MONITORING A HIGH-ARCTIC FOOD WEB FROM SPACE WITH MACHINE LEARNING

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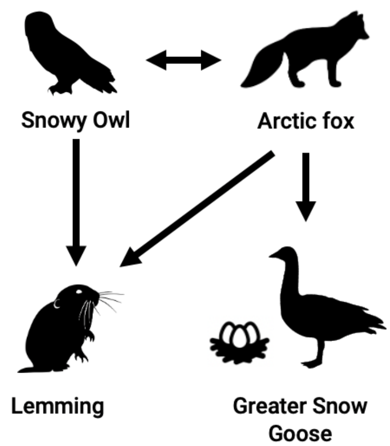
Abstract under double-blind review

ABSTRACT

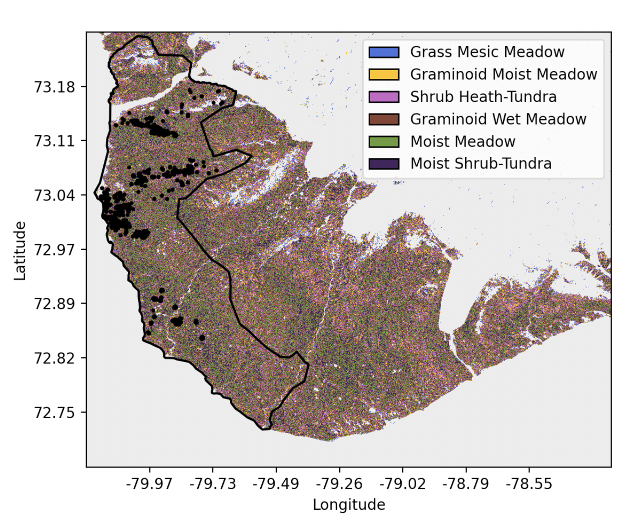
Long-term monitoring of northern ecosystems is necessary to address the challenges posed by climate change and evolving human needs and stressors. Such efforts to survey wildlife in hostile and remote areas can however be hindered by several logistical challenges. A notable example is the lockdown imposed by COVID-19 in 2020-2021, which has had tremendous impacts on research activities, especially for long-term monitoring projects. This was particularly the case in the Canadian Arctic, where Northern authorities drastically restricted travel within and outside each territory. Gaps in time series can limit our understanding of ecosystem functioning and jeopardize our ability to detect population trends. To cope with such exceptional situations and limit the loss of data, alternative monitoring strategies should be explored.

We propose a machine learning pipeline to monitor from space a High-Arctic food web (see Fig. 1a) composed of the Arctic fox (*Vulpes lagopus*), the Greater Snow Goose (*Chen caerulescens atlantica*), the Snowy Owl (*Bubo scandiacus*), the brown lemming (*Lemmus trimucronatus*), and the collared lemming (*Dicrostonyx groenlandicus*). We first trained a Faster R-CNN (Ren et al., 2017) neural network model to detect snow geese on WorldView-3 satellite images of Bylot Island (Nunavut), home to the world's largest Greater Snow Goose breeding colony (Lemieux, 1959). Our model was trained and evaluated using a 5-fold cross-validation on a dataset composed of 2314 geese manually identified by ecologists (see Fig. 1b). A mean F1-score of $>$90% is achieved on all of the six vegetation types found in Bylot (Duclos et al., 2006), which suggests that our model is able to generalize well over the entire study area (see Fig. 1c). Geese detection is carried out on two pictures, respectively taken at the beginning and at the end of the incubation period. This core part of our approach allows to perform cluster analyses to identify nesting pairs, which are subsequently used to estimate nest locations based on their centroids.

Our pipeline then leverages the structuring role of the Greater Snow Goose within the food web to infer some key parameters on the remaining species. As a first step, we estimate goose nesting success through a comparative analysis of the number of nests detected at the beginning and at the end of the incubation period, allowing us to evaluate to which extent the predation pressure imposed by the Arctic fox impacted geese reproductive activities. Furthermore, we estimate the number of Snowy Owls nests by taking advantage of the fact that when Snowy Owls are nesting on Bylot Island, their nests are almost always surrounded by snow goose nests (Tremblay et al., 1997; Bêty et al., 2001). In particular, we apply a hierarchical clustering algorithm to identify aggregations of goose nests in areas of the island where Snowy Owls typically breed. Finally, since data collected in the field over the 1993-2019 period reveals a strong relationship between owls nests and lemming densities, we use the number of detected clusters to infer lemming abundance. A graphical representation of our approach is depicted in Fig. 1d. We successfully validate each individual step of our monitoring pipeline by comparing our estimates with historical field data. To our knowledge, our approach is one of the first of its kind that effectively combines ecological knowledge with machine learning algorithms in order to obtain a method that could represent a realistic alternative to the sampling of demographic parameters of Arctic wildlife in the field.



(a)



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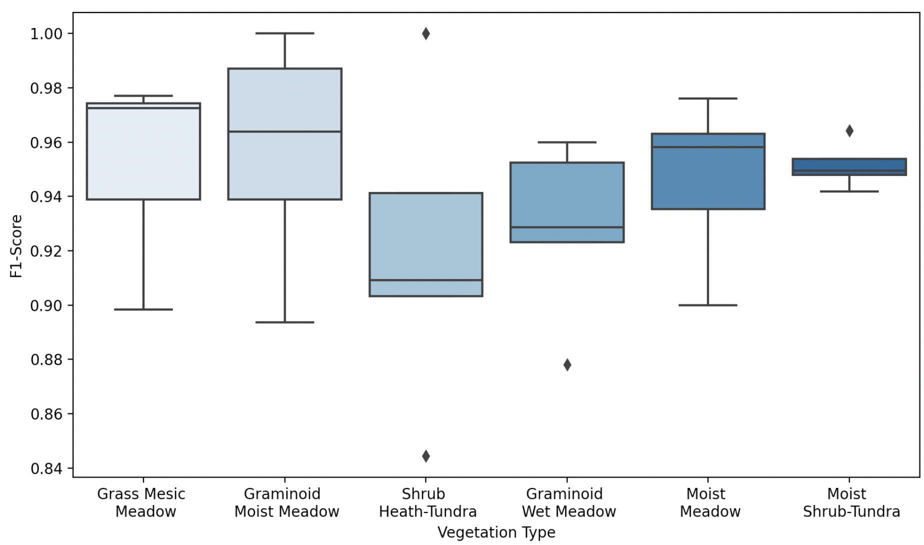

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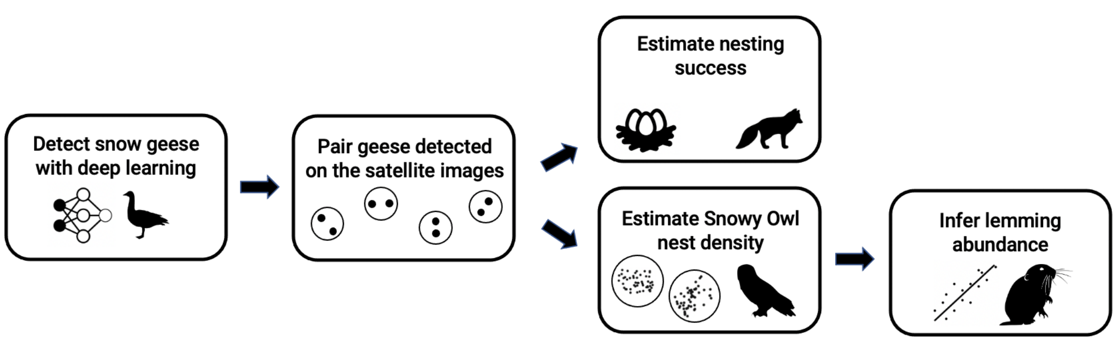

(d)

Figure 1: (a) Network of the vertebrate species at Bylot Island concerned by our monitoring pipeline (b) Vegetation cover map of a region of Bylot Island. The polygon outlined in black represents the coverage of the images acquired from the Worldview-3 satellite. Black dots correspond to the geospatial coordinates of the geese identified by experts in our training dataset. (c) Boxplot of the 5-fold cross-validation results of our neural network model for snow goose detection on high-resolution satellite imagery. (d) Graphical illustration of our monitoring pipeline

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