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Evaluating the spatial distribution of cattle dung pats from UAV images in grazing ecosystems

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Abstract
Livestock excretions play a crucial role in nutrient cycling within pasture ecosystems. However, traditional field observation methods require significant human effort and time. In this study, we developed the Dung Detector (DD) model, which utilizes unmanned aerial vehicle (UAV) images and the You Only Look Once (YOLO) v5 object detection approach, to identify cattle dung in pastures. We have also evaluated the spatial distribution of cattle dung pats in these pastures. The DD model consists of five paddocks, namely Obihiro (OBH), Shintoku (STK), Minokamo (MNO), Miyota (MYT), and Yatsugatake (YGK). A custom dataset containing 1,504 images segmented from UAV orthomosaic images was used for training. The accuracy of the DD model was assessed by comparing it with ground truth data obtained from 2-3 quadrats (10 m × 10 m) in each paddock. Accuracy (F-score) of the DD model in each plot ranged from 0.432 to 0.861, with better results observed in paddocks characterized by simpler grass species and lower surface grass height (SSH). The spatial distribution of cattle dung pats detected by the DD model showed a heterogeneous distribution pattern within the plots due to differences in where grazing livestock stayed due to fences, shaded forests, and water troughs.

Introduction
Cattle dung in pastures constitutes a critical source of soil nutrients; however, it also significantly contributes to greenhouse gas (GHG) emissions, particularly methane (CH_4) and nitrous oxide (N_2O) (Cai and Akiyama, 2017; Lombardi et al. 2022). The application of nitrification inhibitors, such as dicyandiamide (DCD), has been proposed as a mitigation strategy for these emissions; nonetheless, the

application process can be costly and labor-intensive when employed across extensive agricultural fields (Betteridge et al. 2010). Additionally, cattle foraging behavior results in an uneven distribution of dung, particularly in hilly grassland environments (Yoshitake et al. 2014). The real-time mapping of dung distribution could enable targeted application of DCD, thereby contributing to the reduction of GHG emissions.

Current methodologies for monitoring cattle defecation, including global navigation satellite system (GNSS)-based technologies, are encumbered by limitations in battery life and overall usability (Watanabe et al. 2019). Drones have emerged as a promising alternative for the detection of cattle dung, with investigations demonstrating their ability to identify fresh dung based on color and shape. However, challenges remain in detecting older dung, especially within heterogeneous pasture ecosystems where soil coloration may closely resemble that of dung (Yoshitoshi et al. 2015). Geographic object-based image analysis (OBIA) presents potential avenues for improvement; nonetheless, it is also constrained by factors such as site-specific dependency and limited versatility (Blaschke, 2010).

In response to these challenges, the present study employs a deep learning-based object detection methodology to enhance accuracy and adaptability. Among the various algorithms available, YOLO (You Only Look Once) is particularly notable for its efficiency and widespread application in agricultural contexts, including weed and cattle detection (Ahmad et al., 2021; Gallo et al., 2023). The "Dung Detector (DD)" model was developed utilizing YOLOv5, which was selected for its robust performance and adaptability. This model was trained on a custom dataset specifically tailored to drone imagery of cattle dung, thereby addressing the existing gap in available datasets.

Methods

The study was conducted in June-July, 2022 across five pastures in Japan: Obihiro (OBH), Shintoku (STK), Minokamo (MNO), Miyota (MYT), and Yatsugatake (YGK) (Figure 1; Kawamura et al. 2024). These locations include two permanent grazing paddocks (OBH, MNO) and three rotational grazing paddocks (STK, MYT, YGK), with sizes ranging from 0.59 ha (OBH) to 3.72 ha (STK). Terrain varied from flat (OBH, slope = 1.0°) to hilly (MYT, slope = 8.7°), with slopes calculated using 5-m mesh digital elevation models (DEM5A and DEM5B) published by the Geospatial Information Authority of Japan (https://fgd.gsi.go.jp/download/ref_dem.html).

Fig 1 Location of five target paddocks: (a) Obihiro (OBH), (b) Shintoku (c) Minokamo (MNO), (d) Miyota (MYT), and (e) Yatsugatake (YGK) (Kawamura et al. 2024). White letters at the bottom of the pictures are

the dominant grass species of the paddock and the survey dates. KB, Kentucky bluegrass (*Poa pratensis* L.); DC, *Digitaria cilaris* (Retz.) Koeler; OG, Orchard grass (*Dactylis glomerata* L.); PR, Perennial ryegrass (*Lolium perenne* L.); RC, Red clover (*Trifolium pretense* L.); TY, Timothy (*Phleum pretense* L.); WC, White clover (*Trifolim repens* L.); ZJ, Zoysia japonica Steud.

A Parrot Anafi drone was utilized for image capture. The flights were conducted in accordance with the mission parameters established by Pix4Dcapture, which specified an 85% forward overlap and a 75% side overlap at an altitude of 28 meters, resulting in a ground sampling distance of 0.95 cm. Ground control points (GCPs) and ground-truth data were collected using Real-Time Kinematic Global Navigation Satellite System (RTK-GNSS) technology. Two 10 × 10 meter quadrats within five paddocks (OBH, STK, MKB, MNO, MYT) were surveyed to validate the locations of dung.

Orthomosaic RGB images with a resolution of 1 cm were generated using Metashape Pro and subsequently partitioned into 640 × 640 pixel tiles for compatibility with the YOLO model. The images were saved in JPG format for the purpose of annotation and in GeoTIFF format for the extraction of dung location data.

A custom dataset consisting of 1,504 images was developed, allocating 80% of the data for training and 20% for validation. Image labelling was conducted using MakeSense, with two classes designated: dung and stones. The YOLOv5x model underwent training for 500 epochs employing an Nvidia RTX A4000 GPU. The model exhibiting the highest mean Average Precision (mAP) on the validation dataset was selected for subsequent testing.

Dung detection was conducted across four paddocks, with the exclusion of YGK due to the absence of ground-truth data. The assessment of detection accuracy was executed utilizing Precision, Recall, Overall Accuracy (OA), and F-score metrics, which were calculated based on the counts of true positives (TP), false positives (FP), and false negatives (FN). The F-score provided a comprehensive evaluation of model performance, with values approaching 1 indicative of superior accuracy.

Results

Using the DD model, cattle dung detection was conducted in five paddocks across Hokkaido (OBH, STK), Gifu (MNO), Nagano (MYT), and Yamanashi (YGK) prefectures (Figure 1). The detected dung counts were 666 (OBH), 2,429 (STK), 688 (MNO), 165 (MYT), and 3,716 (YGK), respectively. The model achieved high accuracy in OBH (F-score = 0.861) and STK (0.835), where the grass was short and simple in species composition. Dung color variations, from dark brown to white, were also detected effectively (Figure 2a). In contrast, in MNO and MYT, dense vegetation and taller grass (MYT: mean height 38.9 cm) resulted in lower recall (0.500, 0.276), as many dung pats were concealed under the grass despite precision exceeding 0.9.

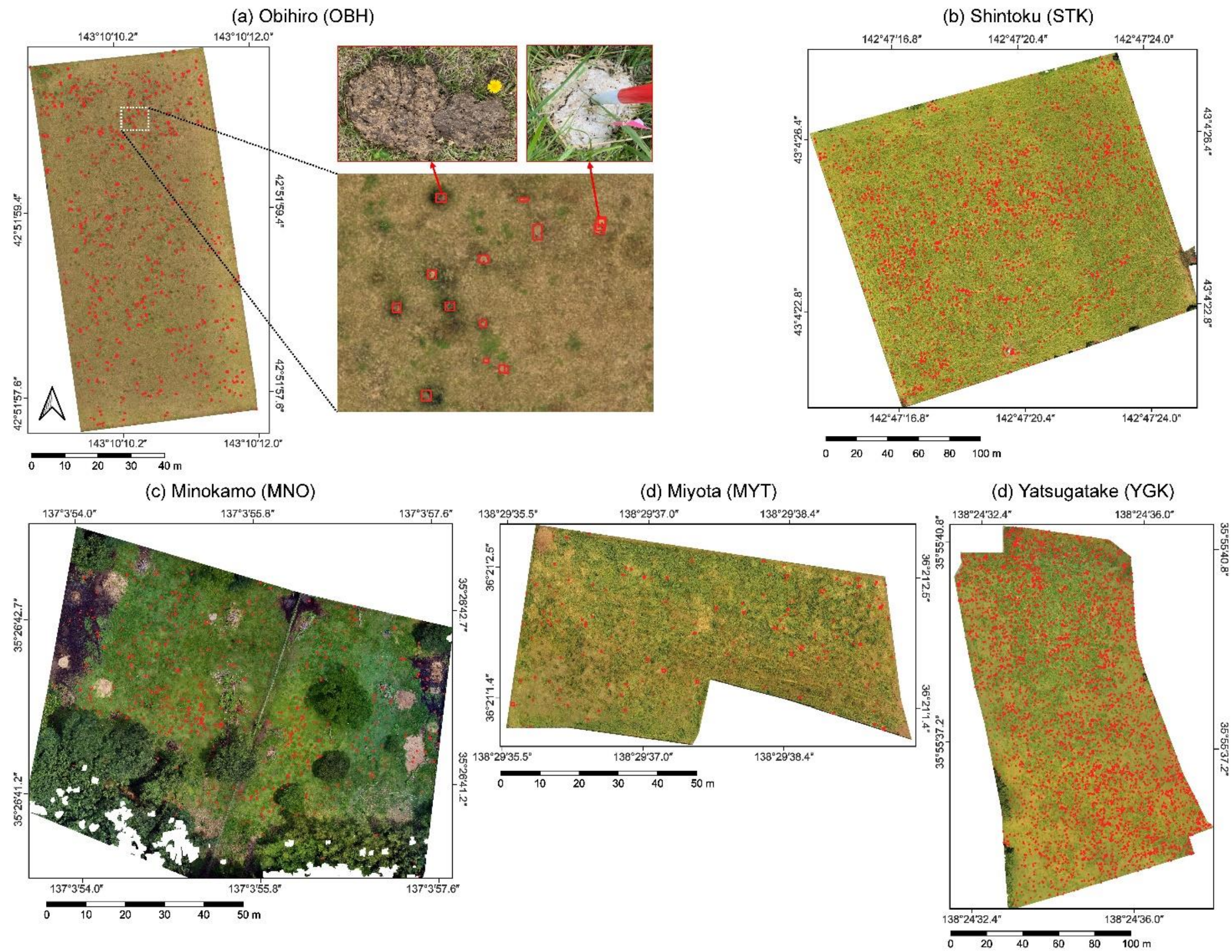

Fig 2 Spatial distribution of cattle dung pats detected from drone images using YOLOv5 in five paddocks (Kawamura et al. 2024).

Discussion

The application of deep learning (DL) for remotely sensed image data is expanding in grassland and livestock management (Muro et al., 2022); however, cattle dung datasets for grassland ecosystems remain underrepresented. This study developed the DD model using YOLOv5 and a custom dataset (1,504 images) to detect dung pats in drone images. The model identified between 666 and 3,716 dung pats per field, consistent with estimates of dung production (8–13 pats per day per cow). These results suggest that the detected dung pats were approximately 10 days old or less.

Dung detection accuracy was highest in short-grass pastures (OBH, STK; F-score = 0.861, 0.835) but exhibited lower performance in tall grass pastures (MYT; Recall = 0.281), where vegetation and terrain obscured dung in the drone images. The camera angle (80°) and the presence of invasive tall grasses, such as *Phalaris arundinacea*, likely contributed to the challenges in detection, indicating a need for methodological adjustments in future studies. Furthermore, updates to the detection models are necessary to enhance performance in complex environments.

In comparison to machine learning and Object-Based Image Analysis (OBIA) methods (Yoshitoshi et al. 2015), YOLOv5 demonstrated versatility across multiple paddocks, albeit with slightly lower accuracy. Enhancements can be achieved by updating the model with newer YOLO versions and incorporating expanded datasets, which could improve performance and applicability to a range of pasture types.

This pilot study highlights the potential of DL and drone technology for identifying the distribution of cattle dung, which can be beneficial for grazing management. However, several challenges persist: the model currently provides only the location and approximate size of dung (bounding boxes) without information regarding dung age or mass. Given that dung mass and age significantly influence nutrient cycling, grass recovery, and GHG emissions, future research should focus on evaluating dung decomposition processes while integrating seasonal and geographic variations (Cai et al., 2017; Saggar et al., 2015).

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