Sea Duck Joint Venture
Annual Project Summary
FY2021 (October 1, 2020 – September 30, 2021)

Summaries should not exceed 2-3 pages, if possible; photos or illustrations are encouraged. Project summaries will be posted on the SDJV website (seaduckjv.org). Please submit the completed report in MS Word format to kate_martin@fws.gov.

Project Title *(including SDJV Project #)*: SDJV Project # 157: Automated Sea Duck Counts from Aerial Photographs

Principal Investigators *(name, affiliation, email address)*: Mikey Tabak, Western EcoSystems Technology, mtabak@west-ulc.ca

Partners *(anyone else providing support)*:

Project Description *(issue being addressed, location, general methodology):* We are using deep learning computer vision methods to automatically detect, identify, and count sea ducks in aerial images.

Project Objectives:

1) Identify and annotate (or 'paint') sea ducks in aerial images that were provided by SDJV.
2) Train computer vision models, including those using computer vision, to automatically detect, identify, and count sea ducks in aerial images.
3) Create an end product of an R package that will deploy the computer vision system, as well as a Shiny Application (a user-friendly HTML-based interface) to easily deploy the system.

Preliminary Results *(include maps, photos, figures/tables as appropriate):*

We have successfully annotated all images provided by SDJV. I have used these images and their annotations to train and evaluate several types of deep learning computer vision models. I have used different model conditions (i.e., models to recognize birds, models to recognize sea ducks vs other types of birds, and models to recognize sea duck species), to train several different model architectures. Model architectures that were most effective at detecting sea ducks were YOLO v.5 (You Only Look Once; Redmon et al., 2016), SSD (Single Shot Detector; Liu et al., 2016), and Faster R-CNN (with a ResNet backbone; Ren et al., 2016).

I used a subset of the data (approximately 200 annotated images) to train and evaluate models and find the best architecture to perform the task, and determined that Faster R-CNN is most effective at detecting birds in these aerial images. Figure 1 shows an example of an image classified by an SSD model. In this figure, the original image was broken into tiles while the original resolution was maintained. The model recognizes all of the sea sucks in the image that were found by our ornithologist experts.

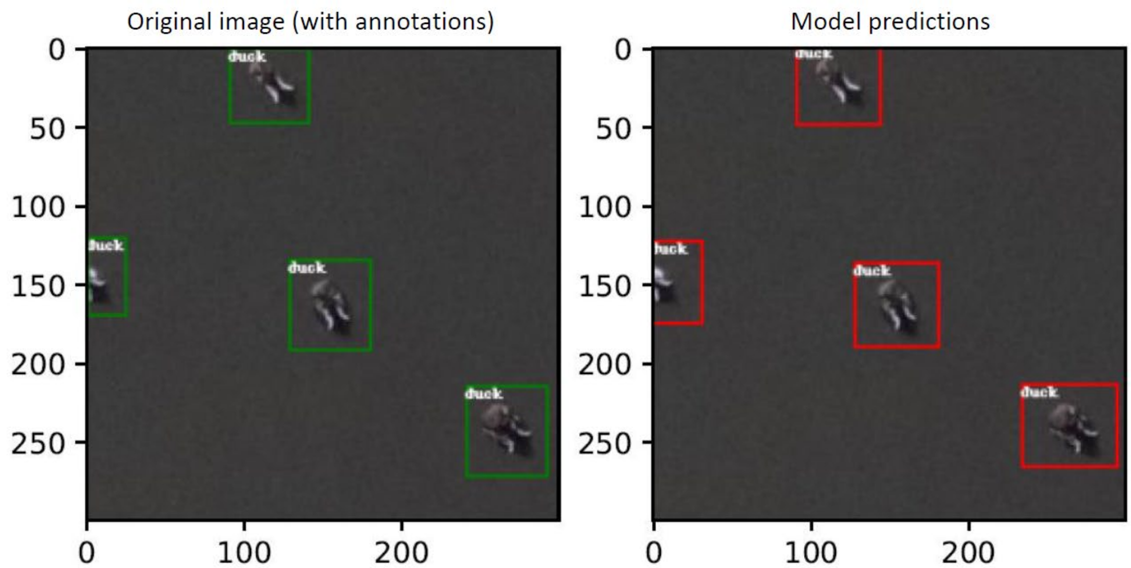

Figure 1: Example model output from an SSD model

The Faster R-CNN architecture does not require that images be tiled before deploying the model. This saves time in deployment and avoids edge effects (birds that are overlapping the edges of tiles might get counted in each of the tiles in which they appear, thus inflating the estimated number of birds). Figure 2 shows model predictions from a Faster R-CNN model. There are > 3,500 boxes in this image, and each represents a bird that was classified by the model. Each of these classifications are correct, although it is difficult for the reader to see at the resolution provided in this report.

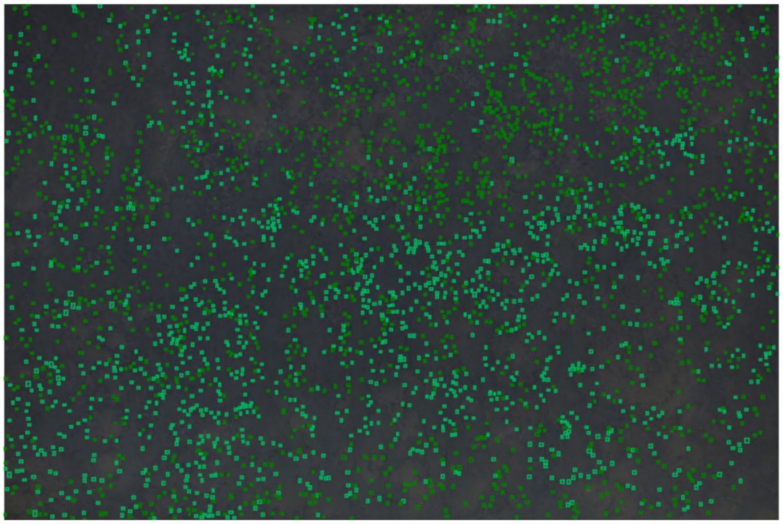

Figure 2: Example model output from a Faster R-CNN model.

Project Status *(e.g., did you accomplish objectives, encounter any obstacles, what are your future plans):*

Objective 1 is complete, we have annotated all of the 814 images provided by SDJV. This process has been challenging because the images are often blurry, as they were taken from high above the birds in a moving aircraft. Nevertheless, our ornithologist was able to identify each bird in each of the images. While most birds are identified to the species level (and sometimes to the sex/age class within species), some are identified to the family level instead.

Objective 2 is ongoing. We have experimented with several types of computer vision models and we have settled on an architecture going forward. We will be using Faster R-CNN as the architecture going forward, and we will provide multiple models, including one that counts all birds in the image, one that counts sea ducks and non-sea duck birds, and one that identifies sea ducks more specifically (to species, age class, and sex).

Objective 3 is ongoing. We have developed several R functions (and performed tests) that will be included in the R package. We will continue development of these functions, wrap them into a package and create R Shiny Applications to facilitate use of the package.

Project Funding Sources (US$). Complete only if funded by SDJV in FY21. This is used to document: 1) how SDJV-appropriated funds are matched, and 2) how much partner resources are going into sea duck work. You may include approximate dollar value of in-kind contributions in costs. Add rows as needed for additional partners.

SDJV (USFWS) Contribution	Other U.S. federal contributions	U.S. non-federal contributions	Canadian federal contributions	Canadian non-federal contributions	Source of funding (name of agency or organization)
$49,600					

Total Expenditures by Category (SDJV plus all partner contributions; US$). Complete only if project was funded by SDJV in FY21; total dollar amounts should match those in previous table.

ACTIVITY	BREEDING	MOLTING	MIGRATION	WINTERING	TOTAL
Banding (include only if this was a major element of study)					
Surveys (include only if this was a major element of study)					
Research	**$49,600**				**$49,600**

References

Liu, W., Anguelov, D., Erhan, D., Szegedy, C., Reed, S., Fu, C.-Y., Berg, A.C., 2016. SSD: Single Shot MultiBox Detector. ArXiv151202325 Cs 9905, 21–37. https://doi.org/10.1007/978-3-319-46448-0_2

Redmon, J., Divvala, S., Girshick, R., Farhadi, A., 2016. You Only Look Once: Unified, Real-Time Object Detection. ArXiv150602640 Cs.

Ren, S., He, K., Girshick, R., Sun, J., 2016. Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks. ArXiv150601497 Cs.