Computers and Electronics in Agriculture 135 (2017) 128–133

Contents lists available at ScienceDirect

Computers and Electronics in Agriculture

journal homepage: www.elsevier.com/locate/compag

Original papers

Urine patch detection using LiDAR technology to improve nitrogen use efficiency in grazed pastures

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ARTICLE INFO

Article history:
Received 23 August 2016
Received in revised form 7 February 2017
Accepted 9 February 2017

Keywords:
LiDAR
Nitrogen use efficiency (NUE)
Pasture
Urine patch
Detection

ABSTRACT

In grazed dairy pastures, the largest N source for both nitrate (NO_3^-) leaching and nitrous oxide (N_2O) emissions is urine-N excreted by the animals. Additional application of N on urine patches as fertilizer may increase these losses. Identification of urine patches could reduce N losses in grazed pastures through more efficient fertilizer application and improved fertilizer N use efficiency (NUE). The aim of this study was to determine if remote sensing using Light Detection and Ranging (LiDAR) technology could accurately identify urine patches in grazed pastures based on height variation of the grass canopy in close proximity. Synthetic cow urine (7 g N L^{-1}) was applied to two blocks (20 m × 20 m) in a well-established pasture in Canterbury, New Zealand, which had no recent exposure to grazing animals or N fertilization. Urine patches were scanned weekly for five weeks. LiDAR based contour maps of the pasture were shown to accurately detect the asymmetric urine patches as well as calculate a percent area of urine based high N as early as one week after a simulated grazing event.

1. Introduction

Nitrogen is essential for plant growth, however, inadequate soil nitrogen (N) is often a key limiting factor in intensively grazed pasture systems (Lambert et al., 2004). Although legumes can provide N in ryegrass-clover predominated systems, deficits in soil N have increasingly been met through increased use of N based fertilizers (Parfitt et al., 2012). Nitrogen application to agricultural soil can occur from fertilizer application as well as animal urination directly to soils during grazing (Di and Cameron, 2002). While both fertilization and urine deposition from grazing animals can lead to increases in nitrate (NO_3^-) levels, urine patches have been identified as a major source of N leaching losses in grazed pasture (Ledgard et al., 1999).

Excess soil N can pollute water resources and contribute to environmental, animal, and human health risks such as methemoglobinemia (Keeney and Follett, 1991; Hudak, 2000; World Health Organization, 2011). Between 60% and 90% of the total N in urine is present as urea (Doak, 1952; Haynes and Williams, 1992; Whitehead, 1995). Once deposited onto the soil, the urea in urine is transformed to NO_3^- through a series of chemical and biological processes (Doak, 1952; Ball et al., 1979; Whitehead and Bristow, 1990; Haynes and Williams, 1992). In intensively grazed pastures, this results in areas of high concentration of plant available N in the soil covering between 20% and 30% of the pasture area annually (Silva et al., 1999; Moir et al., 2011). The N loading rate under a cow urine patch can range between 700 and 1200 kg N ha^{-1} following a single urination event (Haynes and Williams, 1993; Jarvis et al., 1995), depending on the diet and water intake of the cow (Betteridge and Andrews, 1986). This is far more than the 200–400 kg N ha^{-1} required annually by pasture plants under the growth and pasture management conditions in New Zealand (Moir et al., 2007). This surplus of soil N increases the potential for N leaching losses under urine patches. In addition to leaching NO_3^-, losses of N from the urine patch can occur through ammonia volatilisation (Whitehead and Raistrick, 1993) and nitrous oxide (N_2O) (Owens et al., 2016). Additional N-fertilization on such patches may also increase unwanted greenhouse gas emissions.

Despite the environmental risks, high amounts of N fertilizer are often applied to modern intensively grazed pastures to achieve the high yields required for grazing animals and to boost biomass growth in times of unexpected low feed supply (Williams and Haynes, 1990; Dillon et al., 2002). However, applying N fertilizer to a urine patch can exacerbate NO_3^- leaching through the soil (Buckthought et al., 2015) and leads to high NO_3^- concentrations in plants. Strategies to reduce N application to grazed pasture soils

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http://dx.doi.org/10.1016/j.compag.2017.02.006
0168-1699/© 2017 The Authors. Published by Elsevier B.V.

with a high number of urine patches are urgently needed. Decreasing the amount of N applied as fertilizer could help save costs by reducing fertilizer application and minimizing the occurrences of NO_3^- induced bloat in animals, while also alleviating environmental impacts related to agricultural N use. One strategy to reduce to amount of N applied to pasture soils is to reduce the amount of fertilizer applied to soils that already have high N from urine deposition due to continuous grazing. This requires reliable and sufficiently accurate methods for the detection of urine patches, and any other N rich areas on pastures.

LiDAR (Light Detection and Ranging) has increased in popularity within several agricultural industries for mapping various canopies (Rosell et al., 2009; Llorens et al., 2011), controlling sprayers (Chen et al., 2011), measuring spray drift (Miller et al., 2003), and assessing topography (McCoy et al., 2011). This technology works by way of an infrared laser emitting a beam from a rotating mirror. The time it takes the beam to return from its target back to the receiver will then dictate a distance and the frequency of emitted beams, and this will inform the spatial resolution of the data (Walklate et al., 2002). These distance data and the direction of the beams can then be used to construct a data model of the grass canopy. From these point clouds, contour maps can be derived which represent the position and heights of the reflected surfaces. This paper investigates the feasibility of using LiDAR to acquire such spatial data for urine patch identification in grazed pastures as these N rich areas will have a faster rate of regrowth. The main objective of this study was to test if urine patches could be identified using a LiDAR system at varying distances, speeds, and resolutions, as well as to test the accuracy of assessing physical size and spatial area of the high-N locations on a pasture.

2. Materials and methods

The LiDAR system tested for these experiments (SICK LMS-511 PRO-HD Type 20100, SICK, Düsseldorf, Germany) uses a 905 nm, class 1 laser at a scanning frequency of 25–100 Hz. For the current study, 25 Hz was selected to provide the most detailed angular resolution of 0.167°.

2.1. Proof of concept

A small tractor was fitted with the LiDAR mounted 2100 mm above the ground, a real-time kinematic global navigation satellite system (RTK-GNSS) (Model R10, Trimble Navigation Limited, Sunnyvale, California, USA) and ruggedized laptop (Fig. 1). To achieve a high spatial/lateral resolution of LiDAR data the tractor gear ratio was set to deliver a slow, consistent speed of $0.18\ m\ s^{-1}$ ($0.65\ km\ h^{-1}$).

The trial site was a commercial dairy farm (Burnham, New Zealand; 43°34′30.84″S 172°19′15.73″E) where a single, known urine patch was identified and isolated. A 50 mm × 50 mm × 2000 mm pipe was installed directly adjacent to urine patch in order to orient the point cloud and provide scale for the area of interest during post-processing (Fig. 2). For initial validation, the detectable distance was deemed the most important variable to assess any potential limitations of the LiDAR for future phases. Therefore, ten measurements were taken from 0.5 m to 10.0 m from the nearest edge of the urine patch; these distances where chosen based the typical fertilizer swath of 20 m.

2.2. Full scale detection validation

To validate that this method could accurately detect urine patches in realistic situations, a site was chosen that was well maintained and not recently exposed to animals (Lincoln, New Zealand; 43°38′06.02″S 172°27′10.55″E). This pasture consisted of two year old drilled rye-grass with level terrain. Experimental design consisted of two 20 m × 20 m blocks, each block treated as a separate experimental run. In each block, 30 plots ('patches') were randomly staked for simulated urination. So that urine patch size would vary, half of the plots were randomly selected to receive either 1 L or 2.5 L of synthetic urine; these volumes were chosen to be within the acceptable volume of actual urination events of 1.6 L and 2.2 L from dairy cattle (Haynes and Williams, 1993). The synthetic urine was made using a modified recipe from Clough et al. (1998) for a urine concentration of $7\ g\ N\ L^{-1}$ using water as well as $16.31\ g\ KHCO_3\ L^{-1}$, $2.08\ g\ KBr\ L^{-1}$, $2.94\ g\ KCl\ L^{-1}$ $1.61\ g\ K_2SO_4\ L^{-1}$, $3.39\ g\ L^{-1}$ glycine, and $13.6\ g\ L^{-1}$ urea.

Tractor setup remained as previously described Section 2.1. Driving speed was added as a treatment and included $0.18\ m\ s^{-1}$ ($0.65\ km\ h^{-1}$), $1.14\ m\ s^{-1}$ ($4.1\ km\ h^{-1}$), and $1.7\ m\ s^{-1}$ ($6.1\ km\ h^{-1}$). At scanning events, each block was scanned independently with a single pass in the center of the blocks. To correlate LiDAR derived percent area data, an aerial photograph was taken using a remotely piloted aircraft system (RPAS/UAV). These measures were taken

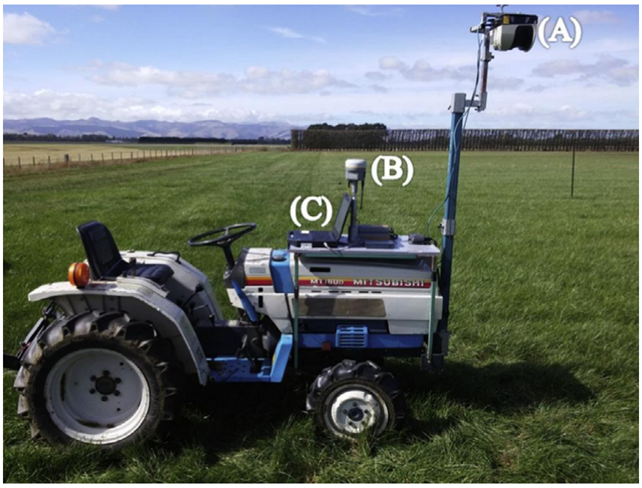

Fig. 1. Tractor showing attachment of the LiDAR unit (A), RTK-GPS (B), and ruggedized laptop (C).

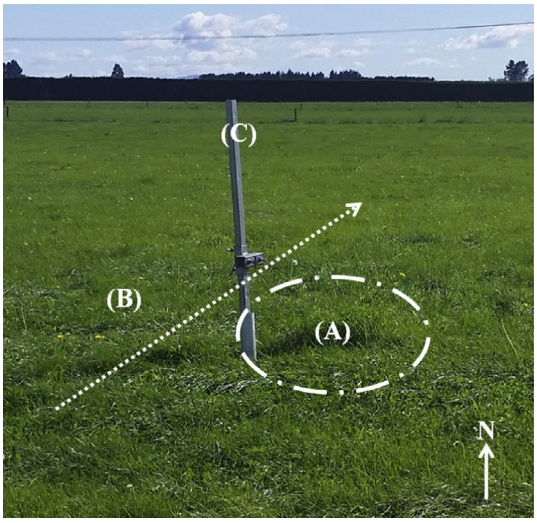

Fig. 2. Site chosen for validation work with a clear urine patch (A) as well as driving direction (B) and a pipe/indicator (C) which was used in the post processing of data.

weekly for five weeks with a simulated grazing at two weeks; grazing was accomplished by mowing the experimental area to a height of ca. 50 mm and all clippings were removed off site.

2.3. Analysis

For the proof of concept and full scale validation, LiDAR distance data were converted to three dimensional data spaces and visualized as point clouds using Matlab (version 7.2). To minimize the LiDAR data processing load/time, every second scan line (perpendicular to the travelling direction) was used. In order to accurately identify the urine patches within the point cloud, it is essential to assign a ground plane within the contour map. To do so in 3D-data space, an algorithm, based on the random sample consensus (RANSAC) method, was used to identify the ground plane (Fischler and Bolles, 1981). From here, a height threshold is set to indicate areas of pasture above the ground plane which corresponds to the increased height/biomass of a given urine patch; this parameter of thresholding was set 25 mm. From this, the contour maps were created and areas of identified urine-patch clumps calculated. Proportional sizes (%) of clump areas were image derived using the RPAS/UAV photograph and constructing polygons over individual, visual patches using ImageJ (Version 1.50; Schneider et al., 2012; National Institutes of Health). The areas derived with the LiDAR-method and the manual delineated areas (RPAS/UAV) were then correlated using Sigmaplot (version 13.0). For the purpose of these studies, GNSS data were collected for speed only and not part of the identification of urine patches.

3. Results

The proof of concept trial showed that it was possible to identify a single urine patch within a point cloud using the height map derived from the LiDAR measurements (Fig. 3) up to 10 m from the LiDAR. Therefore, the study was expanded for a full scale validation.

As expected, the artificial urine created areas of better vigour, biomass, and color[1] (Fig. 4) which provided an ideal site to test the capabilities of the LiDAR unit. The LiDAR was able to detect urine patches based upon the differentiation of grass height as early as one week after simulated grazing (Fig. 5). There was a strong correlation between physically measured and LiDAR scan estimated urine patch areas taken one week after simulated grazing with r-square values of 0.80 and 0.96 for blocks 2 and 1, respectively (Fig. 6). The LiDAR calculated areas in block 2 were biased towards smaller plots which is directly related to height and the set threshold that is indicative of a urine patch (i.e. anything over the threshold is assumed to be a urine patch, or an area of increased pasture growth). Physical height measures confirmed that plots on the right side of the second block had a mean height of 195 ± 25 mm whereas all other plot areas had a mean height of 216 ± 21 mm. The control height, where no urine was applied, was 140 ± 18 mm. Manual measurements of urine patch area were taken around the perimeter, encompassing the entire urine patch as indicated by difference in color compared to areas void of urine (i.e. light versus dark green). As can be seen from the contour map (Fig. 5) the overall shape of the patch is that of a bell curve which will inevitably cause some percentage of the patch to be below the set ground plane threshold. Therefore it is expected that the computed areas will slightly underestimate the actual area. As the study continued, the correlation for block 2 increased by the final scan ($r^2 = 0.94$) which is a result of the extra growth above the ground plane threshold.

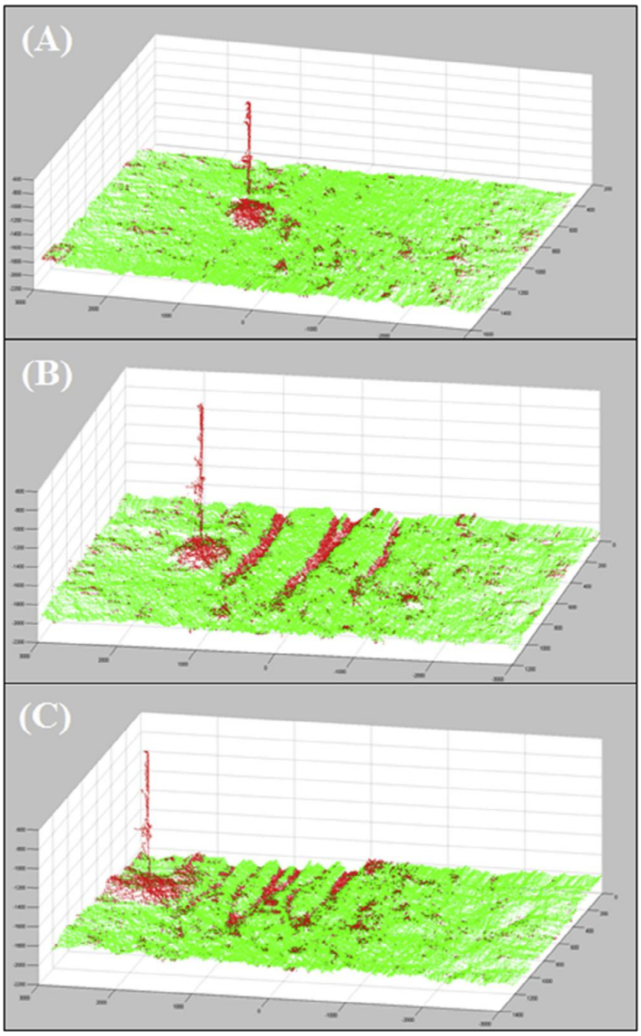

Fig. 3. LiDAR produced data-space (point cloud) illustrating ability to detect areas of high (and low) grass at distances of 1, 1.5 and 2.5 m (images: A, B and C, respectively); x-axis is distance where 0 mm is LiDAR center; y-axis represents the sequential scans from the LiDAR; z-axis is the measured height (mm) of the grass canopy. Detection of up to 10 m not illustrated due to quality degradation in the point cloud.

Speed of travel had a large impact on reliable data collection with 0.18 m s^{-1} (0.65 km h^{-1}) capturing the most reliable data set. However, the method of data processing using every other scan line suggests that a speed of 1.3 km h^{-1} (0.36 m s^{-1}) could be used for data capture provided excessive vibration of the LiDAR unit was controlled. Increasing speed of travel to 1.14 m s^{-1} (4.1 km h^{-1}) and 1.7 m s^{-1} (6.1 km h^{-1}) increased vibration and introduced noise making LiDAR data unreliable. Modifications to the LiDAR mounting system to reduce vibration will be needed to enable this system to be utilised at faster speeds.

4. Discussion

One strategy to reduce N application to grazed pasture includes the reduction of fertilizer applied to soils that already have high N from urine deposition from continuous grazing. To achieve this, reliable and accurate methods for the detection of urine patches and other N rich areas on pastures are required. Further, spatial information on the distribution of urine patches is important for modelling and managing the N in the grazed pasture systems (Draganova et al., 2016; Moir et al., 2010). It is believed that the

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[1] For interpretation of color in Fig. 4, the reader is referred to the web version of this article.

Fig. 4. Aerial photograph of the second block of the validation experiment illustrates the plot layout with 15 small volume (S 1–15) and 15 large volume (B 1–15) simulated urine patches (subplots).

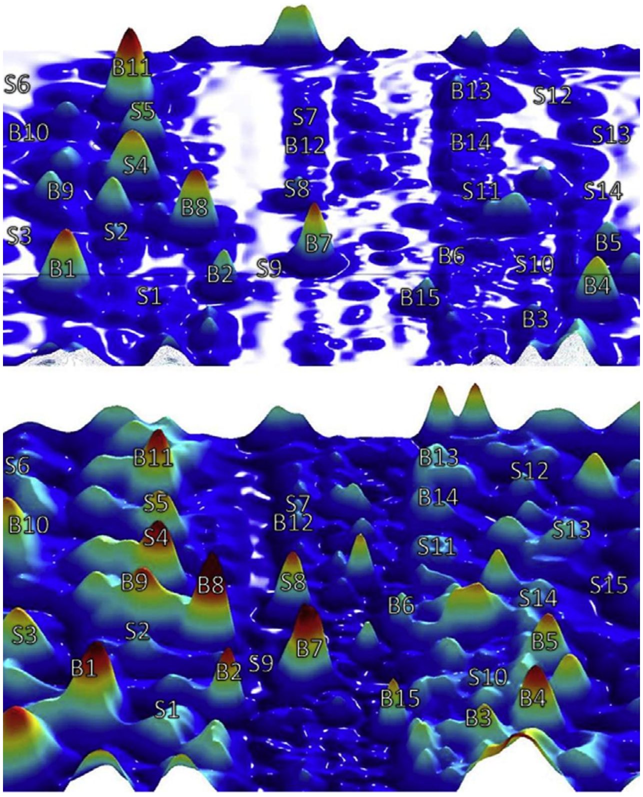

Fig. 5. Contour maps of the second block for one and three weeks after simulated grazing (top and bottom, respectively) which can be compared with the layout of the urine patches in Fig. 4.

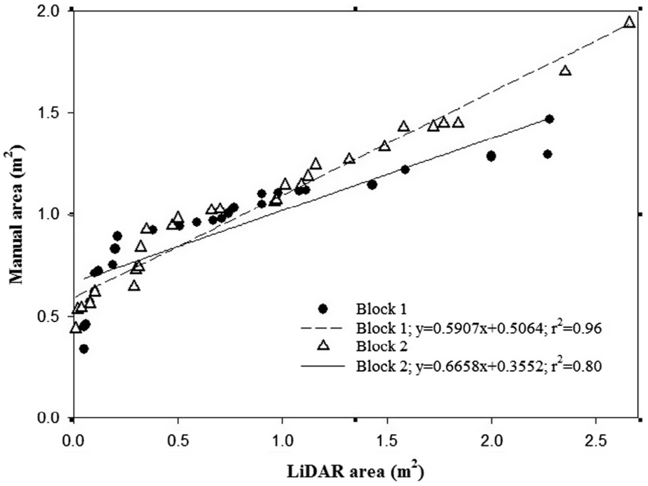

Fig. 6. Correlation of image based and LiDAR derived area measurements of all 30 urine patches one week after simulated grazing.

accurate detection of urine patches can be integrated into technologies that aim for precise delivery of the N fertilizers. Unfortunately, literature regarding the detection of urine patches using sensors and other technologies such as LiDAR is scarcely available and, to date, the current study is the first use of LiDAR to identify and measure areas affect by N rich urine patches on farm in mixed pastures.

Previous research on urine patch detection and the reduction of N fertilizer on N rich areas has involved the application of liquid fertilizer to avoid visible urine patches (Mackenzie et al., 2011). Two key limitations of this approach are the field of view of the sensor and the resolution to which the current spreading technology can apply liquid N or liquid N inhibitors. For example, the Smart-N system, which uses the optical sensing device of a WeedSeeker®, has a small field of view of ca. 300–380 mm. The scanners use VIS/NIR (visual near infrared) to identify grass areas high in N by differentiating greener pasture area. The number of urine patches detected is closely related to the sensitivity of the sensors and this number is highly variable between two different sensitivities. Hence, this system requires precise calibration, and calibration is decided objectively by the operator for the sensing event (Mackenzie et al., 2011).

Other active optical sensors that are on the market include the Yara N-Sensor™ ALS (tec5, Oberursel, Germany) and the Crop Circle™ (Holland Scientific Inc., Lincoln, Nebraska, USA) which also work using VIS-NIR. They are capable of estimating selected vegetative indices "on-the-go" such as water index, simple ratio, and NDVI, based on canopy reflection. Past studies have shown that sensors that can measure in wavelengths between 730 and 970 nm can be used to estimate such indices which, in turn, can be used to predict crop health, dry matter content, N content and above ground N-uptake (Erdle et al., 2011). Application of N fertilizer is directed accordingly with these estimations, mostly in arable crops. However, these existing optical canopy sensing systems are primarily designed for mono-cropped agriculture where variability would not be as large as would be seen in a mixed species pasture. For example, the Yara N-sensor uses a dual sensor approach whereby the scanners are sensing from both sides of the tractor, scanning upwards of 40% of the treated area. This strategy is suitable for most monocrop systems that do not require the pin-point accuracy as would be the case for urine patch application. It is important to note however, that a direct correlation between these sensors' estimated outputs and quantitative crop parameters have not been shown in grazed mixed pastures. More research is required to investigate whether the above noted vegetative indices correctly reflect the status of grazed pastures. The only current method available for accurately verifying the status of grazed pastures is destructive assessment (Erdle et al., 2011).

One of the key advantages of using LiDAR for urine patch detection is the wide angle of view. The system chosen for the present study was selected due to its 190° angle of view and the ability to scan up to 40 m either side of the LiDAR. However, a target that is far away will have less spatial resolution due to the limiting angular resolution (Beland et al., 2015). In the present study, the 20 m swath width appeared to be approaching the outer limits of the practical resolution for detection. However, greater distances are practical depending on the given LiDAR system, size of the target(s), and mounting height of the LiDAR. Regardless, the system presented here would be suitable for the working widths of typical sprayers used for applying liquid fertilizer. Fertilizer spreaders in New Zealand that are mounted on tractors or trucks often have working widths that are too wide to be suitable for the demonstrated approach as they are not able to differentiate the fertilizer onto the size of areas between urine patches. Pneumatic spreaders do have the capacity to variably apply granular fertilizer as they are equipped with several large separated outlets (Crozier and Roberson, 2014); these could potentially be used for precision application depending on the applied resolution of the spreader itself. Further research into the use of LiDAR and other sensor technologies combined with precise granular fertilizer application is needed.

5. Conclusions

A study was performed to determine the ability and practicality of using a LiDAR system to detect urine patches created during grazing on an intensively managed pasture by identifying differences of sward height. LiDAR based contour maps of the pasture were shown to accurately detect the asymmetric urine patches as well as calculate a percent area of urine-based, high N as early as one week after a simulated grazing event, which fits within the typical fertilization scheme. The LiDAR system in the present study performed well at the lowest speed of 0.65 km h^{-1} and could potentially work at 1.3 km h^{-1} with an optimal scanning swath width of no more than 20 m. Though this speed is not practical for commercial farming operations, results indicate promise for further investigation. Other uses for LiDAR data acquisition include LiDAR units on center pivot irrigators to acquire data to create prescription maps as well as potentially gain knowledge of the available biomass of individual pastures. Lastly, the literature accounts for >20% pasture affected by urine deposition over a grazing year. An active LiDAR urine detection system combined with accurate variable rate granular fertilizer application could reduce N application, minimize environmental effects of N leaching and improve economic gains for farmers.

Acknowledgements

This work was funded through a grant from The New Zealand Ministry of Business Innovation and Employment under the research grant, *Optimum N – Nitrogen Sensing and Management*, (contract No.: CONT-29854-BITR_LVL). The authors would also like to recognise the support from Lincoln University staff Stephen Moore for his assistance gathering materials, Plant and Food Research (Lincoln) for their contribution of a field site, and AgResearch (Lincoln) for their contribution of the simulated grazing. Lastly, thank you to Paul Riding (Lincoln Agritech) for the RPAS/UAV flights.

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