungsschritt in Richtung sensorunterstützte Entscheidungsgrundlage für die automatische Zuteilung von Weideflächen dar. Es wäre von Vorteil, wenn diese Zuteilung in Zukunft auf tierindividuellen Messungen im Vergleich zur Herdenebene basieren würde.

Weitere Forschungsansätze sollten sich auf der Identifizierung aussagekräftiger Schwellenwerte für das tierindividuelle Weideverhalten fokussieren, die dann in sensorgestützte Entscheidungshilfen implementiert werden können. Nach der Entwicklung und Validierung solcher Systeme könnte die Anwendung im Bereich Weidemanagement die Effizienz und Resilienz von weidebasierten Milchproduktionssystemen verbessern.

CHAPTER 1: GENERAL INTRODUCTION

Pasture grazing was evolutionary cows' natural behaviour for feed intake. Changes in animal husbandry influenced the feeding of dairy cows in the last century from extensive grazing systems to intensive confinement systems with silage feeding and high concentrate input. However, recently there is a renewed interest in pasture-based milk production systems due to changes in the economy, increase in food demand and security and a stronger consumer awareness.

In order to ensure and maintain a high productivity of dairy cows on pasture as well as high standards of animal welfare, a sensor-based management support is needed. The advancement in sensor technology enables continuous measurement of behaviour for long-term periods, which is contrary to visual observation by the farmer as this can only be carried out over relatively short periods during the day. Consequently, the development of sensor technology has mainly focused on measuring feeding behaviour of cows indoors, thus the calibration and application of sensor technology for measuring grazing behaviour has not progressed to the same extent. This thesis is therefore validating two sensor systems for measuring grazing behaviour and assessing the application potential for commercial usage or research approaches. Furthermore, first investigations on the use of cow behaviour as an indicator of sufficient grass allocation were conducted. This would have potential to add value to existing grass measurement data in a grass allocation decision support tool.

Pasture-based milk production systems

During evolution humans realized that food security can be maintained with domesticating animals as a food source. Ruminants were especially focused on as they have an advantage of converting high fibrous feedstuff into milk or meat and would not compete against humans for food sources (van Wieren, 1996). However, in the last century the development of dairy husbandry changed. Extensive, mainly pasture-based milk production of small-scale dairy herds developed into larger scale intensive confinement systems (Pinxterhuis et al., 2015). Since around the mid-20th century, the mechanisation of agricultural production advanced significantly, which resulted in replacing human labour and reducing required time and costs for feed harvest, conservation, storage as well as ensuring daily feed provision indoors (Knaus, 2016). There were also other reasons for the uptake of intensive confinement systems for dairy cows. Breeding led to successful high-yielding cows, this resulted in a requirement to provide a consistent high nutritional diet to the cows, to prevent hunger and maintain their milk yields (Kolver and Muller, 1998). Furthermore, developments with regards to the uptake of robotic milking, limited land availability for pasture-based production and climatic factors including heat stress, adverse and unpredictable weather conditions supported the continuous housing of dairy cows in recent years (Arnott et al., 2017).

Nowadays dynamics of global agriculture are constantly changing due to the endless fluctuation of international food markets, policy changes nationally and internationally, greater societal expectations and environmental constraints (Hanrahan et al., 2018). Based on these factors there is a requirement for resilient sustainable agricultural systems. For milk production systems this might be achieved with increasing the proportion of grazed grass in the feed of dairy cows, as feed costs contribute around 50 % of the total costs of milk production (Hemme et al., 2014).

Given the versatility of global dairy husbandry systems, it is difficult to compare these systems. In Central Europe, dairy farming is mainly based on indoor-feeding due to the long dormancy period of vegetation in the winter (Hofstetter et al., 2014). However, there is an increased interest in pasture-based milk production (see as an example the Northern German "Charta Weideland", written by agricultural and political organizations and stakeholders and is aiming to promote and maintain pasture-based milk production in North Germany).

Due to the digital revolution and the integration of new technologies into farming practices to increase production and reduce costs (Yahya, 2018), there is a possibility of intensification of pasture-based production. One example is the technical support of automated sensor systems in measuring and managing pasture production (Hanrahan et al., 2017). Despite the changes, only 10% of global milk production originates from intensive grazing systems of production similar to the traditional Irish system (Dillon 2017). This system is mostly prevalent in Ireland, New Zealand and parts of Australia. The Irish grazing system is based on a low input system with less concentrate and a seasonal spring calving system to meet feed demands with pasture grass during the main growth period. Grazed pasture is the dominant source of forage from March to October and usually contribute 95%-97% of the diet as fed in the summer period (O'Brien, personal communication).

There are distinct advantages of pasture-based milk production systems compared to high- input confinement systems. A review of Dillon et al. (2005) revealed that pasture-based milk production can decrease unit production costs through lower feed and labour expenses. In total, the confinement production systems have higher milk output per cow, but also higher costs. Grazing systems can also be associated with greater global sustainability. Some aspects of greater global sustainability are mentioned by Dillon et al. (2005) with reduced use of fuel, herbicides and pesticides.

From an animal welfare perspective, pasture-based milk production systems are beneficial to allow the cows to express natural behaviour (Charlton and Rutter, 2017) and improve health issues, such as lameness prevalence (EFSA 2009). Also consumer interest in food production is rising and a study of Weinrich et al. (2014) revealed that consumers have a preference for milk production from pasturing cows.

However, there are also some challenges associated with pasture-based systems. A proportional increase in required land to graze the cows, which is easily accessible from the milking parlour, is needed to facilitate the increased herd sizes (van den Pol et al., 2008). Subsequently, increased area of land around the farm also increases the walking distance to the paddocks. This might have negative effects on cow claws health (Laven and Lawrence, 2006) as well as an increased labour demand associated with herding the cows to and from the pasture (Ofner-Schröck et al. 2009). Depending on prevalent climatic conditions and location of individual farms, the intensive pasture-based milk production system can be challenging, as approx. 1000 mm of rainfall (evenly distributed throughout the year) is ideally required (Dillon et al., 2005).

The objective of grass-based systems is to match the supply of feed with feed demand at the lowest cost possible. However, the correct calculation and allocation of grass to the cows can be challenging. It depends on grass growth, grass quality and grass utilization of cows. McCarthy et al. (2011) also mentioned that the balance between feed supply and demand is critical as an imbalance will result in either underfeeding of the herd or waste of excess feed and that will result in reduced growth or reduced grass quality.

From an economic perspective, the profitability of grazing systems is driven by the degree of grass utilization (Shalloo et al., 2011). Therefore, French et al. (2015) are highlighting that the farmer requires accurate real-time measurement of pasture biomass to optimise grazing management. Contrary to the approach of assessing pasture biomass, there is the possibility of the integration of individual animal behaviour to gain additional information on optimal grazing management. Therefore, the development and application of sensor technology to measure grazing behaviour automatically would be beneficial.

Sensor development for measuring feeding behaviour

In previous years, the measurement of feeding behaviour was mostly based on visual observations or on video recordings. This is still considered as gold standard (Burfeind et al., 2011, Elischer et al., 2013). Although, the analysis and data collection with those methods is very time consuming. As a result there are a number of new approaches to develop automated sensors in the last two decades. The sensor technologies can be divided into different measurement methods. Some systems use electrical signal sensors (Beauchemin et al., 1989, Rutter et al., 1997) or pressure sensors to detect jaw movements (Dulphy et al., 1997). Büchel and Sundrum (2014) showed in their study, that it is suitable to use electromyography to measure electrical potential oscillation during jaw movements to determine feeding behaviour. The measurement of acceleration, as another option, is often used to define either locomotion activity (Alsaaod et al., 2015) or feeding behaviour (Delagarde et al., 2015). The position of those systems on a cow could be varying within head or neck collar devices, pedometers or even ear-mounted tags with an accelerometer integrated (Bikker et al., 2014, Borchers et al., 2016). Most commercially available systems use accelerometers to predict oestrus events (e.g. Heattime® by SCR Engineers, Netanya, Israel) and/or feeding behaviour (e.g. FeedPhone by Medria, Châteaubourg, France). Another method is acoustic monitoring to determine feeding behaviour (Tani et al., 2013). There are also systems, which can measure the access of cows to the feeding trough with an ear-attached passive transponder (DeVries et al., 2003).

Feeding behaviour differs between grazing cows and cows fed indoors with silage or total- mixed ration (TMR), which will be addressed in the next paragraph. Therefore, there is a calibration or adaptation of algorithms required, when sensor technology is used for measuring grazing behaviour.

Grazing behaviour versus feeding behaviour

Kilgour (2012) highlighted in his review, that cows have an extensive repertoire of behaviour, comprising 40 identifiable categories and 90-95 % of their time is spent with grazing, ruminating and resting, if there is little human interference. He also mentioned that grazing is the most common behaviour with two main grazing events per day. Furthermore, cows perform their grazing activities mostly during daytime with a longer and more intensive grazing event around dusk. This timing of grazing events classifies cows as crepuscular animals, and light plays a role in shaping daily grazing patterns (Gregorini et al., 2006). Grazing behaviour of cows is also influenced by other cues such as social herd structures, sward quality and grass palatability as well as herd management (Albright, 1993).

Based on a definition of Hodgson (1979) grazing is the “defoliation by animals of rooted plants in the field” and defoliation is defined as “the process of the complete or partial removal of the above-ground parts of the plants, living or dead”. In a bigger picture, Andriamandroso et al. (2016) defined the grazing activity based on studies of Gibb (1996), Gregorini et al. (2006), de Faccio Carvalho (2013) as a complex combination of various movements and activities in different spatial-temporal scales (see Figure 1).

Compared to grazing behaviour, the feeding behaviour of indoor cows may be considered different. Roca-Fernandez et al. (2013) found in their study, that cows in confinement systems spent less time feeding and the feeding time was spread throughout the day compared to two main events for grazing cows. With regards to the feed intake behaviour, the cows on pasture need to use the tongue to rip the grass, whereas in confinement systems the cows mainly eat by gathering the feed with the tongue and sucking it into the mouth (Albright, 1993). Depending on the feeding management, the feed for cows indoors is already mixed in TMR or the feed particles are relatively small, which may influence the feed intake behaviour of cows with regards to less biting action (Albright, 1993).

Furthermore, the cows on pasture naturally show a selective grazing behaviour based on preferences between the sward composition (Hodgson, 1979), whereas TMR type feed may be more consistent and the selection of feed is then more limited. Also with regard to the spatial aspect of grazing behaviour, the selective grazing that occurs over pasture does not occur over feed indoors, where the feeding trough or bunk is the only source of feed availability.

Physiological and behavioural differences in feed intake between cows on pasture and indoors may therefore influence the performance of automated measurement systems with regard to accurately measuring grazing behaviour.

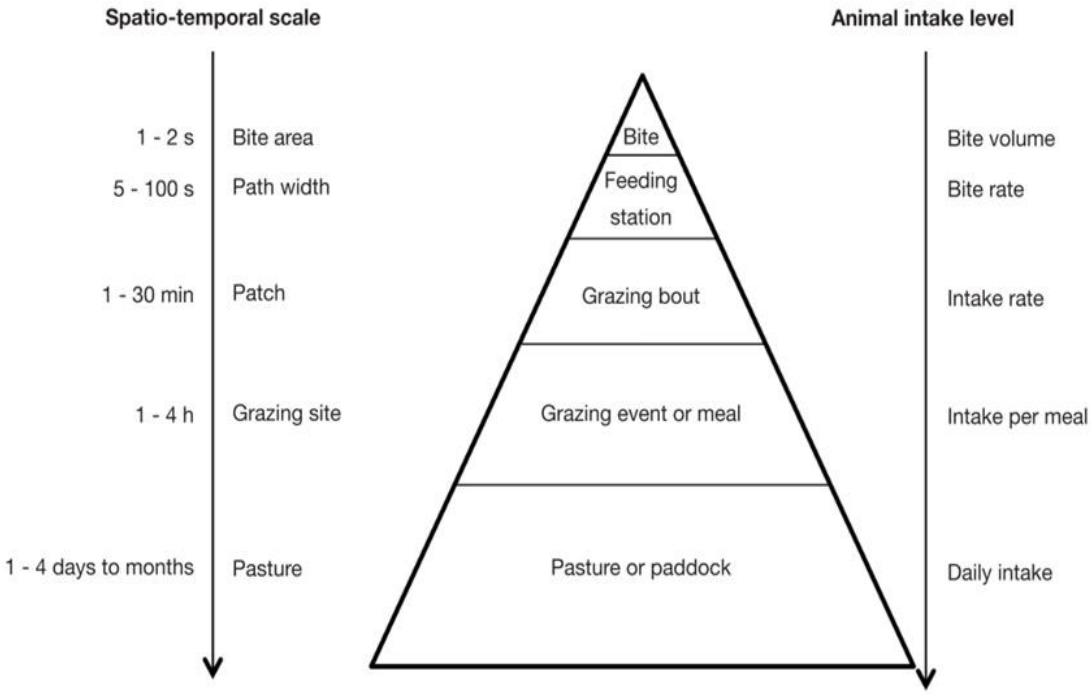

Figure 1: Spatio-temporal components of grazing behavior after Andriamandroso et al. 2016 (adapted from Gibb, 1996; Gregorini et al., 2006; de Faccio Carvalho, 2013).

AIMS OF RESEARCH

The PhD thesis aimed to improve the performance and application potential of sensor technologies to measure grazing behaviour of dairy cows in a pasture-based milk production system.

The first step was to validate a previously calibrated sensor system to measure feeding behaviour indoors in a grazing environment. This sensor system had the ability to measure detailed grazing behaviour appropriate for research-focused purposes.

The second study evaluated a commercially applied sensor technology, developed for oestrus detection in pasture-based systems. The different application potentials of research focused and commercially used sensor technologies as well as end-user requirements was also investigated.

The third paper aimed to apply the previously validated sensor system to identify potential indicators in cows grazing behaviour for insufficient grass allocation, which may be possible to be implemented in a decision support tools for grazing management.

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CHAPTER 2

Evaluation of the RumiWatchSystem for measuring grazing behaviour of cows

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Abstract

Feeding behaviour is an important parameter of animal performance, health and welfare, as well as reflecting levels and quality of feed available. Previously, sensors were only used for measuring animal feeding behaviour in indoor housing systems. However, sensors such as the RumiWatchSystem can also monitor such behaviour continuously in pasture-based environments. Therefore, the aim of this study was to validate the RumiWatchSystem to record cow activity and feeding behaviour in a pasture-based system. The RumiWatchSystem was evaluated against visual observation across two different experiments. The time duration per hour at grazing, rumination, walking, standing and lying recorded by the RumiWatchSystem was compared to the visual observation data in Experiment 1. Concordance Correlation Coefficient (CCC) values of CCC = 0.96 for grazing, CCC = 0.99 for rumination, CCC = 1.00 for standing and lying and CCC = 0.92 for walking were obtained. The number of grazing and rumination bouts within one hour were also analysed resulting in Cohen`s Kappa (κ) = 0.62 and κ = 0.86 for grazing and rumination bouts, respectively. Experiment 2 focused on the validation of grazing bites and rumination chews. The accordance between visual observation and automated measurement by the RumiWatchSystem was high with CCC = 0.78 and CCC = 0.94 for grazing bites and rumination chews, respectively. These results indicate that the RumiWatchSystem is a reliable sensor technology for observing cow activity and feeding behaviour in a pasture based milk production system, and may be used for research and management purposes in a grazing environment.

Introduction

With increasing scale on farms, and declining available labour, there is a requirement for technologies that assist farmers in their day to day management. Animal management involves ensuring the health and welfare of the animals; reacting to certain events in the animal reproductive cycle and improving efficiency in feed provision for conversion into an animal product, such as milk or meat. Especially in a pasture based system the balance between the feed offered and the herd demand needs to be optimized to maximise grass utilisation while simultaneously ensuring that animals are well fed at pasture. Shortage in labour and time to observe animals makes it difficult for farmers to monitor all animals intensely. Automated monitoring for quantifying physiological and behavioural parameters, e.g. oestrus, somatic cell count and feeding behaviour, can give an insight into overall health status, important animal events as well as helping with feeding management. For a continuous monitoring of these physiological and behavioural parameters sensor-based, easy-to-use tools for farmers need to be developed.

One of the best indicators of health and welfare of dairy cows is feeding behaviour. A study by Bareille et al. (2003) showed that feed intake was influenced by a number of different diseases such as milk fever, ketosis or hoof lesions. There is a benefit to detect emerging diseases earlier by monitoring the feeding behaviour of dairy cows automatically. Previous research has shown that a decline in rumination time can be used as a reliable predictor of both health and fertility events and is also mentioned to be an indicator for cow stress (Herskin et al., 2004). Feeding behaviour can also be used to optimise grassland management decisions with a focus on increasing animal intake and reducing grass residuals. It is of key importance to measure, manage and allocate accurately the feed available and offered to the cows, irrespective of the farming system in order to optimise farm efficiency and profitability.

The estimation of feed intake based on behavioural parameters, such as feeding time or bite frequency, provides valuable information that can be used to manage cows. Pahl et al. (2015) conducted a study in an indoor feeding system to compare feeding and chewing time with measured intake data obtained by weighing of the feeding troughs. They concluded that it was appropriate to use feeding behaviour for estimating intake in barn systems.

Some methods have been developed to predict intake in grass-based systems (Undi et al., 2008), such as the N-alkane-method (Dillon and Stakelum, 1988). This method determines the feed intake by the usage of an orally applied bolus with synthetic faeces marker. These measurements are labour-intensive, time-consuming and invasive, as the cows have to be dosed orally twice a day over a 2-week period. An alternative approach used to determine feed intake was the IGER animal recording system (Mezzalira et al., 2014). This consisted of a noseband sensor that measured jaw movement by electrical resistance (Rutter et al., 1997). It could identify and measure grazing and rumination. However, the maximum recording period of this system is 24 hours, and the analysis of the data via the “Graze software” is very laborious (Rutter, 2000). Furthermore, the distribution and commercial support for this technology has ceased in recent years. But a new technology, the RumiWatchSystem may have the potential to improve data capture and replace the IGER animal recording system.

The RumiWatchSystem was initially developed by Nydegger (2010) at the Swiss Federal Research Institute (Agroscope, Tänikon, Switzerland) for behavioural measurements on cows fed indoors and is commercially distributed by the company (Itin+Hoch GmbH, Liestal, Switzerland) since 2010. It is well established as a sensor technology in indoor housing systems (Ruuska et al., 2016) and has undergone a number of modifications in development as a research and advisory tool (Zehner et al., 2012). It is absolutely critical that any animal behaviour sensor operates correctly in monitoring the appropriate parameters and is validated correctly.

Thus, the objective of this study was to validate an updated version of the RumiWatchSystem for the measurement of grazing behaviour in a pasture-based milk production system. Two separate experiments were conducted to validate parameters such as grazing, rumination, walking, standing and lying time, as well as grazing bites and rumination chews.

Material and Methods

Validation of the RumiWatchSystem was conducted in two separate experiments with individual cow herds at Teagasc, Animal and Grassland Research and Innovation Centre (Fermoy, Co. Cork, Ireland, 50°07′N; 8°16′W). Experiments 1 and 2 took place in the periods of 10th to 19th of May 2016 and 31st of May to 2nd of June 2016, respectively. The experimental grazing areas represented permanent grassland with 70% perennial ryegrass and 30% annual meadow grass. This study was part of a larger study where different levels of feed allowance were allocated to dairy cows across different periods of the lactation and for different durations.

Sensor technology

The RumiWatchSystem consists of two separate devices with associated software packages for managing the sensors (RumiWatch Manager) and analysing data (RumiWatch Converter). The RumiWatch noseband sensor, integrated in a halter, is able to detect jaw movements and classifies them into grazing bites/chews, rumination chews or any other activity. Additionally, the time duration of those different classifications is recorded. The RumiWatch pedometer measures activity and can classify standing, walking, lying as well as amount of strides. Raw data were recorded in a 10 Hz resolution. Further information about technical components can be found in Zehner et al. (2012), Werner et al. (2016) and Alsaaod et al. (2015).

The RumiWatch Manager 2 (V.2.1.0.0) and the RumiWatch Converter (V.0.7.3.36) were used for Experiments 1 and 2 of the current study. There were two different approaches for time resolutions. For 1-min summaries, the output by the RumiWatch Converter was categorical as the behaviour was classified for the focal minutes.

All other time resolutions, e.g. 5-min, 10-min or 1-hour summaries were based on numerical data, which meant that the minutes of focal behaviour in each defined time resolution were counted. The algorithms were adapted to increase accuracy in detection under grazing conditions.

The RumiWatch Converter V.0.7.3.36 used three different parameters to monitor and calculate feeding time. Two parameters considered in this study were used to calculate feeding time. EAT1 determined grazing with head position down, EAT2 determined grazing with head position up. Furthermore, there were parameters for grazing and rumination bout behaviour integrated in the RumiWatch Converter V.0.7.3.36 with grazing bouts and rumination bouts. A grazing bout was defined as an event, where grazing was detected for a minimum duration of 7 minutes and the inter-bout interval was defined with a minimum threshold of 7 minutes. That means, if a cow was not showing any grazing behaviour for ≤ 7 minutes or she commenced to ruminate, the detection of the grazing bout was stopped. These definitions were similar to those used in a study by Pérez-Ramírez et al. (2009) after Brun et al. (1984). A second bout parameter, a rumination bout was defined as having a minimum duration of 3 minutes and an inter-bout interval with a minimum threshold of 1 minute. The study of Wolfger et al. (2015) applied similar criteria.

Experiment 1

Animals and Treatments:

A group of twelve spring calving dairy cows from a herd of 15 in a pasture-based milk production system was used. The cows were on average 91 ± 12 days in milk at the start of the experiment. The group consisted of an equal number of Holstein-Friesian (HF) and Jersey crossbred (JEX) cows with four primiparous and eight multiparous cows, ranging in lactation from 2 to 6.

The mean bodyweight was 477 ± 65 kg and the average body condition score (BCS) was 2.8 ± 0.2 ranging from 1 to 5, measured under the Edmonson et al. (1989) scoring system. The average milk yield over the experimental period was 22.5 ± 4.5 kg/cow/day.

All cows followed a similar milking routine. Cows were milked twice a day (6:30 h and 14:30 h) and spent approximately 1.5 - 2.0 hours per milking away from the paddock.

Cows were on a grass only diet and received a grass allocation twice daily after milking. Pre- and post-grazing sward height was measured daily with a rising plate meter (diameter 355 mm and 3.2 kg/m2; Jenquip, Fielding, New Zealand). Pre-grazing height of grass averaged 11.9 ± 2.5 cm, while post-grazing height averaged 4.5 ± 0.8 cm during the experimental period. All cows were identifiable by numbers painted on their sides (1-12).

<u>Experimental design:</u>

Cow behavioural data was collected by visual observation and by automated recording of the RumiWatchSystem. Two previously trained observers according to Table 2 were used to monitor the cows. The cow group was divided into 4 subgroups of 3 cows each. Each subgroup was observed by each observer on 3 occasions per day over a 4 day period (Table 1). Observations took place over 2-hour periods between dusk (05:00) and dawn (21:00) excluding milking times, which extended from 7:00 to 9:00 and 14:00 to 17:00 hrs.

Table 1: Experimental protocol for data collection of cow behaviour by visual observation.

Day	Time	Observer 1 Cow numbers	Observer 2 Cow numbers
1	09:00-11:00	1,2,3	4,5,6
	12:00-14:00	4,5,6	1,2,3
	17:00-19:00	1,2,3	4,5,6
2	09:00-11:00	7,8,9	10,11,12
	12:00-14:00	10,11,12	7,8,9
	17:00-19:00	7,8,9	10,11,12
3	05:00-07:00	4,5,6	1,2,3
	11:00-13:00	1,2,3	4,5,6
	19:00-21:00	4,5,6	1,2,3
4	05:00-07:00	10,11,12	7,8,9
	11:00-13:00	7,8,9	10,11,12
	19:00-21:00	10,11,12	7,8,9

Visual observation was performed by 1-min scan sampling as used in the study of Büchel and Sundrum (2014). Behavioural data was categorized as feeding behaviour (FB) and activity behaviour (AB). Feeding behaviour was further classified as grazing, ruminating and other activities, while activity behaviour was classified as standing, walking and lying (Beauchemin et al., 1989). The different behaviour classifications are described in Table 2. The data were recorded on a spreadsheet and were transferred manually to an electronic spreadsheet (Microsoft Excel Version 2010; Microsoft Corporation, Redmond, USA) for analysis.

Table 2: Definition of different behaviour categories for observers, adapted from Bikker et al. (2014) and Alsaaod et al. (2015).

	Behaviour	Definition
Feeding behaviour	*Grazing*	Cows' muzzle is located near or above the grass and makes biting motion to ingest grass, or cow's head position up and making chewing motion
	Ruminating	Regurgitation, chewing, salivation and swallowing of ingested grass
	Other activities	Any other movements of the muzzle, which are not associated with grass intake
Activity behaviour	*Standing*	Cow is in an upright position but is not walking
	Walking	Cow takes at least 3 consecutive strides in the same direction (forward or backward)
	Lying	Cow is resting on the ground (not standing)

With regard to the automated data collection, the RumiWatchSystem comprised of two devices, a halter placed on the head and a pedometer placed on the left hind leg. The RumiWatch Manager 2 was used to synchronize both RumiWatch devices to UTC (Universal Time Coordinated) at the beginning of the experiment.

Data preparation:

There were 144 hours (8640 min) of valid observations. This visually recorded data were assembled in three ways. Firstly the data was assigned to the appropriate classification within the categories of FB and AB at 1-min intervals. Secondly, the time duration of the specific classifications of FB and AB were totalled for 1-hour intervals. Finally, the number of started grazing bouts and finished grazing bouts and the number of started rumination bouts and finished rumination bouts were calculated for each 1-hour period.

The automatically captured data were converted with the RumiWatch Converter (V.0.7.3.36) in 1-min and 1-hour summaries. Those summaries comprised comparable parameters to those outlined above for the visual data (classification at 1-min intervals, duration of specific behaviour classification per hour and numbers of grazing and rumination bouts). For the analysis of grazing time, the total of EAT1TIME and EAT2TIME was calculated.

Experiment 2

Animals and Treatments:

The objective of this trial was to validate the RumiWatch noseband sensor for the number of grazing bites and rumination chews. A group of twelve spring calving dairy cows were fitted with RumiWatch noseband sensors. All cows were identifiable by numbers (1-12) painted on both sides of each cow. The experiment extended over a 2-day-period with an adjustment period to the noseband sensor of 8 days prior to the starting of the experiment. Two cow breeds were included with 7 Holstein-Friesian (HF) and 5 Jersey crossbreds (JEX). The group consisted of 3 primiparous and 9 multiparous cows, ranging from 2-6 parities. Average cow milk yield over the experimental period was 20.8 ± 4.7 kg/cow/day. Cows had an average body weight of 496 ± 69 kg and a BCS of 2.9 ± 0.2. The cows were on a grass only diet and were maintained in the same paddock throughout the experimental period.

They had ad libitum access to water, and fresh grass was provided once daily directly after morning milking. Milking times were twice daily (6:30 h and 14:30 h) during which the cows spend 1.5-2.0 hours per milking away from the paddock. Pre- and post-grazing sward height was measured with an automated rising plate meter which is a grass measuring device (Grasshopper, True North Technologies, Shannon, Co. Clare, Ireland; (McSweeney et al., 2015)) on one occasion during the experiment. Average pre-grazing and post-grazing height were 14.7 cm and 6.1 cm, respectively.

Experimental design:

Firstly, the accordance between all four observers was measured over two days in 24 5-min periods, during which time all observers monitored the behaviour of the same cow independently. Four previously trained observers then monitored one cow per observer for 5-min periods to validate the number of grazing bites and rumination chews. The number of grazing bites and rumination chews was recorded using a handheld computer with a specially programmed application. A grazing bite was defined as a combination of jaw, tongue and neck movement to rip grass with an under-laid acoustic sound (Bailey et al., 1996). Rumination chews were counted after regurgitation took place and a bolus travelled through the oesophagus to reach the mouth (Schirmann et al., 2009). As in Experiment 1, the observational periods were extended to 2-hour periods and occurred three times a day (Table 3). All observations took place between 04:30 and 21:00 hrs. Every 5-min observation period was alternated with a 5-min break period. Cows were rotated across observers for every 5-min observation period, such that the observer monitored each of the 12 cows during each 2-hour observation period.

Table 3: Experimental protocol for data collection on cow behaviour (rumination chews and grazing bites), by visual observation. Observed cows were monitored in 5-min periods in the stated order ascending or descending by each observer.

		Observer 1	Observer 2	Observer 3	Observer 4
Day	Time	CowNo.	CowNo.	CowNo.	CowNo.
1	09:30-11:30	1→6 7→12	7→12 1→6	6→1 12→7	12→7 6→1
	12.00-14.00	1→ 6 7→12	7→12 1→6	6→1 12→7	12→7 6→1
	17:00-19:00	1→6 7→12	7→12 1→6	6→1 12→7	12→7 6→1
2	04:30-06:30	1→6 7→12	7→12 1→6	6→1 12→7	12→7 6→1
	11:00-13:00	1→6 7→12	7→12 1→6	6→1 12→7	12→7 6→1
	19:00-21:00	1→6 7→12	7→12 1→6	6→1 12→7	12→7 6→1

<u>Data preparation:</u>

The data recorded on the handheld computer included the number of visually observed rumination chews and grazing bites. This data was subsequently totalled within a spreadsheet application. In total 249 observation periods were analysed, which had been collected over the 2-day period. The observation periods consisted of 181 periods of grazing bite observations and 71 periods of rumination chew observations.

Data were excluded, when two different behaviour types (grazing bites and rumination chews) were monitored within one 5-min period. Periods where neither grazing bites nor rumination chews were observed, were also excluded from the data set.

With regard to the data automatically recorded by the RumiWatch noseband sensor, these data were classified into the categories of grazing bites and rumination chews. The data were then converted by the RumiWatch Converter (V.0.7.3.36) into 5-min intervals, summarizing the numbers of rumination chews or grazing bites. For analysing rumination chews, the algorithms with the plausibility check function for minimum duration of 3 min were turned off.

Statistical analysis

Statistical analysis was performed using R version 3.3.1 (R Foundation for Statistical Computing, Vienna, Austria). The following analyses were carried out to assess agreement between the RumiWatchSystem and visual observations, depending on the type of data recorded at different time periods.

In Experiment 1, Cohen's Kappa (κ) was calculated to assess agreement between RumiWatchSystem and visual observations when FB and AB were recorded at 1-min resolution (Cohen, 1960). The κ – values were interpreted in a similar manner as by Landis and Koch (1977), where: poor: $\kappa < 0.00$, slight: $\kappa = 0.00$–0.20, fair: $\kappa = 0.21$–0.40, moderate: $\kappa = 0.41$–0.60, substantial: $\kappa = 0.61$–0.80, and almost perfect: $\kappa = 0.81$–1.00.

The percentage agreement (PA) of the 1-min resolution data for both categories of FB and AB and specific classifications, e.g. grazing, rumination, standing, walking, etc. recorded by visual observation and RumiWatchSystem was computed using the following formula, used by Martin et al. (1993):

$$\frac{total\ numbers\ of agreement}{total\ numbers\ of agreement + total\ numbers\ of disagreement}\,x100$$

A number of tests were conducted on the variables with numeric values to assess agreement between data of the RumiWatchSystem and visual observations. The behavioural data from the RumiWatch noseband sensor and from the pedometer were subjected to a graphical analysis in a Bland-Altman-Plot and a Spearman's Rank correlation (r_s) and a concordance correlation coefficient (CCC) was calculated, using the U-statistics (Carrasco et al., 2007). Interpretation of r_s -values and CCC were based on criteria defined by Hinkle et al. (2003) as follows:

Negligible = 0.0 - 0.3, low = 0.3 - 0.5, moderate = 0.5 - 0.7, high = 0.7 - 0.9 and very high = 0.9 - 1.00.

The Bland-Altman-plots demonstrated the agreement between both measurement methods and the Bland-Altman-analysis indicated the mean differences (bias) between the paired automatically recorded and visually observed values, with 95%-confidence intervals (CI). It also displayed the lower and upper limits of agreement along with their relative 95%-confidence intervals. The limits of agreement were calculated as ± 1.96*standard deviation from mean difference. Although the parameters itself were not normally distributed, the Bland-Altman-plots were used as the differences between the paired values followed a normal distribution. In addition, a method to determine significant differences between two measurements by Giavarina (2015) was also applied on the Bland-Altman-analysis. The bias (or mean difference) was considered to be significant when the line of equality was not within the 95% CI of the mean difference. Therefore, a significant under- or overestimation was declared when the line of equality was not included in the 95% CI of the mean difference.

For the validation of bouts (grazing and rumination), there were values between 0 and 2 for bouts started or finished within each 1-hour period measured. Therefore, these values were treated as ordinal variables. The agreement for grazing and ruminating bouts was assessed using weighed kappa statistics and percentage agreement, as explained above.

In Experiment 2 grazing bites and rumination chews were counted by human observers during 5-min periods. Agreement between every paired observer was evaluated using CCC and among all observers via overall CCC. Number of grazing bites and rumination chews per 5-min period were analysed using the same methods for numeric variables as described in Experiment 1, including Spearman's Rank correlation, CCC and Bland-Altman-Analysis.

Results

Experiment 1

The comparison of categorical data of the noseband sensor and of the pedometer is shown in Table 4. The Cohen's Kappa value was κ = 0.84 for the visual feeding behaviour measurements compared with the noseband sensor and κ = 0.89 for the visual activity measurements compared to the pedometer. Using an interpretation of Landis and Koch (1977), these results indicate an almost perfect agreement of visual and automatically recorded data on a 1-min resolution. This result is supported by the overall agreement of 91.1% for the noseband sensor and 95% for the pedometer.

Table 4: Cohen's Kappa (κ) and percentage agreement between visual observations and automated measurements by RumiWatch for feeding and activity behaviour on a 1-min resolution.

Category	Cohen's κ	Agreement between visual and automated measurement (%)	Classification	Agreement between visual and automated measurement (%)
Feeding behaviour (Grazing, Ruminating, Other Activities)	0.84	91.1	Grazing	91.5
			Ruminating	94.3
			Other Activities	81.4
Activity behaviour (Standing, Walking, Lying)	0.89	95.0	Standing	96.3
			Walking	95.4
			Lying	98.7

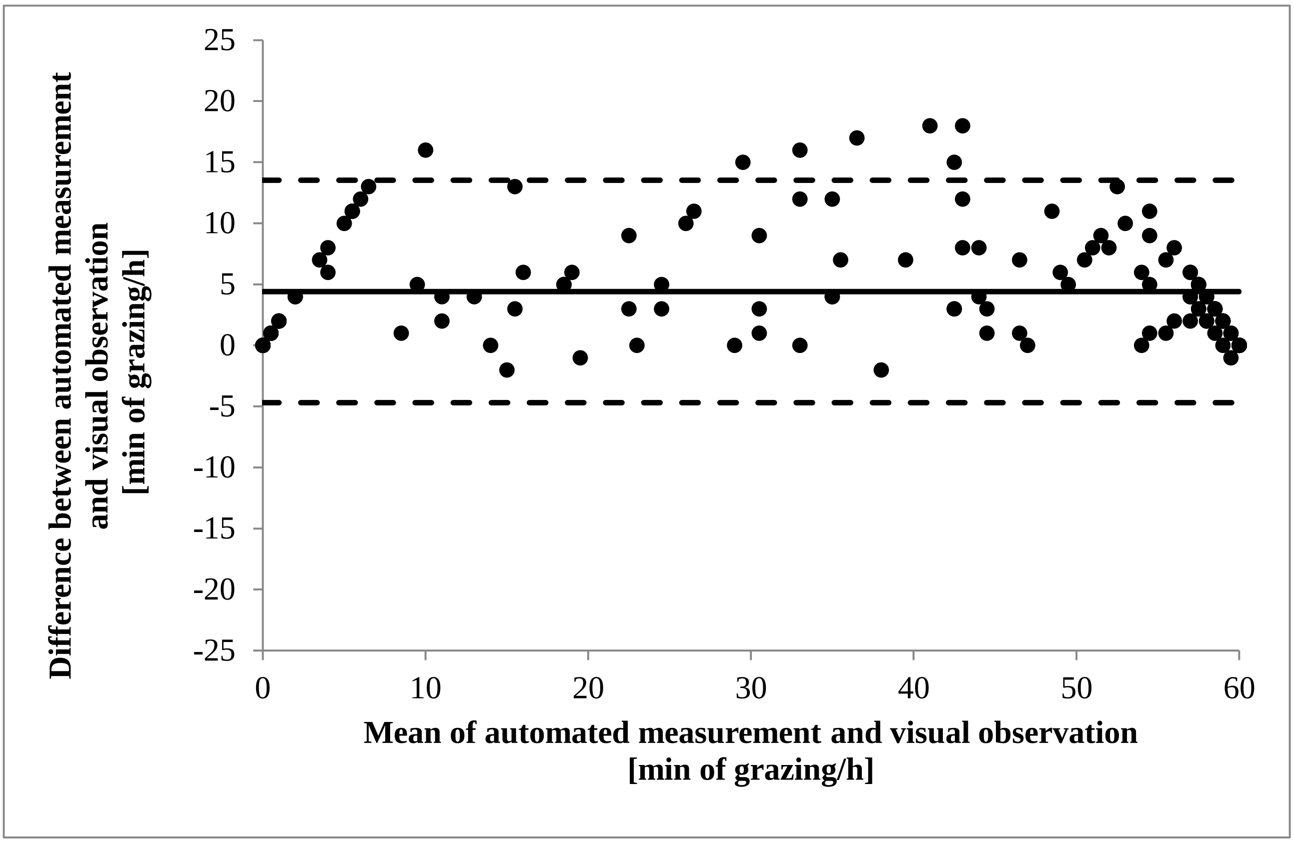
The evaluation of 1-hour summaries of feeding behaviour measured by the visual observation and by the noseband sensor is presented in Figure 1 and Table 5. Grazing was detected by visual observation as having occurred for 40.5 min/ hour (median), while grazing time detected by the automated sensor system was recorded with a median of 47 min/hour. A slight overestimation of the automated system in grazing min per hour is displayed in Figure 1a. According to Bland-Altman-Statistics the mean difference was 4.41 min/hour, and this overestimation is shown as the solid line in Figure 1(a). The correlation of $r_s = 0.96$ and a CCC = 0.96 is classified as very high for determine grazing time.

The comparison of rumination time measured by visual observation and by the automated method is shown in Figure 1 and Table 5. The correlation of $r_s = 0.98$ and a CCC = 0.99 is very high. The automated system recorded a range of measured min of rumination between 0 and 59, with a median of 0. Alternatively, the observers recorded a range from 0 to 57 min with a median of 2 min rumination per hour. In Table 5 the analysis of the Bland-Altman-Plot is presented. The bias of 0.03 min/hour along with the 95% CI of -3.04 and 3.10 demonstrated a perfect agreement between the automated system and the observers.

The mean of all values was completely accurate and 95% of all recorded values distributed themselves in a difference range of ± 3 min/hour.

The total agreement for measuring started and finished grazing bouts within 1-hour periods was PA = 84.7% and PA = 85.4%, respectively, whereas the agreement for rumination bouts started and finished was PA = 93.1% and PA = 93.8%. The weighed kappa values showed a moderate agreement between visual and automated measurement with values of $\kappa = 0.62$ and $\kappa = 0.66$ for grazing bouts started and finished, respectively. The rumination bouts showed improved performance, with an almost perfect agreement of $\kappa = 0.86$ for bouts started and bouts finished.

(a) Grazing time



(b) Rumination time

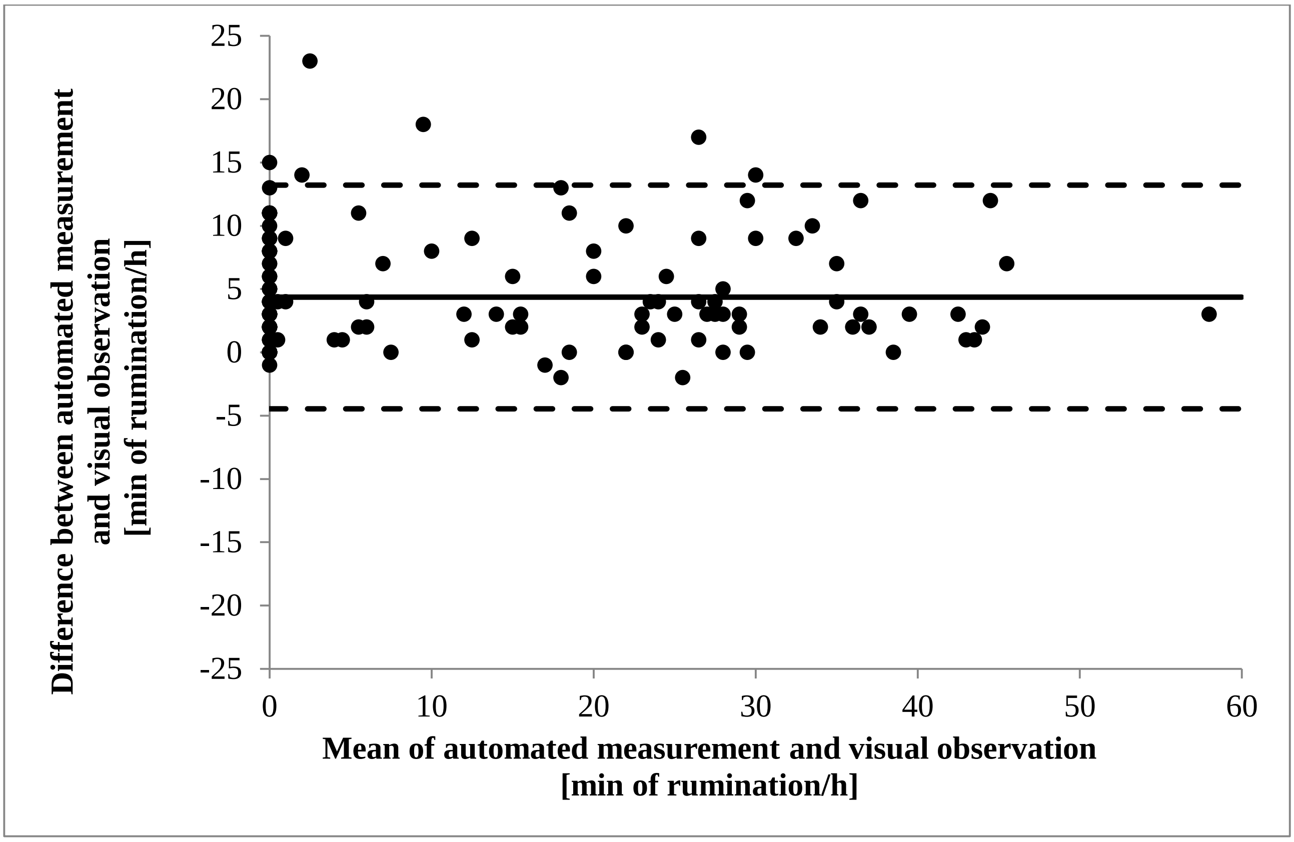
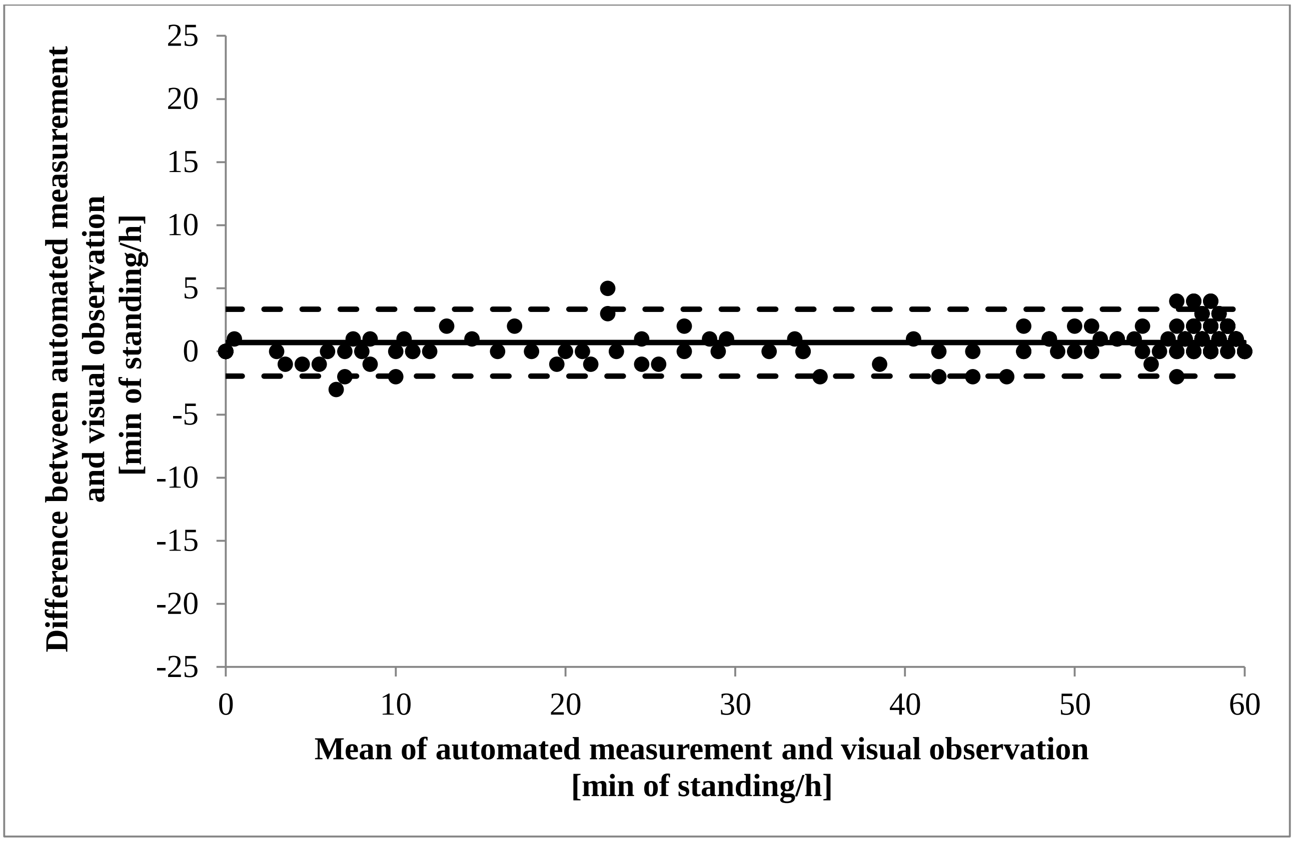


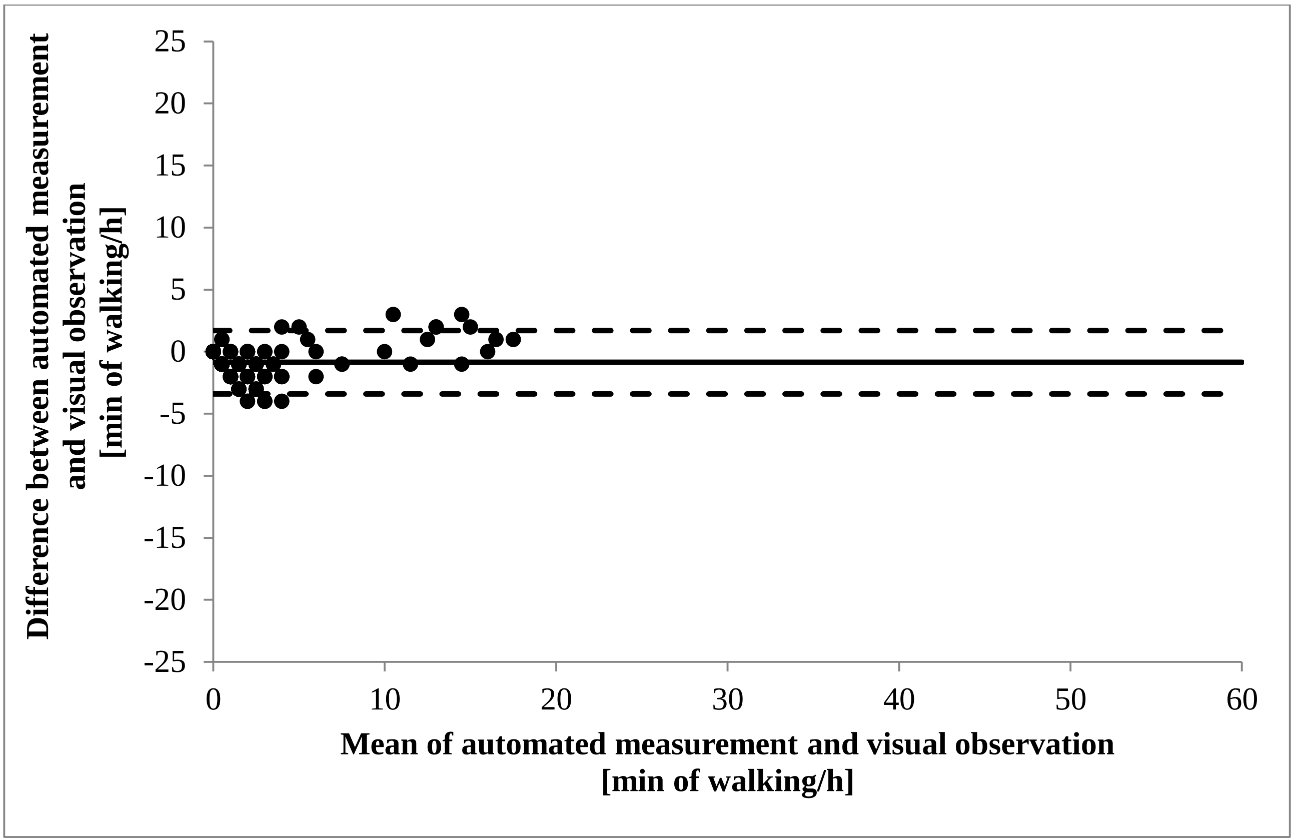
Figure 1: Agreement of automated RumiWatch noseband sensor measurements and visual observations of feeding behaviour (a) grazing and (b) rumination time in 1-hour periods, displayed in Bland-Altman-plots.

The validation of the pedometer in terms of measuring activity behaviour in a pasture-based system is shown in Figure 2. Standing time and lying time were determined accurately by the sensor system with a correlation of $r_s = 0.99$, while walking time was less accurately determined by the sensor with a correlation of $r_s = 0.77$. There were less minutes per hour of walking detected in comparison to standing and lying. The median of walking time was 1 min for visual observation and ranged from 0 to 18 min per hour whereas the automated system recorded 2 min per hour, ranging from 0 to 17 min per hour. Grazing time was significantly overestimated and time at other activities was significantly underestimated. Significant differences of bias were also observed between the pedometer and visual recordings in standing time and walking time (Table 5).

(a) standing


Difference between automated measurement and visual observation [min of standing/h]
25
20
15
10
5
0
-5
-10
-15
-20
-25
0
10
20
30
40
50
60
Mean of automated measurement and visual observation [min of standing/h]

(b) walking


25
20
15
10
5
0
-5
-10
-15
-20
-25
0
10
20
30
40
50
60
Difference between automated measurement and visual observation [min of walking/h]
Mean of automated measurement and visual observation [min of walking/h]

(c) lying

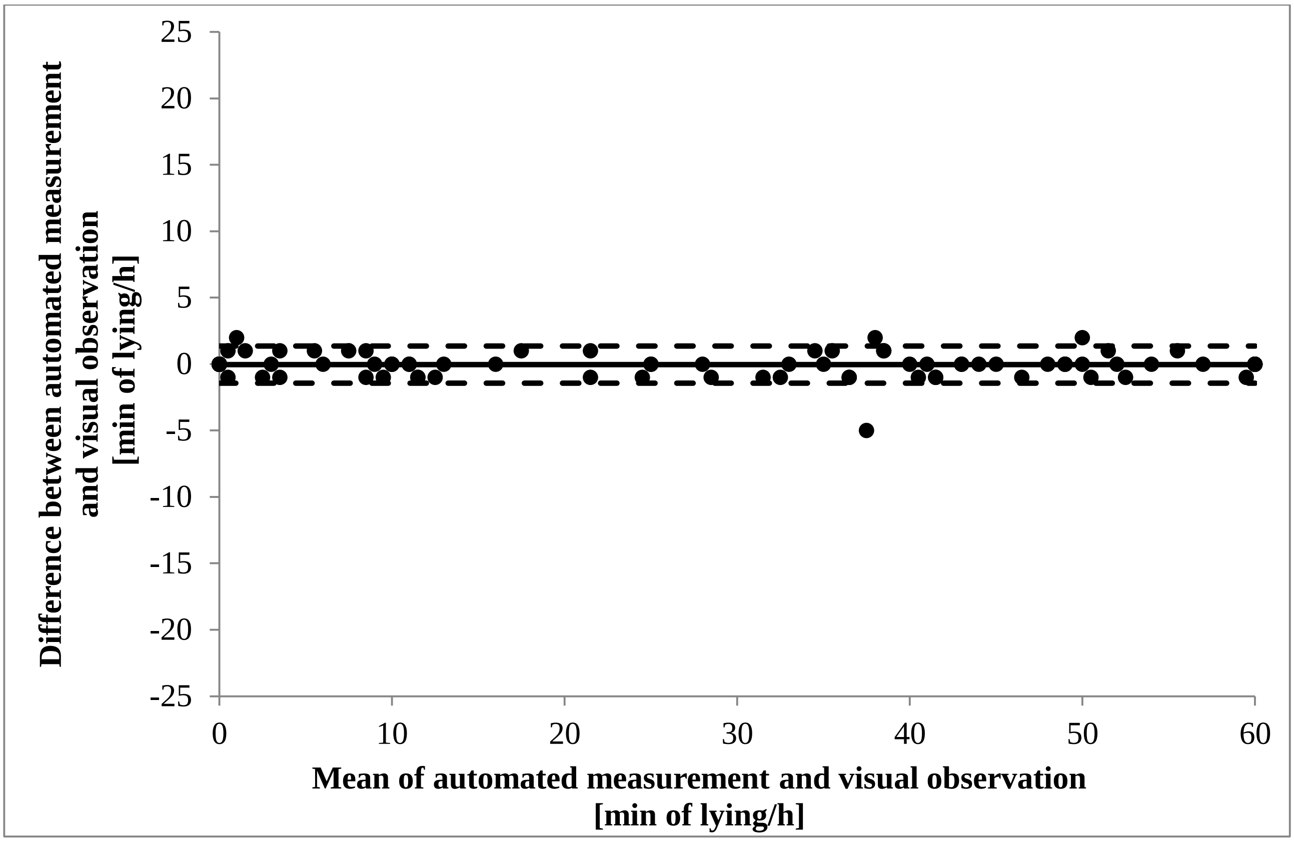


Figure 2: Agreement of automated RumiWatch pedometer measurements and visual observations for activity behaviour (a) standing; (b) walking; (c) lying in 1-hour periods displayed in Bland-Altman-plots.

Table 5: Spearman's rho (r_s), Concordance Correlation Coefficient (CCC), and Bland-Altman-analysis (Bias, upper and lower 95% limits of agreement with 95% CI) of automated measurements versus visual observations in a 1-hour resolution for different behaviour classifications.

Behaviour time in min/h	r_s	CCC	Bias (95% CI)	Lower (95% CI)	Upper (95% CI)
Grazing	0.96	0.96	4.41 (3.64; 5.17)	-4.69 (-6.02; -3.37)	13.51 (12.19; 14.84)
Rumination	0.98	0.99	0.03* (-0.22; 0.29)	-3.04 (-3.48; -2.59)	3.10 (2.66; 3.55)
Other activities	0.91	0.90	-4.38 (-5.12; -3.63)	-13.20 (-14.49; -11.92)	4.45 (3.17; 5.74)
Standing	0.97	1.00	-0.69 (-0.92; -0.47)	-3.35 (-3.74; -2.96)	1.96 (1.57; 2.35)
Lying	0.99	1.00	0.05* (-0.07; 0.17)	-1.35 (-1.55; -1.15)	1.45 (1.24; 1.65)
Walking	0.78	0.92	0.85 (0.63; 1.06)	-1.71 (-2.08; -1.33)	3.40 (3.02; 3.77)

*= no significant over- or underestimation between automated system and visual observation

Experiment 2

In this experiment the accuracy of the RumiWatchSystem in measuring grazing bites and rumination chews was examined. The degree of agreement between observers was analysed initially (Table 6). The CCC-values determined for grazing bites and rumination chews were CCC = 0.98 and CCC = 1.00 respectively, which demonstrated a very high agreement between all four observers.

Table 6: Concordance Correlation Coefficient (CCC) for each observer paired with all observers and overall CCC between all four observers in measuring grazing bites and rumination chews.

Behaviour [n/5min]	CCC				Overall CCC
	Observer 1	Observer 2	Observer 3	Observer 4	
Grazing bites	1	0.97	0.97	0.99	0.98
	2		0.99	1.00	
	3			0.99	
Rumination chews	1	1.00	1.00	0.99	1.00
	2		0.99	0.99	
	3			0.98	

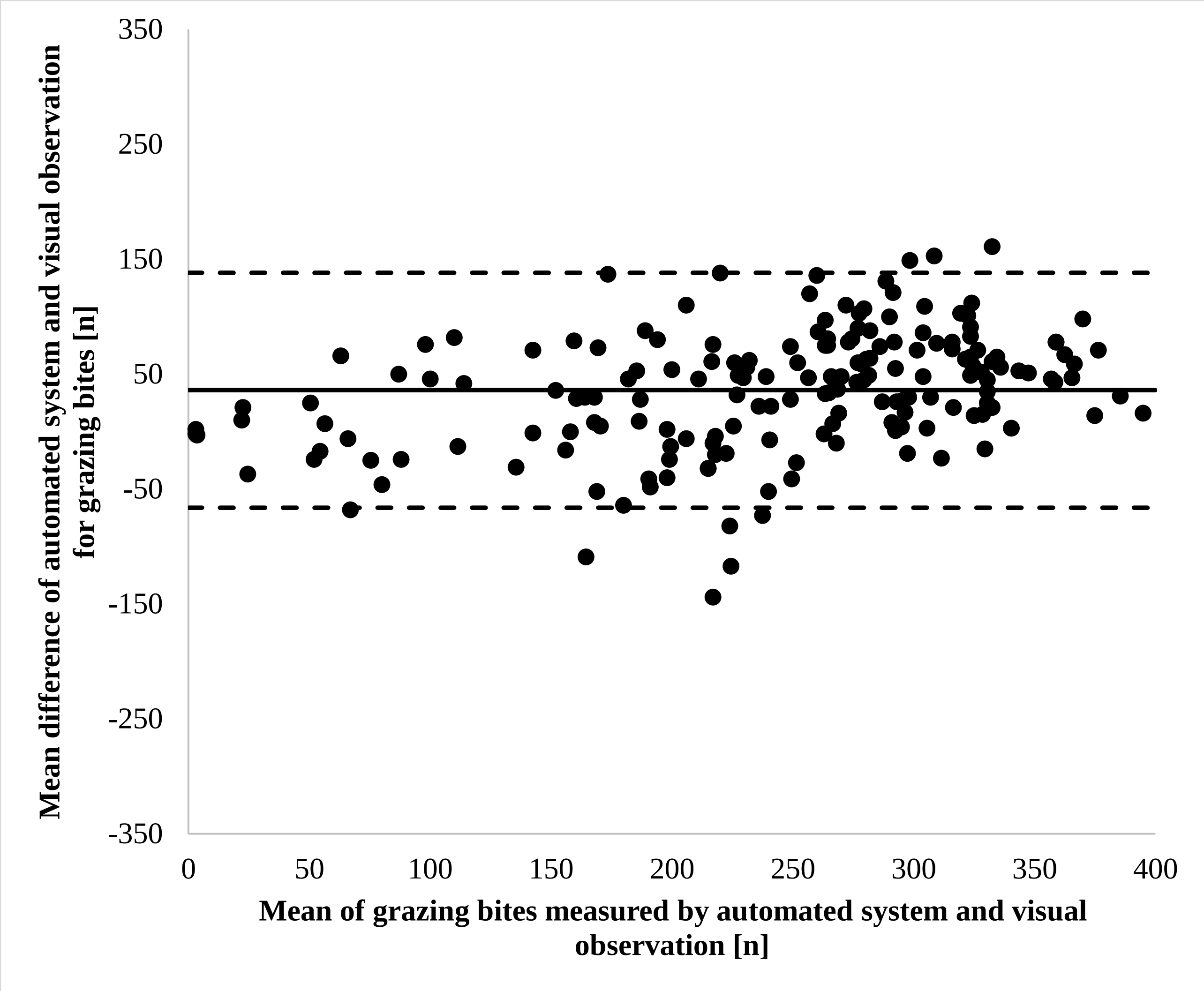
The comparison between the automated system and visual observations in measuring grazing bites are presented in Figure 3a) and Table 7. The visually counted grazing bites ranged from 0 to 387 per 5-min period, with a median of 232 bites. However, the RumiWatchSystem recorded grazing bites between 0 and 419, with a median of 280 bites. The Bland-Altman-Plot showed that the automated measurement slightly overestimated the numbers of grazing bites. A bias of 36 grazing bites, with a lower 95% limit of agreement of -66 grazing bites and an upper 95% limit of agreement of 138 grazing bites confirmed the significant overestimation of grazing bites by the RumiWatchSystem. Overall, the agreement for grazing bites between the two measurement approaches for grazing bites was high, with $r_s = 0.81$ and a CCC = 0.78 (Table 7).

Table 7: Spearman's rho (r_s), Concordance Correlation Coefficient (CCC), and Bland-Altman-analysis (Bias, upper and lower 95% limits of agreement with 95% CI) of automated measurements against visual observations of grazing bites and rumination chews in 5-min periods.

Behaviour (n./5min)	r_s	CCC	Bias (95% CI)	Lower (95% CI)	Upper (95% CI)
Grazing bites	0.81	0.78	36.01 (28.36; 43.66)	-66.16 (-79.41; -52.93)	138.19 (124.95; 151.44)
Rumination chews	0.81	0.94	7.24 (-0.15; -14.33)	-51.44 (-63.72; -39.17)	65.92 (53.64; 78.19)

The evaluation of the measured rumination chews by visual and automated recordings demonstrated positive results as shown in Figure 3(b). The visually counted rumination chews ranged from 2 to 386 chews/5-min period with a median of 323 chews. Alternatively, the RumiWatchSystem recorded a median of 330 rumination chews. The agreement between observer and automated system is higher compared to that for grazing bites, with a correlation of r = 0.81 and a CCC = 0.94. The Bland-Altman-plot of Figure 3(b) also illustrated graphically, that the mean difference between both measurement methods is very small with a value of 7.24 rumination chews per 5-min period. Limits of agreement (dashed lines in Figure 3(b) indicate that the mean differences between automated measurement and visual observation lie between -51.44 and 65.92 chews per 5-min period.

(a) Grazing bites



(b) Rumination chews

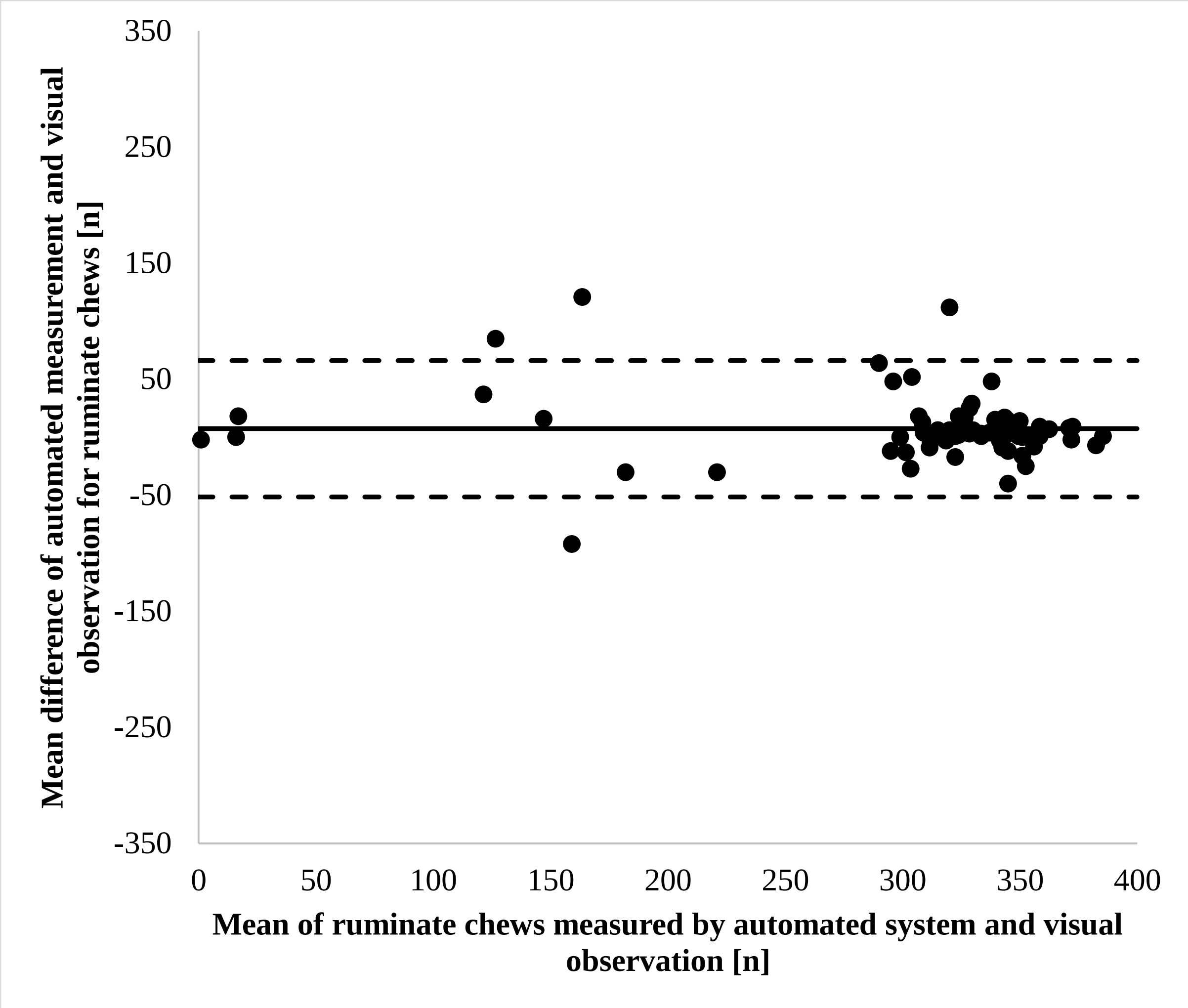


Figure 3: Agreement of automated RumiWatch noseband sensor measurements and visual observations for (a) grazing bites and (b) rumination chews, in 5-min period, displayed in Bland-Altman-plots.

Discussion

Experiment 1

The automated measurement of grazing time by the RumiWatchSystem was compared with visual observation and a high level of accuracy with a very high correlation of $r_s = 0.96$ was observed. The correlation was slightly higher than that of other systems used to detect feeding behaviour in the study of Borchers et al. (2016). In that study, an r = 0.88 and CCC = 0.82 was established for the CowManager 'SensOor' system (Agis, Harmelen, Netherlands) and r = 0.93 and CCC = 0.79 for the 'Track A Cow' system (ENGS, Rosh Pina, Israel). The results in the current study also indicated that the RumiWatch sensor slightly overestimated grazing time in comparison to visual observation. When the parameter 'EAT1TIME' (head position down) was considered in isolation, the correlation was increased to $r_s = 0.97$ and CCC = 0.99. This showed that the parameter 'EAT2TIME' (head position up) may have included some behaviours which should not be considered as feeding behaviours (e.g. licking). Thus, it may be beneficial to define in greater detail, the behaviours that should be included in the different output parameters of the RumiWatch Converter.

Rumination time was not significantly different between the RumiWatch noseband sensor and visual observation. This result is comparable to a study of Kröger et al. (2016), in which the noseband sensor was validated for different feeding regimes in an indoor situation. Furthermore, a study of Borchers et al. (2016) showed the RumiWatchSystem to be slightly more accurate (CCC = 0.99) than the Smartbow system (Smartbow GmbH, Jutogasse, Austria) (CCC = 0.96) in detecting rumination time.

Although the applied algorithms of the RumiWatch Converter differed depending on the chosen output resolution, the accuracy in 1-min summaries and 1-hour summaries was very high.

For 1-min summaries the challenge for the algorithms was to evaluate each minute separately without any major plausibility checks on time periods before or after the measured minute. Additionally, error detected between automated and visual observations has potential to be more obvious with 1-min summaries than 1-hour summaries, as some of the errors may be compensated for, in the totalling of the 60 min (1-hour) value. While the high resolution of 1-min recording might not be as important for a commercial application, the benefit for research purposes is significant. Particularly, in behavioural research, the reaction to treatments on a very high time resolution is valuable.

Visual observations, on the other hand, are more difficult due to the persons and time commitment required, as well as the reduced practicability of conducting high resolution 1-min scan sampling during night hours. Therefore, an automated measurement system would allow increased measurement and adds functionality to many of the experiments conducted on an on-going basis.

Due to the experimental set up used for validating bout parameters against visual observations there were limitations for the automated system in using the plausibility algorithms. The plausibility checks can be performed best on continuous data. However, the short periods of 1-hour observations as used in this study accumulated too many cut-off points. Therefore, the results of a moderate agreement between visual and automated measurement might be explained in this overall context. It is likely that with continuous observations over extended periods of time, those errors of falsely allocated started or finished bouts within 1-hour periods would be reduced.

The results of the RumiWatch pedometer were very accurate in detecting standing and lying behaviours. Alsaaod et al. (2015) described and validated the algorithm for the RumiWatch pedometer in their publication and achieved similar accurate results for standing and lying times. The accuracy of detecting walking correctly in the current study was weaker with $r_s = 0.78$ than the other classifications of standing with $r_s = 0.97$ and lying with $r_s = 0.99$. This may be due to the fact that behaviours of lying and standing are more easily detected, and therefore more correctly detected than walking behaviour.

Experiment 2:

The intra-observer reliability was successfully tested to ensure the validity of the results. The overall result among all observers for grazing and rumination was indicated by a CCC = 0.98 and a CCC = 1.00, respectively. Similar results were considered by Schirmann et al. (2009) to be a sufficiently accurate reference to be used as a gold standard in place of visual observation to validate another sensor system. Furthermore, the observational periods in the current study were adjusted from 10 min periods as outlined in Werner et al. (2016) to 5-min periods. This was to ensure maximum concentration by the observer with potentially greater accuracy in counting all grazing bites. Additionally, the focus was placed on grazing bites and rumination chews to improve reliability. Recording every individual jaw movement (e.g. licking, chewing, etc.) was identified as challenging for the observers.

The RumiWatchSystem slightly overestimated the number of grazing bites. This may be due to the noseband sensor being very sensitive in detecting pressure differences. However, an error in visual observation of grazing bites was also detected. This was likely due to the high frequency of grazing bites. Therefore the true or correct number of grazing bites may lie between the values recorded by automated measurement and visual observation. A study by Champion et al. (1997) did consider that detection of grazing bites by the automated system may be more accurate than detection by visual observation.

A further study by Delagarde et al. (1999) also showed, the RumiWatchSystem to be as strongly correlated to visual observation in recording number of bites per min as the audio recording system they used in their study with the R^2 values ranging from 0.72 to 0.98.

In a recently published study by Kröger et al. (2016), the RumiWatchSystem was compared to visual observation in terms of accuracy in capturing rumination chews at 10-min resolution, and a CCC of 0.92 was observed. In the current study, a CCC value of 0.94 was observed for a similar comparison. This represented a slight increase in accuracy, which may be a consequence of an updated version of the RumiWatch Converter used in the current study. However, it is also true that the diet differed in both studies, with a feeding regime including roughage, concentrate and a mixed diet being used in the study of Kröger et al. (2016) while a grass diet was predominant in this study. The observational periods also differed between the studies, with the Kröger et al. (2016) and current studies using 10-min and 5-min resolutions, respectively. As the plausibility checks for rumination are based on continuous data the threshold of a minimum of 3 minutes to detect rumination had to be turned off. Therefore, the results of the two studies are not entirely comparable. For recording of continuous data over long-term periods, this plausibility check function should not influence the accuracy in detecting rumination chews.

In contrast to most commercially available systems in use on-farm, the cost of the RumiWatchSystem and its application involving a halter might not be feasible for widespread use on farms. However, as a research tool it could be very valuable. With the wide ability of recording every jaw movement, the specific differentiation in grazing bites and rumination chews, as well as the quantification of time durations of rumination and grazing, the RumiWatchSystem is a unique tool for measuring grazing behaviour long-term. With further development, it may be suitable to estimate feed intake of dairy cows on pasture, based on measuring bites and chews.

As Berckmans (2006) mentioned, visual observation can represent a limiting factor in behavioural research, due to the necessity for restricted observation periods and a high demand in labour. Therefore, the availability of an accurate and reliable automated technology may be very useful and appropriate.

Conclusions

Overall, the results indicated that the RumiWatchSystem showed a high level of accuracy in measuring feeding behaviour of cows in a grazing environment, even though it was originally developed for cows in indoor feeding systems. The accuracy of 1-min summaries and 1-hour summaries was very high with kappa-values between 0.85 and 0.89 and CCC-values ranging from 0.92 to 0.99, respectively. The noseband sensor tended to overestimate grazing time and grazing bites slightly, whereas the detection of rumination time was very accurate. The accuracy between observer and automated measurement was moderate for detecting rumination chews due to issues regarding plausibility checks for the specific experimental periods. The validation of the newly implemented parameters in the RumiWatch Converter V.0.7.3.36 for grazing and rumination bouts delivered moderate or high concordance. The pedometer showed very promising results with CCC-values ranging from 0.92 to 1.00. Its performance in detecting walking was slightly weaker than in detecting standing and lying, but still appropriate for a measurement system. Based on those results, it may be concluded that the RumiWatchSystem is a reliable sensor technology to monitor grazing behaviour and thus, is a useful tool for research and management purposes in a grazing environment.

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CHAPTER 3

Evaluation and application potential of an accelerometer-based collar device for measuring grazing behavior of dairy cows

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Abstract

The commercially available collar device MooMonitor+ (Dairymaster, Ireland) was evaluated with regards to accuracy and application potential for measuring grazing behavior. These automated measurements are crucial as cows feed intake behavior at pasture is an important parameter of animal performance, health and welfare as well as being an indicator of feed availability. Compared to laborious and time-consuming visual observation, the continuous and automated measurement of grazing behavior may support and improve the grazing management of dairy cows on pasture. Therefore, there were two experiments as well as a literature analysis conducted to evaluate the MooMonitor+ under grazing conditions. The first experiment compared the automated measurement of the sensor against visual observation. In a second experiment, the MooMonitor+ was compared to a noseband sensor (RumiWatch, Itin+Hoch GmbH, Switzerland), which also allows continuous measurement of grazing behavior. The first experiment on n = 12 cows revealed that the automated sensor MooMonitor+ and visual observation were highly correlated as indicated by the Spearman's rank correlation coefficient (r_s) = 0.94 and Concordance Correlation Coefficient (CCC) = 0.97 for grazing time. An r_s - value of 0.97 and CCC = 0.98 was observed for rumination time. In a second experiment with n = 12 cows over 24-hour periods, a high correlation between the MooMonitor+ and the RumiWatch was observed for grazing time as indicated by an rs-value of 0.91 and a CCC-value of 0.97. Similarly, a high correlation was observed for rumination time with an r_s-value of 0.96 and a CCC-value of 0.99. While a higher level of agreement between the MooMonitor+ and both visual observation and RumiWatch was observed for rumination time compared to grazing time, the overall results showed a high level of accuracy of the collar device in measuring grazing and rumination times. Therefore, the collar device can be applied to monitor cow behavior at pasture on farms. With regards to the application potential of the collar device, it may not only be used on commercial farms but can also be

applied to research questions when a data resolution of 15 minutes is sufficient. Thus, at farm level, the farmer can get an accurate and continuous measurement of grazing behavior of each individual cow and may then use those data for decision-making to optimize the animal management.

Implications

Monitoring feed intake behavior of cows is important for determining the health status of the cow and the onset of estrus as well as the feed budget for the cow. As herd sizes increase and the availability of labor decreases, the monitoring of each individual cow may be supported by automated sensors. There are limited sensors available for measuring grazing behavior. The validation study conducted here for the MooMonitor+ showed a very high accuracy in measuring grazing behavior. These results proved that the sensor can be applied on the farm and can assist the farmer in managing the herd.

Introduction

Sensor technology has developed and improved rapidly in recent years. Technological systems have advanced to measure a broad range of parameters, such as acceleration, temperature and pH, which has had a positive impact on the application range of sensors. Technical progress can be observed in different areas of the agricultural sector. In dairy farming, the application of sensor systems should assist farmers to manage larger animal groupings. With higher numbers of cows and less available time per animal, farmers in their daily routine may be supported in decision making by an automated continuous measurement of parameters to maintain good animal management. Animal management in a dairy system involves ensuring health and welfare of the animals; reacting to certain events in the animal reproductive cycle and improving efficiency in feed conversion to the animal product e.g. milk.

The parameter “feed intake behavior” is one of the best indicators of health and welfare of dairy cows. Bareille et al. (2003) found that feed intake decreased at the initial stages of ketosis and mastitis. These findings were underlined by a study of Gonzalez et al. (2008), where ketosis, lameness and mastitis all had a negative impact on feeding behavior. Mastitis is recognized as one of the major causes of reduced profit (Kossaibati and Esslemont, 1997). Thus, early detection of this emerging disease would not only be beneficial to the animal through earlier treatment, but would also improve farm profitability. As well as a potential indicator of health issues, feeding behavior and especially rumination, may be a valuable parameter in determining the status of the reproductive cycle of dairy cows. Rumination time may be used to predict calving (Soriani et al. 2012) as well as determining an estrus event (Mahmoud et al., 2017). A study by Stangaferro et al. (2016) successfully linked the identification of metabolic disorders with rumination and physical activity. Further, the knowledge generated on detailed grazing behavior may also assist in efficient grazing management. Based on results of a study by Chilibroste et al. (1997), the grazing time is affected by the presence of indigestible material in the rumen as well as the degree of starvation before the actual grazing. Additionally, it is identified that the rumination time decreases with less available material in the rumen to digest (Kennedy et al., 2009). These facts may be used to optimize the correct grass allocation to the cows, considering grazing and rumination time of cows as measured by these automated sensors.

The importance of sensor systems is also increasing as the availability of labor decreases on family farms due to increases in scale and less frequent involvement of adult children in the family (Barkema et al., 2015). As farm size increases, there is a general tendency for the businesses to involve more hired labor rather than experience-based family workers (Eastwood et al., 2016). These facts all support the inclusion of sensor technology as a decision support tool on farms.

The MooMonitor+ (Dairymaster, Tralee, Ireland) is a collar device with an integrated 3-axis accelerometer designed for heat detection and has been commercially available since 2014. Subsequently to further development, this device may have the capability to record grazing and rumination time accurately. However, an independent evaluation of the suitability of the sensor device for accurate measurement of grazing behavior was not published yet. Thus, the primary objective of this study was to validate this automated sensor against visual observation with regard to accuracy in monitoring grazing behavior. A secondary objective was to compare the MooMonitor+ with the RumiWatch noseband sensor as this device allows continuous observation as well and has been previously validated for measuring feeding behavior in research (Werner et al., 2017). Finally as a third objective, the application potential of these used sensors and sensors in literature is discussed with regard to measurement of grazing behavior in both scientific and commercial scenarios.

Material and Methods

Experiment 1

The first experiment was conducted between May 10 and 19, 2016 on a group of 18 spring calving dairy cows on the Teagasc research farm in Moorepark, Fermoy, Ireland. The data of six of these cows were analyzed to align times between the visual observations and the automated sensor (MooMonitor+, Dairymaster, Ireland). Due to the technical specification of the internet connection at the research farm, the timestamp on the base station linked with the sensors was not correct. Therefore, to investigate the correct time stamp, data of six cows were used to validate the automated sensor against human observer. Those data were excluded afterwards from the experimental data set.

Animals and Treatments:

Twelve cows were used for validation. This group consisted of 6 Jersey crossbred (JEX) and 6 Holstein-Friesian (HF) cows. There were 4 primiparous and 8 multiparous cows involved, the range of lactation was from 2 to 6. The mean body condition score (BCS) ± standard deviation (SD) was 2.8 ± 0.2 (based on a 1 to 5 scoring system with 0.25 increments; Edmonson et al. (1989)). Average bodyweight (BW) was 477 ± 65 kg. The milk yield was 22.5 ± 4.5 kg/cow/day over the experimental period and average days in milk (DIM) was 91 ± 12 at the beginning of the experiment. All cows followed a similar milking schedule, being milked twice daily at 7:00 h and 14:30 h with approximately 1.5 - 2.0 hours away from the paddock during each milking. Cows were fed with only grass on the paddocks with no additional supplementation of concentrate. A fresh allocation of pasture was provided after each milking. Pre- and post-grazing grass heights were measured daily using a rising plate meter (diameter 355 mm and 3.2 kg/m^2; Jenquip, Fielding, New Zealand). Pre-grazing heights and post-grazing heights were 11.9 ± 2.5 cm and 4.5 ± 0.8 cm, respectively during the experimental period. These values represented a non-restrictive grazing management strategy in Ireland, where cows received a daily herbage allowance of 16.3 ± 2.6 kg dry matter (DM)/cow/day, measured above 3.5 cm sward height, on average during the experimental period (McCarthy et al., 2013). The chemical composition was analyzed once weekly resulting in an average dry matter content of 15 %, an average crude protein content of 22 % and an average content of neutral and acid detergent fiber of 41 % and 23%, respectively.

Experimental design:

Grazing and rumination time data were collected by visual observation according to a 1-minute scan sampling protocol, similar to the method used in the study of Büchel and Sundrum (2014) and by the MooMonitor+ (Dairymaster, Ireland). Two previously trained observers were monitoring 18 cows in total (12 cows for validation; 6 cows for time alignment). The cows were divided into 6 subsets with 3 cows each for the purpose of observation. Each subgroup was observed by each observer on 3 occasions over 6 days (Table 1). Observations took place over 2-h periods between dawn (05:00) and dusk (21:00) excluding milking times from 07:00 to 09:00 and 14:00 to 17:00 hrs. After the first three days, the times were changed to cover the full range of daylight hours within the days.

Behavioral data of each minute were categorized into grazing and rumination, considering the main activity within each minute. Grazing was defined as cow's muzzle being located near or above the grass and making a biting motion to ingest grass or chewing ripped grass with the head position down, or cow's head position up and making a chewing motion to masticate the grazed grass. Alternatively, rumination was defined as regurgitation, chewing, salivation and swallowing of ingested grass (Bikker et al., 2014). The data were recorded on a manual spread sheet. Subsequently, the data were transferred manually to an electronic spread sheet (Microsoft Excel Version 2010; Microsoft Corporation, Redmond, USA).

Table 1: Experimental protocol for cow grazing and rumination data collection by visual observation.

Day		1	2	3		4	5	6
	Time	Cow Number	Cow Number	Cow Number	Time	Cow Number	Cow Number	Cow Number
Observer 1	09:00-11:00	1,2,3	7,8,9	16,17,18	05:00-07:00	4,5,6	10,11,12	16,17,18
	12:00-14:00	4,5,6	10,11,12	13,14,15	11:00-13:00	1,2,3	7,8,9	13,14,15
	17:00-19:00	1,2,3	7,8,9	16,17,18	19:00-21:00	4,5,6	10,11,12	16,17,18
Observer. 2	09:00-11:00	4,5,6	10,11,12	13,14,15	05:00-07:00	1,2,3	7,8,9	13,14,15
	12:00-14:00	1,2,3	7,8,9	16,17,18	11:00-13:00	4,5,6	10,11,12	16,17,18
	17:00-19:00	4,5,6	10,11,12	13,14,15	19:00-21:00	1,2,3	7,8,9	13,14,15

The MooMonitor+ was used for the automated data collection. It is a collar device on the cow's neck containing a box with a 3-axis accelerometer was positioned on the right sight of the neck. This accelerometer measured activity in a 10 Hz resolution. On-board data analysis with a generic algorithm, which was identifying specific pattern for different categories such as rumination, grazing, resting, developed by Dairymaster, summarized activities occurring in the raw data into time spent at those activities for 15-min periods. These summarized periods were then transmitted wirelessly to a base station with a range of up to 2000 m. The base station is usually linked with the internet connection in a normal farm environment and corrected itself in time, based on a deviation of ± 5 minutes. This time is also corrected on the sensors once they were in the range. To ensure correct positioning of the accelerometer box on the cow's neck, a weight was applied at the lowest point of the collar. Cows within the group were identifiable by numbers painted on their sides.

Data preparation:

The 1-min visually recorded data in the experimental dataset were summarized in 15-min and 1-h grazing and rumination periods to allow direct comparison with the data recorded by the automated method. The automatically captured data were classified into the categories of grazing and ruminating in 15-min summaries. Then four 15-min summaries were totaled to form 1-h summaries. Consequently, there were 504 15-min periods and 72 1-h periods of valid observations across the full database.

Statistical analysis:

For the statistical analysis, R version 3.3.1 (R Foundation for Statistical Computing, Vienna, Austria) was used (statistical code see Supplementary Material S1). To assess agreement between numeric value data of the MooMonitor+ and visual observation, the Spearman's Rank correlation (r_s) and a concordance correlation coefficient (CCC) was calculated. The interpretation of r_s-values and CCC were based on definitions by Hinkle (2003) as follows: Negligible = 0.0 - 0.3, low = 0.3 - 0.5, moderate = 0.5 - 0.7, high = 0.7 - 0.9 and very high = 0.9 - 1.00. Furthermore, the Bland-Altman-analysis was applied to assess the agreement between visual observation and automated system. This was conducted in Microsoft Excel calculating the mean differences (bias; MooMonitor+ - visual observation) against the means of visual observation and MooMonitor+. The limits of agreement were calculated as ± 1.96 * standard deviation from the mean difference. Although the parameters themselves were not normally distributed, the Bland-Altman-analysis was used as the differences between the paired values did follow a normal distribution.

Experiment 2

Animals and Treatments:

This experiment was conducted between October 18 and 30, 2016. A group of twelve cows was used in this study. The group of cows had an average of 255 ± 11 DIM and was maintained in a herd of 55 cows in a spring calving dairy system. The cow group consisted of eight Jersey crossbred, three Holstein-Friesian and one Norwegian Red cows. There were three primiparous and nine multiparous cows, ranging from 2 to 5 lactations. Daily milk yield in the experimental period averaged 12.4 ± 2.5 kg/day/cow and the average BW was 527 ± 71 kg with a BCS of 2.9 ± 0.1. The cow herd was milked twice daily and was away from pasture for approx. two hours at each milking time, i.e. 7:00 to 9:00 and 15:00 to 17:00 hrs. All cows had a grass-based diet with an additional 2 kg concentrate offered per day. Grass height was measured daily with a rising plate meter (diameter 355 mm and 3.2 kg/m^2; Jenquip, Fielding, New Zealand). Pre-grazing height of pasture averaged 12.1 ± 1.2 cm and post-grazing height averaged 4.1 ± 0.2 cm. Grass quality was analyzed once weekly resulting in an average dry matter content of 16 %, an average crude protein content of 27 % and an average content of neutral and acid detergent fiber of 41 % and 23%, respectively. The average daily herbage allowance was 14.9 ± 0.8 kg DM/cow/day during the experimental period.

Sensor technology and data collection:

All twelve cows in the group were simultaneously equipped with the Moomonitor+ collar and the RumiWatch noseband sensor (Itin+Hoch GmbH, Liestal, Switzerland) to determine grazing and rumination time. The RumiWatch noseband sensor, integrated in a halter, has the capability to detect pressure peaks and classifies them into grazing or rumination behavior, such as grazing bites or rumination chews. Additionally, the total time duration of those different classifications was recorded continuously. Raw data were recorded in a 10 Hz resolution. Further information about technical components can be found in Zehner et al. (2017). In the current study, the RumiWatch Manager 2 (V.2.1.0.0) was used to manage time synchronization and raw data recording of the devices. The RumiWatch Converter (V.0.7.3.36) was used for analyzing the raw data. Two recorded parameters of the RumiWatch halter were used to determine grazing time. They were EAT1TIME, which monitored grazing time with head position down. This included biting and chewing of ripped grass and EAT2TIME, which recorded grazing time with the head position up with chewing of grazed grass. Grazing time (referred to as EATTIME) was calculated as EAT1TIME+EAT2TIME. The internal time on the RumiWatch noseband sensors was synchronized to internet time (Coordinated Universal Time (UTC) +1 h) prior to the commencement of the experiment. A period of 2 days was allowed for adaption of the cows to the halter. The recording of one noseband sensor stopped after 6 days, therefore there were just 6 full days instead of 10 days included for one cow. The Moomonitor+ collar was applied at the start of the breeding season and the correct attachment of tag number and cow identification number was checked before the experiment. The time on the base station was synchronized and operated at UTC time.

Data preparation:

The raw data of the RumiWatch noseband sensor were converted in 30-min summaries using the RumiWatch Converter V.0.7.3.36. The output of the MooMonitor+ was delivered in 15-min summaries and was totaled in 30-min summaries to allow comparison with the RumiWatch output. For analysis, the data were matched in an electronic spread sheet (Microsoft Excel Version 2010; Microsoft Corporation, Redmond, USA) with a time adjustment of -1 h for the RumiWatch data, due to the difference between summertime and UTC time. The 30-min values were then totaled to generate daily values. In total, there were n = 5579 valid observations at the 30-min resolution level, and n = 116 values at the daily level.

Statistical analysis:

For statistical analysis the R version 3.2.2 (R Foundation for Statistical Computing, Vienna, Austria) was used (statistical code see Supplementary Material S2). Comparison between the numerical data of the RumiWatch noseband sensor and the MooMonitor+ was analyzed using different statistical approaches.

For the analysis of 30-min summaries, the Anderson-Darling test was applied to evaluate if the data followed a normal distribution. Due to the data not being normally distributed, same statistical analysis and interpretation of results was used as in Experiment 1. The data summarized at a daily level followed a normal distribution based on the results of the Shapiro-Wilk normality test. Therefore, Pearson's correlation coefficients (r) were calculated as well as the CCC - values. The values were interpreted by using the same categories as outlined above for the 30-min summaries. There was also a graphical analysis of the agreement with Bland-Altman-Plots used to determine the agreement between the automated systems. This was conducted by plotting the differences (RumiWatch - MooMonitor+) against the means of RumiWatch and MooMonitor+. The Bland-Altman-analysis indicated the mean difference (bias; solid line Fig. 1; 3 and 4) between the paired automatically recorded values and their associated 95%-limits of agreement, displayed as dashed lines in Fig. 1; 3 and 4. The limits of agreement were calculated as ± 1.96 * standard deviation from the bias.

Results

Experiment 1

The results of the comparison between visual observation and automated measurement are presented in Table 2. Median grazing time of 12 min/15 min and 38 min/h were recorded by visual observation. Alternatively, median grazing time of 12 min/15 min and 37.5 min/h were recorded by the automated sensor. However, overall grazing time was slightly overestimated by the automated measurement compared to visual observation. This fact is observed in mean differences of 0.27 min/15 min, and 1.0 min/h. The correlations between the paired measurements were very high with r_s = 0.90 and CCC = 0.95 for 15-min summaries and r_s = 0.94 and CCC = 0.97 for 1-h summaries.

However, the correlation between visually captured data and automatically recorded data was higher for rumination time than grazing time at both the 15-min and 1-h resolutions. Due to a small proportion of time associated with rumination in the observation periods, median rumination times of 0 min/15 min and 8 min/h for rumination time were recorded by visual observation. Alternatively, median rumination times of 0 min/15 min and 6.5 min/h were recorded by the automated sensor. For rumination time, the correlation between paired measurements by visual observation and automated recording may be described by r_s = 0.93 and CCC = 0.98 for 15-min summaries. This was weaker than for the 1-h summaries with r_s = 0.97 and CCC = 0.98.

Table 2: Spearman's rank correlation coefficient (r_s), Concordance Correlation Coefficient (CCC), and Bland-Altman-analysis (Bias, upper and lower 95% limits of agreement) of cow grazing and rumination data, recorded by visual observation and by automated measurements in 15-min and 1-h resolutions.

Behavior	r_s	CCC	Bias	Lower	Upper
Grazing time (min/15min)	0.90	0.95	0.27	-3.76	4.31
Rumination time (min/15min)	0.93	0.98	0.10	-2.09	2.30
Grazing time (min/h)	0.94	0.97	1.01	-10.18	12.21
Rumination time (min/h)	0.97	0.98	0.00	-4.93	4.93

Experiment 2

The correlation of grazing time measured by the MooMonitor+ and the RumiWatch noseband sensor in 30-min summaries was very high. An r_s -value of 0.91 and a CCC-value of 0.95 was observed. Median grazing times of 3.5 min/30 min and 5.8 min/30 min were recorded by the MooMonitor+ collar and the RumiWatch noseband sensor, respectively. In analysis of daily values, grazing time averaged 513 ± 75 min/day with the MooMonitor+ and 576 ± 66 min/day with the RumiWatch. The accordance of grazing time per day between the two automated systems was analyzed using a Bland-Altman-Plot (Figure 1). The 95% limits of agreement ranged between -2 and 129 min/day. Additionally, a mean bias of 63 min/day was observed indicating a higher value of grazing time measured by the RumiWatch in comparison to the MooMonitor +. This higher value of grazing time was also captured in a lower Pearson's correlation coefficient of 0.89 and a CCC of 0.63 in the daily summaries.

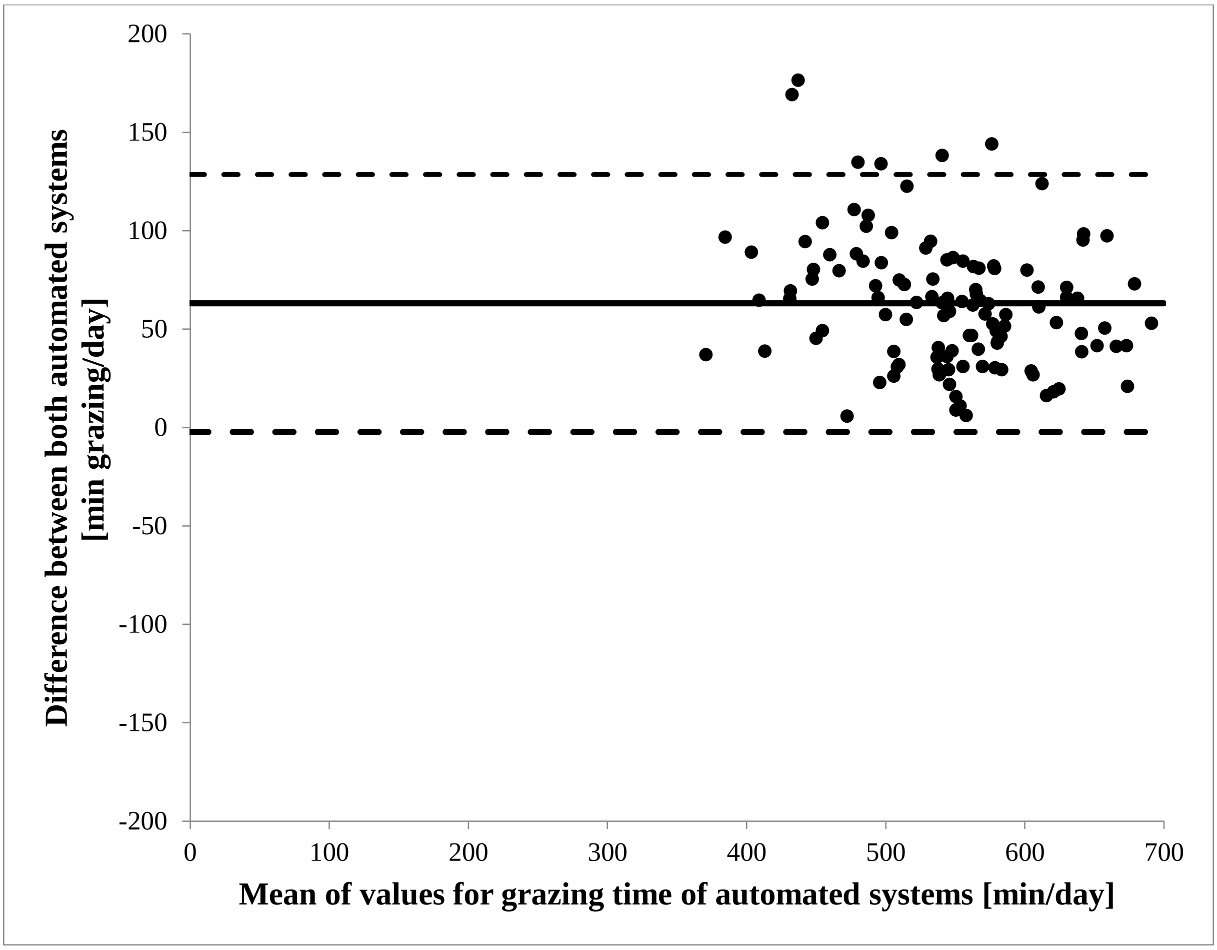

Figure 1: Agreement of MooMonitor+ collar and RumiWatch noseband sensor measurements of cow grazing time per day, displayed in a Bland-Altman-Plot (solid line indicates the mean difference; dashed lines indicate upper and lower 95% limits of agreement), when grazing time was defined as EATTIME by the RumiWatch noseband sensor. EATTIME represents the sum of grazing time with head position down (EAT1TIME) and head position up (EAT2TIME).

When examining grazing time of MooMonitor+ and RumiWatch above in terms of correlation in 30-min summaries and total grazing time per day, this time was a measurement of the sum of EAT1TIME and EAT2TIME. This represented biting and chewing (head position down) and chewing the grazed grass (head position up). The graphical analysis in Figure 2 demonstrated an overestimation by the RumiWatch when using the parameters EAT1TIME + EAT2TIME.

Alternatively, when the EAT1TIME parameter was used, it only focused on grazing behavior with head position down (biting and chewing) and this resulted in a median value of 3.1 min/30 min. In this scenario, the correlation between the automated sensor systems was higher with an r_s-value of 0.94 and a CCC of 0.98 for 30-min resolutions.

Daily grazing times recorded by the RumiWatch noseband sensor, using the EAT1TIME averaged 482 ± 75 min/day compared to 576 ± 66 when the sum of EAT1TIME and EAT2TIME was used. This relationship between the MooMonitor+ and the RumiWatch (considering EAT1TIME as grazing time per day) is shown in Fig. 3. The RumiWatch parameter EAT1TIME recorded a lower grazing time compared to MooMonitor+, captured with a mean bias of -31 min/day and the 95% limits of agreement ranged from -105 to 43 min/day. However, comparing daily grazing time recorded by the MooMonitor+ to the RumiWatch noseband sensor when EAT1TIME was used increased the CCC-value to 0.80, but decreased the Pearson's r slightly to r = 0.87 for daily grazing time.

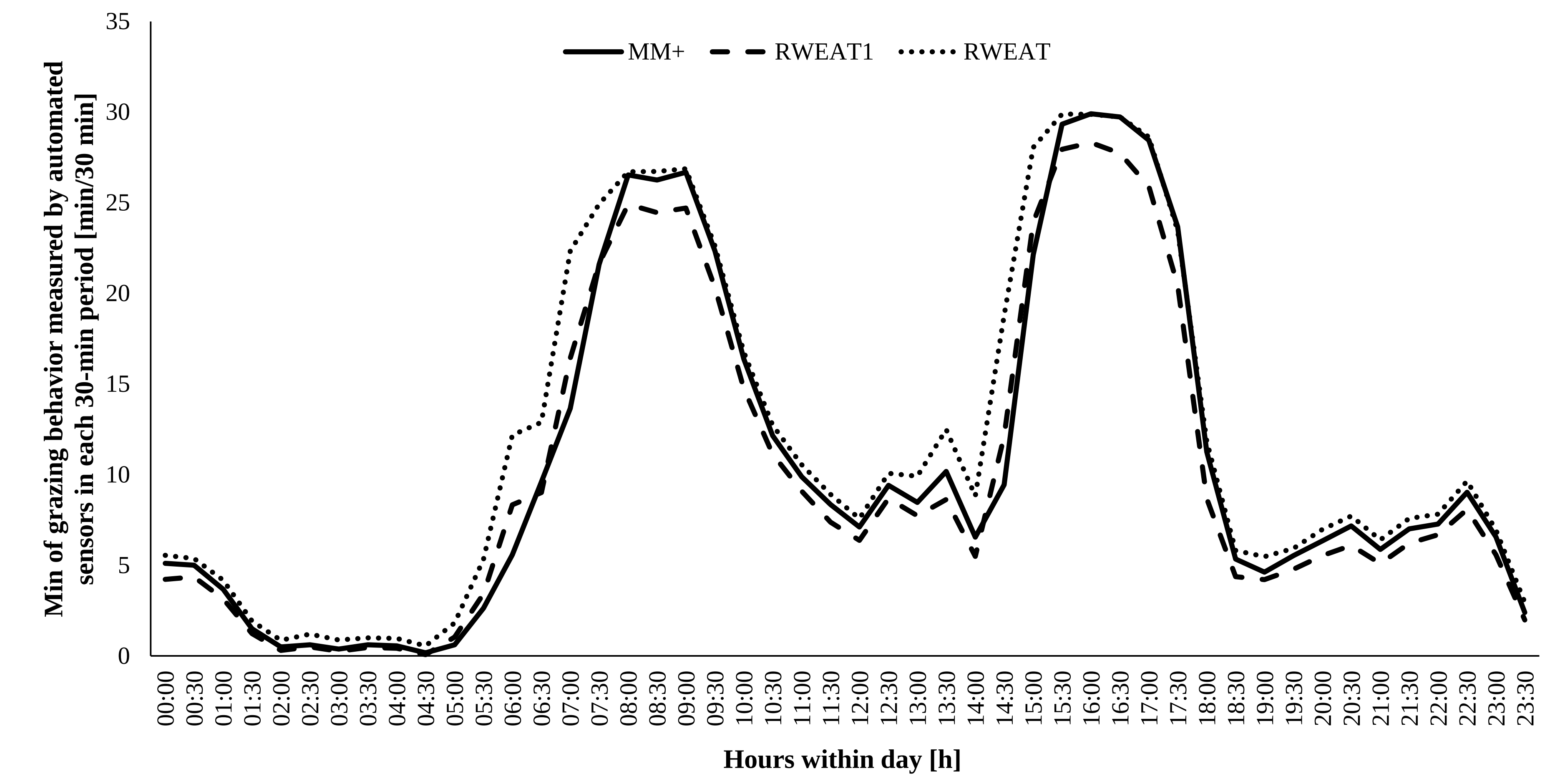

Figure 2: Graphical analysis of diurnal grazing time of cows defined by the MooMonitor+ (MM+) and by the RumiWatch noseband sensor with the parameter “RWEAT1”, which represents the grazing time with head position down (EAT1TIME) and with the parameter “RWEAT”, which represents the sum of grazing time with head position down (EAT1TIME) and head position up (EAT2TIME) averaged in 30-min periods.

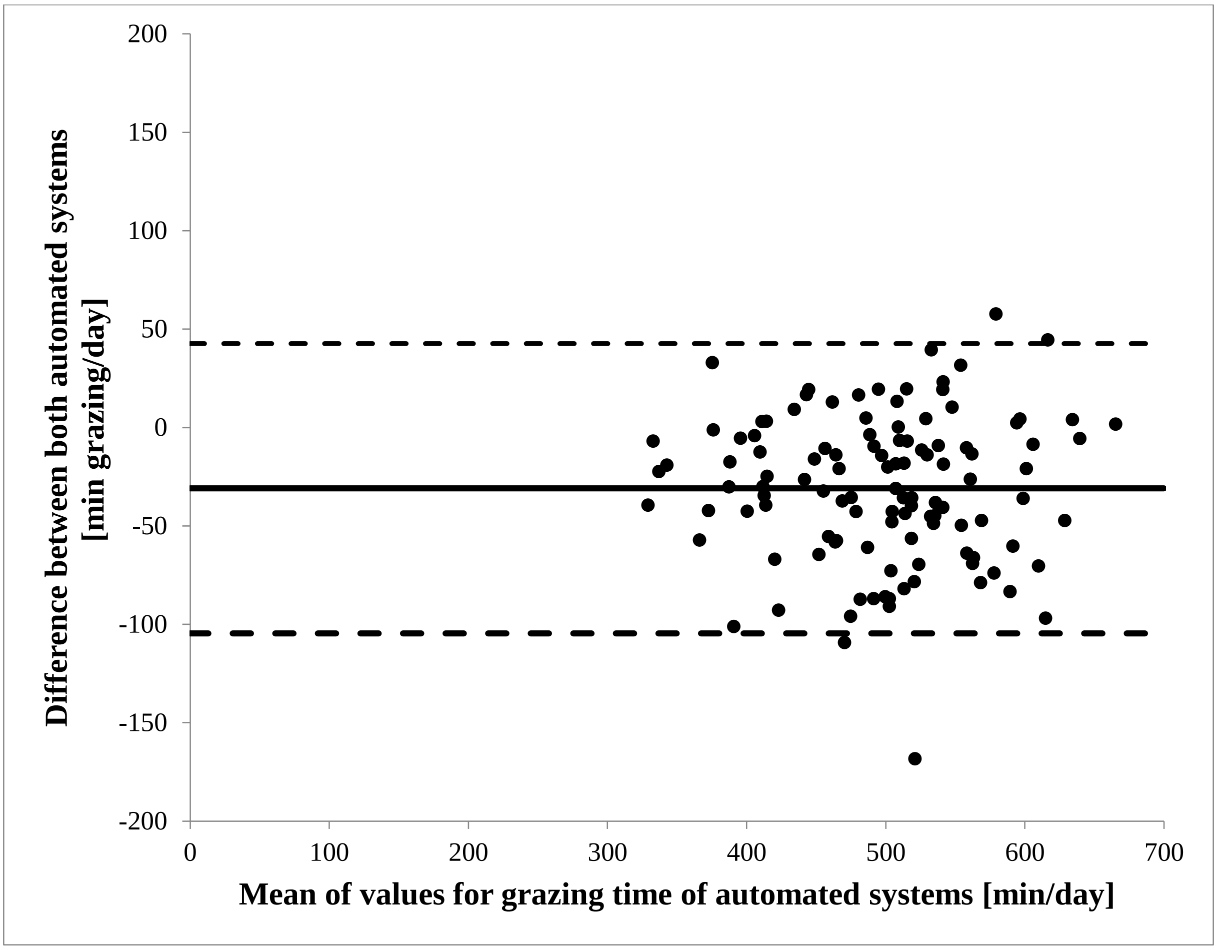

Figure 3: Agreement of MooMonitor+ collar and RumiWatch noseband sensor measurements of cow grazing time per day, displayed in a Bland-Altman-Plot (solid line indicates the mean difference; dashed lines indicate upper and lower 95% limits of agreement), when grazing time was defined as EAT1TIME by the RumiWatch noseband sensor. EAT1TIME represents the grazing time with head position down.

The data captured by the MooMonitor+ and the RumiWatch showed a higher accordance in detecting rumination time. Rumination time was recorded at a 30-min resolution. Median rumination times of 3.8 min/30 min and 3.6 min/30 min were recorded by the MooMonitor+ collar and by the RumiWatch noseband sensor, respectively. The correlation with r_s-value of 0.96 and a CCC-value of 0.99 highlight the high accordance between the MooMonitor+ and the RumiWatch noseband sensor in detecting rumination based on 30-min summaries.

In the analysis of the daily values, rumination time averaged 463 ± 58 min/day for the MooMonitor+ and 407 ± 57 min/day for the RumiWatch. The MooMonitor+ measured a slightly higher rumination time compared to the RumiWatch, which may be observed in Figure 4 with a negative mean bias of -14 min/day. Additionally, the 95% limits of agreement ranged between -35.5 and 7.5 min/day. However, there is a very high correlation between both systems in recording daily rumination time with a Pearson's r-value of 0.98 and a CCC-value of 0.95.

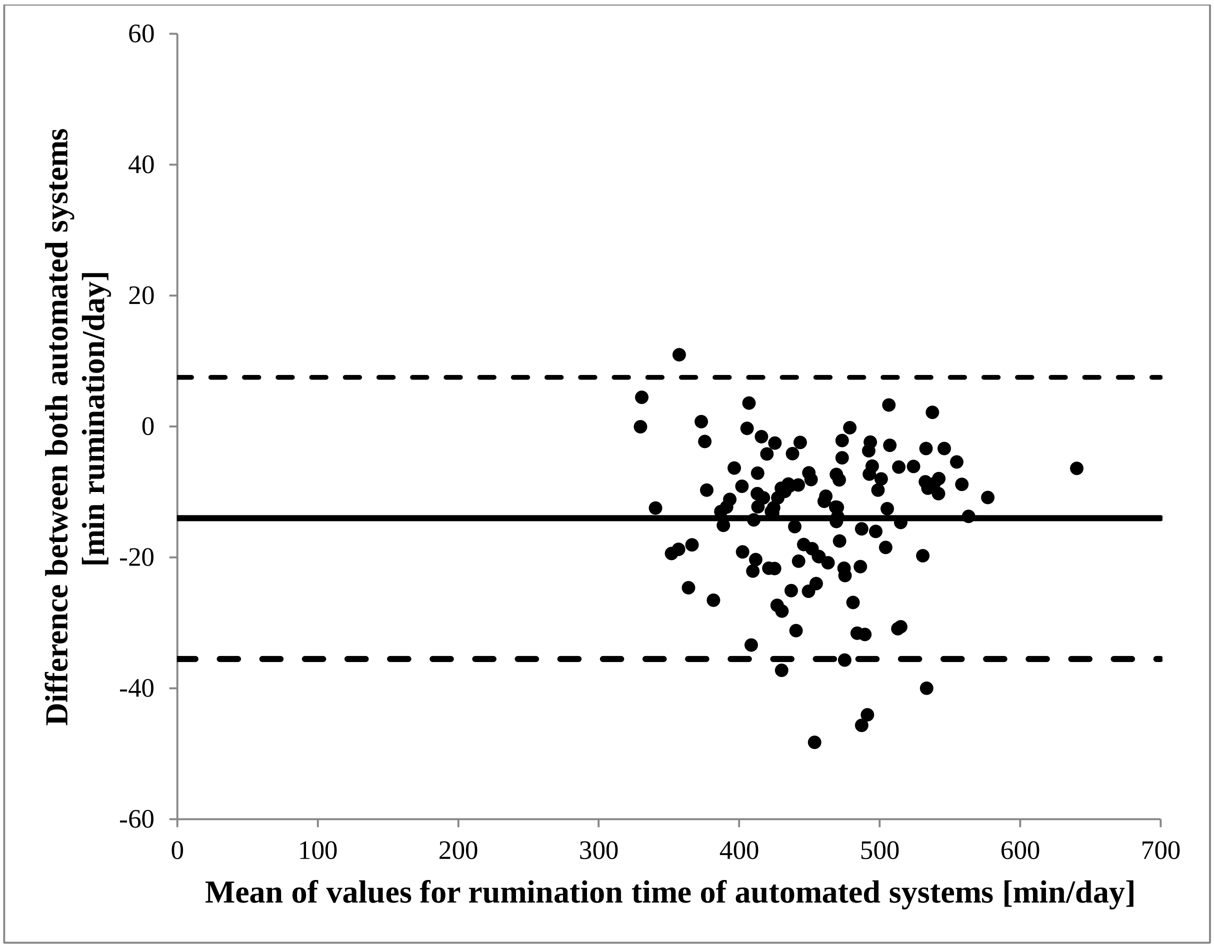

Figure 4: Agreement of MooMonitor+ and RumiWatch noseband sensor measurements of cow rumination time per day, displayed in a Bland-Altman-Plot (solid line indicates the mean difference; dashed lines indicate upper and lower 95% limits of agreement).

Discussion

The comparison between visual observations and automated measurements of grazing time showed a very high correlation in Experiment 1. The results demonstrated a higher correlation compared to other commercial sensors with an r_s-value of 0.90 and CCC = 0.95 for a 15-min resolution and r_s-value of 0.94 and CCC = 0.97 for a 1-h resolution. For example, in a study by Borchers et al. (2016), an r = 0.88 and CCC = 0.82 was established for the CowManager 'SensOor' system (Agis, Harmelen, Netherlands) and r = 0.93 and CCC = 0.79 for the 'Track A Cow' system (ENGS, Rosh Pina, Israel). In contrast to the current study, those systems were validated by measuring feeding time of housed dairy cows with a total-mixed ration fed twice daily. There are some sensors available to measure grazing behavior with a high accuracy for research purposes, e.g. the IGER system, a microcomputer/based system for digital recording of jaw movements, for determining grazing time and grazing bites (Rutter et al., 1997), or the Lifecorder Plus for measuring grazing time and pattern used in an experiment of Delagarde and Lamberton (2015). Any of these mentioned sensor systems were not applied on a larger scale on commercial farms. However a study by Molfino et al. (2017) investigated the accuracy of a commercially applied sensor compared to visual observation with results of CCC = 0.99 and 0.80 for measured grazing and rumination time, respectively.

The measurement of rumination time was more accurate than the measurement of grazing time by the MooMonitor+ when compared against visual observation with a very high correlation of r_s-value of 0.93 at 15-min resolution, and r_s-value of 0.97 at 1-h resolution. Those values are comparable with the Hi-Tag rumination monitoring system (SCR Engineers Ltd., Netanya, Israel), which was validated against visual observation in the study of Schirmann et al. (2009) showing an r-value of 0.93. In contrast to this result Elischer et al. (2013) found that a rumination collar with an integrated microphone, which was used in an automatic milking system on pasture, had a moderate correlation against visual observation with an r-value of

0.65. Those findings were explained by possible malfunction of the microphone or improper placement of the sensor on the cow's neck. In the current study, similar issues with the MooMonitor+ were not observed.

The correlation between the MooMonitor+ and the RumiWatch was lower for grazing than for rumination time. The RumiWatch noseband sensor recorded a higher value of grazing time. This prompted some more detailed analysis to be conducted in comparing the grazing time of the MooMonitor+ against the EAT1TIME recording parameter of the RumiWatch, which represented recording of grazing time with the head position down. This comparison showed higher correlations with r_s = 0.94 and a CCC of 0.98 for the 30-min resolution and a smaller mean difference between the two systems. This was presumably caused by exclusion of time recorded by the EAT2TIME parameter. On further investigation it was established, that if a cow was walking, the sensitive noseband pressure sensor was recording a portion of feeding time, due to the head movement while walking. This effect was eliminated by using just the parameter EAT1TIME. The described movement effect could not be identified in an indoor environment, which was the primary environment for the development of the RumiWatch noseband sensor. This issue may be addressed in further development by applying new algorithms for analyzing grazing behavior of dairy cows in a new RumiWatchConverter. Nevertheless, the accuracy of the MooMonitor+ against the RumiWatch noseband sensor was very high.

The results demonstrated that the MooMonitor+ is an accurate measurement tool for monitoring grazing behavior of cows in a 15-min data resolution. Other studies have also identified different sensors validated for measuring various grazing parameters. A selection of these is presented in Table 3. This information is based on an extensive literature analysis in which the application of different sensors for research purposes or commercial use was examined. Similar criteria may be applied to the sensors used in the current study to assess their attributes for research or commercial situations. Measurement of grazing bites and chews as well as the combined 'chewbites' using acoustic measurements is presented in studies by Navon et al. (2013) and Milone et al. (2012). Both systems were limited to grazing jaw movements and therefore rumination chews were not detected. The system validated by Navon et al. (2013) focused on grazing jaw movements showed a high accuracy and may be feasible to use for research applications. Nevertheless the commercial application is limited as the data analysis is very laborious and the attachment of the sensor in middle of the animal's forehead with rubberbands is not practical. In grazing behavior research, the IGER behavior recorder was used intensively in various studies. It consisted of a jaw movement sensor and a datalogger and was able to measure rumination and grazing times as well as rumination chews and grazing bites/chews. The raw data was analyzed via an associated software (Rutter, 2000). Alternatively, the parameters of grazing bites and chews were validated against visual observation but were reported as being difficult to distinguish in a study by Champion et al. (1997). However, this technology and data collection is outdated and the production of the dataloggers has been discontinued. The RumiWatch noseband sensor, compared to the MooMonitor+ in the current study, may be considered as a more advanced technology than the IGER behavior recorder due to longer data recording periods and a more simplified application and data analysis. Rombach et al. (2018) conducted a comprehensive validation study on grazing and supplemented cows to evaluate the accuracy of the RumiWatch noseband sensor. There was also the performance of a newly developed analysis software investigated, with an improved accuracy on measuring grazing behavior parameters such as total number of eating chews, number of rumination chews and times spent engaging in these activities. A validation study by Werner et al. (2017), in which a subsequent version of the analysis software used in the study of Rombach et al. (2018) was used, also demonstrated a high accuracy in measuring different parameters of cows' grazing behavior, such as rumination time and chews as well as grazing time. The parameters of grazing bites as well as grazing bouts and rumination bouts are solely measured by the newest algorithms in the RumiWatch Converter. These measurements were also proven to be very high in accordance with the visual observation based on the study of Werner et al. 2017.

However, most studies apply accelerometers to measure different parameters of grazing behaviour. But as shown in Table 3, there are different approaches to record and use the acceleration data. The position of the accelerometer on a cow may be attached to a halter (Decandia et al., 2017) or a neck collar (Umemura, 2013), and the measured parameters may vary, eg. grazing time or grazing bites. Studies by Molfino et al. (2017) and Ipema (2015) investigated the accuracy of commercially applicable sensors and showed a high accuracy in measuring grazing time in both studies and rumination time in the study of Molfino et al. (2017).

Table 3: A selection of validation studies to measure grazing behavior of cows, combined with an assessment of feasibility for research purposes (R) or commercial application on farms (F).

Measured parameters	Technology used	Resolution as listed in reference	Assessment[1]	Reference
Foraging, resting and walking	Global positioning system (GPS) collar	1 min sampling	R: + F: --	Spink et al. (2013)
Grazing jaw movements	Wireless microphone	1 min recording, 10 min analysis	R: + F: --	Navon et al. (2013)
Bites, chews and compound chewbites	Wireless microphone	13 minutes	R: - F: --	Milone et al. (2012)
Grazing, ruminating or other activities	Jaw movement sensor	Continuous measurement for 24h	R: + F: --	Rutter et al. (1997), Rutter (2000)
Grazing bites and chews	Jaw movement sensor	Continuous measurement for 24h	R: - F: --	Champion et al. (1997)
Grazing, ruminating or other activities, Grazing bites and chews, Rumination chews, Grazing and rumination bouts	Noseband pressure sensor	Grazing/rumination times: 1 min and 1 h resolution Grazing bites/rumination chews. 5 min resolution	R: ++ F: -	Werner et al. (2018)
Grazing time	Accelerometer	4 s sampling periods or Preprocessed data 2 min	R: + F: --	Delagarde and Lamberton (2015)
Grazing bites	Accelerometer	Storage 1 day or 1 h on the pedometer	R: + F: --	Umemura (2013)
Rumination Activity	Cow rumination monitors	2 h blocks	R: - F: -	Elischer et al. (2013)
Grazing, ruminating and resting	Accelerometer	Raw data: 1 s intervals Analysis of 1 min resolution data	R: + F: --	Decandia et al. (2017)
Grazing, resting and ruminating	Accelerometer	1 min intervals	R: ++ F: ++	Molfino et al. (2017)
Grazing time	Accelerometer	15 min periods	R: + F: ++	Ipema (2015)

[1]The assessment results are based on accuracy in measured parameters and applicability;
++ = highly suitable, + = partial suitable, - = partial usable, -- = not applicable.

Focusing on comparing both sensor systems of the current study in terms of their application potential and requirements for each focal group in using those sensors, the purpose of the systems must be considered. The main purpose of the MooMonitor+ is usage and support in decision-making on commercial dairy farms, whereas the RumiWatch system was mainly designed for research purposes as a high precision measurement sensor. The RumiWatch noseband sensor has the ability to detect and record each individual jaw movement of the cow. This high-resolution information is particularly important when using the device for investigating research questions as researchers need a very detailed measurement of cow behavior. Contrary to this, from a farmer's perspective it is not feasible for daily use in a commercial farm environment, as its integration into a halter is not as practical as in a collar. Also, the extensive amount of data that may be collected is not required by a farmer, as the farmer generally wishes to just monitor his animals and might want to get some easy-to-use decision support in terms of health, breeding or grazing issues as herd sizes increase. These requirements might be better fulfilled by the MooMonitor+. It is still able to measure grazing behavior on a high resolution with 15-min summaries, but does summarize analyzed data into clear information to the farmer, which will be communicated via an application on the smartphone. This does include e.g. alerts, when an individual cow's behavior is deviating from the herds behavior. Thus, since the research and farming communities have different requirements, both the MooMonitor+ and the RumiWatch can address these requirements through their different measurement approaches.

Conclusion

The MooMonitor+ collar indicated a very high correlation when measured against visual observation and the RumiWatch noseband sensor. The recording of rumination time by the MooMonitor+ had a greater agreement with both visual observation and the RumiWatch sensor than the recording of grazing time. This might be due to the fact that rumination is easier to detect with a steady rhythm and obvious signs of boluses travelling up the oesophagus. However, the correlation of detecting grazing time with visual observation and the RumiWatch was also very high. Considering the MooMonitor+ as a sensor technology for measuring grazing behavior, it has a number of benefits for commercial use on farms. The farmer gets an easy-to-use, robust, long-lasting device with a very high accuracy in measuring grazing behavior on a daily basis, calculated from 15 min summaries.

Depending on the research question, the MooMonitor+ collar can be used for scientific purposes. However, it must be recognized that detailed information about the grazing behavior in 1-min resolutions cannot be detected with the device in its current format. Thus, in further sensor technology development, it is crucial to consider the main focus of the application potential and try to address the requirements for each focal group. Whereas the volume and detail of data should be very high for researchers, the farmer does not require a similar level of data detail. A precise and distinct usage of the sensor, summarizing analyzed information with defined action points by the decision support tool is mainly what should be aimed for in regard to the application on farms.

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Declaration of interests

We wish to confirm that there are no known conflicts of interest associated with this publication and there has been no significant financial support for this work (except that mentioned in the acknowledgements) that could have influenced its outcome.

Ethics statement

Ethical approval was received from the Teagasc Animal Ethics Committee (TAEC; TAEC100/2015) and procedure authorisation was granted by the Irish Health Products Regulatory Authority (HPRA) (AE19132/P045).

Software and data repository resources

All research data is stored in Oracle (Release 12.1.0.2.0 - 64bit Production) which is a relational database management system from the Oracle Corporation. The database resides on a Dell PowerEdge R730 server with operating system Red Hat Enterprise Linux. This server is located in a secure data centre. The data can be accessed via a web application by research staff only. The database is maintained by a database administrator.

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CHAPTER 4

Identification of possible cow grazing behaviour indicators for restricted grass availability in a pasture-based spring calving dairy system

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Abstract

Precision livestock farming uses biosensors to measure different parameters of individual animals to support farmers in the decision making process. Although sensor development is advanced, there is still little implementation of sensor-based solutions on commercial farms. Especially on pasture-based dairy systems, the grazing management of cows is largely not supported by technology. A key factor in pasture-based milk production is the correct grass allocation to maximize the grass utilization per cow, while optimizing cow performance. Currently, grass allocation is mostly based on subjective eye measurements or calculations per herd. The aim of this study was to identify possible indicators of insufficient or sufficient grass allocation in the cow grazing behaviour measures. A total number of 30 cows were allocated a restricted pasture allowance of 60 % of their intake capacity. Their behavioural characteristics were compared to those of 10 cows (control group) with pasture allowance of 100 % of their intake capacity. Grazing behaviour and activity of cows was measured using the RumiWatchSystem for a complete experimental period of 10 weeks. The results demonstrated that the parameter of bite frequency was significantly different between the restricted and the control groups. There were also consistent differences observed between the groups for rumination time per day, rumination chews per bolus and frequency of cows standing or lying.

Introduction

The primary goal of precision livestock farming (PLF) is to generate reliable data using biosensors and process it to create added value for the farmer, the environment and the animal (Neethirajan et al., 2017). Although the development and accuracy of sensor technology has improved rapidly in recent years, the interpretation and implementation of measured data are still not fully adopted for decision making processes at farm level (Rutten et al., 2013). Currently, there are many relevant technologies available, but their value for farmers is not clear or recognized (Steeneveld et al., 2015). This is particularly true on pasture-based milk production systems where the progress in implementing PLF is slower than in indoor housed dairying. This may be explained by the smaller market potential for technology for pasture-based grazing systems (French et al., 2015).

Pasture-based systems of milk production are often associated with more positive characteristics than high-input confinement systems (Dillon et al., 2005) such as greater global sustainability, improved product quality, better animal welfare and increased labour and economic efficiency (Dillon et al., 2008, O'Brien et al., 2012, Hofstetter et al., 2014). Efficient and profitable milk production from pasture centres around the utilisation of grazed grass (Shalloo et al., 2011) as this is the cheapest home produced feedstuff on dairy farms (Finneran et al., 2010). Consistent allocation of sufficient pasture on a daily basis can result in ~ 10 % higher milk yield (Fulkerson et al., 2005). Pasture allocation is dependent on a number of factors such as the assessment of the quantity of biomass, animal requirements which can be influenced for example by stage of lactation and the quality of the pasture, but the primary determinant is available biomass. Therefore, to achieve a maximum utilization of grazed grass, dairy farmers need an accurate real-time measurement of pasture biomass and quality to optimise grazing management (French et al., 2015).

A combination of grass height measurements and estimations and grass quality estimations is presently used to allocate the appropriate pasture biomass for the herd. These measurements can vary from experience-based eye estimation (O'Donovan et al., 2002) to automated measurement using precision tools such as the Grasshopper device (McSweeney et al., 2015). A mostly subjective determination of the correct allocation of grass to the herd is most common as quantitative measurement tools are not routinely used on a widespread basis. Even when quantitative measurements are used, absolute accuracy in allocating the total maximum amount that the dairy herd will consume is extremely difficult. Optimum accuracy is necessary to prevent wastage of grass or poor subsequent growth rates. However, pasture is allocated on a herd basis rather than an individual animal which can result in competition for feed and difficulty in regulating the feed allowance to individual animals. There is also great variability in grazing efficiency between cows. This may be due to genetic potential or individual traits (Prendiville et al. (2010). Cows can change their grazing behaviour based on vegetative status of the grass and the decline of grass quality (O'Driscoll et al., 2010) as well as adapt their behaviour to restricted pasture access over different time periods (Kennedy et al., 2011). Thus a precise indicator of grass availability and consequently, the appropriate time to deliver additional allocation would be a powerful tool particularly in a grass-based system. Potentially, it could be incorporated into a grassland based decision support tool, such as PastureBase Ireland (Hanrahan et al., 2017). Detailed information regarding cow’s grazing behaviour using measures such as number of grazing bites or rumination chews may be possible indicators of correct allocation of pasture biomass or the suitability of the pasture, essentially including the individual animal in the decision making process of grass allocation.

The objective of this paper represents a relatively novel concept of using animal behaviour characteristics recorded automatically to correctly manage herbage allowance per individual animal. Combined with appropriate decision support tools this may be a useful approach for improving animal performance and grass utilisation simultaneously. As a first step of the development process, it is crucial to determine potential indicators of cow grazing behaviour or activity that are influenced by pasture allowance. While most previous measurements of cow behaviour were based on laborious visual observations or short-term automated measurements, e.g. for 24-hours, the RumiWatchSystem (noseband sensor and pedometer) was used in this study and provides a very robust automated solution to monitor detailed grazing behaviour and activity over a period of 10 weeks. Therefore the key aim of this study was to identify cow grazing behavioural parameters that are influenced by grass availability and therefore may potentially be used to inform on correct grass allocation or optimum availability of grass to cows.

Materials and methods

This study was part of a larger overall experiment, which was conducted at Teagasc, Moorepark Dairy Research Farm, Animal & Grassland Research and Innovation Centre, Fermoy, Co. Cork, Ireland. Ethical approval was received from the Teagasc Animal Ethics Committee (TAEC; TAEC100/2015) and procedure authorisation was granted by the Irish Health Products Regulatory Authority (HPRA) (AE19132/P045). Experiments were undertaken in accordance with the European Union (Protection of Animals Used for Scientific Purposes) Regulations 2012 (S.I. No. 543 of 2012). A permanent grassland site was used with pastures contained 70 % perennial ryegrass and 30 % annual meadow grass. The research was carried out in springtime which coincided with the early lactation stage of cows in a spring calving herd. The overall experiment examined the effects of restricted pasture allowance on milk production, immunology and indicators of reproductive health of grazing dairy cows. This provided a platform for the current study aiming to analyse potential indicators in cow grazing behaviour to identify insufficient grass allocation.

Experimental design

Animals

The overall experiment had 105 spring calving dairy cows which were blocked and randomly assigned to one of 7 experimental herds contained 15 animals. Of the total number of animals, forty (21 Holstein-Friesian and 19 Holstein-Friesian x Jersey crossbred) cows were stratified across the 7 experimental groups and were monitored in this current study. Cows were balanced on parity (30 multiparous and 10 primiparous cows), milk production from the two weeks prior to the start of the experiment (25.3 ± 4.3 kg/cow/day), average body weight (BW) (460 ± 77 kg) and days in milk (34 ± 12 days). All cows followed a similar milking schedule; milked twice daily at 07:00 h and 15:30 h with approximately 1.5 - 2.0 hours per milking away from the paddock.

Treatments:

Cows were offered a pasture allowance of either 100 % of their intake capacity (IC) or 60 % IC. Intake capacity was calculated according to the equation of Faverdin et al. (2011) and was dependent on age, parity, days in milk, stage of pregnancy, BW, Body Condition Score (BCS) and potential milk yield. In the overall experiment, there were seven individual herds of 15 cows per herd; six of these herds were assigned to restricted pasture allowance (PA) during the early lactation period in spring. The remaining herd functioned as a control group (0) offered 100 % IC. To maintain a post-grazing sward height of 3.5 cm for the control group the PA was adjusted daily, thereby catering for the increasing demand of the cows due to stage of lactation, consequently all other treatments increased proportionately (e.g. if the control group were offered 18 kg DM/cow/day, the restricted groups were offered 10.8 kg DM/cow/day).

In this study, 5 cows were randomly selected within each of the 6 restricted groups and 10 cows were randomly selected in the control group. The 40 selected focal cows were subjected to behaviour recordings. The six restricted treatment groups had different durations of restricted pasture allowance, either 2 weeks (2) or 6 weeks (6). The experimental period of 10 weeks was divided into five 2-week blocks (A-E). Separate groups of cows commenced their PA restriction period (either 2 or 6 weeks) at one of three time points in early lactation (S=Start), mid (M=mid) (2 weeks after the S restriction commenced) or late (L=late) (4 weeks after the S restriction commenced). The behaviour of the non-restricted herd (Control) was monitored over a 10-week period (Figure 1). The 3 cow groups on the 2-week restricted treatment had their behaviour recorded during the full 2-week periods, whereas the 3 cow groups on the 6-week restricted treatment had their behaviour recorded during the last 2 weeks of their 6-week treatment period. All herds grazed individually but adjacent to one another. Herds were separated using a temporary electric fence. A fresh grass allocation was allocated after each milking access to water was provided at all times. Pasture allowances were calculated above 3.5 cm. Cows received a grass only diet with no additional concentrate.

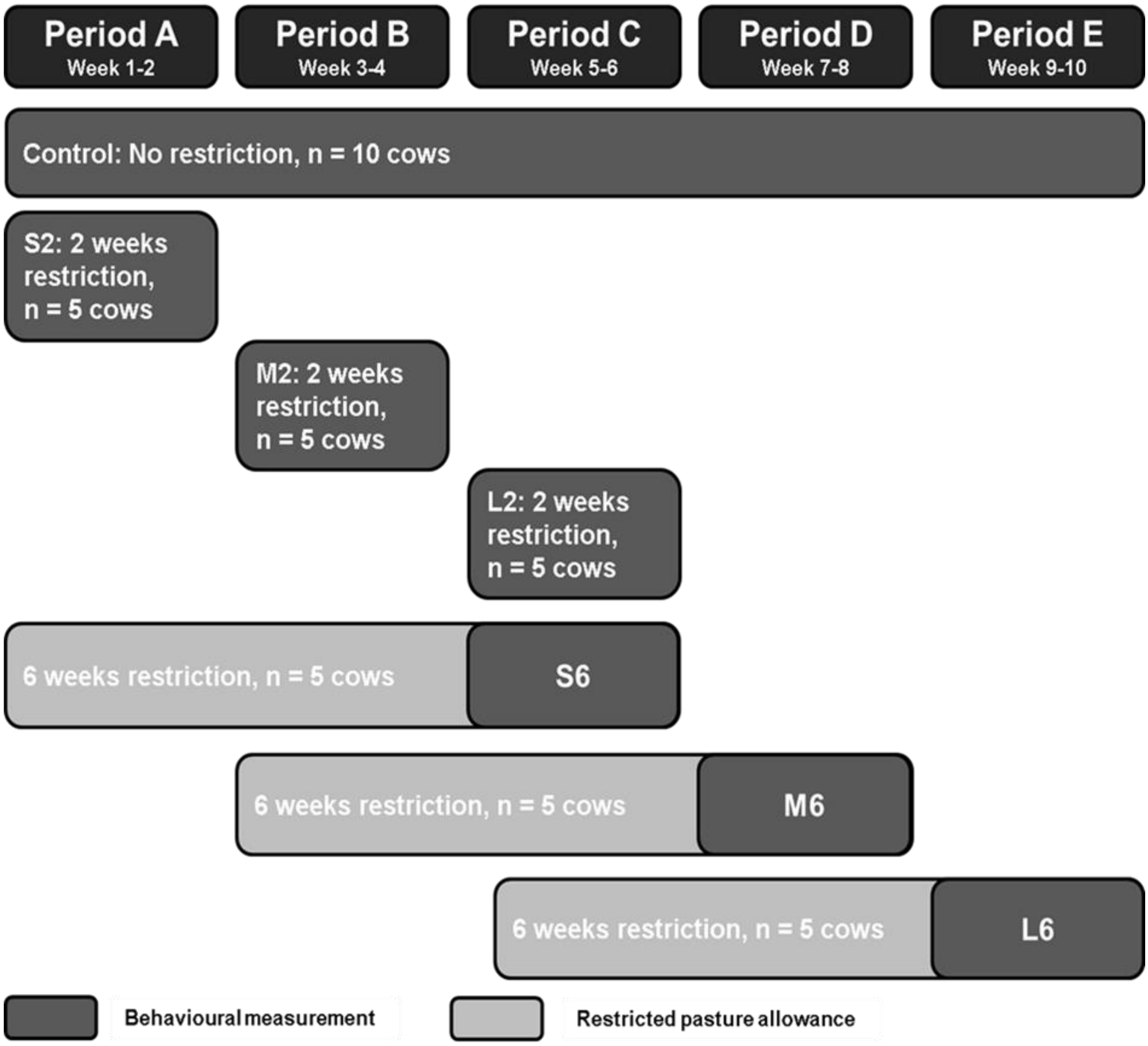

Figure 1: Study design for assessing the effect of restricted (60 %) pasture allowance compared to control (100 %) pasture allowance on cow behaviour with two different durations of restriction (2 week s (2) and 6 weeks (6)) and three different commencement periods during spring lactation (S=Start, M=Mid, L=Late); before and after the 60 % restriction cows were offered a 100 % intake capacity.

Periods of high rainfall were encountered during the experimental period, during this time cows were offered restricted access to pasture (removed from pasture after 3 hours grazing and housed until the following milking) in accordance with the guidelines outlined by Kennedy et al. (2009); Kennedy et al. (2011). During this period they had access to water and cubicle accommodation but had no access to feed. The weather conditions, especially high rainfall, caused an ON/OFF grazing situation on 1 of 14 days for Period A and 10 of 14 days for Period B.

Data collection

Weather:

A weather station situated at the Moorepark research farm was used to monitor weather during the experiment. Maximum distance between the weather station and the pasture was 1.0 km. The station measured air temperature using a platinum resistance thermometer (Sensing Devices, US) placed 1 m above the soil. A tipping bucket rain gauge (Casella, UK) was used to monitor rainfall. All sensors were connected to a data logger (CR series, Campbell Scientific, US) that processed all the readings and transmitted them to the Irish National Meteorological Service (Met Éireann) server via a broad-band connection.

Grass measurements:

Pre- and post-grazing sward height measurements were taken daily using a rising plate meter (diameter 355 mm and 3.2 kg/m^2; Jenquip, Fielding, New Zealand); approximately 40 heights per treatment across the two diagonals of each paddock were taken. Pasture offered to each treatment group was sampled weekly with Gardena hand shears (Accu 60, Gardena International GmbH, Ulm, Germany) to the post-grazing sward height of each individual treatment in order to represent the grass defoliated by the cows. A subsample was stored at –20°C before being freeze dried and milled through a 1-mm sieve before chemical analysis.

Herbage samples were analysed for dry matter (DM), crude protein (CP), Neutral Detergent Fibre (NDF) and Acid Detergent Fibre (ADF) by wet chemistry in a commercial laboratory (Dairy One Forage Laboratory, Ithaca, NY, USA).

Grazing and activity behaviour:

The RumiWatchSystem (Itin+Hoch GmbH, Liestal, Switzerland) was used for measuring grazing behaviour and activity of the cows. It incorporated the RumiWatch noseband sensor and the RumiWatch pedometer. Both sensors were validated in a pasture based milking system against visual observation (Werner et al., 2017). Raw data were recorded in a 10 Hz resolution. In the current study, the RumiWatch Manager 2 (V.2.1.0.0) was used to manage time synchronization and raw data recording of the devices. The RumiWatch Converter (V.0.7.3.36) was used for analysing the raw data. Further technical information about the RumiWatchSystem is reported by Alsaaod et al. (2015) and Zehner et al. (2017). The RumiWatch noseband sensor is capable to record grazing behaviour in a detailed manner. In Table 1, there are the grazing behaviour parameters and the corresponding RumiWatch output variables listed which are included in the analysis of this experiment. After two weeks of continuous recording the raw data were downloaded and the sensors were applied to the cows again on the following morning. Only complete daily records were included in the analysis. All relevant data regarding cow performance were merged together in an electronic spread sheet (Microsoft Excel, Version 2010, USA).

Table 1: Grazing behaviour parameters measured by the RumiWatch noseband sensor.

Parameter	RumiWatch output	Definition
Grazing time (min/day)	EAT1TIME	Grazing time with head position down
Grazing bouts (n/day)	GRAZINGSTART	Number of grazing bouts started per day (Definition grazing bout = minimum duration of 7 min and intra-bout interval is smaller than 7 min, Werner et al. 2017)
Time of feeding (min/day)	GRAZINGTIME	Duration (in min) of feeding (head position up or down) with time totalled for all grazing bouts per day
Grazing bout length (min/bout)	GRAZINGTIME/ GRAZINGSTART	Calculated value for mean grazing bout length
Grazing bites (n/day)	GRAZINGBITES	Number of jaw movements (prehensions) for ripping of grass
Bite frequency (n/min)	GRAZINGBITES/ EAT1TIME	Calculated value for grazing bites per min
Rumination time (min/day)	RUMINATETIME	Total rumination time per day
Rumination chews/bolus (n/bolus)	RUMINATECHEWS/ BOLUS	Calculated value for mean number of rumination chews per bolus
Rumination bouts (n/day)	RUMIBOUTSTART	Number of rumination bouts started per day (Definition rumination bout = minimum duration of 3 min and intra-bout interval is smaller than 1 min; Werner et al. 2017)
Time of rumination within all rumination bouts (min/day)	RUMIBOUTTIME	Duration (in min) of rumination behaviour with time totalled for all rumination bouts per day
Rumination bout length (min/bout)	RUMIBOUTTIME/ RUMIBOUTSTART	Calculated value for mean rumination bout length per day

Intake estimation:

The n-alkane technique was used to estimate grass dry matter intake (DMI) (Dillon and Stakelum, 1988) on the last two weeks of the treatment periods in each of the 6 restricted groups. The control treatment was divided into two subgroups and grass DMI was estimated every two weeks on alternative groups. As part of the n-alkane technique cows were dosed twice daily with a paper filter (Carl Roth, GmbH and Co. KG, Karlsruhe, Germany) containing an indigestible marker (C32) by a trained member of staff for 12 days. From day seven of dosing, faecal samples were collected in the paddocks twice daily, before both a.m. and p.m. milking for the remaining 6 days. On occasion, faecal grab samples were obtained manually from the cow. Based on the marker amount in the faeces, it was possible to estimate the amount of grass the cow was ingesting. Further information about the method can be found in Kennedy et al. (2011).

Animal performance:

Milk yield was measured individually (kg) twice daily at each milking (Dairymaster, Tralee, Co. Kerry, Ireland). Milk fat, protein, lactose, casein, dry matter, urea and somatic cell count (SCC) was determined once weekly. The concentrations of these components were measured using Milkoscan 203 (Foss Electric-DK-3400, Hillerød, Denmark). All cows were weighed weekly. Bodyweight was recorded weekly using a portable weighing scale and Winweigh software package (Tru-test Limited, Auckland, New Zealand). BCS measurements were conducted every second week by two alternating trained observers during the study on a 1 to 5 point scale (1 = emaciated, 5 = extremely fat; Lowman et al. (1976))

Statistical analysis

The data were analysed using the Mixed procedure in SAS 9.4 (SAS Institute Inc., Cary, NC, USA). As control animals were measured repeatedly, the resultant correlations were included in the modelling as a covariate structure in the residual error. There were a number of combinations of measurement period (A-E) and restriction treatment (2 weeks or 6 weeks) in the experiment. However, a complete factorial set for all combinations of period and restriction was incomplete. Therefore a linear model was used to fit a one-way classification where each measured combination of period and restriction was fitted as a separate treatment. These combinations were analysed using the following model:

$$Yij = \mu + Ti + e\ ij$$

where μ = mean, Ti = Treatment (combination of period and restriction), eij = residual error term.

Within the set of treatment combinations there were subsets of measurement period and restriction (either 2 week or 6 week) with complete factorial structure. Interaction and main effects (measurement period or restriction) were examined in these subsets using contrasts of the coefficients from the one-way analysis. These contrasts were equivalent to fitting the following factorial model to the subsets:

$$Yijk = \mu + Pi + Rj + PRij + e\ ijk$$

where Yijk = response; μ = mean, Pi = measurement period, Rj = restriction, eijk = residual error term.

Comparisons of means were made with adjustment for multiplicity using the Multtest procedure. Residual checks were made to ensure that the assumptions of the analysis were met. Boxplot figures were created with the Sqplot procedure and means were calculated with the means procedure in SAS 9.4.

Results

Sward measurements

The sward measurements indicated that each restricted group had similar pre-grazing sward heights to its comparable control group in the respective measurement period (Table 2). However, the post-grazing height was always lower for restricted groups compared to the control group. Cows assigned to the control treatment had a post-grazing height above 3.5 cm (range: 3.6 – 4.7 cm); alternatively cows offered 60 % IC grazed below the 3.5 cm horizon (range: 2.5 – 3.1 cm). There was no difference in the chemical composition of swards offered to all groups. Focal cows in all restricted groups showed a higher individual grass DMI compared to the calculated daily herbage allowance.

Table 2: Sward measurements, grass quality, dry matter intake of individual cows and calculated daily herbage allowance for experimental periods per group (mean and standard deviation).

Period	A		B		C			D		E	
Cow group*	Control	S2	Control	M2	Control	L2	S6	Control	M6	Control	L6
Pregrazing height in cm	7.2 ± 1.7	6.9 ± 1.3	7.5 ± 1.4	7.4 ± 1.6	7.4 ± 1.3	7.1 ± 0.7	7.3 ± 1.6	9.9 ± 1.6	10.1 ± 1.2	12.5 ± 2.5	11.9 ± 2.1
Postgrazing height in cm	3.6 ± 0.2	2.5 ± 0.4	4.0 ± 0.5	3.0 ± 0.5	3.7 ± 0.3	2.8 ± 0.5	2.8 ± 0.3	4.0 ± 0.4	3.1 ± 0.5	4.7 ± 0.6	3.0 ± 0.5
Daily herbage allowance above 3.5 cm in kg/cow/day[a]	14.1 ± 0.5	8.5 ± 0.4	15.3 ± 0.2	9.2 ± 0.1	15.9 ± 0.2	9.6 ± 0.1	9.6 ± 0.1	15.8 ± 0.8	9.9 ± 0.7	16.1 ± 1.4	9.7 ± 0.8
DryMatter Intake[b] (kg/cow/day)	11.1 ± 1.8	10.3 ± 0.6	13.7 ± 1.6	9.7 ± 1.9	17.5 ± 2.3	20.1 ± 2.1	17.2 ± 3.7	20.0 ± 2.1	17.7 ± 2.0	16.4 ± 3.6	15.0 ± 2.2
Drymatter above 3.5 cm in kg DM/ha	1371 ± 475	1296 ± 193	1129 ± 351	1063 ± 367	1110 ± 237	1056 ± 312	971 ± 321	1769 ± 292	1743 ± 310	1766 ± 383	1690 ± 357
Crude protein (%)	19.9 ± 0	19.1 ± 0.1	20.0 ± 3.4	20.4 ± 3.0	22.4 ± 2.5	20.3 ± 2.7	21.9 ± 3.7	20.5 ± 1.6	18.6 ± 0.1	21.2 ± 1.2	22.9 ± 0.1
ADF (%)	27.1 ± 0.8	25.3 ± 1.2	24.7 ± 0.8	25.7 ± 5.1	22.7 ± 2.0	24.0 ± 1.0	21.3 ± 3.3	22.3 ± 1.6	21.0 ± 0.7	22.4 ± 0.5	23.7 ± 0.2
NDF (%)	45.0 ± 0.8	44.5 ± 0.5	39.2 ± 3.8	38.6 ± 3.2	37.8 ± 2.2	37.7 ± 2.2	35.9 ± 3.0	38.4 ± 2.2	38.0 ± 1.9	40.8 ± 0.1	40.6 ± 0.2

[a] Daily herbage allowance was offered to the experimental herds based on calculation of intake capacity
[b] Intake estimation of dry matter intake (kg/cow/day) based on individual focal cows chosen for behavioural measurements
* Cow group: Control cow group received a 100% pasture allocation, all other treatment groups commenced their restriction period (either 2 or 6 weeks) at one of three time points in early lactation (S=Start), mid (M=mid) (2 weeks after the S restriction commenced) or late (L=late) (4 weeks after the S restriction commenced).

Behavioural measurements

The results of the behavioural measurements (means and standard deviation) of cow groups per period and statistically significant effects are presented in Table 3-5. Overall, the results demonstrated that there were only a few very distinguishable effects of the restricted pasture allocation on cow grazing behaviour. There was also a strong effect of the measured period on some parameters.

Grazing

The effects of restriction in pasture allocation and measurement period on grazing behaviour are displayed in Table 3. Bite frequency was consistently affected by the restriction, with the measured parameter being significantly higher for the restricted cow groups compared to the control groups for the 2-week and 6-week restricted cows as presented in Table 3 and Figure 2. Cows on the restricted allocation generally recorded a numerically lower number of grazing bouts/day within each period, except for cow group M2 during Period B. The lower number of grazing bouts/day was associated with extended length of the grazing bouts for the restricted cows in comparison to the control cows. However, while this trend was observed, it was not statistically significant. All grazing parameters measured (other than bite frequency) were significantly influenced by the effect of the measurement period. The number of grazing bites/day recorded in Period B was significantly reduced compared to Periods A and C. Meanwhile the occurrence of grazing bouts/day was significantly lower during Period B compared to Periods A and C and higher for Period D compared to C and E.

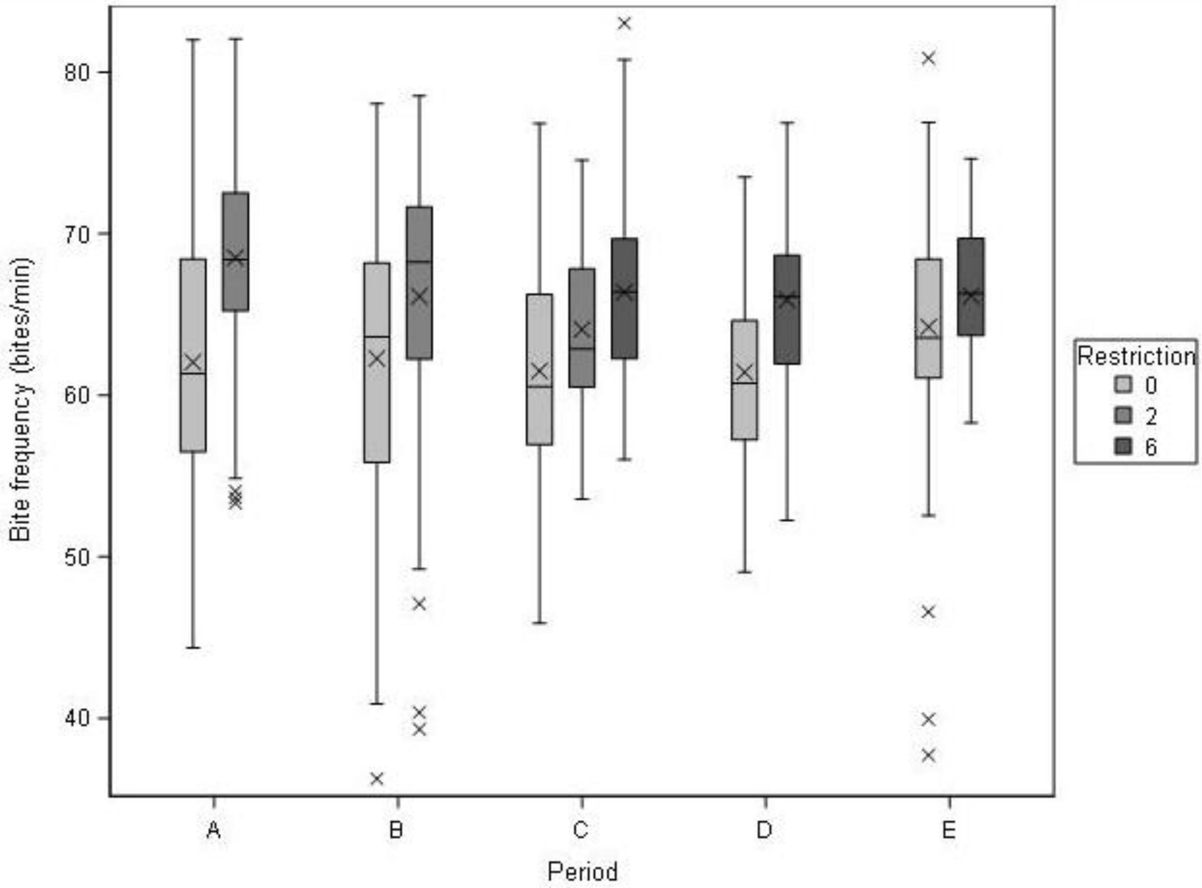

Figure 2: Effect of treatment (2-week restricted PA (2) and 6-week restricted PA (6)) versus control group (0) in bite frequency. Data are presented as box plots indicating observed median, first and third quartiles and absolute range of data with outliers, displayed as crosses, as well as observed mean displayed within boxes as crosses.

Rumination

The effects of restricted pasture allocation and measurement period on rumination behaviour parameters are displayed in Table 4. Cows with a restricted pasture allocation generally recorded a significantly shorter duration of rumination time/day and less rumination chews/day except during Period A, where no significant effect was found. Restricted pasture allocation also significantly reduced the mean length of rumination bouts of the restricted cows compared to control cows for both the 2-weeks and 6-weeks restriction. However, within Periods A-C, there was also a significant decrease in mean rumination bout length detected for Period B compared to Period A and C. The restriction also significantly affected the number of rumination chews/bolus, which was lower for the restricted cows compared to the control groups for the 6-week restriction. With regard to the mean number of rumination bouts/day, there was no significant effect found for either the restriction or the measurement period.

Activity

Restriction in pasture allocation had no clear effect on cow activity (Table 5). Cows on the restricted allocation spent similar time durations in lying and standing positions compared to the control group within each period. Statistically, there was a significant difference observed among measurement Periods A-C on standing and lying time. Significant differences also occurred with respect to time spent walking by cows. But a clear pattern was not observed across measurement periods throughout the experiment. The number of standing and lying events during the day numerically differed between the restricted cows and the control cows. The restricted cows changed from a standing to a lying position on fewer occasions than the control cows in all measurement periods. This was statistically different for just the 2-week restricted groups.

Table 3: Effects of restriction or period on grazing behaviour parameters, behavioural measurements are displayed as means with standard deviation and significance of effects.

Period	A		B		C			D		E		Significant effects[a]
Cow group*	Control	S2	Control	M2	Control	L2	S6	Control	M6	Control	L6	
Grazing time (min/day)	504 ± 67	510 ± 74	425 ± 103	384 ± 86	531± 71	576 ± 58	545 ± 82	511 ± 67	506 ± 54	531 ± 72	469 ± 109	Period A-C *p <.0.001*
Grazing bites (n/day)	31302 ± 6044	35046 ± 6157	26520 ± 7344	25497 ± 6700	32769 ± 6080	36981 ± 5019	36233 ± 6637	31486 ± 5524	33468 ± 5157	34258 ± 6037	31364 ± 8697	Period A-C *p <.0.001*
Bite frequency (bites/min)	*62.0 ± 7.9*	*68.5 ± 3.8*	*62.2 ± 8.0*	*66.1 ± 8.3*	*61.5 ± 6.5*	*64.1 ± 4.5*	*66.4 ± 5.8*	*61.4 ± 5.3*	*65.9 ± 5.3*	*64.2 ± 6.6*	*66.2 ± 4.0*	*Restriction 0/2* *p = 0.022* *Restriction 0/6* *p = 0.038*
Grazing bouts (n/day)	9.3 ± 2.6	8.4 ± 2.6	6.5 ± 2.4	6.5 ± 2.3	8.4 ± 1.8	8.0 ± 2.5	8.0 ± 2.1	9.5 ± 2.0	9.0 ± 2.6	7.8 ± 1.8	7.7 ± 2.1	Period A-C *p <.0001* Period C-E *p = 0.001*
Grazing bout length (min/bout)	67.5 ± 14.7	73.6 ± 17.7	85.3 ± 32.5	81.5 ± 31.5	74.9 ± 17.8	87.0 ± 25.9	82.8 ± 23.9	65.3 ± 16.7	74.9 ± 20.5	80.7 ± 19.7	82.7 ± 24.2	Period A-C *p = 0.002* Period C-E *p = 0.009*

Italics = parameter is consistently numerically higher for restricted groups compared to the control group

[a] Significant effects are reported, either significant effect among Period A-C or C-E, significant effect between restriction 0/2 or 0/6 or significant interactions between period x restriction

* Cow group: Control cow group received a 100% pasture allocation, all other treatment groups commenced their restriction period (either 2 or 6 weeks) at one of three time points in early lactation (S=Start), mid (M=mid) (2 weeks after the S restriction commenced) or late (L=late) (4 weeks after the S restriction commenced).

Table 4: Effects of restriction or period on rumination behaviour parameters, behavioural measurements are displayed as means with standard deviation and significance of effects.

Period	A		B		C			D		E		Significant effects[a]
Cow group*	Control	S2	Control	M2	Control	L2	S6	Control	M6	Control	L6	
Rumination time (min/day)	**456 ± 69**	**456 ± 73**	**431 ± 86**	**327 ± 90**	**490 ± 78**	**395 ± 85**	**383 ± 70**	**504 ± 72**	**446 ± 61**	**491 ± 66**	**430 ± 59**	**Restriction 0/6** ***p <.0001*** **Period C-E** ***p = 0.013*** **Period A-C x restriction 0/2** ***p = 0.001***
Rumination chews (n/day)	**30387 ± 5290**	**28676 ± 5227**	**27841 ± 6667**	**20313 ± 6524**	**32343 ± 5775**	**24236 ± 5050**	**23061 ± 4408**	**33985 ± 5902**	**29520 ± 4991**	**32192 ± 5072**	**26202 ± 3825**	**Restriction 0/6** ***p <.0001*** **Period C-E** ***p = 0.002*** **Period A-C x restriction 0/2** ***p = 0.008***
Rumination chews/bolus (n/bolus)	**56.8 ± 6.0**	**55.5 ± 4.3**	**55.6 ± 5.7**	**52.7 ± 5.2**	**56.2 ± 5.7**	**51.5 ± 5.0**	**47.7 ± 4.1**	**55.3 ± 5.9**	**51.7 ± 5.0**	**54.1 ± 5.4**	**49.1 ± 4.2**	**Restriction 0/6** ***p = 0.018***
Rumination bouts (n/day)	12.8 ± 2.7	13.4 ± 2.1	13.1 ± 2.4	12.3 ± 2.6	12.8 ± 2.5	12.3 ± 2.0	13.7 ± 2.6	13.7 ± 2.5	14.8 ± 2.4	13.2 ± 5.4	14.8 ± 2.7	No significant effect
Rumination bout length (min/bout)	**37.5 ± 8.3**	**34.0 ± 6.3**	**34.0 ± 8.3**	**27.1 ± 6.7**	**39.9 ± 8.8**	**32.6 ± 6.2**	**28.9 ± 5.9**	**38.4 ± 7.8**	**31.5 ± 6.9**	**38.9 ± 8.3**	**30.2 ± 6.9**	**Restriction 0/2** ***p = 0.006*** **Restriction 0/6** ***p <.0001*** **Period A-C** ***p = 0.003***

Bold= parameter is consistently numerically lower in restricted groups compared to the control group

[a] Significant effects are reported, either significant effect among Period A-C or C-E, significant effect between restriction 0/2 or 0/6 or significant interactions between period x restriction

* Cow group: Control cow group received a 100% pasture allocation, all other treatment groups commenced their restriction period (either 2 or 6 weeks) at one of three time points in early lactation (S=Start), mid (M=mid) (2 weeks after the S restriction commenced) or late (L=late) (4 weeks after the S restriction commenced).

Table 5: Effects of restriction or period on activity parameters, measurements are displayed as means with standard deviation and significance of effects.

Period	A		B		C			D		E		Significant effects[a]
Cow group*	Control	S2	Control	M2	Control	L2	S6	Control	M6	Control	L6	
Lying time (min/day)	477 ± 170	485 ± 140	428 ± 117	428 ± 126	566 ± 92	583 ± 98	535 ± 85	565 ± 102	556 ± 100	569 ± 95	603 ± 84	Period A-C *p <.0001*
Standing time (min/day)	873 ± 158	873 ± 136	921 ± 110	911 ± 118	800 ± 83	791 ± 87	823 ± 78	785 ± 96	782 ± 91	788 ± 93	749 ± 75	Period A-C *p <.0001*
Walking time (min/day)	90 ± 32	83 ± 20	90 ± 21	102 ± 35	75 ± 18	667 ± 22	82 ± 35	91 ± 19	102 ± 26	83 ± 15	89 ± 18	Period A-C *p <.0001* Period C-E p = 0.001
Standing up/lying down events (n/day)	**8.4 ± 3.2**	**6.4 ± 2.6**	**9.1 ± 3.1**	**6.7 ± 2.1**	**9.0 ± 2.7**	**7.6 ± 2.0**	**7.7 ± 2.7**	**9.2 ± 3.6**	**7.8 ± 2.4**	**7.9 ± 2.0**	**7.0 ± 2.2**	**Restriction 0/2** ***p = 0.004***
Strides (n/day)	2792 ± 952	2550 ± 596	2832 ± 680	3069 ± 899	2268 ± 534	2002 ± 270	2483 ± 970	2870 ± 521	3141 ± 675	2654 ± 469	2794 ± 524	Period A-C p <.0001 Period C-E p <.0001

Bold= parameter is consistently numerically lower in restricted groups compared to the control group

[a] Significant effects are reported, either significant effect among Period A-C or C-E, significant effect between restriction 0/2 or 0/6 or significant interactions between period x restriction

* Cow group: Control cow group received a 100% pasture allowance, all other treatment groups commenced their restriction period (either 2 or 6 weeks) at one of three time points in early lactation (S=Start), mid (M=mid) (2 weeks after the S restriction commenced) or late (L=late) (4 weeks after the S restriction commenced).

Discussion

The results of this study showed that bite frequency was consistently affected by the restricted pasture allowance. Furthermore, there were some parameters which were consistently numerically lower for the restricted cows, such as rumination time/day, mean rumination bout length and rumination chews/bolus. However, there was no clear significant effect of restriction for those parameters over all experimental periods. This may be either due to the stronger effect of measuring period or the small sample size of cows.

Even though new technologies were used in the current study to monitor cow grazing behaviour continuously over prolonged periods, the results are comparable to previous studies when cow grazing behaviour was studied over 24-h periods under restricted access times to pasture (Kennedy et al., 2011). Kennedy et al. (2009) reported that cows with full time access to pasture showed a higher number of grazing bouts of shorter duration than that of restricted access groups. A study of Soca et al. (2014) confirmed that restricted pasture access resulted in a longer initial grazing bout for those cows, but the overall grazing time was longer for cows with unlimited access to pasture. Thus, those studies showed that the cows restricted in either time on pasture or as in the current study in grass availability spent a longer time grazing per bout and engaged in fewer grazing bouts. It is likely that cows alter their grazing behaviour to compensate for the restriction, e.g they graze more efficiently with a higher bite rate or bite frequency (Patterson et al., 1998; Gregorini et al., 2009). Chilibroste et al. (2015) explained the increased bite rate and adaption to restricted grazing conditions with decreasing sward heights as being associated with reduced bite mass. As a response to reduced bite mass, cows increase their bite rate, as a compensatory mechanism to maintain their intake. This is also represented in the results of the current study, as bite frequency was significantly higher for all restricted groups in all periods.

With regards to rumination behaviour, Chilibroste et al. (2007) indicated that increases in intake rates, based on bite rate and bite mass, occur at the expense of rumination time, which they demonstrated in various studies (Chilibroste et al., 1997; Soca et al., 2014). Contrary to the current study, Kennedy et al. (2011) found longer rumination times for the cows with restricted access to pasture compared to cows with full-time access. Those cows also showed a higher number of rumination bouts as well as longer bouts. However in the current study, the restricted cows recorded a lower total rumination time and also the length of rumination bouts was shorter compared to the control group. This might be explained by the fact that the cows in the study of Kennedy et al. (2011) were restricted by access to pasture contrary to the current study where the cows were restricted in grass availability in the paddock. Therefore, when cows had no access to pasture and were housed, they adapted their rumination times to compensate for a reduction in available grazing time (Gregorini et al., 2012). The reduced rumination time associated with restricted cows in the current study may be due to the fact that there is less material in the rumen to digest or the grass pieces in the rumen might be already sufficiently reduced for digestion as a consequence of a shorter grass sward (Kennedy et al., 2009). Gregorini et al. (2012) explained reduced rumination times of cows with restricted access to pasture as a compensatory mechanism to enhance rumen digestion.

There are only a few comparable studies in the literature with analysed activity behaviour during a period of restriction in pasture access or grass availability. However a study of O'Driscoll et al. (2015) demonstrated that the extent of lying bouts was also affected by restriction of pasture. Restricted cows had a smaller number of lying bouts, which is in accordance with the current study when restricted cows showed less events of lying or standing. The differing number of occasions when cows were lying down/standing up might be also due to a more consistent lying behaviour of the restricted cows due to reduced grass availability.

After entering the fresh paddock, there were longer initial grazing bouts and once they depleted the grass allocation the restricted cows rested for longer periods. Considering the results of activity measurements, there was just a small degree of difference shown within the treatments. All cows spent a similar amount of time either standing or lying. This may be due to the paddock sizes, which are constrained in strip grazing rotational management. Similar walking times, which are more affected by the measurement period than the restriction may be explained by the fact, that all cows, either restricted or control groups, were grazed in paddocks with similar distances to the milking parlour. Therefore the amount of walking to the grazing paddocks was comparable.

The measured DMI based on the n-alkane method, showed that the restricted individual cows consumed more grass than was allocated to them based on a calculated intake capacity. These cows grazed lower than the 3.5 cm sward height, which was used as the basis for the herbage allowance calculations. This may have influenced restriction somewhat, as cows may not have experienced a restriction of 60 % in reality. However, even with an actual restriction of approximately 80 %, a strong effect on bite frequency was still detected. Some cows in both the control and restricted herds may have had a lower DMI than that which would be associated with the calculated herbage allocation, as the calculated allocation is conducted at a herd or group level, and high ranking cows could potentially increase their intake at the expense of low ranking cows. With automated sensors, it is possible to gain feedback per individual cow and this could be used to improve grazing management at an individual animal level. Individual cow data for grazing behaviour and possible grazing efficiency may be then also used for automated phenotyping for breeding purposes.

Bite frequency was significantly affected in all restricted groups. Furthermore, rumination parameters such as rumination time/day, rumination chews/bolus and rumination bout length were also continuously of shorter duration for the cows in restricted groups compared to the control group, but not statistically significant for both restriction treatments or over all measurement periods. Caution may need to be exercised in relation to the importance of statistically significant effects with a small sample size of 5 animals per group. Alternatively, it may be considered that an effect detected even with a small sample size of individual animals strengthens the importance of the parameters, such as bite frequency. The effects of restriction may also be influenced by the fact that cows received two pasture allocations per day.

The results emphasised that further research should focus on parameters such as bite frequency and rumination time/day, rumination chews/bolus or mean rumination bout length. These may then be used as potential indicators in decision support tools to help farmers improve grazing management. A huge variability among individual animals as well as among days or even hours may mean that an extension of this study with more individual animals would be required. Also the variability of individual cows compared to the herd needs to be analysed to develop thresholds for insufficient grass allocations. These thresholds at individual animal levels could be integrated in the decision support tool to give farmers feedback on their grazing management. Based on this feedback, new grass allocations could be adapted to improve grazing efficiency and productivity in a pasture-based milk production system.

Conclusion

The study demonstrated that the parameter bite frequency was significantly affected by the restricted pasture allowance regardless of the duration of restriction. The restricted cows had a higher bite frequency in all measurement periods. A significantly lower number of rumination chews/bolus was detected for the 6-week restricted groups compared to the control groups, but not for the restricted groups experiencing a 2-week restriction. Furthermore, other rumination parameters such as rumination time/day and mean rumination bout duration were generally reduced for the restricted groups compared to the control groups. However, there was also an influence of the measurement period detected. The activity behaviour was significantly different between the control group and the restricted groups with respect to occasions of standing and lying for the groups with a two week restriction but not for the groups with a six week restriction. However, most measurable parameters of grazing behaviour or activity behaviour were not detected to be suitable as an indicator for insufficient grass allocation, as they were not strongly influenced by restricted pasture allowance. This might be due to the significant interaction between measured period and restriction, or the fact that the restricted groups grazed below 3.5 cm thus negating some of the restriction. Further research should focus on identifying the thresholds of grazing behaviour parameters, such as bite frequency, rumination time/day, rumination chews/ bolus or mean rumination bout length, which may represent insufficient grass allocation. These thresholds could then be integrated and implemented within a decision support tool for farmers and could potentially optimize the grazing management for dairy cows.

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CHAPTER 5: GENERAL DISCUSSION

The development of sensor technology to measure feeding behaviour of cows in intensive confinement systems has been successful in recent years (Borchers et al., 2016). However, the intake behaviour of cows differs with regards to grazing. Grazing is a complex combination of various movements and activities performed at different temporal and spatial scales, ranging from the intake bite with ripping the grass, to a grazing meal or event and to the grazed paddock (Andriamandroso et al., 2016). Therefore, the performance of sensors, which were developed for housed cows may not be entirely satisfactory for grazing cows (Elischer et al., 2013). Further, there are only a few commercially available sensors to-date, which are validated for measuring grazing behaviour of cows (Ipema, 2015, Molfino et al., 2017).

Considering this background, the present thesis (Chapter 2 and 3) was aiming at the validation of two sensors with different application potentials, which were either research focused or commercially applicable. A third study (Chapter 4) in this thesis focused on applying the previously validated sensor technology to investigate, if automated measurement of grazing behaviour could be used as a valid indicator of grass availability or scarcity for the cow, and thus, could be integrated in a decision support tool for grazing management.

The following discussion will focus on the validation of sensor technologies and the different behavioural indicators within the animal and the herd will be examined. Furthermore, the application potential of sensor technologies at farm level, including farmer’s acceptance, will be reviewed. Finally, a future outlook in the area of automated measurement of grazing behaviour and digitalization of animal management will be presented.

Validation of sensor technology

In the past, behavioural recordings for research purposes were generally obtained by visual observation (Kilgour, 2012). This also applied for livestock management, when the farmer relied on experienced visual assessment of the animal as the basis for his decisions (Frost et al., 2003). However the application of visual observation may be insufficient to monitor increasing numbers of animals in expanded herd sizes. Visual observation is a time-consuming and laborious task and can only be conducted over a limited time duration (Berckmans, 2006). As the development of sensor technologies progressed, the availability of sensors improved, therefore the automated measurement of behaviour using sensor technology became more prevalent. In literature, the most recognized reference method to validate sensors is visual observation (Burfeind et al., 2011, Bikker et al., 2014) or video recording with visual assessment in a subsequent step. There are only a few possible methods by which visual behavioural recording may be obtained, based on definitions by Martin and Bateson (1993). Both sampling rules and recording rules must be clearly defined. In literature, there is either continuous recording (Elischer et al., 2013) or a scan sampling method linked with instantaneous sampling (Büchel and Sundrum, 2014) conducted.

To adapt the appropriate reference method for validating the system correctly, the researcher needs to understand the technology and the measurement method of the sensor. There is also a requirement to clarify with the manufacturing company, if the raw data are available and in what format. It is also important to adjust the experimental design and the recording method for visual observation depending of the objective of the conducted study. Furthermore, the measurement and output resolution of the sensor needs to be taken into account, when choosing the recording method.

During development stages of sensor technology, it might be more appropriate to measure the behaviour of animals continuously to determine every event, when the behaviour changes, and match the correct timestamp of the observation with the sensor technology. Therefore it is also important to understand the time settings of the technology, e.g. when will the time be synchronized and to which time.

Due to rapid release of new or updated sensor technologies of companies, the question arises if there is an automated mechanism to validate sensor technologies scientifically. This would substitute the expensive, laborious and time-consuming need of validating every new or updated technology against visual observation. Zysman and Kenney (2016) have indicated that computing capacity is increasing, with a doubling of processing power every two years, based on Moore’s law. This represents a fast rate of development in sensor technology. The RumiWatch noseband sensor, which was validated in Chapter 2, may have the potential to function as a gold standard for validating other sensor technologies for measuring grazing behaviour as the data resolution of 10 Hz is very high. An automated validation approach was demonstrated in Chapter 3 when the RumiWatch noseband sensor was compared to another collar device over a prolonged period. This study revealed an overestimation of grazing time by the RumiWatch noseband sensor due to sensitivity of the noseband sensor while the cows were walking. In a subsequent study, a successful development of a new version of the analysis software was addressed, which showed high performance in measuring grazing behaviour (unpublished data).

A further gap between industry and science with regard to validation of sensor technology is the long process of peer-reviewed publication of conducted studies. As demonstrated above, the development and advancement of sensor technology in industry is rapid. However, there is a time lapse of at least 1.5 years from the planning of an experiment to scientific validation of the sensors to the published validation paper.

Thus, there is an increased likelihood, that the validated technology may be already outdated before the validation study is published. Alternatively, some products will be released without appropriate validation or only with an in-house validation by the manufacturing company. This may be then reflected in an insufficient performance at farm level or the sensor may not subsequently be accepted as a valid sensor in the scientific field. For the scientific world, these facts are challenging and researchers need to meet these challenges, and one possibility may be accepting automated validation of sensors as a new gold standard. This would expedite the process of validation if the element of time-consuming visual observation was not involved.

Behavioural characteristics as indicators

The measurement of detailed data of cows' grazing behaviour is possible with validated sensors as proven in Chapter 2 and 3. However, especially for grazing cows in pasture-based milk production systems, the usage of the measured data may be improved. Important factors that need to be considered are the variability of the behaviour of an individual animal during the day, based on the circadian rhythm. Furthermore, there is also a difference in the behaviour of an individual animal compared to that of the herd. In pasture-based systems, grazing efficiency is referred to in terms of the herd, likewise with the link between feed conversion and performance. But now, there is the possibility to gather detailed information about individual cows (within the herd) with automated measurements of grazing behaviour. This might facilitate more quantitative research with regard to different influencing parameters on cow grazing behaviour, such as environmental effects e.g. weather (Graunke et al., 2011), herd dynamics (Rind and Phillips, 1999), sward height (Gibb et al., 1999) and possibly specific characteristics of the individual animal (Dado and Allen 1994). While Lassen et al. (2006) have highlighted that "people with a background in modern animal production probably have a bias towards focusing on the average", this focus may need to change to the individual animal, if automated sensor systems will be increasingly used in future.

The successful identification of potential indicators in grazing behaviour for restricted grass allowance of dairy cows was demonstrated in Chapter 4. However, there is still a need to identify a significant deviation within the grazing behaviour of cows at a more detailed level to implement meaningful thresholds. These thresholds do not only need to be identified at an individual animal level but also at the herd level. Depending on the parameter or situation, the herd level may be more appropriate than the individual animal level or vice-versa.

With regard to health issues, it is important to identify the deviation of the individual animal from both the herd performance but also from the individual animal's own usual daily pattern. The grazing or ruminating pattern might be influenced by the diurnal pattern of the cow or the decreased or increased time at these activities may indicate some other influence, e.g. at a mastitis occurrence, a decline in rumination time in the initial 24 h after infection has been observed (Fogsgaard et al., 2012). Furthermore, there is also a decrease in rumination time per day when a cow is in heat (Reith and Hoy, 2012); compared to that of the herd, the activity of an individual cow is increased (Cavestany et al., 2008). Some sensor systems (Dairymaster personal communication) compare the values of individual animals to the values of the overall herd to exclude false positive measurements of heat events; the whole herd could be showing an increased activity for a reason other than heat, thus it is necessary to compare the individual to the herd. Therefore, the algorithms need to do calculations of the individual animal within the animal measurements, but also compared to the herd level.

However, when the whole herd is showing a decrease in rumination time compared to the previous day, this may mean that the herd had insufficient grass allocation as rumination behaviour was identified as a potential indicator in Chapter 4. In a subsequent step, it should also be checked if the herd behaviour at specific times is deviating from the previous day, e.g. grazing time after milking is shorter than the previous day. This could also be representative for an insufficient grass allocation after milking, which could be corrected at the next grass allocation. Decision support tools at this level would be only realisable with the availability of real-time data. For the development of applicable decision support tools, it is therefore crucial to consider and implement meaningful thresholds for all different levels and effects on cows grazing behaviour as well as connecting and combining available and valid data.

Review of application of precision technologies at farm level

The terms "Precision Livestock Farming" or "Smart Farming" describe a hot topic in modern agricultural research. The development of biosensors has improved in recent times, resulting in a great variety of available sensors. These sensors are cheaper to produce, are more robust and more affordable and can measure parameters at a very detailed level (Berckmans, 2014). However, the literature review in Chapter 3 showed that there is still a gap between research focussed and commercially applied sensors in measuring grazing behaviour of cows. The acceptance of precision technology is also slow in other areas of farming (McBratney et al., 2005). But in recent years there has been an upscaling of farms with more animals per unit, and the increased efficiency in animal production was achieved by intensification (Lassen et al., 2006, Berckmans, 2014). Therefore, the implementation of technology can be seen as a potential response to the increased management complexity facing dairy farm managers (Eastwood et al., 2016).

Eastwood and Kenny (2009) stated that the adoption of precision farming technologies are competing with existing management practises, e.g. conventional dairy management based on experiences or tradition. But Kassler (2001) had previously stated that the capability to build a machine to carry out a particular task does not imply that it is economic for someone to use the machine in place of human labour to do it. A study of Steeneveld et al. (2015) also revealed that the productivity on Dutch dairy farms did not change after investment in sensor systems. The authors suggested, that providing more guidance and information to the farmer might improve the performance of the sensors. Reichardt and Jürgens (2009) highlighted that most of the farmers using technology face many difficulties in managing a large amount of data and in using them efficiently. The main problem is the correct interpretation of the data.

A further reason for the low level of commercial usage of precision technology in its potential applications may be the low level of trust in the collected data. According to Eastwood and Kenny (2009) this is influenced by the perceived accuracy, certainty (relates to availability of data, when its required) and consistency (data should be consistent, even if there is an over-/ or underestimation, farmers can mentally adjust). Perception of technology is also dependent on the technical background of the farmer. To improve the performance at farm level, specific training and support of users on-farm may be beneficial (Eastwood et al., 2016). Further, farmers may be more likely to invest in technology if they could see a successful operation of sensors on other farms (Eastwood and Kenny, 2009).

Besides economic considerations, there are also other motivations for the decisions of farmers to implement technology on the farm. A French study by Kling-Eveillard (2017) revealed that the motivation for better working conditions or improvement of technical management were reasons for investing in sensor technology. This study also found that there was a broad satisfaction among the farmers considering the simplification of their work with sensors and automated machines. In contrast to those findings, a negative impact of sensor technologies on the farmer's quality of life (with increased proportion of technology on the farm) was discussed. Forester and Morrison (1994) stated that the quality of life could be degraded because of the deskilling of the workforce, which reduces control responsibility and job satisfaction as well as increasing stress and depersonalization. Especially in the phase of the initial implementation of new technology, there could be an increase in the stress level of a farmer. Hostiou et al. (2017) mentioned that if the tools are not adapted to farmers' skills and needs, the adoption of technology could have a negative impact on both farmers and animals.

With regard to animal welfare, the benefits of monitoring individual animals continuously 24/7 are obvious. Especially in early detection of diseases or lameness events, the sensor technology may support the farmer and improve animal welfare.

However, there might be a risk that automated measurement of behavioural parameters of animals would reduce the time the farmer spends monitoring his animals personally (Rushen et al., 2012). There may also be a risk of the farmer losing the caring skills of a stockperson because of his new role in management and control of sensors. Cornou (2009) highlighted in her study, that automated systems might also influence the perception towards animals being seen as a product. The study also revealed that farmers might recognize animals only as a combination of parameters to monitor. It may be a concern too that a change in the animal-human relationship would occur where the farmer's sensitivity to the animal is negatively impacted on. Alternatively, there might be also a positive change in the animal-human relationship, when new technologies can lighten farmers' workloads and eliminate any potential for manhandling of animals, for example use of an automated drafting gate rather than manual handling of animals (Hostiou et al., 2017) .

Future outlook

The use of technology at farm level will change rapidly in future considering the advancement in sensor technology, modelling and data processing. At the moment, there is the possibility to collect detailed and valid data. However, there is still a low utility of data in terms of its analyses and processing of the information to the farmer for various reasons. Lyons et al. (2016) mentioned that progress on the usefulness of animal technologies is based around their integration in decision support software and combining data from different sources and processing information with powerful data analytics tools. The study also revealed, that to-date, automation technologies which are labour saving are more popular with farmers than those designed to collect data for decision making. Especially for physically demanding tasks, such as milking, there are robots, coupled with sensors, to replace the farmer (Hostiou et al., 2017). A future outlook for technology at farm level will be the part substitution of the thinking ability of the farmer's work force with the accumulation and connection of different information from different sources. Artificial intelligence will learn and advance from management decisions and definitions of actions based on human verification. This verification is functioning as a teaching of the technology. After the step of teaching, the aim is an improved accuracy of technology. One important part in developing automation at farm level is merging data and information of different data sources or sensors. The subsequent step will be to convert data into analysed information with checking for specific patterns, which were trained by the human verification. The automation at farm level will be finalized by conducting an action.

An example at farm level leading to enhanced productivity and profitability might be the automation of correct pasture allocation to the herd (French et al., 2015). In future, there might be possibilities to automatically assess the pasture production with biomass and pasture quality, based on image analysis with drones (Von Bueren and Yule, 2013).

These data can be combined with either a virtual fence technology (Umstatter, 2011), which is herding the cows on pasture, or an automated way to move fences or open gates (e.g. Batt-Latch, Novel Ways Ltd, New Zealand). Furthermore, the automated measurement of the grazing behaviour at individual animal level and herd level will be integrated. The merged data can then be processed to an action, where the cows will get the correct amount of pasture allocated based on background information from a farm database (such as individual milk yield or body weight). Not only data collected at farm level can be joined in a “virtual herd manager”, but also environmental data such as weather data. Depending on the weather forecast, the herd management can be adapted to prevent poaching. There might also be positioning or location data of individual cows at pasture collected. These data may then be linked with the image analysis of the drones and botanical composition or grass quality to allocate the best available pasture for the demand of the animals. Positioning data of cows could also be used for calculating the adequate fertilization including urination and faeces distribution on the pasture.

A further approach of this data collection and merging of data sources besides increased productivity and profitability may be the benefit with regard to food security and transparency in producing food. As McBratney et al. (2005) mentioned, there is the possibility that precision agriculture would have the ability to track a product through a system with the ultimate aim to add a label capable of being read by a consumer’s handheld computer/phone/organiser that describes the operations that have been undertaken to produce the product. However, on the other side, there might be legal issues with personal data security and some farmers might not agree with sharing personal management data.

There is a fourth revolution, which is building on the third, the “digital revolution”, and it is characterized by a fusion of technologies that is blurring the lines between the physical, digital, and biological spheres (Schwab 2018).

Based on Yahya (2018) this also has an influence on the agricultural sector with the definition of Agriculture 4.0, which is referring to systems that employ drones, robotics, Internet of Things (IoT), vertical farms, artificial intelligence (AI), and solar energy. Yahya (2018) also postulated that the successful implementation of conceptual frameworks and intentions is the main global challenge. For intensive pasture-based systems, these studies have progressed the successful research of automated measurement of cow grazing behaviour thus increasing the potential for refinement of a decision support tool for grazing management.

GENERAL CONCLUSION

The results of this thesis demonstrated, that it is possible to measure grazing behaviour of cows accurately. Different sensor systems can be used depending on the user requirements for application duration, farm set-up or the resolution of collected data. A first step towards the integration of behaviour measures into developing decision support tools was achieved in identifying possible behavioural indicators representing restricted grass availability. Future research should focus on quantifying significant changes in behaviour at individual animal and herd level. After the quantification of specific thresholds those should be implemented and tested on an extended data collection to validate the decision support tool. These findings are contributing to improve the efficiency and productivity of intensive pasture-based milk production systems.

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AFFIDAVIT

pursuant to Sec. 8(2) of the University of Hohenheim's doctoral degree regulations for Dr.sc.agr.

1. I hereby declare that I independently completed the doctoral thesis submitted on the topic *Measuring grazing behaviour of dairy cows: Validation of sensor technologies and assessing application potential in intensive pasture-based milk production systems*

2. I only used the sources and aids documented and only made use of permissible assistance by third parties. In particular, I properly documented any contents which I used - either by directly quoting or paraphasing - from other works.

3. I did not accept any assistance from a commercial doctoral agency or consulting firm.

4. I am aware of the meaning of this affidavit and the criminal penalties of an incorrect or incomplete affidavit.

I hereby confirm the correctness of the above declaration. I hereby affirm in lieu of oath that I have, to the best of my knowledge, declared nothing but the truth and have not omitted any information.

....

(Place, date) (Signature)