Idaho State University

Prairie Dog Burrow Detection Using sUAS Imagery and Deep Learning Tools

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1. Introduction

1.1 Remotely Sensed Imagery for Burrow Detection

The range of burrowing rodents, such as marmots and marmots, is generally quite large, making field surveys time consuming and costly. Satellite imagery has been reliably used for mapping marmot burrows (Koshkina et al., 2019) and prairie dog burrows (Sidle et al., 2002). In addition to the use of satellite imagery, imagery from small uncrewed aerial systems (sUAS) have been used to detect prairie dog burrows (Kearney et al., 2023) and estimating Texas kangaroo rat burrow counts (Stuhler et al., 2024).

Colorado Parks & Wildlife (2020) visually analyzes National Agriculture Imagery Program images to identify colonies and uses aerial and ground truthing. Shiels et al. (2022) obtained imagery and video using a copter drone and visually counted burrows. Sidle et al. (2002) used high-resolution panchromatic satellite imagery to identify colonies. Kearney et al. (2023) used multispectral sUAS imagery and deep learning to detect burrows and is the basis for the methods used in this study. Specifically, they used imagery with red, green, and blue bands, as well as topographic position index (TPI), and normalized difference vegetation index (NDVI) to train a convolutional neural network (CNN) with an F1 score of 0.84 to 0.87. TPI was calculated using the digital surface model generated from the imagery, and NDVI was calculated using the near infrared and red bands.

1.2 Objectives

Prairie dogs are ecosystem engineers, digging burrows that are often used by other species, such as mountain plovers and burrowing owls (Knowles et al., 2002), as well as amphibians and reptiles (Kearney et al., 2023). They are also the primary food source of black-footed ferrets, an endangered species that is being reintroduced to various sites in the West (Dierenfeld et al., 2021). Prairie dog burrow counts are used to estimate the prairie dog population. The success of black-footed ferret reintroductions is dependent on healthy prairie dog populations, which is why it is important to effectively monitor their populations.

The purpose of this study was to investigate the use of deep learning tools to detect prairie dog burrows from derived UAS products. Objectives for this study include:

- Evaluate the effectiveness of the Faster-RCNN object detection architecture for prairie dog burrow detection using previously identified burrow openings as a starting point for training data
- Identify previously unidentified prairie dog burrows using the Faster-RCNN object detection model

1.3 Study Area

The study area for this analysis is located on the western edge of the Fort Belknap Reservation in the northern part of central Montana (Figure 1). It is part of the North American Great Plains region. This is a perfect habitat for prairie dogs, which is the primary prey of the black-footed ferret population that were reintroduced to Fort Belknap Reservation from 1997 to 1999. However, in 1999, a sylvatic plague outbreak devastated both the prairie dog and black-footed ferret populations (Delparte et al., 2019). From 2013-2015, more black-footed ferrets were reintroduced to Fort Belknap, and tools for plague management were put into place (*Returning Black-footed Ferrets to the Wilds of the Northern Great Plains | Magazine Articles | WWF*, n.d.).

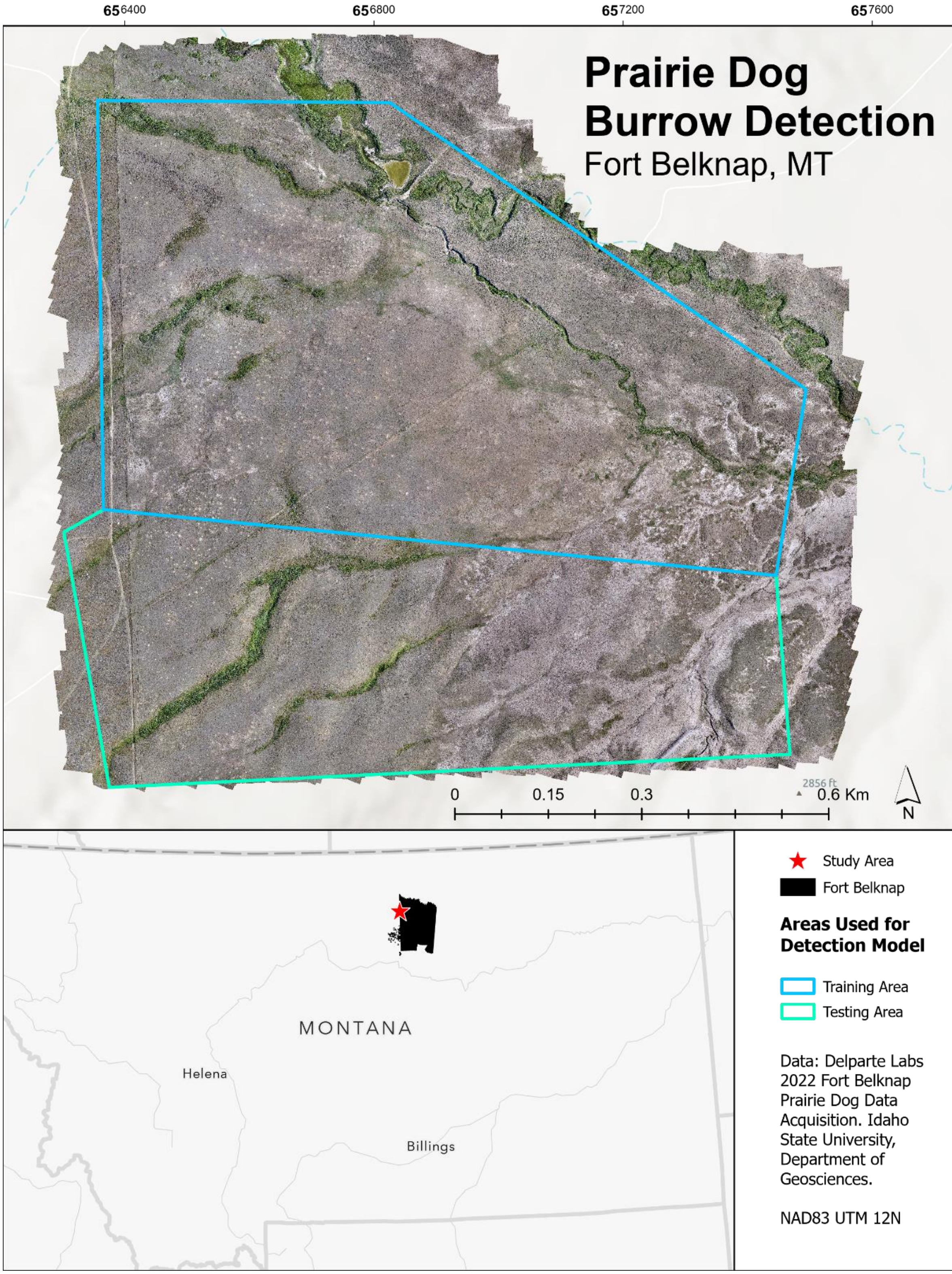

Figure 1 - Map of the study area, which is in the Fort Belknap Reservation in Montana. The map also shows the areas selected for training and testing the model.

2. Data and Methods

2.1 Data

The imagery used in the analysis was acquired at the request of the World Wildlife Fund and the Fort Belknap Indian Community using a Trinity drone. The purpose of these data was to estimate the population of prairie dogs in support of the black footed ferret reintroduction on the Fort Belknap tribal lands. The drone collected images with red, green, and blue bands. From the images, an orthomosaic and a digital elevation model (DEM) were produced with resolutions of 1.85 centimeters and 3.7 centimeters, respectively.

Prairie dog burrow locations were detected using the DEM. First, the voids in the DEM were filled. Then the original DEM was subtracted from the filled DEM, and a height classification was used to identify potential burrow locations. These locations were manually cleaned to remove locations that were not burrows, and the results were output as a point feature class. All data were in NAD 1983 UTM Zone 12N.

2.2 Methods

ArcGIS Pro was used for all analyses. A tool to generate the TPI raster using the DEM was created using Model Builder (Figure 2) based on a workflow from a case study (*Aloha! A GIS vacation—Analytics | Documentation*, n.d.). A circle neighborhood with a radius of three cells was used to calculate the mean using Focal Statistics. The mean was then subtracted from the cell value to calculate the TPI for that cell. The TPI raster was then resampled to the same cell size as the orthomosaic and coregistered with the orthomosaic. Lastly, the red, green, and blue bands from the orthomosaic and the TPI band were stacked.

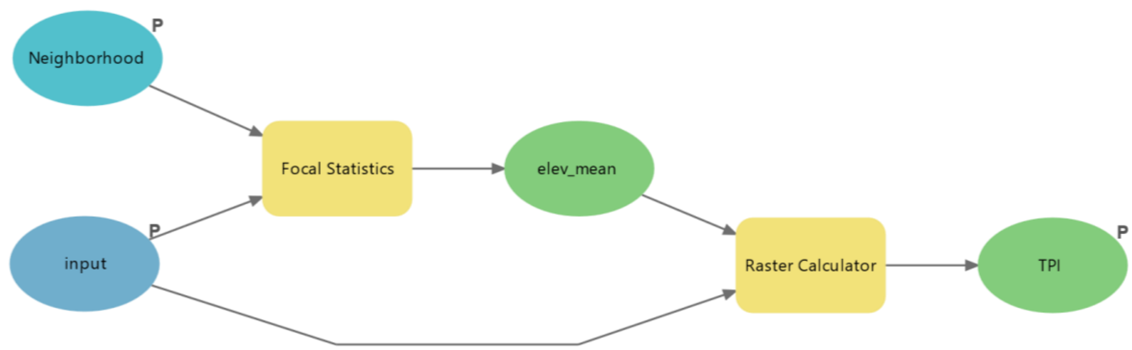

Figure 2 - ArcGIS Pro Model Builder for calculating Topographic Position Index.

Two subsets of the stacked raster were created, one for training the model, and one for testing the model (Figure 3). This resulted in 6,234 out of 8,311 burrow points for training the model. Prairie dog burrow openings have different characteristics, such as a large mound surrounding the opening, a small mound surrounding the opening, excavated soil to the side of the opening, or simply a hole in the ground. A 0.5-meter buffer was created around each point to use as the training data for the model because it captured many of the burrow opening unique features; however, this resulted in many overlapping features with varying degrees of overlap (Figure 3).

The training data was exported with a tile size of 192 pixels by 192 pixels using a stride of 96 pixel, and the data was augmented using a 90-degree rotation. Only tiles containing features were used, and at least 60% of a feature had to be in the tile. The resulting training data was used to train a Faster-RCNN model for 20 epochs, and the loss graph can be seen in Figure 4.

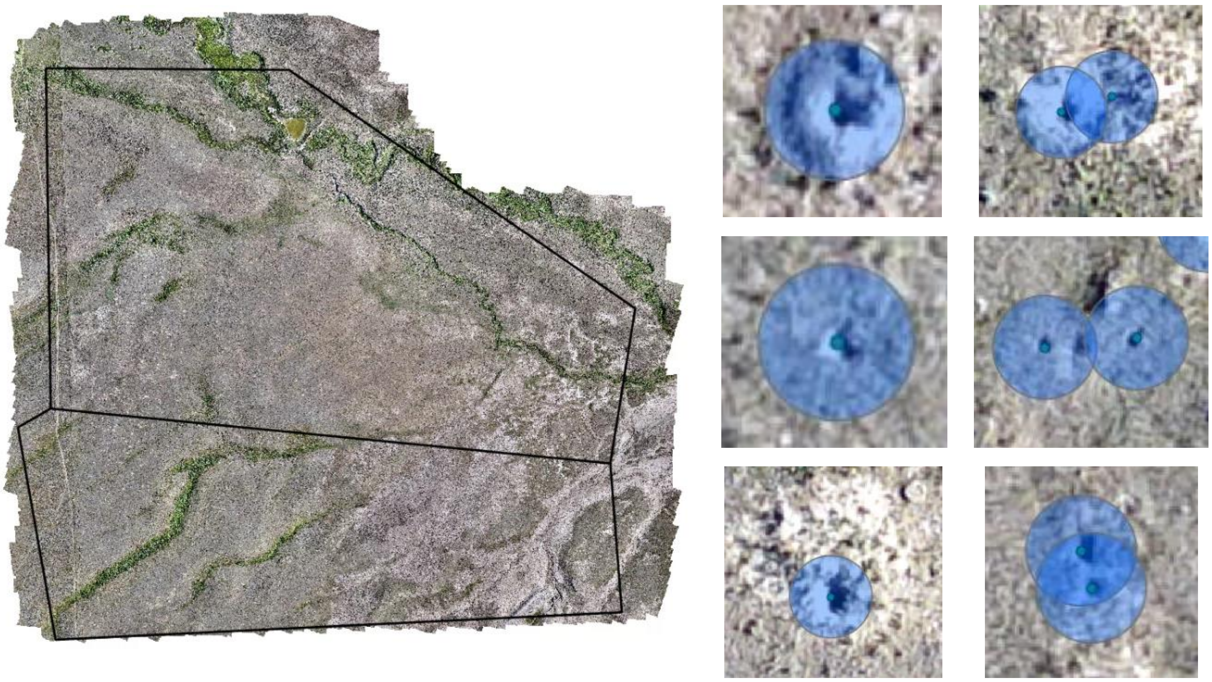

Figure 3 - Left: Orthomosaic with training area polygon (top) and testing area polygon (bottom). Middle: Prairie dog burrow openings with different characteristics with 0.5-meter buffer training features. Right: Overlapping training features.

The trained model was then used to detect prairie dog burrows in the testing subset of the stacked raster. A confidence threshold of 50 percent was set, and non-maximum suppression was set to remove duplicate objects (maximum overlap ratio of 20 percent), keeping the object with the higher confidence.

To determine the precision of the model, the Summarize Within geoprocessing tool was used to count the number of burrow points (further referred to as "points") inside each detection polygon (further referred to as "polygon(s)"). The polygons containing burrow points were marked as true positives and the remaining polygons were marked as false positives. Next, the points that did not intersect with polygons were marked as burrows that were not detected. Some points were not directly on burrow openings, and some burrow openings/points, were very close together. Since the model was set to remove duplicated objects, with more than 20-percent overlap, some of the points marked as not detected might have been detected by the model, but the duplicate object was removed. Points within 0.5 meters of a polygon were evaluated to determine if they were true positives. Then polygons within 0.5 meters of detected points that were previously marked as not detected were evaluated. Model precision was calculated with the following equation:

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

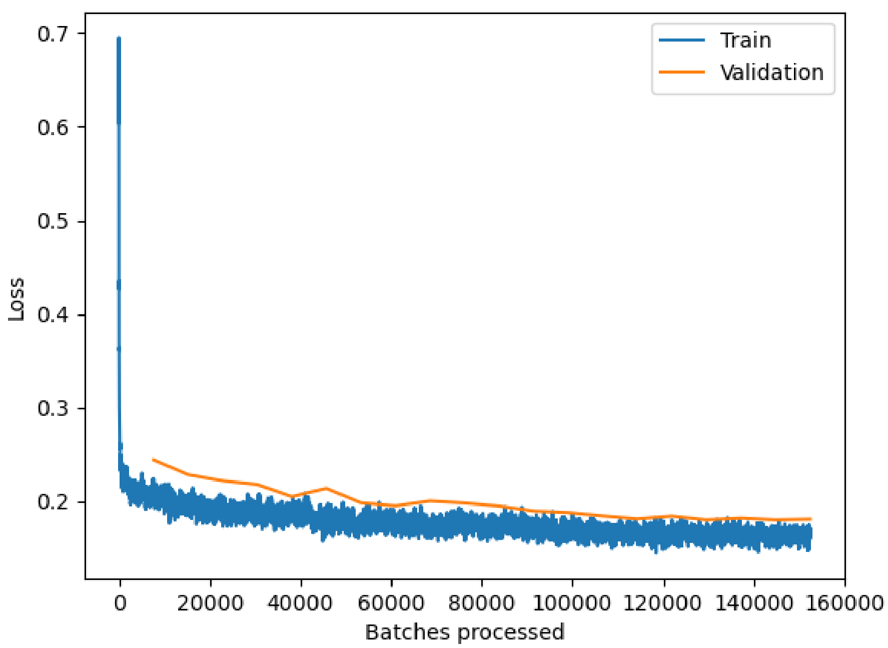

Figure 4 - Loss graph for the Faster-RCNN model training.

A series of steps were performed to isolate false positive polygons to possibly identify prairie dog burrows that were not previously identified in the training data. However, the identification of new burrow locations was limited to the testing area. Since burrows openings are clustered together, polygons not near identified openings were likely not true positives. The Average

Nearest Neighbor geoprocessing tool was used on the points to determine the mean distance between neighboring points, which was approximately 5.11 meters. Polygons within 5.5 meters of a point were selected for potential evaluation.

The TPI value of many identified burrow openings was about -0.02 or less. Pixels with a value of -0.02 or less were extracted from the TPI raster and converted to polygons. Detection polygons containing TPI polygons with a confidence of 75 percent or greater were selected for evaluation. This resulted in 392 polygons to evaluate. The polygons were evaluated using the true color image, TPI, and the hillshade of the DEM. Each polygon was marked as a shadow, low-confidence burrow, or med-to-high confidence burrow.

3. Results and Discussion

The model detected 17,389 burrows, and 2,054 burrows were previously identified in the training area. There were 1,840 polygons marked as true positives based on the polygon containing a point. Additionally, 1 polygon contained 3 points, and 25 polygons contained 2 points. There were 189 points that did not fall within a polygon. Two points were marked as misidentified burrows, 3 points were marked as unsure and 32 were marked as possible detections due to inaccurate point location or possibility of an overlapping polygon that was removed during detection. Also, 5 polygons were changed from false positives to true positives due to inaccurate point locations. Examples of these can be seen in Figure 5. This left 152 burrows undetected and 15,544 false positive burrow detections. The precision of the model is approximately 10.1 percent.

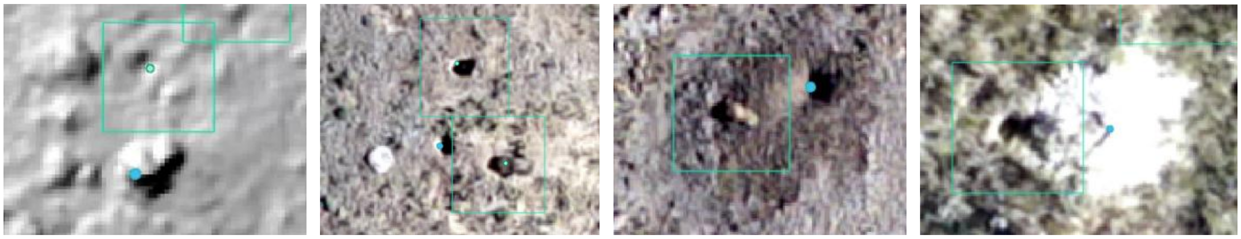

Figure 5 - Left: Hillshade of DEM with misidentified burrow (blue point). Middle Left: Burrow that could have been potentially identified by the model but was removed because it was an overlapping feature. Middle Right: Burrow that was not detected by the model and a false positive burrow detection. Right: Inaccurate burrow point location.

Of the 392 polygons that were evaluated to identify burrows that were not previously identified as training points, 23 were marked as low-confidence burrows, 84 were marked as medium-to-high confidence burrows, and 285 were marked as shadows (Figure 6).

If only medium-to-high confidence burrows were considered, an additional 0.23% of burrows were identified in relation to the original number of burrows identified in the training data. Before narrowing down the number of false positives to evaluate by selecting only those with a confidence of 75 percent or greater, there were 907 polygons. Of the true positives, only 258 had a confidence of less than 75 percent; therefore, it is unlikely that the 515 with a lower confidence would have yielded additional potential burrows. Additionally, if the threshold confidence for the burrow detection had been 75 percent, that would have resulted in 9,798 fewer false positive polygons. Using the higher confidence threshold, the precision of the model would have increased to 21.6 percent, but the number of undetected burrows would have increased to 410.

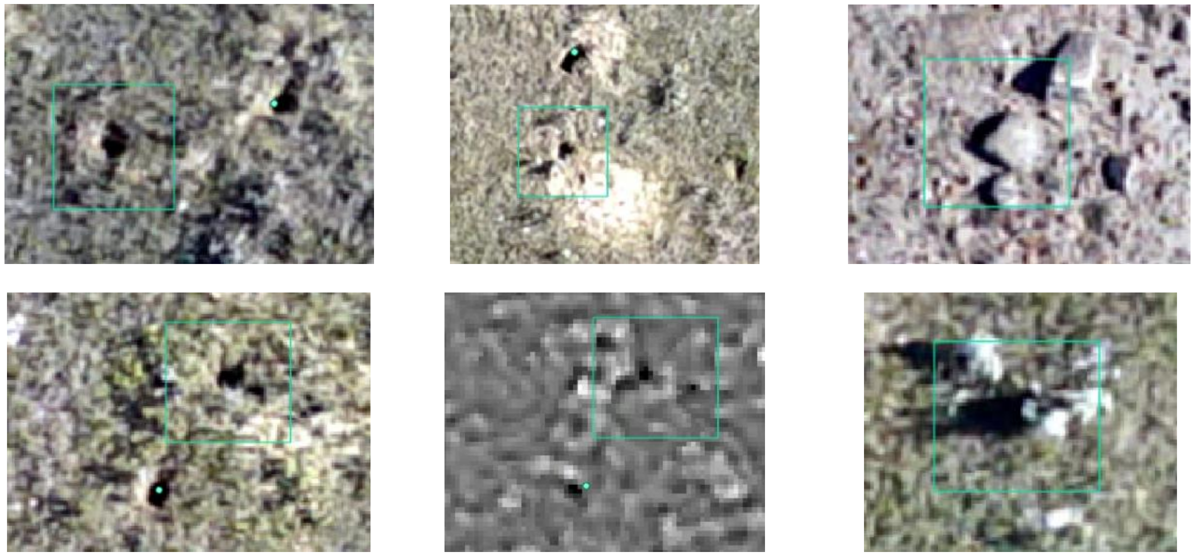

Figure 6 - Top Left & Middle: Potential previously unidentified burrows. Top & Bottom Right: Shadows from a rock and a bush identified as false positives. Bottom Left & Middle: RGB and TPI of potential previously unidentified burrow.

4. Conclusion

The Faster-RCNN object detection architecture has the potential to be a useful tool for detecting prairie dog burrows; however, modification of model inputs is necessary to create a more accurate model. Rather than using a 0.5-meter buffer around the burrow points, training samples could be manually generated to capture only the unique features of the burrows. Not only would this more narrowly define the burrow itself, but it would provide more information on non-burrow areas for the same tile size. Additionally, in situ collection of burrow locations would provide more accurate training data for the model. The training data used for this study did not differentiate between active and inactive burrows. As a result, regardless of the model's accuracy, detected burrows would not necessarily be a good representation of active burrows. To accurately estimate prairie dog populations, the model would need to be trained to detect only active burrows. While it might be possible to differentiate between active and inactive burrows from the sUAS imagery, in situ training data collection would provide more accurate differentiation.

Adding NDVI to the raster stack could also improve the model, since it appears there are not any burrow openings in areas with dense, green vegetation. Although a 90-degree rotation of training samples was used for image augmentation, additional image augmentation could be utilized, such as random rotation, center crop, and Gaussian blur. This would generate even more training data for the model. Experimenting with different learning rates could also improve the model’s accuracy. Instead of using the Faster-RCNN object detection architecture, a different CNN architecture could be used. Also, different deep learning architectures could be experimented with, such as YOLO.

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