MONITORING OF REINTRODUCED RARE PLANTS USING UAV DATA

L.A. Gorodetskaya[1], A.Y. Denisova[1,3*], L.M. Kavelenova[1], A.V. Pomogaybin[2], I.V. Ruzaeva[2], V.A. Fedoseev[1,3]

[1] Samara National Research University, Samara, Russia - denisova_ay@geosamara.ru
[2] Botanical Garden of Samara University, Samara, Russia - botaniksad@yandex.ru
[3] IPSI RAS - Branch of the FSRC "Crystallography and Photonics" RAS, Samara, Russia - vicanfed@gmail.com

KEY WORDS: Reintroduction, Natural Areas of Special Value, Biodiversity, UAV Data, Neural Networks, YOLOv3.

ABSTRACT:

Species reintroduction is one of the most important tasks for biodiversity conservation. In the Samara region, the Department of Ecology, Botany, and Nature Protection of Samara University is constantly working to return rare plants to their natural habitat. Field surveys are carried out to monitor the process of plant development in the natural environment. However, the complex terrain and the special conservation status of the territories, where reintroduction is carried out, require the development of methods for monitoring plants that reduce human contact with the natural environment. As such a method, the article proposes using data from unmanned aerial vehicles (UAVs) in conjunction with the detection of reintroduced plant species using object detection neural networks, namely YOLOv3. The proposed method reduces the anthropogenic impact on the territory during the monitoring process and simplifies plant observations.

1. INTRODUCTION

Due to anthropogenic impact, the number of plant species facing extinction is constantly growing. To protect rare plants and preserve biodiversity, ecologists worldwide are engaged in species reintroduction. This process involves artificially grown plants being moved into their natural habitat (Malone et al., 2018).

In the Samara region, the Botanical Garden and the Department of Ecology, Botany, and Nature Protection of Samara National Research University (Samara University) have been working on species reintroduction for over 10 years. One of the plants reintroduced through their efforts is Paeonia Tenuifolia, which is included in the Russian Federation Red Book and classified as a decreasing population in the UCN Red List (Bilz, 2011). Ecologists cultivated Paeonia Tenuifolia in the Botanical Garden and relocated it to a protected area near the village of Chubovka in the Samara region.

The process of reintroduction requires constant monitoring of the health and population of reallocated plants. Ecologists conduct field surveys to obtain up-to-date information about the characteristics of the plant population. Traditionally, these surveys involve manual plant counting through ground surveys. However, conducting ground surveys over large territories with complex relief demands a significant amount of human labor and time. To minimize them and reduce the anthropogenic impact of surveys, remote sensing tools can be employed for species monitoring.

Existing research on species monitoring using remote sensing data primarily focuses on unmanned aerial vehicle (UAV) data for direct detection and sampling of species due to their high resolution (Randin et al., 2020). The monitoring methods include data collection from various sensors mounted on a UAV platform, manual mapping of species of interest, and the application of machine learning algorithms.

Cao et al. classified mangrove species using a fusion of hyperspectral images, light detection, and LiDAR data obtained from UAV-based sensors and the rotation forest (RoF) ensemble learning algorithm (Cao et al., 2021). Belcore et al. detected tree species using multi-spectral and multi-temporal UAV data and a random forest algorithm (Belcore et al., 2021). Alvarez-Taboada et al. applied the nearest neighbour algorithm to recognize Hakea sericea in UAV and World View-2 satellite images (Alvarez-Taboada et al., 2017). Both Belcore et al. and Alvarez-Taboada et al. considered complex sets of features, including vegetation indices, different spectral bands, and texture features. Li et al. exploited a support vector machine algorithm for classification in the wetland area (Li et al., 2017). They are concerned with UAV-based hyperspectral images and digital surface models (DSM) derived from photogrammetric point clouds as source data. Thus, it is evident that species mapping and quantification were primarily conducted using classical machine learning algorithms with multi-sensor UAV data.

In recent times, the success of neural networks has led to their widespread use in ecological monitoring as well. In Fan et al., 2018) Fan et al. used deep neural networks for tobacco plat classification using UAV data. The review (de Castro et al., 2021) mentioned some algorithms based on Mask R-CNN for potato and lettuce mapping, as well as ResNet50 CNN with the SegNet semantic segmentation architecture for mapping raised bog vegetation communities. In both cases, deep learning-based methods outperformed classical machine learning methods. (Kattenborn et al., 2019) developed a method for fine-grained mapping of vegetation species and communities using a U-net network. They achieved 84% accuracy in semantic segmentation. However, the current research focuses primarily on the segmentation problem, neglecting the detection and counting of individual plants in the image.

Our aim is to develop a method for counting Paeonia Tenuifolia plants using an object detection neural network and UAV data. The main goal of this method is to simplify the collection of plant population statistics and reduce the need for manual labor and anthropogenic impact during monitoring. The proposed method was tested using UAV images obtained by scientists from the Botanical Garden, the Department of Ecology, Botany, and Nature Protection, and the Department of Information Security and Geoinformation Science at Samara University. In our research, we analyzed the following questions: 1) whether the network can be trained using images of plants grown artificially instead of gathering training data in a natural environment, 2) what are the best augmentation methods, and 3) what is the optimal number of epochs.

The paper is structured as follows: Section 2 describes the proposed method and UAV data processing. Section 3 presents the main research results. Finally, the conclusion and acknowledgments are provided.

2. PROPOSED METHOD

2.1 General method pipeline

The proposed method for monitoring Paeonia Tenuifolia includes four steps:

Step 1. Capturing UAV images of Paeonia Tenuifolia in an artificial environment within the Botanical Garden during the flowering period.

Step 2. Collecting UAV data of reintroduced plants in the natural environment during the flowering period.

Step 3. Training the object detection neural network using the images obtained in the Botanical Garden, employing a transfer learning approach.

Step 4. Classifying the images acquired in the natural environment and computing the quantity of the target plants.

The first step involves collecting training data. We propose using artificially grown plants as reference samples for training the neural network. The Botanical Garden offers a more accessible and abundant territory compared to the plants' natural habitat, making the data collection process simpler, more cost-effective, and convenient. The data can be collected once and used for several years. An important aspect of the data collection process is the shooting time. It is crucial to gather the data during the flowering period when the plants are most distinguishable from their surroundings.

The second step involves conducting a field survey to collect test data. The field survey focuses solely on UAV data capture without any additional movements of personnel and equipment. This approach is sufficient because the reintroduced plants' natural habitat is a conservation area, and UAV monitoring ensures the safest possible data collection process. Another advantage of UAV data collection is the reduction in human labor, as the natural habitat of Paeonia Tenuifolia features complex terrain that makes manual monitoring more challenging compared to automated methods.

During the data collection process, it is important to set the camera and flight parameters as closely as possible to the training data collection process. This includes capturing the data during the flowering season, at a similar height above the ground, and approximately the same time of day. However, it should be noted that these guidelines do not guarantee a high degree of similarity between the test and training data due to the following reasons: 1) differences in species composition between the natural habitat and the Garden, 2) variations in weather and lighting conditions, and 3) discrepancies in soil and terrain characteristics. Consequently, the process of plant detection using only images captured in the Garden for training becomes more complex.

In this study, we propose using a transfer learning approach in Step 3 for training the neural network. The rationale behind this choice is that the artificial habitat used for training the plants is relatively small, limiting the opportunity to collect a large amount of training data. Transfer learning allows us to leverage the pre-trained weights of another neural network, thereby benefiting from the knowledge and capabilities of the parent network. Additionally, the transfer learning approach simplifies the training process as it requires fewer epochs to train the network.

The training process involves specific preparation of training data and the selection of appropriate hyperparameters. In our paper, we explore various methods of data augmentation and consider the number of epochs. Data augmentation allows for an artificial expansion of the training set and enhances network generalization. On the other hand, selecting the appropriate number of epochs determines the optimal duration for the training process.

In the final fourth step, the images obtained in the natural environment are classified using the selected neural network, and the number of plants in each UAV image is computed. To evaluate the quality of the network, we manually labeled the images and calculated the percentage of accurately detected flowers (true positive rate, TPR) and falsely detected flowers (false positive rate, FPR) of Paeonia Tenuifolia in each test image.

$$TPR = \frac{N_1}{N}, FPR = \frac{N_2}{N}, \quad (1)$$

where N_1 is the number of correctly detected peony flowers,
N_2 is the number of incorrectly detected peony flowers,
N is the total number of peony flowers in the image.

2.2 Study Area

The Botanical Garden (53°12′52.25″N, 50°10′18.6″E) served as the source of training data and is located near Samara University in the territory of Samara city, Russia. The Garden was established in 1932 and has been designated as a nature conservation area since 1995. It serves both scientific and public purposes, cultivating more than 4500 plant species, including Paeonia Tenuifolia, within its territory.

The natural habitat of the reintroduced peony plants is located near the village of Chubovka, in the Kinelsky district of the Samara region, Russia. In 1983, this territory was designated as a protected area of regional significance called "Chubovskaya steppe". The territory consists of a grassy meadow steppe, housing rare and endangered species of steppe flora. The test site encompasses a section of a watershed slope with a height difference of up to 10-15 meters. In recent years, ecologists from the Department of Ecology, Botany, and Nature Protection have transplanted some peony flowers into the test site. Currently, they are monitoring the growth of the peony population. The UAV image fragments of Paeonia Tenuifolia for both sites are shown in Fig. 1-2.

Figure 1. Paeonia Tenuifolia in Botanical Garden.

Figure 2. Paeonia Tenuifolia in natural habitat.

2.3 Flight Campaign and Fieldwork

We conducted two flight campaigns in sunny and windless weather, covering an area of approximately 8000 and 6200 square meters in the natural habitat and the Botanical Garden, respectively. For these campaigns, we utilized an unmanned aerial vehicle, specifically DJI Phantom 4 PRO v2 (Bârliba et al., 2020), equipped with an RGB camera.

The first flight campaign took place on May 18th, 2022, in the Botanical Garden. The flight altitude was set at 10 meters above the ground. Adjacent frames were captured with an 80% intersection in both the longitudinal and transverse directions relative to the flight path, resulting in an equivalent spatial resolution of 0.01 meters.

The second flight campaign was conducted on May 23rd, 2022, covering four different parcels of the natural habitat ranging in size from 2000 to 8000 square meters. During this campaign, the UAV flew at an altitude of 10 meters above the highest point of the slope. The spatial resolution at the highest point of the slope was 0.01 meters.

2.4 UAV Data Processing

The UAV data processing involved the preparation of orthophotos. We utilized Drone Deploy software (https://www.dronedeploy.com/) for generating the orthophotos. As a result, we obtained two training images for the parcels in the Botanical Garden, with dimensions of 4608×4096 and 6912×6400, respectively. Additionally, we acquired four test images for the parcels in the natural habitat. The characteristics of the test images are provided in Table 1.

To prepare the input for the neural network, each image was divided into regions of equal size. For generating the training set, we used the Botanical Garden image fragments of various sizes: 230×205, 345×320, 461×410, and 691×640. Fragments that did not contain peonies were excluded from the sample set. The resulting training set consisted of a total of 128 images.

Image	Size in pixels	Number of peonies
Parcel 1	3584×6400	42
Parcel 2	4096×8960	46
Parcel 3	6400×6900	13
Parcel 4	4096×3840	97

Table 1. Test Image Characteristics.

Due to the limited number of images, we implemented three types of augmentation to generate larger training datasets. The augmentation process involved applying a set of random transformations to each input image using the Roboflow software (https://roboflow.com/). The parameters for augmentation are provided in Table 2. In the "simple" augmentation type, all transformations were performed without interpolating the data. The "geometry" augmentation type included geometric transformations such as scaling and random rotations applied to the spatial domain of the original image. In addition to geometric transformations, the "geometry+brightness" augmentation type also incorporated random changes in brightness of the original image.

Augmen-tation type	Algorithm	Total number of images in augmented dataset
Simple	**Flip:** Horizontal and vertical, **90º Rotate:** clockwise, counter-clockwise, upside down	228
Geometry	**Simple augmentation** **Scale and Crop:** min zoom 0%, max zoom 30% **Rotation:** between -20º and 20º	434
Geometry + Brightness	**Geometry augmentation** **Saturation:** between -28% and 28% **Brightness:** between -30% and 30% **Exposure:** between -14% and 14% **Blur:** up to 1 pixel	1019

Table 2. Augmentation parameters.

For the test dataset, we utilized image fragments measuring 600×600 pixels, derived from the four test images captured in the natural peony habitat. The test dataset included all image fragments, whether they contained peonies or not. The total number of images in the test dataset was 280.

Both the training and test datasets were manually labeled using the LabelImg software (https://github.com/heartexlabs/labelImg). Each peony in the image was enclosed within a bounding box. Therefore, the target object for detection was an individual peony flower. The process of data labeling is depicted in Fig. 3.

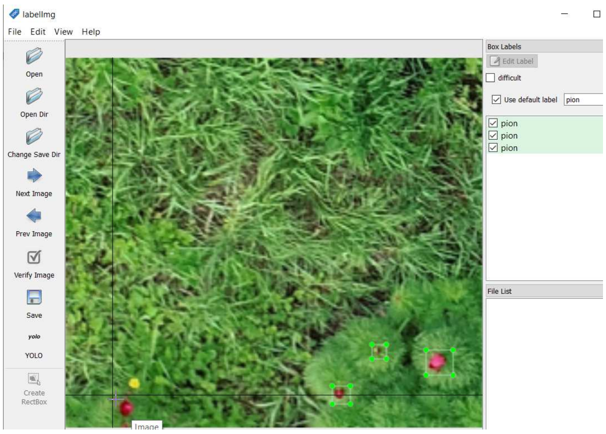

Figure 3. Labeling peonies in LabelImg software.

2.5 Network Architecture

We propose to apply object detection neural networks (ODNN) for peony monitoring using UAV data. Among the top-performing ODNN architectures, YOLO (Dhillon and Verma, 2020) stands out. This architecture, based on GoogLeNet, offers a combination of speed and accuracy (Du, 2018).

The YOLO family encompasses several network variations. In our study, we used YOLOv3 due to the availability of an implementation with pre-trained weights.

YOLOv3 tackles the task of predicting bounding boxes for objects in an image by solving a logistic regression problem. It leverages 53 convolutions for feature extraction and incorporates skip connections (similar to ResNet) as well as 3 prediction heads (like Feature Pyramid Network) that process the image at different spatial resolutions (Almong, 2020). The feature extraction block of YOLOv3 is commonly referred to as Darknet-53. A comprehensive technical review of the architecture enhancements for YOLOv3 can be found in (Redmon and Farhadi, 2018). These improvements contribute to faster training and detection while maintaining good detection performance.

The network architecture is illustrated in Fig. 4 (sourced from (Katuria, 2018)).

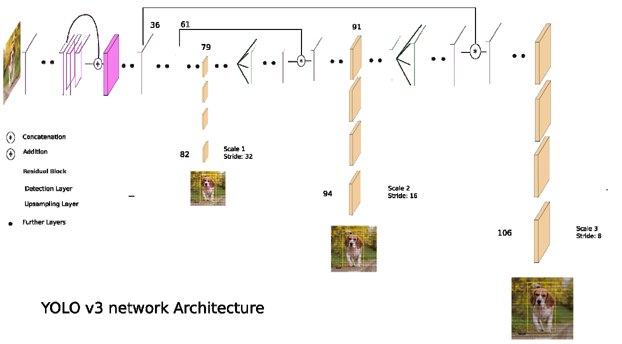

Figure 4. YOLOv3 architecture from (Katuria, 2018).

We obtained the code of the network and the pre-trained YOLOv3 weights from the public repositories of the authors of the paper (Wang et al., 2021). Wang, C. Y., Bochkovskiy, A., and Liao, H. Y. M. trained the YOLOv3 model using the MSCOCO 2017 object detection dataset and made the weights available in their repositories.

2.6 Object Detection

To implement object detection, we utilized a transfer learning approach and trained the YOLOv3 network using our training data captured in the Botanical Garden. The resulting weights were then applied for peony object detection in the images of natural habitats.

Before performing the detection, we resized the input image to the size of 416×416, which is one of the valid input sizes for the network. Following the prediction of bounding boxes, we considered only those with a score threshold of 0.3 or higher and applied a non-maximum suppression threshold of 0.4. These threshold values were determined through multiple runs of the detection without augmentation, resulting in the best detection performance for our specific case. Finally, the recognized peonies were marked by bounding boxes in each test image fragment, as shown in Fig. 5.

Figure 5. Peony detection example.

We evaluated the object detection performance by measuring TPR and FPR using the equation (1) for the entire test image. The number of true and false detections was calculated by summing the values for all image fragments.

3. EXPERIMENTAL RESULTS

In our first experiment, we evaluated the effect of different epoch numbers ranging from 1000 to 6000 for network training without augmentation. The purpose of this experiment was to determine the optimal number of epochs for object detection. Throughout the experiment, the false positive rate (FPR) remained consistently zero across all epoch number values. The true positive rate (TPR) for the four test images is presented in Figure 6.

Figure 6 illustrates that the highest TPR values for the majority of the test images were achieved at an epoch number of 3000. At this epoch number, the average TPR was 0.87. The second best epoch number in terms of average TPR value was 4000, with an average TPR of 0.83. For our subsequent experiments, we focused on testing these two epoch numbers for training.

As for the different types of augmentation mentioned in Table 2, we conducted tests to evaluate their impact. The average TPR and FPR values are provided in Table 3. The highest TPR value of 0.93 was achieved when using the geometry and brightness augmentation type with an epoch number of 4000. This resulted in a TPR increase of 10.75%, while the FPR value remained below 1%. However, we anticipate that further improvements in performance can be achieved by generating a larger number of samples during augmentation.

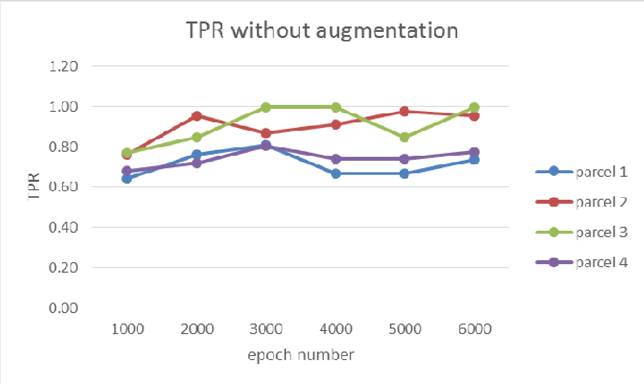

Figure 6. Test TPR values after training without augmentation.

One additional observation is the overall decrease in performance when using the geometry type of augmentation. Based on our findings, we conclude that brightness changes play a more significant role in achieving successful training, while the interpolation of data has a negative impact on performance. As a result, we recommend excluding interpolation effects during training. To address this, we suggest preparing data of the appropriate input size for both the training and testing stages of the network. In our study, we used random input sizes and resampled the data before testing, which led to a decrease in network performance.

Augmentation type	Epoch Number 3000		Epoch Number 4000	
	Average TPR	**Average FPR**	**Average TPR**	**Average FPR**
Simple	0.84	0	0.84	0
Geometry	0.86	0	1	0.34
Geometry + Brightness	***0.92***	***0.01***	***0.93***	***0.005***

Table 3. Classification quality for different augmentation types.

The detailed TPR and FPR values for the best training parameters are listed in Table 4.

Image	TPR	FPR
Parcel 1	0.74	0.00
Parcel 2	1.00	0.02
Parcel 3	1.00	0.00
Parcel 4	0.98	0.00

Table 4. TPR and FPR values for the best augmentation and epoch number.

The testing of the network demonstrated that the proposed monitoring technology can be effectively utilized for peony monitoring. Moreover, the average accuracy of the monitoring is 93% with a false detection rate of less than 1%. It is remarkable that such impressive results were achieved using only two images captured in artificial habitats for training. Incorporating images from natural habitats in the training process will further enhance the peony detection quality. However, it is important to consider the potential increase in anthropogenic impact on the natural habitat when conducting additional field surveys. In this regard, we recommend prioritizing data collection in artificial habitats, which are easily accessible and relatively small. Nonetheless, it is crucial to ensure that data capture is carried out under varying illumination conditions to improve the robustness of the monitoring system.

4. CONCLUSION

This study presents a method for monitoring rare plants using UAV data and the YOLOv3 neural network. The proposed method enables the automatic mapping of reintroduced peony flowers in their natural habitat and the assessment of flower population size. By leveraging UAV data, we provide an affordable, environmentally friendly, and labor-efficient flower monitoring technology.

The proposed method achieves an average detection accuracy of 93% for correct detection and a false detection rate of 0.5%. A crucial aspect of this method is training the network exclusively using images of plants grown in artificial habitats. To fulfill this requirement, we employed a transfer learning approach along with data augmentation techniques.

In our study, we determined the optimal parameters for neural network augmentation and epoch number. The best results were obtained by employing geometrical and brightness types of augmentation (as outlined in Table 2) and conducting training with 4000 epochs.

Our main findings are:
1) Images obtained from artificial habitats can be effectively utilized for network training without the need for additional images from natural habitats.
2) The interpolation of images during training reduces the detection performance.
3) In this specific task, brightness augmentation proves to be more advantageous than geometric augmentation.

Further improvements to the method should focus on the following aspects: excluding interpolation effects during augmentation and network input preprocessing, expanding the training set through additional surveys in artificial habitats, and increasing the number of random brightness transformations per image during augmentation.

ACKNOWLEDGEMENTS

The study was supported by RSF project № 23-11-20013.

REFERENCES

Almong, U., 2020. YOLO V3 Explained. Towards data science. https://towardsdatascience.com/yolo-v3-explained-ff5b850390f (9 June 2023).

Alvarez-Taboada, F., Paredes, C., Julián-Pelaz, J., 2017. Mapping of the invasive species Hakea sericea using unmanned aerial vehicle (UAV) and WorldView-2 imagery and an object-oriented approach. Remote Sensing 9(9), 913. doi.org/10.3390/rs9090913.

Bârliba, F. C., Bârliba, L. L., Bârliba, C. (2020). Methods of acquisition and data processing carried out with DJI Phantom 4 Pro v2. 0 UAV equipment. Research Journal of Agricultural Science, 52(1), 14-23.

Belcore, E., Pittarello, M., Lingua, A. M., Lonati, M., 2021. Mapping riparian habitats of Natura 2000 network (91E0*, 3240) at individual tree level using UAV multi-temporal and multi-spectral data. Remote Sensing 13(9), 1756. doi.org/10.3390/rs13091756.

Bilz, M. 2011. Paeonia tenuifolia (Europe assessment). The IUCN Red List of Threatened Species 2011: e.T165143A5981869. https://www.iucnredlist.org/species/165143/5981869 (09 June 2023).

Cao, J., Liu, K., Zhuo, L., Liu, L., Zhu, Y., Peng, L., 2021. Combining UAV-based hyperspectral and LiDAR data for mangrove species classification using the rotation forest algorithm. International Journal of Applied Earth Observation and Geoinformation 102, 102414. doi.org/10.1016/j.jag.2021.102414.

de Castro, A.I., Shi, Y., Maja, J.M., Peña, J.M., 2021. UAVs for Vegetation Monitoring: Overview and Recent Scientific Contributions. Remote Sensing 13, 2139. doi.org/10.3390/rs13112139.

Dhillon, A., Verma, G.K. 2020. Convolutional neural network: a review of models, methodologies and applications to object detection. Progress in Artificial Intelligence 9(2), 85–112. doi.org/10.1007/s13748-019-00203-0.

Du, J., 2018. Understanding of object detection based on CNN family and YOLO. Journal of Physics: Conference Series, 1004(1), 012029. doi.org/10.1088/1742-6596/1004/1/012029.

Fan, Z., Lu, J., Gong, M., Xie, H., Goodman, E. D., 2018. Automatic Tobacco Plant Detection in UAV Images via Deep Neural Networks. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing 11(3), 876-887. doi.org/10.1109/JSTARS.2018.2793849.

Kattenborn, T., Eichel, J. Fassnacht, F.E., 2019. Convolutional Neural Networks enable efficient, accurate and fine-grained segmentation of plant species and communities from high-resolution UAV imagery. Scientific reports 9(1), 17656. doi.org/10.1038/s41598-019-53797-9.

Katuria, A., 2018. What's new in YOLO v3? Towards data science. https://towardsdatascience.com/yolo-v3-object-detection-53fb7d3bfe6b (9 June 2023).

Li, Q. S., Wong, F. K. K., Fung, T., 2017. Assessing the utility of UAV-borne hyperspectral image and photogrammetry derived 3D data for wetland species distribution quick mapping. The International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences 42, 209.

Malone, E. W., Perkin, J. S., Leckie, B. M., Kulp, M. A., Hurt, C. R., Walker, D. M., 2018. Which species, how many, and from where: Integrating habitat suitability, population genomics, and abundance estimates into species reintroduction planning. Global Change Biology 24(8), 3729-3748. doi.org/10.1111/gcb.14126.

Randin, C. F., Ashcroft, M. B., Bolliger, J., Cavender-Bares, J., Coops, N. C., Dullinger, S., Dirnböck, T., Eckert, S., Fernández, N., Giuliani, G., Guisan, A., Jetz, W., Joost, S., Karger, D., Lembrechts, J., Lenoir, J., Luoto, M., Morin, X., Price, B., Rocchini, D., Schaepman, M., Schmid, B., Verburg, P., Wilson, A., Woodcock, P., Yoccoz, N., Payne, D., 2020. Monitoring biodiversity in the Anthropocene using remote sensing in species distribution models. Remote sensing of environment 239, 111626. doi.org/10.1016/j.rse.2019.111626.

Redmon, J., Farhadi, A., 2018. Yolov3: An incremental improvement. arXiv preprint arXiv:1804.02767.

Wang, C. Y., Bochkovskiy, A., Liao, H. Y. M., 2021. Scaled-yolov4: Scaling cross stage partial network. Proceedings of the IEEE/cvf conference on computer vision and pattern recognition, 13029-13038.