Preliminary Detection of Rhino Middens for Understanding Rhino Behavior

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Abstract

Black and white rhino are threatened with extinction due to recent increases in poaching. While both species are intensively protected, monitoring and field observations are difficult, and many aspects of their behavior and space use are not well known. The detection of relevant landscape features, particularly rhino middens, can facilitate a better understanding of the spatial behavior of black and white rhino and consequently support more targeted conservation efforts. Middens are communal defecation sites used for territorial marking and social communication across sex and age. Middens have not been previously mapped at the landscape scale, and doing so would provide important insights into how these megaherbivores use and shape their savanna habitats. We propose a preliminary system to gather data that will ultimately enable us to detect rhino middens in high-resolution orthomosaics derived from remotely sensed RGB and thermal data. This system is based on thresholding and morphological filters as a first step to support data labeling, with a promising initial reduction in midden search space and labeling time. We also present current challenges and next steps.

1. Introduction

Understanding animal habitat use is key to both investigating animal-driven ecosystem processes [9] and to improving species-specific conservation management [8]. This is especially important for threatened and endangered species that require extensive management and protection. Many of these species, however, are elusive and therefore difficult to monitor and study, resulting in a lack of species-specific ecological knowledge [17]. Black (*Diceros bicornis*) and white (*Ceratotherium simum*) rhino in particular are threatened with extinction due to the exponential rise in poaching over the past two decades [5], and are therefore managed and protected accordingly. However, little is known about their ecology, particularly their spatial behavior, as rhino are considered elusive, intractable, and dangerous to study in the wild [12]. Traditional monitoring efforts, such as direct observation, are additionally constrained by limited human and financial resources, especially in areas that are large and difficult to access [1].

Figure 1. RGB orthomosaic showing the location of an example midden in the landscape. Rhino middens closely resemble the ground and surrounding vegetation, making detection challenging.

Advances in remote sensing technology have been increasingly applied to ecological research, providing an efficient and cost-effective tool for both surveying wildlife and mapping the landscapes they occupy [15]. In particular, a variety of sensors, including RGB, thermal, and Lidar, have been mounted on unoccupied aerial vehicles (UAVs) to collect key habitat data [11], detect and survey animal populations [6], and study animal behavior [4].

Rather than directly searching for the animals themselves via remote sensing techniques, we instead propose to locate rhino *middens* (Fig. 1). Both species of rhino defecate in communal middens used for territorial marking and social communication by individuals of all ages and sexes [16, 13]. The role of middens as information centers signaling age, sex, territorial, and oestrous state has been demonstrated in white rhino [13, 14], but has been less rigorously studied in black rhino. In both species, it is believed that individuals rely on olfactory investigations at communal middens to gather critical population information, and thus middens likely influence rhino movement and space use across species. However, midden networks have never been mapped across an entire rhino population, and thus this approach could yield important ecological and conservation insights. Specifically, a greater understanding of the spatial patterning of middens will yield insights into rhino spatial behavior, such as home range and habitat use information critical to conservation management and anti-poaching strategy, and its implications for the surrounding landscape, including the redistribution of nutrients by rhino to these concentrated defecation sites. As a practical consideration, rhino middens also provide a more static landmark to detect compared to the animals themselves [1].

Currently, large quantities of thermal and RGB data exist and are still being collected using UAVs in known rhino ranges throughout southern Africa. To analyze such large datasets, ecologists have increasingly turned to automation and machine learning techniques for consistent and efficient object detection and pattern recognition [10, 2]. We similarly wish to automate the detection of middens to expedite mapping and facilitate behavioral understanding. A midden detection system would ideally identify middens in orthomosaics, which could then be verified by ground-truth surveys. That said, we currently do not have labeled examples of middens in the UAV imagery, though we anticipate the presence of many middens (on the order of hundreds) from the multiple field sites where data have and will be collected. In this paper, we use high resolution thermal and RGB data collected in Kruger National Park, South Africa, in combination with simple thresholding and morphological filters, as a first step towards labeling and later detecting rhino middens in aerial imagery.

2. Methods

2.1. Remote sensing data

UAV remote sensing data were collected over a 284 hectare site in January 2020 in an area of Kruger National Park known to have rhinos. Photos, thermal images, and Lidar data were acquired simultaneously using the Harvard Animal Landscape Observatory (HALO) sensor package, which consists of a Riegl VUX-1LR Lidar scanner, a Sony A6000 camera (24 megapixels), and a FLIR Tau-2 thermal camera (327,680 pixels). The sensor package was flown on a DJI M600 multicopter at an altitude of 100m and a speed of 8 m/s. The UAV's trajectory was refined using base station data to achieve an absolute accuracy of 4 cm or less along its flight path.

[1]Note that spatial patterning of middens will likely shift over time with changes in population demographics, still requiring regular mapping but less quickly than animal movement.

Thermal infrared images were converted into false-color images using ThermoViewer software and an automatic color scale. All imagery was rectified and mosaicked in the Terrasolid software suite using a terrain model derived from the coincident Lidar data. The relative accuracy of the Lidar ground data was 4.5 cm. The photos were rectified and mosaicked at a resolution of 5 cm, while the thermal images were at a resolution of 0.5 m.

2.2. Midden labeling

We used both RGB and thermal infrared orthomosaics for the same site in Kruger National Park. At this site, rhinos are the only known animals that create middens with the unique features used in our search. Middens have certain identifiable characteristics in RGB imagery, such as their texture and color, but they are difficult to distinguish in a large, heterogeneous RGB orthomosaic (Fig. 1). Fortunately, middens tend to be warm and are therefore bright in thermal infrared imagery. As a result, the easiest way for ecologists to identify middens from aerial imagery is to first look for candidates in the thermal imagery and then verify them in the RGB imagery. We sought to build a simple automated version of this process in order to make labeling easier by identifying hotspots in the thermal imagery and recording their GPS coordinates.

To do this, we first created a mask using a simple threshold of values in the thermal imagery, followed by a closing morphological operator in order to group very nearby bright points. We finally carried out connected component analysis to get the centroids for these groups. We converted these from pixel coordinate to GPS location using gdal, and wrote out these candidate GPS locations as a CSV. The CSV file was then loaded into QGIS with the RGB and thermal IR orthomosaics.

We evaluated the quality of these candidate predictions by zooming into the candidate GPS locations and alternating between the RGB and thermal IR views (Fig. 2). We manually verified candidates, classifying each point across a spectrum of certainty based on midden characteristics and placement. Verification classes included: yes, lean yes, uncertain, lean no, and no. In our preliminary analysis, we evaluated two candidate data sets at 80 and 75 percent thresholds (i.e., percentage of the maximum digital count in the images). At each threshold, we also conducted a manual assessment of hotspots that were not automatically identified but, to our best knowledge, should be classified as middens. Manual verification and assessment of candidates was conducted by one coauthor. We report the results below.

3. Preliminary Results

Using an 80% threshold, 66 candidate GPS locations were identified in the thermal orthomosaic. Of the candidate hotspots, roughly 32% were verified as likely middens

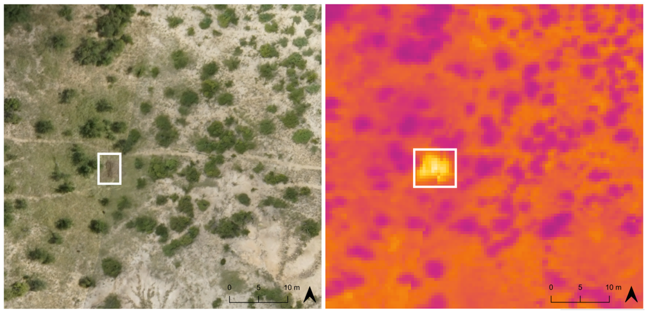

Figure 2. Example detection of a midden using thresholding and morphological filters in the thermal imagery (right) and manually verified using the RGB (left).

(n = 10 yes; n = 11 lean yes), about 23% were uncertain (n = 15), 39% were unlikely to be middens (n = 15 no; n = 11 lean no), and 6% were duplicate locations (n = 4). A manual search of the thermal orthomosaic found 21 additional hotspots that were confirmed as likely middens in the RGB imagery. Fig. 3 shows an example of both a false positive (i.e., a candidate incorrectly detected as a midden) and an undetected midden in the thermal and RGB imagery.

Using a 75% threshold, 230 candidate GPS locations were identified in the thermal orthomosaic, over 3 times as many as found in the 80% threshold. The number of candidates verified as likely middens increased by about 35% when the threshold was lowered (n = 17 yes; n = 15 lean yes). Unfortunately, the number of candidates unlikely to be middens increased far more drastically, with 6 times the number of likely false positives identified (n = 102 no; n = 54 lean no). In the manual search of the thermal orthomosaic for undetected hotspots, 13 locations were identified as likely to be middens. The results for both thresholds are summarized in Table 1, including the total number of pixels in the thermal orthomosaic for reference.

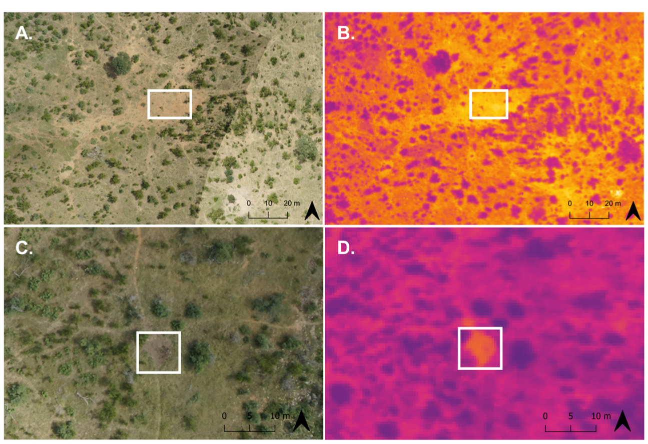

Figure 3. (Top) Example false positive where bare ground was identified as a candidate location, shown in RGB (A) and thermal (B). (Bottom) Example undetected midden in RGB (C) and thermal imagery (D).

Verification class	80% threshold	75% threshold
Yes	10	17
Lean yes	11	15
Uncertain	15	34
Lean no	11	54
No	15	102
Duplicate	4	8
Total candidates	66	230
Undetected middens	21	13
Total pixels	9532992	9532992
Orthomosaic area	238.3 ha	238.3 ha

Table 1. Manual classification of candidate middens at the two thresholds sampled, along with total number of pixels and area for the thermal orthomosaic.

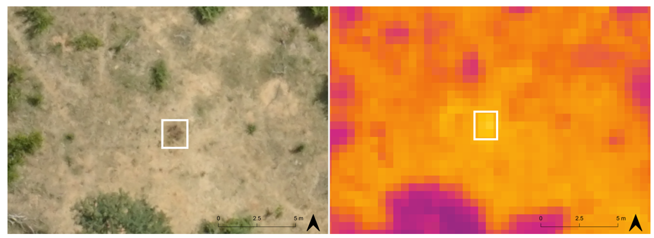

Figure 4. Example of a midden detected as a threshold candidate that would likely be overlooked in a manual search due to its small size and the relatively homogeneous pixel brightness in the area. Shown in RGB (left) and thermal (right).

Despite the overall prevalence of false positives, the use of thresholding and morphological filters to create candidate GPS locations provided organization and structure to the manual verification, which overall increased the efficiency of searching for middens in the thermal and RGB imagery. We estimate that using candidate locations saved at least 4-6 hours of manual detection effort for a single site orthomosaic (9532992 pixels in the thermal / 238.3 ha). The automatic identification of hotspots also detected areas that may have otherwise been overlooked in a manual search, especially in areas with relatively homogeneous pixel brightness or where middens were small or less fresh, resulting in a less pronounced thermal signature, e.g., Fig. 4.

The occurrence of undetected middens at both thresholds is, in part, the result of brightness variation among flight lines in the thermal orthomosaic. Across thresholds, we observed a clear bias in the occurrence of candidates corresponding to the brightest regions of the orthomosaic, as shown in Fig. 5. We similarly observed that almost all undetected middens occurred within the darkest flight lines, where hotspot brightness was prominent relative to the surrounding pixels but was low relative to the entirety of the orthomosaic, and was therefore excluded by the thresholding process. We expand upon this challenge below.

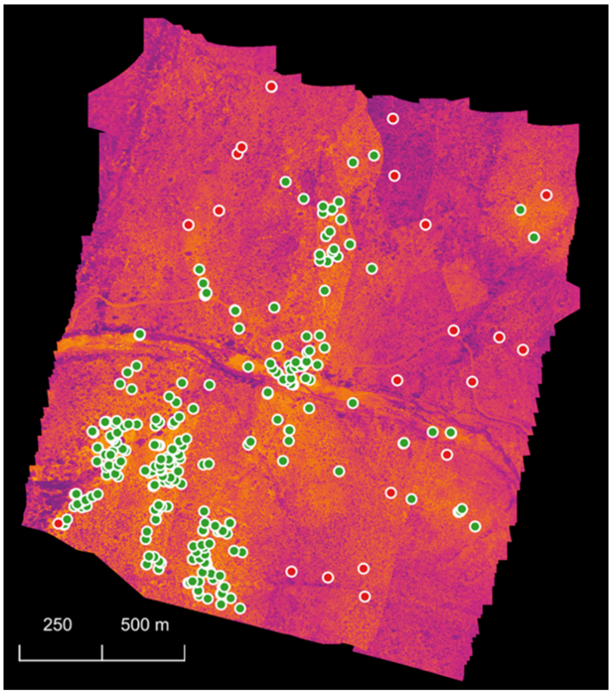

Figure 5. Thermal orthomosaic showing brightness variation among flight lines, the resulting candidate bias (green circles), and consequential identification of undetected middens (red circles) in the darkest regions of the imagery.

4. Challenges and Future Work

While the use of thresholding and morphological filters confirmed that we can, in an efficient manner, use thermal imagery to label rhino middens in savanna landscapes, our primary goal moving forward is increasing the accuracy and precision of candidate locations to ensure easier labeling over the additional orthomosaics currently on hand, and in anticipation of numerous planned UAV flights covering an estimated 500,000 hectares.

Our first priority is to address the artificial variation in brightness among flight lines in the thermal imagery. We are currently evaluating two options aimed at reducing candidate bias. First, we will run the same thresholding process described above, but on a new version of the orthomosaic that more consistently maps to temperature throughout. Brightness differences between individually rectified images could also be corrected with histogram matching or equalization, e.g., contrast limited adaptive histogram equalization. Ideally, this would allow pixel brightness to be evaluated at a more localized extent, which should decrease the number of undetected middens. After this, we will choose the optimal threshold using middens we have found from this analysis to evaluate the trade offs.

In addition to refining the thresholding process using the thermal data, we plan to further reduce the number of false positives detected by incorporating information from the RGB imagery as well as Lidar-derived products. For example, middens are generally a dark brown color and, although they vary in size, tend to have characteristic oblong or circular shapes. After the pixel coordinates identified in the thermal imagery are converted to GPS locations, we can loop through each coordinate in the RGB imagery and determine if the candidates have these midden characteristics. In addition, we may also be able to use Lidar-derived DTMs or DSMs to compare variation in elevation at candidate points, which will provide a means of differentiating middens from bare ground, termite mounds, or rocks. Together, these additional criteria will help better exclude false positive candidates.

Of critical importance to the manual verification process is the ground truthing of candidate GPS locations via field surveys. We currently do not have ground truth data with which to evaluate the accuracy of either the thresholding process or the manual assessment of midden presence, but we plan to collect these data at the next available opportunity. Although the ground truth data will be collected asynchronously with flight occurrence, we expect, based on knowledge of rhino life history traits and home range establishment, that the majority of middens will still be in use, and that those that are not will persist long enough to be detectable by ground survey.

Beyond refining our detection and assessment process, we also plan to expand our midden search both within and outside of Kruger at sites with known rhino presence. With additional sites, we expect to gain a clearer understanding of the landscape features influencing midden patterning, such as placement along animals paths and in proximity to key resources, which is suggested by the results observed here. In expanding our analysis, we also aim to build an image dataset that, in the future, can be used to train automatic detection algorithms, such as convolutional neural networks (CNNs), to improve our ability to identify rhino middens. Although we will likely be limited in the amount of training samples we can capture, fine-tuning has been successfully used on other small image datasets to accurately train a CNN and detect target objects in thermal data [3]. Moving toward automatic detection will further increase efficiency while reducing bias that has been documented in manual methods [7].

Although these complex challenges exist, we have shown that the use of simple thresholding and morphological filters is an effective first step towards the efficient and accurate detection of rhino middens from remotely sensed imagery. As we move forward to address these challenges, we are confident that our improved ability to map rhino middens across landscapes will both advance our understanding of rhino spatial behavior and support the management and conservation of these iconic endangered species.

5. Acknowledgments

We would like to thank Andrew Davies and the team at Kruger National Park for all of the support and guidance.

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