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Original Research

Unmanned Aerial Vehicle–Based Remote Sensing of Cattle Dung: Detection, Classification, and Spatial Analysis of Distribution☆

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ABSTRACT

Documenting the distribution of cattle dung across grazed pastures is an important part of understanding nutrient cycling processes in grasslands. However, investigation of distributions at adequate spatial scales and over extended time periods is hindered by the lack of a time- and cost-efficient method for documenting and monitoring dung pat locations. To address this research challenge, an unmanned aerial vehicle and multispectral sensor were used to identify and classify dung pats. Imagery was collected on 12 flights over a subirrigated meadow in the Nebraska Sandhills, in which two different grazing strategies were being evaluated: an ultrahigh stocking density and a low stocking density. The images were classified using supervised classification with a support vector machine algorithm, and post-classification accuracy was assessed using a confusion matrix. In addition, Ripley's K was used to identify high-density dung areas at varying densities and spatial extents. The classification had an overall accuracy of 82.6% and a Kappa coefficient of 0.71. The user's accuracy of dung classification was higher (0.91) than the producer's (0.73). The majority of classification errors were related to the misclassification of dung as vegetation, often in spectrally complex areas where shadowing affected the ability of the classifier to correctly identify dung. Classification accuracy declined precipitously after dung reached 10-14 d of age, both because of the change in spectral reflectance due to drying and because of the regrowth of vegetation. The density-based cluster analysis found no clustering in the low stocking density treatment; dung in the ultra-high stocking density treatment was most frequently found to be clustered near water sources, in corners, and near supplement feeders. This approach to dung identification, mapping, and spatial cluster analysis is a promising alternative to existing methods and deserves further exploration at additional spatial scales and in diverse ecological settings using current technologies.

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Introduction

Remote sensing has a long history of providing insightful data in the fields of agriculture, range management, and natural resource management. It has been instrumental in the development of precision agriculture (Mulla 2013; Raptis et al. 2023); has aided novel methods of detecting biodiversity (Wang et al. 2016; Wang et al. 2018) and has been used for monitoring vegetation changes in rangelands (Boswell et al. 2017; Eddy et al. 2017; Boucher et al. 2023). Most imagery has historically been obtained by either satellite or manned aircraft, but more recently, unmanned aerial vehicles (UAVs), or drones have also been used for the collection of remotely sensed data and imagery. UAVs offer the advantages of high spatial resolution imagery (e.g., centimeters instead of meters), greater flexibility in timing of obtaining imagery, and cost savings (compared with owning or chartering a plane or helicopter). Previous applications of UAV technology in agronomy and natural resource management include high-throughput phenotyping projects (Haghighattalab et al. 2016), monitoring senescence in crops (Potgieter et al. 2017; Hassan et al. 2018), and mapping

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and monitoring invasive plants (Martin et al. 2018; Bergamo et al. 2023).

However, UAVs have not, to our knowledge, been used to detect and map a more neglected component of agricultural data: the distribution of cattle dung in pastures or on rangelands. Previous methods used to assess distribution and density of dung in a pasture include manual mapping of dung across a pasture (Auerswald et al. 2010); transect establishment (Nuñez et al. 2019); use of the line intercept method (Oliver and Young 2012); quadrat placement either randomly or along transects (Yoshitake et al. 2014; Oñatibia and Aguiar 2018); or simply walking and marking pats and returning at a later date to observe changes (Dubeux et al. 2014). Other researchers used “artificial” dung pats created from the bulked manure of confined cattle and then placed them in a pasture area separate from cattle for observation and analysis (Aarons et al. 2009; Evans et al. 2019).

All of these methods are temporally and spatially limited in their scope and give only a small glimpse into the dynamics of dung distribution and the way it influences and is influenced by vegetation communities, grazing dynamics, and management strategies. On a typical ranch or grazing allotment that may encompass hundreds or thousands of hectares, it is not logistically possible to map and monitor dung at scales that are relevant or meaningful for these operations. As such, remote-sensing technology, particularly UAV-sourced imagery, holds the potential to revolutionize our ability to map and monitor dung distribution at much higher spatial and temporal resolutions than have previously been possible. With centimeter-scale resolution, a high temporal frequency of repeat image capture, and the expanded analytical possibilities that multispectral sensor data and geographic information system (GIS) integration offer, UAV imagery presents an opportunity to gain new insight and open additional analysis options in important areas of research that have thus far been fairly elusive and understudied.

In extensively managed grazing lands, where little to no inorganic fertilizer is applied to pastures, the dung and urine from livestock constitute the majority of nutrient inputs back into the system (Bardgett and Wardle 2003; Rumpel et al., 2015; Bastani et al. 2023). The redistribution of nutrients from where they were consumed (via grazing) to where they were deposited (in dung) can have landscape-scale effects on everything from the soil microbial community (Eldridge et al. 2020), to water quality (Muirhead 2023), to the phytochemistry of the plant communities in the pasture (Hunter 2016). Thus, understanding the drivers of dung distribution patterns, as well as their long-term effects, is crucial for making grazing management decisions and managing nutrient cycling on rangelands. For instance, studies have shown that cattle congregation sites with high dung densities have lasting impacts on soils and vegetation (Gillet et al. 2010; Porensky et al. 2016). As such, knowledge of the spatial distribution patterns of dung in different grazing systems can be an important component of understanding grazing behavior (Dubeux et al. 2014), carbon sequestration in pastures (Piñeiro et al. 2010; Rumpel et al., 2015), and pasture ecology (Yoshitake et al. 2014). Previous research addressing these drivers has demonstrated the site-specific nature of dung distribution patterns, which may be influenced by climate, season, and/or weather (Dubeux et al. 2014); topography (Ren et al. 2018); stocking strategy or density (Oñatibia and Aguiar 2018) or management decisions, including placement of water and minerals, the location of shade, or the size and shape of a pasture (Augustine et al. 2013; Oñatibia and Aguiar 2018).

Despite abundant knowledge about the effects of dung on soils and vegetation and the keystone role dung plays in the nutrient cycles of rangelands, there has been relatively scant research devoted to studying the spatially relevant and spatially dependent cascading effects of dung within the grazed pasture ecosystem, especially over extended periods of time. This research project utilized a UAV-mounted multispectral sensor to capture high-resolution images of a Nebraska Sandhills meadow, which contained pastures being managed using two different grazing strategies: one with an ultrahigh stocking density and one with a much lower stocking density. The imagery obtained over each treatment was then classified, and dung distribution was mapped and analyzed using spatial statistics methods. The objectives of this study were to 1) detect and classify cattle dung using UAV-based remote sensing and 2) evaluate dung distribution under different grazing strategies (ultrahigh and low stocking densities) on a subirrigated meadow in the Nebraska Sandhills.

Methods

Site description

The research site was located at the University of Nebraska’s Barta Brothers Ranch, approximately 40 km southwest of Bassett, NE (lat 42°13′13″N, long 99°38′27″W), in the Nebraska Sandhills ecoregion (Fig. 1A). The pastures that were part of this research were used in a long-term grazing study (2010–2017) that investigated the effects of different grazing strategies on animal performance, vegetation characteristics, and dung beetle communities (Wagner et al. 2021; Andrade et al. 2022) and were located on a subirrigated meadow site with a seasonally high water table. Vegetation communities are dominated by cool-season grasses, with a lesser occurrence of warm-season grasses and forbs. Soils at this site are sandy to fine sandy loam in texture and classified as mixed, mesic Aquic Ustipsamments. Average summer temperatures range from 21°C to 25°C, and average yearly precipitation (past 20 yr) at the site is 665 mm, with approximately 40% of the yearly total falling during the summer months of June–August (High Plains Regional Climate Center 2023).

Grazing treatments

The grazing site was divided into two different treatments, with two replications each, arranged in a randomized complete block design (Fig. 1B). The two grazing treatments included an ultrahigh stocking density rotation (214 138 kg live weight ha^{-1}, n= 36 steers) in which cattle were moved twice per day across 120 paddocks (0.058 ha each) over the 60-d grazing season (hereafter this treatment is referred to as “MOB”); and a four-pasture rotation (4PR) in which cattle grazed each 0.435 ha pasture for 15 days once during the season (7 138 kg live weight ha^{-1}; n=9 steers; hereafter referred to as “4PR”). Stocking rates were held constant across the treatments (7.4 AUM ha^{-1}). Table 1 summarizes the grazing treatment information for this study.

Table 1
Grazing information for Nebraska Sandhills meadow study from 2010 to 2017. Stocking density and stocking rate varied slightly each year because of differences in yearling cattle weight. Grazing treatments included the ultra-high stocking density (MOB) and the low stocking density (4PR).

Grazing Information	MOB	4PR
No. of paddocks	120	4
Hectare per paddock	0.058	0.435
Grazing cycles	1	1
Grazing duration (d)	60	60
Stocking density (kg live weight ha^{-1})	214,138	7,138
No. of animals	36	9
Grazing period length (d)/paddock	0.5	15

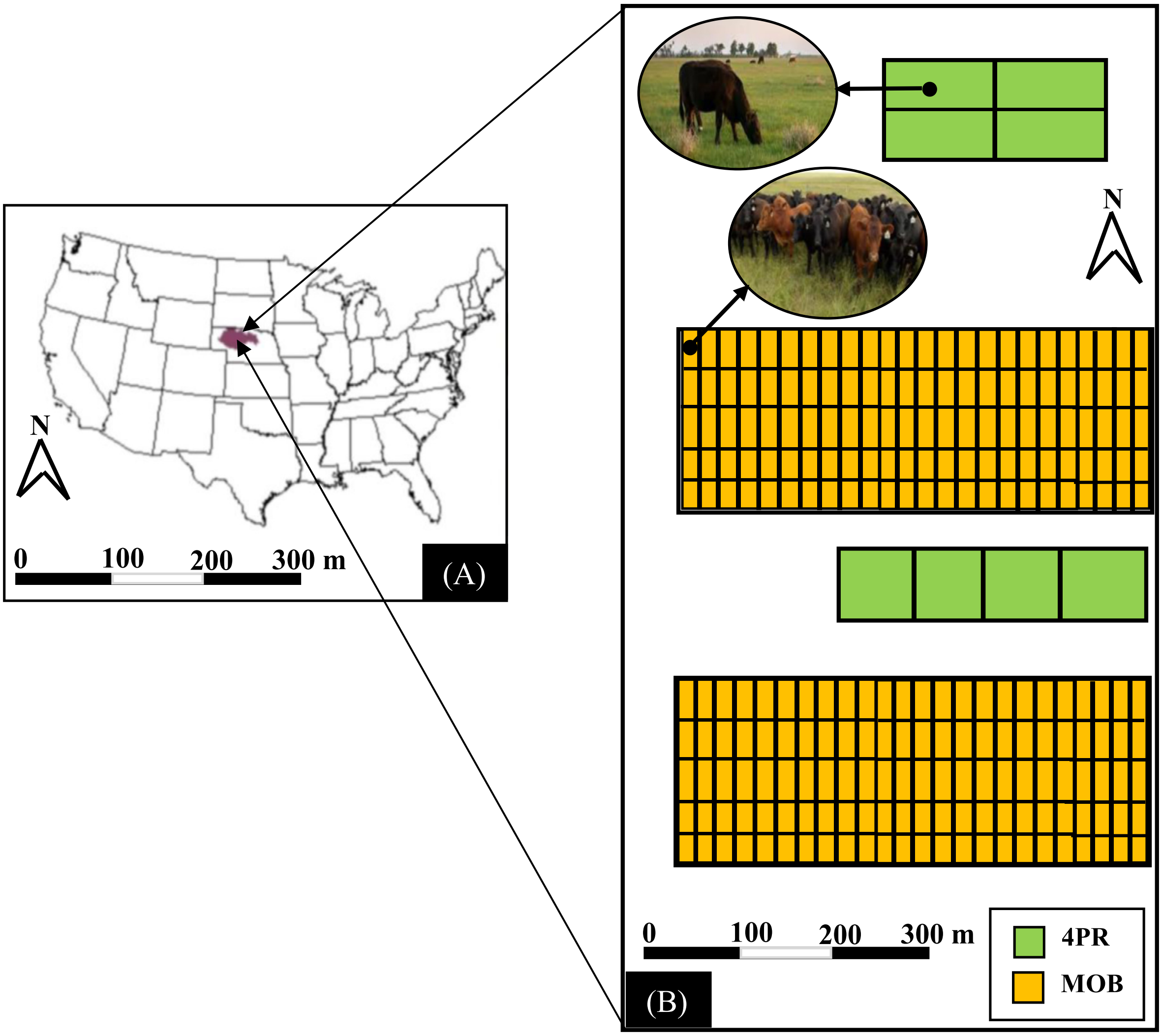

Figure 1. The Nebraska Sandhills meadow study area (**A**) and the experimental layout (**B**) where the grazing took place. Only grazing treatments that were part of this study are outlined. Grazing treatments included the ultrahigh stocking density (MOB) and the low stocking density (four-pasture rotation [4PR]).

Table 2
Summary of unmanned aerial vehicle flight dates in 2017, dung ages, and ground truth data points used in the image classification accuracy assessments. Grazing treatments included the ultrahigh stocking density (MOB) and the low stocking density (four-pasture rotation [4PR]), with two replications each.

Date	Pasture	Replicate	Age of dung being classified (d)	No. of ground truth points
30 June	MOB	1	1–15	49
7 July	MOB	2	7	25
7 July	MOB	2	1–4	13
10 July	4PR	1	3–14	39
10 July	MOB	1	1–2	21
10 July	4PR	2	1–14	40
21 July	MOB	1	1–7	24
21 July	MOB	2	1–12	25
6 August	MOB	1	1–7	57
6 August	MOB	2	1–10	37
8 August	4PR	1 and 2	1–15	52

Imagery acquisition and postflight data processing

Aerial imagery for this study was taken from the two grazing treatments, with 12 flights (Table 2) over six dates being executed in June, July, and August of 2017 (eight flights from MOB and four flights from 4PR [Fig. 2A]). Compared with the MOB imagery, 4PR imagery was more challenging to obtain and perform ground truth validation because of the continued presence of the steers in the paddock after UAV imagery acquisition. This complicated effort to take Global Positioning System (GPS) ground truth data and perform validation, whereas steers were still walking around the pen, grazing, dunging, stepping on dung piles, etc. Flights paired with ground truth data were used only after the steers left the paddock. Figure 2B summarizes the workflow for the entire process, from imagery acquisition to final spatial analysis.

To fly the research site and collect both Red Green Blue (RGB) (i.e., true color) and multispectral images, a Sequoia multispectral sensor (Parrot SA, Paris, France) was used with the UAV platform (senseFly eBee SQ, Lausanne, Switzerland). The Sequoia multispectral sensor contains a 16-megapixel RGB camera as well as four individual bands that record reflectance in the green, red, red edge, and near-infrared wavelengths. Band centers are located at 550 nm, 660 nm, 735 nm, and 790 nm, with ranges of 530–570 nm, 640–680 nm, 730–740 nm, and 770–810 nm, respectively. The sensor is integrated with an irradiance sensor which, when combined with calibration target readings taken before a flight, uses at-sensor radiance to calculate absolute surface reflectance across dates and flying conditions. This sensor also houses the GPS unit, the inertial measurement unit, and magnetometer. Radiometric calibration was performed before each flight using an Airinov

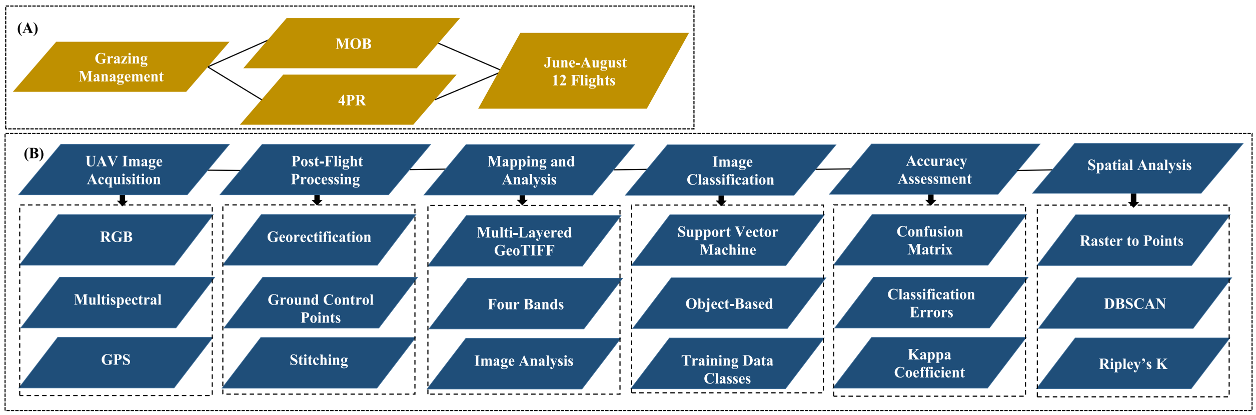

Figure 2. **A,** Grazing management treatments. **B,** The methodological flowchart to detect and classify dung. Grazing treatments included ultrahigh stocking density (MOB) and low stocking density (four-pasture rotation [4PR]).

calibration panel supplied as part of the Sequoia system. senseFly eMotion flight control software was used for flight planning, execution, and in-flight operations, as well as for initial processing of the flight and geotagging of images.

Flights took place within 2–3 h of local solar noon, except when wind or weather conditions necessitated data collection either slightly before or after this ideal time period. Flight altitudes were consistently around 70 m above ground level and stayed constant regardless of topographical variation, which resulted in a ground sampling distance (GSD) of between 6 and 7 cm for all flights and images. Flight line overlap was maintained at 75% for each flight. Normal flight times for a single flight that covered one entire MOB pasture (6.96 ha) and one 4PR pasture (1.74 ha) ranged from 35 to 50 min, depending on wind speed and direction, as well as flight patterns. Ground control points were selected by identifying fixed, readily identifiable features (e.g., wood corner posts, corners of exclosure cages, water tanks) on the landscape and recording their GPS locations using a Trimble Geo 7X unit (Trimble, Inc, Sunnyvale, CA, USA). These points were then used in Pix4D (Pix4D SA, Lausanne, Switzerland) to increase horizontal accuracies during image processing (to achieve final accuracies of 15–40 cm).

Postflight processing (georectification and addition of ground control points, image stitching/mosaicking, and reflectance calculations) occurred in Pix4D. The resulting individual reflectance files were then exported to ArcMap (ESRI, Redlands, CA, USA) and stacked together into a multilayered GeoTIFF that contained all four bands, plus an "artificial" blue reflectance band calculated using reflectance values from the visible green band and the near-infrared (NIR) band. This file was then used as the base for all further image analysis.

Image classification

Supervised classification of the 5-band image was performed in ArcPro 2.4.0 (ESRI) using the image classifier tool with a support vector machine learning algorithm. Object-based classification was chosen over pixel-based to include information relating to size, shape, texture, and location of features (especially dung) in the training data (Hay and Castilla 2008; Pande-Chhetri et al. 2017). Continuing advances in the science of geographic object-based imagery analysis (GEOBIA) have helped to make this method a preferred option for image classification work (Maxwell et al. 2018), and it was particularly applicable to this analysis, which required classification at vastly different spatial scales and the separation of small objects from a background of varying spectral characteristics that were sometimes nearly identical to the object itself (Blaschke et al. 2014). In each image set, training samples were selected across the image to represent the eight thematic classes shown in Table 3. Between 200 and 300 dung training samples were selected to use in the model training process for each image file. In terms of absolute number, polygons of classes other than dung made up a fraction of the dung samples (approximately 5–25 polygons of each class). In terms of total number of pixels, however, they greatly outnumbered the pixels contained collectively in all dung training samples (dung pixels usually represented less than 1% of the total number of pixels selected for training). Figure 3 is representative of a typical image with multiple training data classes highlighted.

Accuracy assessment

Accuracy assessment of the classified images was performed manually due to the slight discrepancies in geolocation between ground truth data and image data, even after postflight corrections using ground control points. These discrepancies fell within the normal range of accuracies expected for the UAV imagery and the GPS unit data points and were consistently within 0–40 cm of each other. When verifying the accuracy of classification, pixels (and groups of pixels) were deemed correctly labeled when they fell within seven pixel lengths (42–49 cm, depending on GSD) of the GPS ground truth point that referred to them. This allowed for some leeway in accommodating the limits of the precision of the equipment that was used to collect the data without overextending the accommodation to pixels that were too far from the GPS point. Ground truth data for vegetation were not collected in the field with the GPS unit, so an alternate method of assessing classification accuracy was used. Accuracy assessment points (2 000 per image set) were randomly generated in ArcPro across the classified raster. Points in all four of the vegetation categories were available for use, and of those available, approximately 25 points in each pasture, per image date, were used as substitute ground truth data. Pixels were considered correctly classified if they were labeled as any one of the four vegetation categories.

The primary way to measure the success of an imagery classification project is through the creation of a confusion matrix, or an accuracy assessment in table form (Jensen 2005; Krenz et al. 2019). This matrix not only shows the overall accuracy of classification but also breaks down the results into individual categories so that classification errors can be assessed between and within classes, giving more insight into which class categories are the most problematic. In addition, scores are calculated for the producer's accuracy and the user's accuracy, which measure errors of omission and commission, respectively. The Kappa coefficient of agreement

Table 3
Description of classes used for classifier training in this study.

Class	Description
Dung	Identifiable dung pats from a range of ages (1–10 d old)
Soil	Bare soil patches within pastures and along farm roads; gopher mounds
Wet Soil	Saturated soil found near watering points
Water	Watering troughs
Lush vegetation	Ungrazed vegetation with a relatively homogeneous spectral signature
Trampled vegetation	Vegetation that was trampled or showed trampling lines was not grazed
Grazed vegetation	Heavily grazed areas with little vegetation left
Fencelines	Vegetation beneath fencelines that was not heavily grazed or trampled
Cows	Cows are visible in the final image
Cages	Exclosure cages used for vegetation sampling

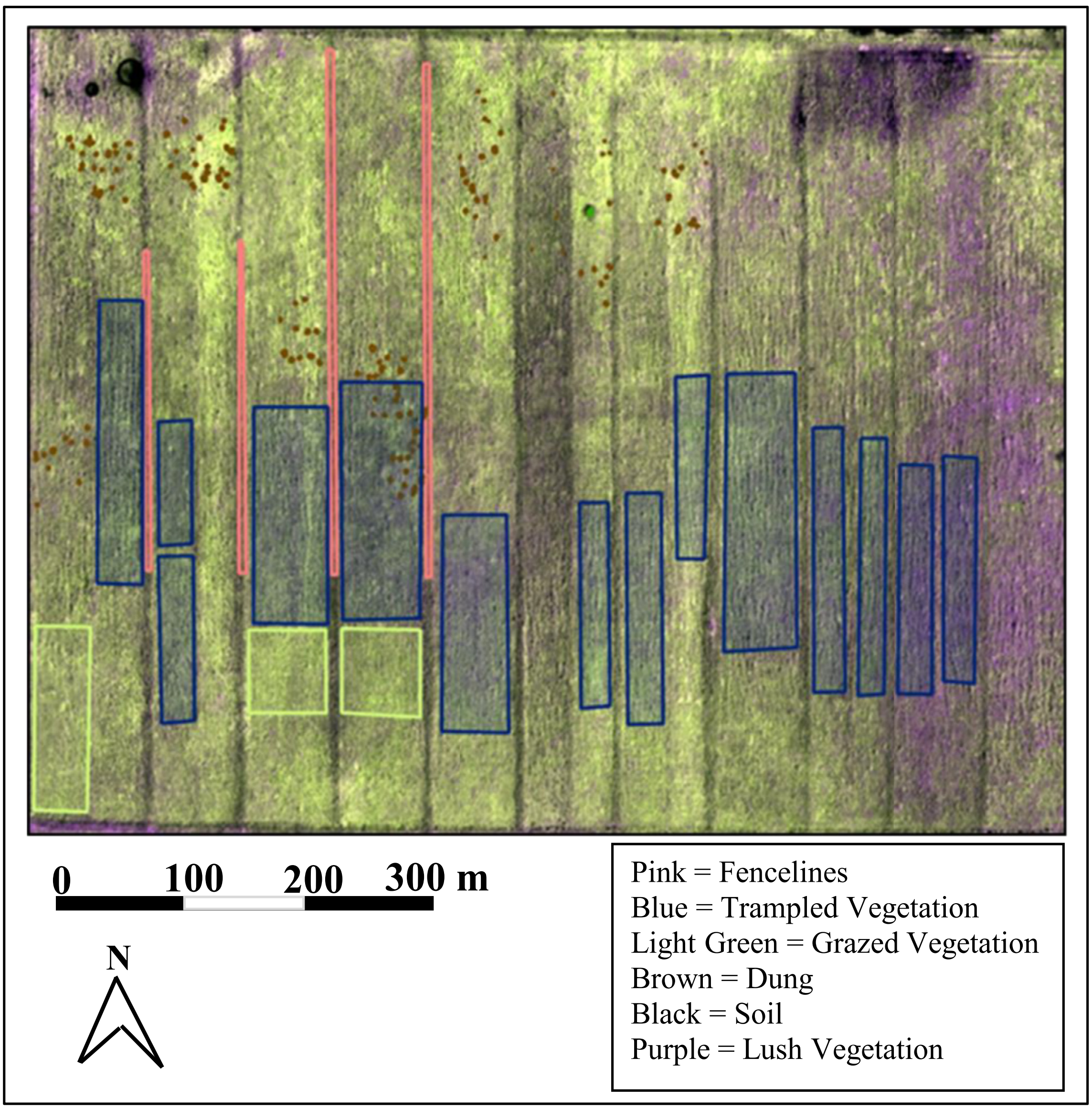

Figure 3. Example of training data selection in an image of the ultrahigh stocking density (MOB) grazing treatment on 21 July 2017. Colors represent different training classes.

is a commonly used measure of how accurate the classification is as compared with the ground truth, or reference, data. Unlike the measure of overall accuracy, it takes into account the errors of omission and commission, and therefore it may differ from the overall accuracy if large numbers of these marginal errors were present in the classification (Congalton and Green 2019).

Spatial analysis

Classified raster data have limited use in spatial analyses. Because each pixel is still classified as just one distinct class, the data are not in a form amenable to object-based analysis of distribution or clustering patterns. Therefore, after classification and accuracy

Table 4
The confusion matrix of the accuracy assessment results from all image analysis dates using supervised classification and a support vector machine algorithm.

Class	Dung	Soil	Vegetation	Total	User's accuracy
Dung	221	11	6	238	0.93
Soil	13	52	1	66	0.79
Vegetation	70	15	278	363	0.77
Total	304	78	285	667	–
Producer's accuracy	0.73	0.67	0.98	–	–
Overall accuracy		–	–	82.6%	–
Kappa	–	–	–	0.71	–

analysis were performed for each of the image dates, the raster data were converted to polygons using the raster-to-polygon tool in ArcPro, which transformed each group of similarly classified pixels (i.e., segments) into a polygon. Point data were then extracted from the polygons, which allowed the dung distribution to be modeled and analyzed as discrete points, a task not possible using raster data alone.

After all of the polygons were transformed into points, the subset of points that were classified as dung were extracted from the shapefile, and a new feature class layer was formed that contained only dung data. Each pasture was then clipped from the larger image so that the subsequent spatial analysis was confined to one replication of a grazing treatment at a time. The density-based clustering tool with the defined distance method was used to identify clusters. With this tool, the spatial scale of clusters and the density of dung pats within them could be set manually after iteratively exploring different combinations of distance and density.

We performed Ripley's K-function analysis (Mitchell, 2009, Ripley 1976) using the multidistance spatial cluster analysis tool to assess the magnitude of dung clustering across imagery dates and pastures.

Results

Image classification

The confusion matrix and Kappa statistic below (Table 4) display the accuracy assessment results for this study. The UAV methodology paired with the described classification techniques had an overall accuracy of 82.6%, with even better results for individual classes (Table 4). The user's accuracy for dung was 0.93 (93% of the pixels classified as dung were actually dung), and the producer's accuracy for vegetation was 0.98 (98% of pixels that should have been classified as vegetation were classified correctly). The corresponding Kappa coefficient for this error matrix was 0.71 (Table 4), indicating "substantial" agreement between ground truth data and the classification after accounting for statistical chance in agreement with the results. The results for the vegetation subcategories (e.g., trampled, lush) were not assessed for accuracy in this analysis because the focus was on delineating dung from vegetation and soils, not classifying specific vegetation patterns or types. Thus, only the accuracy results for a generalized vegetation class were calculated. Although the producer's accuracy of 0.98 is impressive for the vegetation class, the user's accuracy was much less, 0.77 (Table 4). Nearly 20% of all pixels classified as vegetation were, in reality, dung pats. In early classification attempts, trampled vegetation was a prominent source of error, in which vegetation pixels were classified as dung and vice versa.

A classified image for this study can be seen in Figure 4A. Classes such as trampled vegetation, lush vegetation, and fencelines were added as classes during the training phase to help improve the accuracy assessment results for this study. Figure 4B shows the spectral signatures of these classes. As seen in this figure, the spectral signatures of several classes closely overlap, and the spectral signatures of dung and vegetation are typically quite distinct (Fig. 4B). Image exploration using known areas of trampling revealed that these areas had a complex mix of reflectance patterns, with spectral characteristics of abundant vegetation, soils, and dung, corresponding to, respectively, high NIR reflectance (characteristic of both soils and healthy vegetation) and high NIR absorption (shadowed areas deep in the vegetation).

There were several errors in dung misclassification in this study (Fig. 5). Trampled vegetation was one of the common causes of dung classification errors (Fig. 5A). Another classification pitfall was that of obtaining imagery while cattle were still in the photo (Fig. 5B). Also, polywire fencelines and soil moisture had significant impacts on the successful detection and classification of dung (Fig. 5C). In the absence of clearly defined pats, the distinction between dung and soil became much more difficult for the classifier. This was seen most often in the heavily trafficked areas (corners, watering points) of pastures where dung was trampled and spread on top of the soil surface. Under these conditions, the classifier often produces nearly solid blocks of dung pixels (Fig. 5E) when, to the naked eye, they appear to be either easily identified as pats or soil (Fig. 5D). This was particularly evident in the MOB pastures, as shown in Figures 5D and 5E (as well as later in Figure 7).

Overall, the most successful classification of dung occurred when it was found in areas that had a consistent spectral response pattern across pixels (e.g., an expanse of homogeneous vegetation). In this instance, the dung "object" is more readily identifiable by the computer-based classification method as something that is its own entity, separate from the background class. When the spectral background is more complex, it becomes more challenging to assign a class to an object (dung) that is itself spectrally heterogeneous (e.g., wet interior, dry edges). Dung must be fresh enough to send a strong spectral signal that distinguishes it from soil or other features due to its moisture characteristics, but at the same

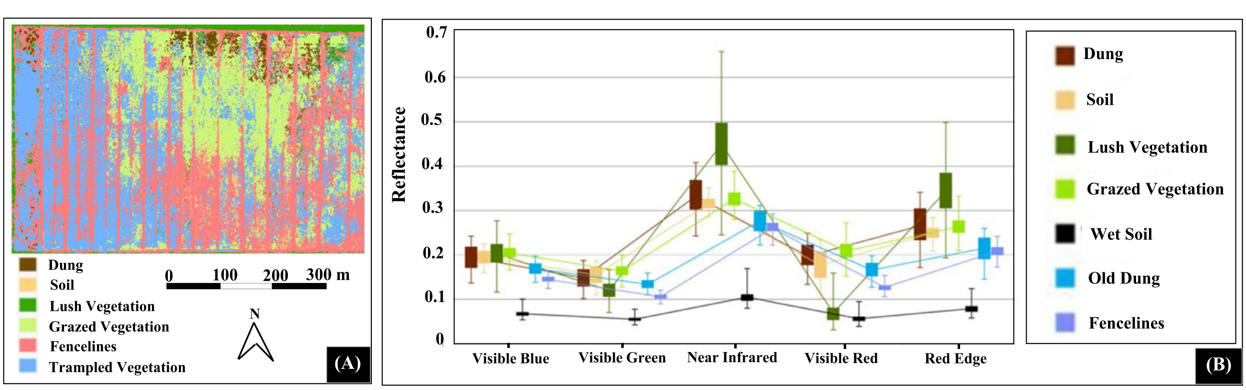

Figure 4. A, Example of a classified image from the ultrahigh stocking density (MOB) grazing treatment. **B,** Spectral signatures of selected classes.

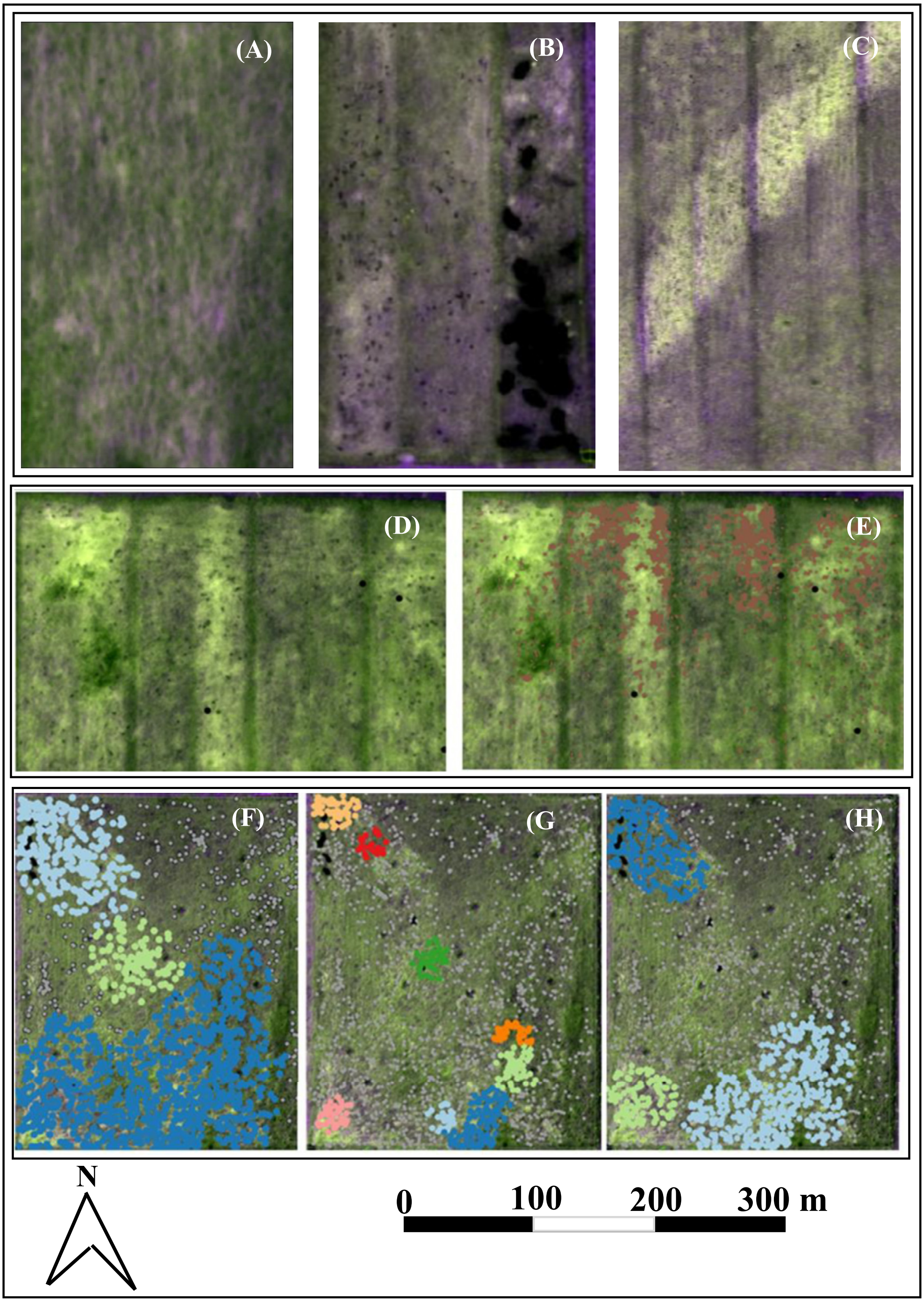

Figure 5. **(A–C)** Three common causes of classification error. **A,** Trampled vegetation and its complex spectral pattern: trampled areas are dark green, and standing vegetation is light purple. Note especially the large amount of variation in reflectance qualities (represented by different hues) across short distances. **B,** The presence of cows and shadows from their movements during unmanned aerial vehicle image capture over multiple flight lines. **C,** Fenceline effect on vegetation height and structure under temporary fencelines and its effect on spectral reflectance, and the change in reflectance due to the wetter soils (bright yellow-green stripe) underlying an ephemeral stream through the pasture. (**D–E**) Overclassification of dung in highly-grazed and trampled areas of the pasture. **D,** False-color image (3 of 5 bands loaded to different color guns). **E,** A classified image with only dung-classified pixels colored (brown pixels), where it is easy to see that many more pixels were assigned a dung classification than were actually dung. (**F–H**) Results of density-based clustering using parameters of 50 points in 6.1 m. **F,** 25 points in 3 m. **G,** 75 points in 6.1 m. **H,** Colors only represent different clusters and have no analytical or classification significance.

time, vegetation must be at a height and density that allow detection of dung. In this subirrigated meadow, there was a window of 7–10 d during which dung was most easily identified. This was adequate for the MOB grazing trial, where cattle were moved off of the grazing strip after 24 h, but in the 4PR, where stocking density was lower and residence time in the paddock was longer, it was challenging to see dung in the deep vegetation during the first few days. By the end of the rotation 15 d later, dung distribution was apparent, but a significant proportion of total dung had dried or been decomposed enough that it was no longer visible to the sensor (or to the human eye).

Spatial analysis

Figures 5F–H show three iterations exploring the process of choosing optimal distances and dung points to accurately represent clustering at a meaningful spatial scale. Because there is no definition of what qualifications a grouping of dung pats has to meet to be considered a "cluster," the results of the analysis had to be weighed against the knowledge of what is likely to be significant clustering for not only the system under study but for other grazing strategies as well. A distance of 6.1 m was chosen as a large enough area for multiple animals to potentially be present for an extended time, and a density of approximately 12 dung pats per meter gave rise to statistically significant clusters (Fig. 5H) that were neither too large and poorly defined (Fig. 5F) nor so small that the clusters could have been the result of a short duration of dung accumulation by a few animals instead of from heavy and/or repeated utilization (Fig. 5G). Additionally, a distance of 6 m is approximately the width of each grazing strip in the ultrahigh stocking density (MOB) treatment. This allowed an assessment of clustering to be conducted at a scale that corresponded to the smallest grazing unit (both spatially and temporally) being used in this study. Ripley's K was closely aligned with the density-based clustering, with the added benefit of assessing how it changed over increasing distances.

Results from the density-based clustering analysis clearly showed differences in distribution across MOB-grazed strips and the 4PR pastures (Fig. 6). Figure 6A is an image from 8 August 2017 of the 4PR pasture. The density-based cluster analysis found no clustering at the end of this rotation of the 4PR treatment (Fig. 6A). Ripley's K mirrored this result, showing that clustering was close to what was expected for a random distribution until a search distance of 12 m was reached, at which point the observed values fell below the expected, indicating a more dispersed pattern (Fig. 6B). In the MOB treatment imagery from 6 August 2017, we find similar good agreement between the cluster map and Ripley's K, with clustering relatively stable across the examined distances (Figs. 6C and 6D). Most often, dung was concentrated on the side of the strips near water sources, in corners, and near supplement feeders (Fig. 6C).

Discussion

UAVs have been widely used in the field of agriculture, helping producers make better farming decisions (Carpinelli et al. 2020; Grüner et al. 2020; Hassan-Vásquez et al. 2022). However, the use of UAVs to detect spatial distribution of cattle dung on pastures or rangelands has not been explored previously. This is the first study using UAV-based remote sensing to perform detection, classification, and spatial analysis of cattle dung, which has been shown to impact soil and plant productivity (Yoshitake et al. 2014; Wagner et al. 2021). Due to our study using an unexplored usage for UAVs, there are no results from similar studies that we can compare ours with.

Potential of using UAV imagery for dung classification

It was not expected that classification errors between dung and vegetation would be prevalent in this study (Table 4). However, the majority of dung misclassifications were in fact due to it being assigned to a vegetation class and not to a soil class, as had been hypothesized, due to the very similar spectral signatures between soil and dung (Fig. 4B). Trampled vegetation resulted in dung classification errors due to the finding that trampling produces a spectrally diverse pattern that shows rapid change over fine spatial

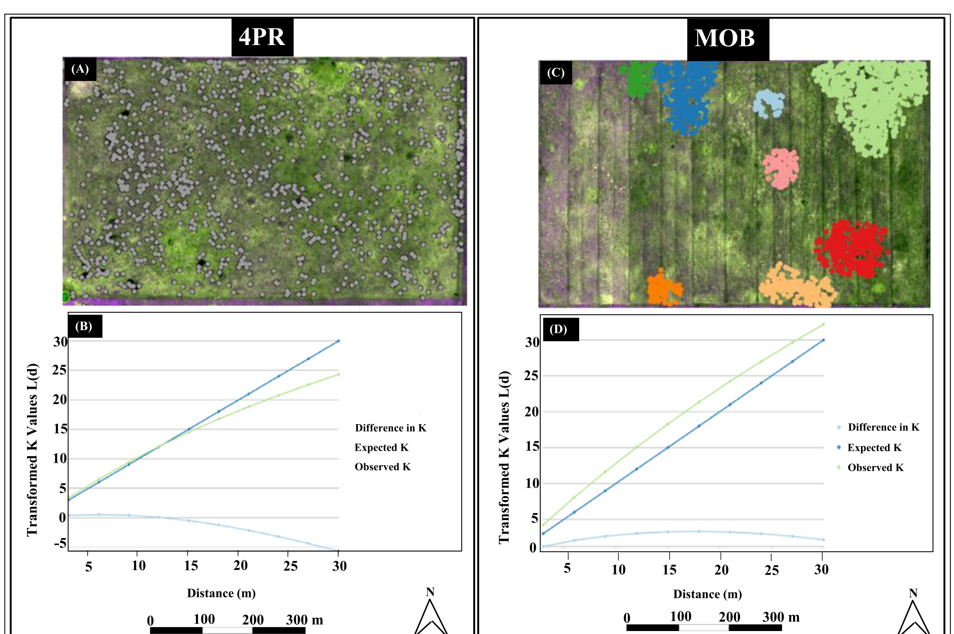

Figure 6. A, Density-based cluster analysis showing no statistically significant clusters (gray dots are dung locations). **B,** K clustering analysis for the low stocking density (four-pasture rotation [4PR]). grazing treatment from 8 August 2017. **C,** Density-based cluster analysis. **D,** K clustering analysis for the ultrahigh stocking density (MOB) grazing treatment from 6 August 2017.

scales, producing the dung-sized shadowed areas that were often misclassified in this study. The addition of trampled vegetation as a separate category caused a significant reduction in the number of vegetation pixels misclassified as dung. On the other hand, it was rare for dung to be wrongly assigned to vegetation pixels in areas of lush vegetation with deep shadowing. This may have been a result of the strong vegetation signal that was consistent across the canopy, even when shadowed areas existed below it, and which made the vegetation more spectrally distinct from dung.

It was also found that the presence of cows during UAV image acquisition caused dung misclassifications (Fig. 5B). The final image contained shadowy cows in different locations across the pasture due to their movement during and between UAV flight passes. Depending on how active the cattle were during the UAV flight, this can create substantial noise in the image and cover up underlying details of the vegetation and dung patterns due to the shadowing. Cattle (Black Angus, in this research) are apparently very dung-like in their reflectance characteristics and can be easily misclassified as dung. Training sample selection of cows was most successful when it included a generous boundary around the animal that also captured their dark shadow on the ground around them (otherwise, those areas were often classified as dung).

Although the use of GEOBIA played an important role in helping to discriminate dung pats from soil patches in this study, misclassifications were also due to dung pixels being assigned to a soil class. The area beneath polywire fencelines in the grazing treatments (especially MOB) was often undergrazed due to the vegetation's proximity to the electrified polywire. The dark shadowing found under these fencelines (Fig. 5C) mimics a reflectance pattern characteristic of dung, which led the classifier to easily misclassify these areas. Adding "fencelines" as a class during classifier training caused a significant reduction in the number of bare soil and gopher mound pixels that were misclassified as dung. Soil moisture also has the potential to have significant impacts on the successful detection and classification of dung. If soil moisture is high and there is a significant amount of bare soil visible, NIR absorption is increased, which makes discerning patches of dung from bare soil more difficult. A visual example of the change in spectral reflectance due to soil saturation and/or standing water in this subirrigated meadow pasture can be seen in Figure 5C. This changed the overall spectral profile of the vegetation and soils in these areas, making it more difficult to classify them along with the soils and vegetation in drier areas of the pasture using the same training data set.

The poor performance of the classifier in areas where there was both a lot of exposed soil and manure (e.g., near watering troughs and in the fence corners) in this study requires more investigation. There are two possible causes for this error. First, the soil signal is probably much stronger in these areas due to heavy trampling and grazing where the soil is exposed. The similarity between soil and dung then leads the classifier to blanket-classify large areas as dung (Figs. 5E and 7). Another possibility for this error may be associated with a large amount of dung having been spread more thinly across the surface of the pasture by trampling, walking, resting, and ruminating the animals. This dung is not visible to the naked eye, but the spectral signature is still intact enough that the algorithm correctly classifies it as dung. Returning to these areas within a short timeframe after classifying the image would reveal if this was, in fact, the case.

Dung distribution patterns for grazing management

Although the goal of this project was primarily to assess the potential for a new methodology for detecting and mapping dung, it was also hoped that the research would provide insight into the changing patterns of dung distribution between different grazing strategies: an ultrahigh stocking density treatment with fast rotations and a low stocking density treatment with longer residence

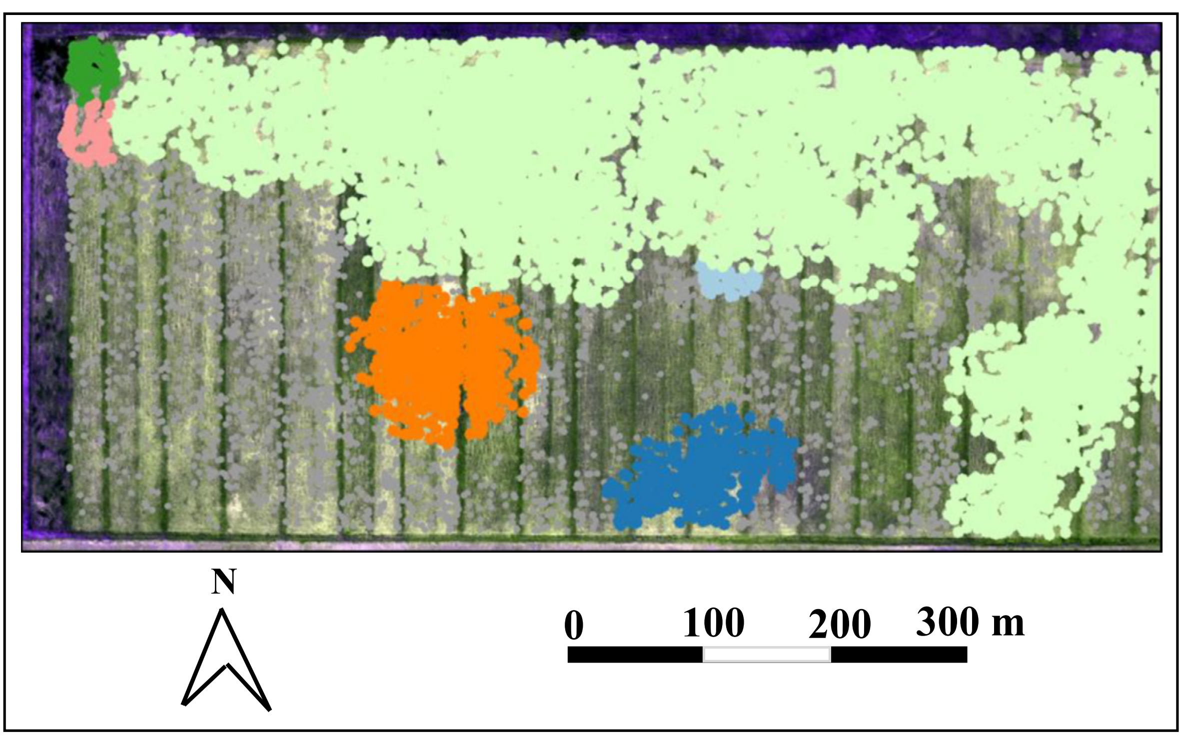

Figure 7. Overclassification of dung in the ultrahigh stocking density (MOB) grazing pasture. Colors represent independent clusters and have no other analytical or classification significance.

times in each pasture. As mentioned previously, relatively small errors in classification of dung can have impacts on the assignment of clustering for a given date and over a range of dates in the same pasture. However, the process of converting raster to point data in this study gave a highly accurate rendering of actual dung locations. The transformation from raster to point data served to visually minimize error, as each of the larger polygons of contiguous dung pixels became a single point. This led to a clearer overall picture during the visual inspection of the accuracies of points vs. actual dung visible in the image. Another advantage of transforming raster data for dung into point data is that it makes it possible to increase the accuracy of the final shapefile by manually performing an accuracy analysis of the point data against the orthomosaic and eliminating points that are not clearly associated with dung on the ground before spatial analysis. As mentioned previously, lack of literature regarding this use of UAVs means that our study will be a blueprint for future studies.

Although the belief exists that ultrahigh stocking densities lead to more even dung distribution, the density-based clustering analysis results in this study showed that the ultrahigh stocking density grazing treatment did not consistently lead to more dispersed or more evenly distributed dung deposition. This assumption may neglect to account for basic cattle biology and behavioral science, as well as abundant research on the preferences of cattle for specific lounging and ruminating areas (e.g., near watering points or mineral feeders) that naturally give way to higher densities of dung accumulation over time in certain areas (Bailey et al. 1996; Augustine et al. 2013; Oñatibia and Aguiar 2018). Additionally, Tate et al. (2003) have documented that spatial patterns of vegetation use do not always mimic dung distribution patterns, and thus a more homogeneous use of vegetation under high stocking densities does not necessarily translate into more homogeneous dung distribution. This assessment of dung clustering under two different grazing management strategies supports the finding that the drivers of when and where dung accumulates are both predictable (corners, watering points, shade) and complex, potentially influenced by the heterogeneity of vegetation and forage quality factors across a pasture; cattle behavior; paddock size and shape, etc.

The advantage of a short-duration, ultrahigh stocking density rotation, however, is that the clusters are limited in scale due to the limited duration of the grazing in a given paddock or section. Therefore, the areas that are prone to accumulating dung in a pasture, such as near water sources, only get used at a high intensity for a short duration, instead of being used at a high intensity for a long time, as they would be in pastures with longer residence times. It is important that conversations regarding patchy dung (and, by extension, nutrient) distribution include a temporal component as well as a spatial component, since both the short- and long-term effects of nutrient additions and cycling involve both of these components.

Scale has always been an essential piece of both the philosophical and the scientific discussions surrounding the management, ecology, and sustainability of grazing lands (Kothmann et al. 2009; Sayre 2017). Oñatibia and Aguiar (2018) highlight the difficulty of disentangling scale (in this case, paddock size) from other factors such as increasing vegetation heterogeneity at larger paddock sizes, stocking density, and watering locations. They also address the nonlinearity inherent in grazing effects at different scales. This research is no exception: scale once again must be addressed to answer the most basic questions regarding dung nutrient and organic matter inputs and what they mean for rangeland health and grazing management. At what scale does clustering become meaningful? At what scale is it no longer meaningful? If our analysis stops at the pasture fence, are we missing landscape-scale patterns that continue on the other side?

Nutrient cycling, soil microbiology, and landscape-scale grazing impacts

Perhaps one of the most promising aspects of creating spatially accurate dung maps is the potential for multilayered analyses across dates, both within a grazing season and across years.

There is a large body of work surrounding the impact of grazing on soil properties and soil microbiological communities (Abagandura et al. 2019; Wu et al. 2022). However, given the complexity of ecosystem variables and processes at play in any given pasture, researchers often report that it is challenging or impossible to separate out the most meaningful influences of aboveground drivers, such as dung and urine, trampling, and grazing, on belowground processes (Bardgett and Wardle 2003; Schrama et al. 2013). Tying specific dung locations and their effects on associated soil microbiological communities and soil physical and chemical properties at a very fine scale may help refine our understanding of these impacts (Ford et al. 2013; Odriozola et al. 2014). The availability of a dung map could also help identify areas of high use and high dung densities across large acreages, which could, in turn, be used in estimating annual nutrient inputs and to inform adaptive and responsive management decisions to achieve both ranch- and landscape-level goals. Finally, as increasing numbers of ranchers participate in the carbon offset market, high-resolution dung mapping can help provide validation data for carbon return to the ecosystem via dung when combined with knowledge of carbon cycling dynamics (Evans et al. 2019; Shine et al. 2022).

Applications beyond the ranch gate

The potential applications of this work are not limited to the fields of grazing management, nutrient cycling, or rangeland ecology. Dung maps might serve as a locational guide and spatial record-keeping resource for entomologists studying dung-dwelling and dung-feeding insect ecology (Holter 1979; Holter 2016). When combined with hydrology data, accurate dung maps could help predict the potential for nonpoint source pollution of water by dung and manure in susceptible areas (Tate et al. 2000; Vadas et al. 2011; Oliver and Young 2012), especially if the technology could be applied to map manure spread on cropland. With the ever-increasing concern around antibiotics and antibiotic-resistant genes in livestock manure and their movement across and below the soil surface into both surface and subsurface water supplies (Burch et al. 2023), being able to study patterns of transport in relation to the aboveground locations of manure mapped across large landscapes could provide valuable insight regarding the conditions that facilitate their movement and persistence in the environment (Tian et al. 2021; Wang et al., 2022). In the field of wildlife biology, the ability to locate and map dung from different wildlife species using a UAV may allow wildlife biologists to better understand the movements and population dynamics of wildlife efficiently and at scales that would otherwise be difficult to achieve on the ground (Meier et al. 2021).

Research Recommendations

This study has demonstrated the feasibility of using UAV-based remote sensing to detect and classify cattle dung distribution. Future research needs to evaluate methodology components that were not able to be rigorously evaluated in this project (such as inclusion of the visible blue band, achieving higher pixel resolution, using different machine learning classification methods, and adding more training samples). The limitations of this method for a more widespread application at larger spatial scales are 1) the high degree of spatial accuracy needed from the UAV platform and sensor(s) for reliable classification and ground truthing, 2) the high frequency of data capture required for accurately identifying and classifying dung over time, 3) the changing spectral signature of dung over time as it dries, leading to misclassification or inability to identify dung, 4) the impact of vegetation regrowth after grazing on accurate dung detection, 5) the grazing method being utilized (long pasture residence times make accurate detection of dung over time more challenging), and 6) lack of data on how the method performs across diverse ecological sites which have different soil types, vegetation communities, topography, and seasonal weather patterns. Future research will need to consider these challenges to explore the use of UAVs to document dung distribution in more depth.

Conclusion

The results of this research show that using multispectral imagery from a UAV for the identification, mapping, and spatial analysis of dung distribution has the potential to change the scales at which land managers and scientists are able to monitor and analyze a variety of nutrient cycling processes, animal grazing behavior, and landscape-scale ecological interactions. However, classification consistency and accuracy across flight dates and between different pastures in the same image set are, for now, a significant barrier to obtaining a useful data layer to be used in additional spatial analyses. There are also unexplored questions regarding the proposed method's widespread applicability on different rangeland and pasture types in different climates, as well as which spectral bands are optimal to use for identifying dung and discriminating it from soil and vegetation.

Declaration of competing interest

The authors declare no conflict of interest.

CRediT authorship contribution statement

Amanda E. Shine: Data curation, Formal analysis, Investigation, Methodology, Visualization, Writing – original draft, Writing – review & editing. **Martha Mamo:** Conceptualization, Funding acquisition, Methodology, Project administration, Resources, Supervision, Writing – review & editing. **Gandura O. Abagandura:** Data curation, Visualization, Writing – review & editing. **Walt Schacht:** Conceptualization, Funding acquisition, Methodology, Project administration, Supervision, Writing – review & editing. **Jerry Volesky:** Conceptualization, Funding acquisition, Project administration, Resources, Supervision, Writing – review & editing. **Brian Wardlow:** Supervision, Writing – review & editing.

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