Validating a Remote Sensing / Machine Learning Framework for Wildlife Monitoring

Background

Observers frequently make substantial errors (40% – 150%[1]) in estimating the size of large groups of animals– not through inexperience, but due to bias in human perception. Counting animals from aerial imagery is more precise[2], but time consuming. Automating counts through machine learning can make aerial imaging for wildlife population surveys more feasible[3]. However, we need to understand where and how bias enters this new survey workflow so that decisionmakers can make informed choices.

Remote Sensing / Machine Learning Wildlife Survey Workflow

Wildlife Management Decision

Aerial imaging surveys

We worked with the US Fish and Wildlife Service to conduct drone surveys at Bosque del Apache National Wildlife Refuge

Image annotation

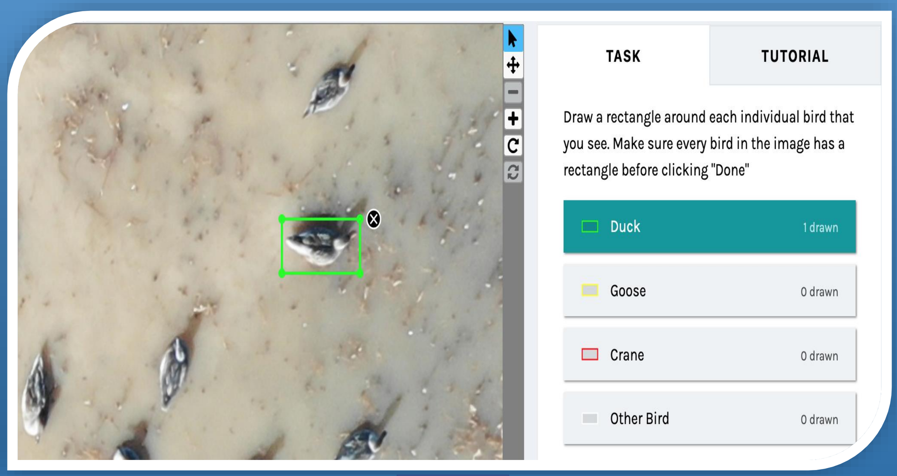
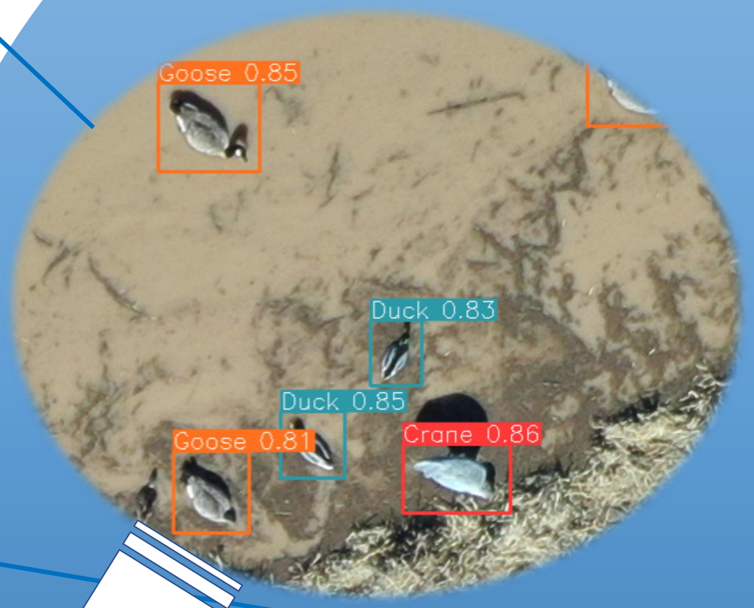


Image annotations were crowdsourced using Zooniverse, a web platform for citizen science

Convolutional neural network training

A YOLOv5 deep learning architecture was used for object detection and classification

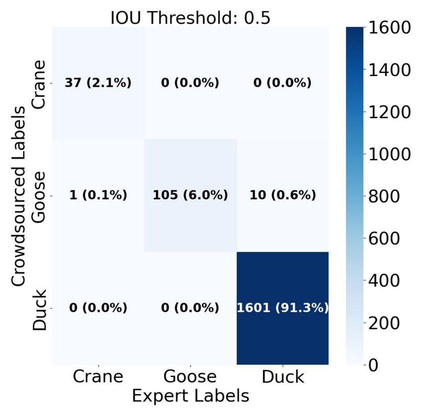


Machine detections & classifications → population data

1 Observer Bias in Image Annotations

Method: Measure agreement among experts and volunteers counting and identifying wildlife from aerial imagery, quantify image characteristics and assess impacts on observer agreement

Result: One expert or a group of ~5 volunteers can reliably identify broad types of birds from aerial imagery. Neither group could reliably identify species of ducks.



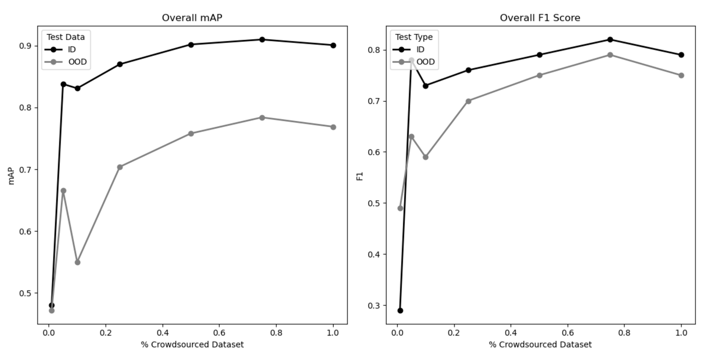
Confusion matrix comparing expert agreement to crowdsourced agreement. Between the two groups, total bird counts matched 91%, annotation locations matched 81%, and where location matched, identification nearly always matched (99.4%)

Recommendation: Tile imagery to reduce observer fatigue, use constant scale to avoid size confusion

2 Bias in Model Learning

Method: Perturb training dataset size, composition, and quality to determine which characteristics of the dataset are most important to model learning to inform field collection and annotation strategies.

Result: A small but diverse sample of images provided the best accuracy per effort ratio



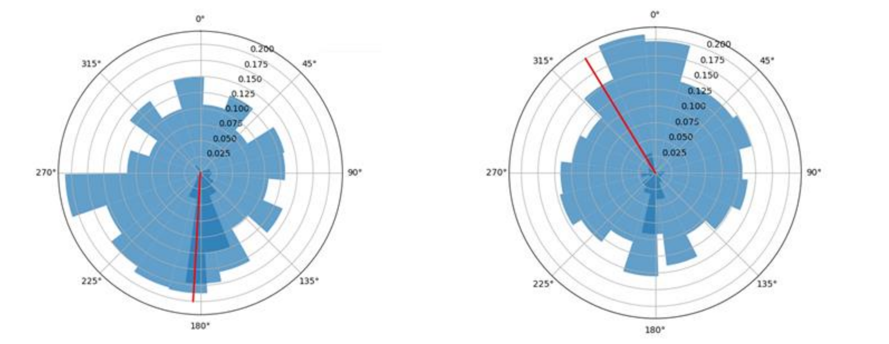
We found a threshold at ~5,000 image annotations / 70 original images, after which model learning slowed. Redundant examples seemed to harm model learning for some time, particularly against novel data.
ID = in domain test data (images and annotations from the same dataset held independently during training and validation),
OOD = out of domain test data (new sensor, new sites, different year)

Recommendation: Select few (<100) but diverse aerial images; annotate random tiles

3 Platform Bias in Aerial Surveys

Method: Measure differences in counts and positions of animals between spatially overlapping image captures to assess whether the imaging platform biases population counts

Result: Different drone platforms appear to provoke movement responses from some types of birds, though count differences were not significant



Duck movement vectors, normalized to drone flight direction, during (a) DJI Mavic surveys, and (b) Wingtra One Gen II surveys. Ducks seemed to move in opposite directions in response to the different platforms.

Recommendation: Fixed wing drones seemed to disturb birds less than copter style drones

Summary: We have developed a rigorous framework for assessing bias throughout the workflow as well as a set of best practices for field data collection and image annotation that can be used by practitioners surveying a variety of wildlife species

References
.[1] Davis, K.L., Silverman, E.D., Sussman, A.L., Wilson, R.R. and Zipkin, E.F. 2022. Errors in aerial survey count data: Identifying pitfalls and solutions. Ecology and Evolution. 12, 3 (2022), e8733.
[2] Hodgson, J.C., Mott, R., Baylis, S.M., Pham, T.T., Wotherspoon, S., Kilpatrick, A.D., Raja Segaran, R., Reid, I., Terauds, A. and Koh, L.P. 2018. Drones count wildlife more accurately and precisely than humans. Methods in Ecology and Evolution. 9, 5 (2018), 1160–1167
[3] Converse, R.L., Lippitt, C.D., Koneff, M.D., White, T.P., Weinstein, B.G., Gibbons, R., Stewart, D.R., Fleishman, A.B., Butler, M.J., Sesnie, S.E. and Harris, G.M. 2024. Remote sensing and machine learning to improve aerial wildlife population surveys. Frontiers in Conservation Science. 5, (Jun. 2024).

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