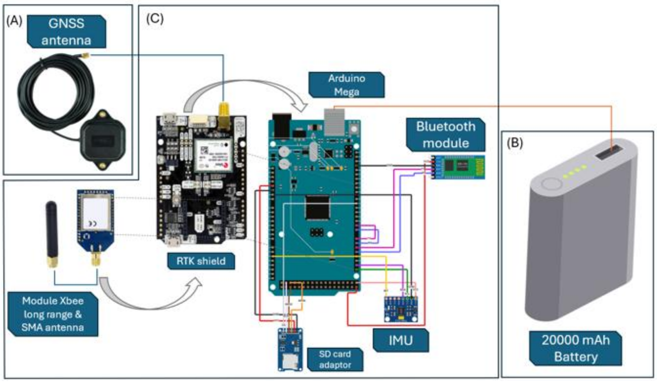
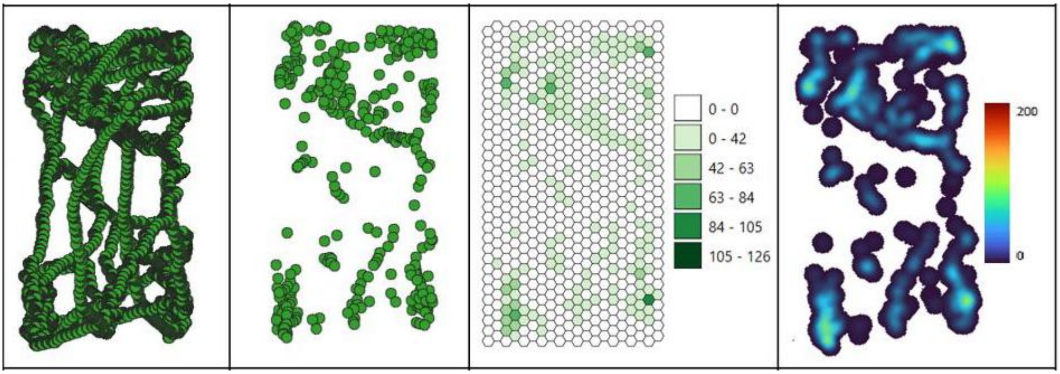
Enhancing insights into the behaviour of grazing cattle through Precision Livestock Farming tools

Nicolas TILKENS





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Améliorer la compréhension du comportement du bétail à l'aide d'outils d'élevage de précision

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Abstract

In recent decades, agricultural landscapes have been deeply affected by a process of intensification. Mixed crop-livestock systems have been replaced by specialized monocultures and intensive livestock production areas leading to landscape simplification. Herd sizes have increased significantly to meet the growing demand for animal products. This intensification has led to a degradation of natural resources. These issues are raising consumer awareness and are pressing farms to reconcile productivity and sustainability. Although progress is being made, such as the adoption of agroecological practices, reductions in certain pesticide uses, and advancements in precision agriculture, these efforts remain insufficient. Innovative and systemic solutions are still needed to address the full scope of environmental and social challenges in agriculture. Grasslands are emerging as a key component of this transition. By leveraging grass, a renewable resource, they support ecosystem services, carbon sequestration, and local economies. An agroecological approach to livestock systems means adapting practices to local contexts, optimizing livestock distribution according to available resources to balance economic and ecological benefits. Such a key local resource can be found in grasslands and managing grassland-based systems requires a good understanding of the complexity of plant-animal relationships. Precision Livestock Farming (PLF) offers promising tools to meet the challenge of monitoring those interactions.

This thesis explores the potential of PLF to improve pasture management through the high-resolution automated monitoring of grazing behaviour. A custom wearable system was developed, integrating a Real-time Kinematics (RTK)-corrected global navigation satellite system (GNSS) and a triaxial accelerometer sampling at 8 Hz. Using a two-step Machine Learning (ML) model, ingestion behaviour was classified with 98.9% precision, 99.1% recall, and 98.2% accuracy. Bite quantification achieved an average Root Mean Square Error (RMSE) of 3.19 ± 0.41 bites per 10-second window and a 15.3% prediction error. The model also accurately identified feeding stations (94.7%) and meals (91.9%) and spatialized them within grids, with compartments of $< 1m^2$. Continuous analysis of grazing patterns revealed a behavioural threshold occurring when Holstein cows had consumed approximately 41% of the pre-grazing Sward Height (SH) (12.5 ± 2.5 cm). This threshold was characterised by measurable increases in both locomotive activity and ingestion behaviours. The incorporation of RTK correction technology significantly enhanced positional accuracy, facilitating precise spatial analysis of grazing patterns within grid cells $< 1m^2$. This advancement allowed for detailed correlation of animal movement and behaviour data with concurrent vegetation measurements and environmental parameters.

These technological developments expand the practical applications of PLF in modern livestock management. Beyond future applications such as developing behaviour-based pasture quality indicators or optimizing rotational grazing schedules, the methodology shows promise for investigating less conventional systems including silvopastoral arrangements, mixed-species grazing scenarios or night grazing activities, for which empirical behavioural data remain limited. Finally, while PLF technologies show strong potential for sustainable pasture management, their adoption must be guided by clear ethical, legal, and ecological frameworks to ensure they support long-term environmental stewardship alongside productive agriculture.

Keywords: Grassland, precision livestock farming, sensors, inertial measurement unit, cattle, behaviours, grazing, agroecology.

Résumé

Au cours des dernières décennies, les paysages agricoles ont été profondément affectés par un processus d'intensification. Les systèmes mixtes cultures-élevage ont été remplacés par des monocultures spécialisées et des zones de production animale intensive, conduisant à une simplification des paysages. La taille des troupeaux a considérablement augmenté pour répondre à la demande croissante en produits animaux. Cette intensification a entraîné une dégradation des ressources naturelles. Ces problématiques sensibilisent les consommateurs et poussent les exploitations agricoles à concilier productivité et durabilité. Bien que des progrès soient réalisés, tels que l'adoption de pratiques agroécologiques, la réduction de certains usages de pesticides, et les avancées en agriculture de précision, ces efforts restent insuffisants. Des solutions innovantes et systémiques sont encore nécessaires pour relever l'ensemble des défis environnementaux et sociaux liés à l'agriculture. Les prairies émergent comme un élément clé de cette transition. En valorisant l'herbe, une ressource renouvelable, elles soutiennent les services écosystémiques, la séquestration du carbone et les économies locales. Une approche agroécologique des systèmes d'élevage consiste à adapter les pratiques aux contextes locaux, en optimisant la distribution du bétail selon les ressources disponibles afin d'équilibrer bénéfices économiques et écologiques. Une ressource locale clé est donc la prairie, et la gestion des systèmes herbagés nécessite une bonne compréhension de la complexité des relations plante-animal. L'élevage de précision (*Precision Livestock Farming*, PLF) offre des outils prometteurs pour relever le défi du suivi de ces interactions.

Cette thèse explore le potentiel de la PLF pour améliorer la gestion des pâturages grâce à la surveillance automatisée et à haute résolution du comportement de pâturage. Un système portable personnalisé a été développé, intégrant un système global de navigation par satellite (*Global Navigation Satellite System,* GNSS) corrigé en temps réel par cinématique (*Real Time Kinematics,* RTK) et un accéléromètre triaxial échantillonnant à 8 Hz. Grâce à un modèle d'apprentissage automatique (Machine Learning, ML) en deux étapes, le comportement d'ingestion a été classifié avec une précision de 98.9 %, un rappel (*recall*) de 99.1 % et une exactitude de 98.2 %. La quantification des bouchées a atteint une erreur quadratique moyenne (*Root Mean Square Error*, RMSE) moyenne de 3.19 ± 0.41 bouchées par fenêtre de 10 secondes, avec une erreur de prédiction de 15.3 %. Le modèle a également identifié avec précision les stations d'alimentation (94.7 %) et les repas (91.9 %), et les a spatialisés dans des grilles avec des compartiments de moins de 1 m^2. L'analyse continue des schémas de pâturage a révélé un seuil comportemental se produisant lorsque les vaches Holstein avaient consommé environ 41 % de la hauteur de couvert pré-pâturage (SH) (12.5 ± 2.5 cm). Ce seuil se caractérisait par une augmentation mesurable de l'activité locomotrice et des comportements d'ingestion. L'intégration de la correction RTK a significativement amélioré la précision de position, facilitant une analyse spatiale précise des schémas de pâturage au sein de cellules de grille

inférieures à 1 m². Cette avancée a permis de corréler en détail les données de mouvement et de comportement animal avec des mesures concomitantes de végétation et des paramètres environnementaux.

Ces développements technologiques étendent les applications pratiques de la PLF dans la gestion moderne de l'élevage. Au-delà d'applications futures telles que le développement d'indicateurs de qualité de pâturage basés sur le comportement ou l'optimisation des calendriers de pâturage tournant, la méthodologie montre un fort potentiel pour étudier des systèmes moins conventionnels, notamment les dispositifs sylvopastoraux, les scénarios de pâturage multi-espèces ou les activités de pâturage nocturne, pour lesquels les données comportementales empiriques restent limitées. Enfin, bien que les technologies PLF présentent un fort potentiel pour une gestion durable des pâturages, leur adoption doit être guidée par des cadres éthiques, juridiques et écologiques clairs afin de garantir qu'elles soutiennent la gestion environnementale à long terme en parallèle d'une agriculture productive.

Mots-clés: Prairie, élevage de précision, capteurs, centrale inertielle, bovins, comportements, pâturage, agroécologie.

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List of acronyms

AG: After Grazing

ASM: Angular Second Moment

BG: Before Grazing

BT: Bagged Tree

CSH: Compressed Sward height

CSV: Comma Separated Values

DBA: Dynamic Body Acceleration

DM: Dry Matter

DMI: Dry Matter Intake

DST: Decision Support Tool

ECPLF: European Conference for Precision Livestock Farming

ESML: Supervised Ensemble Machine Learning

FA: Forage Allowance

FAO: Food and Agriculture Organization of the United Nations

FM: Forage Mass

FFT: Fast Fourier Transform

FS: Feeding Station

GD: Grazing Down

GLCM: Grey Level Co-occurrence Matrices

GNSS: Global Navigation Satellite System

GPS: Global Positioning System

ICLS: Integrated Crop Livestock Systems

IMU: Inertial Measurement Unit

KNN: *k*-nearest neighbours

LMM: Linear Mixed Model

LOAO: Leave-one-animal-out cross-validation

LOVO: Leave-one-video-out cross-validation

LW: Live weight

ML: Machine Learning

NDVI: Normalized difference vegetation index

OBDA: Overall Body Dynamic Acceleration

PLF: Precision Livestock Farming

RFID: Radio Frequency Identification

RMSE: Root Mean Square Error

RTK: Real-time Kinematics positioning

SH: Sward height

SR: Stocking Rate

STIB: Short Term Ingestion Behaviour

SVM: Support Vector Machine

UAV: Unmanned Aerial Vehicle / drone

UWB: Ultra-Wideband system

VeDBA: Vectorial Dynamic Body Acceleration

Chapter 1

General introduction

1. Context

1.1. Livestock farming in the context of agricultural intensification

Over the past century, agriculture and agricultural landscapes have undergone a significant intensification process. This intensification has led to widespread depletion of natural resources, including challenges related to water accessibility and quality, soil health, biodiversity loss, climate change, greenhouse gas (GHG) emissions, animal welfare, and ethical concerns about livestock farming (Kumar, 2022; O'Grady et al., 2024). Now, the necessity of a global shift towards more sustainable livestock farming has become a major concern (Fraser et al., 2022) and consumer awareness of these issues has amplified public concerns about the environment and animal welfare.

In Western Europe, mixed crop-livestock systems have largely given way to uniform landscapes dominated by specialized cropping systems and concentrated zones of intensive livestock production (Carvalho et al., 2021). Herd sizes have expanded considerably to meet the growing global demand for animal-based products (Kumar, 2022; Papakonstantinou, 2024). Among the popular livestock breeds, high-yield dairy cows have become the dominating animals. With their high nutritional needs requiring supplementation since pasture grass alone cannot support their full productive potential, they have led to a major shift in the role of grasslands in dairy farming (Poux and Aubert, 2018). Consequently, dairy farms face a dual challenge: enhancing efficiency while transitioning to more sustainable agricultural systems (Carvalho et al., 2021; Bianchi et al., 2022; Papakonstantinou, 2024). Despite progress in recent decades, significant improvements are still needed, calling for the development of innovative solutions (Kumar et al., 2022).

Grasslands are integral components of such solutions, as they represent one of the most sustainable resources (grass), present lower environmental risks compared to intensive systems, and provide numerous ecosystem services (Harmon et al., 2023). Additionally, they play a crucial role in supporting local economies (Niu et al., 2025) and are key to increased carbon sequestration, covering approximately 28% of the world's land area and holding more carbon than global forests (Pergola et al., 2024). While grazing, fertilisation, mowing, and burning practices significantly influence GHG emissions of grasslands, a meta-analysis covering 40 years found that light and moderate grazing had minimal impacts on CO2 emissions (Cao et al., 2025). Strategies such as supplementing livestock with high-sugar feeds, reducing fertilisation levels, and limiting grassland burning could further curb GHG emissions (Cao et al., 2025). Animal products contribute approximately 15% of global per capita calorie supply and 31% of protein supply, and around 30% of global ruminant meat and 6% of milk production comes from grazing systems, often located on land unsuitable for cropping (Godde et al., 2021). The entire livestock sector provides income to part of the 844 million people working in agriculture and accounts for about

40% of agricultural added value (Godde et al., 2021). In countries like France and Belgium, cattle grazing in outdoor pastures ranges from 50% to over 90% of the herds, depending on the administrative areas (FAO, 2023; Malek et al., 2024; UNFCCC, 2024). Globally, grazed grasslands constitute vital components of our food systems (Cao et al., 2025), covering a significant share of the world's exploitable land mass and providing a multitude of services. These services include the provision of food (meat and milk) at reduced costs, as the animals collect the forage themselves, along with the regulation of the water cycle, carbon storage, and support for biodiversity, including habitat provision for wildlife and organisms that contribute to the functioning and sustainability of agroecosystems (Duru et al., 2019, Richter et al., 2021). Moreover, grasslands lie at the heart of both the most criticized and the most sensitive livestock farming systems (Sollenberger et al., 2019). As intensive systems face significant public scrutiny, there is a societal inclination towards grassland-based systems, perceived as ensuring quality, enhancing livestock production, and upholding animal welfare standards. Given the pivotal role of grazed systems in food production, social perception, and ecosystemic service provision, a better understanding of their functioning is a crucial aspect of livestock production.

1.2. An agroecological approach

Agroecology is a science and a set of practices that aims at reducing the ecological footprint of agricultural systems while enhancing resilience. Applied to livestock farming, agroecology emphasizes adapting systems to local social, economic, and environmental contexts rather than promoting one-size-fits-all solutions (Jouven et al., 2022; Lv et al., 2024; Niu et al., 2025, van der Ploeg et al., 2019). This approach involves optimizing livestock distribution according to available resources to balance economic and ecological benefits, reducing dependence on external inputs, promoting self-sufficiency, diversifying production, for example, through integrated crop–livestock systems (ICLS) and fostering synergies between ecosystem services (Bonaudo et al., 2014; Cao et al., 2024; Jouven et al., 2022). For example, optimizing grazing in areas with high aboveground net primary productivity and protecting those with significant belowground productivity, due to their substantial contribution to the soil carbon pool, could foster sustainable grassland use (Cao et al., 2024). Agroecology emphasizes the adaptation of agricultural systems to local ecological, social, and economic contexts. It values biodiversity, resource efficiency, animal welfare, and ecosystem resilience (Van der Ploeg et al., 2019). In grazing systems, this means managing livestock in ways that allows grazing to take place when pastures reach their optimal resting period (Filho et al., 2021). These practices lead to increased soil C uptake and soil health, boost water retention, and protect water quality (Filho et al., 2021). Agroecological practices prioritize observation, feedback loops, and adaptive management rather than standardized, intensive control.

While promoting more ethical and sustainable practices may initially reduce short-term profits, such as the widespread ban on antibiotic use in livestock farming (Tullo et al., 2019), the ultimate goal is to optimize animal welfare and farm profitability

(Chelotti et al., 2024). Agroecological systems often yield higher incomes than conventional farms, producing healthier food, creating more jobs per hectare, consuming fewer fossil fuels, and contributing to the preservation of scenic landscapes and biodiversity (van der Ploeg et al., 2019). On the other hand, inappropriate grazing regimes degrade natural capital, reducing productivity and increasing costs due to heightened input requirements or the need for pasture rehabilitation (O'Grady et al., 2024). These challenges are not merely technical but are embedded in socio-political and economic contexts. Agroecological transitions must be accompanied by shifts in education, governance, market structures, and cultural norms, reflecting the interconnection between knowledge systems, biodiversity, resource use, food and health, social relations (Wezel et al., 2014). This includes the place of technologies in our society.

1.3. The importance of animal behaviour in grazing

Grassland-based systems are livestock farming systems where animals primarily graze on natural or managed grasslands for their nutrition, rather than being fed high levels of concentrate or grain-based feeds. Such systems not only include dairy and beef grassland-based systems, but the concepts relating to grazing management are more general as they can apply to other systems, as long as a grazing herbivore is involved, such as mixed crop-livestock systems, integrated crop-livestock systems, silvopastoral systems, etc. Temperate lowland grazing-based dairy systems, more specifically, play a crucial role in future food systems, especially within Europe, where improving their efficiency is seen as a key strategy for developing future-proof agroecology-based agriculture in Europe (Poux and Aubert, 2018).

Adopting such systems implies numerous challenges for the farmer, such as good management of the resources, to maintain a good production while avoiding environmental degradation, and accepting a lower productivity and outputs (milk or meat) that are often lower than in intensive systems. They will also be confronted with climate vulnerability and face a disconnection of the policy concerning the valuable ecosystemic services provided by the pasture, which are not compensated by the market (Delaby et al., 2020).

Managing grassland-based systems means for the farmer having a good overview of the grazing calendar, to bring the animals into the pastures at the right time, finding trade-offs to avoid overgrazing while maintaining good resource utilization and good productivity. Therefore, several levers can be applied. These levers imply deciding which forages to use in the case of artificial grasslands, selecting which paddocks are to be grazed and which ones are to be mowed for forage preservation and determining the exploitation calendar. For grazed pastures, it is also important to decide on the setting of a stocking rate and whether paddocks will be continuously grazed or not. In the case of rotational grazing, the setting of grazing targets, occupation times, resting periods are crucial for preserving the good condition of the vegetation and the soil. Moreover, it is also critical from the animal's perspective as recent works (Carvalho, 2013) have demonstrated the crucial role of sward structure in the efficiency of the harvesting process by the animal, the quality of what is consumed and the secondary productivity (Zubieta et al., 2021) as well as some externalities of grass-based systems (Savian et al., 2021). This highlights the fact that understanding the animal behaviour is central to both advancing behavioural science and informing sustainable grazing systems. While grazing management remains a long-term application, the primary contribution of this work lies in improving our understanding of grazing behaviour itself. This understanding requires focusing on the plant-animal interface, where grazing behaviour is directly shaped by sward structure and availability.

Indeed, the relationship between the structure of the grass and the grazing behaviour of herbivores should be a critical parameter (Fonseca et al., 2012; Mezzalira et al., 2014), to be considered by farmers when adjusting their targets for letting animals enter and leave paddocks (Schons et al., 2021; Jordon et al., 2022). Herbivores continuously sense the ever-changing grazing environment to adapt their decisions. Short-term decisions made at the level of each individual bite have consequences for the efficiency of the grazing process, herbivore performance, and grassland health. Hence, one of the main focuses in the development of any type of sustainable grazing management strategy is to find the right balance between the severity and frequency of defoliation, to allow on the one hand a good regrowth of the plant and accumulation of biomass before the next grazing event and, on the other hand, the ease with which domestic herbivores can graze and take bites. Finally, herbivores are not only consumers of forage. They actively shape grassland dynamics by continuously adjusting their foraging strategies in response to environmental stimuli such as sward structure, forage quality, and spatial heterogeneity. These micro-scale decisions, down to the level of individual bites (Andriamandroso et al., 2016), directly influence not only short-term intake and long-term animal performance but also the regenerative capacity and ecological balance of pastures.

Providing an ideal grazing environment for the herbivore requires to focus on what happens at the interface between the plant and the animal. Bite rate in grazing animals shows a dome-shaped functional response to grass structure (Figure 1-1), especially sward height, with intake efficiency peaking at a sward height that is specific to the forage species (Mezzalira et al., 2017). Since animals have a limited capacity to adjust grazing time to compensate for non-optimal grass conditions, diverting from this optimal point results in an increase in grazing times for animals to fulfil their dietary requirements and a possible underuse or overgrazing, compromising pasture health (Rombach et al., 2022). Alterations of the dynamics at the bite level reflect also at higher spatio-temporal scales such as the total daily grazing time, meal duration, time spent on feeding stations and the movements of animals during these different instances. Feeding stations are described as specific spots where an animal stops moving its legs to take several consecutive bites (Andriamandroso et al., 2016). A series of these feeding stations makes up a grazing bout, which usually spans a few square meters and lasts between 10 and 100 seconds (Andriamandroso et al., 2016).

A rise in the number of feeding stations for the same bite frequency would mean that the cow is changing locations more often during the grazing process in order to find the grass she wants to graze.

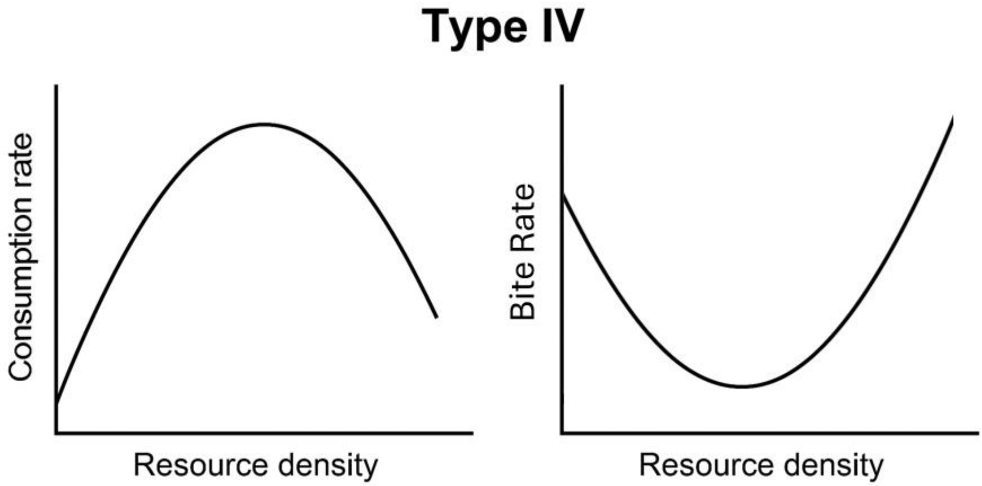

Figure 1-1: Simplified representation of a Type IV dome-shaped functional response of ruminants to grass density from Mezzalira et al. (2017).

Bite frequency, jaw movements, and movement patterns provide insights into short-term intake rates, making them essential indicators for animal health and productivity (Mezzalira et al., 2017; Gibb et al., 1997; Rombach et al., 2022). Historically, such behaviours have been studied through direct observation, often limited to daylight hours and short timeframes. This traditional approach captures only a fraction of the grazing process, overlooking important periods such as nocturnal grazing, which can be significant during warm seasons.

Such high-resolution monitoring opens the door to a more complete understanding of the determinants of both qualitative and quantitative intake, something that until now has largely relied on indirect indicators or incomplete data. By focusing on individual behaviour rather than group averages, it also becomes possible to detect subtle behavioural shifts that signal changes in environmental conditions or animal health: often early indicators of stress, illness, or environmental discomfort, they can be detected using PLF technologies (Berckmans, 2017; Thomas et al., 2024). Group-level measurements can mask these individual deviations, particularly when animals differ substantially in their baseline behaviours. Accounting for individual variability is therefore essential, not only to improve detection accuracy but also to enable truly individualized management. Animals exhibit consistent differences in behaviour, referred to as behavioural types, as well as differences in how variable their behaviour is over time, a trait known as behavioural predictability (Thomas et al., 2024). Capturing these individual-level dynamics requires high-resolution data collected over extended periods, which is now feasible through wearable sensor technologies.

The methodological advances introduced in this study, through the combination of several PLF technologies, represent a transformative shift. These tools allow researchers to capture these fine-scale foraging behaviours with unprecedented accuracy. These tools enable a more detailed understanding of how grazing animals interact with their environment, shedding light on the processes behind bite selection, movement patterns, and resource use at infra-meter-scales. Such insights are crucial for developing grazing strategies that align animal needs with ecosystem resilience, contributing to both animal welfare and sustainable pasture management.

1.4. Agroecology and PLF

Agroecology and PLF technologies might seem, at first glance, like opposing paradigms: one rooted in holistic, often low-input systems, the other in data-driven, high-tech solutions. But agroecological grazing systems demand careful control of stocking rates and rotation to prevent overgrazing, soil degradation, or the loss of biodiversity. However, undergrazing can be equally problematic, allowing unpalatable species to dominate and altering successional dynamics. Agroecology requires navigating this delicate equilibrium, especially in variable environments where plant recovery rates and animal foraging behaviours are difficult to predict without detailed monitoring.

PLF technologies can complement agroecological principles by offering fine-grained, real-time insights into animal behaviour and environmental conditions. Behavioural monitoring (e.g., via accelerometers and Inertial Measurement Units (IMU)) allows farmers to understand how animals interact with their grazing environment: when, where, and how they forage (Andriamandroso et al., 2016).

Rather than viewing agroecology and PLF as opposing paradigms, one rooted in holistic, low-input systems, the other in high-tech, data-intensive methods, this thesis explores their potential convergence. Used judiciously, PLF can enhance farmers' observational capacity and enable more adaptive, ecologically grounded decision-making.

According to Wezel et al. (2014), agroecology can be applied to herbivore farming systems through six key principles: knowledge, culture and socio-economics; biodiversity conservation and management; resource management; system management; food and health; and social relations. A list of the positive and negative impacts that PLF technologies are bringing to those six principles is described in Figure 1-2.

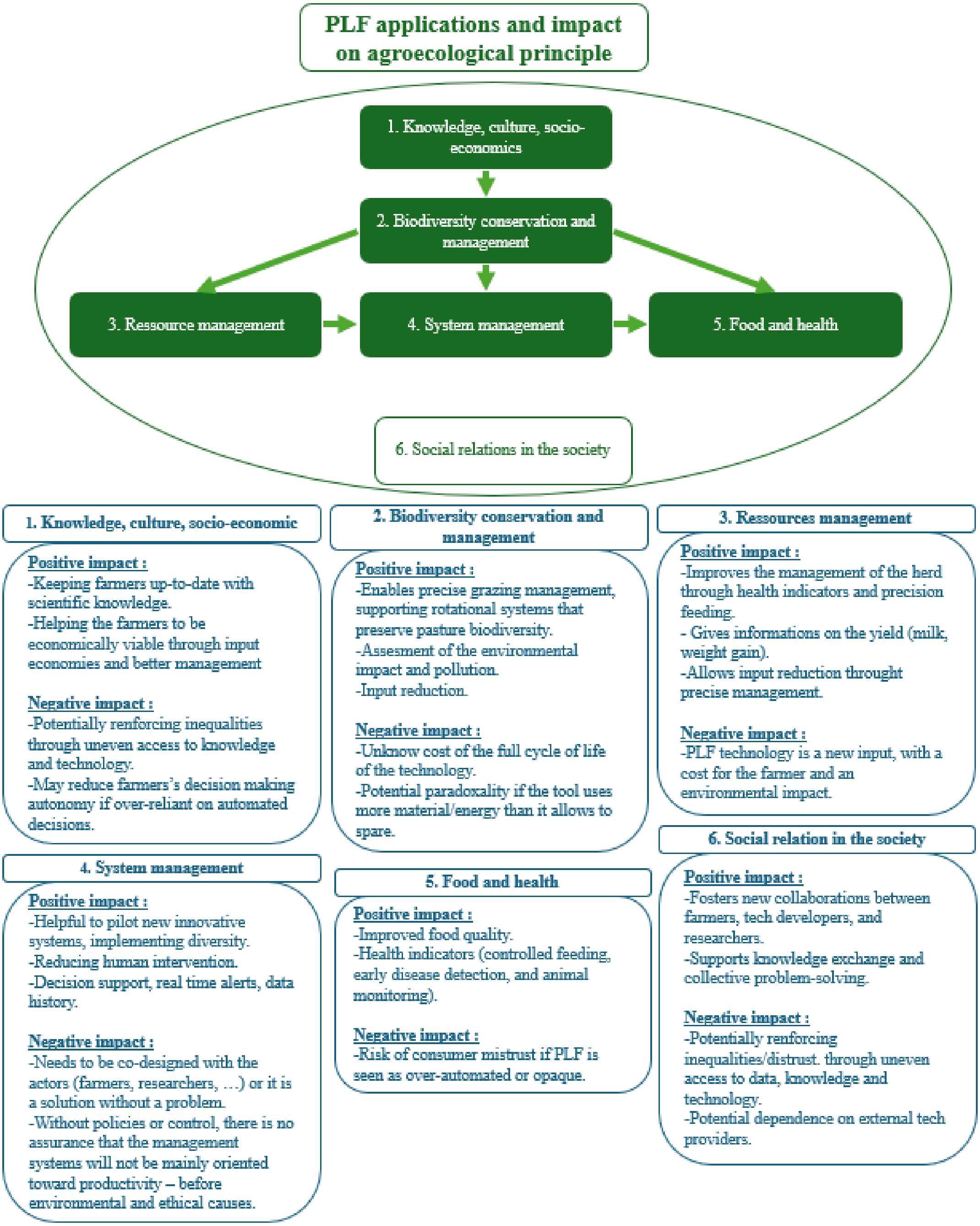

Figure 1-2: PLF applications and impact on the 6 agroecological principle proposed by Wezel et al. (2014).

For example, accelerometers, IMU, and GNSS tools enable real-time monitoring of behavioural data that offer detailed insights into how animals interact with their environment under various sward structures and climatic conditions (Aquilani et al., 2022; Mao et al., 2023). They can reveal early signs of nutritional deficits, environmental stress, or system imbalances, supporting biodiversity conservation, resources and systems management.

Concerning resources management, PLF tools may also reduce dependence on delayed or indirect indicators (e.g., milk yield, weigh gain), offering a pathway for managing grazing in real time based on animal behaviour. They can assist in aligning grazing pressure with carrying capacity, reducing unnecessary inputs, and reinforcing animal-centric, ecologically informed practices. Some researchers even propose using behavioural monitoring data for participatory research or as the basis for welfare and ecological certification systems (Chelotti et al., 2024). To that extent, spatial tracking (e.g., with GNSS) makes it possible to study grazing patterns, revealing how animals select patches or respond to heterogeneity (Arablouei et al., 2023; Brennan et al., 2021). Vegetation monitoring (e.g., through unmanned aerial vehicles or UAV and remote sensing) supports non-invasive biomass assessments, helping to align grazing pressure with ecological carrying capacity (Maake et al., 2023; Monsalve et al., 2023).

However, PLF has a social impact that must be weighed against significant risks and limitations. The high cost and complexity of PLF tools often restrict their accessibility, particularly for small-scale or low-resource farms (Papakonstantinou, 2024; Parra-Lopez et al., 2024). Adoption also depends on training, infrastructure, and digital literacy, which are unevenly distributed. Ethical and legal concerns, including data ownership, privacy, and cybersecurity, are also growing, particularly in the absence of regulatory frameworks (Chelotti et al., 2024; Alahe et al., 2024). There is also the risk of co-optation: that PLF will serve to intensify production and reinforce industrial models, rather than support ecological complexity and animal well-being. Moreover, the environmental footprint of PLF, linked to material extraction, energy consumption and electronic waste, is rarely assessed and may conflict with the sustainability goals of agroecology (Parra-Lopez et al., 2024; Tullo et al., 2019).

While some technologies may detect early welfare issues, such as changes in lying or drinking times (Mao et al., 2023), their overall effectiveness in improving welfare or reducing environmental impact remains contested (Bianchi et al., 2022). The increasing reliance on high-frequency, individualized data introduces new vulnerabilities related to surveillance, loss of farmer autonomy, and cyber risk. Without strong legal safeguards and farmer-led governance, PLF may privilege productivity and control over ethics and ecological health (Papakonstantinou, 2024). Therefore, PLF should not be seen as an end in itself but as a tool whose value depends on its integration into a broader agroecological framework. Its design, use, and governance must be shaped by the principles of knowledge sharing, biodiversity conservation, responsible resource management, and social equity.

Despite these strict instructions, technological innovation, when carefully aligned with agroecological principles, may offer tools to address some of the challenges modern agriculture has to face. PLF technologies represent one such possibility.

1.5. The farmer, at the center of the system

In the end, as illustrated on Figure 1-3, the farmer is the central actor in grassland-based livestock systems. Their agency and decision-making capacity are explored, as well as how they see, use and adopt new approaches and tools, ranging from agroecological practices to PLF technologies, based on their specific socio-technical contexts.

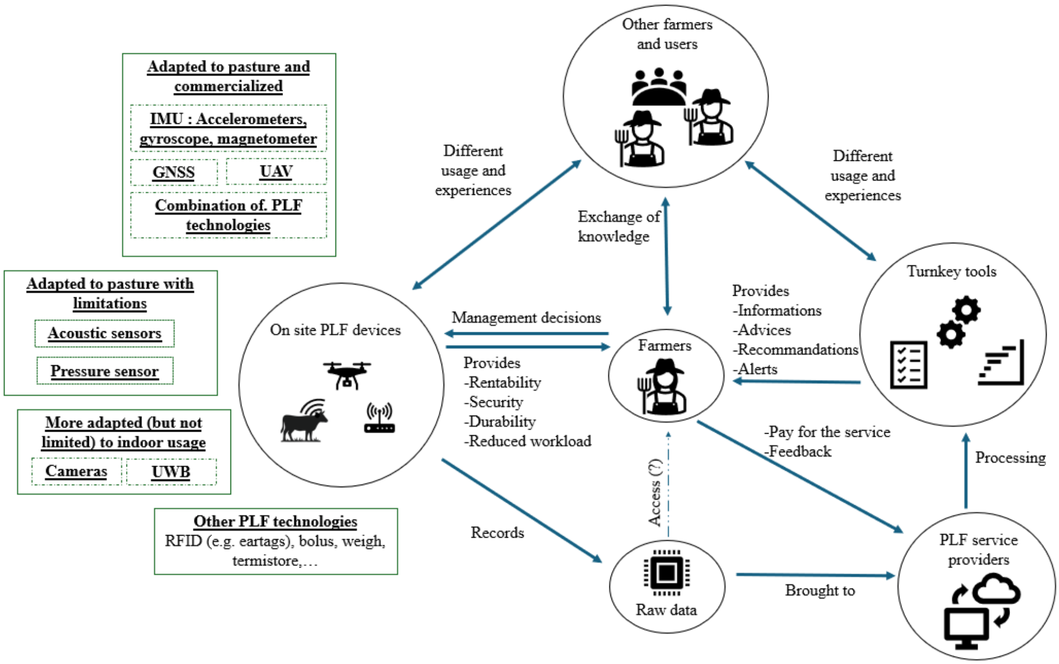

Figure 1-3: Diagram of the place of the farmers towards the other actors and component of grassland PLF tools.

Farmers occupy a pivotal role in grassland systems, not only as managers of animals and pastures but also as key decision-makers shaping the ecological, economic, and social dimensions of their farms (Krampe et al., 2024; Selvaggi et al., 2024; Tindale et al., 2024). Their knowledge, values, and practices influence pasture maintenance, animal health management, and the way innovations are adopted and adapted to local conditions (Krampe et al., 2024). Rather than being passive recipients of technical advice, farmers actively navigate constraints and opportunities, often blending traditional know-how with emerging technologies (Selvaggi et al., 2024). Recognizing this diversity and autonomy is essential for designing sustainable systems that align with both environmental objectives and farming realities.

Each farmer develops a unique management strategy shaped by personal goals, risk perception, climate, learning style, and farm structure. These strategies are influenced by factors such as pedoclimatic conditions, professional networks, and knowledge exchanges with peers and stakeholders (Petit et al., 2022). Given the diversity in farming systems, whether intensive, extensive, or organic, their responses to new technologies vary widely. This heterogeneity makes one-size-fits-all solutions ineffective (Jouven et al., 2022). Instead, effective support for farmers requires more than just technical tools. It needs to respond to their specific objectives and perceptions. A survey of French farmers found that the primary indicator of a “good grassland” was species diversity, both floral and forage, followed by productivity (Di Blasi et al., 2023). Similarly, when describing what makes a “healthy animal,” farmers highlighted normal feeding behaviour (i.e., no feeding problems and proper rumination) ranking it just behind general condition and appearance, and on par with productivity. At a broader level, the maintenance of grasslands is increasingly tied to their capacity to meet both farm-level and regional expectations, whether environmental, agronomic, or economic (Petit et al., 2022). This illustrates how closely health, ecology, economy and pasture management are interlinked in the eyes of farmers. Finally, a study by Krampe et al. (2024) involving dairy and pig farmers in Finland, the Netherlands, and Spain showed that the top concern of farmers concerning PLF was data governance: specifically, who controls their data. This was followed by interest in early-warning systems and data-sharing options for innovation and certification. Data ownership and transparency have thus become central to farmer acceptance of PLF tools.

As seen in the previous section (1.4.), the adoption of PLF technologies presents both challenges and opportunities. The farmer's role now extends beyond the animal-pasture relationship to include interactions with technology providers, market actors, certification bodies, and other farmers. Indeed, technical tools alone are insufficient; broader support integrating agronomic, environmental, and social dimensions is required. The literature emphasizes that to support the adoption of PLF and other innovations, participatory governance structures are needed, alongside clear evidence of technical, economic, and personal benefits (Hammes et al., 2016; Krampe et al., 2024; Petit et al., 2022; Selvaggi et al., 2024). Multi-actor networks, built on existing or newly developed regional platforms, can align innovation with the foundational goals of agroecology: resilience through ethical, profitable, and environmentally responsible practices.

2. Objectives and research questions

The main objective of this thesis is to explore the potential of PLF techniques and tools to document the grazing behaviour of herbivores at the finest spatio-temporal scale to enable reactive pasture management based on the understanding of plant-animal interactions. By implementing methods for monitoring the grazing strategy of each individual through the use of PLF technologies as well as the evolution of the grass in relation to these behaviours.

Using cattle as an animal model and rotational grazing as a vegetation management strategy, the four research questions that were defined as part of this work are:

1. what sensors and techniques are most suitable for monitoring the behaviour of ruminants in grasslands under rotational grazing strategies?
2. what are the main differences in grazing behaviour in response to different grassland structures (biting frequency, travelled distance, movement speed, time per FS, etc.) that these sensors and techniques allow us to observe?
3. what methodological framework should be used to develop an efficient model for observing the evolution of both animal behaviour and SH and heterogeneity?
4. can observation of animal behaviour and location derived from IMU/GNSS sensors be used to detect in advance changes in grazing patterns as markers of increasing difficulty in collecting forage during grazing, at the individual and herd level?

3. Research Strategy

2.1. PLF technologies selected to monitor the plant-animal interface

To answer these research questions, it appeared necessary to use sensors that exceed human performance in terms of precision and continuity of data collection. It was therefore necessary to first analyse the different PLF tools and techniques used for monitoring the plant-animal interface on pasture. Among the available technologies (Aquilani et al., 2022), three seemed usable jointly to achieve the objectives stated above:

(1) accelerometers and IMU offer promising avenues for monitoring grazing behaviour with practicality and good sensing performance (Pavlovic et al., 2021; Aquilani et al., 2022). These tools have been proven to detect grazing, rumination, or idling behaviours with accuracy and, on average, 91% correct classification (Andriamandroso et al., 2017), facilitating a deeper understanding of animal grazing dynamics. They have not yet been commonly used to monitor the bite frequency, the

atom of grass consumption by the animal (Andriamandroso et al., 2016). A level of precision that needs to be accomplished, as explained in Chapter 3.

(2) GNSS offer valuable insights into animal movements but often lack the precision required to understand grazing decisions at the bite and FS scales. RTK technology has emerged as a solution, providing centimetric precision in monitoring grazing herbivores. While plant productivity and intake rate depend on local sward characteristics at small scales, most grazing studies use average sward characteristics over larger extents, overlooking spatial heterogeneity in the grazing process (Andriamandroso et al., 2017). Combining bite-scale ingestion behaviour with precise spatialization offers a nuanced understanding of grazing dynamics. While GNSS are commonly used for free-ranging animals (Bailey et al., 2018; Plaza et al., 2022; McIntosh et al., 2022), their spatial accuracy is insufficient for smaller paddocks and detailed documentation of grass-severing bites, which occur at scales of several cm^2.

(3) Unmanned aerial vehicles (UAV), even though not strictly considered PLF technologies (Berckmans, 2017), have emerged as valuable vegetation-monitoring tools for assessing pasture biomass and chemical composition, offering non-destructive and less time-consuming alternatives to traditional field measurement methods (Michez et al., 2020). Remote sensing techniques, such as the Normalized Difference Vegetation Index (NDVI), further contribute to vegetation monitoring by providing indicators of standing biomass and crop phenology (Defalque et al., 2024, Monsalve et al., 2023).

To push forward a more efficient use of those technologies and turn it into sensible data usable by both researchers and farmers, it was necessary to explore the concrete information they can give and define what methodology to use to reach those objectives.

2.2. Structured Step-by-Step Strategy

Already existing and recent meta-analyses were reviewed in the section “1. Context” of Chapter 1. This analysis directed, on the one hand, towards the use of UAVs to characterize the distribution of grass and the available biomass present on the plot (Chapter 2). The importance and potential of these techniques for characterizing heterogeneity were presented during 10th European Conference on PLF (ECPLF 2022, Vienna, Austria). On the other hand, concerning the animal side, research has focused on the development of both behavioural sensors (IMU) and positioning (GNSS) with a correction greater than those usually found in research (RTK correction).

The first step in this research was the development and validation of a ML model that could identify the periods of ingestion and quantify the number of bites taken by the animal in order to meet the precision challenges required for the sensors (Chapter

3). It presents a model developed for an initial prototype using an iPhone 4 as the sensing unit, recording IMU data only, at a frequency of 100 Hz. It has been published in the journal Smart Technologies in Agriculture in 2024.

Once the model's performances were validated, the second step was to develop and test prototypes of collars combining these two sensors. To our knowledge, such sensors do not yet have standard commercial versions, a self-made prototype was built. After a pilot test, two field experiments using the implemented prototype took place, in parallel with frequent and regular measurements of the evolution of vegetation in the field. Chapters 4 to 6 took focus on that final prototype, which combines an IMU sensor with a GNSS sensor corrected by RTK technology, recording data at a frequency of 8 Hz. Due to changes in hardware and sensor configuration between these stages, it was necessary to repeat the feature selection and model training processes rather than reuse earlier models. Preliminary exploration was conducted to assess whether applying the previously developed model would yield satisfactory results with the new sensor. While the results showed some consistency, the differences in sensor characteristics ultimately required a complete redevelopment of the modelling approach. Although this iterative work is described in less detail in the later chapters, since the methodologies are quite similar, it was essential to develop a model adapted to the new characteristics of the prototype.

The first field experiment consisted in a series of short-term grazing sessions on different average grass heights investigated the spatial dimension of detecting ruminant behaviour (Chapter 4). The developed method and the results were presented at the 11th European Conference on PLF (ECPLF 2024, Bologna, Italy). Then, the second experiment, focused on the "Grazing Down" (GD) process (process during which the pasture is grazed continuously until it reaches a determined SH, here the limit was 3 cm), explored the changes in animal behaviour and their motions to identify the "FS", i.e., locations where the animal stops moving to take several consecutive bites, and how they change with a decreasing grass availability (Chapter 5). This article has been submitted to Biosystems Engineering. This methodology made it possible to evaluate among the observable parameters whether or not it was possible to observe critical thresholds in animal behaviour during the gradual decline of available grassland, reflecting discomfort on the part of the animal and a need to bring the animals to the next pasture (Chapter 6). This article will be submitted to Biosystems Engineering and is currently under review. Finally, Chapter 7 discusses the originality of the device, its domain of validity, and its concrete potential for application, both in research settings and, in the long term, within Decision support tools (DST). The chapter also addresses the device's sustainability implications and outlines necessary future improvements, offering guidelines and exploring how it could contribute to other fields of research.

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Chapter 2

Assessing the heterogeneity of grazing through remote sensing

This study begins with the analysis of the concept of SH heterogeneity, introducing the use of UAV to assess the spatial distribution of grass and the available biomass on a grazed paddock. The reason for opening the work with this UAV-based approach lies in the ability of this technology to highlight grazing heterogeneity, which is important to understand the complexity of plant-animal interactions in pasture systems. While a prototype sensor used to quantify animal bites is the main technology presented in the thesis, it is through the UAV perspective that the need for data spatialization becomes evident, as it allows for a parallel analysis: the spatial and temporal evolution of the grass sward via UAV, and the corresponding behavioural impacts and adaptations of grazing animals, captured through on-animal sensors. The results presented in this chapter were previously published in a peer-reviewed conference proceeding and presented during *10th European Conference on PLF* (ECPLF 2022, Vienna, Austria). The content has since been adapted to better align with the format of the manuscript. Please note that, while the work underwent scientific review, the process may have involved a lower degree of scrutiny than that typically applied in full-length journal articles.

Heterogeneity of sheep grazing a cover crop as measured using remotely sensed vegetation indices

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Abstract

Integrated crop and livestock systems (ICLS) that rely on grazing of cover crops to control weed infestation and cover development deal with heterogeneous effects of grazing in space and time, as opposed to chemical or mechanical destruction. This heterogeneity affects grazing management, and a method is proposed to evaluate its evolution using remotely sensed vegetation indices. The study was performed on the ECOFOODSYSTEM platform of AgricultureIsLife in Gembloux (University of Liège, Belgium) on four experimental fields of 0.15 ha each, sown with multispecies cover crop composed of oat, phacelia and two clover varieties. The four fields were grazed consecutively by ewes over 7-day periods from February to March 2021. UAVs equipped with a multispectral camera were flown before and after the passage of the sheep on each field. NDVI and grey level co-occurrence matrices (GLCM) were used to calculate the Angular Second Moment (ASM) to measure the local homogeneity of the grazing intensity within 5x5m² windows, with values ranging between 0 and 1. Results show distinct patches of homogenous and heterogenous grazing on each field and strong differences in the heterogeneity in grazing between the fields. In future works, the level of heterogeneity in grazing could be crossed with data from portable sensors to allow a better management of animals when they are used as an agroecological lever to control cover crops in ICLS.

Keywords: pasture heterogeneity, grazing, multispectral camera, ICLS

1. Introduction

ICLS are farming systems in which animals are present on agricultural fields at a given moment within the crop rotation. If correctly managed, such systems allow to benefit from advantages linked to the presence of animals such as diminished needs of fertilisers or complementary feed, profitability of cover crops that are of no use usually and improvement of nutrients cycles (Lemaire et al., 2014).

The grazing of cover crops by ruminants in ICLS implies that the biomass will be destroyed by repetitive defoliation and trampling of the animals. Heterogeneity of the vegetation height and biomass after the grazing session is a factor of importance in grazing management and especially in ICLS. It has been observed in ICLS conditions that a homogenous vegetation after grazing can be a sign of intensive grazing and sometimes overgrazing (Nunes et al., 2019). The latter is something that farmers want to avoid: the grazing target in ICLS being to effectively destroy the cover crop without having an animal experiencing excessive hunger or damaging the ability of the field to produce biomass. It has been also shown that heterogeneity can be managed by adapting the stocking method on the field and is a parameter that must be integrated in future grazing management planning (Pontes-Prates et al., 2020).

The use of UAVs for the assessment of pastures biomass and/or chemical composition is a verified practice in the field of PLF with a great potential to assess plant-animal interactions and spatial heterogeneity of pastoral systems (Michez et al., 2020). It has also the advantage of being non-destructive and less time-consuming than usual field measurement methods, with a better accuracy (Michez et al., 2019). One of the most common indexes used in remote sensing for vegetation monitoring is NDVI. It provides an indication of the standing biomass (Michez et al., 2019) and allows to assess the evolution of crop phenology or yield (Wang et al., 2005; Zhao et al., 2009). Nonetheless, this index must be calibrated for each type of cover and geographical location, which implies that a lot of data must have been collected beforehand, especially if the cover composition or the location has not been studied before. The lack of pre-existing data, especially in the case of unusual mixed-species composition, makes it challenging to compare the evolution of vegetation between different pasture or crops. To bypass this limitation, another treatment of UAV images that can be done especially on multispectral images to extract information is to work with texture, by assigning a defined value and resolution to the image's primitives (Haralick, 1979). This is done in two steps: (1) create a nuanced matrix of several classes, represented by shades of grey (GLCM (Haralick, 1979)), (2) then apply a second layer to obtain data on the spatial interrelationships of the matrix (Haralick, 1979). This second layer allows to extract many different indexes that reflect heterogeneity, homogeneity, entropy, etc. What needed to be verified in this work if it was possible to use the GLCM technique to extract normalised, quantified, and comparable information between the fields concerning the heterogeneity of the grazing process without any other measurement of the vegetation than multispectral imaging.

2. Materials and methods

2.1. Experimental data

Measurements were carried out between the 2nd and 30th of March 2021 on one 75 x 14 m² and three 84 x 14 m² experimental paddocks (P1 to P4 - Figure 2-1) of the ECOFOODSYSTEM platform of AgricultureIsLife of Gembloux Agro-BioTech (University of Liège, Belgium). This project is a 30-hectare plot divided into 32 experimental plots of 84 x 14 m² on which four different experimental rotations are implemented. The four plots studied in this experiment were part of the "ICLS" rotation, whose cover crops were destroyed by sheep grazing. The soil, weather and shade were similar on every paddock, the orientation of P1, the shortest paddock, was perpendicular to the three others, and the proximity of a path with frequent passages (including cyclists and domestic dogs) on the north-west of P2 and P3 was a possible source of stress for the animals.

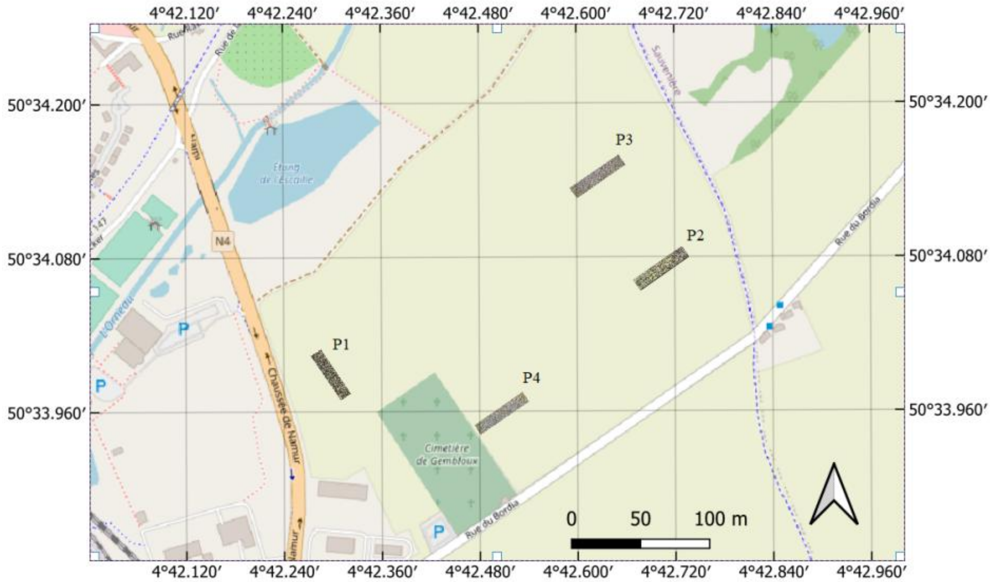

Figure 2-1: Location of the four paddocks (P1, P2, P3, P4) of the experiment.

The cover crop was sown the 3rd of December 2020 with the following grain density: oats (*Avena sativa*, 20 kg.ha^{-1}), Phacelia (*Phacelia tanacetifolia*, 4kg.ha^{-1}), Crimson Clover (*Trifolium incarnatum*, 10 kg.ha^{-1}) and Berseem clover (*Trifolium alexandrinum*, 10 kg.ha^{-1}). The crops were partially damaged due to freezing temperatures and snow between the 7th and 14th of February. Dry matter (DM) was measured through the sampling of five 0.25 m² quadrats on each paddock both before grazing (BG) and after grazing (AG). Biomass collected on each quadrat was placed in perforated plastic bags and oven-dried at 40 °C for a minimum of 72 hours. Once dried, the samples were weighed using a precision balance to determine the dry matter content. The dry above-ground biomass before grazing reached a mean (±standard deviation) of 1333 ± 193 kg/ha. Concerning the grass height compressed sward height (CSH) measurements (n = 30 per paddock) obtained using a self-built Rising Plate Meter (RPM) indicated a compressed sward height of 3.34 ± 0.6 cm before the grazing session and 1.76 ± 0.5 cm after the grazing sessions. Each field was grazed during 7 consecutive days by three four-year old crossbred French Texel ewes. For each paddock, two UAV flights survey were planned with a DJI Phantom 4 Pro (DJI, Shenzen, China) equipped with both an optical sensor (RGB) and a multispectral camera Micasense RedEdge (MicaSense, Seattle, USA). One flight was carried out the day before the grazing session began, and a second flight took place the day after it ended, once the sheep had been removed from the paddock. The flights height was set to 30 m with cameras oriented to the nadir, with 80% front overlap and 85% side overlap. Ground control points (GCPs) were placed on each corner of each plot to calibrate the received imagery with the accuracy of an Emlid Reach RS+ GPS (EMLID, St Petersburg, Russia).

2.2. Data analysis

First, the correlation between spectral data (NDVI values) and ground measurements (canopy sward height, CSH, and dry matter, DM) was assessed using the Pearson correlation coefficient for each pair of variables. This preliminary analysis served as a pre-test to evaluate the feasibility of calibrating NDVI with ground-truth data.

Subsequently, the multispectral images were then processed with the QGIS software (OSGeo, Chicago, USA) with the GRASS GIS software suite, as seen in figure 2-2. Firstly, the multispectral images were processed following the NDVI formula (Raster calculator NDVI). Then the difference between NDVI values BG and AG was calculated. To ensure spatial consistency, the Projection (warp) tool was applied to reproject and align the resulting NDVI difference rasters to a common Coordinate Reference System (CRS), specifically Belgian Lambert 72, at a resolution of 0.1 m². These aligned rasters were subsequently aggregated into two new spatial resolutions: 1 m² and 2 m² grids.

Further analysis was performed using the GRASS GIS software integrated within QGIS. The r.recode module was used to convert the NDVI difference rasters into discrete class values (also referred to as "grey levels" in this study) with two configurations tested: 5 and 8 classes (figure 2-3). These class numbers were chosen to create regularly spaced thresholds across the range of NDVI differences, allowing for meaningful categorization of vegetation changes. Specifically, the 5-class scheme used thresholds at -0.2, -0.1, 0, and 0.1 (noting no values occurred beyond 0.2), while the 8-class scheme used finer thresholds at -0.2, -0.15, -0.1, -0.05, 0, 0.05, and 0.1 (with almost no values beyond 0.15). This reclassification was a necessary preprocessing step for the subsequent GLCM analysis, which operates on categorical raster data. The r.texture module was then applied to generate textural features from these classified rasters (as illustrated in Figure 2-4). Two moving window sizes were considered for texture extraction: 3×3 and 5×5 quadrats.

This process produced several texture-based rasters from which three specific indices were selected for detailed analysis: ASM, Entropy, and Correlation.

$$NDVI = \frac{(NIR-Red)}{(NIR+Red)} \tag{1}$$

In equations 1, NIR represent the Near-Infrared reflectance (wavelengths typically between 0.7 and 0.11 µm) and Red represent the Red light reflectance (wavelengths typically around 0.4 and 0.7 µm). Healthy vegetation will be richer in chlorophyll, which strongly absorbs visible light (Red), while the cellular structure of the leaves strongly reflects near-infrared light (NIR), which generates a high index. Conversely, unhealthy or sparse vegetation (low index) reflects more visible light and less near-infrared light (Measuring Vegetation (NDVI & EVI), 2000).

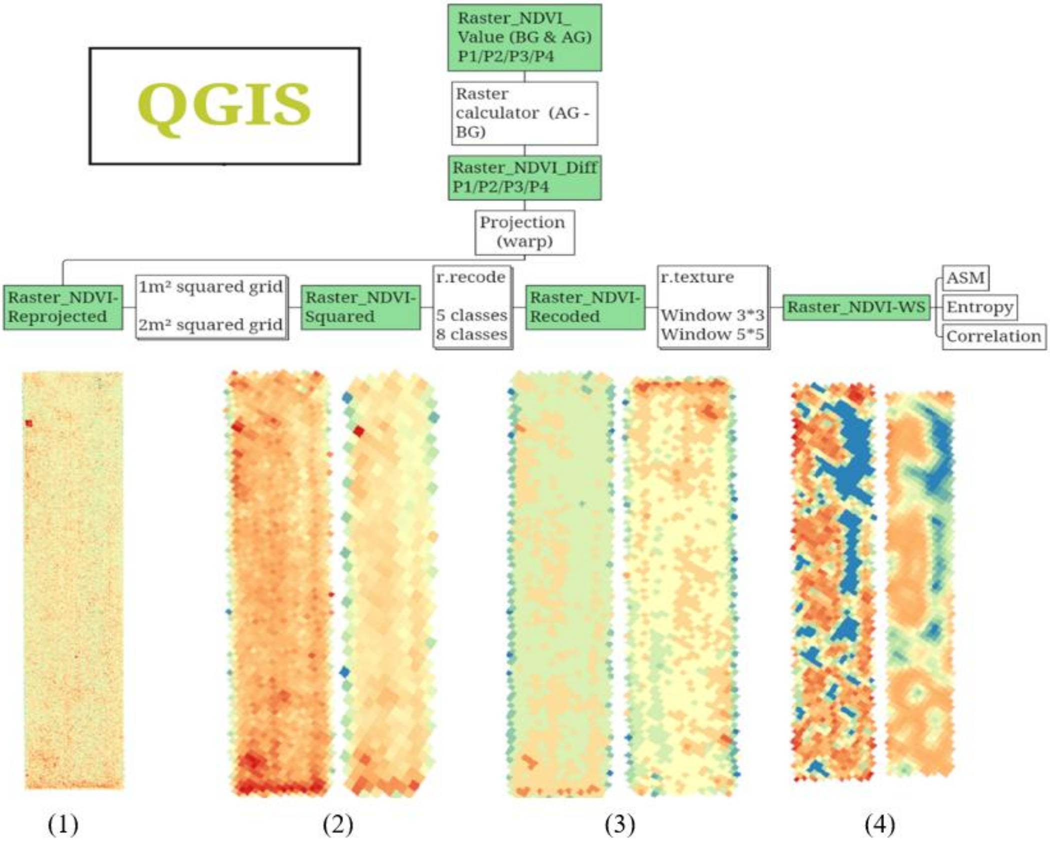

Figure 2-2: List of the operations and intermediate rasters used to determine the most accurate way of describing grazing heterogeneity. All raster examples are for the paddock N°3. The rasters show (1) a gradation of the NDVI diminution at a 0.1 m² resolution, (2) the reprojection in new spatial resolutions of 1 m² and 2 m² grids, (3) the classification in 5 and 8 grey levels for the 1 m² resolution, and (4) the ASM values for moving windows sized 3×3 and 5×5 quadrats, for the 1 m² grid with 5 classes. Warm colors indicate higher values.

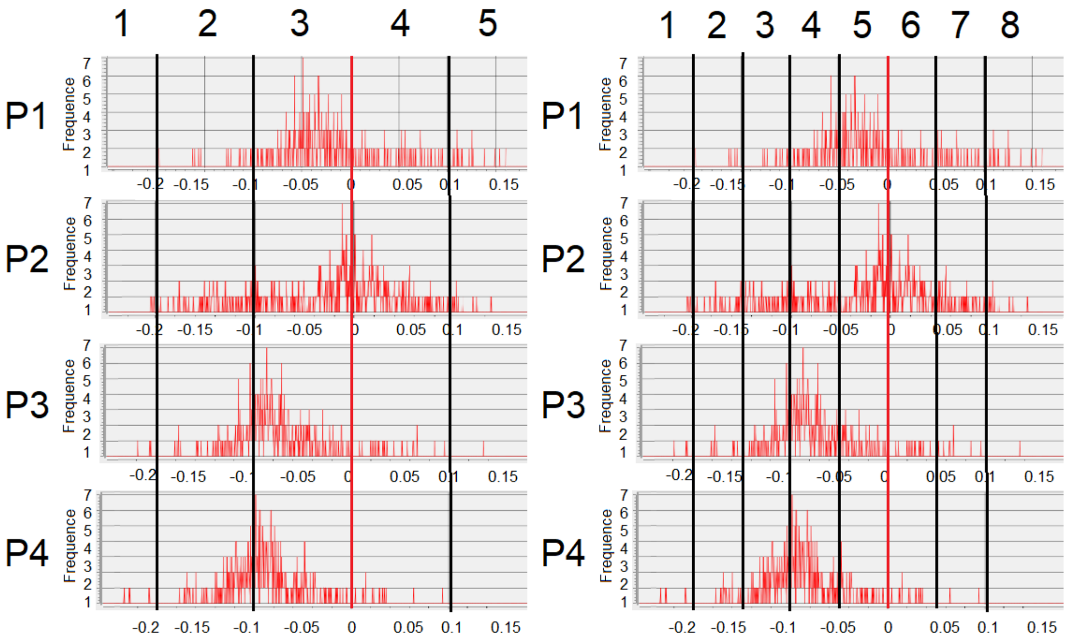

Figure 2-3: Separation of the NDVI into 5 or 8 classes. The values represent the difference of NDVI between AG and BG.

As shown on figure 2-4, GLCM calculates texture indexes for each quadrat by analysing its relationship with neighbouring quadrats positioned at angular directions of 0°, 45°, 90°, and 135° (clockwise). The window size defines the extent of the neighbourhood considered for each calculation. In this study, 3×3 and 5×5 moving windows were used, allowing for the detection of broad spatial patterns and areas of pronounced heterogeneity. Due to the limited size of the paddocks (14 meters wide), and the 1 m^2 spatial resolution, using larger windows such as 7×7 was not feasible, as the number of quadrats available for analysis would have been too small to produce meaningful or statistically robust texture data.

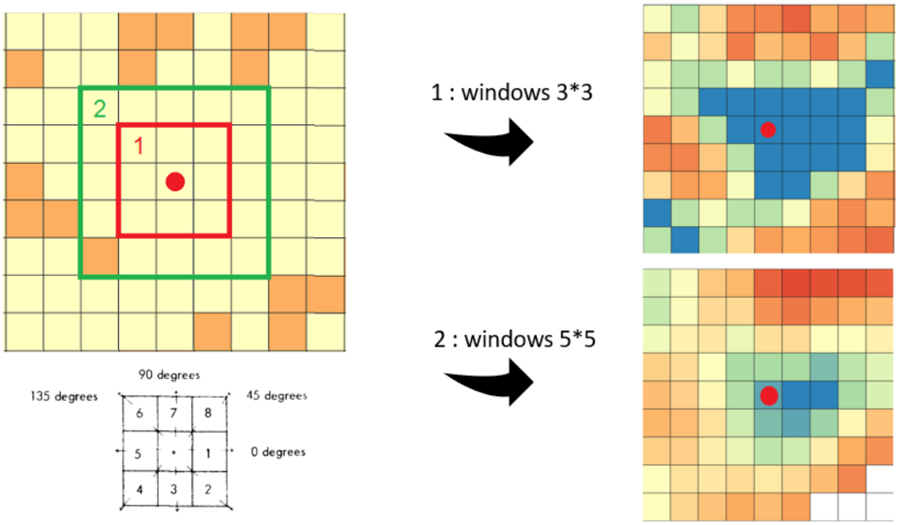

Figure 2-4: Representation of GLCM index calculation for two different sizes of windows.

Many different indexes based on relative distribution frequency have been proposed in the works of Haralick (1973). Three of them have been observed in this survey: ASM, contrast and entropy.

$$Angular\ Second\ Moment\ (ASM) = \sum_i \sum_j \{p(i,j)\}^2 \quad (2)$$

$$Contrast = \sum_{n=0}^{N_g-1} n^2 \left\{ \sum_{\substack{i=1 \\ |i-j|=n}}^{N_g} \sum_{j=1}^{N_g} p(i,j) \right\} \quad (3)$$

$$Entropy = -\sum_i \sum_j p(i,j)\ log\ (p(i,j)) \quad (4)$$

Where p(i,j) is the (i,j)th entry in a normalized grey-tone spatial-dependence matrix and N_g is the number of grey levels in the image (Haralick, 1973).

3. Results

Among the GLCM texture indices tested, the ASM had the advantage over the two others to only give values between 0 and 1, this allows to give an information on homogeneity that is both easily comparable between different paddocks, and quantified (Figure 2-5). It can be observed that the first paddock (P1), smaller than the 3 others (350 m²/sheep instead of 392 m²/sheep), presents homogeneous tendencies: ASM values of 1 represent moving windows of 5x5 quadrats (5m²) where all quadrats have the same grey level of NDVI diminution. This corresponds to the previous statement that more intensive grazing leads to more homogeneity (Nunes et al., 2019). A similar process was followed for the NDVI for BG and AG and showed that the homogeneity had indeed increased on paddock 1 (average ASM: 0.176±0.048 BG, 0.291±0.099 AG) where it had decreased on paddock 4 (average ASM: 0.186±0.056 BG, 0.171±0.044 AG).

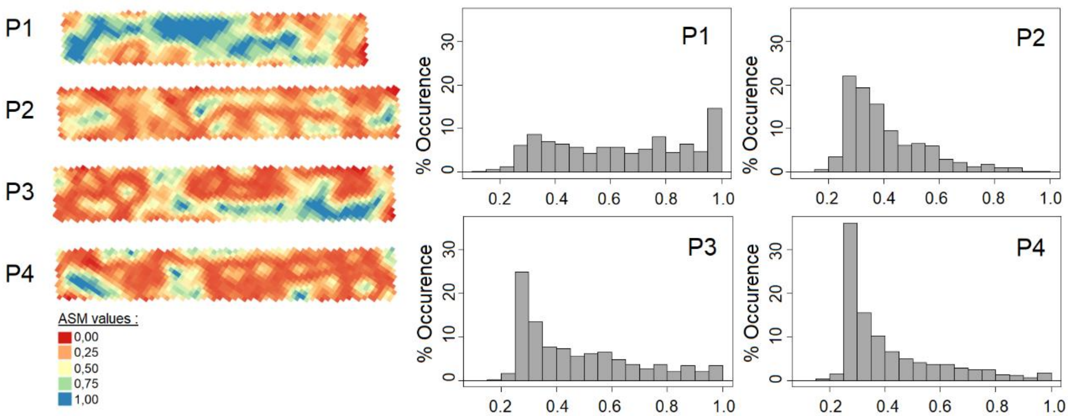

Figure 2-5: ASM symbology and percentage repartition for each paddocks difference of NDVI. High values represent high heterogeneity.

Concerning the Pearson correlation coefficient (Table 2-1), NDVI showed a moderate correlation with RPM (r = 0.48), but a very weak correlation with dry matter yield (r = 0.03), suggesting that in this experiment, NDVI is not a reliable indicator for estimating the exact biomass directly.

Table 2-1: Pearson correlation matrix between DM, RPM measurements, and the NDVI.

	DM	RPM	NDVI
DM	1	0.49	0.03
RPM	0.49	1	0.48
NDVI	0.03	0.48	1

4. Discussion

This study demonstrated the potential of using multispectral drone imagery and GLCM-derived texture indices, particularly ASM, as a means to assess the spatial heterogeneity of grazing impacts. While the NDVI difference alone provides a quantitative indicator for grazing intensity, texture analysis through ASM offers complementary insight by highlighting how uniformly or unevenly the biomass has been grazed. The ability to map and compare heterogeneity across paddocks, without requiring direct recalibration, is a key advantage of this method.

Recoding NDVI values into grey levels was a necessary step for conducting GLCM analysis, which requires discrete class inputs. Two recoding strategies were tested: 5 classes with 0.1 NDVI intervals and 8 classes with 0.05 intervals. The 5-class system proved more interpretable, revealing spatial patterns more effectively, while the 8-class system generated high heterogeneity and numerous isolated quadrats that were harder to interpret. The choice to use regularly spaced thresholds rather than data-driven methods such as cluster analysis was motivated by the need for consistent and interpretable classification across all samples. Regular spacing ensures that each class corresponds to a fixed range of NDVI differences, facilitating straightforward comparison of texture features between classes and study sites.

1 m^2 quadrats offered a more accurate representation of grazing impacts and aligned well with the spatial scale of animal behaviour. This resolution corresponds approximately to the area of a single FS, defined as the location where an animal stops walking to take several consecutive bites (Andriamandroso et al., 2016; Gibb, 1996). Using larger quadrats (2 m^2 and more) is an alternative but implies a significant loss of precision, likely due to reduced sensitivity to localized vegetation changes.

Resolutions finer than 1 m^2 were not pursued, as current technology does not allow for the monitoring and spatialization of individual bites and would have entailed excessive computational costs without delivering ecologically meaningful insights. For the GLCM, 3×3 and 5×5 moving windows were used. The 5×5 moving windows allowed to observe patterns of heterogeneity/homogeneity through the paddocks. In contrast, smaller windows such as 3×3 tend to produce numerous isolated quadrats, limiting the ability to capture larger-scale texture features.

While quantitative statistical comparisons of texture indices, class numbers, and spatial resolutions are possible, this study primarily relied on visual assessment of the resulting spatial patterns to guide parameter selection. This approach was chosen because the ecological relevance of grazing impacts is often best interpreted through spatial heterogeneity patterns. Parameters that yielded clearly interpretable and ecologically meaningful maps, such as the ASM index, 5-class recoding, and 1 m^2 quadrat resolution, were prioritized. These choices enabled effective differentiation of grazing heterogeneity at a scale relevant to animal foraging behaviour, providing intuitive insights into spatial patterns of biomass removal. While acknowledging that more formal statistical validation could complement this approach, visual interpretability remains a key criterion in landscape-level remote sensing studies where spatial context and pattern recognition are critical.

The approach has the potential to be particularly useful for identifying zones where animals used space more uniformly, potentially indicating either efficient pasture use or overgrazing, depending on the context (Nunes et al., 2019). This supports its potential value for rotational grazing management: homogeneous grazing at the end of a grazing session suggests full paddock uses, while excessive heterogeneity may signal underused areas, leading to weed growth or loss of pasture quality (Pontes-Prates et al., 2020). Conversely, too much homogeneity can also indicate overgrazing.

Moreover, this method could be applied in research contexts to compare experimental treatments across paddocks using only two drone flights (before and after grazing). And for long term perspectives, the gridded output of ASM values can be integrated into research or decision-support tools by overlaying it with additional layers such as animal GPS tracking data, environmental features (shade, slope, water points, fencing…), and plant composition (See section 3.2 of the Chapter 7).

Although the study did not aim to deliver a fully calibrated measurement tool, it succeeded in establishing a method for qualitatively assessing the spatial heterogeneity of NDVI reduction. Future work should apply this methodology across different contexts to test the robustness and transferability of the selected parameters and texture indices. Particularly in more standard vegetation and meteorological settings, as in this case no field-based measurements (e.g., RPM) were found to correlate with NDVI values, making it impossible to calibrate the NDVI's accuracy. This discrepancy may result from the heterogeneous composition of the cover crop and from difficult weather conditions that damaged biomass, leading to unusually low RPM values.

Ultimately, this method highlights the utility of drone-based remote sensing for visualizing and quantifying the spatial footprint of grazing, offering new avenues for both research and practical pasture management.

5. Conclusions

This study highlights the potential of UAV-based multispectral imagery combined with GLCM texture analysis, particularly the ASM index, to assess spatial heterogeneity in grazing impact. Unlike traditional ground methods, this approach offers a time-efficient, scalable solution that does not require prior NDVI calibration. A 1 m² resolution was found optimal, aligning with the spatial scale of FS, while five-class NDVI recoding provided interpretable results.

The method offers practical applications for grazing management and research, especially when integrated with animal tracking technologies. It enables spatial monitoring of biomass use, helping to detect overgrazing or underutilization. Although NDVI was not correlated with field data in this study, the framework proved effective for mapping the heterogeneity of grazing. Future work should validate its transferability across varied conditions.

This advance could be useful in research or for DST, for ICLS or more classical application, if combined with other PLF devices such as behavioural monitoring sensors based on accelerometers and/or GNSS to track the animal's trajectory and favourite or avoided parts of the paddock, and behaviour. From there it was possible to evaluate the correlation with biomass evolution, its intensity and heterogeneity. For example, in pasture composed of mixed species or to evaluate different duration of grazing in a rotational system.

6. Acknowledgements

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Chapter 3

Quantification of grass-severing bites performed by grazing cattle using halter-mounted accelerometers and machine learning.

From the previous chapter, the relevancy of a precise prediction of the individual's behaviour was shown as an important tool for paddock monitoring (see section 1.2. of the Chapter 1). This chapter will describe in detail the method developed in this thesis to develop and validate a ML model that could identify the periods of ingestion and quantify the number of bites taken by the animal based on data acquired through wearable acceleration sensors. As part of this process, different sensor technologies for behaviour prediction were reviewed and compared, leading to the choice of IMU as the most appropriate and effective solution.

Quantification of grass-severing bites performed by grazing cattle using halter-mounted accelerometers and machine learning.

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Abstract

Grasslands represent a key element of agroecosystems for sustainable food systems. A better understanding of the grazing behaviour of domestic herbivores is essential to support innovations for grassland management and define grazing practices that support rather than enter into conflict with biodiversity. A key component of the grazing process is the grass-severing bite by which the herbivore collects forage from a pasture. How often, where, and when such bites are performed are relevant indicators of the grazing behaviour of cattle and could be used as indicators to guide farmers in pasture management. In this work, a methodology to create a ML model was developed for identifying grass-severing bite events from the IMU signals of a sensor placed on the neck of cows. The two-phase process consisted of classifying every period of behaviour of cattle into two mutually exclusive behaviours: “ingestion” and “other” (phase 1), and then counting the number of bites taken during each period classified as “ingestion” (phase 2). Seven dry red-pied Holstein cattle and two Blonde d’Aquitaine x Belgian White and Blue crossbreds were observed. A total of 39 hours and 25 minutes of video were recorded and tagged for the different behaviours to train several ML algorithms. During phase 1, four different window segmentations and two different splits of the data were used to train and test four ML classification algorithms: Bagged Tree, Medium KNN, Fine tree and linear Support Vector Machine (SVM). The results show that Bagged Tree algorithms with 30-second windows and 90% overlap gave the best results during the first phase, with an accuracy of 97.83% for split 1 and 98.07% for split 2. During phase 2, the same four window segmentations as for phase 1 were used, to test regression algorithms to quantify the number of bites taken during each time-window. Two ML algorithms were tested: Bagged Tree and Medium KNN, on 5 sessions of 30 minutes. The sessions ranged between 0% and 94% of ingestion time. Phase 2 results showed that Bagged Tree regression algorithms with 10-second windows and 90% overlap performed the best, with an average RMSE of 1.83 for the tested value and an error percentage of -1.93% and 0% for the session with 94% or 0% of ingestion time, and between +15.06% and +26.97% of error for sessions where the animal alternates frequently between both behaviours. The data and code used in this study are openly available on a public depository.

1. Introduction

The global shift toward more sustainable livestock farming has become a major concern (Fraser et al., 2022), with a focus on the role of grasslands in the transition of food systems (O'Mara, 2012). Various levers are available to influence the provision of services by grassland ecosystems, among which are stocking methods (Duru et al., 2019; Sollenberger et al., 2019). Those can differ widely according to the occupation times, the stocking rate, the grazing targets, the grazing intensity, etc., impacting the ability to deliver or not the expected services (Biondini et al., 1998; Zubieta et al., 2021). At the heart of the grazing process lies the removal of leaves from the plants through grass-severing bites (Ungar et al., 2006). The way it is performed by the herbivores will not only determine short-term outputs (Savian et al., 2021) but also the long-term impact of grazing on the stability of the grazed ecosystems. As the selective nature of grazing is influenced by the sward structure, better management of grazing systems requires considering what happens at the plant-animal interface on the field (Gonçalves et al., 2018). According to Mezzalira et al. (2017), the bite rate of cows follows a type IV dome-shaped functional response to grass density (see Figure 1-1). When bite rate (bite min^{-1}) is at its lowest, it means that bite mass (g DM min-1) and short-term intake rate (g DM min^{-1}) are at their highest. In tall swards, the number of bites increases to compensate for a lower bulk density, while shorter grass means shallow bites that reduce the volume taken by the animal per bite. Previous research from Gibb et al. (Gibb et al., 1997) studied the impact of SH on grazing jaw movements (GJM) and showed that the ability of cows to increase their daily grazing time enough to compensate for the reduction in intake rate linked to non-optimal grass structure is limited. Rombach et al. (2022) worked on estimating the dry matter intake (DMI) of grazing animals and observed longer eating time (+4.9%) and shorter rumination time (-10.3%) for low pre-grazing herbage mass (589 kg DM compared to high pre-grazing herbage mass at 2288 kg DM/ha). Hence, changes in bite frequency indicate that the animal is not able to correctly optimize the time allowed to graze, causing a possible loss in production (Gibb et al., 1997; Mezzalira et al., 2017) and putting the ecosystem at risk of underuse of forage or, even worse, overgrazing, with negative impacts on ecosystem services and pasture health (O'Mara, 2012).

The grass-severing movement can be decomposed into four phases:

- Prehension: The cow lowers her head and surrounds a bunch of grass with her tongue and lips.
- Grab: The cow uses her lower jaw and gum to squeeze the grass.
- Cut: The cow makes an upward movement with the lower jaw combined with a movement of the head to sever the grass from the ground.

- Swallowing: The animal chews and/or swallows the grass down the oesophagus (with or without chewing) using muscular contractions.

The movement that removes plant material from the pasture is the "cut" phase, which can be considered the grass-severing bite. The movement is visible with the increase in distance between the mouth and the sward baseline (Andriamandroso et al., 2016). This bite can also define the functional responses of the animal to the available plant material and nutrients, depending on vegetation structure and composition (Bonnet et al., 2015). Finally, it is also the climax event that comes after research, selection, and apprehension of forage, and it results from a complex series of decisions made by the animal (Carvalho et al., 2018). However, it has been mostly overlooked as an indicator to assess the animal's grazing strategies, mostly because bite mass is the most variable and difficult component to predict concerning feeding behaviour (Andriamandroso et al., 2017). It is, on the other hand, possible to evaluate bite frequency and quantity of jaw movements to understand the different rates at which the animals will ingest plant material and nutrients without any information on individual bite mass or volume, as Mezzalira et al. (2017) underlined a correlation between bite frequency, bite mass, and short-term intake rate, making bite frequency (bite min-1) in itself a sensible parameter to observe.

Among the several tools that new technologies might offer to continuously monitor the biting process and individual animal behaviours (Fraser et al., 2022), IMU with tri-axial accelerometers and gyroscopes are one of the most promising technologies (Aquilani et al., 2022; Pavlovic et al., 2021). Although other options such as acoustic sensors (Shorten, 2023) or unmanned aerial vehicles (Los et al., 2023) could also be considered, IMU are the most widely used sensors to predict and classify animal behaviour for cows (da Silva Santos et al., 2023; Mao et al., 2023), and more specifically, pasture management through behavioural classification of data from sensors placed on collars (Bailey et al, 2018; González et al., 2015) and allow the differentiation of behaviour profiles between grazing individuals on pasture (Bouchon et al., 2022).

Several other PLF technologies used for behaviour prediction were considered but dismissed for specific reasons: acoustic sensors, while offering detailed insights into jaw movements and feed type through sound, require heavy signal processing and are highly sensitive to environmental noise, with limited energy efficiency for long-term field use (Chelotti et al., 2024); pressure sensors, although effective at detecting chewing cycles, may alter animal behaviour and require frequent calibration (Aquilani et al., 2022; Chelotti et al., 2024); image-based sensors allow low-stress and real-time monitoring but lack precision on fine-scale behaviours like mastication, are sensitive to lighting conditions, and demand large data storage (Chelotti et al., 2024); infrared thermography, while helpful for welfare assessments, is impractical in free-range settings due to positioning and environmental constraints (Aquilani et al., 2022); and ultra-wide band (UWB) technology, although effective indoors, suffers from signal limitations in open pastures (Benaissa et al., 2023).

Given these limitations, it was therefore decided to base our work on IMU technology, due to its proven accuracy and versatility in free-ranging behaviour analysis. In another work, Andriamandroso et al. (2017) were able to identify the ingestion behaviour of grazing cows with an accuracy of 91.0% using a manual thresholding classification model and the IMU of a smartphone. Hu et al. (2023) also used a semi-supervised linear regression model in order to predict bite rate with a RMSE of 5.73 bites per minute. These works show the possibility of discriminating with a high level of accuracy the unitary behaviours of grazing herbivores, e.g., grazing from ruminating, and quantifying the frequency of bites based on IMU signals. However, to the best of current knowledge, no prediction model has been found that separates ingestion behaviour from other behaviours in order to focus specifically on the number of bites during grazing sessions. This work addresses the possibility of going one step further by identifying, within grazing behaviour, the specific grass-severing biting events to monitor this key component of the plant-animal interface through ML algorithms. The prediction accuracy of ML algorithms and their ability to improve over time through self-learning has led to a constant increase in research that uses ML to record animal behaviour based on sensor data since 1999. With a substantial quantity of work on this subject being released since 2014 (Shine et al., 2021). ML algorithms used to detect animal behaviour are divided into six categories: supervised machine learning (SML), supervised ensemble ML (ESML), unsupervised machine learning (UML), deep learning (DL), statistical models (SM), and manual thresholding (MT) (Riaboff et al., 2022), and not all perform with similar efficiency and accuracy. Moreover, various factors can impact the outcome of ML, starting from data collection and pre-processing to the actual development of the model. Among those, two critical elements that have no established optimum are the window sizes used during the segmentation process and the method used to split the data, which will both play a very important role in the evaluation of the model (Riaboff et al., 2022). This work will be divided into two objectives: (1) to find the best algorithm and time-window to establish a ML classification model able to separate grazing behaviour identified as "ingestion" from all other behaviours based on the acquired IMU data; and (2) within the "ingestion" periods, find the best algorithm and time-window for a regression model able to estimate the number of bites taken by the animal.

2. Materials and methods

Data were obtained between September 2012 and August 2016 on two experimental sites in Wallonia (Belgium) with two different breeds to achieve a variable dataset and obtain more robust models. Two Blonde d'Aquitaine x Belgian White and Blue crossbreds were observed on the first experimental site (Corroy-le-Grand, commercial farm, 50°39’43.4’’N 4°40’43.0’’E, CLG), and seven dry red-pied Holstein on the second site (Gembloux, Gembloux Agro-Bio Tech, University of Liège experimental farm, 50°33’54.6’’N 4°42’04.6’’E, GBX) (Figure 3-1). All animals were females aged between 4 and 12 years old and weighed between 450 and 650 kg. In both cases, the pasture was composed of a mix of ryegrass (*Lolium perenne*) and white clover (*Trifolium repens*), with no trees or edges inside or around the pasture. The animals had free access to water. Five data acquisition experiments were conducted as follows:

- fall of 2012 and spring of 2013 (GBX), two red-pied Holstein cannulated dry cows (RPc1 and RPc2) grazing a 0.19-ha pasture, disregarding sward characteristics.
- summer of 2014 (CLG): two Blonde d’Aquitaine x Belgian White and Blue crossbreeds (BAB1 and BAB2), performed on a commercial farm;
- summer and fall of 2014 (GBX), four red-pied Holstein dry cows (RP1 to RP4), with three pre-grazing forage allowances (1000, 2000, and 3000 kg DM ha^{-1}) as measured from a rising plate meter used with an in-house calibration.
- summer and fall of 2015 (GBX), five red-pied Holstein dry cows (RP1 to RP5) on 1.4 ha pastures with two pre-grazing forage allowances (1000 and 3000 kg DM ha^{-1}).
- summer of 2016, three red-pied Holstein dry cows (RP1, RP3, and RP5) on 1.4 ha pastures with two pre-grazing forage allowances (1000 and 3000 kg DM ha^{-1}).

The animals listed here are the ones whose data have been used in this paper; the cows were always in groups of six on the paddocks, all equipped with the same device.

Figure 3-1: Aerial view of three 1.4 ha-pastures of Gembloux.

2.1. Description of the sensor

The used sensors are the STMicro STM33DH 3-axis accelerometer and the STMicro AGDI 3-axis gyroscope (STMicroelectronics, Geneva, Switzerland) Both are components of the iPhone 4S (Apple, Cupertino, CA, USA) (Andriamandroso et al., 2017). An additional external battery (Anker Astro E5 16000mAh portable charger, 150 × 62 × 22 mm, 308 g, Anker Technology Co. Limited, CA, USA) was added to the 3.7 V 1420 mAh Li-Polymer battery to reach 24-hour autonomy. Data from the IMU were captured and stored using an application installed on the iPhone 4S (Apple, Cupertino, CA, USA), recording accelerometer and gyroscope data at 100 Hz, equivalent to 8.625.000 data points per day, alongside 34 additional signals (Andriamandroso et al., 2017). For this experiment, only the acceleration on x-axis (G_x), y-axis (G_y) and z-axis (G_z) given by the accelerometer and the Euler angles (pitch, roll, and yaw) given by the gyroscope were used, excluding complementary data from the gyroscope that are not typically available with all IMU systems (see Andriamandroso et al., 2017, for the complete list of available data provided by the sensors).

The iPhone 4S was protected by a waterproof box (Otterbox Pursuit Series 20, 152.4 × 50.8 × 101.6 mm, 142 g, Otter Products, LLC, USA) fixed with a halter, placing the sensors on the top of the cow's neck (Figure 3-2). The external battery was attached as a collar around the neck of the animal. This position of the sensor already gave good results to assess feeding behaviours (Riaboff et al., 2022) with a weight that does not create a disturbance for the animal (Dickinson et al., 2020) and a low risk of the device being moved or damaged by the movement of the cattle or during interaction with other cows. An adaptation time of at least 7 days before each observation was planned so the animals could get used to the harness and external battery.

The accelerometer differentiates gravitational and user-induced acceleration, and the gyroscope measures rotation (Euler angles), both types of sensors along three axes. The X-axis was aligned with the head-to-tail symmetry of the plan of the animal, the Y-axis was aligned with the left-to-right vector of the animal, and the Z-axis was aligned with the bottom-up vector as shown in Figure 3-2. After every day of observation, the halter was removed and the iPhone 4S was retrieved to download the data.

2.2. Acquisition of the video recordings of the animal behaviour

The direct observation of the cows on pastures totaled 81 videos lasting between 15'00" and 35'14" (28'07" ± 4'38"). These videos were shot by an observer standing next to the paddock, continuously tracking the behaviour of the cow. Six iPhones were simultaneously equipped and used to record six cows in the same paddock. All video sequences were shot in daylight, between 9:00 and 18:00. Special attention was given to mouth and jaw movements when filming the grazing process, as the ability to register each individual bite was one of the priorities of this experiment.

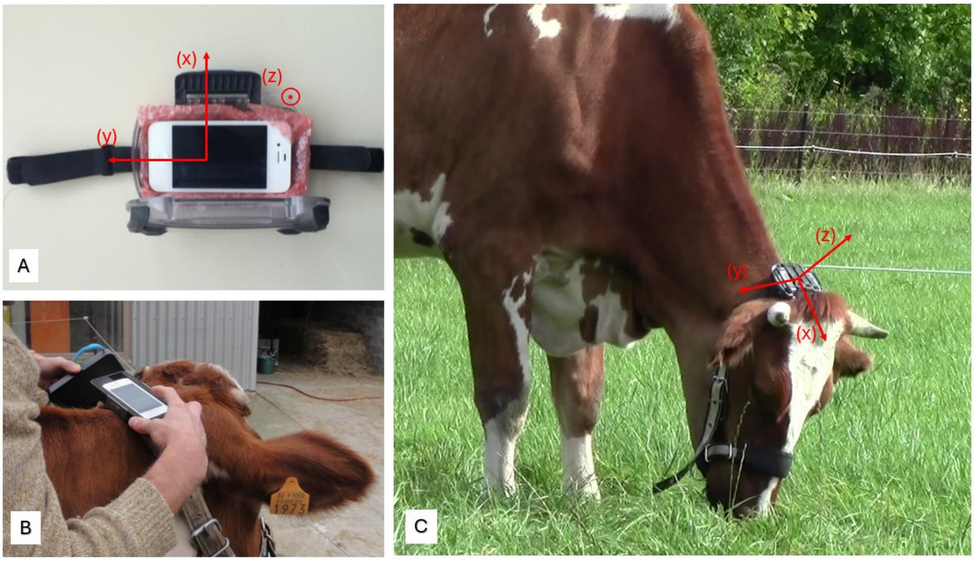

Figure 3-2: Visualization of the orientation of the 3 axes of acceleration on the smartphone in the waterproof box (A), the smartphone being installed in the box on the animal's neck (B), and the 3 axes of acceleration when the smartphone is on the cow (C).

2.3. Video preprocessing and compilation with IMU data

The dataset was originally composed of separated videos (n = 81), in the form of a timestamp, and the data from the six IMU signals (see section 2.1.). The corresponding behaviour vector was added for each timestamp. The observed behaviours are described in the ethogram (Table 3-1). All 81 videos went through a first observation treatment, during which three keywords were used: "ingestion", "other" and "NoView". "NoView" describes every moment when the animal's behaviour is indiscernible. For example, when the animal is turning its back to the observer with no direct view on its head, hiding behind an obstacle or another individual, or if the observer is moving the camera to get a better point of view on the studied animal.

Behaviour data were plotted on the same line graph with the 6 IMU features to apply a corrective shift of the recorded timestamps of the IMU data to better match the observed behaviour's timestamps if needed, based on the discernible trends of IMU activity. greater IMU activity was observed during "ingestion" compared to "other" behaviours. Corrections were applied with a maximum precision of 1 second. Those corrections were based on naked eye observations of the plotted IMU data superposed with the vectorization of the behaviour from the corresponding video on MATLAB R2021b (Mathworks, The Netherlands).

Every video (n = 17) that contained more than 80% of ingestion was used to collect data to train the algorithm for the second part of the model and went through a second treatment with the three keywords ”bite”, “NoView”, “View”. 5 hours and 51 minutes of video were processed for data training. Chews, as described in Table 3-1, were not recorded but were identified as different from bites; special attention was paid during the observation of the videos not to mix those two grazing jaw movements (Laca et al., 1994). Four additional videos were treated to test the data, ranging between 35.7% and 94.3% of ingestion time (35.7%, 52.6%, 72.5%, and 94.3%), plus one video with 0% of ingestion time that didn’t need to be treated. For each of the 22 videos used for the second part of the model, a second dataset containing a timestamp for every bite observed was created.

CowLog 2.0 (Hänninen & Pastell, 2009) was used to create the behaviour vector for each video at a frequency of 2 Hz, i.e., every change of behaviour and every bite was recorded with a maximum error of 0.5 seconds.

Table 3-1: Ethogram used to vectorize the behaviours observed in the videos during phase 1 and 2 of the construction of the model.

	Code	Definition
Phase 1	Ingestion	The animal is standing up, searching for food with its head down, and performs prehensive grass-severing bites with maximum interruptions between bites of 10 seconds.
	Other	All other behaviour observed: rumination, rest, drinking, moving head up, searching for food without bite for more than 10 seconds and other active behaviours (González et al., 2015).
	NoView	Due to visual obstruction and/or the absence of a direct view of the animal’s head and mouth, it is impossible to evaluate if the animal is currently performing bites or not.
Phase 2	Bite	The grass is seized following a prehension movement by the tongue and lips, and taken into the mouth, then grabbed by the lower jaw and gum and cut by one upward movement, it is torn from the root to be ingested by the animal (Andriamandroso et al., 2016). This corresponds to the ‘Cut’ phase (Section 1. Introduction of this chapter). *Note: Bites were only taken into account with standing animals*

Chew	The lower jaw follows a rotational movement, cutting the grass in smaller pieces in the mouth of the animal, without severing new grass from the ground (Laca et al., 1994). *Note: Although chews are described in this ethogram to aid in distinguishing it from bites, they were deliberately excluded from the recorded behaviours during observations.*
NoView	Due to visual obstruction and/or the absence of a direct view of the animal's head and mouth, it is impossible to evaluate if the animal is currently performing bites or not.
View	The observer can get a direct view of the animal's head and mouth; it is possible to evaluate if the animal is currently performing bites or not.

2.4. IMU data pre-processing

The IMU data were processed using MATLAB R2021b (Mathworks, The Netherlands). The whole process, from raw observations to final model validation, is described in Figure 3-3. It consisted of the cleaning of the raw data, the selection of signals and extraction of additional time-series, the selection of features, and, finally, the segmentation of the time-series as detailed below.

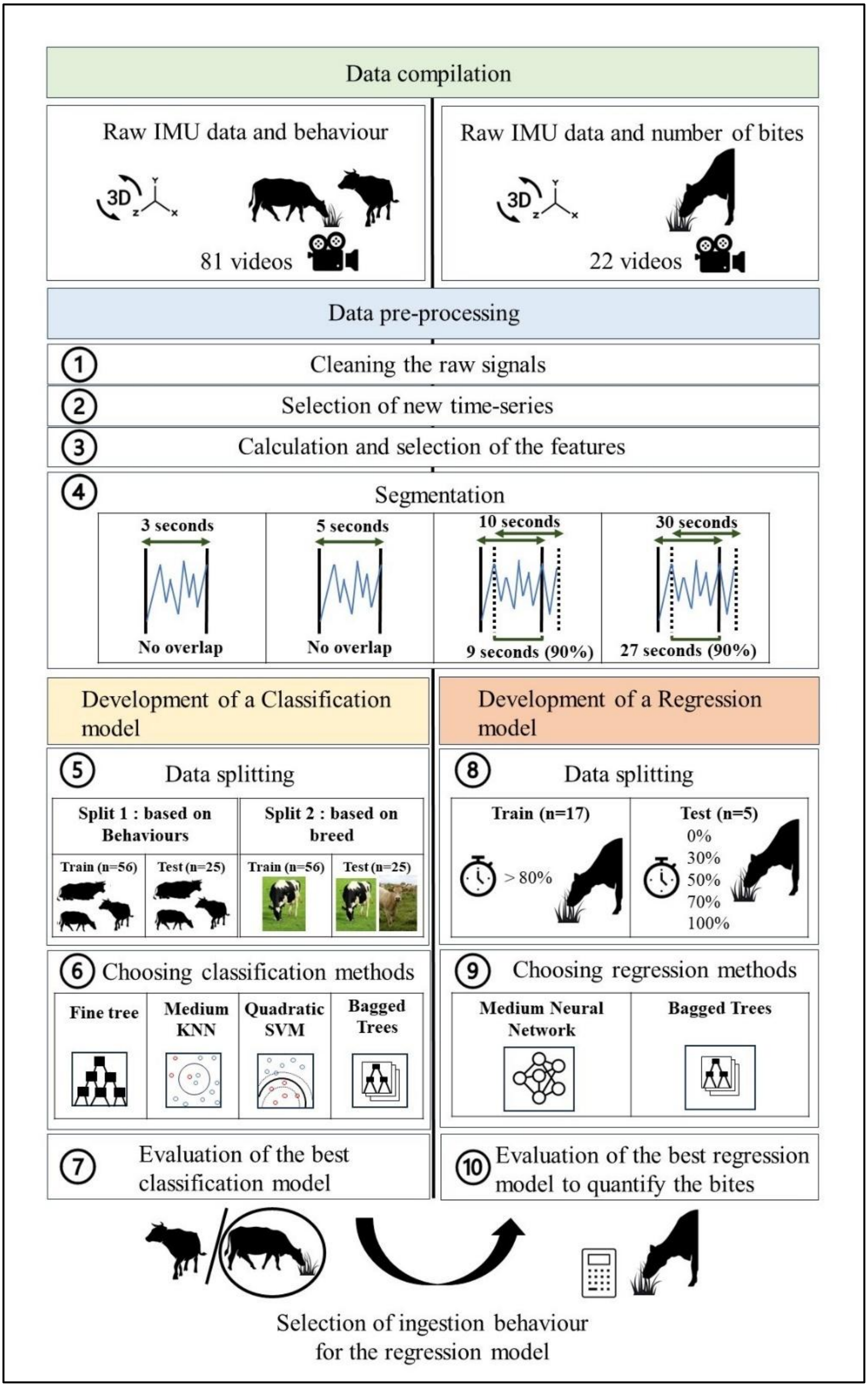

Figure 3-3: Description of the methodology used to quantify the number of bites taken by a

grazing cow from raw data from an IMU and video recordings. The left column is referred to as phase 1, and the right column is referred to as phase 2.

2.4.1. Cleaning the raw signals

None of the videos used had missing lines of data, as the sensor seems to have successfully kept a frequency of 100 Hz for every video. All data recorded as "NoView" were removed from the dataset, as well as a window of 3 seconds before and after any observed change of behaviour. Transitional phases in between meals and other behaviour were indeed not used to train the model. They were however not removed from the test datasets.

2.4.2. Selection of additional time-series

Based on previous work on the same sensors (Andriamandroso et al., 2017), acceleration on x (Gx) and the Euler angle "roll y" were the most appropriate to follow head movements during the ingestion behaviour. They were kept from the six available raw signals (Table 3-2) and used to extract features to develop the model. Acceleration on z (Gz) was also considered and added to the raw signals used to train the model, as the gravitational component along the z-axis increases when switching to grazing as the cows lower their heads (Andriamandroso et al., 2017). Three additional time-series were also used: (1) the magnitude of the acceleration (Amag) (Fida et al., 2015; Riaboff et al., 2019), which is a very commonly used indicator that doesn't depend on orientation and thus is less impacted by changes of position of the sensor around the neck; (2) the Overall Body Dynamic Acceleration (OBDA) and (3) the Vectorial Dynamic Body Acceleration (VeDBA), which are both obtained from the Dynamic Body Acceleration (DBA) (Benaissa et al., 2019; Khanh et al., 2016). These time-series provide an estimation of the energy spent during movement (Qasem et al., 2012) and have been identified as effective indicators for distinguishing between high- and low-dynamic behaviours (Khanh et al., 2016; Lush et al., 2018).

Table 3-2: List of signals captured by the iPhone 4S analysed for the conception of the model**.**

Sensors	Measured signals	Unit
Accelerometer	Acceleration on x (Gx), y (Gy) and z (Gz)	g
Gyroscope	Euler angles (pitch x, roll y, yaw z)	radian

$$DBA_{it} = A_{it} = |G_{it} - \mu_{it}| \quad (1)$$

$$OBDA = A_x + A_y + A_z \quad (2)$$

$$VeBDA = \sqrt{A_x^2 + A_y^2 + A_z^2} \quad (3)$$

$$Amag = \sqrt{G_x^2 + G_y^2 + G_z^2} \quad (4)$$

In equations 1-4, *A, G,* G_{it} and μ_{it} represent the dynamic acceleration, the raw acceleration, the raw acceleration for axis *it* (where *it* denotes either the x, y, or z axis), and the current average for the axis *it*, respectively.

2.4.3. Calculation and selection of the features

Out of the six time-series that were kept, 60 features were calculated (see Table 3-3) on a smaller sample of 10 videos, which was enough to spot the main tendencies in the IMU signal and less time-consuming than using the whole dataset. All 10 presented between 33% and 70% of "ingestion" behaviour and between 27% and 59% of "other" behaviour. This dataset was replicated four times, with each replication segmented into time-windows of different lengths (3, 5, 10, and 30 seconds). A correlation matrix was used for each set of data, as highly correlated features can lead to overfitting and make the algorithm less effective at adapting to new data (Aha et al., 1991). Those four matrices were used to identify which features to keep, avoiding correlations superior to 0.98 between the features. The 29 features that were kept (Table 3-3) were used for both phases 1 and 2.

Table 3-3: Quantitative features selected to describe the time-series into each time-window, organized by information-category.

Category	Time-series	Features calculated	Features kept for the time-serie
Motion Intensity (MI)	G_x	Std, MvtVar, med, Q1 Q3, IQ, min, max, range, RMS	Std, MvtVar, IQ, min, max, range
	G_z		Std, MvtVar, IQ, min, max, range
	Amag	Mean, Std, MvtVar, med, Q1, Q3, IQ, min, max, range, RMS	Mean, Std, MvtVar, med, Q1, Q3, IQ, min, max
	OBDA		Mean, Std, MvtVar, IQ, min
	VeBDA		MvtVar
Orientation of the body (OB)	G_x	Mean, med	Mean
	G_z		Mean
	Roll y	Mean, med, Std, min, max	Mean

Note: Abbreviations used in the table: Std: Standard deviation; MvtVar: Movement Variation; med: median; Q1: First quartile; Q3: Third quartile, IQ: interquartile; min: minimum; max: maximum; RMS: Root Mean Square. Equations are detailed in Appendix 4.

2.4.4. Segmentation

The literature suggests using time-windows ranging between 3 and 30 seconds, with an overlap for windows over 10 seconds (Riaboff et al., 2022). For phase 1 (detection of behaviours), the data were replicated four times, and all 29 features were calculated for each replicate using different time-windows: 3 seconds, 5 seconds, 10 seconds with 90% overlap, and 30 seconds with 90% overlap. The same segmentation was used on the 17 videos used for phase 2, with the number of bites recorded within each time-window as the response variable.

2.5. Model development phase 1: classification of unitary behaviours

To classify the unitary behaviours in the first phase, the first step was the splitting of the dataset with two different techniques, and then four different classification methods were tested on each dataset. This observation was repeated for each of the four segmentation methods, resulting in a total of thirty-two models.

2.5.1. Data splitting

As the technique used to split the data can lead to overly optimistic results, its choice plays a primordial role in the perspective of applying the model to future field applications. A first random split (Datasplit 1) was made with the training (n = 56) and testing (n = 25) data equally composed of videos with high, medium, and low levels of grazing behaviours. A second split (Datasplit 2) was made using individuals as the criterion, as recommended to obtain more robust models (Rahman et al., 2018; Riaboff et al., 2022). For Datasplit 2, the training data (n = 56) were recorded on only Holstein cattle observed in Gembloux, and 20% of the testing data (n = 5 out of 25) were recorded on the two Aquitaine x Belgian White and Blue crossbreeds from Corroy-le-Grand.

It was important to keep both behaviours well represented to train the algorithm (Ingestion = 51.6%; Other = 48.4%; based on 1-second time-windows of the whole dataset; 39 hours, 25’ 50’’).

2.5.2. Choosing classification method

The MATLAB R2021b graphical tool named “Classification Learner” was used to train the data set for each of the four time-window segmentations. Two categories of ML algorithms were used: (a) SML: k-Nearest Neighbours (KNN), support vector machines (SVM), and decision trees (TD); and (b) ESML: Bagged Trees. Both categories are the most used for model training: in the systematic review (Riaboff et al., 2022), 56% of the research used SML and 18% used ESML. The KNN is a method that classifies the data based on the majority class of its KNN in the feature space. Support vector machine finds an optimal hyperplane that maximizes the margin between different classes and is efficient with high-dimensional spaces. Decision trees split the data into subsets, making a series of decisions to classify each data point, and are the most simple and fast models to be trained in this work. Finally, Bagged Trees create multiple decision trees using different subsets of the training data (generated through bootstrapping), which can be more complex and less interpretable but reduces variance and helps prevent overfitting compared to a single decision tree. The hyperparameters used for each method are available in Appendix 1.

The four classification methods proposed were tested through a 5-fold cross-validation to spot the best accuracy results during data training on a set of randomly chosen videos. They were then used for each of the four window sizes and two split criteria (Appendix 2). Each of the thirty-two resulting models was tested on a dataset composed of the 25 "test" videos.

2.5.3. Evaluation of the best classification model

As presented in Table 3-4, the models for phase 1 were evaluated through F-score, accuracy, recall for "ingestion", and specificity for "ingestion". The F-score is calculated from recall and precision.

Table 3-4: Algorithm quality evaluation criteria from phase 1.

Parameter	Equation
True positive (TP)	The behaviour is correctly classified as ingestion
True negative (TN)	The behaviour is correctly classified as other
False positive (FP)	The behaviour is incorrectly classified as ingestion
False negative (FN)	The behaviour is incorrectly classified as other
Recall for "ingestion" (R)	TP / (TP + FN)
Specificity for "ingestion".	TN / (TN + FP)
Accuracy	(TP + TN) / (TP + TN + FP + FN)
Precision (P)	TP / (TP + FP)
F-score	2.P.R / (P + R)

2.6. Model development phase 2: quantification of the bites

2.6.1. Data splitting:

Out of the twenty-two videos with a recording for the number of bites, seventeen videos containing a high frequency of bites and more than 80% of ingestion were used to develop the model for phase 2. Five videos with different percentages of grazing time (0%, 35.7%, 52.6%, 72.5%, and 94.3%) were used to test it. In order to make the lecture simpler, they were renamed 0%, 35%, 50%, 70%, and 100%, respectively.

2.6.2. Choosing regression methods:

Using the MATLAB R2021b tool named "Regression Learner", all regression methods were used through a 5-fold cross-validation to train models on a smaller set of ten 30-minute videos in order to spot the most accurate results. Bagged Tree and Medium Neural Network were selected to train a model able to predict the number of bites. The first method uses the bagging process and focuses more on reducing variance; it is known for being robust and stable. The second is based on interconnected layers of neurons that process inputs to make predictions and can capture complex, non-linear relationships. The hyperparameters used for each method are available in Appendix 1. For this step, the segmentation was made using only 10-second windows.

2.6.3. Evaluation of the best regression model to quantify the bites:

The five tested videos were segmented according to the four time-windows used (3, 5, 10, and 30 seconds, with no overlap for this step). Four models trained during phase 1, one for each time-window duration, were used to remove all windows where behaviour was identified as "other". Then, the model from phase 2, trained only to work on grazing behaviours identified as ingestion, was used to count how many bites were taken during the remaining windows.

The performances of the models were evaluated through RMSE and the total percentage difference between the real number of bites (observed through CowLog) and the number of bites predicted by the model, separately for each of the five videos.

3. Results

3.1. Algorithm calibration for phase 1 - identification of the "ingestion" behaviour

A total of 32 combinations were trained and tested, including four different segmentations, two splits, and four different algorithms. Regarding the differences between the two splits (see 2.5.1), Datasplit 2 gave the overall best results for each of the four segmentations tested (Figure 3-4), even though it was supposed to test the robustness of the model with data from a different breed present exclusively in the "testing" dataset. Overall, the results followed the same progression for both splits. The full table of the results can be found in Appendix 2. Regarding the segmentation, it is very noticeable that longer windows with significant overlap gave better accuracy, with the best results provided by 30-second time-windows with 90% overlap (Figure 3-5).

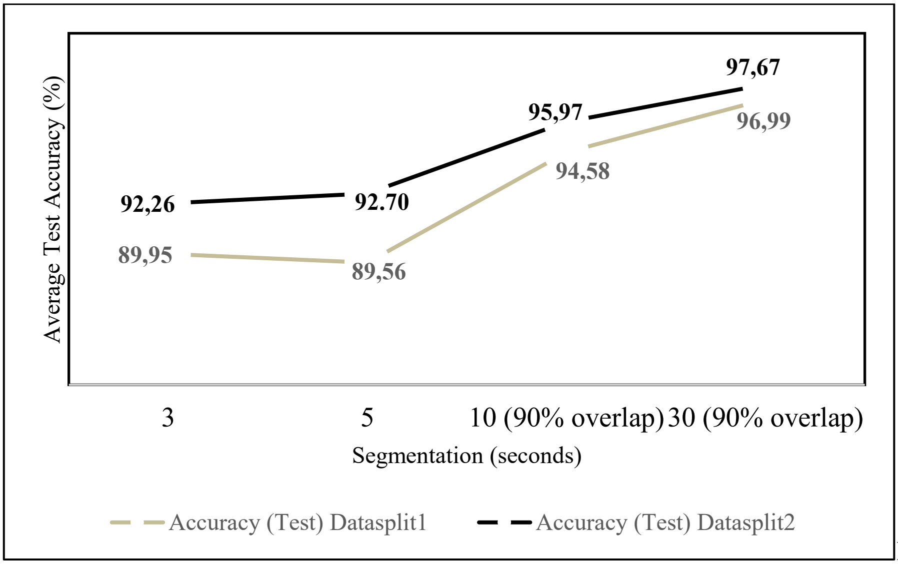

Figure 3-4: Comparison between Datasplit 1 and 2 on the average accuracy of the tested phase 1 model for each segmentation.

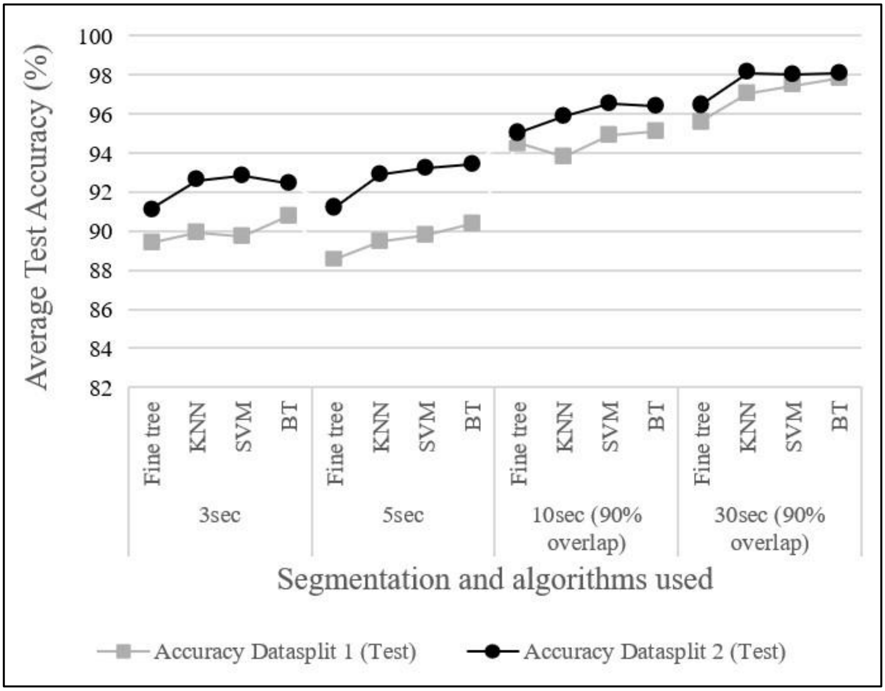

Figure 3-5: Comparison between Datasplit 1 and 2 on the average accuracy of the tested phase 1 model for each segmentation.

3.2. Validation of the model to use for phase 2

All models had an accuracy of over 95.6% when 30-second windows with 90% overlap were used. However, Bagged Tree (BT) models, the only ESML used, gave the best overall accuracy, followed by the SVM ML algorithm. For Datasplit 2, the recall for "ingestion" behaviour was lower for BT and SVM than for k-Nearest Neighbours (KNN) (Table 3-6), meaning that the BT algorithm had a greater tendency to "miss" more "ingestion" behaviour windows, even if its overall performance was satisfying. Both KNN and BT models with 30-second time-windows with 90% overlap have been tried on the five video samples used for phase 2 (Table 3-5). To prevent overfitting, separate datasets were used for training the models and testing the models' performance.

Both presented perfect accuracy for 4 out of 5 samples, the KNN algorithm made 1 FP and 2 FN for the 50% grazing video, and the BT algorithm made 4 FN for the 70% grazing video. The best overall accuracy was achieved by the BT ESML classification algorithm, which was used to classify the five videos, whose analysis was then sent to phase 2.

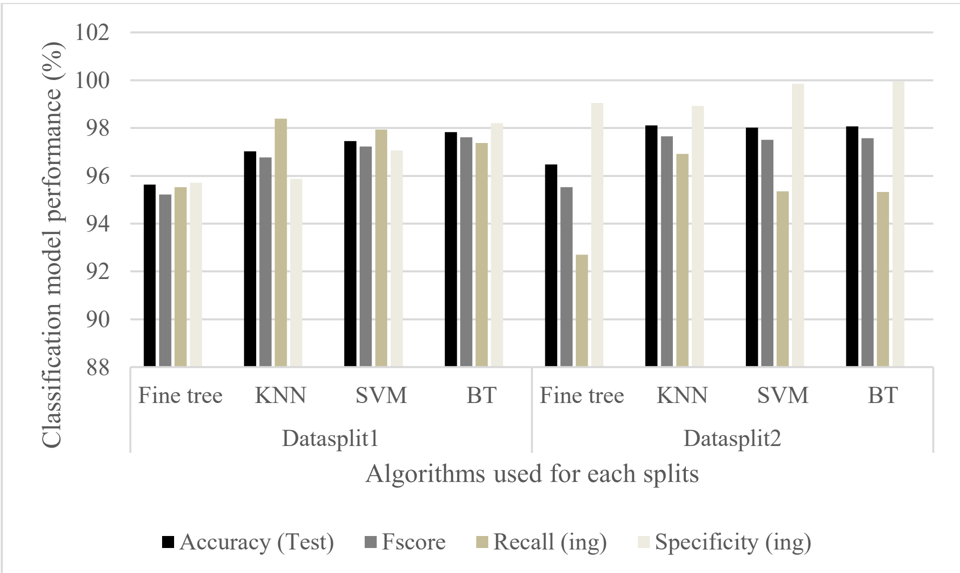

Figure 3-6: Evaluation of the performances of 4 Classification ML algorithms trained and tested following two different splits for the datasets with a segmentation of 30-second windows with 90% overlap.

Table 3-5: Performance of a KNN and a BT model with 30-second windows and 90% overlap to classify 30-second windows of behaviour as "ingestion" or "other".

Algorithm	Sample (Grazing time)	TP	TN	FP	FN	Accuracy	F-score	Recall	Specificity
KNN	1 (0%)	0	589	0	0	100%	100%	100%	100%
	2 (35.7%)	103	236	8	0	97.7%	96.3%	100%	96.7%
	3 (52.6%)	124	160	5	0	98.3%	98.0%	100%	97.0%
	4 (72.5%)	277	101	0	0	100%	100%	100%	100%
	5 (94.3%)	487	0	0	0	100%	100%	100%	100%
BT	1 (0%)	0	589	0	0	100%	100%	100%	100%
	2 (35.7%)	103	244	0	0	100%	100%	100%	100%
	3 (52.6%)	124	165	0	0	100%	100%	100%	100%
	4 (72.5%)	273	101	0	4	98.9	99.3	98.6	100
	5 (94.3%)	487	0	0	0	100	100	100	100

3.3. Algorithm calibration for phase 2 – quantification of bites within ingestion-only sequences

A total of eight combinations have been trained using the data from seventeen videos and tested on an independent sample of five videos, representing a range of grazing behaviour from 0% to 94.3% (see 2.6.1.). The parameters tested were the same four segmentations as for classification and two different algorithms. Video 1, with 0% of grazing time, was always successfully classified during phase 1 and thus is not shown in the following analysis. The full table of the results can be found in Appendix 3. Both ML regression algorithms showed the same responses toward increasing time-windows (Figure 3-7): smaller windows (5 seconds and 3 seconds) tend to under-evaluate the number of bites taken during a grazing session, while longer windows with 90% overlap tend to overestimate them. At high percentages of grazing during the video, the longest windows (30 seconds with overlap) achieved the best results. However, once grazing bouts became scarce and comprised less than 50% of the observed time, the model significantly overestimated the number of bites taken during the session.

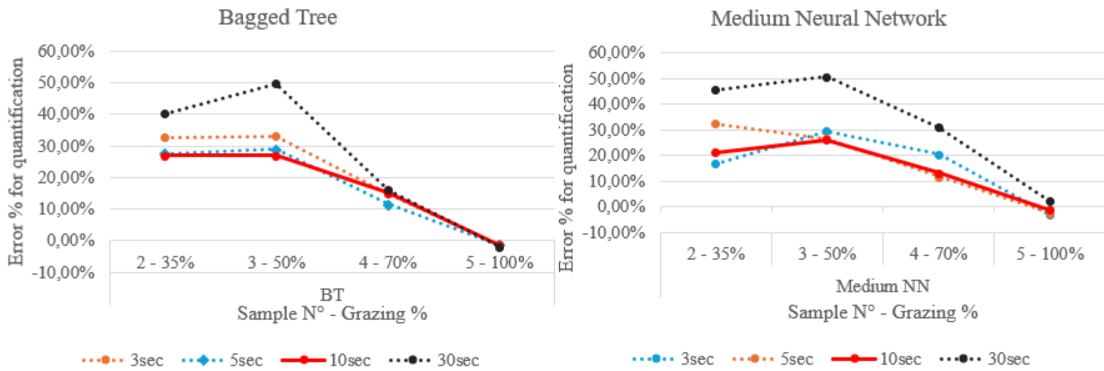

Figure 3-7: Comparison between Medium Neural Network (left) and BT (right) regression methods trained and tested with 4 different time-windows on the error % for the evaluation of the number of bites recorded during a set of five 30-minute samples of grazing. Sample N°1 is not shown, as the model made a 0% error for all parameter combinations.

When looking more closely at the pattern generated by the most performant 10-second model (Figure 3-8), it can be observed that the predictions from the regression model faithfully follow the pattern of increases and decreases in bite frequency observed during grounded observations, with a consistent tendency to remain near the mean grazing frequency.

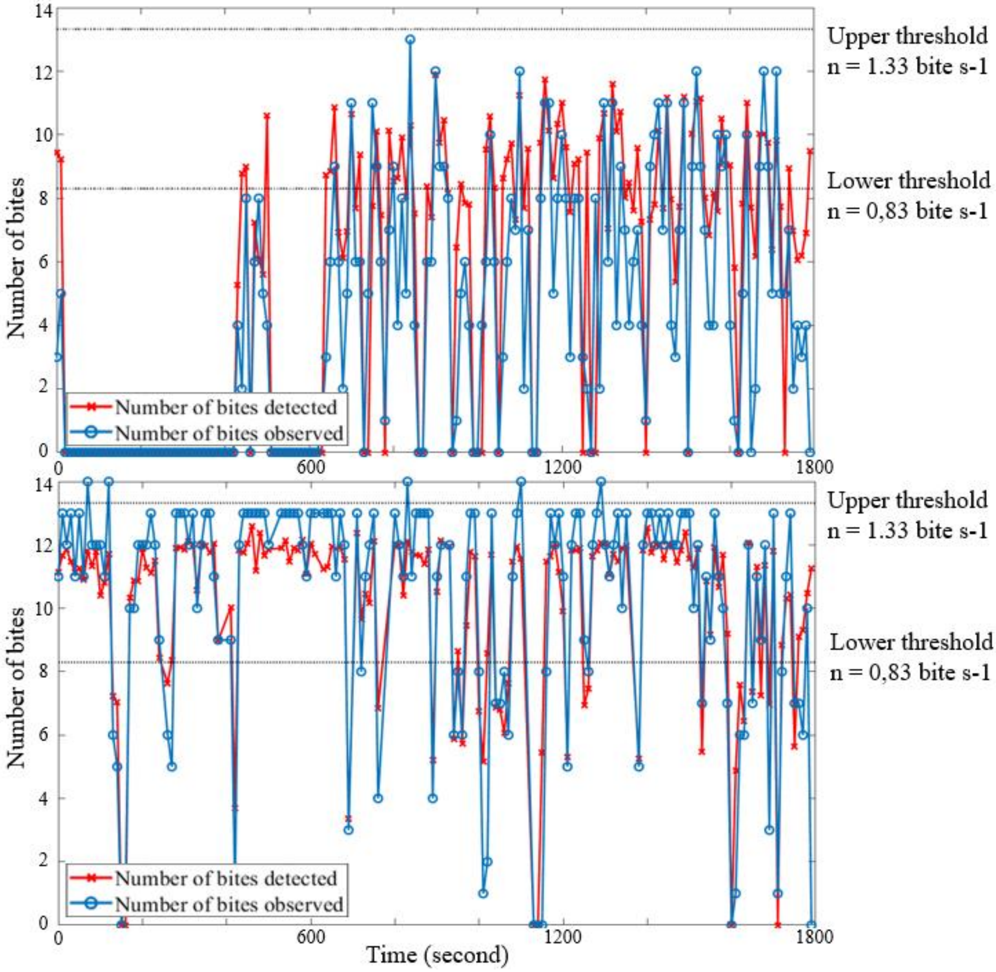

Figure 3-8: Quantification of the number of bites predicted in 10-second windows by a phase 2 model based on a BT regression algorithm after using a BT classification algorithm from phase 1. The sample with the highest (upper graph, for 35.67% of "ingestion" time) and lowest (lower graph, for 94.28% of "ingestion" time) error percentages for this ML algorithm are shown (+26.91%; RMSE = 2.62 and -1.15%; RMSE = 1.72). Details of the results can be found in Appendix 3.

In terms of relative RMSE, the 10-second segmentations gave the best results, with an average error of prediction of 0.18 bites per second for each 10-second segment, followed by 5-second windows (0.22), 30-second windows (0.23), and 3-second windows (0.24). Across the entire dataset, the model predicted an average bite frequency of 1.01 bites per second, closely aligning with the observed average of 1.03 bites per second. Figure 3-9 illustrates the error of bite quantification for the most performant model, with the number of bites predicted for each 10-second window and using the BT regression algorithm.

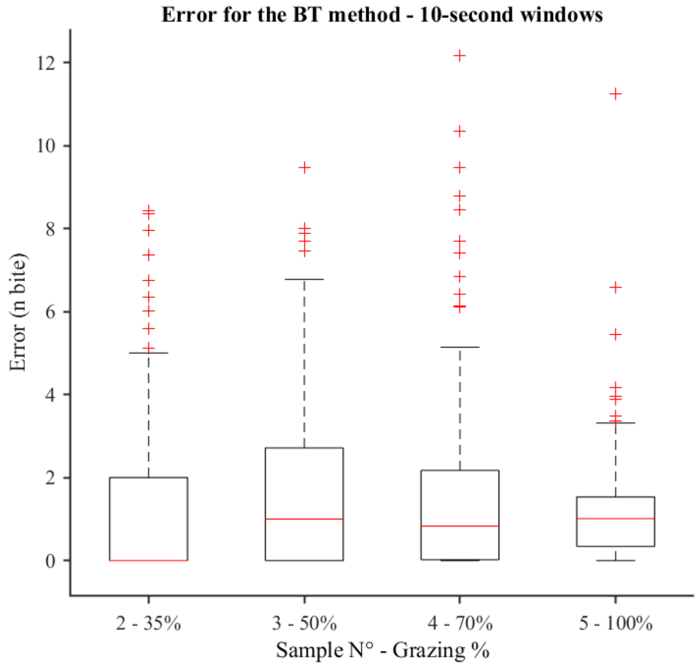

Figure 3-9: Boxplot of the error for bite quantification predicted for 10-second windows by a phase 2 model based on a BT ML algorithm after using a BT classification algorithm from phase 1.

4. Discussion

The aim of this work was to demonstrate the feasibility of developing a method to quantify the number of grass-severing bites taken by a cow on a short-term scale using the IMU signals of a smartphone mounted on the neck of the animal and ML algorithms. This work is not the first to address bite frequency or Jaw Movement (JM) observations; however, most previous systems used in research were either more labour-intensive (Bonnet et al., 2015) or relied on more invasive and complex technologies, such as pressure sensors placed on the animal's mouth (Gibb et al., 1997) which can interfere with natural behaviour and require frequent calibration (Aquilani et al., 2022; Chelotti et al., 2024). In contrast, IMU offer a non-invasive, reliable alternative and are currently the most widely used sensors for animal activity recognition, particularly when placed on the neck, where they provide strong performance for behaviour classification tasks (Mao et al., 2023).

Other PLF technologies, such as acoustic, image-based, infrared, or UWB sensors, were considered but ultimately dismissed due to practical limitations in outdoor grazing environments, such as sensitivity to noise or light, storage demands, or limited range (Chelotti et al., 2024; Aquilani et al., 2022; Benaissa et al., 2023). Given these constraints, IMU represent a robust and scalable solution. Their integration with ML, as shown in this study, further enhances their potential for accurately monitoring ingestion behaviours in pasture-based systems (Riaboff et al., 2022).

As expected, ML classification algorithms performed with high accuracy. The exploration and selection of several specific parameters during sections 2.4 to 2.6. allowed to establish an optimal combination, as demonstrated in the Result section, in this case a Bagged Tree algorithm used on a 100 Hz IMU signal segmented into 30-second time-windows with an overlap of 90%.

The 100 Hz frequency used in this work exceeds the advised maximum of 20 Hz for behaviour classification, as approximately 70% of the studies based on accelerometers achieve satisfactory results with frequencies of 20 Hz or lower (Riaboff et al., 2022). It might be unnecessarily high; however, for the detection of the quantity of bites, it was decided to use the full potential of the available sensors, even if the computation time was consequently higher. Future research should explore lower frequencies to determine the optimal balance between computational cost and accuracy.

The optimal parameter combination selected in this work achieves an accuracy of 97.8% to 98.1% (depending on the split of the data) over a total of over 12 hours of tested behaviour. Concerning the number of bites detected, based on the estimation of Andriamandroso et al. (2016), usual bite frequencies should range between 0.83 and 1.33 bites per second. Other studies have recorded between 1.23 and 1.33 bites per second during 1 hour of short-term grazing observation(Gibb et al., 1997), while Rombach et al. (2022) observed 1.14 bites per second on low pre-grazing herbage mass and 1.19 bites per second on high pre-grazing herbage mass. In this experiment, the average bite frequency observed in the field was 1.03 bite per second, and the most effective model developed predicted 1.01 bite per second.

One of the key questions in developing the algorithm is the trade-off between accuracy and robustness: a system that performs very accurately in controlled experiments but fails under real-world conditions is of limited practical use. While maximizing accuracy may yield excellent results in ideal settings, robustness is needed to be adapted to practical deployments. An example of this trade-off can be the choice of the data sampling of 10 seconds for bite quantification. It was based on the performances that were superior to the other windows tested (3-, 5-, or 30-second windows) within the 3 to 30 seconds recommended in the literature (Riaboff et al., 2022). Using larger windows might have given a systematically average data, and the algorithm would be insensitive to variance and not suitable for detecting changes in behaviours such as bite frequency. On the other hand, smaller windows (< 3s) would need specific pre-processing of the data and could have produced a very sensitive algorithm that would be unusable in other conditions.

This trade-off became particularly evident during model development. It was observed that, contrary to the observations during phase 1, using very long time windows such as 30 seconds led to less precise bite quantification. When cows took only a small number of bites, the model often predicted more than were actually taken, interpreting the entire segment as sustained grazing. Conversely, very short windows (e.g., 3 or 5 seconds) performed less effectively, as they involved a narrower distribution of bite counts and produced less generalizable patterns. This is reflected in their higher relative RMSE compared to 10-second segmentations. The 10-second window thus appears to strike a middle ground, balancing detection accuracy with robustness across conditions, though further exploration of the 10- to 30-second range may reveal even more optimal configurations.

The results of the development of the detection of the number of bites in the second phase give encouraging results, showing coherence between the model's prediction and data verified by an observer. Even for the 30-minute test sample with the highest error percentage (+26.91%; RMSE = 2.62) for the chosen model, the graph shows that the predictions closely follow the true bite frequency as it changes over time (Figure 3-8, upper graph).The margin of error for bite quantification is less than 2% when the animal is continuously grazing, with detection accuracy exceeding 95% for 10-second windows and over 97% for 30-second windows. Long periods of rest are accurately predicted with up to 100% accuracy. However, the model tends to overestimate the number of bites when the animal alternates between eating and grazing.

To achieve such a quantification based solely on IMU data would be an opportunity for farmers and researchers to easily determine the amount and frequency of bites at the scale of a day. It would provide insights for farmers aiming to develop more agroecological practices into both the state of the pasture and the well-being of the animal. Observing animal behaviour at the individual scale is crucial because subtle signs of stress or disease often manifest as deviations from an individual's typical behaviour, rather than from group norms (Thomas et al., 2024). Since livestock vary in their baseline behaviours and in how consistently they express those behaviours over time, identifying true anomalies requires understanding each animal's normal behavioural patterns (Thomas et al., 2024). PLF technologies enable the continuous, high-resolution monitoring needed to capture these individual-level dynamics. This information can be utilized to monitor and manage livestock activity, thereby enhancing pasture productivity and resilience by maximizing animal intake rates while minimizing the risk of overgrazing. This dual objective of productivity and sustainable use of local natural resources represents a potential contribution of PLF towards climate-smart agriculture (Rahman et al., 2018). Additionally, it can be applied to study plant-animal ecological interactions in innovative agroecological practices such as rotational grazing systems (Jordon et al., 2022; Schons et al., 2021)], high-diversity pastures (Jordon et al., 2022), or silvopastoralism (Vandermeulen et al., 2018). In the latter case, where spatial heterogeneity plays an important role in pasture management strategies, the IMU could be coupled with a precise GNSS (Arablouei et al., 2023; Obermeyer et al., 2023; Trieu et al., 2022) to step further into PLF and have information on the geolocation of the number of bites taken. This information could be very insightful to better understand the reactions of animals facing new environments that are more diverse than what they are used to. Although this project did not aim to implement real-time monitoring, it is currently feasible to enhance these experimental methods towards real-time applications, as already demonstrated by several PLF tools (Aquilani et al., 2022). However, such practices would imply more complex and potentially more expensive devices.

This work was a first exploration of this concept, and future should extend its application to longer time scales beyond short 30-minute videos. Documenting the grazing behaviour of dairy cattle over larger periods, such as a day or a week, with strategically distributed recordings of short-term bite counts throughout the day, would enable further evaluation of the model's effectiveness. It would also be necessary to assess its performance across different SH measured prior to grazing sessions to determine if the model's accuracy varies with grass height. This investigation could validate observations made by (Mezzalira et al., 2017) and (Gibb et al., 1997), who noted that cows exhibit lower ingestion and grazing jaw movement rates at intermediate SH, and higher rates at shorter or taller grass heights. Such insights could potentially help identify an optimal bite rate, indicative of optimal grass density and availability. Regarding grass types, while temperate grass species may have minimal influence on the grazing behaviour of dairy cows (Soder et al., 2022), it would be valuable for agroecological reasons to assess the methodology's performance on less conventional forages.

It is important to note that this methodology was used in the specific environment of Belgian ryegrass (*Lolium perenne*) and white clover (*Trifolium repens*) temperate grasslands, grazed by seven red-pied Holstein cattle and two Blonde d'Aquitaine x Belgian White and Blue crossbreds. According to the literature (Riaboff et al., 2022), the model should be tested in long term experiments with a larger sample size and across different parameters such as breed, growth stage, and genders of cattle. This would also enable the training of models on a more diverse range of environmental characteristics, including weather conditions and pasture densities, to develop more robust and versatile models using the same methodology.

5. Conclusion

The present study shows the development of a methodology that predicts the number of bites taken from cows at an individual level and at a timescale of 10-second windows. It is based on data collected at a frequency of 100 Hz by accelerometer and gyroscope sensors from a smartphone positioned on top of the necks of cows. The resulting method uses Bagged Tree classification model which cuts the signal into 30-second time-windows with 90% overlap during phase 1 and a Bagged Tree regression model that quantifies the number of bites taken during 10-second time-windows with 90% overlap. The whole process has been tested on 5 samples, each consisting of 30 minutes of recorded behaviours, presenting various grazing frequencies, and gave results with an error for the detected total number of bites ranging between < 2% for continuous grazing and > 25% for sporadic grazing. It is thus possible to affirm that values can be extracted from raw IMU data to obtain a relevant estimation of the number of bites a cow takes during the grazing process using a halter-mounted device containing an accelerometer and a gyroscope. Further research is needed to confirm that the developed model can measure the quantity of bites under varying parameters such as animal race, grassland species, and climate. Other devices with lower recording frequency sensors and less intrusive fixation methods, such as collars that do not apply pressures around the jaw area, could also be used using the same methodology. Finally, it is also considered for further research to combine this bite-quantification model with a GNSS sensor.

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Chapter 4

Designing a new method using both inertial measurement unit (IMU) and satellite-based position sensor with real-time kinematics correction (RTK GNSS) for the study of grazing cows' behaviours

In the previous chapter, a method was developed to obtain a model able to quantify the number of bites during a grazing session. This chapter uses data from a wearable sensor developed in the context of this thesis, used on short-term grazing sessions. Among the various PLF technologies considered, GNSS with RTK correction were selected to integrate geolocation into bite prediction. This first step demonstrated that through PLF, it is now possible to predict and spatialize grazing behaviour at the bite scale within grids of less than 1 m² resolution. The results presented in this chapter were previously published in a peer-reviewed conference proceeding and presented during the *11^th^ European Conference on PLF* (ECPLF 2024, Bologna, Italy). The content has since been adapted to better align with the format of the manuscript. Please note that, while the work underwent scientific review, the process may have involved a lower degree of scrutiny than that typically applied in full-length journal articles.

Designing a new method using both inertial measurement unit (IMU) and satellite-based position sensor with real-time kinematics correction (RTK GNSS) for the study of grazing cows' behaviours

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Abstract

Grass structure has a key impact on the short-term grazing behaviour of cows, and sward-height is one of its most important features. Cows modify their exploration of the grazable area and adapt their bite frequency when the SH diverges from the optimal height, maximizing their short-term intake rate. The objective of this research was to test to what extent wearable geolocation and activity sensors, monitoring the behaviour of cows at high resolution, could be combined to grasp these changes in grazing behaviour according to changes in SH. Using groups of 3 Holstein cows, 48 short-term ingestion periods lasting 1 hour each were conducted on 15×30 m² paddocks with different sward-heights ranging from 7 to 21 cm. The positions of the cows were continuously recorded by a GNSS system corrected with RTK technology, fitted on a collar worn by the animals, while an IMU recorded the accelerations and rotations. On-field sward-stick measurements enabled the determination of grass-height distribution before the grazing period and classify the paddocks into four categories based on different sward-height levels. A ML algorithm was developed to identify grazing behaviour and estimate bite frequency for each animal at a 30-second temporal resolution. The main outcome was represented as a grid of 1m spaced hexagons, illustrating the distribution of animal bites on each paddock. The results showed that the cows increased the median explored area by 13% on low grass heights and 18.7% on high grass heights compared to medium grass heights. Additionally, the median bite frequency increased by 14.4% on short grass. Behaviours that correspond to the usual functional responses exhibited by ruminants under short-term intake rate conditions.

Keywords: cattle, behaviour, inertial measurement unit, grazing, Machine Learning

1. Introduction

The relationship between grass structure and the grazing behaviour of herbivores plays an important role in grassland management (Fonseca et al., 2012; Mezzalira et al., 2014). It is particularly important in the case of rotationally managed pastures, as it should guide graziers when adjusting their targets for letting animals enter and leave paddocks (Schons et al., 2021; Jordon et al., 2022). The most significant feature of grass structure in its relationship with grazing behaviour is the SH (Bindelle et al., 2021), which is measured using a sward stick. From the animal's perspective, grazing is a very complex process, as a paddock represents a multitude of potential bites. Depending on the grass height, herbivores are able to maximize their short-term intake rate (STIR) through an optimal combination of bite mass and time required to manipulate the vegetation before severing and swallowing it (Carvalho., 2013). Plotting changes in STIR against SH usually produces a bell-shaped curve that is specific for each forage species. Hence, as heterogeneity is an inherent property of the grazed environment, herbivores will constantly be making trade-offs between the search for ideal FS and the energy expenditure needed to search these best grazing spots. A better understanding of those dynamics of exploration and intake during a meal is essential for the monitoring of grazing dynamics on complex pastures providing more varied ecosystem services, such as agroforestry systems (Vandermeulen et al., 2018) or pastures characterised by higher plant species diversity

(Jordon et al., 2022) as the animal heterogenously selective behaviour will shape the vegetation structure and composition impacting its ability to provide those services. There are already numerous studies using PLF to focus on the different behaviours of grazing cattle (Riaboff et al., 2022; da Silva Santos et al., 2023), but most of them consider unitary behaviours in the grazing process, overlooking the inner mechanisms that contribute to the building of the daily grazed diet of a herbivore: the precise monitoring of the atomic element of the grazing process, namely the grass severing bite (Bonnet et al., 2015; Andriamandroso et al., 2016). A review of the existing literature on PLF indicates that 6DOF inertial units (6 degrees of freedom: rotations and accelerations along three axes) placed on the neck of the animals are a reliable, accessible, and reproducible method of monitoring the behaviour of grazing herbivores (Aquilani et al., 2022; da Silva Santos et al., 2023). But very few combines the study of ingestion behaviour down to the bite scale with the spatialization of these behaviours at a centimeter level of precision, allowing to grasp the heterogeneity of the grazing process (Andriamandroso et al., 2017). Indeed, GNSS systems used to track the positions and movements of animals indicate an error level of several meters and are often used for free-ranging animals or grazing in extensive settings (Manning et al., 2017; Mc Intosh et al., 2022). Such spatial accuracy is too low for smaller paddocks and is not relevant to document the grass-severing bites, whose sizes cover several cm². This research focused on the relationship between the grass structure and the animal behaviour at the bite scale. Therefore, RTK technology was used to allow GNSS sensors to be tracked down with centimetric accuracy.

This work aimed to assess the effect of grass structure on short-term ingestion behaviour (STIB) in grazing cattle on fenced paddocks, as observed through the following parameters on STIB in grazing cattle: research areas, spatialization of the bites and bite frequency, using a prototype of sensors consisting of IMU and GNSS geolocation corrected with RTK signals installed on a collar. An algorithm was built to count bites taken by dairy cattle using the accelerometer data, and a map was created to analyse the positions of the observed bites using the GNSS and RTK data. The proposed methodology further supports the exploration of spatialized monitoring of short-term ingestive-related behaviour of dairy cattle related to spatialized sward characteristics.

2. Materials and methods

2.1. Experimental data

The experiment was conducted at the Agricultural Technologies Center of Strée-Modave (Belgium) between May and July 2023 on a set of 12 15×30 m ray grass paddocks (Figure 4-1). The parameters of the experiment are described in Figure 4-2. The SH of each paddock was measured using a sward stick (Barthram, 1986). A sequence of grass cuttings and re-growths were controlled to have a complete set of average pre-grazing SH ranging between 6.1 cm and 21.2 cm. This allowed a classification of the paddocks into four categories: high (>16 cm), medium (between 16 cm and 12 cm), low (between 12 cm and 8 cm), and short (<8 cm) heights. These thresholds were defined to ensure a balanced distribution across categories, with an average of approximately 22 observations per category (±6.7 standard deviation). In the literature, Gibb et al. (1997) evaluated grass height of 5, 7 and 9 cm, while Peyraud & Delaby (2005) stated, based on rising plate meter measures, that grass height above 16 cm was difficult to graze for the animals, and the optimum to bring the cows in the pasture was between 12 and 14 cm. Mezzalira et al. (2017), on the other hand, worked with the SH of *Cynodon dactylon* of 10 to 35 cm and SH of 15 to 50 cm for *Avena strigosa*. Concerning the animals, eight heifers and four dry Holstein cows were split into four groups composed of two heifers and one dry cow each. The ages and physiological stages of the individuals were mixed on purpose in to increase the robustness of the developed algorithm, as recommended by Riaboff et al. (2022). Dry Holstein cows are expected to have an ingestion frequency reduced by 16% compared to lactating animals (Gibb et al., 1997; 1999), however, this has no significant impact on short-term measurements. The short-term grazing behaviour of the cows was measured during 48 grazing sessions of 1 hour, 12 sessions for each group during which one group was put on a paddock after a fasting period of 3 to 6 hours to stimulate the ingestion behaviour without provoking subnormal intake rates (Patterson et al., 1998). The behaviour of the animals was recorded through handheld cameras equipped with microphones. Synchronization of the sensors and the cameras was achieved by manually shaking the sensor while simultaneously recording a video showing both the physical motion of the sensor and a visible reference clock. This allowed us to align the time registered in the IMU data with the observed motion in the video, ensuring accurate temporal matching between the behavioural annotations and the sensor signals. Two observers were present next to the field. Each took a 20-minute video of each cow during the session, with the focus of the camera on the head, mouth, and front legs. The "ingestion" behaviour was assigned to 30-second segments during which the animal was performing grass-severing bites, with maximum interruptions between bites of 10 seconds. All other behaviours, including exploring FS without intake, were considered "other". Individual bites were recorded when grass was actually severed from the sward to be consumed by the animal (Andriamandroso et al., 2016).

Figure 4-1: Satellite view of the experiment. P1 to P12 are the paddocks used for the experiment, each sized 30×15m. The animals were left in the remaining area of the pasture day and night in between experiments. Experimental paddocks were delimited by electric fences. The wearable sensors were installed on the cows in the barn, where the animals were also kept for the fasting sessions.

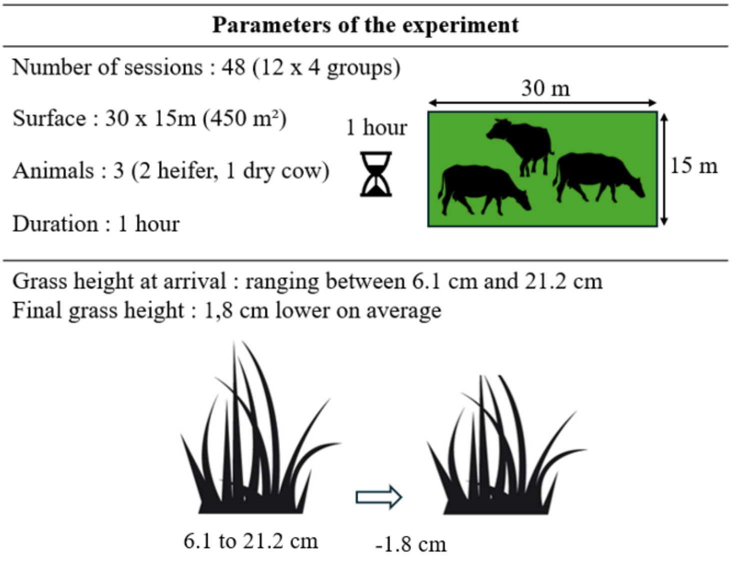


Figure 4-2: Description of the experimental parameters.

2.2. Sensors

The cows were equipped with collars fitted with a Mega 2560 Rev3 Arduino (Arduino.cc, Monza, Italia) connected to a GY-521 MPU-6050 module (ZHITING, London, UK) with 6 DOF (3 accelerations and 3 rotations) as well as a GNSS SimpleRTK2B shield (ArduSimple, Lleida, Spain) offering a reported positional accuracy of <3.8 cm for 99.76% of the points recorded, according to the manufacturer's specifications (ArduSimple, 2023). The system parameters were optimized to achieve the best possible accuracy in field conditions. It was observed that the recorded coordinates were separated by minimum distances of approximately 45 cm in longitude and 7 cm in latitude, corresponding to the precision limits of the system. This resulted in a positional error of less than 45 cm. The system recorded both geolocation and IMU at a frequency of 8Hz on a SD card that was retrieved after the grazing session. The system was composed of a box for the sensor, a battery box containing a 5 V external lithium-ion battery with 20000 mAh capacity with a maximum runtime of approximately 48 hours and a multi-band u-blox ANN-MB-00 IP67 GNSS antenna (ArduSimple, Lleida, Spain) (Figure 4-3). The complete system weighed 1.005 kg, less than the maximum 1.2% of the animal's weight recommended to avoid interference with behaviour (Dickinson et al., 2020).

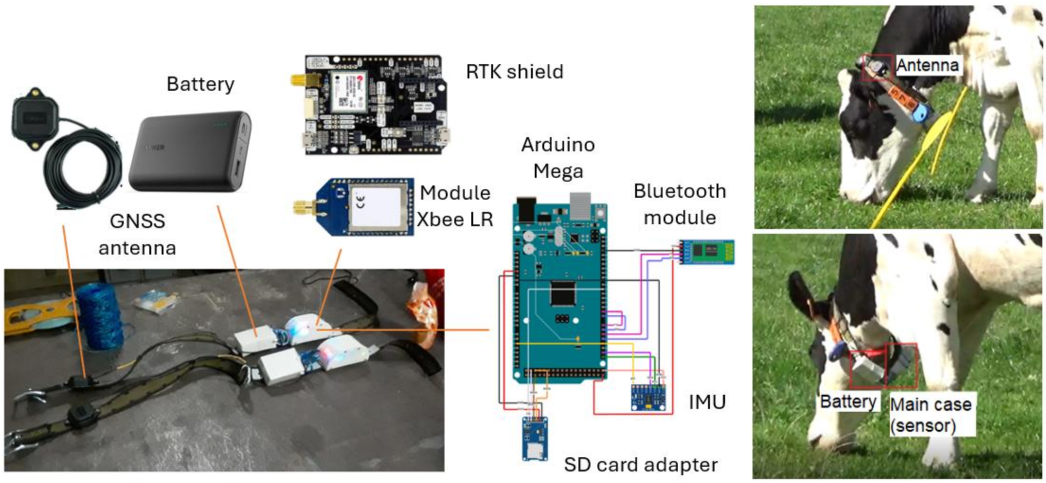


Figure 4-3: Collar and sensors used during the research (left) and position of the collar on the animal (right).

2.3. Data processing

The data processing was performed using MATLAB (Release 2019b, MathWorks, Natick, USA) for the creation of behaviour and bite detection algorithms, as well as the processing of geolocation data, and QGIS (OSGeo, Chicago, USA) to arrange and extract the geolocation data. A total of 31 hours and 42 minutes were used to train the model. Due to changes in hardware and sensor configuration between the prototype used in this chapter and the IMU from chapter 3, it was necessary to repeat the feature selection and model training processes rather than reuse earlier models.

The algorithm built for bite quantification followed the same two-step process consisting of (1) separating "ingestion" behaviour from "other" behaviours for 30-second time windows and (2) developing an ensemble regression model for the quantification of the number of bites inside 10-second time-windows. For both steps, the "Bagged tree" preset from MATLAB was used, and an overlap of 90% was used to expand the database used to train the models. The 20 features used for both steps were selected through a selection of the most sensible time series through visual observation of the differences of signal compared to the behaviours (see Table 4-1). Since the IMU was placed on a collar rather than a halter, all acceleration-related features were selected from time series that are not affected by sensor orientation (e.g., Amag, OBDA, and VeDBA). Features extracted from the frequency domain, such as spectral entropy, were also included to potentially improve the model's performance. A correlation matrix was used to avoid using features that were too highly correlated (> 0.98), as this could lead to overfitting (Aha et al., 1991). The models were trained using an animal-based split (see Table 4-3), excluding the data from one individual to train the 2 models, then using the excluded data as the testing sample and repeating the process for each animal (N = 12). Normality of the bite rate and percentage of area grazed variables across grass height categories was assessed using the Shapiro–Wilk test. Since several groups showed significant deviations from normality ($p < 0.05$), non-parametric Kruskal–Wallis tests were used to compare groups. Post hoc pairwise comparisons were conducted using Dunn–Šidák corrections to control for multiple testing. Data visualization was performed using boxplots.

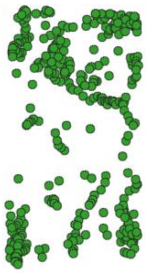
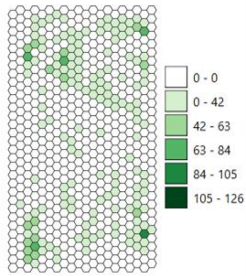
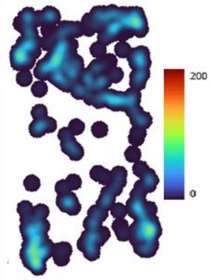
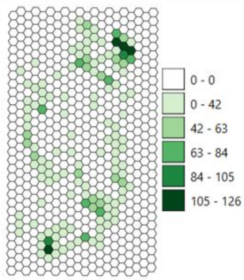
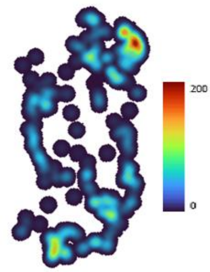
Table 4-1: Features selected to describe the time-series into each time-window.

Time-series	Features	Features selected
Roll (y), Yaw (z)	Mean, Std, med, min, max, SpecEnt, 2MaxPSD	Roll_mean, Roll_Std, Roll_min, Roll_max, Roll_SpectEnt, Roll_ 2MaxPSD, Yaw_mean, Yaw _Std, Yaw _min, Yaw _max, Yaw _SpectEnt, Yaw _ 2MaxPSD,
Amag, OBDA, VeBDA	Mean, Std, MvtVar, med, Q1 Q3, IQ, min, max, range, RMS, SpecEnt, 2MaxPSD	Amag_mean, Amag_Std, Amag_MvtVar, Amag_min, Amag_SpecEnt, Amag_2MaxPSD, OBDA_min, OBDA_2MaxPSD

Note: Abbreviations used in the Figure: Std: Standard deviation; MvtVar: Movement Variation; med: mediane; Q1: First quartile; Q3: Third quartile, IQ: interquartile; min: minimum; max: maximum; RMS: Root Mean Square, SpecEnt: Spectal entropy; 2MaxPSD = Second maximum power spectral density. The MATLAB 2024a scripts used to extract the features are detailed in Appendix 8.

Once the two-phases bite quantification model was developed and its performance tested, it was used on 1-hour recordings of the grazing animal. For each 10-second time window, the average coordinates were calculated and linked to the number of bites estimated by the model on a comma separated values (CSV) table. The resulting coordinates were projected on the BD72 / Belgian Lambert 72 SCR (EPSG:31370) and projected on a hexagonal grid covering the whole paddock (Table 4-2). The grid was set for a 1-m spacing between the centres of neighbouring hexagons, resulting in 0.86 m² hexagons. The total area of hexagons in the grid containing predicted bites was compared to the total area of the paddock (S = 450m²) to estimate the percentage of the explored area during grazing. The tools "Count Point in Polygons" and "Heatmap" from QGIS (OSGeo, Chicago, USA) were then used to estimate the number of bites taken in each hexagon and create a heat map of the grazing locations of each individual cow. The resulting layers were extracted as CSV tables.

Table 4-2: QGIS processing for each sample of two sets of 1 hour (H10 and H81). The samples are from two different cows ('Big Spot' and 'small').

	All points (8Hz frequency)	10-second segments	n bites -1 meter spaced hexagons	Heat maps
H10_CTA n_bites : 3452 S_grazed : 145,34 m²				
H81_CTA n_bites : 4139 S_grazed : 116,1 m²				

n_bites: number of bites calculated by the model for each sample; S_grazed: total of the area of all hexagons where at least 1 bite occurred.

3. Results

3.1. Behaviours classification

The F-score precision, sensitivity, and specificity of the Bagged Tree algorithm for the ingestion behaviour are presented in Table 4-3. As the pondered accuracy (98%) and F-score (99%) were high, the sensitivity was higher (99%) than the specificity (78%) which is most likely due to a larger sampling of "ingestion" - 30-second segments compared to "other", due to the fact that the animals were observed right after the fasting sessions. This indicates a trend to identify "other" behaviour as "ingestion". Nevertheless, this will have a reduced impact since the cows spent most of their time grazing during the 1-hour sessions.

Table 4-3: Results of the 2-steps model through an animal-based data split.

Individuals	Dataset: n 10sec segments	Dataset: Weight in the total dataset	Train performance: Accuracy 30sec segments	Train performance: RMSE 10 sec segments
'Dark'	4253	4%	99.6%	1.97
'Shadow'	4452	5%	99.7%	1.93
'Triangle'	4846	5%	99.6%	1.98
'Eyes'	6807	7%	99.6%	1.97
'Bosse'	6858	7%	99.6%	1.92
'Spots'	6974	7%	99.6%	1.98
'Small'	8493	9%	99.6%	1.96
'Glass'	8960	9%	99.7%	1.96
'Nose'	9468	10%	99.7%	1.96
'Albinos'	10232	10%	99.6%	1.98
'Heart'	12052	12%	99.6%	1.90
'Big Spot'	14782	15%	99.7%	1.99

Individuals	Test performance (behaviour): Accuracy test	Test performance (behaviour): F-score	Test performance (behaviour): Sensitivity	Test performance (behaviour): Specificity	Test performance (bites): RMSE test	Test performance (bites): Accuracy
'Dark'	99%	100%	100%	89%	4.13	142%
'Shadow'	99%	100%	100%	NaN	3.89	85%
'Triangle'	100%	100%	100%	NaN	2.31	95%
'Eyes'	100%	100%	100%	75%	2.44	105%
'Bosse'	100%	100%	100%	92%	3.71	116%
'Spots'	99%	100%	99%	NaN	2.77	87%
'Small'	98%	99%	100%	82%	3.79	86%
'Glass'	99%	99%	99%	86%	3.28	85%
'Nose'	94%	97%	100%	55%	3.65	98%
'Albinos'	100%	100%	100%	63%	2.53	92%
'Heart'	96%	98%	96%	90%	3.97	83%
'Big Spot'	97%	99%	99%	77%	3.37	108%
Pondered	98%	99%	99%	78%	3.34	87%

3.2. Bites quantification

Out of the 144 available sessions, a total of 92 (63.9%) sessions were selected based on the quality of the recording, and the pre-grazing SH. Table 4-4 shows that the animals spent on average 90% of their time grazing, performing bites on an area representing between 22 and 37% of the total available. Concerning the number of bites detected, the average of 0.98 is lower than what can be found in some other studies (Gibb et al., 1997; Rombach et al., 2022), but still within the range between 0.83 and 1.33 bites per second, as approximated by Andriamandroso et al. (2016).

Table 4-4: Results for the 92 1-hour sessions of post-fasting grazing.

	Minimum	Maximum	Average +/- Std
% of the area (450m²) grazed	11.8%	46.2%	29.6+/-7.3%.
Ingestion time	21.2%	100%	90+/-18%
Total number of bites	389	4382	3217+/-922
Frequency of bites (bites.sec-1)	0.47	1.22	0.98+/-0.16

Figure 4-4 presents boxplots of bite frequency (bites/sec) and the percentage of paddock area explored across grass height categories. Post hoc pairwise comparisons revealed an effect of grass height on both bite rate and grazing area. Animals grazed significantly less on short grass compared to low ($p < 0.001$) and medium ($p = 0.036$). Low grass promoted greater exploration than medium ($p = 0.001$) and high grass height ($p = 0.0045$). The bite rate was lower on short grass compared to low grass ($p < 0.001$), low height swards had higher bite rates than short, medium and high swards ($p < 0.001$). No difference in bite rate was observed between medium and high grass. Detailed statistical outputs are provided in Appendix 5.

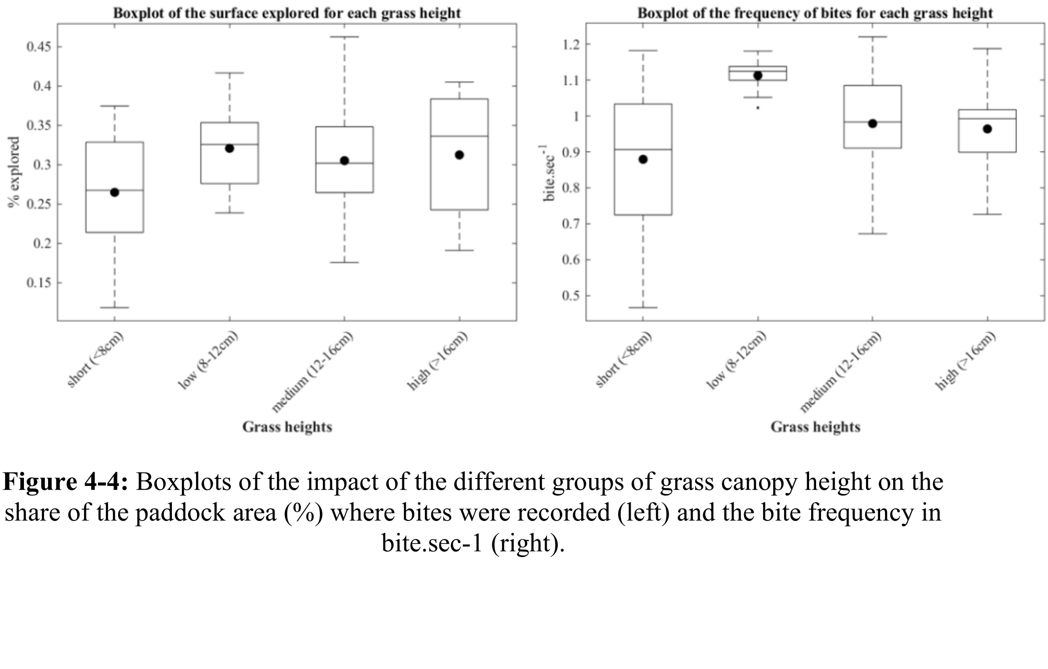


Figure 4-4: Boxplots of the impact of the different groups of grass canopy height on the share of the paddock area (%) where bites were recorded (left) and the bite frequency in bite.sec-1 (right).

4. Discussion

The aim of this chapter was to use data from a wearable sensor developed in the context of this thesis, tested during short-term grazing sessions. Among the various PLF technologies considered, GNSS with RTK correction were selected to integrate geolocation into bite prediction. This first step demonstrated that, through PLF, it is now possible to predict and spatialize grazing behaviour at the bite scale within grid cells of less than 1 m² resolution. This spatial resolution provided valuable insight into pasture use by the animals. During the experiment, cows spent on average 90% of their time grazing, performing bites on an area representing only 22% to 37% of the total available area. A preliminary exploration of spatialized behaviour through grid-based and heatmap visualizations was also presented, highlighting the potential for future research and DST.

Behavioural responses to SH revealed nuanced patterns. When confronted with short grass, cows tended to explore smaller areas and display lower bite frequencies, suggesting a reduced motivation to search for optimal bites. Field observations confirmed that hunger induced by a fasting period is not always sufficient to stimulate grazing in less attractive areas (e.g., swards under 8 cm). Interestingly, cows previously exposed to taller, more abundant grass often even refused to graze in these lower-quality paddocks, even after fasting, but resumed grazing immediately upon returning to their original, more favourable environments. Conversely, cows accustomed to shorter swards before the test were more willing to graze in similarly short paddocks. This suggests that recent environmental context, particularly prior forage quality, plays a significant role in grazing motivation and acceptance to sward structure diverging for the optimum from a grazing efficiency perspective. Paradoxically, bite frequency under low grass conditions was both high (up to 1.11 bites/sec) and consistent, as shown by a narrow boxplot distribution. This may indicate that this SH corresponds to a preferred grazing condition, contrary to the general assumption that animals increase bite rate primarily under foraging constraints (Gibb et al., 1997; Mezzalira et al., 2017). A possible explanation lies in the experimental design: fasting followed by brief grazing bouts, which may have enhanced feeding motivation and access to palatable forage, even under favourable conditions. These results deviate from common patterns in the literature and require further investigation.

Concerning the height category limits, they also reflect the variability in how sward height is considered in the literature. For instance, Gibb et al. (1997) studied grazing behaviour on grass heights of 5, 7, and 9 cm, categorizing relatively short swards. Peyraud and Delaby (2005), using rising plate meter data, reported that grass taller than 16 cm was difficult for cows to graze efficiently and recommended bringing cows into pasture when the height was between 12 and 14 cm. In contrast, Mezzalira et al. (2017) worked with taller sward heights in Brazil, ranging from 10 to 35 cm for

Cynodon dactylon and 15 to 50 cm for *Avena strigosa*. These examples highlight how the perception of what constitutes "short" or "tall" grass can vary significantly depending on species, measurement methods, and experimental context. Therefore, the classification adopted here was based on the structure of the dataset from this specific experiment.

This study also underscores the trade-offs between sensor sampling frequency, model accuracy, and real-world robustness in developing wearable bite-detection devices. In Chapter 3, optimal performance was achieved using a 100 Hz accelerometer. Incorporating the RTK-GNSS module limited sampling to 8 Hz, leading to a drop in bite prediction accuracy from ±1.8 to ±3.2 bites per 10-second window. These results support prior recommendations that a minimum IMU sampling rate of 10–20 Hz is necessary for reliable bite detection (Riaboff et al., 2022). Nevertheless, in PLF, exact bite counts are less critical than the ability of the model to detect meaningful behavioural fluctuations over time. Our model was thus designed to prioritize sensitivity to within-animal variation rather than minimizing per-window prediction error. Although precision declined at lower sampling rates, cumulative bite prediction error over 20-minute sessions remained within acceptable limits.

Key design choices aimed to enhance generalizability across real-world farm conditions. These included the use of robust algorithms (e.g., Bagged Trees), orientation-independent features (e.g., Amag, OBDA, VeDBA) (Khanh et al., 2019, Benaissa et al., 2019). What the model still lacks is greater data diversity. It is necessary to improve its robustness (Riaboff et al., 2022). While higher precision may be possible under controlled settings, practical applications demand tolerance to noise and consistent behaviour detection across varied environments and with various animal breeds and vegetation types, even at the expense of accuracy.

Having demonstrated the effectiveness of the model in short-term ingestion experiments, a next step would be to test such a prototype under continuous, long-duration grazing scenarios. This would allow for the evaluation of cow behaviour across diverse spatio-temporal scales, as described in Andriamandroso et al. (2016), and further assess usefulness of such system for adaptive and sustainable pasture management.

5. Conclusions

This study demonstrates the potential of PLF tools, specifically neck-mounted IMU and RTK-corrected GNSS sensors, to assess how grass structure influences short-term ingestion behaviour in grazing cows. By capturing bite frequency, grazing area use, and spatial distribution of bites within grids smaller than 1 m², the tracking system enabled fine-scale behavioural analysis. Findings showed that cows concentrated their grazing on 22 to 37% of the available area only, despite spending over 90% of their time grazing. Interestingly, bite frequency did not always decline under less favourable conditions; in some short swards, cows maintained or increased bite rates, suggesting an influence of prior exposition to grazing environmental context and short-term motivation. In terms of technological performance, this research also emphasizes the trade-offs between sensor sampling frequency, model accuracy, and robustness under real-world farm conditions. While a 100 Hz accelerometer previously achieved higher precision in bite quantification, the addition of RTK-enabled GNSS limited the system to 8 Hz, slightly reducing per-window accuracy. However, the model remained sufficiently robust to detect meaningful behavioural variations, which are more relevant for PLF applications than exact bite counts. Finally, this study confirms the feasibility of using integrated PLF systems not only to quantify ingestion behaviour but also to spatialize it at unprecedented resolution. These findings pave the way for future research aiming to monitor grazing behaviour continuously over longer periods and at multiple spatial and temporal scales. The approach holds promise for refining pasture management strategies, improving animal welfare, and supporting the development of agroecological livestock systems that align productivity with ecological sustainability.

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Chapter 5

Designing new methodologies integrating accelerometers and geolocation sensors toward a monitoring of grazing cows' behaviours at the finest scale.

In the previous chapter, it was demonstrated that quantifying bites and assessing their spatial distribution on pasture was possible. This chapter develops a clear methodology on how to treat the data from the wearable sensor. It decomposes the individual behaviour of cows at different scales: meals, FS, and shorter time-windows. This chapter uses the data from both "grazing down" and short-term grazing experiment. The methodological framework developed will then be used in the following work to observe and describe changes of behaviours of dairy cows in relation with the evolution of the SH.

Designing new methodologies integrating accelerometers and geolocation sensors for the high-resolution monitoring of the grazing behaviour of cows.

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Abstract

The global shift towards sustainable livestock farming highlights the importance of grazed grasslands, which offer vital services like food provision and ecosystem regulation. Pastures play a central role in livestock farming systems, which face social and environmental pressures. These pressures call for more grassland-based systems that emphasize quality assurance, durability, and animal welfare. Understanding grazed systems is crucial for both food production and ecosystem services, with effective management being key to pasture health and service delivery. PLF tools, such as IMU, are valuable for monitoring grazing ruminants' behaviour, including quantifying bites, the fundamental unit of grazing. Geolocation systems can track animals' movements and interactions with available biomass, potentially enhancing the precision of these measurements when combined with IMU. However, past research has shown low accuracy in geolocation using IMU and GNSS, which is problematic for studying grazing behaviours. In this study, a prototype collar-mounted wearable sensor was tested on Holstein cattle grazing on ryegrass pasture. By integrating RTK-corrected GNSS technology with IMU, the precision of geolocation significantly improved from meters to centimeters. This allowed us to accurately identify behaviours (91.9% accuracy), meals (91.9% accuracy), and FS (94.7% accuracy), with bite frequency estimations having an error of 7.8±8.4%. The integration of precise GNSS and IMU data offers new possibilities for observing grazing behaviours, providing valuable insights for future PLF applications in sustainable livestock management.

Keywords: Precision Livestock Farming; Machine Learning; Sensors; Feeding behaviour; Grassland; Cattle.

1. Introduction

As the demand for animal source foods grows, it is essential to meet this increasing demand without compromising animal welfare, the social impact of livestock production, or environmental sustainability (Bretas et al., 2023). It also seems imperative to reconnect pasture farming to cropping systems, through specialization reduction of farms and territories (Carvalho et al., 2021) in order to restore biogeochemical cycles and the functioning of multifunctional ecosystems, increase the socio-economic resilience of agricultural systems (Carvalho et al., 2021), and reduce the climate impacts through a better management of the available agricultural space (Delandmeter et al., 2023). Managing pastureland and grazed ecosystems is a complex task as it deals with the interface of a vegetation and herbivores grazing upon it. Both the vegetation and the herbivores have their own spatial and temporal dynamics to fulfil their different and sometimes antagonistic requirements from the grazing process. Additionally, feedback exists between both actors of the grazing process as the vegetation shapes the selective grazing behaviour which in turn impacts the structure and composition of the vegetation and its heterogeneity (Bindelle et al., 2021). Hence, understanding the grazing behaviour is crucial for the development of management strategies that address current productivity and sustainability challenges in livestock production (Rivero et al., 2021). From the animal perspective, herbivores have co-evolved with grasslands for millions of years, becoming very efficient at adapting their grazing behaviour to the state of the vegetation. They modulate their grazing behaviour at several scales in space and time, ranging from the entire paddock over a grazing season to the smallest unit of the grazing process, that is the grass-severing bite, which occurs in a matter of a second and covers a few square centimetres (Andriamandroso et al., 2016).

Sensors show the potential to capture with a certain accuracy the different events that constitute the grazing process. They have the advantage of enabling the monitoring of animals over long and continuous periods of time (Aubé et al., 2022; Kaur et al., 2023). Indeed, studies of animal behaviour by direct observation or by video recordings are rarely continuous, and are labourious and time-consuming, with many hours of recording to review, an exhausting task for researchers (Amorim et al., 2024; Siegford et al., 2023). However, sensor-based applications are not yet widely available at the farm level, particularly in applications concerning grazing (Aubé et al., 2022). In research, there are methodologies for monitoring the eating behaviour, but most protocols are adapted for indoor cows and do not include certain parameters necessary for monitoring grazing animals (Aquilani et al., 2022; Aubé et al., 2022). The outdoor and mobile aspects of such sensors still pose a challenge for algorithms, which can limit the possibilities for researchers in these fields (Chelotti et al., 2024).

Based on previous research (Gibb et al., 1997; Mezzalira et al., 2017), variations in bite frequency indicate that herbivores cannot always adjust the time dedicated to grazing and the exploration of the pasture area to compensate for suboptimal grass structure that results in decreased intake rates. Gibb et al. (1997) analysed the effect of grass height on grazing jaw movements (GJM) and showed that the ability of cows to increase their daily grazing time sufficiently to compensate for a decrease in feed rate due to non-optimal grass structure is limited. This information indicates short-term decisions made at the individual bite level by the animal in response to changes in the vegetation structure and aiming to maintain grazing efficiency (Andriamandroso et al., 2016). Should sensors and the signal interpretation algorithms be able to identify these changes in biting patterns and spatial distribution, the recording of such data would unlock the potential for a deeper understanding of the decision process made by herbivores.

Among the available sensors, several meta-analyses demonstrate that accelerometers are the most frequently used sensor type in animal activity recognition, and that they are frequently combined with other types of sensors (Aquilani et al., 2022; Shine & Murphy, 2021; Mao et al., 2023). Their use in commercial or research contexts to observe the behaviour and activity level of grazing cattle is becoming common practice (Aquilani et al., 2022; Riaboff et al., 2022; Piña et al., 2023; Amorim et al., 2024). The addition of the GNSS represents an added value in the context of grazing herbivores as it allows to better understand the link between herd level and spatial variables and the behaviour of grazing cattle: stocking rate, location of water troughs and shade areas, weather conditions, and the characteristics of the terrain and vegetation. In addition to these parameters related to environmental factors, it is crucial to focus on the spatial heterogeneity of behaviours. For example, while the defoliation process caused by grazing is initially heterogeneous—since animals selectively graze certain areas—this heterogeneity tends to decrease as grazing progresses and more biomass is removed across the paddock. As a result, SH becomes increasingly homogeneous with higher overall grazing intensity (Benot et al., 2011).

In addition, when grass is tall, its upper layers are often less dense and less palatable, leading animals to take smaller bites (Mezzalira et al., 2014). This behaviour contributes to spatial heterogeneity in SH and biomass distribution across the meadow. Moreover, animals adapt to a changing grazing environment by modifying the travelled distance over the day during meals, the area covered during meals, or the density and frequency of bites per FS. For these reasons, it is important to add the spatial dimension to the behaviours described earlier.

However, GNSS are limited in terms of accuracy with a resolution of several meters as compared to the few cm² a grass-severing bite entails (Manning et al., 2017; McIntosh et al., 2022). To overcome this constraint, Post-Processing Kinematics and RTK technology have been proposed. They are still mainly used for drones and agricultural machinery, but also more recently in livestock farming to study interactions between sheep (Keshavarzi et al., 2021; 2022). This advance makes it possible to improve GNSS performances with centimeter precision for animal wearable sensors.

In terms of interpretation algorithms, the prediction accuracy of ML approaches is regularly called upon, as an alternative to manual thresholding and statistical models. Their ability to improve over time through self-learning has led to a steady increase in their use to record animal behaviour based on sensor data since 1999. A substantial amount of work using ML for animal behaviour analysis has been carried out since 2014 (Shine & Murphy, 2021). It is also becoming common to obtain models reaching accuracies exceeding 90% to distinguish animal behaviours (Mao et al., 2023). In practice, it is common to use classification algorithms to distinguish categorical variables, such as types of behaviour, and regression algorithms for quantitative variables, such as bites or steps (Bretas et al., 2023). Supervised ML is usually the most common method, followed by Deep Learning and Unsupervised ML (Riaboff et al., 2022).

For this research, a prototype behaviour-and-position wearable sensor was developed, combining IMU and GNSS technologies, with RTK-correction for geolocation. This allows a very precise method of measuring animal activity at spatial and temporal scales where the current knowledge is limited (Arablouei et al., 2023; Mancuso et al., 2023b; Romero-Ruiz et al., 2023). Although studies combining GNSS and accelerometers remain rare, they offer more complete monitoring than those using only one type of sensor (Mancuso et al., 2023b; Obermeyer & Kayser, 2023). This has the potential, in addition to improving the localization of specific behaviours, to estimate the travelled distance and speed of the individuals. It was therefore decided to add RTK technology to the range of tools used for PLF and to couple it with inertial units. The performance of the wearable sensor was tested through two types of experiments. The first experiment involved short-term STIB observations, preceded by fasting periods, to focus on the ingestion behaviour and number of bites. The second experiment involved GD sessions to monitor the evolution of the behaviours with the reduction of the available grass.

This research starts with the hypothesis that the bite movements of cows during ingestion differ at various scales, depending on the structure of the grazed vegetation, which is characterised by grass height. The objectives of this research are to test whether wearable sensors, such as the one presented above, are able to recognise the animal's ingestion behaviour at multiple spatio-temporal scales, described by Andriamandroso et al. (2016) and precisely delimited in Table 5-2. Grazing bouts were not included in this paper because their spatial delimitation is subjective, in contrast to the more objectively identifiable FS. FS are defined as discrete locations where an animal stops moving to perform multiple consecutive bites. Multiple FS collectively constitute a grazing bout, which typically covers a few square meters and lasts between 10 and 100 seconds (Andriamandroso et al., 2016).

The first experiment consisted of a series of STIB observations with groups of three cows wearing the wearable sensors. The observation was specifically focused on bite execution, to calibrate and validate a two-phase bite quantification model. The parameters studied in this first experiment were (1) the bite frequency (bite.sec-1) and (2) the number of FS. The second experiment followed four GD sessions on a plot for several consecutive days (Gonçalves et al., 2018). The objective is to determine if the animal is adopting new behaviours corresponding to the evolution of the availability of grass and its structure on the plot, which will be no longer optimal for its requirements at some point and might lead to the phenomenon of overgrazing. The parameters studied in this second experiment were (3) the percentage of time spent performing ingestion behaviour and (4) the number and length of meals during the sessions. The longer periods of observation during GD sessions did not allow to have a proper continuous observation for bite frequencies and FS.

This study aims to build on existing work that develops methodologies for such applications (Chelotti et al., 2024). It focuses on raw signal processing parameters. Additionally, it examines the ML methods employed for these applications. This tracking system will have to answer very specific questions concerning the interactions between animals and the structure of the grass.

2. Materials and Methods

Figure 5-1 provides an overview of the methodological framework that was applied. Every step will be described in this section.

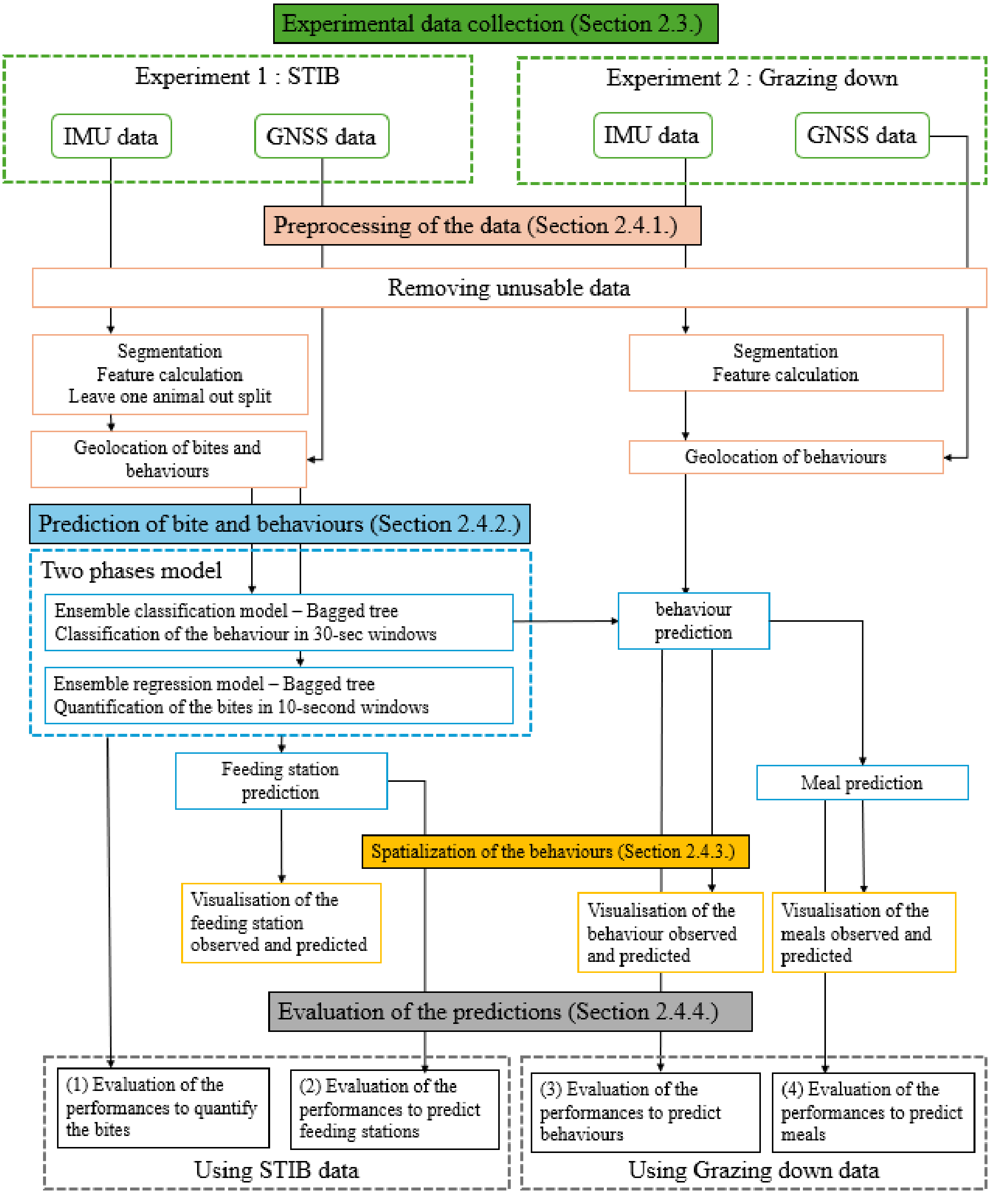

Figure 5-1: Framework of the steps followed to evaluate the behaviours at four spatio-temporal scales, based on two experiments (STIB and GD).

2.1. Wearable sensor construction and settings

The cows were equipped with collars fitted with a Mega 2560 Rev3 Arduino (Arduino.cc, Monza, Italy) connected to a GY-521 MPU-6050 module (ZHITING, London, UK) with 6 DOF (3 accelerations and 3 rotations) as well as a GNSS SimpleRTK2B shield (ArduSimple, Lleida, Spain). The placement around the animal's neck is advised to provide good results regarding the detection of activities (Mao et al., 2023) while ensuring minimal disturbance to the animal. The system recorded both geolocation and IMU signals at a frequency of 8 Hz on a SD card used to read, process, and save the sensor data, which was retrieved after the grazing sessions.

The sensor data reading and processing program was developed in C/C++ using the Arduino Integrated Development Environment. The program activated the writing process for IMU data with every reading of the GNSS data. Both IMU and GNSS were registered on the same line of a CSV table, providing a total of 9 signals (Table 5-1). The accelerometer range was ±8G and the gyroscope range was $500°s^{-1}$. The x-axis detected up-and-down head movements and y-axis lateral head movements; the z-axis detected backward-forward head movements (Figure 5-2). The static position error for geolocation is estimated at <1 cm with a base station up to 35 km. However, as explained in the section 2.2. of the Chapter 4, the parameter selected to reach the best compromise in terms of performance in the field allowed a precision level with an error of <45 cm.

The system was composed of a box for the sensor and a battery box, both custom-built tough polylactide (PLA) 3D-printed and smoothed with acetone to be waterproof, with 5 mm case walls.

Table 5-1: List of the signals taken by the wearable sensor.

Sensors	Signal	Information
Accelerometer	Acceleration on x, y and z	Unit: g[a]
Gyroscope	Euler angles (pitch x, roll y, yaw z)	Unit: Radian
GNSS	Latitude and longitude	Unit: degrees
	RTK statut	Classes (RTK ; RTK FLOAT ; DGNSS ; GNSS)
Clock	Timestamp: date and time	yyyy-mm-dd-hh:mm:ss

[a] g: acceleration of gravity (g = 9.81 $m.s^{-2}$).
RTK status classes precision: RTK: centimeter level; RTK FLOAT: decimeter level; DGNSS: sub meter; GNSS: more than 1 meter

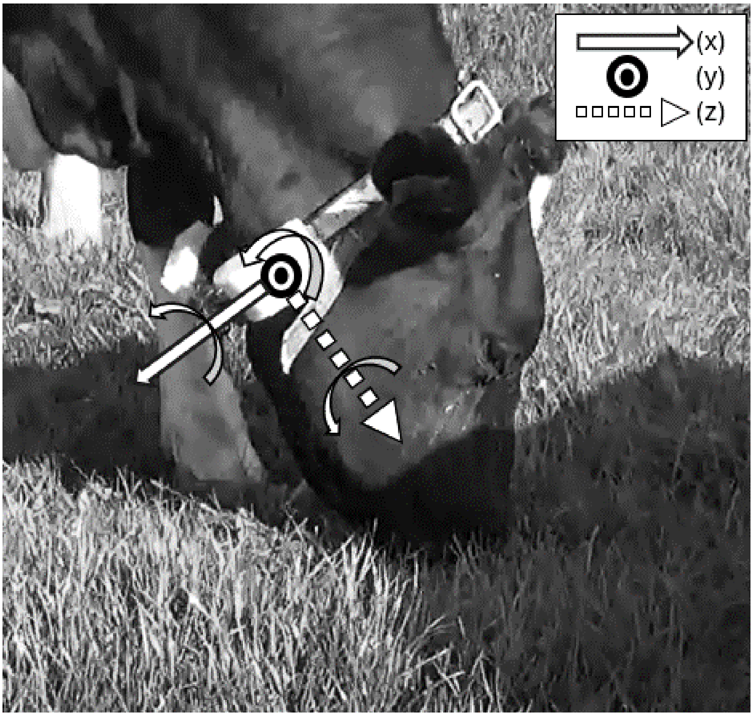

Figure 5-2: Wearable IMU and GNSS sensor fixed on the collar of the cow. The three coordinate axes of the accelerometer are displayed, and rotation arrows indicate the gyroscope rotational axes.

A multi-band u-blox ANN-MB-00 IP67 GNSS antenna (ArduSimple, Lleida, Spain) was fixed on top of the collar (Figure 5-3). The battery powering the sensor was a 5 V external lithium-ion battery with 20000 mAh capacity which enabled a maximum runtime of approximately 48 hours. The complete system weighed 1.005 kg, less than the maximum 1.2% of the total animal weight recommended to avoid interfering with behaviour (Dickinson et al., 2020). The total cost of the setup at the time of purchase (April 2022) was approximately 380 euros per unit.

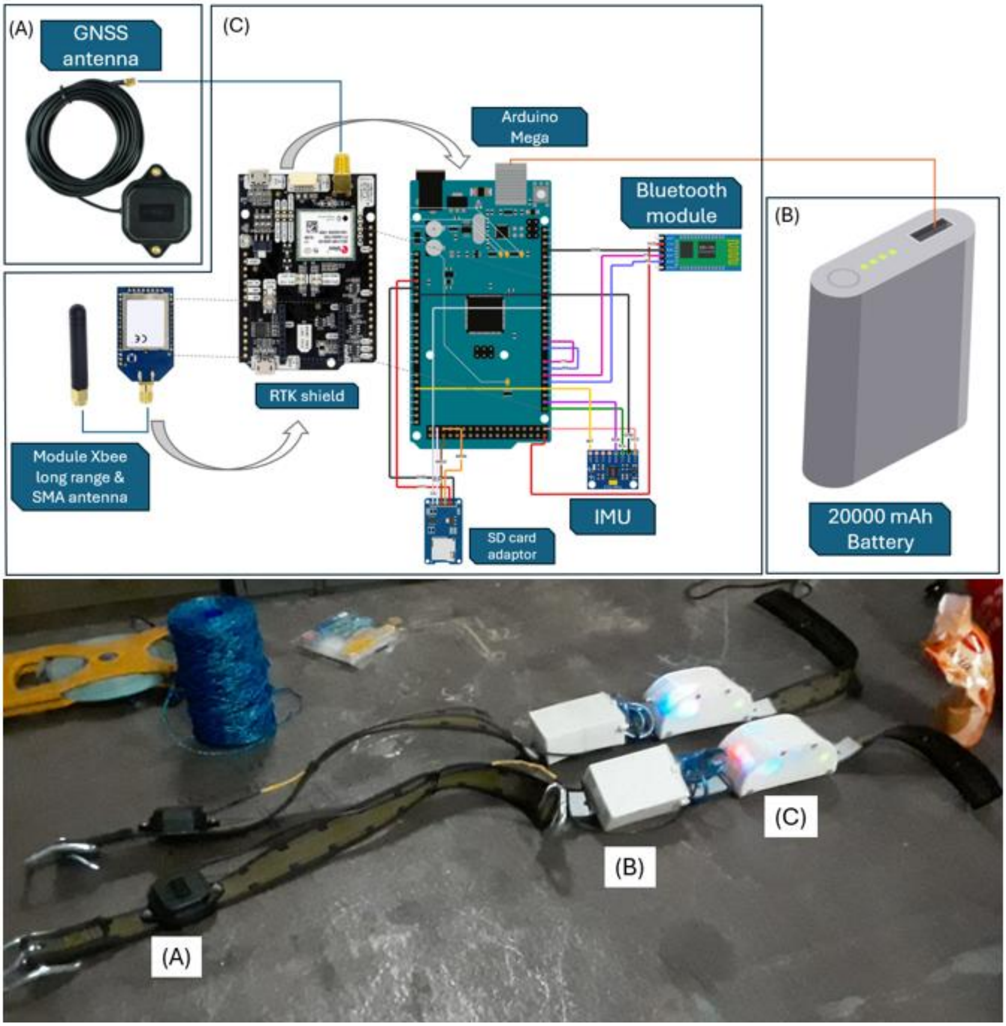

Figure 5-3: Wiring of the wearable sensor including (A) the GNSS antenna, (B) the 5 V external battery with 20000 mAh capacity and (C) the Arduino Mega, the simpleRTK2B shield and the different modules and antennas attached.

2.2. Farm, animals and conditions

The experiment took place at the Agricultural Technologies Center of Strée-Modave (Belgium) (N 50°50'716", E 5°31'645") between May and July 2023 on a set of twelve 15×30 m and two 25×25 m² ryegrass paddocks. Eight heifers and four dry Black Pied Holstein cows were split into four groups composed of two heifers and one dry cow each. The groups were composed according to the weight of each animal to avoid differences in total weight between groups. All animals were accustomed to the center and well adapted to the grazed pastures. The average age of the cows was 20 ± 5 months for the heifers and 51 ± 5 months for the dry cows (mean ± std). Animals of different ages and physiological stages were mixed to increase the robustness of the developed algorithm as recommended by Riaboff et al. (2022), and with no lactating animals, to avoid the need to return to the barn for milking. The average weight of the heifers and dry cows was 522 ± 108 kg and 792 ± 56 kg (mean ± std) respectively. The cows were kept day and night on a pasture next to the experimental paddocks. No supplementary feed was given to the animals during or in-between observation sessions. During the grazing periods an average of 13 hours and 40 minutes of sunshine per day was recorded, with little to no nebulosity. The average daily temperature was 13.6 °C, ranging from 4.2 °C at the coldest time of day to 31.9 °C. Out of the 60 days of experiments that took place, 12 had at least 1 mm of daily rainfall, and five days had daily rainfall above 2 mm with a maximum of 5 mm on June 20th, 2023. The wind speed was never above 30 km/h.

2.3. Data collection

Two complementary grazing experiments were conducted to build a behaviour database by combining visual observations with the measured signals recorded by the collars, see the synthetic table 5-2.

Table 5-2: Materials and Methods synthetic table - Data Collection.

Component	Description
Experiments description	Two complementary experiments: (1) short-term grazing sessions (STIB), and (2) 72-hour grazing-down sessions.
Sensor Deployment	All cows equipped with collar-mounted wearable sensors (IMU + GNSS). Devices synchronized with video at start of each session.
Pasture Conditions	Flat terrain; no slope, waterlogging, or specific structural elements. See satellite map (Fig. 5-4).
(1) STIB Setup	48 one-hour grazing sessions after 3–6 h fasting (with water) to stimulate ingestion behaviour without provoking intake rates that are superior to average (Patterson et al., 1998); 3 cows per session on 15×30 m ryegrass paddocks (SH: 6.1–21.2 cm); no water access during sessions; grass availability kept consistent. (Figure 5-5).
(2) GD Setup	72-hour continuous grazing on two 25×25 m ryegrass paddocks; four groups of three cows; average pre-grazing SH: 12.5 ± 2.5 cm; post-grazing SH: 5.0 ± 0.7 cm; water provided ad libitum. The protocol was adapted from Gonçalves et al. (2018). (Figure 5-5).
Behaviour Recording	(1) Dual observers with video (head, mouth, legs), total 80h20m video data. (2) 1-minute ethogram-based (Table 5-3) observation grid from 6:30–18:30 (12 h/day).
Vegetation Measurements	(1) Pre/post every session: CSH: 30 EC20 plate meter measures (Jenquip, Feilding, New Zealand); SH: 60 sward stick measures (Barthram, 1986).; 3× biomass cuts (50×50 cm quadrats).

Component	Description
	(2) CSH: 30 measures every 3h; SH: 60 measures and 3× biomass cuts twice daily.
Total Data Collected	(1) 238 videos, 22 ± 8 min avg (2) 305 hours of observed data across animals.

Table 5-3: Ethogram and rules used to register the cows punctual action, behaviours, and to define spatial and temporal components of the ingestion behaviour.

	Behaviour	Description	Rules used
Actions	Bite	The grass is torn from the root to be consumed by the animal (Andriamandroso et al., 2016). Bite was only taken into account with standing animals	Each time grass is cut during the bite, a timestamp is recorded.
	Chew	The lower jaw follows a rotational movement, cutting the grass in smaller pieces in the mouth of the animal, without severing new grass from the ground (Laca et al., 1994).	Chews are described here to aid in distinguishing it from bites, they were deliberately excluded from the recorded behaviours during observations.
	Step	Every step from one of the front leg of the animal	Each time the animal lifts one of its front hooves from the ground, a timestamp is recorded.
Behaviour	Ingestion	The animal is standing up, searching for food with its head down, and performs prehensive grass-severing bites with maximum interruptions between bites of 10 seconds.	The "ingestion" behaviour was assigned to 30-second windows during which the animal was performing at least one bite.
	Other	All other behaviour observed: rumination, rest, drinking, moving head up, searching for food without bite for more than 10 seconds and other active behaviours (Gonzáles et al., 2015).	Every observed 30-second window without bites was considered as "other"
Spatio-temporal component of the	Feeding station	Several bites performed in a row by an animal without interruption > 10 seconds, covering the path width of the	The number of FS was evaluated based on the observations as duration of 1 to 10 successive 10-

ingestion behaviour		animal, and lasting between 5 to 100 seconds (Andriamandroso et al., 2016).	second time windows containing > 1 bite and ≤ 1 step
	Meal	The number of meals over a day is estimated by counting periods of ingestion of at least 5 minutes separated by intervals > 5 minutes (Gibb et al., 1999).	For each succession of "ingestion" windows > 5min, any "other" sessions < 10min* preceding or following that session is considered as part of the meal. The process is iterated until each meal is delimited.

* Although the literature considers that an interruption of less than 5 minutes does not constitute a true meal break, a 10-minute threshold was used for meal detection. This decision was based on preliminary tests, which showed poor performance with a 5-minute threshold. The full analysis process was therefore conducted exclusively using the 10-minute threshold.

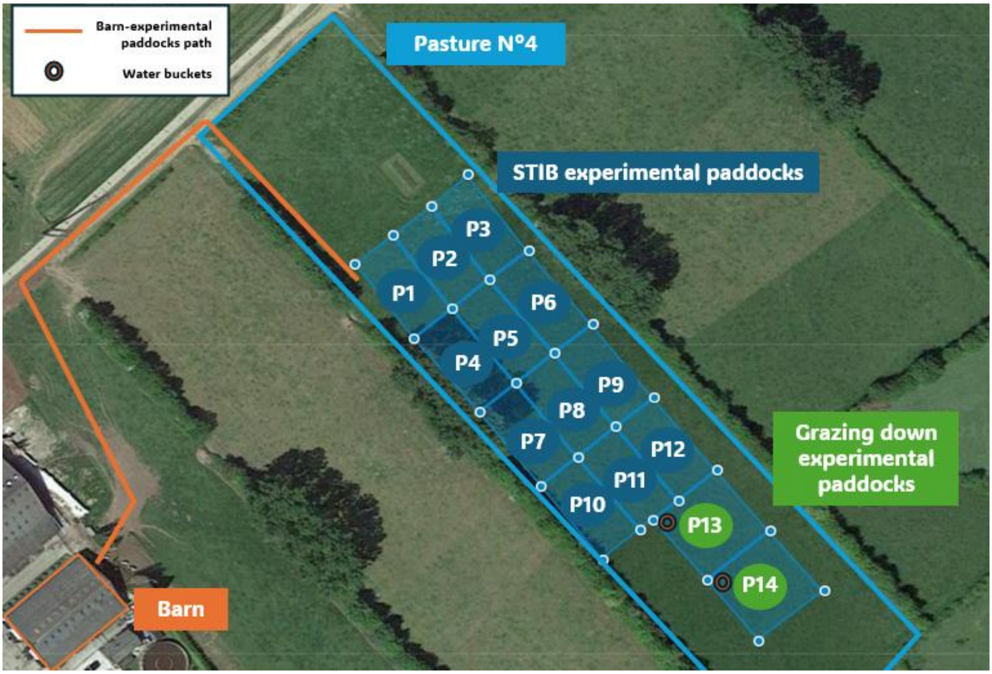

Figure 5-4: Satellite view of the experiment. P1 to P12 are the paddocks used for the STIB experiment, each sized 30×15m. P13 and P14 are the paddocks used for the GD experiment, each sized 25×25m. The animals were left in the remaining area of pasture N°4 day and night in between experiments. The delimitation of the experimental paddocks were electric fences. The wearable sensors were installed on the cows in the barn, where the cows were also kept for the fasting sessions during the STIB experiment.

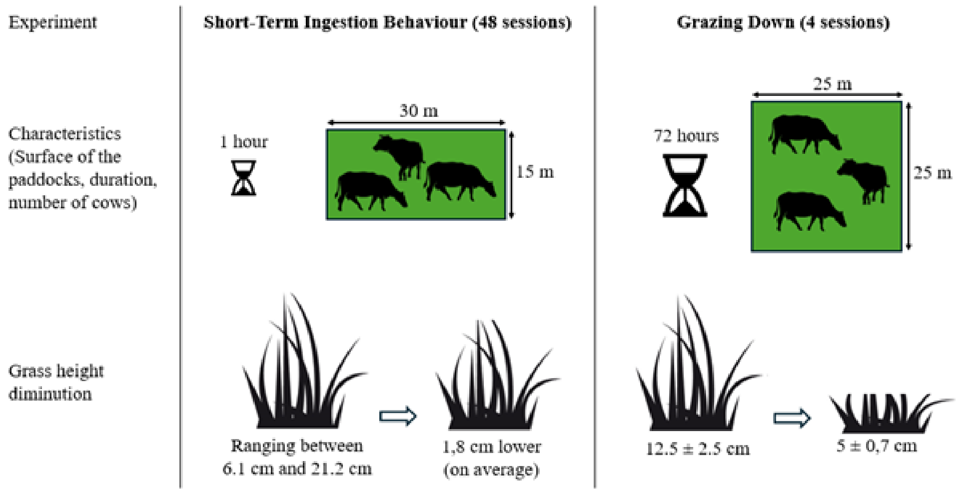

Figure 5-5: Differences between the STIB and the GD experiments.

2.4. Data processing

The data processing was performed using MATLAB 2024a (MathWorks, Natick, USA) for the creation of behaviour and bite detection algorithms, as well as the processing of geolocation data, and QGIS (OSGeo, Chicago, USA) to extract and model the geolocation data. The bite quantification approach builds on the same two-phase model introduced in Chapters 3 and 4, consisting of (1) classifying 30-second time windows as "ingestion" or "other" behaviours, and (2) applying a regression model to estimate the number of bites within 10-second ingestion windows. Unlike previous chapters, where default hyperparameters were used, this chapter explores a range of parameter and hyperparameter configurations to identify the most effective combination. Only the best-performing models are presented here, with full testing procedures detailed in Appendix 6.

2.4.1. Data preprocessing

The pre-processing of the raw data is described in Table 5-4.

Table 5-4: Materials and Methods synthetic table - Data preprocessing.

Component	Description
	Data sources
Raw sensor Data	Time-stamped IMU and GNSS data: 3D acceleration, 3D angular rotation, latitude, longitude, RTK correction status.
Video Ground Truth (STIB)	-63h38min of usable video from 80h20min recorded; -32h45min ethogram-based (Table 5-2) annotations at 1 Hz with CowLog 2.0 (Hänninen and Pastell, 2009) to create a labelled bite, step, and rumination datasets. *Data removal* -Malfunction of the GNSS data (10.4%), -Malfunction of the IMU data (5.7%) -Poor video-taping (4.7%),
Ethogram-based observation grid (GD)	- 24 continuous sessions of 3 to 12h annotated every minute, with corresponding sensor data, for a total of 186h. (List of sessions in appendix 7).
	Preprocessing steps
Segmentation Strategy	- Phase 1 (STIB): 30-sec windows with 90% overlap - Phase 1 (GD): 30-sec windows, no overlap (not used for training) - Phase 2: 10-sec windows without overlap within ingestion-labelled segments
Time Series Used	Roll (Rx), Yaw (Rz), Amag, OBDA, VeDBA
Feature selection	- 68 time & frequency features calculated; 20 retained after Pearson correlation filtering (<98%) (listed in Table 4-1) - Features standardized and used for both phase 1 and 2 - The same features were used for both phases 1 and 2.
Data Splitting	- Leave-one-animal-out (LOAO) cross-validation (n = 12) - The number of time windows available to train the model for each cow is listed in Table 5-5.
GNSS Features	- Averaged coordinates over 10-sec windows, 80.7± 9.0 data points for every segment. - Steps from ethogram annotations (Table 5-2) - Distance: Pythagorean theorem applied on an equirectangular projection. *Formulas* Distance = $\sqrt{(\Delta long.\cos(mean\ lat))^2 + (\Delta lat)^2}.\ R$ (1) Where Δlong and Δlat are the differences in longitude and latitude between two 10-second windows, respectively, converted to radians, and R is the Earth's radius (estimated at 6,371,000 m). This method is both computationally efficient compared to the Haversine formula and is sufficiently accurate for short distances (Arablouei et al., 2023).

Table 5-5: Data available for each individual cow to train the two phases of the model.

Animal ID	Physiological stage	10-sec windows	% 10-sec windows	"ingestion" 30-sec window	"other" 30-sec window	Total 30-sec window	% 30-sec windows
7055	Heifer	4846	4.8%	1574	0	1574	4.7%
7040	Heifer	5173	5.1%	1582	106	1688	5.0%
6931	Dry cow	6807	6.7%	2119	16	2135	6.4%
7074	Heifer	6858	6.7%	2011	119	2130	6.4%
7056	Heifer	6974	6.9%	2185	0	2185	6.5%
7069	Heifer	6996	6.9%	2214	0	2214	6.6%
0544	Heifer	8493	8.4%	2607	243	2850	8.5%
7062	Heifer	8960	8.8%	2829	55	2884	8.6%
7057	Heifer	9468	9.3%	2961	471	3432	10.3%
6289	Dry cow	10 232	10.1%	3250	16	3266	9.8%
6886	Dry cow	12 052	11.9%	3818	111	3929	11.7%
6885	Dry cow	14 782	14.5%	4724	467	5191	15.5%

2.4.2. Methods for data analysis

This step aimed to train the 2-phase model to be able to predict the ingestive behaviour expressed by the 12 dairy cows over the two experiments. The considered ML algorithm, "Bagged tree" is a bootstrap-aggregated ensemble of fine decision trees, a method that can be used to train both classification and regression algorithm. It samples training data with replacement (bootstrap) and averaging or voting over class labels (Breiman, 1996); the bagging process focuses more on reducing variance compared to alternatives such as boosting, which focuses more on reducing bias (Shahhosseini et al., 2022). Bagging model trees outperform state-of-the-art decision tree ensembles on problems with numeric and binary attributes and frequently excel on problems with multi-valued nominal attributes as well (Kotsiantis et al., 2005). The training and testing process are presented in Table 5-6. All the hyperparameters and options have been tested individually and jointly to search for the best performances. The hyperparameters and details for the two final (= most performant) algorithms are shown in Table 5-7.

Table 5-6: Materials and Methods synthetic table – Methods for data analysis.

Component	Description
Model Structure, two-phase ML model:	Phase 1 – classification of behaviour (ingestion vs other); Phase 2 – regression of bite count within ingestion periods.
Training Approach	- Leave-one-animal-out cross-validation (n=12) for Phase 1 and 2 training on STIB dataset. Data from one animal was excluded to train the algorithms with data from the other 11, using the excluded data as the testing sample. - Phase 2 trained only on ingestion windows
ML Algorithm	Ensemble of Bagged Trees (MATLAB 2024a) for both classification and regression; tuned via hyperparameter search. (See Table 5-7). *Classifier Hyperparameters modified* - Lowered from 21684 to max 5000 splits: simpler trees improved robustness and generalization *Regressor Hyperparameters modified* - Augmented from 30 to 100 learners: more learners yielded higher accuracy
Bite frequency prediction testing (STIB data)	-36 sessions of 20 minutes (3 per individual) were selected to test the capacity of the two-phase model to predict and characterize bite frequencies and FS. The sessions were selected based on the continuity of the observation (i.e., no period with no direct line of view between the observer and the mouth of the animal). - Leave-one-video-out (n=36) for final testing on STIB dataset (32h 25min of annotated video). Data from one 20-minute session was excluded to train the algorithms with data from the other 32h25', using the excluded data as the testing sample, and repeating the process for each session (n = 36).
FS predictions testing (STIB data)	-The same 36 sessions of 20 minutes as for bite frequency (3 per individual). -Delimitation of a FS = 1–10 successive 10-sec windows with "ingestion" behaviour only, and limited movements. *Thresholds tested for the movement, first iteration:* Maximum number of steps: max 0; max 1 step per window; GNSS distance thresholds of 0.5, 0.75, 1 m from the first window of the FS. *Thresholds tested for the movement, second iteration* -Ignored thresholds for the maximum number of step and only used GNSS spatial distances (> 1 m) to determine the separation between FS.
Meal & Behaviour prediction	-The long-term grazing behaviour of heifers reflects patterns similar to those observed in short-term studies of foraging and harvesting processes (Da Trindade et al., 2012). Therefore, a last

Component	Description
testing (GD data)	two-phase model was trained with data from all individuals during the STIB experiment for prediction of the meals and behaviours during the GD sessions. - 24×3h sessions tested, none of those data points were used to train the model. -“Ingestion” detected from 30-sec windows with the phase 1 of the model; -1-min observer logs converted using ingestion majority rule (if a minute contained at least one window identified as 'ingestion', the whole minute is considered as 'ingestion') - Meal = periods of ≥5 min of ingestion, with ≤5-min (observation) or ≤10-min (model) interruption

Table 5-7: Parameters and hyperparameters of the algorithms used for phase 1 and 2.

Algorithm	Parameters of fitted models	
Phase 1: Ensemble Classification model	Hyperparameters	Preset: Bagged Trees Ensemble method: Bag Learner type: Decision tree Maximum number of splits: 5000 Number of learner: 30 Number of predictor to sample: Select all
	Feature selection	20/20 individual features selected
	PCA	Disabled
	Misclassification Costs	Default
Phase 2: Ensemble Regression model	Hyperparameters	Preset: Bagged Trees Minimum leaf size: 8 Number of learners: 100 Number of predictor to sample: Select all
	Feature selection	20/20 individual features selected
	PCA	Disabled

2.4.3. Ingestion time and bites spatialization

The aim of this step was to model the overall cow position in pastures while they were performing ingestion behaviour and bites on the paddocks. In order to spatialize said behaviours into meals and FS within square grids covering the whole paddock, The characteristics of the pasture were mostly homogeneous for both experiments. The point here was mostly to test it as a possibility in order to be able to reproduce the same experiment on paddocks showing heterogeneity of structural elements (trees, ponds, hedges), slopes or botanical classes (Riaboff et al., 2020).

For each FS and each 10-second time window, the longitude and latitude were linked to the number of bites estimated by the model on a CSV table.

The resulting coordinates were projected on the BD72 / Belgian Lambert 72 SCR (EPSG:31370) and then on a hexagonal grid covering the whole paddock with the QGIS (OSGeo, Chicago, USA) QAD extension. The grids consisted of squares measuring 2 x 2 m, extending 50 cm beyond each edge of the meadow to account for instances where the animals might stick their heads under the wire to graze.".

The total area of hexagons in the grid containing bites was compared to the total area of the paddock (S=450m² for STIB and S = 625 m2 for GD) to estimate the percentage of the explored area during the grazing events observed (meals, X-hour GD sessions, 20-minute STIB sessions).

The tool “count point in polygons” was then used to estimate the number of bites taken in each hexagon. The resulting layers were extracted as CSV datasets.

Those datasets were processed using MATLAB R2024a (Mathworks, The Netherlands) to estimate the total area of hexagons containing bites during the grazing events observed by summing the areas of hexagons where at least one bite was taken. The ingestion time and number of estimated bites were therefore computed in each hexagon of the pastures for individual cows.

2.4.4. Evaluation of the predictions

The evaluation methods and the metrics used for model assessment for the 4 spatio-temporal scales studied are listed in Table 5-8.

Table 5-8: Summary of Evaluation Methods and Metrics Used for Model Assessment.

Evaluation Context	Model Phase	Metric(s) Used	Details
Bite frequency (STIB session)	Phase 1	Cohen’s Kappa (Cohen, 1960), Accuracy, Precision, Recall, Specificity, F1-score	- Metrics computed per 30s window for classification; (see Table 5-9 for the formulas)
	Phase 2	RMSE, Prediction Accuracy	- Accuracy = Ratio of predicted to observed bites per 10s window; - Predicted bites set to 0 in windows labelled “other” during phase 1.
Feeding Station prediction (GD)	Combined	Precision, Recall, F1-score	- Predicted FS considered TP if matched with observed FS within 10s; - Unmatched predictions / observations are FP/FN respectively -Table 5-10 for the formulas

Evaluation Context	Model Phase	Metric(s) Used	Details
Meal detection (GD)	Phase 1	Accuracy, Precision, Recall, F1-score, RMSE	- Predicted meal is TP if overlaps observed meal; - True meals with no match are FN, predicted meals with no match are FP - RMSE used to evaluate duration error (see equation (2)) -Table 5-10 for the formulas

$$\text{RMSE}=\sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i-\hat{y}_i)^2} \qquad (2)$$

Where
n is the number of observations
y_i is the actual number of bites
$\hat{y}_i$ is the predicted number of bite

Table 5-9: Algorithm quality evaluation criteria for the phase 1 model.

Parameter	Equation
True positive (TP)	The behaviour is correctly classified as ingestion
True negative (TN)	The behaviour is correctly classified as other
False positive (FP)	The behaviour is incorrectly classified as ingestion
False negative (FN)	The behaviour is incorrectly classified as other
Recall (R)	$\frac{\text{TP}}{(\text{TP} + \text{FN})}$
Specificity for “ingestion”.	$\frac{\text{TN}}{(\text{TN} + \text{FP})}$
Accuracy (= Observed agreement)(po)	$\frac{\text{TP} + \text{TN}}{(\text{TP} + \text{TN} + \text{FP} + \text{FN})}$
Precision (P)	$\frac{\text{TP}}{\text{TP} + \text{FP}}$

F-score	$\frac{2.P.R}{(P + R)}$
Expected agreement (pe)	$\frac{(TP + FP).(TP + FN) + (TN + FN).(TN + FP)}{(TP + TN + FP + FN)^2}$
Cohen's Kappa (K)	$\frac{(po - pe)}{1 - pe}$

Table 5-10: Algorithm quality evaluation criteria from phase 1 for FS and meals.

Parameter	Equation
True positive (TP)	The FS / meal is correctly predicted
False positive (FP)	A FS / meal is predicted where there is none
False negative (FN)	A true FS / meal is not predicted
Recall (R)	$\frac{TP}{(TP + FN)}$
Accuracy	$\frac{TP}{(TP + FP + FN)}$
Precision (P)	$\frac{TP}{TP + FP}$
F-score	$\frac{2.P.R}{(P + R)}$

3. Results

In this section, the performance of the proposed 2-phase model for bite detection and behaviour identification are tested, as described in Section 2.4.4. A visual analysis is provided, showing the combination of GNSS data with the results from the 2-phase model. Finally, the MATLAB code for reproducing the presented results is made publicly available in Supplementary Data.

3.1. Performances of the 2 phases model

3.1.1. Frequency of bites for 20-min sessions during STIB

The performances of phase 1 are presented for each animal in Table 5-11. It shows that the model performs especially well in identifying ingestion, with an average precision of 98.9±1.7%, a recall of 99.1±1.2%, and an average accuracy of 98.2±1.8. However, the lack of "other" behaviour segments in the training data gives some room for improvement in specificity (78.2±9.4%). Cohen's Kappa is substantial (> 61) and supports the reliability and robustness of the model's predictions. Overall, these results suggest that the model is very effective in its task, with a minor issue in correctly identifying non-ingestion cases.

Table 5-11: Performance of the phase 1 and 2 of the model –- measured based on a leave-one animal-out method.

Phase 1 - Classification				Phase 2 - Regression			
	Average		STD		Average		STD
TP	2628	±	911	RMSE	3.19	±	0.41
TN	100	±	120	Predicition Accuracy	95.0 %	±	18.0 %
FP	34	±	56	Mean Absolute Error	15.3%	±	10.3%
FN	28	±	44				
Accuracy	98.2%	±	1.8%				
Precision	98.9%	±	1.7%				
Recall	99.1%	±	1.2%				
Specificity	78.2%	±	9.4%				
F-score	99.0%	±	1.0%				
CohensKappa	74.1%	±	14.5%				

The performances of phase 2 are presented in Table 5-11, with an average RMSE of 3.19±0.41 bites for each 10-second window and an error of prediction of 15.3±10.3%. The detailed results for each individual are available in Appendix 9 and 10. This shows that the lower frequencies of the sensor due to hardware limitations give lower results than previously used 100 Hz sensors (Chapter 3). However, for the combinations of phases 1 and 2 on individual sessions of 20 minutes (n = 36), the average RMSE is 2.34±0.69 bites for each 10-second window, and the error of prediction is 7.8±8.4%. It is shown in Figure 5-6 that a pattern is observable between the true and predicted bite numbers and average frequencies during the different tested grazing sessions. The Pearson correlation coefficient between the predicted and true values was 0.90 for the frequency of bites and 0.93 for the number of bites, suggesting a high degree of linear association. The details of the statistics for the 36 sessions are available in Appendix 12.

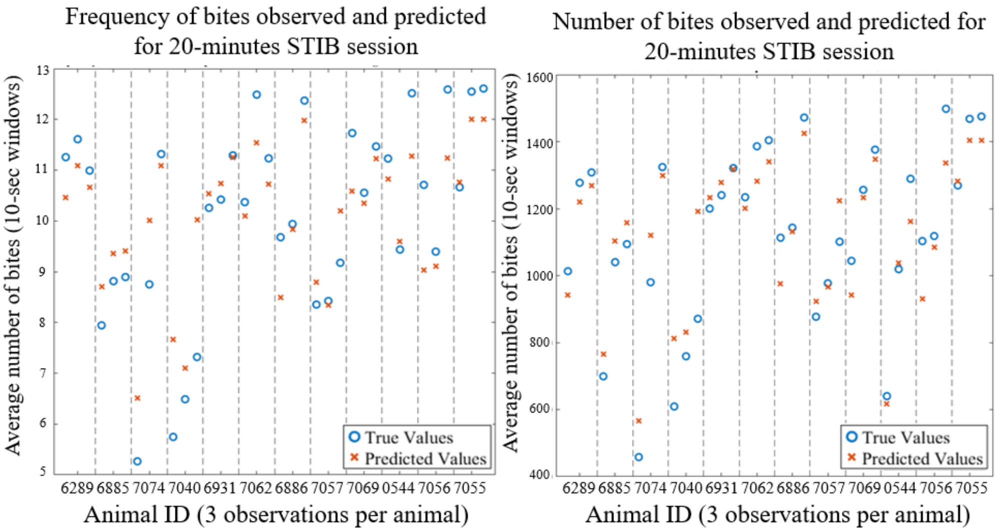

Figure 5-6. Performance of the 2-phase model on 36 sessions on 20 minutes (3 sessions per individual).

3.1.2. FS observation during STIB

The classification accuracy of the considered algorithms is evaluated via a leave-one-video-out (LOVO) cross-validation using the labelled datasets, STIB and GD.

The first method used the number of steps to identify true FS, aiming to match them with the distances travelled detected by the model. However, this approach yielded unsatisfactory results, with a maximum accuracy of only 53.0% (see Appendix 13). The bad performance was mainly due to a mismatch between the number of observed steps and the actual distances covered during FS visits.

A second approach was tested, relying exclusively on GNSS data for both true and predicted FS locations. This allowed a more direct evaluation of the IMU's ability to detect the start, stop and bite frequency of FS, leading to improved performance (see Table 5-12) with an F-score of 97.1± 4.8% and an accuracy of 94.7± 8.1% to predict FS. Concerning the details of every matching FS, the average observed durations were slightly shorter (62.4±33.6 sec) than the predicted duration (64.2±33.4) with a RMSE of 14.5±13.5. The average observed number of bites per FS was very close (69.4±42.2) to the prediction (68.3±37.8), with a RMSE of 14.5±13.5. These results show that the method offers an overall good characterization of the number of FS as long as the GNSS used gives precise geolocation. It should be noted that the number of steps taken by the animal, however, was not relevant to provide an accurate correlation with its movements during ingestion. A time series plot and a spatialized representation of the FS are shown in Figures 5-7 and 5-8 to illustrate the differences in prediction between the first and second methods.

Table 5-12: FS prediction and characterization based on the GNSS method with a 0.5m threshold. Results based on 36 sessions of 20 minutes of uninterrupted observation.

Precision	98.3%	± 4.7%
Recall	96.0%	± 5.7%
F-Score	97.1%	± 4.8%
Accuracy	94.7%	± 8.1%
Duration average (True)	62.4	± 33.6
Duration average (predicted)	64.2	± 33.4
Duration RMSE	10.2	± 15.7
Average n_bites (True)	69.4	± 42.2
Average n_bites (predicted)	68.3	± 37.8
n_bites RMSE	14.5	± 13.5

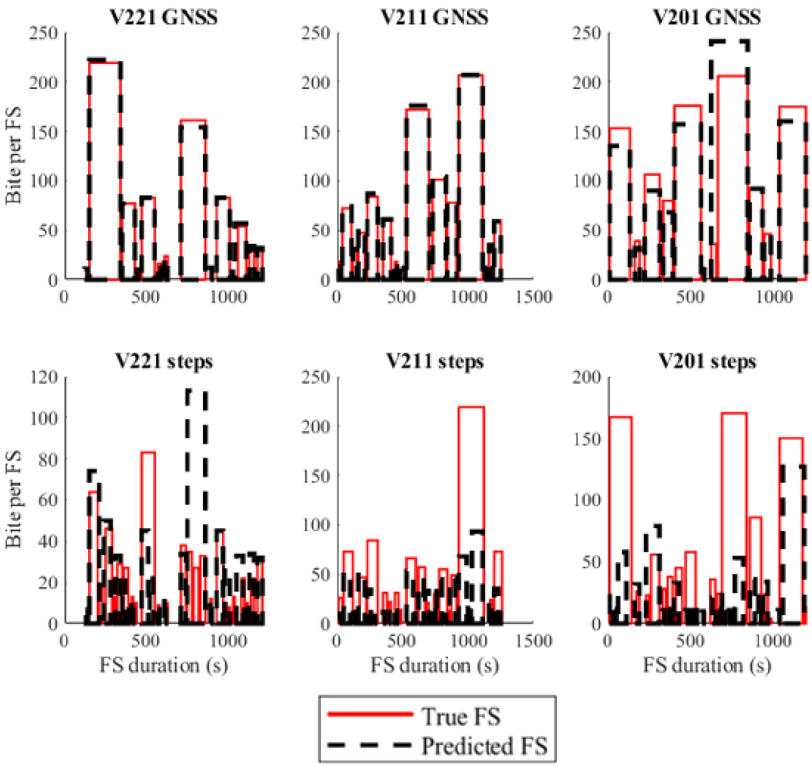

Figure 5-7: Plot representation of the true and predicted FS for three samples. The true FS were determined using the GNSS geolocation data for the first row and number of steps for the second row, as explained in section 2.4.2. The sample were selected based on their RMSE for bite prediction based on the geolocation method (V221: RMSE = 2.1; V211: RMSE = 14.6; V201: RMSE = 65.9).

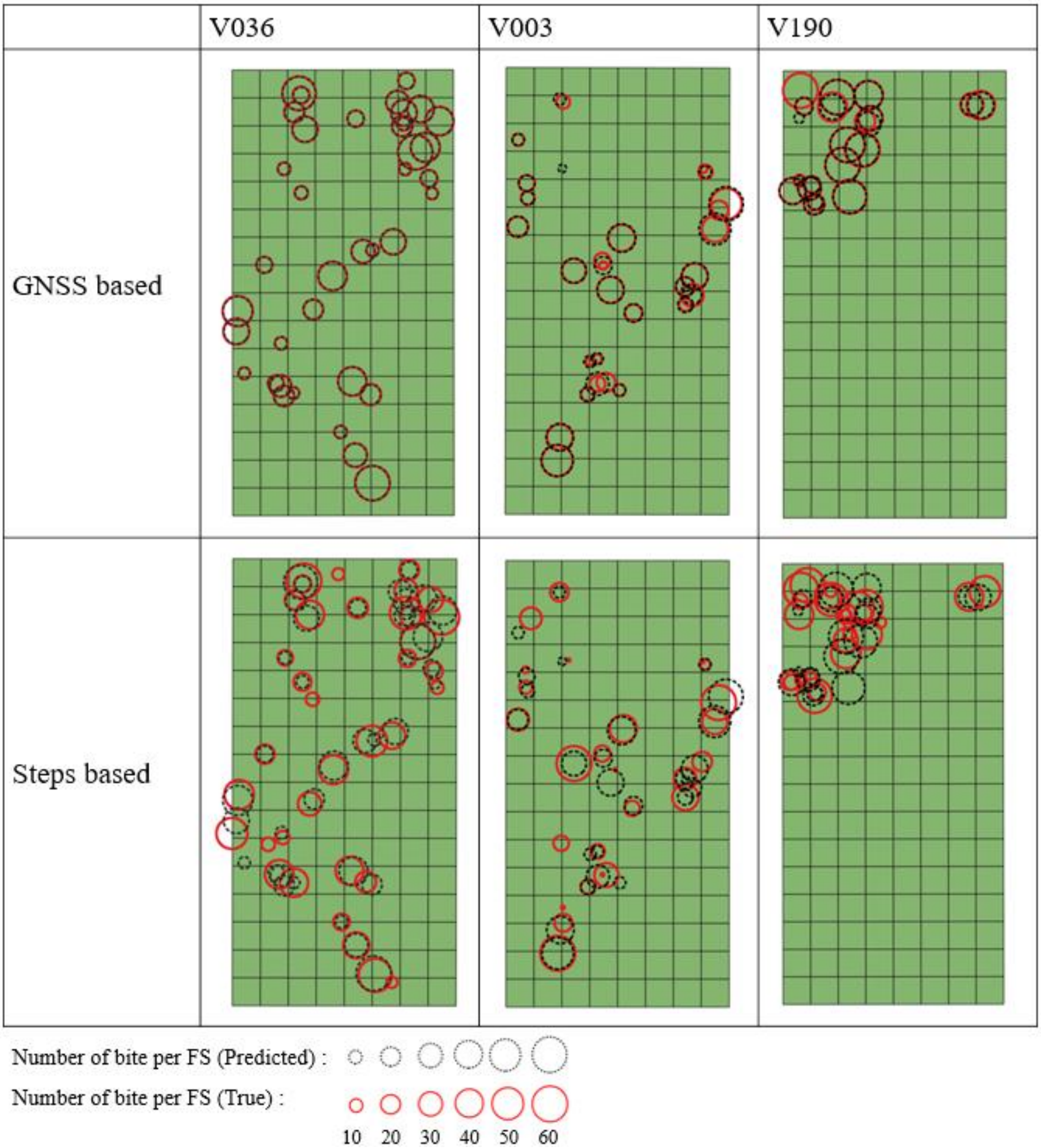

Figure 5-8: QGIS representation of the true and predicted FS for three samples on 15×30 m paddocks (each square is a 4m²). The true FS were determined using the GNSS geolocation data for the first row and number of steps for the second row, as explained in section 2.4.2. The samples are the same as for figure 5-7.

3.1.3. Prediction of the behaviours during grazing down

The overall performance of phase 1 of the model to predict behaviours for all studied GD sessions is presented in Table 5-12. The values have been pondered based on the length of the sessions (in minutes). The performances were high for accuracy (92.4), recall (94.3), and the F-score (91.4), a little bit lower for precision and specificity (88.9% and 90.4%, respectively, with respective minimums of 74.2% and 77.8% on two different sessions), which means that the "other" behaviour was more frequently interpreted as "ingestion" than the contrary. Cohen's Kappa average was above 81 on average (84.2), which is considered "almost perfect agreement," and its minimum value (71.3) is above 61, therefore considered "substantial agreement" (Cohen, 1960). The detailed performances for each session are available in Appendix 14.

Table 5-12: Performance of the phase 1 model to predict behaviours.

	Average		Minimum	Maximum	Weighted average
Accuracy	91.9%	± 2.8%	87.2%	96.9%	92.4%
Precision	87.8%	± 6.2%	74.2%	95.3%	88.9%
Recall	93.7%	± 5.8%	73.6%	100.0%	94.3%
Specificity	89.7%	± 5.6%	77.8%	96.8%	90.4%
F-Score	90.4%	± 4.3%	79.7%	96.3%	91.4%
Cohens Kappa	82.8%	± 5.9%	71.3%	93.7%	84.2%

3.1.4. Prediction of the meals during pasture

The overall performance of phase 1 of the model to predict meals for all studied GD sessions is presented in Table 5-13. A total of 106 meals were correctly predicted for the 111 observed, 3 meals were falsely predicted, and 8 meals were missed by the model. When only considering the sessions where all meals were identified with 100% accuracy (15 out of 24 sessions), the RMSE for the prediction of the duration of each meal was on average (± standard deviation) 8.9 ± 6.2 minutes. The detailed performances for each session are available in Appendix 15.

Table 5-13: Performance of the phase 1 model to predict meals.

	Average		Weighted average
Accuracy	91.9%	± 12.7%	92.2%
Precision	98.4%	± 4.1%	97.7%
Recall	93.2%	± 12.3%	94.2%
F-Score	95.2%	± 8.0%	95.6%
Duration RMSE (min)	15.1	± 14.8	14.7
Duration RMSE for perfectly matched session (min)	8.9	± 6.2	7.8

3.2. Visualization of GNSS data

Figure 5-9 shows an example of the GNSS-estimated positions (longitude and latitude coordinates) of all the 10-second during a session of 6 hours of the GD dataset for the same animal on the first day from 12h30 to 18h30 and a second 6h session 48h later. The true and predicted meals are shown, as are the different FS and bite distribution predicted by the algorithm. Even though the vegetation was homogeneous, it can be observed that the animal took one less meal on day 3, took more bites during the total 6 hours, and explored a more important area of the pasture.

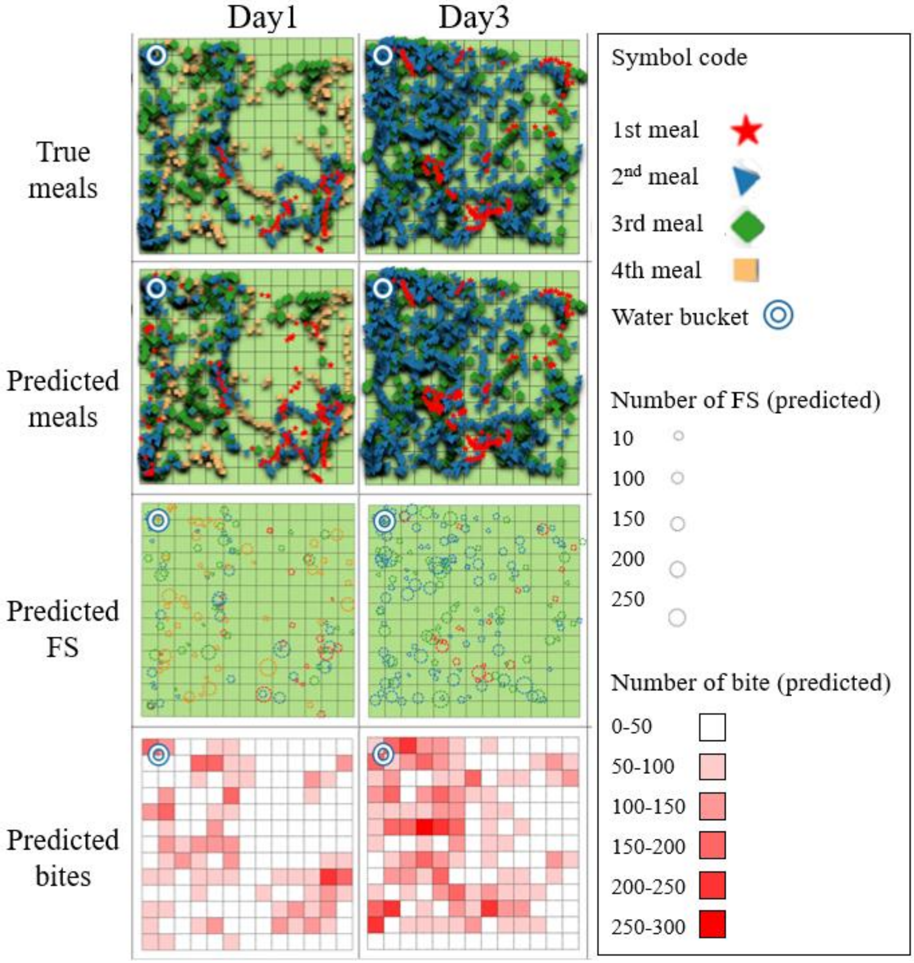

Figure 5-9: Spatial visualization of the behaviour of the same cow between 12h30 and 18h30 on a 25*25m paddock (each square has an area of 4m²) during the first and third days of a GD process. From left to right: the coordinates of each 10-second window during each meal according to the observer (true meals); the coordinates of each 10-second window during each meal as predicted by phase 1 of the model; the FS predicted for each meal by the model; and the predicted distribution of bites by the model.

4. Discussion

The aim of this work was to develop a methodology to be able to predict and visualize the behaviour of grazing cows on pasture using diverse management strategies and on a precise time and space scale.

As expected, RTK technology provides very precise information, and IMU prove to be reliable tools for predicting grazing behaviour, accurately estimating the number of bites, FS, and meals during the grazing process. This ability to spatialize behaviour would provide helpful indicators for farmers and researchers to manage grazing lands. It serves not only to track the preference and selectivity depending on the characteristics of the area in varied environments but also helps monitor bites and optimize pasture utilization by animals. For instance, bite frequency tends to increase as vegetation becomes scarce (Soder et al., 2022) or abundant (Mezzalira et al., 2014; Soder et al., 2022). One of the next steps would be to identify potential 'turning points' where a decrease in grass height leads to changes in animal behaviour, such as alterations in daily activity, meal patterns, or FS visits. This research could lead to the development of DST for farmers to automate grassland allocation in grazing dairy systems (Pina et al., 2022), optimizing grass usage and minimizing inputs to enhance the proportion of grazed grass in the herd's annual diet (Peyraud & Delaby, 2005). However, while monitoring feeding behaviour through PLF systems can enhance yields, it is crucial to ensure that prioritizing productivity does not compromise animal welfare (Chelotti et al., 2024). For example, in some countries, there are proposals to base quality certification and labeling systems for livestock farming on real-time measurements of animal behaviour (Council on Animal Affairs, 2020). Such PLF systems could also provide valuable insights into studying and understanding the dynamics and impacts of climate change on farmed animal ecology (Mancuso et al., 2023b). But at this point, the prototype is still only used in order to increase our understanding of animal–environment interactions, turning this device into a management tool is still several steps further. To achieve these objectives, some technical limitations need to be overcome, and then it will be necessary to co-develop the tool with farmers, while integrating professionals from IT, data science, big data analysis, artificial intelligence, agronomy, and animal sciences with different viewpoints and competences that will be necessary for the comprehensive development of PLF in the coming years (Bretas et al., 2023). Finally, as methodologies to evaluate and spatialize dairy cow behaviour on pasture are being developed, a critical step will be to create easily manageable supports or platforms to facilitate broader use of these models (Delagarde et O'Donovan, 2005).

An unexpected but interesting observation made in this work is that, concerning FS, it appeared that the steps made by the animals were not usable as indicators of changes in FS. As the animal can raise and drop its hooves without actually moving, it poses a new challenge in distinguishing between a step indicating movement and one for trampling or adjusting position, even for experienced observers. Therefore, assessing FS based on the actual position of the cow during consecutive bites seems to be the most effective method, highlighting the added value provided by precise geolocation sensors.

Regarding the algorithms that yielded the best results for building the model, it should be noted that the 'bagging' (bootstrap aggregating) approach primarily focuses on reducing the variance of the model. This means it reduces fluctuations in predictions, improving the model's generalization and providing bite frequency predictions that are closer to the average. While this generally yields good results, it may pose challenges in detecting extremes of high or low bite frequencies. Furthermore, bagged trees tend to reduce overfitting compared to single decision trees, although overfitting can still occur, and they are sensitive to noisy data, such as outliers or measurement errors in the training data. Looking ahead to the future of the sensor itself, several improvements could and should be made to enhance signal quality and continuity. All data were collected using a self-made prototype, which will soon become outdated as PLF technologies continue to advance. Key issues with this prototype included recurring robustness problems, particularly damage to the antenna cable during the GD process, leading to the loss of multiple hours of data. Additionally, the frequency of the signal was limited to 8 Hz, with occasional decreases, whereas a minimum of 10 to 12 Hz is recommended. Lastly, battery durability was another challenge, lasting a maximum of 48 hours during tests. Battery life remains a common challenge in the development of automated animal activity recognition (AAR) tools (Mancuso et al., 2023a; Mao et al., 2023).

A more general limitation of this study is the predominance of 'ingestion' behaviour in the training data compared to 'other' behaviours, due to fasting periods preceding the observations. Class imbalances in the training data can be problematic, as ideally there should be balanced representation across all behaviour classes to avoid performance degradation in the model (Mao et al., 2023). However, in this case, the imbalance is justified, as maximizing ingestion time was necessary for training the bite quantification phase. The sensors and algorithm developed and used in this work also need to be tested for their robustness. If the methodology presented can be promising, it is important to develop algorithms based on the IMU data, that show robustness and/or adaptability in various or atypical grazing situations and in terms of performance when used with independent datasets, as it is one of the main weakness underlined during meta-analysis on the topic (Riaboff et al., 2022). In this case, the data collection was only carried out on one breed of dairy cattle grazing typical ryegrass (*Lolium perenne*) pastures on temperate lands in Belgium, and the number of individuals was limited, meaning that the data collected might not be sufficient to form a generalizable model and high robustness. This was observable as the LOVO method gave more satisfying results (average RMSE = 2.34 ± 0.69 bites / 10-s; error of prediction = 7.8 ± 8.4%) than the LOAO from Chapter 4 (average RMSE = 3.34 ± 0.65 bites / 10-s; error of prediction = 13.3 ± 10.3%), meaning that without including data from the observed animal in the trained model, the predictions were less accurate. To develop models that can be generalized to different cattle breeds, grazing environments, pasture types and pasture management strategy, future models will need further validation across more diverse conditions.

It is also necessary to point out that this work primarily focused on ingestion behaviour, classifying all other behaviours as 'others.' Although rumination behaviour was practically absent in the STIB experiments, it plays an essential role in understanding changes in grazing behaviour depending on grass availability (Edward et al., 2024).

This study represents a preliminary exploration of this concept, and future research should explore new possibilities regarding the impact of spatial observations. Livestock behaviour in small enclosures may differ significantly from that in extensive grazing systems. Therefore, future studies could investigate more extensive grazing systems where livestock spatial configurations vary by scale. For example, analysing the relative time animals spend on various behaviours across the grazing area could help identify overused areas (grazing hotspots), resting sites, and underutilized areas. Now that centimeter precision can be achieved, it is feasible to divide the study area into squares, hexagons, or other irregular zones of different scales, depending on the researcher's or farmer's needs. This information could guide the development of management strategies aimed at improving livestock distribution across landscapes. Strategies could include reducing overgrazing, limiting nutrient accumulation in small resting areas, and strategically placing water, shade, salt, and mineral stations (Rivero et al., 2021). The impact on the cows' behaviour of the inclusion of new component elements in pastures, such as trees, hedges, water points, plant species presenting interesting ecosystem services, could also be studied. With the addition of spatial data to temporal behaviour analysis, future studies should incorporate various additional factors to observe their impact on ruminant behaviours, such as vegetation indexes obtained through remote sensing, precipitation, humidity, soil fertility, and temperature. These data can be obtained from sensors and integrated with wearable sensor data to develop comprehensive models (Bretas et al., 2023). Some studies even aim to create digital twins based on the environmental elements of grazed areas (Chen et al., 2024).

5. Conclusion

This study highlights the potential role of PLF tools, such as IMU combined with RTK geolocation systems, in advancing the management of grazing systems. By integrating these technologies, the ability to accurately predict and map spatially grazing behaviours is demonstrated. It includes bite frequencies, at the scale of FS and meals, and with adequate accuracy. Mapping these behaviours provides invaluable insights for optimizing pasture use, enhancing animal welfare, and improving overall farm management. Applying RTK technology to collar-mounted GNSS wearable sensors significantly improved geolocation precision, addressing previous limitations in spatial accuracy and enabling a more detailed analysis of grazing patterns. These findings suggest that precise geolocation combined with IMU data can serve as robust indicators of animal behaviour, helping to identify behaviour changes, grazing hotspots, resting sites, and underutilized areas. In conclusion, this research lays the foundation for the next generation of PLF tools poised to revolutionize livestock management through precise, real-time insights into animal behaviour and pasture utilization. As these technologies continue to evolve, they hold the potential to improve both the sustainability and productivity of livestock farming, ensuring a better balance between economic goals and sustainability.

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7. References

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Chapter 6

Using a wearable sensor to detect turning points in behaviour during the grazing down process.

Using the methodology described in the previous chapter, the evolution of the behaviours of the cows in relation with the decrease in SH during grazing down sessions of 72 hours was monitored through PLF technologies and ML. This was the final step to demonstrate that observations of animal behaviour and location derived from IMU/GNSS sensors can be used to detect in advance changes in grazing patterns as markers of changes in individual's behaviours during grazing.

Using a wearable sensor to detect turning points in behaviour during the grazing down process

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Abstract

Pasture management strategies, such as rotational grazing systems, can be implemented to preserve quality grassland ecosystems, while meeting efficient food productivity objectives though domestic herbivores. To pilot those rotations, studies concerning the plant-animal relation during the GD process that happens during the occupation of a paddock in the rotation are essential to better understand how to optimize the daily intakes and pasture preservation. The ingestion behaviour of an herbivore evolves as the available grass gets scarce. On that basis, the performance of PLF technologies gives access to more information regarding the plant-animal interactions. Moreover, the systems used in PLF are becoming both more accessible and efficient in the domain of pasture management. The objective of this study was to follow four GD processes, each lasting 72 hours, with groups of three dairy Holstein

cows on Ryegrass pastures. All Cows were equipped with wearable sensors combining an accelerometer, a gyroscope and a GNSS corrected by RTK technology. The evolution of the number of bites, frequency of bites, FS, movements, grazed area and SH have been observed as parameters to try and determine thresholds in the herbivore behaviours assessing discomfort and thus, the need to proceed to a rotation using cows as model. Our results show that when the SH was greater than 8 cm, a significant change in ingestion time, number of bites, number of FS and grazed area is observable, and the movements of the animal rise through the day (travelled distance and surface grazed). Finally on the last day, when SH was equal to 5 cm, the activity of the cows drops for all observed parameters.

1. Introduction

Grassland ecosystems play an important role in the development of agroecology. The latter is based on practices aimed at using the resources available in a system to sustainably meet the production needs of farms while improving the health and welfare of animals and reducing the environmental impacts of livestock farming (Dumont et al., 2013, Jouven et al., 2022). At the heart of the management dynamics of these grasslands, grazing impacts the functioning of pastoral ecosystems (Carvalho, 2013). On the one hand, the ingestion behaviour of animals is the result of the characteristics of the sward shaped by the animal (Hirata et al., 2010). On the other hand, the structure of the sward influences the ingestion behaviour of the animal through the short-term forage ingestion rate (Fonseca et al., 2012). Therefore, grassland management should be based on the observation of plant-animal interaction dynamics. Such knowledge would prove most useful for farmers that are engaged in innovative grazing management practice and are looking for tools able to give them sensitive indicators to help them pilot their gazing systems. This observation of the grazing process requires a clarification of the behavioural components of the herbivore, at different spatial and temporal scales, during the process of searching for and ingesting grass by the animal (Carvalho et al., 2013). By better understanding how animals meet their needs by grazing a vegetation, it will be possible to optimize plant production, forage ingestion, and animal performance (Carvalho et al., 2013).

A typical application of cow monitoring devices in grasslands is to use accelerometers to assess differences in time allocation to some key behaviours (Aquilani et al., 2022; Riaboff et al., 2022; Mao et al., 2023). These methods can be enhanced by GNSS technologies because the spatial component carries additional information and can provide other variables for the classification of a given behaviour, such as occupied location, identification of preferred or avoided grazing areas (Lush et al., 2018), travel path or movement speed. These combined technologies of PLF sensors based on accelerometers and GNSS are not yet widespread (Mao et al., 2023). Commercial solution still do not exist, but some experiments have been conducted. For example, Arablouei et al. (2023) use two separate commercial wearable sensors in conjunction: a GPS ear-tag and a collar with IMU. Obermeyer and Kayser (2023) have developed an open source, neck-mounted cow tracker that combines an accelerometer, a gyroscope and GNSS sensors. This work is based on a sensor developed in Chapter 4 to 6, adding the use of RTK. This real-time correction of the geolocation of the GNSS sensors allows to achieve centimeter precision, necessary for a finer interpretation of the behaviour. This work is the continuity of a previous study (Chapter 5), that developed a methodological framework to predict a series of behavioural indicators of dairy cows at pasture from accelerometer and GNSS data, including the evolution of the number of bites, the frequency of bites, FS, movements, area grazed. This work applies this new methodology to explore behavioural changes due to an evolution of the pasture structure during a GD process, a decrease in grass height due to the grazing activity of ruminants on a plot for several consecutive days (Gonçalves et al., 2018). It is expected that when grazing pastures dominated by *Lolium perenne* whose height gradually decreases from 12.5 cm to 5 cm, ingestive behaviour is limited by grass availability. The measurements are based on the measurement of SH with a sward stick as a management tool (Barthram, 1986).

The objectives of this study were to identify patterns of grazing discomfort related to the evolution of grass structure, which would make it possible to define levers indicating a change in animal behaviour. The cow alters its grazing behaviour while the available forage is no longer sufficient for an efficient forage intake process. The ultimate aim of such development would be to shift from a management based on human perception of grass to the animal's own perception, translated through PLF tools.

The hypotheses were as follows: (1) it is possible to classify observed cow behaviours in a grazing context using a non-commercial, laboratory-built wearable sensor; (2) in the final grazing phase, the lower SH constrains cattle normal ingestive behaviour, compared to early and intermediate grazing phases; (3) break-point can be observed with the wearable sensor when the lowered SH starts inducing a change of grazing behaviour.

2. Materials and Methods

2.1. Experimental area and context

The experiment took place at the Agricultural Technologies Center of Strée-Modave, Belgium (N 50°50'716", E 5°31'645"), between spring and summer 2023. It was conducted on ryegrass-based (*Lolium perenne*) pastures.

2.2. Experimental design

The experimental design comprised two replicates of 25×25 m² paddocks enclosed by electric fences, grazed by groups of three cows. Two sessions were conducted, for a total of four different groups. All animals were equipped with sensors mounted on a collar. The experiment set up a 72-hour GD process (Gonçalves et al., 2018). The animals entered the paddock on day 1 and left on day 4 around 11:00 a.m.

Daily forage allowance (FA, % LW) at the beginning of each session amounted to 2.41 ± 0.16 % of the total live weight (LW) of the 3 animals, on average. As the potential daily DMI ranges from 2 to 3% of the live weight (Delagarde et al., 2001), the objective was to reach a point where the available grass was scarce enough so that almost all palatable DM would be consumed at the end of the three days of occupation. The FA was calculated according to the following equation: FA (% LW) = ((FM n−1)/SR) *100, where: LW = live weight, FM = average forage mass of each stocking cycle (kg DM ha−1), n = number of days of stocking cycle, SR = stocking rate of each stocking cycle (kg LW ha−1) (Riaboff et al., 2020). It didn't take into account the forage accumulation rate over 3 days.

The sward was predominantly composed of ryegrass (*Lolium perenne*). The average pre-grazing SH was 12.5 ± 2.5 cm (mean ± std) and decreased to an average of 5.0 ± 0.7 cm (mean ± std) at the end. Water was available ad libitum in one corner of the paddocks. Considering the 48-hour battery life, the animals were briefly taken to the barn to replace the batteries, on the evening of day 2 at 18:30, after about 32 hours of GD.

The twelve experimental animals were eight heifers and four dry Black Pied Holstein cows with LW of 522 ± 108 kg for heifers and 792 ± 56 kg (mean ± std) for dry individuals, and an age of 20 ± 5 months for the heifers and 51 ± 5 months for the dry cows. Each paddock received a group of two heifers and a dry cow that remained throughout the experimental period.

The CSH of each paddock was measured every 3 hours between 6:30 and 18:30 with 30 rising plate meter measurements with an EC20 (Jenquip, Feilding, New Zealand) and the SH at 9:30 and 15:30 every day with 60 sward stick measurements (Barthram, 1986). The path of the measurement was based on a grid covering the pasture. The evolution of the leaf-to-stem ratio was recorded at the beginning and end of each grazing experiment, based on measurements of the longest leaf and stem length taken from 100 individual plants each time.

2.3. Wearable sensors

This article is a follow-up to previous research using the same wearable sensors to ensure that the tool is able to recognize the animal's ingestion behaviour and frequency of bites at various grass heights. The construction and settings of the sensor are described in Chapter 5. This wearable sensor is a device mounted on a collar around the animal's neck and records both geolocation and IMU signals at a frequency of 8.07±0.9 Hz on an SD card used to read, process, and save the sensor data, which was retrieved after the grazing sessions. Both IMU and GNSS were registered on the same line of a CSV dataset, providing a raw output of 9 variables: the acceleration and rotations in three dimensions along the x, y and z axes (Figure 6-1), the GNSS coordinates and the RTK correction status (RTK, RTK FLOAT, DGNSS, GNSS, NA).

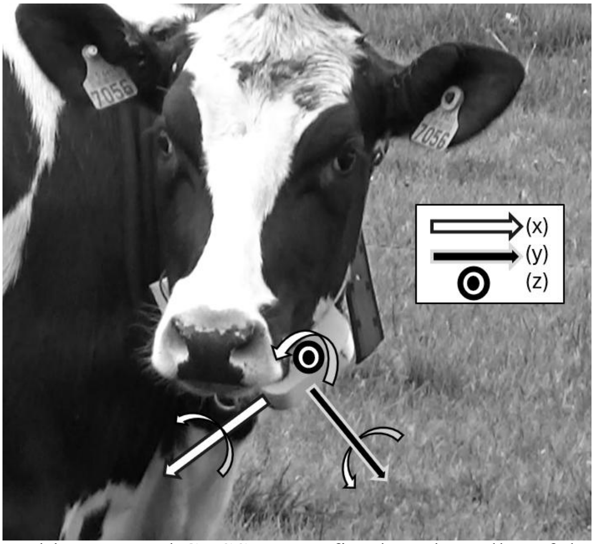

Figure 6-1: Wearable IMU and GNSS sensor fixed on the collar of the cow. The three coordinate axes of the accelerometer are displayed, and rotation arrows indicate the gyroscope rotational axes.

2.4. Data collection

The behaviour of each animal was recorded every minute between 6:30 and 18:30 as ingestion or other behaviours as described in the ethogram (Table 6-1).

Table 6-1: Ethogram and rules used to predict the cows punctual action, behaviours, and performances previously demonstrated for the wearable sensor.

Components of the ingestion behaviour	Description	Prediction performances*
Ingestion	The animal is standing up, searching for food with its head down, and performs prehensive grass-severing bites with maximum interruptions between bites of 10 seconds.	Accuracy: 98.2% ± 1.8%
Feeding station	Several bites performed in a row by an animal without interruption, covering the path width of the animal, and lasting between 5 to 100 seconds (Andriamandroso et al., 2016).	Accuracy: 94.3% ± 8.1%
Bite	The grass is torn from the root to be consumed by the animal (Andriamandroso et al., 2016). Bites are only taken into account with standing animals	RMSE 2.34±0.69 bite per 10-sec window

*See Chapter 5.

2.5. Data pre-processing

The raw output of the wearable sensor comprised nine variables obtained from the IMU which represent the three dimensions of both sensors along the x, y and z (Figure 6-1) axes. With the coordinates and timestamps of the GNSS module as additional raw variables.

The 72-hour recordings were cut into 3-hour segments (n=23), from day 1, 13h to 16h (start + 2 hours, for the first recording) to day 4, 07h to 10h (start + 68 hours, for the last recording). The database was cleaned as follows: sessions containing movements outside of the paddock, for a battery change in the stable for instance, were not included in the dataset. Sessions with obvious mislocated GNSS measurements were removed from the dataset. A substantial portion of the data was also lost due to hardware issues, mainly due to unforeseen damage to the GNSS antenna cable. On average, 32.9% of the total possible GNSS data over the session was recorded for each collar in this study, for a total of 83 sessions with 9 animals.

Subsequently, each acceleration and rotation variable was inspected by computing simple summary statistics including frequency of data recording, mean, variance, minimum and maximum.

Subsequently, each acceleration and rotation variable was inspected by computing simple summary statistics including frequency of data recording, mean, variance, minimum and maximum.

The signal was then segmented into 30-s and 10-s windows, followed by the extraction of 20 features (listed in Table 5-4) frow the raw IMU data for each window. The GNSS coordinates were averaged for each 10-second time window to correspond to the bite quantification windows and to reduce noise in the spatial data (Obermeyer & Kayser, 2023). From those smoothed coordinates, the travelled distance between two windows was estimated and recorded as ‘travelled distance', using the Pythagorean theorem. This method is both computationally efficient compared to the Haversine formula, and is sufficiently accurate for short distances (Arablouei et al., 2023):

$$\text{Distance} = \sqrt{(\Delta \mathrm{long}.\cos(\mathrm{mean\ lat}))^2 + (\Delta \mathrm{lat})^2}\ \mathrm{R}$$

where Δlong and Δlat are the differences in longitude and latitude between two 10-second windows, respectively, converted to radians, and R is the Earth's radius (estimated at 6,371,000 m).

Finally, the data from the visual observations was used to assess "true" ingestion behaviours in order to compare it to the predictions between 07:00 and 16:00, resulting in a mean absolute error of 4.0% between ingestion behaviours registered by an observer and the predictions made by the wearable sensor during the 3-hour sessions.

2.6. Data analysis

The best performing algorithms from the 2-step model developed in Chapter 3 were applied to (1) classify the behaviour into two categories (ingestion and other) for each 30-sec windows and (2) to draw a regression for the three 10-sec windows contained within each 30-sec windows classified as "ingestion", in order to quantify the amount of bites taken by each cow. The method was tested in Chapter 5 with performances displayed in Table 6-1. The parameter predicted in this study are presented on Table 6-2.

Table 6-2: List of the parameter obtained from the wearable sensors' data.

Abbreviation	Full name	Method	Unit
GT	Grazing Time	30-sec windows predicted as "ingestion" by the model.	Percentage of the total time (%)
TB	Total bites	Quantification of the bites within 10-sec windows predicted as "ingestion"by the model.	Bites / 3 hours
AG	Area grazed	Within a grid of 1-meter sided hexagons, the total area of the different hexagon where ingestion behaviour was predicted.	Square meters (m^2) / 3 hours
TD	Travelled distance	The Pythagorean theorem was used between every successive 10-sec window.	Meters (m) / 3 hours
BF	Bite frequency	Total number of bites divided by total ingestion time (in minutes).	Bite / minute
FS	Feeding stations	Durations of 1 to 10 successive 10-second time windows containing > 1 bite and ≤ 1 m of distance with the first window of the FS	FS / 3 hours
BSM	Bites per square meter	BSM = TB / AG	Bite / m^2
BFS	Bites per FS	BFS = TB / FS	Bite / FS
FSSM	FS per square meter	FSSM = FS / AG	FS / m^2

2.7. Statistical analysis

Some sessions (e.g., *Day 2: 10–13h*, *Day 4: 07–10h*) included very few observations, making normality tests such as Shapiro–Wilk or Q–Q plots unreliable. Therefore, a nonparametric Kruskal–Wallis test was used as an initial screening step to identify potentially impacted variables.

Due to the repeated measurements nature of the dataset and imbalanced group sizes, linear mixed models (LMM) were applied to the selected variables. LMM are well suited to handle unbalanced data and account for both fixed effects (e.g., time periods) and random effects (e.g., individual variability), making them appropriate for this design. The reference level (intercept) was set to *Day 2 – 13h–16h*, as it represents the midpoint of the 72-hour grazing-down process and reflects average values across parameters.

3. Results

3.1. Evolution of the behaviour caused by the grazing down

As stated before the SH decreased from 12.5 ± 2.5 cm at the entrance of the animals to 5.0 ± 0.7 cm after 72 hours of GD (Figure 6-2). With a reduction of 2.1 cm over a 6-hour period on day 1, only 0.5 cm on day 2, and 1.3 cm on day 3, it corresponds to -16.8%, -5.6% and -17.6% of the height on a daily basis, respectively. The leaf/stem ratio decreased from 2.7 ± 0.2 cm to 1.8 ± 0.7 cm, with leaves of 16.2 cm of average length in the beginning and 6.8 cm in the end. The stems went from 5.9 cm to 4.2 cm.

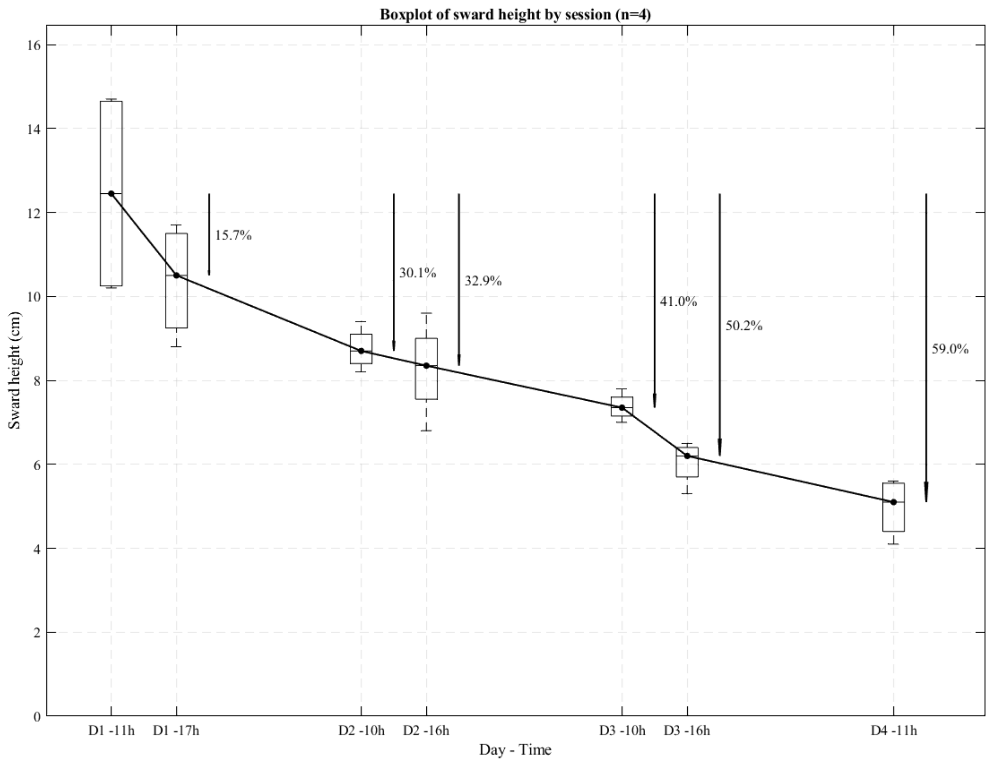

Figure 6-2: Sward height of the 4 sessions during the GD, downward arrows indicate the percentage of initial SH that has been consumed.

The Kruskal–Wallis test identified several variables that were sensitive to temporal effects (Table 6-3). The total number of bites, followed by the percentage of grazing time, the number of FS and the number of bite per square metre were such time-sensitive indicators of the changes in cow's activity between 7h and 22h. In terms of explored areas, The area grazed was the most significant, followed by the travelled distance. The bite frequency, number of bites per FS and number of FS per square meters were not significantly affected in this case.

Table 6-3: Results of Kruskal–Wallis test for each grazing behaviour variable.

Variable	**p Value**
GT	0.010
TB	0.006
AG	0.006
TD	0.036
BF	0.206
FS	0.013
BSM	0.045
BFS	0.152
FSSM	0.493

GT = grazing time (%); TB = total bites (number of bites per 3 hour period); AG = area grazed (m^2); TD = travelled distance (m); BF = bite frequency (bites per minute of ingestion); FS = number of feeding stations (per 3 hours); BSM = number of bite per square meter; BFS = number of bites per FS; FSSM = number of FS per square meter.

LMM confirmed fixed effects for specific periods across multiple parameters. Notably, several time periods showed increases or decreases compared to the reference group (Day 2 – 13h–16h). These results are summarized in Table 6-4, with the full model outputs available in Appendix 15. A first increase in the activity was observed in the evening of the first day, followed by an even greater one on the third day, that started with an average SH of 7.4 ± 0.3 cm. The average values for each parameter can be seen in Table 6-5. The travelled distance, bite frequency, bite per square meter, bite per FS and FS per square meters were not affected though. Travelled distance is less impacted by the day evolution but still affected by the period of the day.

Table 6-4: Results of the LMM - Significant Effects by periods.

Time Slot	Significant variables (Estimate, p-value)
Day 1 – 07h–10h	BSM: −3.48 (p = 0.047)
Day 1 – 19h–22h	GT: +20% (p = 0.006), TB: +2088 (p = 0.003), AG: +77.4 (p = 0.015), TD: +311.1 (p = 0.004), FS: +46.8 (p = 0.004)
Day 3 – 13h–16h	BSM: −4.57 (p = 0.017)
Day 3 – 16h–19h	TD: +262.6 (p = 0.021)
Day 3 – 19h–22h	GT: +22% (p = 0.003), TB: +2438 (p = 0.002), AG: +105.6 (p = 0.001), TD: +379.2 (p = 0.001), FS: +46.5 (p = 0.004)
Day 4 – 07h–10h	GT: −26% (p = 0.004), TB: −2844 (p = 0.002), AG: −100.2 (p = 0.010), FS: −50.0 (p = 0.011)

Table 6-5: Behaviours (means) of dairy cows during GD sessions on pasture.

	Day 1			Day 2			Day 3					Day 4
Sessions	4	3	4	5	2	5	6	4	3	3	4	2
Period	13h-16h	16h-19h	19h-22h	07h-10h	10h-13h	13h-16h	07h-10h	10h-13h	13h-16h	16h-19h	19h-22h	07h-10h
'GT'	42.7 %	51.6%	74.0%	42.0%	41.0%	53.8%	53.1%	58.2%	53.2%	52.4%	75.7%	28.1%
'TB'	3880	4880	7470	4150	3950	5390	5010	5840	5100	5080	7820	2540
'AG'	182	222	291	164	172	214	194	231	249	234	319	114
'TD'	475	494	752	412	570	441	409	550	583	704	821	372
'BF'	50.3	52.6	56.3	54.7	53.5	55.3	52.7	55.8	53.2	53.3	57.3	51
'FS'	90.5	112	155	87.2	87.5	109	98.2	116	110	107	155	58.5
'BSM'	21.6	22	25.9	25.5	23	25.1	26	25.4	20.5	21.6	24.7	22.9
'BFS'	42.5	43.7	48.2	47.8	45.8	50.2	51.5	50.6	46.3	47.1	50.5	44.2
'FSSM'	0.525	0.508	0.537	0.532	0.505	0.502	0.507	0.502	0.443	0.460	0.489	0.517

GT = grazing time (%); TB = total bites (number of bites per 3 hour period); AG = area grazed (m^2); TD = travelled distance (m); BF = bite frequency (bites per minute of ingestion); FS = number of feeding stations (per 3 hours); BSM = number of bite per square meter; BFS = number of bites per FS; FSSM = number of FS per square meter.

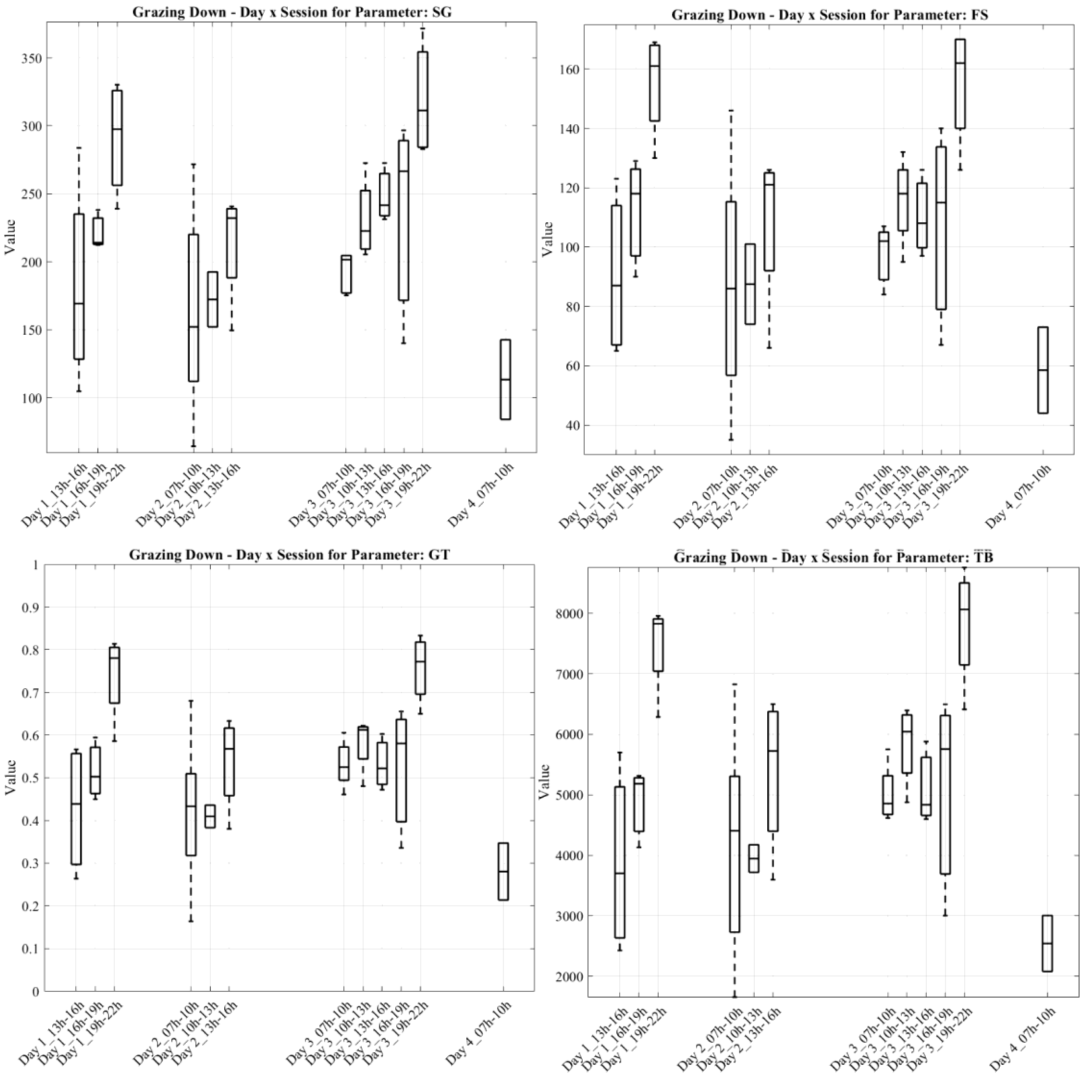

Figure 6-3: Boxplot of the evolution of the (in reading order) area grazed (m²); number of FS; grazing time (%) and total number of bites during 3 hours sessions for all four cow groups.

On the last day, corresponding to a grass height of 5.0 ± 0.7 cm, a diminution of all activity occurred (Figure 6-3), with shorter distances travelled, and areas covered, and shorter grazing time with less bites and FS. The data before 7h and after 22h showed little to no activity as the animals were resting or sleeping.

3.2. Location and movements

The travel distance rose gradually on the third day from 7h to 22h, with average values that ended up doubling over the course of the day (Figure 6-4). No rain (0mm) was recorded by the local weather station during that day and the average temperature was 8.8°C for the first group and 11.7°C for the second. A peak is observable at the end of the day (19h-22h). A similar peak can be observed on day 1. The area grazed is also slowly rising through the day, with values that are higher than for day 1 and day 2 at the same period of the day.

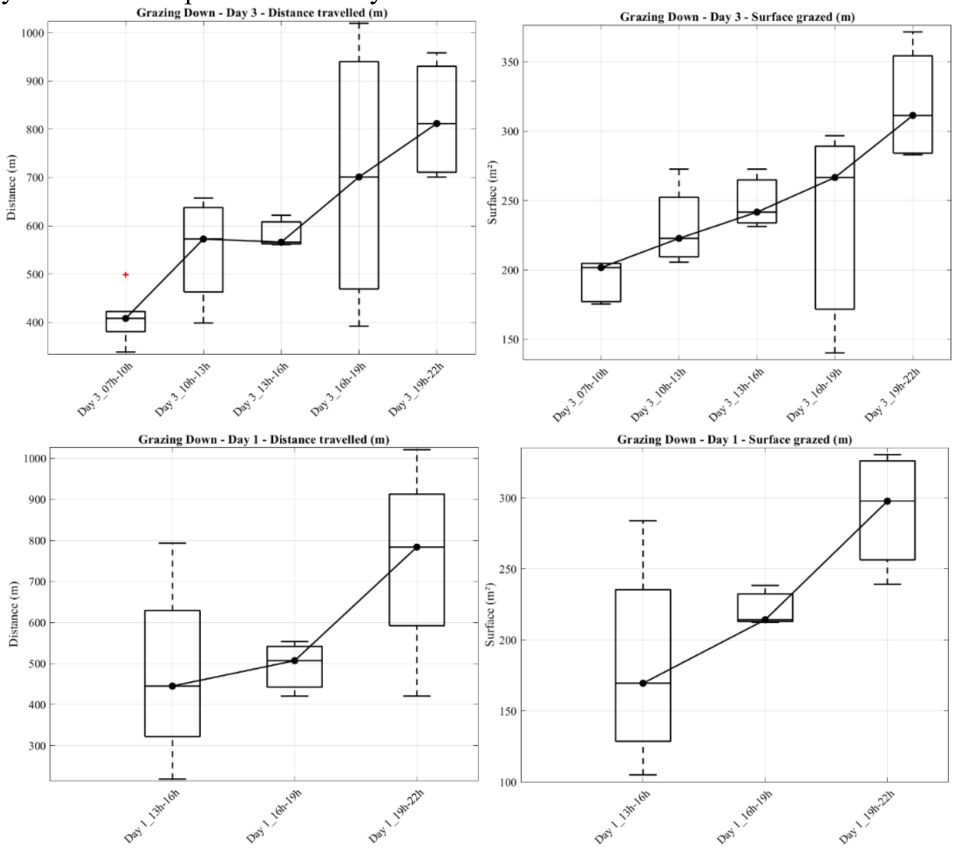

Figure 6-4: Boxplot of the evolution of the (in reading order) travelled distance during day 3 (m); area grazed during day 3 (m²); travelled distance during day 1 (m); area grazed during day 1 (m²).

3.3. Evolution of the bite frequency

The main observation concerning the bite frequency during grazing time is a rise at the end of the day. The average bite frequencies slightly went up between day 1 and day 3 with the lowest median during the arrival on the pasture (Figure 6-5).

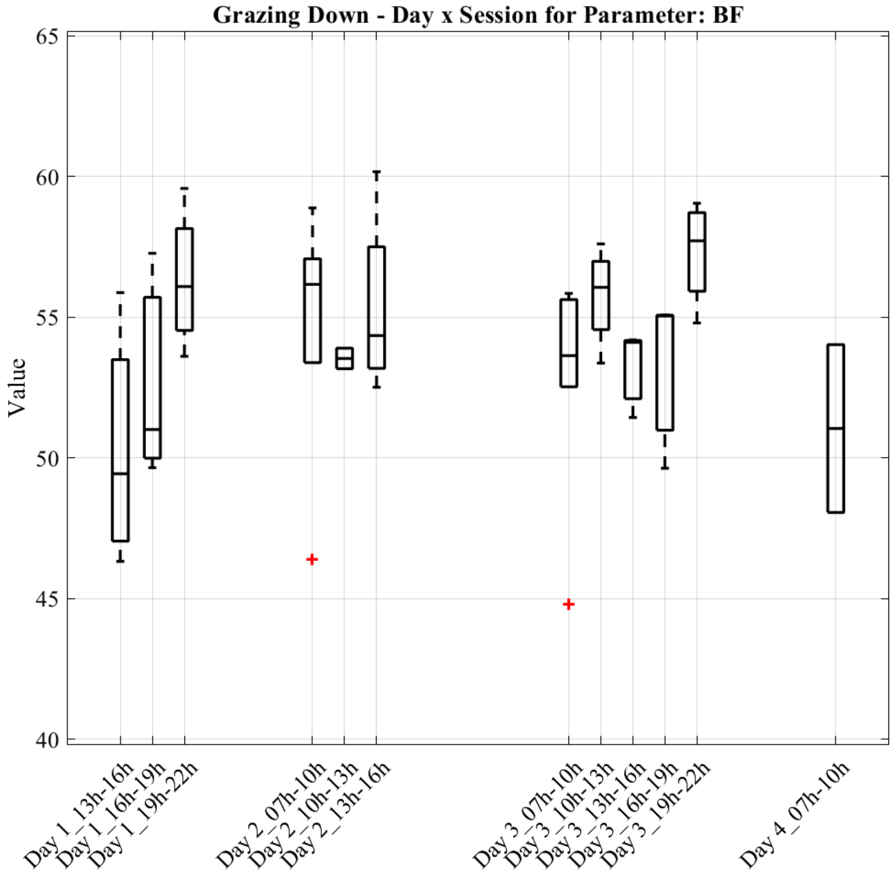

Figure 6-5: Boxplot of the evolution of the bite frequency (bite per minutes) for all four cow groups.

4. Discussion

4.1. The cow's change of behaviour related to the diminishing food availability

Through Figure 6-3, on day 3, for every 3-hour session, the median values are > 200m² of area grazed (32% of the available area), > 50% of grazing time, > 100 FS, > 4500 bites. These diverge from day 1 and 2, where the activity is variable, but generally less important, with lower medians. This correlates to the regression of the SH, most important on day one, when the animals explore the pasture and eat the tallest grass, then on day 2, the diminution is slower and increases again on day 3. What was less expected is the drastic reduction in activity during the last hours of GD, from 7h to 10h, when there was around 5 cm of SH left. This could be explained by a temporary refusal of the grass due to discomfort. The decreasing SH impacting sward structural components such as inflorescences and stems, making the manipulation in the mouth more tedious and can lead to apprehension (Laca et al., 1994; Gonçalves et al., 2018), especially for animals used to rotational systems who will simply wait to be moved to the next paddock to resume their intake. A similarity of grazing behaviours can be observed between the arrival of the cows on the pasture and the third day of grazing, with increasing levels of activity through the day, observable through eating parameters (grazing time, bites, FS) and foraging behaviours that increase through the day, almost doubling (travelled distance, area grazed). Another unexpected result was the evolution of bite frequency. It was initially expected to be one of the main indicators (Mezzalira et al., 2014), yet it rose irregularly from an average of 50.3 to 57.3 bites per minute after 56 hours of grazing. Despite this variability, the increase is consistent with theoretical expectations: as SH decreases below the optimal range of 12 to 18 cm for *Lolium perenne* grazed by cattle (Bindelle et al., 2021), animals increase their biting rate to compensate for the greater effort required to harvest forage (Gibb et al., 1997; Mezzalira et al., 2014, 2017; Soder et al., 2022). Concerning the frequency of bites itself, studies working with cows obtain results that range from 49.8 bite.min^{-1} to 79.8 bite.min^{-1}, with average frequencies usually exceeding 60 bite.minute^{-1} (Gibb et al., 1997; Andriamandroso et al., 2016; Rombach et al., 2022). In this case, the average frequency for 3-hour sessions is 57.3 bite.minute^{-1}. This could be caused by the 2-steps model, that will classify windows of 30-seconds as "grazing" and count bites for the full window. However, when the model was tested, the impact on the quantification at the scale of 1 hour was limited (Chapter 5).

4.2. Detecting a change in the behaviour

The grass height stagnated around 8.5 cm and had a sudden decrease once it reached 7.4 cm, at the beginning of Day 3, when 41% of the pre-grazing SH was consumed, which is just above the recommended limit for an "optimal" pre-grazing sward-height (Gonçalves et al., 2018), knowing that some authors recommend using only 25% (Ibid.). At the end of the session, the GD reaches 60%, and the diminution of the leaf/stem ratio also confirms that there were restrictions applied on the cows behaviour that had consequences on the spatial and temporal scale. While this shift was observed within this specific context, it must be acknowledged that other patterns in behaviour may emerge under different circumstances. For instance, on larger paddocks, ruminants typically spend more time exploring their new environment upon arrival. This exploratory phase can delay the onset of focused grazing and may lead to a compensatory increase in bite frequency later in the day. Furthermore, behavioural shifts could also be caused by changing weather conditions, the presence of unfamiliar animals, or social disruptions such as hierarchy establishment. These potential confounding variables highlight the need for cautious interpretation and underline that any decision-support tools developed from this research will require validation across a variety of environmental and management conditions. While no distinctive "breakpoint" was outlined, the detection of the activity rise through several parameters during the same day can confirm that, given more resilience and battery-power, the sensor-based indicators are able to monitor the expression of the adaptation of the animal when it is put in a sub-optimal grazing situation. Moreover, it seems that the area grazed was as impactful as the grazing time on the evolution between days, giving a real importance to the addition of the GNSS not only for spatialization, but also for behaviour recognition.

4.3. The use of PLF to track animal behaviour

This study proves that the use of technologies in livestock farming is both a great potential and a great challenge. It is now technically possible to predict the behaviour of a ruminant at the scale of the bite, and with a geolocation's precision of < 1m, with a margin of error that will certainly continue to decrease with time for both parameters. This could lead to a detailed understanding of ruminant's behaviours in any kinds of situations.

Moreover, the self-made aspect of the sensor guarantees an open-source solutions for next applications, the possibility to add new modules, and data sovereignty compared to commercial wearable sensors (Fraser, 2022). However, it still needs to surpass some challenges. The combination of such technologies needs to answer to a lot of specifications: a durable sensor, that doesn't disturb the host to the point of impacting its behaviour, resistant to the animal behaviour, chocs, water, cold, with a base station available to correct the position through RTK technology and with sufficient data storage and battery-time. The latest being a recurrent limitation in wearable sensors using both IMU and GNSS technology, due to their low run-time (Riaboff et al., 2020; Obermayer and Kayser, 2023).

Even if a pilot test and a series of 1-hour sessions of observation with the sensor were made before the experiment, a lot of data was lost due to unexpected destruction of material (unplugged batteries, severed cables inside the wearable sensor). Eventually, man-made observations are always still an added value to the research while using such prototypes, to verify or correct the prediction made by the wearable sensor. Another limitation that is common in PLF is the lack of adaptability of the system (Riaboff et al., 2022). It took hours of time and several researchers to train the model for a specific situation: Holstein cows grazing on ryegrass in the Condroz region of Belgium. The next objective would be to see if this kind of sensor adapts to other breed, climates, and vegetation. It could also focus more on rumination time, as it is a core component of ruminants behaviours (Edward et al., 2024).

5. Conclusion

A homemade collar-mounted set of acceleration and rotation sensors combining IMU and GNSS technology was operated during a 72-hours GD experiment, following a method and a two-step model developed in a previous work. It gives the information on the ingestion and position of individual cow, at the scale of < 1m and with a quantification of the number of bites per 10-second window. However, it still could be improved as the battery life is limiting, and the prototype aspect led to data loss. The results show that when 40% of the pre-grazing SH has been consumed, cows increase both their movements and their number of bites. Once the grass becomes too short, cows change their habits and stop their morning grazing behaviour. These observations demonstrate that PLF wearable sensors can effectively track the increase in animal activity that occurs as grass availability declines, until it reaches a point of refusal behaviour, where the animal simply waits to be moved to another paddock and ceases grazing efforts. This methodology opens new opportunities for understanding grazing cows' behaviour and dynamics on pasture.

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Chapter 7

General discussion, perspectives and conclusion

1. General discussion

This thesis presents a novel and significant contribution to science by bridging multiple disciplines: animal behaviour, precision agriculture, data science, and agroecology, through an innovative approach to monitoring and interpreting grazing behaviour in dairy cattle. The originality of this work lies not only in the specific technologies employed but also in the way these tools are conceptually and methodologically integrated to deepen our understanding of plant-animal interactions within grazing systems.

A key methodological innovation is the combination of IMU and RTK-corrected GNSS data to monitor and predict grazing behaviour at the scale of the individual bite. To our knowledge, this is the first study to achieve this level of precision by combining spatial and movement data in real time. Previous systems for detecting bite frequency or jaw movements have often been more invasive or required complex sensor setups, whereas this approach uses a non-invasive, neck-mounted device capable of predicting bite frequency with a RMSE of 2.34 ± 0.69 bites per 10-second window. This level of accuracy allows for a fine-scale, automated, and continuous observation of individual grazing behaviour across entire grazing sessions, a major advancement over traditional methods that typically rely on labour-intensive fieldwork or indirect behavioural indicators.

From a behavioural science perspective, this study significantly enhances our ability to document and interpret the dynamics of grazing. It provides concrete recordings, supported by data from a specific experimental context, that overall activity increases as pasture availability declines, particularly when approximately 41% of the pre-grazing SH has been consumed. This observed behavioural shift may serve as an animal-centered indicator of pasture depletion and could inform adaptive grazing decisions. However, it is important to note that these findings are currently based on a limited set of samples and under specific conditions. Further studies are needed to assess the consistency of these patterns across different environments, breeds, and grazing systems before establishing general rules.

What is especially significant here is not just the behavioural insight itself, but the demonstration that such dynamics can be assessed with quantitative, high-resolution, and objective data. This opens new pathways for understanding how animals respond to their environments and how such responses may vary between individuals. This shift toward individualized, dynamic data enables a deeper understanding of grazing strategies from the perspective of the animal, allowing researchers to move beyond group-level averages and towards context-sensitive diagnosis. Such insights are particularly valuable in detecting subtle behavioural changes that may indicate underlying environmental stressors, health issues, or changes in forage composition.

In this context, individual tracking becomes particularly valuable. While group-level trends may suffice for broader decisions, such as estimating when to move a herd to a new pasture, they are inadequate when the objective is to understand fine-scale behavioural processes like bite rate or small-scale transition of the grazing behaviour.

Moreover, individual data enable the sensor to detect deviations not only from population averages but also from an animal's own behavioural baseline, making it possible to identify changes specific to that individual, such as altered feeding behaviour due to suboptimal forage provisioning or modified health status. For example, the same animal grazing on ryegrass versus a mixed cover crop may naturally exhibit different bite rates due to forage structure and palatability. Rather than developing separate models for each pasture type, monitoring the relative change in bite patterns for that individual offers a more robust and scalable approach. A drop or an increase in the bite rate, regardless of the absolute value, may indicate a meaningful shift, whether related to forage characteristics or animal health. This ability to detect within-individual behavioural changes over time is a critical step toward context-aware, personalized monitoring in livestock systems. For instance, if a cow transitions from grazing on ryegrass to a mixed cover crop, its bite rate may change due to forage characteristics. Yet the more meaningful signal may be a relative drop in the bite rate for that same individual, regardless of the absolute value. This sensitivity to within-animal variation may offer a potential pathway toward developing context-independent behavioural diagnostics, without necessarily requiring model recalibration for each sward type.

2. Answering the research questions

As a reminder, this research started with four questions:

1. what sensors and techniques are the most suitable for monitoring the behaviour of ruminants?
2. what are the main differences in grazing behaviour predictable by such sensors in response to different grassland structures?
3. what methodological framework could be used?
4. can observation of animal behaviour and location derived from IMU/GNSS sensors be used to detect changes in grazing patterns?

The different tools and experiments that were built and ran had the same objectives of answering each of those questions.

2.1. What sensors and techniques are most suitable for monitoring the behaviour of ruminants in grasslands under rotational grazing strategies?

The first research question of this thesis and one of the first decisions that had to be made was the type of sensor that would be used. As listed in the introduction to Chapter 3, motion, acoustic, and image sensors are the primary systems used to collect data on animal behaviour. However, several factors limit direct comparisons between these technologies, particularly the diversity of data and performance metrics (Chelotti et al., 2024). The most used technologies in recent studies remain accelerometers, gyroscopes, magnetometers, GNSS, and UWB (Aquilani et al., 2022). Studies on automated animal activity recognition rely on accelerometers, either alone or combined with other sensors, to record animal movements (Mao et al., 2023), with gyroscopes, magnetometers, GNSS, and UWB devices being the next most used. This success is due to their reliability, maturity, and versatility in behaviour classification tasks.

The next PLF technology that retained our attention was the opportunity to spatialize the environmental impact of grazing animals and to evaluate their responses to disturbances using GPS-derived location and movement data (Swain et al., 2011; Bindelle et al., 2021). Swain et al. (2011) recommended reproducing small-scale experiments (both spatially and temporally) using high-frequency, short-term GNSS data to refine behavioural modelling methods. The combination of remote sensing with ML and other technologies like wearable sensors allows for automated monitoring and estimation of pasture biophysical parameters (Bretas et al., 2023).

Finally, vegetation indices, particularly the NDVI, are key predictors of above-ground forage biomass (Maake et al., 2023). Such methods are an alternative to field-based measurements of pasture biomass and SH and are less time-consuming and better at a high level of spatial resolution (Bindelle et al., 2021). The second chapter of this thesis showed that indices of biomass and heterogeneity of grazing can be calculated and mapped on 2-m² grids to observe the impact of the presence of ruminants on a pasture, using UAV as a less time-consuming and more precise tool than traditional "ground-truth" averages. Chapters 4 to 6 explored a methodology to map the behaviour of cows within similar grids, meaning that a superposition of the two is now possible. Once spatialized data are available, other information obtained by sensors can be added to the models, such as data on precipitation, humidity, soil fertility and temperature (Bretas et al., 2023).

GNSS data can also provide additional spatialized insights, such as the distance to water points and movement data (Arablouei et al., 2023). Different groups of researchers (Arablouei et al., 2023; Benaissa et al., 2023; Brennan et al., 2021; Cunningham et al., 2024) suggest adding high-frequency accelerometers to GNSS units for more accurate classification of behaviours and deeper insights into grazing patterns over time. This sensor combination also shows promise for early detection of livestock diseases and welfare issues (Bailey et al., 2018).

Several other promising technologies were not selected in this work, for specific reasons detailed hereafter:

- acoustic sensors, for instance, capture the sounds produced during ruminant feeding activities, which convey detailed information on jaw movements (JM), types of feeding activity (grazing, rumination), and even the type and quantity of vegetation ingested or regurgitated. Sound signals have been shown to correlate with DMI, but they require intensive processing to extract relevant features and are highly sensitive to environmental noise (wind, birds, nearby animals). Furthermore, their high energy consumption limits long-term field deployment (Chelotti et al., 2024);
- pressure sensors, often embedded in nosebands filled with carbon granules, detect jaw movements by registering changes in electrical resistance as the animal chews. These variations are then processed to identify chewing cycles (Aquilani et al., 2022). While robust against external noise and effective in detecting JM, they can disturb natural behaviour and require frequent calibration (Chelotti et al., 2024);
- image-based sensors offer non-invasive, low-stress monitoring with real-time behavioural understanding. Recent advances in low-cost cameras and computer vision have sparked growing interest in this approach. Nevertheless, while they are useful for classifying behaviours and estimating feed intake, they offer less detail on fine-scale behaviours such as mastication. They are also more sensitive to lighting changes and require large storage capacities (Chelotti et al., 2024);
- infrared thermography is increasingly used to assess thermal regulation and welfare, particularly in tropical climates or intensive systems. It allows rapid health assessments in pasture settings (Aquilani et al., 2022). but it remains difficult to use with free-ranging animals due to requirements for stable positioning, close distance, and the need for unobstructed views. Outdoor factors such as variable light, animal movement, and weather further compromise its effectiveness.
- Ultra-Wide Band (UWB) is a radio positioning technology that enables high-precision, short-range tracking and is mostly used in indoor settings (e.g., free-stall barns). It performs well when combined with accelerometer data to track animal groups, but is unsuitable for outdoor grazing systems due to signal limitations in open or large-scale environments (Benaissa et al., 2023).

GNSS–accelerometer systems are uncommon on farms. Still, it was possible to build the specific prototype needed for this research: a low-cost, open-source GNSS collar equipped with accelerometers. These kinds of devices can be seen in several laboratories and show promising results for accurately identifying grazing locations (Brennan et al., 2021; Obermeyer and Kayser, 2023). Their customizable nature is essential for developing grazing-specific behavioural classification algorithms.

2.2. What are the main differences in grazing behaviour in response to different grassland structures that these sensors and techniques allow us to observe?

Based on the results presented in Chapter 6, the most significant indicators of grazing behaviour changes in response to grassland structure were the travelled distance and the area grazed. These two metrics showed clear variation, reflecting changes in how cows explore and use the pasture.

Interestingly, bite frequency was less affected by decreases in SH than expected. While theoretically, bite frequency should increase as SH decreases, because animals need to compensate for lower forage availability by taking more bites, the observed increase was irregular and modest, from about 50.3 to 57.3 bites per minute after 56 hours of grazing. This aligns with the literature suggesting that below an optimal SH range (12–18 cm for *Lolium perenne*) (Bindelle et al., 2021, Carvalho et al., 2013)., cattle increase their biting rate, but the effect may be less pronounced or more variable than other behavioural indicators.

Another notable pattern was that grazing behaviour on the first day and the third day of grazing showed similarities, with grazing activity intensifying throughout the day. This was evident through increasing values in eating parameters (grazing time, bites, FS) and foraging behaviours, with travelled distance and area grazed nearly doubling over the course of the day.

In summary, these sensors and techniques highlight that movement-based parameters such as travelled distance and explored area are more sensitive and consistent indicators of changes in grassland structure, while bite frequency shows more variable responses. However, more extensive studies with larger datasets are needed to confirm these findings.

2.3. What methodological framework should be used to develop an efficient model for observing the evolution of both animal behaviour and sward height and heterogeneity ?

While there are still some necessary steps to be made before the PLF device can be considered completed and the framework validated, Chapter 6 explains in detail how to use a performing model and IMU + GNSS/RTK sensors to observe the evolution of animal behaviour continuously, at several spatial and temporal scales. The method begins by training the best-performing algorithms from the two-step model developed in Chapter 3:

1. a classification step: Behaviour is classified into two categories (ingestion or other) over 30-second windows;
2. a regression step: For the 10-second sub-windows within each 30-second ingestion window, a regression model quantifies the number of bites taken by each animal.

This approach allows a continuous, fine-scale observation of grazing behaviour at multiple spatial and temporal scales. The key behavioural and spatial parameters derived from the model include:

- Grazing Time (GT) — percentage of total time spent ingesting.
- Total Bites (TB) — total bites quantified over the session.
- Area Grazed (AG) — total area where ingestion was detected, mapped on a hexagonal grid.
- Travelled Distance (TD) — calculated via successive GPS positions.
- Bite Frequency (BF) — bites per minute of ingestion.
- Feeding Stations (FS) — clusters of successive bite events within spatial and temporal thresholds.
- Derived metrics such as bites per square meter (BSM), bites per FS (BFS), and FS per square meter (FSSM).

This framework integrates behaviour classification, bite quantification, and spatial mapping, making it well-suited to capture the dynamic interaction between animal grazing patterns and sward heterogeneity over time. Its continuous multi-scale monitoring capacity allows tracking changes in both animal behaviour and pasture structure efficiently.

2.4. Can observation of animal behaviour and location derived from IMU/GNSS sensors be used to detect in advance changes in grazing patterns as markers of increasing difficulty in collecting forage during grazing, at the individual and herd level ?

Certainly, IMU and GNSS sensor data have the potential to detect behavioural changes indicative of increasing difficulty in forage collection, as demonstrated in the GD experiment from Chapter 5 and 6. Key behavioural signals such as changes in grazing time, area grazed, and bite frequency showed meaningful trends correlating with declining SH and forage quality.

In this study, grass height stagnated around 8.5 cm before dropping suddenly once it reached down to 7.4 cm on Day 3, corresponding to approximately 41% of pre-grazing sward consumption, slightly above the recommended optimal grazing threshold (Gonçalves et al., 2018; Fonseca et al., 2012). This decline was associated with behavioural restrictions observed at both spatial and temporal scales. For instance, animals adapted by modifying their grazing patterns, which was detectable through sensor data.

However, given the limited nature of the experiment, it is not possible to validate a universal “break-point” or a single indicator signalling forage difficulty definitively yet. Instead, a combination of parameters indicating rising activity over the course of a day confirmed that sensor-based monitoring can capture adaptive responses to sub-optimal grazing conditions. The addition of GNSS data was crucial, not only for spatializing the behaviour but also for improving behaviour classification accuracy.

It is important to note that other external factors, such as larger paddock size, environmental conditions, social dynamics, or disturbances such as unfamiliar animals, can influence grazing behaviour, potentially masking or modifying these signals. Therefore, while promising, the development of research and decision-support tools using these sensors requires further validation across diverse grazing contexts and management conditions to reliably detect forage-related behavioural shifts at both individual and herd levels.

3. Originality and domain of validity

3.1. Domain of validity of the results – Boundaries

This thesis presents a reliable and original methodology for analysing grazing behaviour under controlled conditions. Its domain of validity is currently limited to a specific combination of environmental, botanical, and animal-related factors. Acknowledging these limitations is a necessary step toward building a rigorous foundation for broader applications. Expanding the work into more diverse settings, accounting for social, environmental, and individual behavioural variability, is essential for the development of robust, adaptive, and context-aware decision-support systems in grazing management.

The results presented in this thesis are reliable within the clearly defined boundaries of the experimental design. Their validity must be considered in relation to the specific conditions under which the research was conducted. The work was carried out on temperate grasslands composed of Belgian ryegrass (*Lolium perenne*) and white clover (*Trifolium repens*), grazed by Holstein dairy cattle (Chapters 4 to 6). The environmental conditions remained relatively stable throughout the experiment: there were no extreme variations in temperature, humidity, wind, or luminosity, and the physical structure of the paddocks, access to water, shade, and overall size were homogeneous. Additionally, no major external disturbances were recorded during the study, aside from the controlled and familiar presence of observers. These stable and controlled conditions were essential to isolating the variables under investigation and ensuring the internal validity of the behavioural patterns identified.

One example of an indicator that should be generalized with caution is the detection of a behavioural turning point: an increase in bite frequency when approximately 41% of the pre-grazing SH had been consumed. Although it is very consistent with previous literature (Carvalho et al., 2013; Gonçalves et al., 2018), in different grazing environments, particularly in larger paddocks, animals often exhibit a distinct initial phase of exploration, which can delay effective grazing and trigger intensified foraging later in the day. Additionally, factors such as fluctuating weather, the mixing of unfamiliar individuals, or changes in the herd's social dynamics may all influence activity patterns in ways that mimic the signals observed in this experiment (Tables 7-1 and 7-2). Such variability underscores the need for extensive cross-validation of the method under a wider range of conditions before considering it as a reliable foundation for decision-support systems. Moreover, factors like group composition, individual social behaviour, and routine habits were not systematically studied in this work, though all animals belonged to the same herd and were accustomed to the environment. These elements could play a role in behavioural variation (Boyland et al., 2016; Hirata et al., 2022), and their influence should be further examined in future studies. As such, while the current results provide a reliable baseline, the extrapolation of these findings to different breeds, physiological stages, pasture types, or management systems must be done cautiously.

3.2. *Sensible additional data to integrate*

Future perspectives for developing research- and DST using PLF technologies will require the simultaneous integration of several complementary types of data. Based on the research presented in this thesis, some data sources appear especially valuable (See Table 7-1). GPS/GNSS tracking combined with IMU data can provide geolocated behavioural information such as grazing, ruminating, resting, or abnormal patterns. These individual-level data are crucial for detecting early signs of health or welfare issues and for understanding spatial use, grazing paths, and area preferences. Within the IMU system, accelerometers are the most essential sensors (Mao et al., 2023). The frequency of data collection and processing methods will be discussed in a section 3.4. of this chapter. In order to detect spatial preferences at the FS scale with a precision of less than one meter, particularly in small experimental paddocks (< 1000 m² in this work), GNSS data recorded at 10-second intervals is recommended, following observations made in this study.

Biomass availability and quality can be estimated using NDVI data acquired by UAVs or through field sampling. Satellite imagery is unsuitable in this context due to insufficient spatial resolution. Data collected with UAVs are especially well-suited for spatialization, for example when integrated into a grid-based analysis format. Post-grazing regrowth is another critical variable, as it allows researchers and managers to evaluate the impact of grazing pressure, measured as the percentage of standing herbage consumed on the regrowth capacity of the vegetation and overall productivity. Mapping vegetation types is also useful, particularly in mixed-species systems or agroforestry contexts, as it helps assess animal preferences and avoidance behaviour across different vegetation patches. Additionally, data on stocking rates and herd composition, including breed, body weight, and physiological stage, are fundamental for modelling interactions between animals and their grazing environment. The temporal distribution of the animals on the pasture will be also necessary, and is related to the type of grazing management system used (e.g., rotational, continuous).

Depending on the context and the tools available, additional optional data may also enhance the performance of DST. Other PLF technologies such as heat sensors, sound sensors, or pedometers can provide valuable information on animal activity and welfare (Aquilani et al., 2022). Social interactions and dynamics can also be monitored using PLF technologies relying on Bluetooth and UWB (Benaissa et al., 2023; Mao et al., 2023). Soil data, including moisture, compaction, texture, and structure, are also important, as they influence plant growth and animal comfort. Environmental variables such as topography and microclimate can affect animal movement patterns, shade-seeking behaviour, and foraging effort, while weather data (temperature, humidity, daylight duration, precipitation, and wind) help contextualize behaviour and vegetation dynamics. Management inputs such as feed supplementation, fertilizer application, and labour (including mechanical interventions), as well as productivity outcomes like milk or meat yield per animal or per hectare, can also be integrated to support both ecological and economic decision-making.

From the primary data collected, several key indicators can be derived. Grazing pressure can be calculated by analysing the overlap between animal presence and forage zones. Causes for spatial preferences and avoidance areas may be identified by overlaying behavioural data with environmental variables, while changes in activity over time can be assessed in relation to biomass availability and seasonal dynamics. The heterogeneity of the post-grazing biomass and of the level of grazing intensity can reveal if the grazing behaviour and biomass destruction was homogeneous, which is an indicator of either efficient pasture use or overgrazing, depending on the context (Nunes et al., 2019) where on the opposite, a high heterogeneity can be an indicator of an underusage of the pasture, leading to losses of pasture quality (Pontes-Prates et al., 2020).

Table 7-1: Useful data to be included in tools for behaviour prediction and spatialization.

Category	Data Type	Purpose / Use
Core Data	GPS/GNSS & IMU (accelerometers)	Behaviour mapping, spatial use, early detection of welfare issues
	Biomass (NDVI, field sampling)	Assess forage availability and spatial grazing impact
	Post-grazing regrowth	Evaluate pasture resilience and productivity
	Vegetation type mapping	Analyse preference/avoidance, particularly in diverse systems
	Stocking rate & herd composition	Understand animal impact, model grazing dynamics
	Temporal distribution (grazing duration and system)	Reflects the management strategy and helps interpret the data
Optional Data	Animal PLF sensors (heat, sound, pedometers, bluetooth, UWB)	Monitor welfare, detect specific behaviours, detect social interractions
	Soil properties	Assess pasture quality and animal comfort
	Topography & microclimate	Understand movement, shade use, and distribution
	Weather data (temperature, humidity, wind, light)	Contextualize behaviour and pasture condition
	Inputs and management costs	Support economic and logistical decision-making
	Productivity outputs (milk/meat per animal/hectare)	Link behaviour and pasture use to performance
Derived Metrics	Grazing pressure	Measure spatial forage use intensity
	Preferences & avoidance zones	Reveal behavioural patterns through spatial correlation
	Activity evolution over time	Track changes in response to biomass availability
	Pasture heterogeneity	Reveal if the grazing pressure is homogeneous or heterogeneous

Naturally, this list of data inputs and derived indicators must be adapted to the specific objectives and operational constraints of each application. Furthermore, it is likely to evolve as PLF technologies advance and new possibilities for integration and analysis emerge.

Because pastures and paddocks are never strictly homogeneous systems, several environmental factors and structural components of the pasture can significantly influence grazing behaviour. Those must be considered when interpreting data. Fences and barriers, whether physical (e.g., electric fences) or virtual (e.g., GNSS-enabled systems), define grazing zones, limit animal movement, and guide spatial distribution (Table 7-2). Natural obstacles such as trees, hedges, dense vegetation, or steep slopes can restrict accessibility, create shaded areas that affect animal comfort, and influence both resting and grazing patterns. The presence and location of water points play a key role in shaping movement patterns, as animals often travel regularly to drink, affecting their time budgeting and fidelity to specific zones. Additionally, infrastructure elements such as feeders, shelters, or gates can act as attractors or deterrents, concentrating animal presence or creating avoidance zones, depending on management strategies and animal experience. Finally, perturbation factors, such as disturbances caused by humans or predators, and routine behaviours that could impact other results, should be annotated since they influence cow behaviour and may affect data interpretation.

Table 7-2: Environmental and perturbation factors to be included in tools for behaviour prediction and spatialization.

Category	Factor	Purpose / Use
Pasture Structure & Constraints	Fences and barriers (physical or virtual)	Define grazing zones, restrict movement, influence spatial behaviour
	Natural obstacles (trees, hedges, dense vegetation, slopes)	Affect accessibility, shade availability, grazing paths, and resting zones
	Water point location and accessibility	Drive travel distance, influence time budgeting and site fidelity
	Infrastructure (feeders, shelters, gates)	Introduce conditioning zones, can attract or repel animals
Perturbation factors	Disturbances (humans, machines, dogs, predators)	May affect data interpretation, influence cow behaviour

	Routine behaviours, group dynamics	May affect data interpretation, create patterns in cow behaviour

3.3. Data-splitting methods used

The choice of data-splitting strategy plays a critical role in evaluating the robustness and generalizability of ML models, especially in animal behaviour research where individual variability and experimental conditions can significantly influence outcomes.

In Chapter 3, a random split (Datasplit 1) was initially applied using a 70/30 train/test proportion. This first split aimed to balance training and testing sets in terms of behavioural diversity. While this approach helps ensure diversity in the learning process, it may lead to overly optimistic performance estimates, especially if similar contexts or individuals are present in both sets as datasets are not rigorously independent. To counteract this, a second 70/30 train/test split (Datasplit 2) was performed using an individual-based criterion, ensuring that animals in the test set were not seen during training. This approach reflects a more realistic application scenario, where a model trained on a group of animals is later applied to new individuals. The 70/30 train/test ratio used in both splits aligns with common practice in ML, as supported by Vrigazova (2021). Increasing the proportion of test data—for instance, moving from a 70/30 to a 60/40 or even 50/50 split—could, in some cases, enhance the reliability of performance evaluation by testing the model more extensively. However, this comes at the cost of reducing the amount of data available for training, which can impact model generalization, especially with the smaller datasets typically obtained from PLF prototypes used in outdoor livestock farming. Therefore, a balance had to be struck between training model robustness and obtaining an accurate estimate of real-world performance.

In Chapters 4 and 5, a LOAO cross-validation strategy was adopted. This method is particularly relevant in the context of livestock behaviour modelling, where inter-individual variability is high. LOAO offers a robust estimation of model generalizability across individuals, ensuring that model performance reflects its ability to extrapolate to unseen animals. It is a stringent form of cross-validation and aligns with best practices recommended in PLF literature for improving external validity.

Additionally, in Chapter 5, a LOVO approach was also implemented. This step was used to evaluate the model's ability to generalize across different temporal contexts and environmental conditions, capturing day-to-day variability in behaviour. This method complements the LOAO approach by ensuring that the model is not overfitted to specific video sessions or experimental blocks. Together, these strategies aim to reduce bias and better simulate real-world deployment, where the model is expected to operate on new animals and new situations.

3.4. Data sampling frequency

Considering the sampling frequency of IMU data, Riaboff et al. (2022) reported a median frequency of 12 Hz for raw accelerometer data in their systematic review and recommended a sampling rate between 10 and 20 Hz. In this study, two devices were used: the first collected IMU data at a frequency of 100 Hz, while the second collected both GNSS and IMU data at a frequency of 8 Hz. A noticeable decline in performance was observed in the similar ML algorithms developed for each device, particularly during the bite quantification step. The average prediction error increased from 1.8 bites per 10-second window (Chapter 3) to 3.2 bites per 10-second window (Chapter 5). With the sensor prototype used in Chapters 4-5-6, the achievable sampling frequency was limited to 8 Hz by the GNSS + RTK sensor. These findings suggest that an increase of sampling frequency is necessary for good performances, and future prototypes should aim for a minimum IMU sampling rate of 10 Hz. Increasing the frequency beyond 20 Hz may be unnecessary, as it is unlikely to improve predictive performance while significantly reducing battery life (Benaissa et al., 2018).

3.5. Level of expected accuracy

One of the key trade-offs in developing a wearable sensor for bite detection lies between accuracy and robustness. A device that performs very accurately in controlled experiments but fails to generalize in real-world conditions offers limited practical value. In our context, developing a tool for use in diverse farm environments required finding a balance between precision and consistency.

This trade-off shaped our approach to bite detection using a custom-built IMU-GNSS device. While maximizing accuracy can yield excellent results under controlled conditions, our prototype introduces real-world variability. The sensors are collar-mounted, which leads to inconsistent placement depending on the animal's neck size and occasional slipping (see Section 2.2, Chapter 4). Moreover, as a prototype, the device is occasionally affected by firmware issues or environmental disturbances (e.g., weather, animal contact), all of which contribute to signal noise. To remain reliable under on-farm conditions, a slight drop in accuracy must be accepted in exchange for improved robustness.

3.5.1. Defining the performance objective

In some cases, the search for prediction performances can lead to some sacrifices of accuracy. In chapter 5, the 10-minute threshold used to distinguish between two meals differs from the 5-minute limit cited in the literature. This choice was driven by performance considerations: initial evaluations using a 5-minute threshold were inconclusive due to a high rate of misclassification. While this broader threshold may include some short interruptions within the same meal, it ensures greater stability of results within our protocol. In this approach, the goal was not absolute meal detection or bite counting, but detecting meaningful fluctuations in ingestive behaviour. The key performance criterion was sensitivity to within-animal variation, being able to track increases and decreases in bite count across changing conditions for the same animal. As explained in the introduction of Chapter 3, such variation in bite frequency reflects the animal's ability (or inability) to optimize grazing time, which can have consequences on production efficiency and grazing pressure.

A dull ML model might predict exactly 10.3 bites in every 10-second window labelled "ingestion," yielding a low RMSE (< 3 bites/window), but it would miss important behavioural dynamics. This is not the goal of our work. For PLF applications, a margin of error is tolerable if the model can capture behavioural changes across diverse scenarios.

In our case, the model aimed to predict bite rate over 10-second windows based on IMU data. The choice of a 10-second window stemmed from performance tests (Chapter 3), which showed it outperformed other window sizes (3, 5, or 30 seconds) within the 3–30 second range recommended by literature (Riaboff et al., 2022). Larger windows would smooth out variance and obscure behavioural changes, while smaller ones (< 3s) would require more complex pre-processing and risk over-sensitivity, limiting generalizability.

3.5.2. Results across scales and conditions

Over 20-minute grazing sessions, our model showed strong agreement with observed bite counts, with a Pearson correlation coefficient > 0.90 for 36 samples across 12 animals (Chapter 5). A minimum acceptable correlation threshold of r > 0.80 can be proposed, pending further validation.

Per-window accuracy becomes more important when spatializing behaviour. In Chapter 6, the model's ability to detect FS and meals was evaluated. Most FS lasted between 28.8 and 96.0 seconds. Given an average bite rate of 1.03 bites/second (consistent with literature values from 0.83 to 1.33), each FS includes between 24 and 1250 bites. To maintain meaningful spatial predictions, the relative RMSE must remain within a reasonable range. Although no universal RMSE thresholds exist, values exceeding 5 bites per 10-second window likely compromise interpretability. A target of ~3 bites/window appears realistic for balancing granularity and robustness in field applications.

In Chapter 3, using a commercial 100 Hz device, an average error of ±1.8 bites per 10-second window was achieved. With our custom device, modified to include a GNSS-RTK module—this increased to ±3.2 bites. However, the total bite count error over 20-minute periods remained at 15%, showing the model's tendency to selfbalance over time. Including the test animal in the training dataset further improved performance to ±2.3 bites per window and 8% total error. And despite a drop in per-window accuracy, spatial behaviour mapping (Figures 5-8 and 5-9) remained effective with 98% accuracy for detecting FS and 106 meals out of 110 that were correctly detected.

3.5.3. Designing for Generalization

The model was not designed solely for the specific conditions of our experiments, but for future use across varied contexts. This required careful choices in several design aspects:

- Algorithms: BT, a robust method based on bootstrapping that limits overfitting. While Medium Neural Networks were also tested, they were ultimately excluded due to lower performance in generalization (Chapter 4).
- Features: Generalizable features were chosen, like Amag, OBDA, and VeDBA, which are less affected by sensor orientation. However, context-specific features capturing head movement may still be useful to predict behaviours from low- or high-activity animals.
- Data Diversity: Building robust models depends on maximizing both the quantity and diversity of training data, across animals, behaviours, and environmental conditions. Some level of noise during training may even enhance real-world tolerance.

3.5.4. Application-Specific Precision Requirements

While our focus was robustness, some use cases may demand high precision. For example, in controlled research on a single breed, the aim may be to capture detailed behavioural data with minimal environmental interference. In such cases, using a fixed harness—as done in Chapter 3—and thorough pre-processing to eliminate noise might be appropriate. The model would then be used under known, repeatable conditions.

However, this remains more of a theoretical scenario. In practice, animal behaviour research and PLF tools increasingly require adaptability to real-world complexity. As such, robustness often outweighs pinpoint precision.

4. Concrete potential applications of the device in research

This work has enabled the establishment of a methodological framework displaying an accurate mapping and prediction of the grazing behaviours in specific conditions.

It was accomplished through the validation of a two-step methodological framework for model construction, with, for objectives (1) behaviour classification and (2) bite quantification. This framework has been proven to work for different devices and frequencies: here a smartphone taking IMU data at a 100 Hz signal frequency and a self-made system taking IMU signal at an 8 Hz signal frequency. In both cases, regarding the ML classification and regression algorithms, the 'bagging' (bootstrap aggregating) approach yielded the best results for building the model. The exploration and selection of several specific parameters for segmentation during chapter 3 allowed to establish an optimal combination: the use of 30-second time-windows with 90% overlap for behaviour classification and 10-second time-windows with 90% overlap for bite quantification.

The model built for the self-made device had the following performances for identifying ingestion: precision (98.9±1.7%), recall (99.1±1.2%), accuracy (98.2±1.8), specificity (78.2±9.4%) and Cohen's Kappa (74.1%±14.5%). The regression model for bite monitoring gave an average RMSE of 3.19±0.41 bites for each 10-second window and an error of prediction of 15.3±10.3%. The same models were used to predict FS with an accuracy of 94.7± 8.1% to predict FS and 91.9± 12.7% to predict meals. For comparison, the model built for the smartphone gave an accuracy of 98.0% for behaviour prediction and an average error of prediction of 1.8 bites for each 10-second segment.

The addition of RTK GNSS sensors for the self-made device offered improved geolocation precision, enabling a calculation of the number of bites per 10-second windows within squared or hexagonal grids, with compartments of < 1m².

Based on the results achieved, this study has made it possible to assess fundamental grazing behaviours in ruminants. This includes a confirmation of the tendency of grazing cows to lower their bite frequency as grass structure adapts to their needs, an increased cow activity when 40% of pre-grazing SH is consumed, and refusal behaviour, signalling the need for pasture management adjustments.

It has also been proven that this technology has the potential to identify grazing hotspots, grazing patterns, resting sites, and underutilized areas, for individual animals and continuously. As explained in the previous chapters, bite frequency tends to increase when vegetation is either scarce (Soder et al., 2022) or abundant (Mezzalira et al., 2014; Soder et al., 2022). This means that it is possible to identify potential "turning points," where a reduction in grass height triggers changes in animal behaviour. Such shifts in daily activity, meal patterns, or FS visits can be observed through the self-made device presented in chapter 5 and 6.

Beyond the immediate findings, this thesis lays the groundwork for a broad range of future research possibilities. The methodological advances introduced here—

particularly the integration of spatially explicit IMU and RTK-GNSS data—open the door to fine-scale, continuous monitoring of grazing behaviour across multiple spatial and temporal levels, from the bite to the meal to full-day grazing sessions. This constitutes a significant contribution to animal behaviour research by demonstrating, for the first time, that it is technically and methodologically possible to map and interpret such dynamics in real grazing conditions. While battery life and prototype limitations remain practical challenges, the feasibility of long-duration, high-resolution monitoring has been clearly established.

The implications for future research are substantial. On a fundamental level, this work marks the beginning of a pathway toward a more precise understanding of ruminant grazing behaviour. Now that such data can be captured objectively and continuously, it is possible to explore in more depth how animals adjust their behaviour in response to varying sward conditions, species composition, climate variables, or social dynamics. One immediate continuation of this work would be to investigate whether certain "breaking points" in behaviour, such as the one identified near 40% sward depletion, hold true across different pasture types, animal breeds, environmental conditions or management systems. This could ultimately lead to the development of behaviour-based indicators for pasture quality or grazing thresholds, supporting more responsive and ecologically sound management strategies.

The methodology and prototypes presented here could also be used on a broader sample of cow breeds to test how well the developed model generalizes. Given that the literature suggests performance tends to drop as soon as new parameters are introduced, an important next step would be to quantify the amount of data required from a new breed to train a new, adapted model. This could be approached by incrementally increasing sample sizes from the new breed and identifying the optimal trade-off between the time and labour needed to collect data and the predictive performance of each model version. This research pathway would provide both practical insights and methodological tools for extending precision livestock technologies to a wider range of animal populations

A first concrete application lies in the use of this system to explore animal preferences across different types of grasslands. By designing pastures divided into zones, each dominated by a different grass species but controlled for all other factors (such as distance to water, shade, slope, wind exposure - see table 7-2), the system could help identify attraction or avoidance behaviours with objective, quantifiable data. This would be particularly valuable in contexts where farmers are considering introducing new plant species with higher ecosystem services or greater resilience to drought. The ability to ensure that animals do not significantly reject these forages, and to demonstrate this with clear, reproducible data, could significantly ease adoption of more sustainable grazing systems.

In parallel, these tools create opportunities to study plant-animal interactions in less conventional systems that remain understudied. Agroecological practices such as silvopastoralism, intercropping, ICLS and mixed-species grazing could benefit greatly from this kind of high-resolution behavioural tracking. The benefits of these systems compared to best practices in conventional grazing remain inconclusive or incomplete (O'Grady et al., 2024). Wearable sensors could help generate more concrete data to assess their impact.

For instance, understanding how animals move, rest, and forage in complex vegetation can reveal which plant species or configurations support animal welfare and productivity while enhancing ecosystem services. In these contexts, where little behavioural data currently exists, the methods developed here offer a template for building new knowledge and refining agroecological design. For example, in an integrated crop-livestock system combining traditional pasture, intercropped legumes, and silvopastoral elements, high-resolution tracking of animal behaviour using IMU and RTK-GNSS sensors could reveal clear patterns. The spatialized observation of individual cow's behaviours might show a preference for legume-rich zones due to higher forage quality, while shifting to silvopastoral areas during hot hours for shade and rest. Even if the traditional grass zone is more accessible, it may be grazed less as forage depletes, with bite rate data indicating optimal times for rotation. These insights would help refine pasture composition and management because integrating crops, forestry, and livestock adds complexity that clashes with current trends in specialization (Carvalho et al., 2021). Overcoming this requires improved accessibility and mindset shifts. One of the main barriers to agroecological adoption is the lack of guarantees (Jouven et al., 2022), partly due to the scarcity of holistic studies and clear indicators of natural capital and productivity (O'Grady et al., 2024).

5. The future improvement necessary for the application of the device in research

Robustness has been the repeatedly cited weakness for such device (Chapters 3 to 6). Thus, there is a need to adapt and implement the presented PLF device in new environments, with clear methodological approach that balances model robustness with practical feasibility. A logical starting point would be to directly apply the existing model, trained on data from Chapters 4 to 6 to new datasets collected under different conditions (e.g., different cows, breeds, or environments). This "as-is" application would serve as a baseline to assess how well the current model generalizes beyond its original context. Based on the literature, the expected outcome is a significant drop in performance, potentially rendering predictions inaccurate or misleading. Yet, this initial step is essential to quantify the limits of the current model.

Following this diagnostic phase, the next objective would be to identify how to build robust models with minimal additional effort. The focus would be on designing a streamlined pipeline that allows for quick retraining and adaptation in new settings. One practical strategy involves gradually incorporating increasing amounts of data from the new context into the existing training set. By tracking performance improvements as more data is added, it would be possible to determine the minimal number of observation hours or labelled data points required to achieve acceptable accuracy. This stepwise integration would offer valuable insights into the adaptability threshold of the model. The approach described here corresponds to a method known as Incremental Fine-Tuning, which consists in taking an already trained model and refining it incrementally using new, context-specific data, without retraining everything from scratch (Lialin et al., 2024). This strategy is both practical and efficient, particularly when access to labelled data is limited or when rapid deployment is needed.

An alternative avenue, particularly relevant for scaling up, would be to explore the use of deep learning approaches. These methods are already used in PLF (Mao et al., 2023) and have the potential to autonomously learn complex patterns and continuously adapt across diverse datasets. However, they come with trade-offs: they require large volumes of data and may function as "black boxes," limiting interpretability and user control (Rudin, 2019). While promising, such approaches should be pursued in parallel with more transparent and farmer-oriented models. In addition to deep learning, other advanced strategies could also be considered. One is multi-breed training, where data from various breeds and environments are included in the training set from the start, allowing the model to learn more generalized behavioural patterns that are not specific to a single context. This technique creates robust models but needs a large variety of data samples. Another promising direction is Domain Adaptation or Few-Shot Learning, which aim to adapt models to new environments with very limited data—sometimes just a few labeled examples—by leveraging prior knowledge learned in other settings (Parnami and Lee, 2022). These techniques are more complex to implement but offer high potential for fast and lightweight deployment in highly variable field conditions.

In summary, the proposed framework includes:

- Baseline Evaluation: Apply the existing model to new datasets to assess generalizability.
- Incremental Adaptation: Gradually integrate new data and monitor performance to identify minimal retraining requirements.
- Scalability Exploration: Investigate deep learning and multi-breed training as a longer-term solution, while remaining cautious of transparency and data needs.
- Practical Focus: Prioritize methods that allow for rapid retraining and are compatible with real-world constraints in diverse agricultural contexts.

- This framework ensures a rigorous yet pragmatic path forward, enabling the PLF prototype to evolve into a more widely adaptable and resilient tool.

6. The usability of this system as a Decision Support Tool for farmers?

The current prototype is not yet suitable to serve as a DST for farmers. Several limitations need to be addressed before such a tool can be deployed on farms.

Firstly, there are significant technical constraints, including limited battery life and robustness of the hardware. For instance, even short-term monitoring (such as 72-hour grazing sessions) required interrupting the experiment to replace batteries, which is far from ideal in a practical farm context. Moreover, the system does not currently support real-time monitoring, which is essential for timely decision-making such as determining the optimal moment to rotate pastures.

As a second point, the ML algorithms still require training on larger and more diverse datasets, encompassing different animal species, climatic conditions, and farming systems. As it stands, the tool is more suited to generating new behavioural knowledge than to informing daily farm decisions.

As a third point: for this tool to become a true DST, it must meet practical needs and expectations of farmers. For example, some may prefer using traditional indicators like grass height to guide grazing management. Regarding the demand for PLF technologies, both farmers and researchers are asking for more studies and concrete results (Aquilani et al., 2022). As autonomous actors, farmers can both lose or benefit from tools that support their decision-making in the context of agroecological transitions and the development of PLF technologies. Therefore, many farmers remain hesitant to invest in technologies, although younger generations show greater openness to adopting precision tools (Bianchi et al., 2022).

A study by van den Pol-van Dasselaar et al. (2024) investigated the perspectives of young farmers and agricultural students across eight European countries. While motivations for maintaining grazing systems included animal welfare, health, and personal preference for pasture-based farming, the most frequently cited barriers were climate change (e.g., drought stress), land fragmentation, and a lack of knowledge or training. These challenges often raise questions for farmers about which practices or tools to adopt. Therefore, farmer involvement and trust is critical in the co-design process. Surveys and participatory development approaches are necessary to understand the indicators they currently rely on, their concerns, and their management strategies.

As a fourth and final point, economic feasibility is another barrier. The estimated cost was €380 per unit in April 2022, which is likely too high for large-scale adoption, especially when many animals need to be equipped. Additionally, the tool must be simple and intuitive to use, a requirement repeatedly highlighted in studies on DST adoption (see Mancuso et al., 2023). However, this cost estimation was based on the building of single device, and not on its industrialization that, hypothetically, would reduce considerably the price. The maintenance of the tool and the provided service could be also another point that should be considered in the cost, as it is essential to keep a certain quality in the functioning of the tool but also in the analysis of the obtained data, passing through the data collection quality itself. Finally, compared to other DST used in farms, which are nowadays mainly dedicated to the oestrus or disease detection, a service designed for pasture management could get a place in the market and it should start with this kind of study, where experiments will be repeated to let the tool and the related data analysis be more robust and get more maturity.

In summary, before this system can evolve into a viable DST, the following key steps are required:

1. overcome technical limitations (e.g., battery, robustness, data transmission).
2. train and validate ML models on broader datasets across species and systems. The training will be done continuously according to the data that are collected through the users.
3. Co-develop the tool with farmers to ensure it provides real added value and is usable on a daily basis.
4. Ensuring economic feasibility for the farmer, but also for the future company that will provide the service.

7. The sustainability implications: economic, societal, and environmental

By addressing issues related to pasture use and management, as well as the monitoring and control of livestock, PLF contributes to the three pillars of sustainable development: increasing productivity (economic), reducing stress and workload for farmers (social), and limiting input requirements while improving animal health (environmental) (Aquilani et al., 2022; Papakonstantinou, 2024; Rutter, 2017). It has been theorized that combining PLF with digitalization, remote sensing, and artificial intelligence could enable multi-aspect and sustainable management of livestock production, animal health, and the environmental impact of the livestock sector (Tullo et al., 2019; Kumar, 2022). Some studies even highlight the potential of PLF and digital technologies in agriculture to reduce greenhouse gas (GHG) emissions and contribute not only to climate change mitigation but also to system adaptation

(Aquilani et al., 2022; Parra-Lopez et al., 2024; Tullo et al., 2019). Chelotti et al. (2024) also suggest using PLF data to develop certification systems for livestock farming, based on real-time measurements and animal behaviour as quality criteria. PLF contributes to environmental sustainability by improving animal health, reducing inputs like water and fertilizers, and enabling early detection of behavioural changes, allowing timely interventions that support welfare (Mao et al., 2023; Parra-Lopez et al., 2024). Even simple PLF tools like GPS and Radio Frequency Identification (RFID) can reshape farmers' workloads and their relationships with animals (Tullo et al., 2019).

While these arguments are promising, the adoption of digital technologies still faces major challenges, as it was already pointed out in the context section of Chapter 1. These include the environmental impact of their production and use, an aspect poorly documented and paradoxical given the goal of reducing inputs (Parra-Lopez et al., 2024; Tullo et al., 2019). Other barriers include the digital divide, high initial costs, complexity, and concerns over privacy and security (Parra-Lopez et al., 2024). Mitigating environmental impacts and climate change is not its primary function of PLF (Tullo et al., 2019). And some researchers argue that the current effectiveness of these technologies is insufficient to significantly contribute to sustainable, animal-friendly, and efficient livestock production systems (Bianchi et al., 2022). Moreover, although strategies for sustainable pasture-based production should balance meat demand with production capacities (Kumar, 2022), and there is social consensus that agriculture should move away from industrial models (Tullo et al., 2019), the widespread adoption of PLF technologies does not inherently ensure ethical or sustainable outcomes. The growing reliance on technology in agriculture, especially for temporal, spatial, and individual data, raises concerns about cybersecurity vulnerabilities (Alahe et al., 2024) and data ownership and confidentiality (Chelotti et al., 2024). Without a clear legal framework, there is a risk that productivity will be prioritized over ethical and environmental considerations (Papakonstantinou, 2024; Tullo et al., 2019). While the potential benefits of PLF remain underexplored, its environmental life cycle impacts are real and insufficiently studied. Greater attention must be given to issues of cost, complexity, and animal welfare before considering large-scale adoption in livestock systems (Papakonstantinou, 2024).

Concerning the durability of PLF technologies used directly on farms, they offer the advantage of generating valuable, continuous data on animal and herd behaviour over extended periods and in hard-to-reach areas, without the need for constant human presence (Chelotti et al., 2024). Tullo et al. (2019) recommend integrating simple technologies, such as Bluetooth, GPS, and RFID—into farming systems. These tools have the potential to transform the duration, content, and nature of farmers' tasks, reducing mental workload and reshaping their relationships with animals.

Alongside these advancements, it is crucial to promote knowledge-sharing among farmers to enhance the effective use of these technologies (Bianchi et al., 2022).

Equally important is improving the skills of all actors involved: farmers, educators, advisors, and policymakers, to support viable agroecological solutions (Jouven et al., 2022).

But at the root of the hesitation, on European permanent grassland farms (intensive, extensive, or organic), the primary factors influencing management decisions and tipping points are economic. Farmers often feel "pushed" to reduce ecosystem services due to profitability concerns, rather than "pulled" by public policies (Tindale et al., 2024). Agri-environmental measures (AEMs) and subsidies are frequently seen as too rigid and underutilized (Hammes et al., 2016). While both farmers and policymakers desire environmentally beneficial changes, farmers demand that AEMs and subsidies be redesigned to be more flexible and better suited to local realities (Hammes et al., 2016; Tindale et al., 2024).

In other words, before imagining widespread use of multi-sensor collars on regular farms, the tools must be simplified, and parallel research should examine their ethical and environmental implications.

Now, regarding the prototype presented in this work, while its potential as an emerging PLF technology has been described, its broader human, social, and ecological implications remain unassessed. A relevant example of how to approach this comes from The Shift Project, a French nonprofit focused on reducing fossil fuel dependence. In 2024, they published *Which Technologies for a Low-Carbon, Resilient and Prosperous Agriculture?*, which includes PLF and proposes a structured methodology for assessing technological deployment in agriculture (*The Shift Project*, 2024).

This methodology unfolds in two steps:

1. Mapping the technology, including:
    - A clear and general description;
    - Identification of technological dependencies and resource flows (especially energy use and climate-related risks);
    - Mapping of regulatory, socio-technical, financial, and organizational challenges;
    - Evaluation of synergies with other technologies.

2. Assessing adaptability to real farming conditions, based on:
    - Farm size and structure;
    - Geographic location;
    - Current agricultural practices;
    - Applicable regulatory and technical frameworks.

In the case of the sensor presented here, Steps 2 and 3 of Phase 1 should be addressed before promoting it as a decision-support tool. A full life cycle analysis of the materials is needed. The energy efficiency and environmental impact of the hardware components (see Section 2.2, Sensor, Chapter 4) remain undocumented. This might create a paradoxical situation in which tools meant to reduce inputs carry heavy environmental footprints, potentially negating the benefits of agroecological practices if scaled up.

Finally, social and ethical impacts, such as data access, farmer autonomy, and inequality in digital access, must also be examined. Issues of data justice are crucial: ownership and access should not reinforce power imbalances (Rotz et al., 2019). Transparency is also essential: users should understand how decisions are made, especially relevant with AI-powered PLF systems, or at least have access to a simplified explanation of the process.

As PLF holds significant promise for advancing more sustainable, efficient, and informed pasture-based systems, this optimism must remain cautious. Without robust ethical, legal, and ecological frameworks, the risk is high that technological progress will outpace our ability to manage its consequences responsibly.

For the specific prototype discussed in this manuscript, the next steps should include a full life cycle assessment, an evaluation of energy and material efficiency, and a clear analysis of social impacts such as data ownership and access. Only by addressing these dimensions transparently and early on can this tool evolve into a viable decision-support technology, one that contributes meaningfully to agroecological transitions rather than undermining them.

8. The potential application of this technology in the field of animal health?

This technology has potential for applications in animal health monitoring, though this would involve a new research and development effort.

The current system already collects data via GNSS and IMU sensors, which can help detect changes in animal activity patterns, a known indicator of health issues (Chapagaee, Pet al., 2024). However, new algorithms would need to be developed and trained specifically for health-related outcomes, which could form the basis of a separate research project or even a dedicated PhD.

Another possibility is to upgrade the current prototype by integrating additional PLF modules, such as microphones, temperature sensors, or heart rate monitors (Aquilani et al., 2022). Doing so would require both hardware redesign and software adaptation, but the open access aspect of the device provides an adaptable foundation for such extensions.

In indoor systems, other PLF technologies, more adapted to smaller spaces with electricity access could be used. Like 3D cameras, thermal imaging, or UWB localization systems—which may be better suited to certain health monitoring objectives (Aquilani et al., 2022). However, these applications are beyond the scope of the grazing behaviour framework studied in the current work.

Moreover, being able to monitor normal feeding behaviours is already a key step in health management. One can mention the "One Health" or "Eco Health" approaches to integrated health management, which propose a systemic view of animal health (Zinsstag et al., 2011). This systemic approach to livestock health supports the idea that proper feeding supports the stimulation of animals' biological functions, forming the foundation of a healthy livestock system. (Gotti et al., 2023).

9. The adaptability of the system to other species, farming systems, or climatic conditions?

This system is potentially adaptable, but such an extension would require careful testing and adjustments.

The current prototype was developed using Holstein dairy cows on ryegrass pastures in a temperate climate. For other species, such as buffaloes or sheep, modifications would be necessary. For instance, buffaloes often roll in mud or water, which could damage the hardware, necessitating reinforcement. For sheep, the total weight of the system would have to be reduced or redistributed, which could affect battery life or animal comfort.

Similarly, other climates and management systems (e.g., extensive beef systems in remote areas) present different constraints. The ML models would likely perform poorly outside the training conditions, making it necessary to collect new data and retrain the models accordingly.

Two possible strategies could be considered:

- Incremental expansion, starting with additional cattle breeds or physiological stages (e.g., lactating cows), then progressively testing under different systems and climates.
- Robustness testing, by immediately deploying the same device in drastically different settings to evaluate its performance and adaptability.

10. Conclusion

This thesis underscores the transformative potential of PLF technologies, such as IMU integrated with RTK geolocation systems, in optimizing the management of grazing systems. By accurately mapping spatial behaviours at the scale of < 1m and predicting bite frequencies with a RMSE of 2.34±0.69 bite per 10-sec window, these tools provide valuable insights into pasture utilization, animal welfare, and overall farm efficiency. A methodological framework has been developed and described, allowing to predict individual cow's feeding behaviour, FS, meals and movements. Using this method on dairy cows during a 72-hours GD session, the results obtained highlighted an increased animal activity around 40% pasture depletion. This could serve as an indicator for grazing limits from the animal's perspective, emphasizing the potential for PLF tools to support adaptive grazing management. In later studies on more heterogenous pastures, this method could help study grazing hotspots, resting sites, and underutilized areas. Despite their promise, current PLF systems face several challenges, including battery limitations, prototype inefficiencies, and fragmented datasets. The absence of shared, standardized databases hinders the broader applicability and validation of these technologies, emphasizing the need for cooperative research to develop robust, adaptable, and reliable solutions. Furthermore, the ethical and environmental implications of PLF adoption require careful consideration, as productivity-focused implementation risks sidelining sustainability and animal welfare. Addressing cybersecurity vulnerabilities and data ownership concerns is also essential to ensure equitable and secure use of these tools.

The growing awareness of grasslands' multifunctionality and their ecosystem services drives the need for deeper understanding of plant-animal interactions. Sustainable grazing strategies, informed by PLF insights, offer pathways to restore degraded pastures, enhance carbon sequestration, and balance productivity with ecological stewardship. Agroecological practices, such as integrated crop-livestock systems and silvopastoralism, present opportunities for more resilient and sustainable farming systems. However, these approaches face barriers, including their complexity and a lack of guarantees or holistic studies demonstrating their long-term benefits.

In conclusion, while this work serves as the beginning of a much longer scientific journey, the methods developed here can be adapted and improved by future researchers, applied across diverse grazing contexts, and eventually integrated into tools that support both scientific inquiry and on-farm decision-making. Through these first steps, a path has been opened, toward more precise, individualized, and ecologically aligned understandings of grazing behaviour. The next parts will require technological upgrades, interdisciplinary collaboration, long-term investment, and careful translation of behavioural science into practice.

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Appendices

Appendix 1: Hyperparameters of the algorithms tested for phase 1 and 2 – Chapter 3.

Algorithm	Hyperparameters
Classification algorithms	
Decision Tree	Maximum number of splits: 100 Split criterion: Gini's diversity index Surrogate decision splits: Off
KNN	Number of neighbours: 10 Distance metric: Euclidean Distance weight: Equal Standardize data: Yes
SVM	Kernel function: Quadratic Box xonstraint level: 1 Kernel scale mode: Auto Standardize data: Yes
Bagged tree	Ensemble method: bag Learner type: Decision tree Maximum number of split: default Number of learners: 30 Number of predictors to sample: Select all
Regression algorithms	
Bagged tree	Minimum leaf size: 8 Number of learners: 30 Number of predictors to sample: Select all
Medium Neural Network	Number of fully connected layers: 1 First layer size: 25 Activation: ReLU Iteration limit: 1000 Regularization strength (Lambda): 0 Standardize data: Yes

For all models, all features were selected and the PCA was always disabled.

Appendix 2: Details of the results of the 32 compositions of parameters for ML classification – Chapter 3.

Window	Split	Algorithm	Accuracy (Test)	F-score	Recall (ing)	Specificity (ing)	Accuracy (Train)
3sec	Datasplit1	BT	90.75	90.73	91.07	90.45	93.50%
		KNN	89.92	90.2	93.36	86.53	92.80%
		Fine tree	89.42	89.27	88.54	90.29	92.40%
		SVM	89.73	89.8	90.98	88.49	92.20%
	Datasplit2	BT	92.47	91.76	91.92	92.94	92.20%
		KNN	92.6	92.05	93.93	91.49	91.60%
		Fine tree	91.13	90.29	90.52	91.64	91.30%
		SVM	92.84	92.17	92.45	93.16	91.00%
5sec	Datasplit1	BT	90.39	90.36	90.81	89.97	93.70%
		KNN	89.48	89.8	93.34	85.67	92.80%
		Fine tree	88.58	88.74	90.64	86.55	92.30%
		SVM	89.79	89.91	91.63	87.99	92.20%
	Datasplit2	BT	93.43	92.71	92.28	94.39	92.40%
		KNN	92.89	92.33	94.55	91.51	91.50%
		Fine tree	91.24	90.58	93.02	89.77	90.80%
		SVM	93.23	92.55	92.99	93.42	91.20%
10sec (90% overlap)	Datasplit1	BT	95.09	94.97	94.46	95.69	98.80%
		KNN	93.82	93.88	96.29	91.44	97.80%
		Fine tree	94.51	94.42	94.44	94.58	97.60%
		SVM	94.91	94.86	95.57	94.26	97.00%
	Datasplit2	BT	96.42	95.93	94.59	97.89	97.40%
		KNN	95.85	95.35	95.43	96.19	96.40%
		Fine tree	95.06	94.41	93.72	96.14	95.90%
		SVM	96.53	96.09	95.79	97.13	95.60%
30sec (90% overlap)	Datasplit1	BT	97.83	97.61	97.37	98.21	99.70%
		KNN	97.02	96.77	98.39	95.87	99.20%
		Fine tree	95.63	95.22	95.53	95.72	99.40%
		SVM	97.46	97.22	97.93	97.06	99.20%
	Datasplit2	BT	98.07	97.58	95.32	99.96	99.10%
		KNN	98.11	97.66	96.92	98.92	98.30%
		Fine tree	96.47	95.53	92.7	99.05	98.60%
		SVM	98.02	97.51	95.35	99.85	98.30%

Appendix 3: Details of the results of the 40 compositions of parameters for ML regression – Chapter 3.

Window size	Model	RMSE (train)	Video (Grazing time)	Windows (n)	Bites estimated (n)	Bite observed (n)	Error (n bites)	Error	RMSE (test)
3sec	Bagged Tree	0.94	1 (0%)	600	0	0	0	100%	/
			2 (35.7%)	585	690	520	+170	133%	0.89
			3 (52.6%)	600	979	736	+243	133%	1.05
			4 (72.5%)	534	1175	1023	+152	115%	1.06
			5 (94.3%)	574	1758	1783	-25	99%	0.79
	Medium Neural Network	1.06	1 (0%)	600	0	0	0	100%	/
			2 (35.7%)	585	607	520	+87	117%	1.05
			3 (52.6%)	600	953	736	+217	129%	1.22
			4 (72.5%)	534	1023	1023	+209	120%	1.11
			5 (94.3%)	574	1727	1783	-56	97%	0.82
5sec	Bagged Tree	1.28	1 (0%)	360	0	0	0	100%	/
			2 (35.7%)	350	663	519	+144	128%	1.24
			3 (52.6%)	360	946	734	+212	129%	1.5
			4 (72.5%)	315	1111	996	+115	112%	1.79
			5 (94.3%)	340	1727	1750	-23	99%	1.14
	Medium Neural Network	1.53	1 (0%)	360	0	0	0	100%	/
			2 (35.7%)	350	687	519	+168	132%	1.41
			3 (52.6%)	360	927	734	+193	126%	1.64
			4 (72.5%)	315	1112	996	+116	112%	1.83
			5 (94.3%)	340	1705	1750	-45	97%	1.25
10sec		1.47	1 (0%)	180	0	0	0	100%	/

	Bagged Tree		2 (35.7%)	173	655	516	+139	127%	2.25
			3 (52.6%)	180	926	730	+196	127%	2.63
			4 (72.5%)	150	1078	937	+141	115%	2.57
			5 (94.3%)	165	1659	1684	-25	99%	1.72
	Medium Neural Network	1.71	1 (0%)	180	0	0	0	100%	/
			2 (35.7%)	173	625	516	+109	121%	2.58
			3 (52.6%)	180	920	730	+190	126%	2.88
			4 (72.5%)	150	1059	937	+122	113%	2.66
			5 (94.3%)	165	1663	1684	-21	99%	1.91
30sec	Bagged Tree	2.62	1 (0%)	60	0	0	0	100%	/
			2 (35.7%)	54	675	482	+193	140%	9.36
			3 (52.6%)	60	1081	723	+358	150%	10.09
			4 (72.5%)	42	826	712	+114	116%	9.37
			5 (94.3%)	50	1494	1523	-29	98%	5.86
	Medium Neural Network	2.99	1 (0%)	60	0	0	0	100%	/
			2 (35.7%)	54	702	482	+220	146%	9.76
			3 (52.6%)	60	1089	723	+366	151%	10.62
			4 (72.5%)	42	931	712	+219	131%	11.67
			5 (94.3%)	50	1556	1523	+33	102%	6.25

Appendix 4: Features calculated to describe the time-series into each time-window, example for the time-serie Amag. – Chapter 3.

Features	Equation of features

Mean	$\overline{Amag} = \frac{1}{M}\sum_{i=1}^{M} a_{Amagi}$
Standard deviation (std)	$\sigma_{Amag} = \frac{1}{M}\sum_{i=1}^{M}(a_{Amagi} - \overline{A_{Amag}})^2$
Maximum (max)	$Max_{Amag} = Maximum(a_{Amagi})$
Minimum (min)	$Min_{Amag} = Minimum(a_{Amagi})$
Range	$Range_{Amag} = Max_{Amag} - Min_{Amag}$
Median	Median (0.5)
Q1	First quartile (0.25)
Q3	Third quartile (0.75)
InterQuartile (IQ)	$IQ_x = \mathrm{Q}_{3;\mathrm{x}} - \mathrm{Q}_{1;\mathrm{x}}$
Movement Variation (MV)	$MV = \frac{1}{M}(\sum_{i=1}^{M-1}\lvert a_{Amagi+1} - a_{Amagi}\rvert$
Root Mean Square (RMS)	$RMS = \sqrt{\frac{\sum_{i=1}^{M} Amag_i}{M}}$

Appendix 5: Dunn–Sidak Post Hoc pairwise comparisons following Kruskal–Wallis test for bite rate and percentage of area grazed across grass height categorie. – Chapter 4.

Variable	Group 1	Group 2	Difference (Mean Rank)	95% Confidence Interval	Adjusted p-value
Bite Rate	short (<8 cm)	low (8–12 cm)	-41.65	[-62.55 ; -20.76]	< 0.001
	short (<8 cm)	medium (12–16 cm)	-10.50	[-29.47 ; 8.48]	0.61
	short (<8 cm)	high (>16 cm)	-6.98	[-28.89 ; 14.94]	0.95
	low (8–12 cm)	medium (12–16 cm)	31.16	[10.74 ; 51.58]	< 0.001
	low (8–12 cm)	high (>16 cm)	34.68	[11.50 ; 57.85]	< 0.001
	medium (12–16 cm)	high (>16 cm)	3.52	[-17.94 ; 24.98]	1.00
Percentage Grazed	short (<8 cm)	low (8–12 cm)	-50.06	[-70.96 ; -29.16]	< 0.001
	short (<8 cm)	medium (12–16 cm)	-19.80	[-38.77 ; -0.82]	0.036
	short (<8 cm)	high (>16 cm)	-20.36	[-42.27 ; 1.56]	0.084
	low (8–12 cm)	medium (12–16 cm)	30.26	[9.84 ; 50.68]	< 0.001
	low (8–12 cm)	high (>16 cm)	29.70	[6.53 ; 52.88]	0.0045
	medium (12–16 cm)	high (>16 cm)	-0.56	[-22.02 ; 20.90]	1.00

Appendix 6: Models parameters combination tested for the 2 phases of the model. All tested parameters have been tested through a leave-one-animal-out procedure. – Chapter 5.

	Parameter tested		Values or method tested	Best results	Conclusion
Phase 1: Classification model	Model selected		Bagged Tree, Fine Tree, Medium Tree, Quadratic SVM, Medium Neural Network, Medium KNN	Bagged Tree	Combinations of all the hyperparameters giving the best results individually have been tested. The best result was obtained by keeping the original parameters except for the maximum number of split, that was set to 5000.
	Individual hyperparameters for the Bagged tree Ensemble method	Maximum number of splits	Base (Automatically set); 5000; 10 000; 20 000; 40 000	5000	
		Number of learner	Base (30); 50; 75; 100; 200	75	
		Number of predictor to sample	Base (all); 15; 10; 5; 4; 1	4	
Phase 2: Regression model	Model selected		Bagged Tree, Fine Tree, Medium Tree, Quadratic SVM, Medium Neural Network	Bagged Tree	Combinations of all the hyperparameters giving the best results individually have been tested. The best result was obtained by keeping the original parameters except for the maximum number of learners, that was set to 100.
	Individual hyperparameters for the Bagged tree Ensemble method	Minimum leaf size	Base (8); 2; 4; 12; 16	12	
		Number of learners	Base (30); 50; 75; 100; 200	100	
		Number of predictor to sample	Base (20); 1; 4; 5; 10; 15; 18	1	

Appendix 7: Session of GD with observation and wearable sensor data used to evaluate the prediction of the behaviour classification. – Chapter 5.

Day	Animal ID	Start	Stop	Time recorded
1	7057	10h15	18h30	8'15''
1	6885	10h15	18h30	8'15''
1	7040	10h15	14h	3'45''
1	7056	10h15	18h30	8'15''
1	7055	10h15	14h30	4'15''
1	6931	11h00	15h30	4'30''
1	7074	16h30	18h30	2'00''
2	7057	6h30	18h30	12'00''
2	6885	6h30	18h30	12'00''
2	7040	6h30	18h30	12'00''
2	7056	6h30	12h00	5'30''
2	7056	13h30	18h30	5'00''
2	7069	6h30	18h30	12'00''
2	6289	6h30	18h30	12'00''
3	7057	6h30	18h30	12'00''
3	6885	6h30	18h30	12'00''
3	7040	10h00	18h30	8'30''
3	7056	10h00	18h30	8'30''
3	6931	6h30	18h30	12'00''
3	544	6h30	13h00	6'30''
3	7069	6h30	10h00	3'30''
4	7057	6h30	10h15	3'45''
4	7040	6h30	10h15	3'45''
4	6931	6h30	11h00	4'30''
			Total	187'15''

Appendix 8: MATLAB 2024a scripts used to extract the features from the 10-seconds time-window, with Amag as an example time serie. Amagi is the i-th window of the signal. The underlined features are those that were tested, the features in bold are those that were kept in the final model for some of the time-series. – Chapter 5.

Features	MATLAB 2024a scripts
<u>**Mean**</u>	*Mean = mean(*$Amag_i$*) ;*
<u>**Standard deviation (std)**</u>	*std = std(*$Amag_i$*) ;*
<u>**Maximum (max)**</u>	*max = max(*$Amag_i$*) ;*
<u>**Minimum (min)**</u>	*min = min(*$Amag_i$*) ;*

Range	*Range = max – min ;*
SortedData	*sortedData = sort(Amag$_i$);*
Median	*medianValue = median(sortedData);*
Q1	*Q1 = prctile(sortedData, 25);*
Q3	*Q3 = prctile(sortedData, 75);*
InterQuartile (IQ)	*IQ = Q3 – Q1 ;*
Movement Variation (MV)	*a= Amag$_i$(end)- Amag$_i$(1)* *for b=1:a* *MV=(1/a)*(abs(Amag$_i$ (y+1)- Amag$_i$ (b)));* *end*
Root Mean Square (RMS)	*RMS = rms(Amag$_i$) ;*
Fast Fourier Transform (FFT)	*FFT = fft(Amag$_i$);*
Magnitude spectrum (MS)	*MS = abs(FFT);*
Power Spectral Density (PSD)	*PSD = MS .^2;*
Spectal entropy (SpecEnt)	*normalized_MS = MS / sum(MS);* *SpecEnt = -sum(normalized_MS * log2(normalized_MS));*
Second maximum power spectral density (2MaxPSD)	*[~, index] = max(MS);* *N = length(Amag$_i$);* *Fs = N / 10; % number of data / 10 seconds* *frequencies = (0:N-1) * Fs / N;* *[max_power, index_max_power] = max(PSD);*

	PSD(index_max_power) = 0; %Excluding the maximum *[second_max_power,index_second_max_power] =max(PSD);* *2MaxPSD = frequencies(index_second_max_power)*

Appendix 9: Performance of the phase 1 of the model - classification of behaviours - measured based on a leave-one-animal-out method. – Chapter 5.

Animal ID	TP	TN	FP	FN	Accuracy	Precision	Recall	Specificity	F-score	Cohen Kappa
6289	3238	12	4	12	99.5%	99.9%	99.6%	75.0%	99.8%	59.8%
6885	4705	348	119	19	97.3%	97.5%	99.6%	74.5%	98.6%	82.0%
7074	2009	112	7	2	99.6%	99.7%	99.9%	94.1%	99.8%	95.9%
7040	1577	85	21	5	98.5%	98.7%	99.7%	80.2%	99.2%	85.9%
6931	2115	11	5	4	99.6%	99.8%	99.8%	68.8%	99.8%	70.8%
7062	2794	45	10	35	98.4%	99.6%	98.8%	81.8%	99.2%	65.9%
6886	3655	97	14	163	95.5%	99.6%	95.7%	87.4%	97.6%	50.3%
7057	2928	295	176	33	93.9%	94.3%	98.9%	62.6%	96.6%	70.5%
7069	2189	0	0	25	98.9%	100.0%	98.9%	NaN	99.4%	NaN
544	2597	194	49	10	97.9%	98.1%	99.6%	79.8%	98.9%	85.7%
7056	2161	0	0	24	98.9%	100.0%	98.9%	NaN	99.4%	NaN
7055	1573	0	0	1	99.9%	100.0%	99.9%	NaN	100.0%	NaN
Average					98.2%	98.9%	99.1%	78.2%	99.0%	74.1%
STD					1.8%	1.7%	1.2%	9.4%	1.0%	14.5%

Appendix 10: Performance of the phase 2 of the model – quantification of bites - measured based on a leave-one-animal-out method. – Chapter 5.

Animal data		Bite quantification performances (Phase 2)		
ID	% of the dataset	RMSE	Predicition Accuracy	Mean Absolute Error
7040	4.3%	3.44	1.428	42.8%
7069	4.6%	3.72	0.812	18.8%
7055	4.9%	3.31	0.826	17.4%
7074	7.0%	3.50	1.130	13.0%
6931	7.0%	2.68	0.918	8.2%

7056	7.1%	2.70	0.862	13.8%
544	8.7%	3.52	0.834	16.6%
7062	9.1%	3.28	0.840	16.0%
7057	9.7%	3.07	0.981	1.9%
6289	10.4%	2.97	0.848	15.2%
6886	12.3%	3.63	0.834	16.6%
6885	15.0%	2.48	1.032	3.2%
Average		3.19	0.945	15.3%
STD		0.41	0.18	10.3%

Appendix 11: Performances of the 2 phases model to predict the number and frequency of bites during 20 minute sessions (n=36). – Chapter 5.

		Number of bite predicted					Bite per 10-sec windows				
Animal ID	Session	True	Test	Error	Accuracy	Mean Abs. Error	True	Predicted	Mean Abs. Error	RMSE	True
6289	V118	1013	941	-72	0.93	7.1%	11.26	10.46	0.80	2.25	11.26
6289	V182	1277	1220	-57	0.96	4.5%	11.61	11.09	0.52	1.86	11.61
6289	V202	1308	1268	-40	0.97	3.1%	10.99	10.66	0.34	2.14	10.99
6885	V003	699	766	67	1.10	9.6%	7.94	8.70	0.76	2.34	7.94
6885	V082	1040	1104	64	1.06	6.2%	8.81	9.36	0.54	1.97	8.81
6885	V038	1094	1157	63	1.06	5.8%	8.89	9.41	0.51	2.14	8.89
7074	V216	458	567	109	1.24	23.8%	5.26	6.52	1.25	2.49	5.26
7074	V171	980	1121	141	1.14	14.4%	8.75	10.01	1.26	3.63	8.75
7074	V159	1324	1298	-26	0.98	2.0%	11.32	11.09	0.22	2.39	11.32
7040	V095	609	812	203	1.33	33.3%	5.75	7.66	1.92	3.12	5.75
7040	V041	759	831	72	1.09	9.5%	6.49	7.10	0.62	1.72	6.49
7040	V018	871	1192	321	1.37	36.9%	7.32	10.02	2.70	3.67	7.32
6931	V221	1200	1232	32	1.03	2.7%	10.26	10.53	0.27	1.01	10.26
6931	V151	1240	1277	37	1.03	3.0%	10.42	10.73	0.31	2.18	10.42
6931	V133	1321	1317	-4	1.00	0.3%	11.29	11.26	0.03	1.68	11.29
7062	V195	1234	1201	-33	0.97	2.7%	10.37	10.09	0.28	2.09	10.37
7062	V173	1386	1281	-105	0.92	7.6%	12.49	11.54	0.95	2.01	12.49
7062	V218	1404	1340	-64	0.95	4.6%	11.23	10.72	0.51	1.97	11.23
6886	V013	1113	976	-137	0.88	12.3%	9.68	8.49	1.19	2.75	9.68
6886	V107	1143	1131	-12	0.99	1.0%	9.94	9.83	0.10	1.92	9.94
6886	V034	1472	1425	-47	0.97	3.2%	12.37	11.97	0.39	1.22	12.37
7057	V037	877	923	46	1.05	5.2%	8.35	8.79	0.44	2.59	8.35
7057	V068	977	967	-10	0.99	1.0%	8.42	8.34	0.09	3.87	8.42
7057	V091	1101	1223	122	1.11	11.1%	9.18	10.19	1.02	2.06	9.18
7069	V190	1044	942	-102	0.90	9.8%	11.73	10.58	1.15	3.77	11.73
7069	V201	1256	1232	-24	0.98	1.9%	10.55	10.35	0.20	3.13	10.55
7069	V179	1376	1347	-29	0.98	2.1%	11.47	11.23	0.24	2.28	11.47
544	V125	640	617	-23	0.96	3.6%	11.23	10.82	0.40	2.77	11.23
544	V211	1019	1037	18	1.02	1.8%	9.44	9.60	0.17	1.18	9.44

544	V135	1289	1162	-127	0.90	9.9%	12.51	11.28	1.23	2.71	12.51
7056	V075	1103	930	-173	0.84	15.7%	10.71	9.03	1.68	2.84	10.71
7056	V020	1118	1084	-34	0.97	3.0%	9.39	9.11	0.29	2.23	9.39
7056	V031	1498	1337	-161	0.89	10.7%	12.59	11.24	1.35	2.03	12.59
7055	V023	1269	1281	12	1.01	0.9%	10.66	10.76	0.10	2.41	10.66
7055	V024	1468	1404	-64	0.96	4.4%	12.55	12.00	0.55	2.26	12.55
7055	V036	1475	1404	-71	0.95	4.8%	12.61	12.00	0.61	1.61	12.61
Average					1.01	7.8%			0.69	2.34	
Std					0.11	8.4%			0.59	0.69	

Appendix 12: Performances of the step-based method to estimate the number of FS. – Chapter 5.

Threshold defining a FS end		Performance			
Steps	Distance (m)	Accuracy	Recall	F-score	Precision
> 0	> 1	14.9%	27.6%	25.0%	28.9%
> 1	> 1	42.0%	48.7%	57.9%	75.4%
> 1	> 0.75	50.2%	57.5%	66.0%	79.4%
> 1	> 0.5	53.0%	65.4%	68.8%	75.6%
> 1	> 0.4	44.6%	56.2%	60.9%	71.6%

Appendix 13: Performance of the phase 1 model to predict behaviours during grasing down sessions. – Chapter 5.

Day	Animal ID	Start	Stop	Time recorded	% of the dataset	Accuracy	F-score	Recall	Specificity	Precision	Cohens Kappa
1	7057	10h15	18h30	8’15’’	4.5%	87%	86%	95%	82%	78%	74%
1	6885	10h15	18h30	8’15’’	4.5%	94%	94%	96%	91%	92%	87%
1	7040	10h15	14h	3’45’’	2.0%	88%	88%	100%	78%	78%	75%
1	7056	10h15	18h30	8’15’’	4.5%	91%	90%	90%	92%	89%	82%
1	7055	10h15	14h30	4’15’’	2.3%	91%	88%	97%	87%	80%	80%
1	6931	11h00	15h30	4’30’’	2.4%	94%	96%	98%	79%	94%	81%
1	7074	16h30	18h30	2’00’’	1.1%	91%	87%	100%	87%	77%	80%
2	7057	6h30	18h30	12’00’’	6.5%	93%	92%	96%	90%	88%	85%
2	6885	6h30	18h30	12’00’’	6.5%	93%	93%	93%	92%	92%	85%
2	7040	6h30	18h30	12’00’’	6.5%	87%	84%	96%	83%	74%	73%
2	7056	6h30	12h00	5’30’’	3.0%	94%	90%	88%	97%	93%	86%
2	7056	13h30	18h30	5’00’’	2.7%	91%	88%	91%	91%	85%	81%
3	6931	6h30	18h30	12’00’’	6.5%	97%	96%	97%	97%	95%	94%
3	544	6h30	13h00	6’30’’	3.5%	89%	91%	96%	79%	86%	77%
2	7069	6h30	18h30	12’00’’	6.5%	96%	96%	98%	93%	95%	91%
2	6289	6h30	18h30	12’00’’	6.5%	94%	95%	95%	92%	94%	88%
3	7057	6h30	18h30	12’00’’	6.5%	95%	95%	98%	93%	93%	91%
3	6885	6h30	18h30	12’00’’	6.5%	95%	95%	96%	93%	93%	90%
3	7040	10h00	18h30	8’30’’	4.6%	90%	89%	87%	92%	91%	79%
3	7056	10h00	18h30	8’30’’	4.6%	93%	93%	94%	92%	91%	86%
3	7069	6h30	10h00	3’30’’	1.9%	93%	93%	98%	89%	89%	87%
4	7057	6h30	10h15	3’45’’	2.0%	91%	87%	88%	92%	86%	80%
4	7040	6h30	10h15	3’45’’	2.0%	88%	80%	74%	95%	87%	71%
4	6931	6h30	11h00	4’30’’	2.4%	94%	88%	88%	96%	87%	83%
Average						91.9%	90.4%	93.7%	89.7%	87.8%	82.8%

STD	2.8%	4.3%	5.8%	5.6%	6.2%	5.9%
Ponderated average	92.4%	91.4%	94.3%	90.4%	88.9%	84.2%

Appendix 14: Performance of the phase 1 model to predict behaviours during grasing down sessions. – Chapter 5.

Day	Animal ID	Start	Stop	Time recorded	Session Weight (%)	TP	FP	FN	Accuracy	F-score	Recall	Precision	RMSE Duration	RMSE for 100% Accuracy
1	7057	10h15	18h30	8’15’’	4.5%	5	0	0	100%	100%	100%	100%	13	13
1	6885	10h15	18h30	8’15’’	4.5%	5	0	1	83%	91%	83%	100%	28	
1	7040	10h15	14h	3’45’’	2.0%	3	0	0	100%	100%	100%	100%	10	10
1	7056	10h15	18h30	8’15’’	4.5%	7	0	0	100%	100%	100%	100%	6	6
1	7055	10h15	14h30	4’15’’	2.3%	3	0	0	100%	100%	100%	100%	23	23
1	6931	11h00	15h30	4’30’’	2.4%	2	0	0	100%	100%	100%	100%	3	3
1	7074	16h30	18h30	2’00’’	1.1%	2	0	0	100%	100%	100%	100%	6	6
2	7057	6h30	18h30	12’00’’	6.5%	7	1	2	70%	82%	78%	88%	13	
2	6885	6h30	18h30	12’00’’	6.5%	8	1	0	89%	94%	100%	89%	1	
2	7040	6h30	18h30	12’00’’	6.5%	7	1	0	88%	93%	100%	88%	14	
2	7056	6h30	12h00	5’30’’	3.0%	4	0	0	100%	100%	100%	100%	6	6
2	7056	13h30	18h30	5’00’’	2.7%	5	0	1	83%	91%	83%	100%	9	
2	7069	6h30	18h30	12’00’’	6.5%	4	0	0	100%	100%	100%	100%	2	2
2	6289	6h30	18h30	12’00’’	6.5%	4	0	0	100%	100%	100%	100%	5	5
3	7057	6h30	18h30	12’00’’	6.5%	6	0	0	100%	100%	100%	100%	6	6
3	6885	6h30	18h30	12’00’’	6.5%	8	0	1	89%	94%	89%	100%	20	
3	7040	10h00	18h30	8’30’’	4.6%	4	0	0	100%	100%	100%	100%	4	4
3	7056	10h00	18h30	8’30’’	4.6%	5	0	0	100%	100%	100%	100%	7	7
3	6931	6h30	18h30	12’00’’	6.5%	6	0	1	86%	92%	86%	100%	52	
3	544	6h30	13h00	6’30’’	3.5%	3	0	0	100%	100%	100%	100%	17	17
3	7069	6h30	10h00	3’30’’	1.9%	3	0	1	75%	86%	75%	100%	22	

4	7057	6h30	10h15	3’45’’	2.0%	1	0	1	50%	67%	50%	100%	61	
4	7040	6h30	10h15	3’45’’	2.0%	1	0	0	100%	100%	100%	100%	19	19
4	6931	6h30	11h00	4’30’’	2.4%	3	0	0	100%	100%	100%	100%	5	5
Total						106	3	8						
Average									92.2%	95.4%	93.5%	98.5%	14.7	
Standart deviation									12.7%	8.0%	12.3%	4.1%	14.8	
Ponderated average									92.2%	95.6%	94.2%	97.7%	14.1	7.8

Appendix 15: Full table of the LMM employed on significant variables from the GD experiment. 'Day 2 – 13h–16h' was used as the reference group (intercept)

Parameter	Name	Estimate	SE	tStat	DF	pValue
'GT'	Day 2 - 13h - 16h (Intercept)	0.54	0.05	11.12	32	0.000
	Day 1 - 13h - 16h	-0.11	0.07	-1.62	32	0.116
	Day 1 - 16h - 19h	-0.02	0.07	-0.29	32	0.770
	Day 1 - 19h-22h	**0.20**	0.07	2.97	32	**0.006**
	Day 2 - 07h - 10h	-0.12	0.06	-1.81	32	0.079
	Day 2 - 10h - 13h	-0.13	0.08	-1.53	32	0.137
	Day 3 - 07h - 10h	-0.01	0.06	-0.11	32	0.912
	Day 3 - 10h - 13h	0.04	0.07	0.65	32	0.520
	Day 3 - 13h - 16h	-0.01	0.07	-0.07	32	0.945
	Day 3 - 16h - 19h	-0.01	0.07	-0.18	32	0.857
	Day 3 - 19h - 22h	**0.22**	0.07	3.21	32	**0.003**
	Day 4 - 07h - 10h	**-0.26**	0.08	-3.07	32	**0.004**
'TB'	Day 2 - 13h - 16h (Intercept)	5386	497.43	10.83	32	0.000
	Day 1 - 13h - 16h	-1503	703.47	-2.14	32	0.040
	Day 1 - 16h - 19h	-510	759.83	-0.67	32	0.507
	Day 1 - 19h-22h	**2088**	703.47	2.97	32	**0.006**
	Day 2 - 07h - 10h	-1232	667.37	-1.85	32	0.074
	Day 2 - 10h - 13h	-1439	861.57	-1.67	32	0.105
	Day 3 - 07h - 10h	-374	642.18	-0.58	32	0.564
	Day 3 - 10h - 13h	454	703.47	0.64	32	0.524
	Day 3 - 13h - 16h	-281	759.83	-0.37	32	0.714

	Day 3 - 16h - 19h	-301	759.83	-0.40	32	0.694
	Day 3 - 19h - 22h	**2438**	703.47	3.47	32	**0.002**
	Day 4 - 07h - 10h	**-2844**	861.57	-3.30	32	**0.002**
'AG'	Day 2 - 13h - 16h (Intercept)	213.71	21.26	10.05	32	0.000
	Day 1 - 13h - 16h	-31.82	30.07	-1.06	32	0.298
	Day 1 - 16h - 19h	7.88	32.48	0.24	32	0.810
	Day 1 - 19h-22h	**77.40**	30.07	2.57	32	**0.015**
	Day 2 - 07h - 10h	-49.79	28.53	-1.75	32	0.090
	Day 2 - 10h - 13h	-41.28	36.83	-1.12	32	0.271
	Day 3 - 07h - 10h	-19.49	27.45	-0.71	32	0.483
	Day 3 - 10h - 13h	17.20	30.07	0.57	32	0.571
	Day 3 - 13h - 16h	34.83	32.48	1.07	32	0.292
	Day 3 - 16h - 19h	20.78	32.48	0.64	32	0.527
	Day 3 - 19h - 22h	**105.57**	30.07	3.51	32	**0.001**
	Day 4 - 07h - 10h	**-100.19**	36.83	-2.72	32	**0.010**
'TD'	Day 2 - 13h - 16h (Intercept)	441.40	70.81	6.23	32	0.000
	Day 1 - 13h - 16h	34.02	100.14	0.34	32	0.736
	Day 1 - 16h - 19h	52.23	108.16	0.48	32	0.632
	Day 1 - 19h-22h	**311.06**	100.14	3.11	32	**0.004**
	Day 2 - 07h - 10h	-28.94	95.00	-0.30	32	0.763
	Day 2 - 10h - 13h	128.31	122.64	1.05	32	0.303
	Day 3 - 07h - 10h	-32.35	91.41	-0.35	32	0.726
	Day 3 - 10h - 13h	108.64	100.14	1.08	32	0.286

Day 3 - 13h - 16h	141.40	108.16	1.31	32	0.200
Day 3 - 16h - 19h	**262.60**	108.16	2.43	32	**0.021**
Day 3 - 19h - 22h	**379.24**	100.14	3.79	32	**0.001**
Day 4 - 07h - 10h	-69.20	122.64	-0.56	32	0.577