**Inferring successful breeding of a declining bird with remote tracking data**

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**Background:** The past decade has witnessed significant developments in utilizing animal-borne sensors to track key behaviors in the wild, especially in migratory patterns [1, 2]. Recent studies suggest that light-level geolocator and satellite transmitter data can provide insights into other important animal behaviors as well, including the identification of probable den sites, feeding grounds, and reproductive success in a variety of avian and terrestrial species [3, 4]. In this study, I am interested in exploring previously developed R packages (e.g., 'nestR', 'migrateR', and 'H2O'), and developing novel analyses of my own, to remotely monitor the nesting behaviors and reproductive success of Black-tailed Godwits, (*Limosa limosa limosa*; hereafter 'godwit') breeding in The Netherlands [4, 5, 6, 7].

Godwits are medium-sized shorebirds that migrate from their wintering areas in southern Spain and sub-Saharan Africa to their nesting areas in The Netherlands and elsewhere in northwestern Europe [8]. The degradation of their breeding habitat from intensifying farming practices has led to severe population declines (-75% from 1976 to 2015) in Europe-breeding godwits [9]. Given the uncertain future of godwit populations, it is increasingly important to identify proper conservation actions, but this likely requires that we are able to determine conditions that confer the greatest potential for nesting success. Therefore, tools that allow researchers to monitor populations across their range will provide crucial insights into conservation actions that will have the most lasting impacts.

Monitoring shorebird breeding success typically requires large-scale field efforts to identify potential breeders and follow the survival of marked young. For example, without continuous observations to provide ground truths, it is difficult or impossible to determine an individual's reproductive success. Until recently, acquiring such information on birds in difficult to access areas was thus impossible [10, 11]. Animal-borne sensors (e.g., satellite and GPS tags) may make inferences about breeding success from movement tracks possible, but methods are still underdeveloped. Collecting this information across a species range, however, is key to identifying processes driving declines. Methods to remotely assess an individual's reproductive success are therefore critical for monitoring populations and informing conservation efforts [5].

In this proposed work, we will use deep learning, movement-based, and simulation tools to build a model that reliably determines nesting success from remotely collected tracking data. The freely available program R (R Core Team 2020) already hosts many of the Markov models, deep learning techniques, and movement simulation models necessary for our goals [2, 6]. Additionally, we have already collected tracking data from nearly 100 individual godwits for up to 5 years. Combined with data from on the ground observations for a subset of these individuals, we will develop an algorithm to infer breeding success from movement patterns associated with breeding behaviors (i.e., incubation, chick-tending) and extend these methods to assess reproductive success at unsupervised nesting sites [12].

**Research Question:** Can we predict successful nesting efforts for godwits in The Netherlands using deep-learning analyses of movement and observational data?

**Project Goals and Objectives:** The goals of this project are to compare and develop methods that predict nesting success. To accomplish this goal, we will tailor available techniques to fit this system, initialize a standard tool to measure nesting success, and explore the connection between farming practices and nesting success rates. Additionally, we seek to demonstrate that data from animal-borne sensors provide a means to remotely produce viable nesting success behavior metrics and pinpoint critical times that determine an individual's fitness, such as the egg incubation period.

**Project Impact:** If we are successful, these metrics may provide the foundation for future conservation regulations in nesting regions for this shorebird. These efforts will ensure the longevity of this species along with the grassland environments that they call home. Beyond the scope of this initial project, the methodology we create should be easily transferred to another species of shorebird in the Western Hemisphere, and provide an example procedure for other migratory species breeding in inaccessible regions.

**Methodology:** Since movement data has already been collected, we will first perform a literature review to identify previous R packages and methodologies that could be altered to fit our data. After our literature review, we will determine the best data mining methodologies using 15 birds with up to five years of location data from GPS tags. GPS-tags provide the highest quality data for inference about behaviors compared to the lower quality data from other types of tracking devices. We will be transferring this method to these other transmitter types (e.g., Argos microwave tags) later in the study. Preprocessing of the data will consist of cleaning and extracting pertinent information related to nesting success, including longitude, latitude and time while also prescreening for confounding behaviors that mimic a nest site, such as common feeding grounds. Once a deeper understanding of the data has been developed, we will be able to run analyses such as random forests, unsupervised learning networks, and Markov models suited for such data [5, 2]. Borrowing techniques from previous research to identify denning behaviors of terrestrial organisms (elephants, cougars, and coyotes) from geolocations, a similar form of data analysis should be transferable to movements correlated with successful versus unsuccessful nesting [3].

**Project Timeline:**

| **Task Description** | **Project Months** | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Oct | Nov | Winter | Jan | Feb | Mar | Apr | Summer | Aug | Sep |
| Literature Review | X | X | X | | | | | | | |
| R Package Review | X | X | X | | | | | | | |
| Geo-Tag and Argos Data analysis | X | X | X | X | X | X | X | | | |
| Publication Drafting | | | | | | | X | X | X | |
| Publication Review | | | | | | | | | X | X |

**Final Products and Dissemination:** We expect to evaluate and validate a partially unsupervised procedure to detect the success of nesting sites. The result of our research will be published in a peer-reviewed journal article and presented at Discover USC.

**Personal Statement:** I joined Dr. Senner's lab in October 2020. Prior to that, I worked in Dr. Mousseau's Lab (UofSC Department of Biological Sciences) from November 2018 to September 2020. I am working on two degrees (computer and biological sciences) that are the foundations for this project. My previous projects have included collecting data from camera trap surveys utilizing Python, Java, and C++. To strengthen my knowledge in R, I will enroll in courses next semester on genomic data science and data visualization tools. I have previously been awarded the SURF grant for investigating the applications of machine learning to camera trap field surveys in McCrady Training Center, and also presented at the Sustainable Showcase and Discover USC. Currently, this research is being drafted for publication in the near future. Overall, I aspire to use my skills of research data science to address ecological problems and explore unique ways of visualizing data.

## References


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