# Combining modern tracking data and historical records improves understanding of the summer habitats of the Eastern Lesser White-fronted Goose Anser erythropus

Haitao Tian[1], Diana Solovyeva[2], Gleb Danilov[3], Sergey Vartanyan[4], Li Wen[5], Jialin Lei[1], Cai Lu[1], Peter Bridgewater[6], Guangchun Lei[1], and Zeng Qing[1]

[1]Beijing Forestry University
[2]Institute of Biological Problems of the North FEB RAS
[3]Peter the Great Museum of Anthropology and Ethnography RAS
[4]North-East Interdisciplinary Science Research Institute FEB RAS
[5]NSW Department of Planning Industry and Environment
[6]University of Canberra

November 13, 2020

**Abstract**

The Lesser White-fronted Goose (Anser erythropus), smallest of the “grey” geese, is listed as Vulnerable on the IUCN Red List and protected in all range states. There are three sub-populations, with the least studied being the East Asian sub-population, shared between Russia and China. The extreme remoteness of breeding enclaves makes them largely inaccessible to researchers. As a substitute for visitation, remotely tracking birds from wintering grounds allows exploration of their summer range. Over a period of three years, and using highly accurate GPS tracking devices, eleven individuals of A. erythropus were tracked from the key wintering site of Dongting Lake, China, to breeding, molting, and staging sites in north-eastern Russia. Data obtained from that tracking, bolstered by ground survey and literature records, were used to model the summer distribution of A. erythropus. Although earlier literature suggests the summer range is patchy, the model confirms a contiguous summer range. The most suitable habitats are located along the coasts of the Laptev Sea, primarily the Lena-Delta, in the Yana-Kolyma Lowland, and smaller lowlands of Chukotka with narrow riparian extensions upstream along major rivers such as the Lena, Indigirka and Kolyma. The probability of A. erythropus presence is related to sites with altitude less than 500 m with abundant wetlands, especially riparian habitat, and a climate with precipitation of warmest quarter around 55 mm and mean temperature of wettest quarter around 14oC. Human disturbance also affects site suitability, with a gradual decrease in species presence starting around 160 km from human settlements. Remote tracking of animal species can bridge the knowledge gap required for robust estimation of species distribution patterns in remote areas. Better knowledge of species’ distribution is important in understanding the large-scale ecological consequences of rapid global change and establishing conservation management strategies.

## Introduction

The Lesser White-fronted Goose *Anser erythropus* is the smallest of the so-called “grey” geese of the genus *Anser* (BirdLife International 2018). Excluding threatened taxa, grey geese are traditionally used for subsistence and sport hunting in Eurasia. Arctic nations especially continue to consider geese as a sustainable source of fresh meat in spring. However, hunting bans in many European countries, Republic of Korea and Japan have allowed the various species of grey geese to become part of agricultural landscapes. In contrast, several species of grey geese in China prefer to winter on wetlands with typically low levels of human use, rather than exploiting agricultural lands that are densely populated by people and their livestock (Deng *et al.* 2018). Since 1994, following rapid population reduction, *A. erythropus* has been globally list as Vulnerable in the IUCN Red List (BirdLife International 2018).

Three sub-populations can be distinguished: Fennoscandian, West Asian, and East Asian, with potential overlap of the breeding grounds between the West and East Asian sub-populations (Jones *et al* . 2008). Aarvak and Oien (2018) note that the Fennoscandian sub-population appears on the brink of extinction with only 30-35 pairs left, despite captive breeding and restocking in Finland and Sweden during 1981 – 1999 (Ruokonen *et al* . 2000; Andersson and Holmqvist 2010). The number of the West Asian sub-population assessed from counts at stop-over sites during autumn migration has risen from an estimated 10,000-21,000 in early 2000s (Fox *et al* . 2010) to 30,000-34,000 in 2015 (Cuthbert and Aarvak 2016) and perhaps as high as 48,580 ± 2,820 in 2017 (Rozenfeld *et al* . 2019). However, this increase could be attributed to additional survey efforts for *A. erythropus* at previously infrequently or un-visited staging sites in Kazakhstan. The most recent estimate of the East Asian sub-population is 14,000-19,000 individuals (Jia *et al.* 2016), accounting for around 25% of the global *A. erythropus* population (Jia *et al* . 2016 and Rozenfeld *et al* . 2019). The eastern sub-population of *A. erythropus* extends from the Taymyr Peninsula eastward to Chukotka region (Morozov 1995; Morozov and Syroechkovski -Jr 2002; Lei *et al* . 2019a), and in common with other subpopulations, is declining (BirdLife International, 2018). A range of threats, including habitat loss and degradation along the migration route and on the wintering grounds proposed to fragmentation of the formerly continuous breeding range, have all been identified being responsible for past population declines (Madsen *et al* . 1984; Grishanov 2006; Morozov 2006). In addition, illegal and accidental hunting (i.e. the genuine confusion with the similar looking Greater White-fronted Goose *A. albifrons* , a species that can be hunted legally in Russia) are also threats to population viability.

Quantitative knowledge of a species spatial distribution is the cornerstone for its effective conservation. Due to the remoteness and restricted accessibility, historical observations of the summer range of the East Asian sub-population are rather scarce (Ruokonen *et al* . 2004, Morozov 1995; Morozov and Syroechkovski -Jr 2002; Lei *et al* . 2019a) Further, there are no systematic surveys covering the potential range of eastern sub-population of *A. erythropus* (Fig. 1). Current knowledge on the breeding distribution and habitat preference of *A. erythropus* is therefore limited (Egorov and Okhlopkov 2007, Solovieva and Vartanyan, 2011, Degtyaryev *et al.*2014). In the last 25 years, ornithologists generally considered that the East Asian *A. erythropus* had a patchy breeding distribution, and the number, position and shape of those areas changed as new knowledge was acquired from occasional visits to remote sites in East Siberia as illustrated in Figure 1. Furthermore, an intensive multi-year survey in the area adjacent to the breeding grounds along the Rauchua River, West Chukotka, helped locate a number of breeding/molting groups and separated broods, suggesting that the entire survey area was populated by *A. erythropus* (Fig. 2). This suggests that a single survey in one year, the usual method employed to study distribution of geese in remote areas of East Siberia (Egorov and Okhlopkov 2007, Solovyeva and Vartanyan 2011), may not allow for an effective understanding of the summering distribution, limiting potential conservation actions for the species.

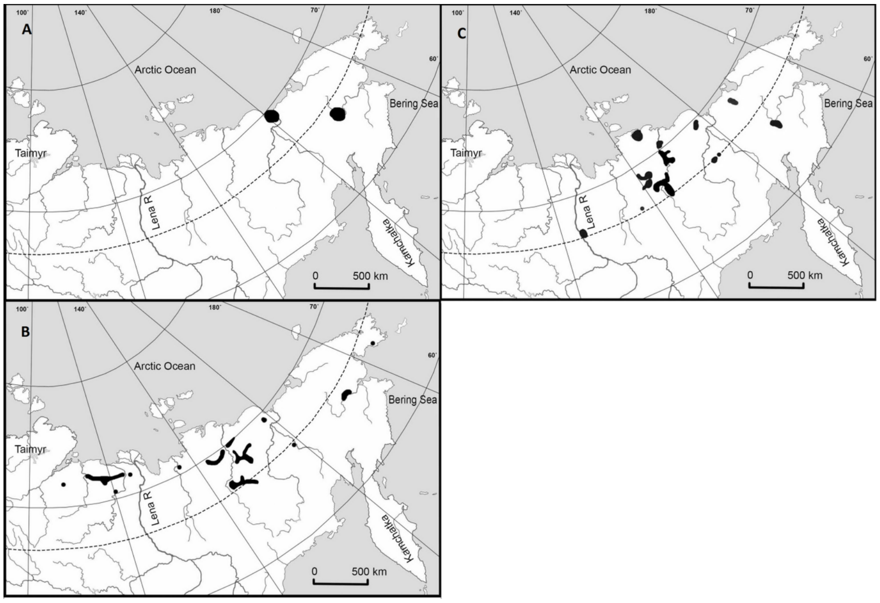



Figure 1 Historical summer (breeding and molting) range of the eastern sub-population of Lesser White-fronted Goose. Black contours indicate known breeding or molting enclaves. A) from Morozov 1995; B) from Morozov and Syroechkovski-Jr 2002; and C) from Cao *et al* . 2018.

As new tracking technologies have developed, the investigation and quantification of spatial and temporal distributions of wide-ranged migratory species, such as *A. erythropus* , now typically involve the deployment of telemetric tracking devices (Jiguet *et al* . 2011; Pimm et al. 2015). Rapid accumulation of tracking data offers new insights to assess distribution ranges and to explore habitat preferences (Kays *et al* . 2015). For example, tracking data can be linked with environmental conditions and used in ecological niche models to predict the overall space use by a population (Jiguet *et al* . 2011). In this context, this paper aimed to quantify to the potential summering range of the East Asian *A. erythropus* sub-population by combining GPS tracking data, historical ground survey records, and literature sources. Using bioclimatic, geomorphological, land cover, and human disturbance layers, we used Maxent (a niche modelling technique, Elith et al. 2006), to predict the summering habitats of *A. erythropus* within East Siberia in an ensemble forecast framework, i.e. averaging predictions from many models (100 in this study) to account for data uncertainties and model variability (Pearson et al. 2006). Niche models using both historical records and recent tracking data could help to get better understanding of the summering distribution of the East Asian *A. erythropus* sub-population, and provide more accurate information for conservation plans including identifying potential threats and prioritizing management actions.

# Materials and methods

## Study Area

The study area was in northeast Siberia, extending eastwards from Olenyok R (119.2 E) to the watershed between the Pacific and Arctic drainage basins, including Republic of Sakha, Magadanskaya Oblast and Chukotskiy Autonomous Okrug. *A. erythropus* was never reported in in the Arctic Archipelagos, these island areas are excluded in our study.

## Surveys in West Chukotka, Russia

During July-August 2002-2019 surveys were undertaken along rivers and lake habitats in the area of 19,260 km$^2$ of assumed*A. erythropus* range in Chukotka (Figure 2). Brood-rearing adult*A. erythropus* with their brood or flocks of molting adult*A. erythropus* were counted during downstream travel in a motorboat from the upper reaches of rivers, which were reached by helicopter. A description of the study area and survey results of 2002-2010 have been previously published (Solovieva and Vartanyan 2011). No *A. erythropus* were found on lakes and only surveys along rivers have been used in this study (Figure 2). Positions and numbers of*A. erythropus* were given as (1) middle point and peak number for each river from surveys in multiply years; (2) middle point and number per river from single survey for the rivers surveyed once. As rivers of the study area are relatively small (up to 320 km) and uniform by habitat type, we considered each river as one data point for the niche modelling. These surveys provided 11 records for the model comprising eight breeding records and three molting records.

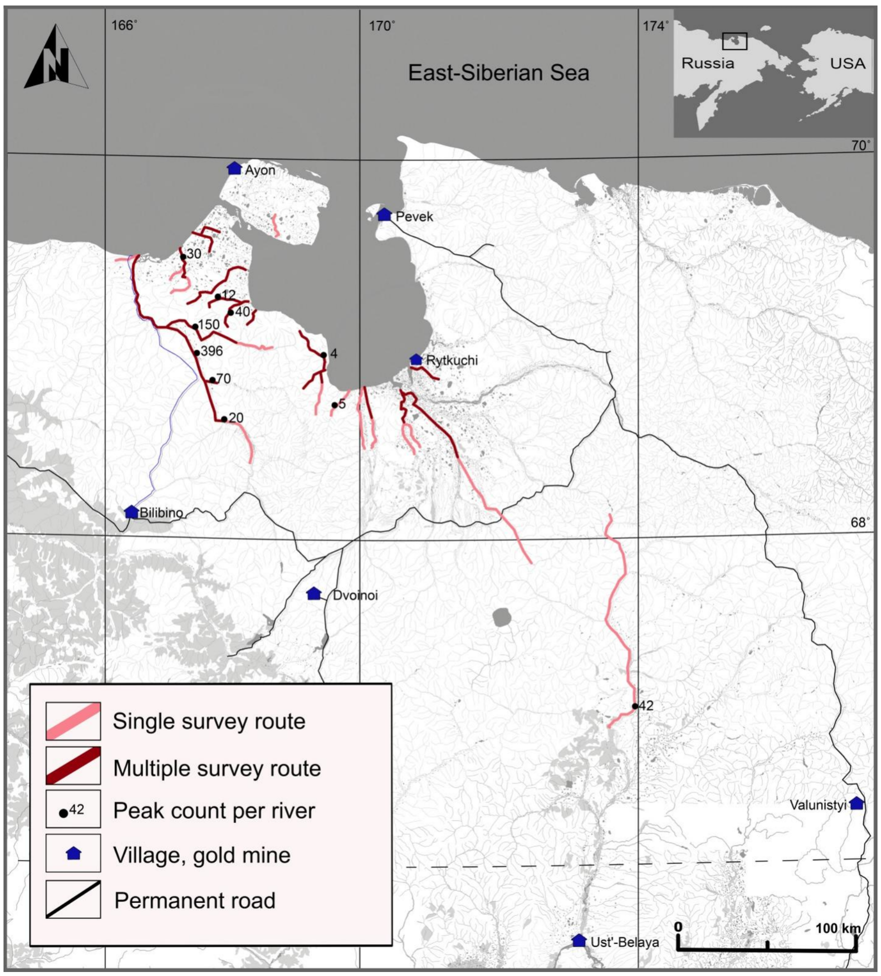



Figure 2 Survey route and peak counts of the Lesser White-fronted Geese on the rivers of West Chukotka, 2002-2019.

### Data extraction from published sources

A total of 13 records of breeding or molting *A. erythropus* were compiled from historical surveys along the rivers dated after 1998. Originally 11 of these records were not attributed to GPS coordinates and to geo-reference them, we converted descriptions of records (river name and distance to the nearest village) to coordinates.

## Capture methods and data tracking

Using techniques described in Lei *et al* . (2019a), individual*A. erythropus* captured, during the winter of 2016/17 at East Dongting Lake, China. This lake is the most important wintering site for the species, supporting more than 70% of the East Asian sub-population (Wang *et al* . 2012). A Total of 88 *A. erythropus* were captured and tagged by experienced hunters using baited clap traps, and 11 individuals returned with a completed wintering-migration-summering-migration-wintering cycle (Table 1).

Table 1. Summary of eleven tagged Lesser White-fronted Geese used for this study.

| ID | Capture Date | GPS Start Date | GPS End Date | Nb days | Nb summers | Nb of GPS fixes |
|---|---|---|---|---|---|---|
| BFUL041 | 20.11.2016 | 23.11.2016 | 16.04.2018 | 509 | 1 | 7,227 |
| BFUL044 | 30.11.2016 | 02.12.2016 | 09.06.2018 | 554 | 1 | 8,459 |
| BFUL050 | 25.11.2016 | 27.11.2016 | 19.05.2018 | 538 | 1 | 8,351 |
| BFUL057 | 30.11.2016 | 02.12.2016 | 17.07.2018 | 592 | 1 | 4,093 |
| BFUL059 | 30.11.2016 | 02.12.2016 | 29.12.2017 | 392 | 1 | 4,050 |
| BFUL065 | 05.12.2016 | 07.12.2016 | 05.09.2017 | 272 | 1 | 4,832 |
| BFUL068 | 15.12.2016 | 16.12.2016 | 28.05.2018 | 528 | 1 | 9,347 |
| BFUL051 | 25.11.2016 | 28.11.2016 | 25.12.2018 | 757 | 2 | 7,812 |
| BFUL061 | 30.11.2016 | 02.12.2016 | 12.05.2019 | 891 | 2 | 11,490 |
| BFUL074 | 15.01.2017 | 19.01.2017 | 14.05.2019 | 845 | 2 | 6,932 |
| BFUL062 | 08.12.2016 | 11.12.2016 | 27.11.2019 | 1081 | 3 | 17,848 |

Birds were fitted with transmitters (Hunan Global Messenger Technology Company, China) programmed to record GPS position and speed every 1-3 hours depending on the battery condition. Transmitters were solar powered to enable the global system for mobile communication (GSM) to transmit data *via* the short message service (SMS). These back-pack design transmitters were 55x36x26 mm in size and weighed 22g (appr. 1.6% of the bird's body mass; Lei *et al* . 2019a). As Mobile network coverage is sparse or non-existent in summering sites of North-East Russia, the stored data obtained from that area were downloaded when birds returned to China.

GPS records of locations (accuracy of <1000 m) were used in the analysis of *A. erythropus* journeys to Russia. For non-breeding *A. erythropus* (the longest one-way migration recorded was 16,172 km in 60 days, Lei *et al* . 2019b), it was assumed the spring migration turned to summering activities when the trans-latitudinal movement became mostly trans-longitudinal. Like spring migration, we assumed summering was terminated when a pronounced southbound movement was detected. For breeding birds, the date of arrival at a breeding site was used to indicate the start of summering. The site was classified as staging if the bird stayed at a location for more than four days.

## Environmental predictors

To model the potential summering habitat, a range of environmental variables were used including bioclimatic, geomorphological, land production and human disturbance.

Bioclimatic Bioclimatic variables were taken from the 30 second WorldClim (v2.1) climate data, downloaded from http://www.worldclim.org, which were generated through interpolation of monthly mean temperature and rainfall data from weather stations for the period of 1970-2000 (Hijmans *et al* ., 2005). We selected five variables that are relevant to geese summering including Max Temperature of Warmest Month (Bio5), Mean

Temperature of Wettest Quarter (Bio8), Mean Temperature of Warmest Quarter (Bio10), Precipitation of Wettest Month (Bio13) and Precipitation of Warmest Quarter (Bio18).

*Geomorphological*Topographic heterogeneity is important for species distribution (Austin and Van Niel 2011). Three topographic variables were included in the modelling, namely elevation, LDFG (Local Deviation from Global Mean) and TRI (terrain ruggedness index). The global 1 km resolution digital elevation model (DEM) for the study area was downloaded from (http://srtm.csi.cgiar.org/) and cropped with the study. Based on the DEM, LDFG and TRI were calculated as:

$LDFG = y_i - y$ (1)

where $y$ is mean evaluation of the 3 by 3 window, and $y_i$ is the elevation of the focus grid. Positive LDFG values represent locations that are higher than the average of their surroundings, as defined by the neighborhood (ridges). Negative LDFG values represent locations that are lower than their surroundings (valleys). LDFG values near zero are either flat areas (where the slope is near zero) or areas of constant slope (where the slope of the point is significantly greater than zero).

$TRI = \left(\sum \left(Z_c - Z_i\right)^2\right)^{1/2}$ (2)

where $Z_c$ is the elevation of the central grid and$Z_i$ is the elevation of one of the eight neighboring grids. The terrain ruggedness index (TRI) is a topographic measurement developed by Riley, *et al* . (1999) to quantify topographic irregularities in a region.

As *A. erythropus* is ecologically dependent on wetlands, and often observed breeding along river valleys (Solovieva *et al* . 2011), we included a layer of distance to steams in the modelling. We generated the raster using polylines in the Global River Widths from Landsat (GRWL) dataset (George, 2018) as the central lines. The polylines were checked to be a good represent of the rivers in the study area.

Land production To characterize land production, we calculated three variables ($\text{EVI}_{\text{max}}$, $\text{EVI}_{\text{hom}}$ and $\text{EVI}_{\text{range}}$) using EVI (Enhanced Vegetation Index) time series (2000-2009). The 10-day global EVI images with 333 × 333 m resolution were downloaded from Copernicus Global Land Service (https://land.copernicus.eu/global/products/ndvi, data downloaded on 28 August 2019). $\text{EVI}_{\text{max}}$ is an indicator of peak land productivity and was calculated as the 10-year mean of annual max EVI. $\text{EVI}_{\text{range}}$ is the range of land productivity (i.e. $\text{EVI}_{\text{max}}$ -$\text{EVI}_{\text{min}}$). $\text{EVI}_{\text{hom}}$ is the similarity of EVI between adjacent eight pixels, and was computed as (Tuanmu and Jetz 2015):

$\text{EVI}_{\text{hom}} = \sum_{i,j=1}^{m} \frac{P_{i,\ j}}{1+(i-j)^2}$(3)

where m is the number of all possible scaled EVI values (i.e. 100) and$P_{i,\ j}$ is the probability that two adjacent pixels have scaled EVI values of $i$ and $j$ , respectively. Both $\text{EVI}_{\text{hom}}$ and $\text{EVI}_{\text{range}}$ can be indicator of habitat diversity.

Human Disturbance Human disturbance can lead to declines and local extinctions of avian species as well as habitat loss (Vollstädt *et al* . 2017). The inclusion of human disturbance data can increase the performance and accuracy of SDM (species distribution model - Stevens and Conway, 2020). We compiled a database of all human settlements including villages and towns in the study area (i.e. Republic of Sakha, Magadanskaya Oblast and Chukotskiy Autonomous Okrug) and generated a layer of distance to settlements as a proxy of human disturbance. Settlements with zero registered inhabitants (abandoned and closed before 2011) were excluded.

Land Cover Forcey *et al* . (2011) found that land use has strong effects on waterbird distribution, and the percentage of waterbird abundance is positively related to the area of wetland. In this study, we used the 2015 global land cover map derived from satellite observations by Land Cover Climate Change Initiative (CCI) and available from*https://maps.elie.ucl.ac.be/CCI/viewer/download.php* . The map classifies the global terrestrial system into 28 major classes using United Nations Food and Agriculture Organization's land cover classification system (Di Gregorio 2005).

R (R Core Team, 2019) packages "raster" (Hijmans *et al* . 2015) and spatialEco (Evans and Ram, 2018) were used for raster manipulation and calculation.

## Modeling

A total of 96 geo-referenced records were compiled by combining the tracking data and historical surveys (post 1999) (Table S2 in Supplementary). To analyze the potential breeding range, maximum entropy implemented in the Maxent package (version 3.4.1) was used. Maxent is among the most robust and accurate SDM techniques (Elith et al., 2006). In the past two decades, it has gained popularity in conservation studies, partly because the technique is less sensitive to the number of recorded sites and uses presence-only data (Elith et al., 2011). In developing the SDM, the program was set to take 75% of the occurrence records randomly for model training and the remaining 25% for model testing. The mean area under the receiver operating characteristic curve (AUC) was used to evaluate model performance, and AUC values > 0.75 are considered as suitable for conservation planning (Lobo et al., 2008). The modelling process was replicated 100 times and we reported the mean as summering ranges to reduce the sampling bias (Merow *et al* ., 2013).

Although collinearity is less of a problem for machine learning methods in comparison with statistical methods (Elith *et al* ., 2011), minimizing correlation among predictors prior to model building is recommended (Merow *et al* ., 2013). We used VIF (Variance inflation factor) to select predictors (Dupuis and Victoria-Feser, 2013). Nine variables with VIF less than 10, including two bioclimatic variables (Bio10 and Bio18), two topographic variables (DEM and LDFG), two productivity variables ($EVI_{hom}$ and $EVI_{range}$), land cover, Distance to stream, and Distance to settlement, were included in model building.

Using the logistic outputs of MaxEnt, we applied the minimum training presence threshold (MTP) to produce binary habitat map. MTP threshold finds the lowest predicted suitability value for an occurrence point and ensures that all occurrence points fall within the area of the resulting binary model (Elith *et al* ., 2011).

# Results

## Potential summering range of the East Asian sub-population of *A. erythropus*

The mean training AUC of the 100 models was 0.9510 suggested these models are very useful (Swets 1988) for predicting the summering range of *A. erythropus* . The standard deviation of AUC was very small (0.0007) indicating the models were stable. Moreover, the mean testing AUC was 0.9356 (SD = 0.0739), which was comparable to the training AUC, suggesting excellent predictive power of the fitted model (Lobo et al., 2008).

The average of summering distribution prediction of the 100 models was presented in Figure 3. The most suitable habitats are located along the coasts of the Laptev Sea, primarily the Lena-Delta, in the Yana-Kolyma Lowland, and smaller lowlands of Chukotka with narrow strips extended upstream to catchments of major rivers such as the Lena, Indigirka, and Kolyma (Fig. 3). The binary map (Fig. 4) produced using the criteria of minimum training presence threshold indicated that 36.44% of the study area was suitable summering habitats.

Lowland wetlands including large deltas, estuaries, tundra, and swampy floodplains (i.e. floodplain contains numerous ponds and shallow lakes), which extend from the Lena Delta at the west to the Kolyma River at the east, provide the most extensive and continuous breeding ground for*A. erythropus* in our study area (Figs. 3 and 4). This is particularly the case for the very large Lena Delta (~29,000 $km^2$, Schneider *et al* . 2009), where the predicted summering habitats include tundra together with numerous interlaced channels and lakes (Dutta *et al* . 2006).

Most of predicted breeding habitats are covered by a range of plant types including grasses, sedges, herbs, as well as abundant mosses and lichens. This tundra vegetation is also characterized by widely spaced shrubs (e.g. *Betula nana (s.l.), Dushecia fruticosa* and several species of *Salix* ) (Yurkovskaya 2011). Such tundra vegetation along major rivers within the taiga biome also have potential to be suitable habitat (Fig. 3).

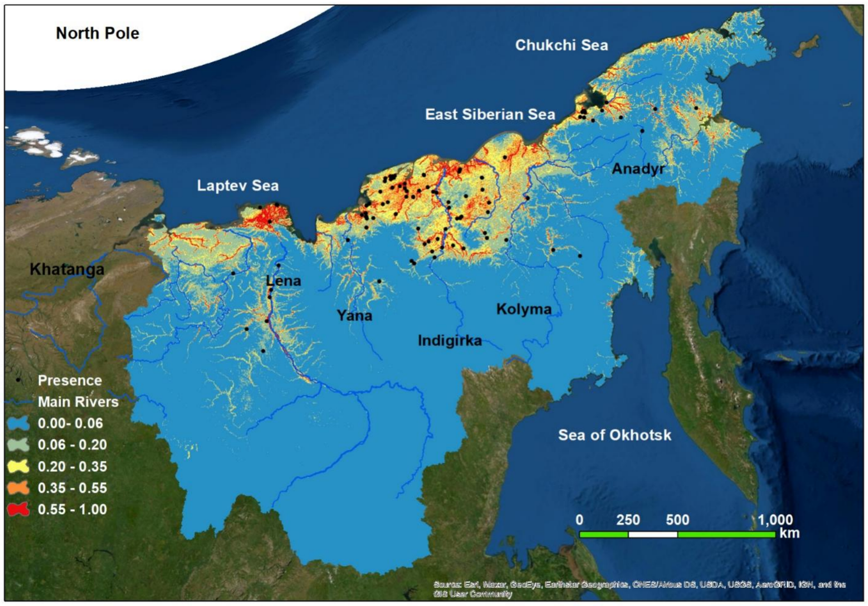



Figure 3 Fitted Maxent model showing the probability of summering habitats of the Eastern population of the Lesser White-fronted Goose. Red color indicates the strongest probability, with orange and yellow less so. Background: Aerial Imagery from ESRI (*http://services.arcgisonline.com/arcgis/rest/services* ). Projection: Asia North Albers Equal Area Conic.

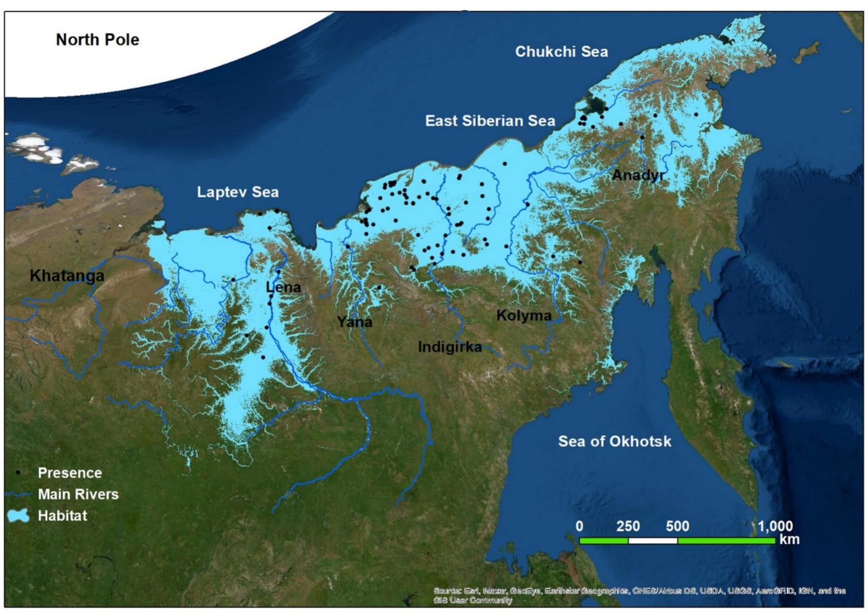



Figure 4 Breeding habitats of the Eastern population of the Lesser White-fronted Goose based on the minimum training presence threshold. Projection: Asia North Albers Equal Area Conic. Background:

World Imagery from ESRI (http://services.arcgisonline.com/arcgis/rest/services).

## Effects of environmental factor on the summering range of *A. erythropus*

Of the nine environmental variables included in model building, elevation was the most important, strongly contributing to the scaling of the Maxent model (59.7% based on the model gain and 50.1% based on re-evaluation of the random permutation of training presence and background data, Table 2). Other highly influential variables (with more than 5% permutation contribution) include precipitation of the warmest quarter, distance to streams, and mean temperature of the warmest quarter (Table 2).

Although highly correlated environmental predictors were excluded from model fitting, there are still collinearities in the remaining variables. For example, the Pearson r between Bio10 (precipitation of the warmest quarter) and Bio18 (mean temperature of the warmest quarter) is relatively high (-0.82) in the study area. Thus, the variable contributions in Table 2 should be interpreted with caution (Phillips 2005).

Table 2 Relative contributions of the environmental variables to the breeding habitat distribution of *A. erythropus* ranked by permutation importance.

| **Predictor** | **Percent contribution** | **Permutation importance** |
|---|---|---|
| Elevation | 59.4 | 54.3 |
| Precipitation of warmest quarter | 5.0 | 25.2 |
| Distance to streams | 20.3 | 6.5 |
| Mean temperature of warmest quarter | 5.2 | 5.8 |
| Range_EVI | 0.9 | 2.6 |
| Distance to settlement | 2.4 | 2.2 |
| Land cover | 5.5 | 2.0 |
| Homogeneity_EVI | 1.0 | 0.8 |
| Local deviation from global | 0.2 | 0.6 |

The marginal effects of the predictors on habitat suitability of*A. erythropus* (i.e. occurrence probability responds to changes in a specific explanatory variable while other covariates are assumed to be held constant as mean) were presented in Figure 5. The response curves showed that the effects of environmental factors on the occurrence of*A. erythropus* were strongly nonlinear.

For topographic variables, the probability of *A. erythropus*presence declines with increasing elevation up to 500 m, with locations higher than 500 m elevation were virtually devoid of *A. erythropus* (Fig 5A). Also, the response curve of LDFG indicated that the geese prefer relatively flat sites (Fig 5I). In terms of bioclimatic variables, the probability of *A. erythropus* presence increases with precipitation of the warmest quarter to around 55 mm and mean temperature of the warmest quarter to around 14°C, after which there is a sharp decrease (Fig. 5B, Fig. 5D). Human disturbance also influences summering habitat, with suitability increasing the further the site is from human settlement (Fig. 5F). The response curve of habitat occurrence probability to distance from rivers (Fig. 5C) suggests that the geese were highly dependent on wetlands and riparian areas (Fig. 5C). Within the riparian zone, the summering habitat suitability decreases sharply with increasing distance from water courses, and after about 4.5 km virtually no birds are found.*A. erythropus* generally prefers land cover types waters (code 210) and shrubland (120; Fig. 5G). The modeling results suggest that the probability of occurrence increases with land productivity range (Fig. 5E) and homogeneity (Fig. 5H).

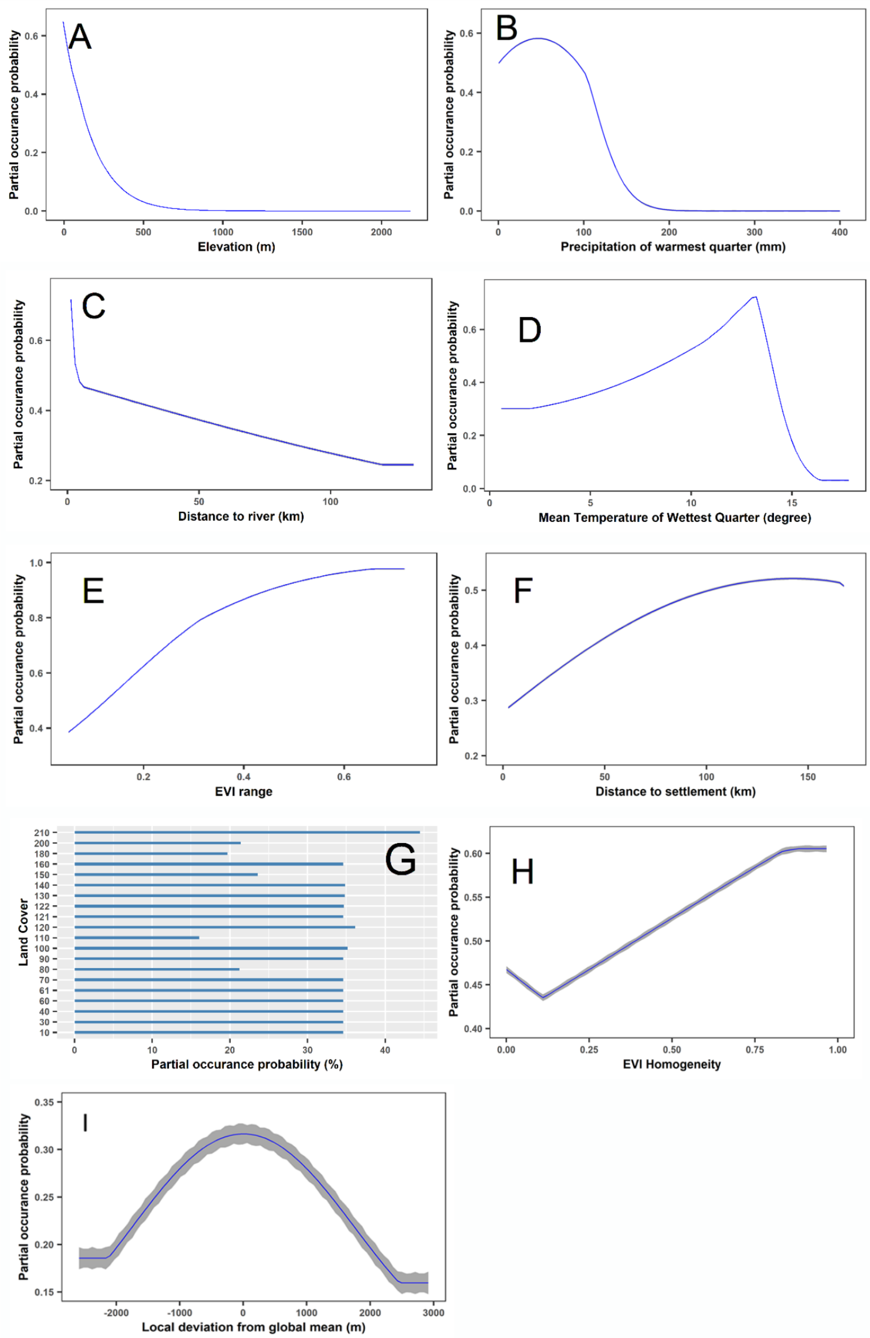



Figure 5 The relationships between the probability of *A. erythropus* occurrence and the top ten environmental variables based on permutation. Blue lines are mean response curves, and grey shades are 1 standard deviation.

# Discussion and Conservation Implications

Due to the remoteness and restricted accessibility, there are few historical observations of the summering ground of this population (Ruokonen *et al* . 2004), and our current knowledge on the breeding distribution and habitat preference is limited (Fig. 1 and see Artiukhov and Syroechkovski-Jr. 1999; Egorov and Okhlopkov 2007; Solovieva and Vartanyan, 2011). In this context, rapid development of animal tracking technologies offers new insights to determine distribution range and habitat preferences (Kays *et al* . 2015). In this study, we combined historical records with recent tracking data to model potentially suitable areas of the east sub-population of *A. erythropus* across the more than 7,400,000 km$^2$ of arctic and subarctic of north-eastern Russia. Our findings assist conservation of this threatened species by identifying the most suitable breeding grounds and assessing existing and future threats. As *A. erythropus* often co-occurs with other geese (e.g. Greater White-fronted goose (*A. albifrons* ), Bean Goose (*A. fabalis* ) and Brent Goose (*Branta bernicla* ) and other waterfowl including ducks and tundra swan (Hodges and Eldridge, 2001; Pozdnyakov, 2002; Krechmar and Kondratiev 2006), the breeding habitat map could also be used for prioritizing waterbird conservation including through identification of high-priority conservation areas.

## Model accuracy and breeding range

In recent years, animal tracking point data have been used in SDM construction either through direct use for model fitting (Williams*et al* . 2017) or for validating the output of the model (Pinto*et al* . 2016). By combining three-year tracking data and historical surveys, our dataset represents the most comprehensive presence record and offers a solid basis to delineate the breeding range of the poorly-known eastern sub-population of *A. erythropus* . The cross-validation results showed that the training and testing AUC are both high (i.e. greater than 0.92) and comparable, suggesting that the output is highly reliable (Phillips and Dudík 2008).

The Maxent output suggested a continuous rather than patchy breeding range of the *A. erythropus* on the plains adjusted to the Laptev, East-Siberian and Chukchi Seas and in the Anadyr Lowland. Within this over 4,000 km area of coastal plains, the Lena Delta, the wide Yana-Kolyma Lowland and smaller lowlands of Chukotka represent the most extensive breeding area with the highest probability of occurrence (Figures 3 and 4). While there are suggestions that breeding ranges of West and East Asian sub-populations overlap between 103 and 118 E, our work did not confirm this. The flat and rolling subarctic tundra is among the most productive wetland system in north-eastern Russia (Gilg*et al* . 2000). Vegetation characteristic in this area is typical tundra, southern tundra with shrubs and forest-tundra with sparse patches of larch (*Larix spp.)* Yurkovskaya (2011). A current IBA (Important Bird Area), including the four main deltas (i.e. the Kolyma, Indigirka, Yana and Lena), covers about 34% of the modeled breeding range (BirdLife International, 2017). However, the majority of the coastal plains, extending up to 450 km inland (Figures 3 and 4), and valleys of large rivers are not included in this IBA. Although there are several Wetlands of International Importance under the Ramsar Convention on the Kamchatka Peninsula, the closest to the study area (Parapolsky Dol) does not contain habitat the modelling suggests as suitable. Highly suitable habitats in the study areas have legal protection through declaration as Federal (State) Nature Reserves: Ust-Lenskiy, Olekminskiy and Magadanskiy, and also by Kytalyyk and Beringia National Parks.

## Environmental characteristics of breeding habitat

The selection of environmental variables is a critical step in SDM (Araujo and Guisan 2006; Fourcade *et al* . 2018), and hundreds of environmental factors have been utilized in Maxent (Bradie and Leung 2017). These predictor variables can be loosely grouped into four main groups: limiting factors that control the ecophysiology of the species concerned (e.g. temperature, precipitation, pH); resource factors (e.g. vegetation, water areas), which are supplies needed by the organisms to survive; disturbance factors including anthropogenic and natural perturbations in the environment; and landscape factors, which can be related to the species dispersal limitations (Guisan and Thuiller 2005; Vuilleumier and Metzger 2006).

The geomorphological predictors (i.e. elevation, distance to streams and local deviation from global) collectively contributed to 61.4% of the model gain based on permutation test. This level of relative importance was considered very high for Maxent modeling (Bradie and Leung 2017). The decisive role of topography in controlling the distribution of summering grounds might be attributed to strong preference of river valleys and lowlands, especially considering reduced mobility of geese during breeding and molting periods (Akesson and Raveling 1982). Kosicki (2017) demonstrated the importance of topography for modeling the distribution of both lowland and upland bird species, and omitting topographic variables could lead to substantial overestimation of distribution range, especially for rare species. The response curves show that *A. erythropus* selects lowlands with a concave shape as preferred habitat, which is consistent with field observations (e.g. Artiukhov and Syroechkovski-Jr. 1999; Egorov and Okhlopkov 2007; Solovieva and Vartanyan 2011), which reported the bird bred and molt in river valleys.

The majority of Maxent models include climate variables as limiting factors, and most studies found temperature and precipitation were very important variables (Bradie and Leung 2017) as climate is believed to be the most important factor for species distributions (Gaston, 2003). It is therefore not surprising that climate variables including precipitation and temperature were also important for *A. erythropus* . A significant finding of the study is that there was an optimal window of mean summer temperature in 9-14°C (Fig. 5D) and dry continental or high Arctic precipitation of the wettest quarter in 55 mm (Fig. 5B), within which the habitat suitability is maximized.

Land cover is also important and contributes strongly to model performance (Table 2). The response curve indicates that two land cover types are favored by *A. erythropus* including shrubland and open-water areas. The land-cover preference can be linked to the requirement of nest shelters during breeding season (Hilton *et al* . 2004) and food resources. In terms of food resources, the *A. erythropus* is an herbivorous browser, i.e. it tends to increase the portion of the selective resources in their feeding range (Markkola*et al* . 2003). The wet sedge meadows on the alluvial floodplains that are preferred by herbivorous geese (Sedinger and Raveling 1984), and are critical for brood rearing (Markkola *et al* . 2003) offer a range of highly nutritious species with an adequate protein–water ratio and low portions of cellulose and lignin, (e.g. grasses*Puccinellia phryganodes* , *Phragmites australis* and sedges

*Carex spp).*

Finally, the most suitable habitats had higher land productivity heterogeneity (Fig. 5E and 5H) which was expected as species richness and abundance often increases with habitat diversity (Chasko and Gates 1982; Wen et al. 2015). Although human disturbance can sometimes increase diversity in such wetland systems, here the habitat suitability decreases with human disturbance (Fig. 5F), reflecting the negative impacts of human presence (Lei et al. 2019b).

## Conservation challenges

The results of this study highlight a major challenge from future climate change on the *A. erythropus* . First, many climate change models predict increasing spring temperatures and earlier snow melting (IPCC 2014), which will lead to flooding, submergence, permafrost erosion and loss and change in low-lying coastal wetlands (Prowse*et al* . 2006). As the predicted summering habitats were concentrated in the lowland coastal zone of the Laptev and East Siberian Seas, the projected sea level rise (IPCC 2014; Wrona *et al* . 2016) and increasing river flows (Karlsson *et al* . 2012; Wrona *et al* . 2016) could cause extensive habitat loss. The response curves of habitat suitability to topographic variables suggest that the relatively hilly and rugged landscape would restrict extension of suitable habitat landward and such “habitat squeeze” (Leo *et al* . 2019) would be highly detrimental to *A. erythropus* . Second, the models suggested that there was an “optimal window” in terms of mean summer temperature and precipitation, which could be interpreted as the realized climatic niche of *A. erythropus* (Merow *et al* . 2016). Rising temperatures under future climate change scenarios means that the temperature niche could shift northerly, which is sea. Third, studies have shown that encroachment of shrubs following projected climate change (e.g. *Salix ovalifolia* and *Dushecia* *fruticosa* ) into the wet meadows (Carlson *et al* . 2018), would likely decrease quantity and quality of available food resources.

Finally, there is the threat from increasing anthropogenic disturbance; *A. erythropus* avoids locations near active mines (although can colonize such areas after mining is finished) (Egorov and Okhlopkov 2007; Solovieva and Vartanyan 2011). Currently, human population levels in the predicted summering range is among the lowest in the world, and the coastal areas of this region are some of the least explored. However, the coast of the Russian Arctic is likely to undergo rapid development as there are reserves of oil, gas, metals and other natural resources which could be exported, with additional infrastructure, through the North-East Passage to European and Asian ports (Martini *et al* . 2019), more information on these potential developments can be found at *http://ecoline-eac.com/proekty/peschanka/deposit.html* ), and these developments present perhaps the most difficult challenges to the future of eastern sub-population of *A. erythropus* .

# ACKNOWLEDGMENTS

We greatly appreciate all the individuals involved in the capture and banding of *A. erythropus* that generated the data for this study. We recognize the contributions of staffs from East Dongting National Nature Reserve of China.

**Funding statement** : This study is supported by National Key Research and Development Program of China (2017YFC0405300). Logistic and transportation support to surveys in Chukotka was provided by Chukotka Gold Mining Co, a subsidiary of Kinross Gold.

**Ethics statement** : All field methods used in this study were approved by the Forestry Department of Hunan Province of China under scientific research license (No.11 Xiang Forest Protection (2014)). Field research was conducted with permission from the Bureau of East Dongting National Nature Reserve.

**Author contributions** : L.G., D.S. and Z.Q. developed the study design, D.S., G.D., S.V. participated the breeding surveys, and T.H. and L.J. participated in the tracking at wintering sites, all authors were involved in analyses and producing figures, D.S., Z.Q. L.W. and T.H. drafted the manuscript, P.B and L. W. edited the manuscript, P.B. L.W. and Z.Q. organized submission materials and revised the manuscript.

**Data deposits** : All data for analysis is available in Dryad.

# Literature cited

Aarvak, T. and I. Oien. (2018). D2 Lesser White-fronted Goose *Anser erythropus* – Fennoscandian population. *A Global Audit of the Status and Trends of Arctic and Northern Hemisphere Goose Populations* (component 2: Population Accounts). CAFF, Conservation of Arctic Flora and Fauna: 40-42.

Akesson, T.R. and Raveling, D.G. (1982). Behaviors associated with seasonal reproduction and long-term monogamy in Canada geese. *The Condor* , *84* (2), 188-196.

Andersson, A. and N. Holmqvist. (2010). The Swedish population of Lesser White-fronted Goose *Anser erythropus* – supplemented or re-introduced. *Ornis Svecica 20* , 202-206.

Araujo, M.B. and Guisan, A. (2006). Five (or so) challenges for species distribution modelling. *Journal of biogeography* , *33* (10), 1677-1688.

Artiukhov, A.I. and E.E. Syroechkovski-Jr. (1999). New data on distribution of Lesser White-fronted Goose in the Abyi Lowland (Eastern Yakutia). *Casarka 5,* 136-143 (in Russian with English summary).

Austin, M.P. and Van Niel, K.P. (2011). Improving species distribution models for climate change studies: variable selection and scale. *Journal of Biogeography* , 38(1), 1-8.

BirdLife International. (2017).*Important Bird and Biodiversity Area (IBA) digital boundaries* . BirdLife International, Cambridge, UK

BirdLife International (2018). *Anser erythropus* . The IUCN Red List of Threatened Species 2018: e.T22679886A132300164. Downloaded on 15 November 2019.

Bradie, J. and Leung, B., (2017). A quantitative synthesis of the importance of variables used in MaxEnt species distribution models. *Journal of Biogeography* , *44* (6), 1344-1361.

Carlson, L.G., Beard, K.H. and Adler, P.B., (2018). Direct effects of warming increase woody plant abundance in a subarctic wetland. *Ecology and evolution* , *8* (5), 2868-2879.

Cao, L., A. D. Fox, V. Morozov, E. Syroechkovskiy, and D. Solovieva. (2018). D1 Eastern Palearctic Lesser White-fronted Goose *Anser erythropus* . *A Global Audit of the Status and Trends of Arctic and Northern Hemisphere Goose Populations* (component 2: Population Accounts). CAFF, Conservation of Arctic Flora and Fauna: 38-39.

Chasko, G.G. and Gates, J.E., (1982). Avian habitat suitability along a transmission-line corridor in an oak-hickory forest region.*Wildlife Monographs* , *82* , 3-41.

Cuthbert, R. and T. Aarvak. (2016). Population estimates and survey methods for migratory goose species in Northern Kazakhstan. *AEWA Lesser White-fronted Goose International Working Group Report Series* 5, 1-96.

Deng, X., Q. Zhao, L. Fang, Z. Xu, X. Wang, H. He, L. Cao, and A. D. Fox. (2019). Spring migration duration exceeds that of autumn migration in Far East Asian Greater White-fronted Geese (*Anser albifrons* ).*Avian Research 10* (1), 19.

Di Gregorio, Antonio. (2005). *Land cover classification system: classification concepts and user manual: LCCS* (Vol. 2). Food and Agricultural Organization of the United Nations. 212.

Dupuis, D.J. and Victoria-Feser, M.P. (2013). Robust VIF regression with application to variable selection in large data sets. *The Annals of Applied Statistics* , *7* (1), 319-341.

Dutta, K., Schuur, E.A.G., Neff, J.C. and Zimov, S.A. (2006). Potential carbon release from permafrost soils of Northeastern Siberia.*Global Change Biology* , *12* (12), 2336-2351.

Egorov, N., and I. Okhlopkov. (2007). New data on nesting of the white-fronted goose (Anser erythropus) from Yakutia. *Zoologichesky Zhurnal 86* (12)*,* 1482-1485 (in Russian with English summary).

Elith, J., S. J. Phillips, T. Hastie, M. Dudik, Y. E. Chee, and C. J. Yates. (2011). A statistical explanation of MaxEnt for ecologists.*Diversity and distributions 17* (1), 43-57.

Elith, J., C. H. Graham, R. P. Anderson, M. Dudik, S. Ferrier, A. Guisan, R. J. Hijmans, F. Huettmann, J. R. Leathwick, and A. Lehmann. (2006). Novel methods improve prediction of species' distributions from occurrence data. *Ecography 29* (2), 129-151.

Evans, J. and Ram, K. (2018). *spatialEco: Spatial Analysis and Modelling Utilities* . R package version, 1-1.

Forcey, G.M., Thogmartin, W.E., Linz, G.M., Bleier, W.J. and McKann, P.C. (2011). Land use and climate influences on waterbirds in the Prairie Potholes. *Journal of Biogeography* , *38* (9), 1694-1707.

Fourcade, Y., Besnard, A.G. and Secondi, J. (2018). Paintings predict the distribution of species, or the challenge of selecting environmental predictors and evaluation statistics. *Global Ecology and Biogeography* , *27* (2), 245-256.

Fox, A.D., Ebbinge, B.S., Mitchell, C., Heinicke, T., Aarvak, T., Colhoun, K., Clausen, P., Dereliev, S., Farago, S., Koffijberg, K., Kruckenberg, H., Loonen, M., Madsen, J., Mooij, J., Musil, P., Nilsson, L., Pihl, S. and van der Jeugd, H. (2010). Current estimates of goose population sizes in the western Europe, a gap analysis and an assessment of trends. *Ornis Svecica 20* (3-4), 115-127.

Gaston, K. J. (2003). *The structure and dynamics of geographic ranges* . Oxford University Press on Demand, New York.

Gilg, O., Sane, R., Solovieva, D.V., Pozdnyakov, V.I., Sabard, B., Tsanos, D., Zockler, C., Lappo, E.G., Syroechkovski Jr, E.E. and Eichhorn, G. (2000). Birds and mammals of the Lena Delta nature reserve, Siberia. *Arctic 53* (2), 118-133.

Grishanov, D. (2006). Conservation problems of migratory waterfowl and shorebirds and their habitats in the Kaliningrad region of Russia. In: G. Boere, C. Galbraith and D Stroud (eds), *Waterbirds around the world* . The Stationary Office, Edinburgh, U.K. 356

Hijmans, R.J., Van Etten, J., Cheng, J., Mattiuzzi, M., Sumner, M., Greenberg, J.A., Lamigueiro, O.P., Bevan, A., Racine, E.B., Shortridge, A. and Hijmans, M.R.J. (2015). *Package 'raster'* . R package.

Hijmans, R.J., Cameron, S.E., Parra, J.L., Jones, P.G., Jarvis, A. (2005). Very high resolution interpolated climate surfaces for global land areas. International journal of climatology, *25* (15), 1965-1978.

Hilton, G.M., Hansell, M.H., Ruxton, G.D., Reid, J.M. and Monaghan, P. (2004). Using artificial nests to test importance of nesting material and nest shelter for incubation energetics. *The Auk* , *121* (3), 777-787.

Hodges, J.I. and Eldridge, W.D. (2001). Aerial surveys of eiders and other waterbirds on the eastern Arctic coast of Russia. *Wildfowl* ,*52* (52), 127-142.

IPCC. (2014). *Climate change 2013: the physical science basis: working group I contribution to the fifth assessment report of the intergovernmental panel on climate change* . Cambridge University Press.

Jia, Q., K. Koyama, C.-Y. Choi, H.-J. Kim, L. Cao, D. Gao, G. Liu, and A. D. Fox. (2016). Population estimates and geographical distributions of swans and geese in East Asia based on counts during the non-breeding season. *Bird Conservation International 26* (4), 397-417.

Jiguet, F., Barbet-Massin, M. and Chevallier, D. (2011). Predictive distribution models applied to satellite tracks: modelling the western African winter range of European migrant Black Storks Ciconia nigra. *Journal of Ornithology* , *152* (1), 111-118.

Jones, T., K. Martin, B. Barov, and S. Nagy. (2008). International single species action plan for the conservation of the western palearctic population of the lesser white-fronted goose *Anser erythropus. AEWA technical series 36* , 1-130.

Karlsson, J.M., Lyon, S.W. and Destouni, G. (2012). Thermokarst lake, hydrological flow and water balance indicators of permafrost change in Western Siberia. *Journal of Hydrology* , *464-465* , 459-466.

Kays, R., Crofoot, M.C., Jetz, W. and Wikelski, M. (2015). Terrestrial animal tracking as an eye on life and planet. *Science* , *348* (6240).

Krechmar, A.V. and Kondratiev, A.V. (2006). Anseriformes of Northeast Asia. North-Eastern Scientific Centre, Far-Eastern Branch of the Russian Academy of Sciences: Magadan, Russia. (In Russian, English summary)

Kosicki, J.Z. (2017). Should topographic metrics be considered when predicting species density of birds on a large geographical scale? A case of Random Forest approach. *Ecological Modelling* , *349* , 76-85.

Lei, J., Y. Jia, A. Zuo, Q. Zeng, L. Shi, Y. Zhou, H. Zhang, C. Lu, G. Lei, and L. Wen. (2019a). Bird Satellite Tracking Revealed Critical Protection Gaps in East Asian–Australasian Flyway. *International journal of environmental research and public health 16* (7), 1147.

Lei, J., Y. Jia, Y. Wang, G. Lei, C. Lu, N. Saintilan, and L. Wen. (2019b). Behavioural plasticity and trophic niche shift: How wintering geese respond to habitat alteration. *Freshwater Biology64* (6), 1183-1195.

Leo, K.L., Gillies, C.L., Fitzsimons, J.A., Hale, L.Z. and Beck, M.W. (2019). Coastal habitat squeeze: A review of adaptation solutions for saltmarsh, mangrove and beach habitats. *Ocean & Coastal Management* , *175* , 180-190.

Lobo, J. M., A. Jimenez-Valverde, and R. Real. (2008). AUC: a misleading measure of the performance of predictive distribution models.*Global ecology and Biogeography 17* (2), 145-151.

Madsen, J., D. Boertmann, and C. E. Mortensen. (1984). The significance of Jameson Land, East Greenland as molting and breeding area for geese: results of censuses 1982–84. *Dansk Ornitologisk Forenings Tidsskrift 78* , 121-131.

Markkola, J., Niemela, M. and Rytkonen, S. (2003). Diet selection of lesser white-fronted geese Anser erythropus at a spring staging area. *Ecography* , *26* (6), 705-714.

Martini, I.P., Morrison, R.G., Abraham, K.F., Sergienko, L.A. and Jefferies, R.L. (2019). Northern Polar Coastal Wetlands: Development, Structure, and Land Use. *Coastal Wetlands.* Elsevier,153-186.

Merow, C., Smith, M.J. and Silander Jr, J.A. (2013). A practical guide to MaxEnt for modeling species' distributions: what it does, and why inputs and settings matter. *Ecography* , *36* (10), 1058-1069.

Merow, C., Allen, J.M., Aiello-Lammens, M. and Silander Jr, J.A. (2016). Improving niche and range estimates with Maxent and point process models by integrating spatially explicit information. *Global Ecology and Biogeography* , *25* (8), 1022-1036.

Morozov, V.V. (1995). Status, distribution and trends of the lesser white-fronted goose (Anser erythropus) population in Russia.*Bulletin of Goose Study Group of Eastern Europe and Northern Asia1* , 131-144. (in Russian with English summary).

Morozov, V., and E. Syroechkovski-Jr. (2002). Lesser White-fronted Goose on the verge of the Millenium. *Casarca 8* ,233-276. (in Russian with English summary).

Phillips, S.J. (2005). *A brief tutorial on Maxent* . ATandT Research, *190* (4), 231-259.

Phillips, S.J. and Dudik, M. (2008). Modeling of species distributions with Maxent: new extensions and a comprehensive evaluation.*Ecography* , *31* (2), 161-175.

Pearson, R.G., Thuiller, W., Araujo, M.B., Martinez-Meyer, E., Brotons, L., McClean, C., Miles, L., Segurado, P., Dawson, T.P. and Lees, D.C. (2006). Model-based uncertainty in species range prediction*. Journal of biogeography* , 33(10), 1704-1711.

Pimm, S.L., Alibhai, S., Bergl, R., Dehgan, A., Giri, C., Jewell, Z., Joppa, L., Kays, R. and Loarie, S., (2015). Emerging technologies to conserve biodiversity. *Trends in ecology & evolution* ,*30* (11), 685-696.

Pinto, C., Thorburn, J.A., Neat, F., Wright, P.J., Wright, S., Scott, B.E., Cornulier, T. and Travis, J.M., (2016). Using individual tracking data to validate the predictions of species distribution models. *Diversity and Distributions* , *22* (6), 682-693.

Pozdnyakov, V.I. (2002). Status and Breeding Ecology of Bewick's Swans in the Lena Delta, Yakutia, Northern Asia. *Waterbirds* , *25* , 95-99.

Prowse, T.D., Wrona, F.J., Reist, J.D., Hobbie, J.E., Levesque, L.M. and Vincent, W.F. (2006). General features of the Arctic relevant to climate change in freshwater ecosystems. *AMBIO: A Journal of the Human Environment* , *35* (7), 330-338.

Riley, S.J., DeGloria, S.D. and Elliot, R. (1999). Index that quantifies topographic heterogeneity. *Intermountain Journal of Sciences* , 5(1-4), 23-27.

R core team. (2019). *R: a language and environment for statistical computing* , version 3.6.1. Vienna, Austria: R Foundation for Statistical Computing; 2019.

Rozenfeld, S.B., G.V. Kirtaev, N.V. Rogova, and M. Yu. Soloviev. (2019). Results of an aerial survey of the Western population of *Anser erythropus* (Anserini) in autumn migration in Russia 2017. *Nature Conservation Research 4* (1): DOI: 10.24189/ncr.2019.003

Ruokonen, M., Kvist, L., Tegelstrom, H. and Lumme, J. (2000). Goose hybrids, captive breeding and restocking of the Fennoscandian populations of the Lesser White-fronted goose (*Anser erythropus* ).*Conservation Genetics* , *1* (3), 277-283.

Ruokonen, M., Kvist, L., Aarvak, T., Markkola, J., Morozov, V.V., Oien, I.J., Syroechkovsky, E.E., Tolvanen, P. and Lumme, J. (2004). Population Genetic Structure and Conservation of the Lesser White-Fronted GooseAnser erythropus. *Conservation Genetics* , *5* (4), 501-512.

Schneider, J., Grosse, G. and Wagner, D. (2009). Land cover classification of tundra environments in the Arctic Lena Delta based on Landsat 7 ETM+ data and its application for upscaling of methane emissions. *Remote Sensing of Environment* , *113* (2), 380-391.

Sedinger, J. S., & Raveling, D. G. (1984). Dietary selectivity in relation to availability and quality of food for goslings of cackling geese. *The Auk* , *101* (2), 295–306.

Solovieva, Diana and Vartanyan. (2011). Lesser White-Fronted Goose*Anser erythropus* : good news about the breeding population in west Chukotka, Russia. *Wildfowl, 61* (61), 110-120.

Stevens, B.S. and Conway, C.J. (2020). Predictive multi-scale occupancy models at range-wide extents: Effects of habitat and human disturbance on distributions of wetland birds. *Diversity and Distributions* ,*26* (1), 34-48.

Swets, J.A. (1988). Measuring the accuracy of diagnostic systems.*Science* , *240* (4587), 1285–1293.

Tuanmu, M.N. and Jetz, W. (2015). A global, remote sensing-based characterization of terrestrial habitat heterogeneity for biodiversity and ecosystem modelling. Global Ecology and Biogeography, *24* (11), 1329-1339.

Vollstadt, M.G., Ferger, S.W., Hemp, A., Howell, K.M., Topfer, T., Bohning-Gaese, K. and Schleuning, M. (2017). Direct and indirect effects of climate, human disturbance and plant traits on avian functional diversity. *Global Ecology and Biogeography* , *26* (8), 963-972.

Vuilleumier, S. and Metzger, R. (2006). Animal dispersal modelling: handling landscape features and related animal choices. *Ecological Modelling* , *190* (1-2), 159-170.

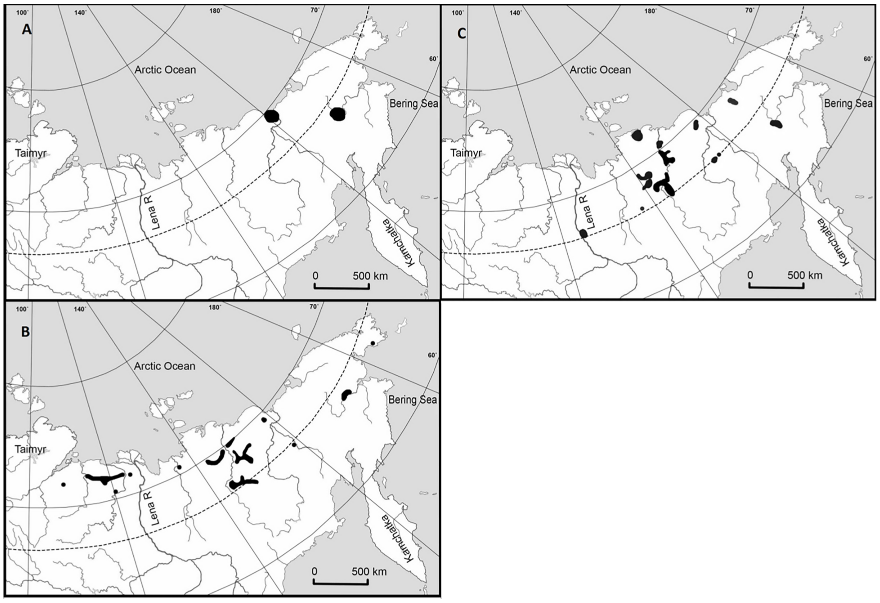
Wang, X., A. D. Fox, P. Cong, M. Barter, and L. Cao. (2012). Changes in the distribution and abundance of wintering Lesser White-fronted Geese*Anser erythropus* in eastern China. *Bird Conservation International 22* (2), 128-134.

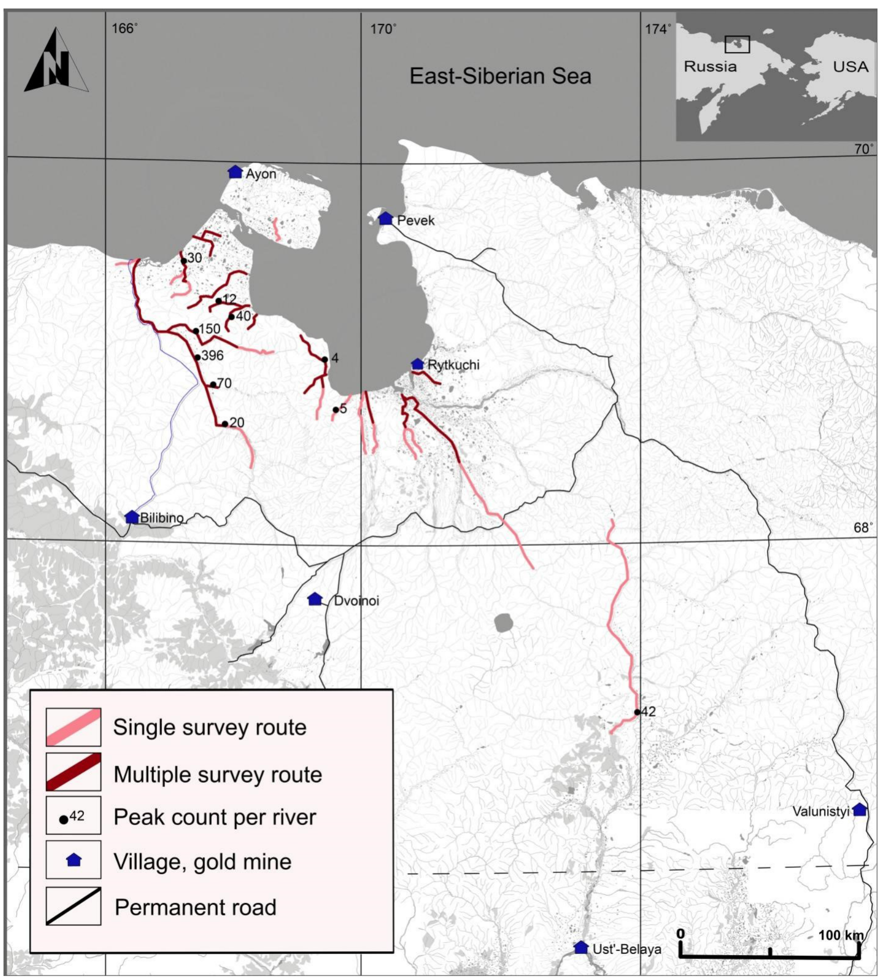
Wen, L., Saintilan, N., Yang, X., Hunter, S. and Mawer, D. (2015). MODIS NDVI based metrics improve habitat suitability modelling in fragmented patchy floodplains. *Remote Sensing Applications: Society and Environment* , *1* , 85-97.

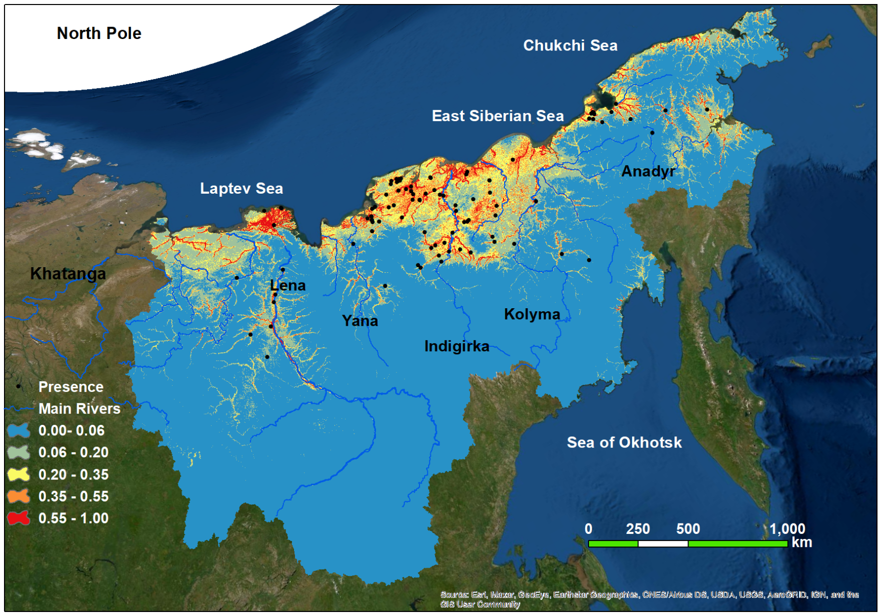
Williams, H.M., Willemoes, M. and Thorup, K. (2017). A temporally explicit species distribution model for a long-distance avian migrant, the common cuckoo. *Journal of Avian Biology, 48* (12), 1624-1636.

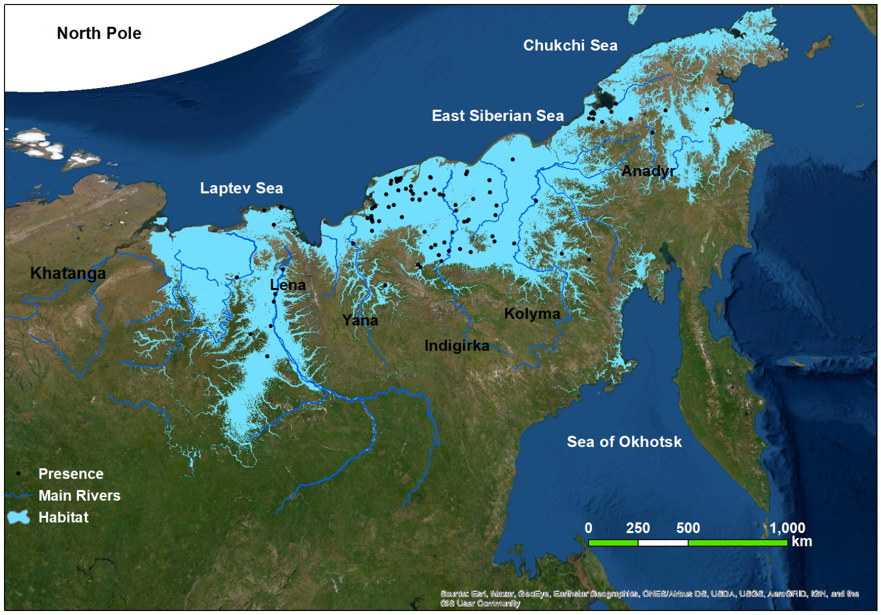
Wrona, F.J., Johansson, M., Culp, J.M., Jenkins, A., Mard, J., Myers-Smith, I.H., Prowse, T.D., Vincent, W.F. and Wookey, P.A. (2016). Transitions in Arctic ecosystems: Ecological implications of a changing hydrological regime. *Journal of Geophysical Research: Biogeosciences* , *121* (3), 650-674.

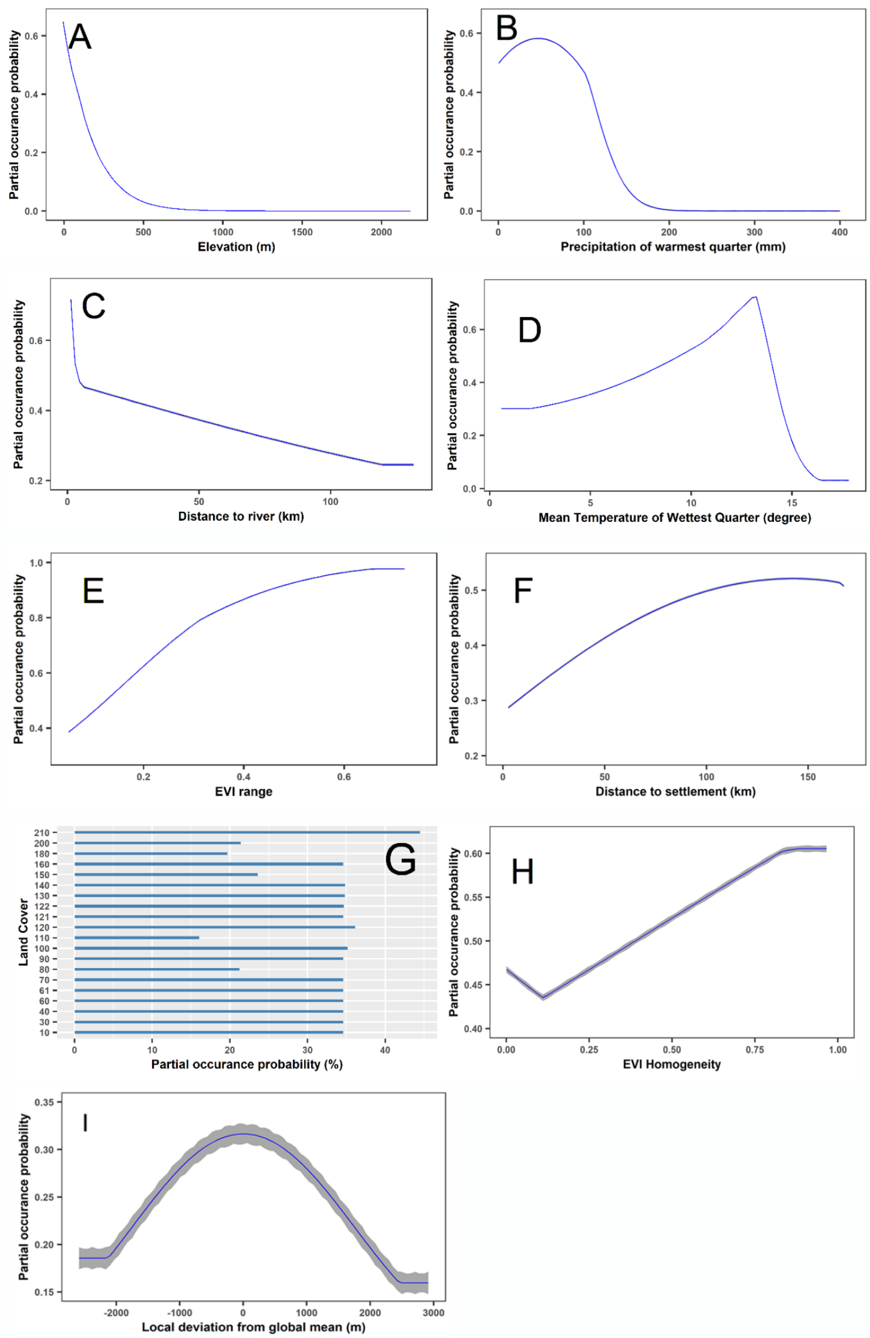
Yurkovskaya, T.K. (2011). Vegetation map. *National Atlas of Soils of the Russian Federation, Moscow State University* , 46-48. https://soilatlas.ru/karta-rastitelnosti (in Russian)


A
B
C
Arctic Ocean
Bering Sea
Taimyr
Lena R
Kamchatka
0 500 km


East-Siberian Sea
Russia
USA
166°
170°
174°
70°
68°
Ayon
Pevek
Rytkuchi
Bilibino
Dvoinoi
Valunistyi
Ust'-Belaya
30
12
40
150
396
70
20
4
5
42
Single survey route
Multiple survey route
Peak count per river
Village, gold mine
Permanent road
0
100 km


North Pole
Chukchi Sea
East Siberian Sea
Laptev Sea
Anadyr
Khatanga
Lena
Yana
Kolyma
Indigirka
Sea of Okhotsk
Presence
Main Rivers
0.00- 0.06
0.06 - 0.20
0.20 - 0.35
0.35 - 0.55
0.55 - 1.00
0 250 500 1,000
km


North Pole
Chukchi Sea
East Siberian Sea
Laptev Sea
Anadyr
Khatanga
Lena
Yana
Kolyma
Indigirka
Sea of Okhotsk
Presence
Main Rivers
Habitat
0 250 500 1,000
km


A
Partial occurance probability
Elevation (m)
B
Partial occurance probability
Precipitation of warmest quarter (mm)
C
Partial occurance probability
Distance to river (km)
D
Partial occurance probability
Mean Temperature of Wettest Quarter (degree)
E
Partial occurance probability
EVI range
F
Partial occurance probability
Distance to settlement (km)
G
Land Cover
Partial occurance probability (%)
H
Partial occurance probability
EVI Homogeneity
I
Partial occurance probability
Local deviation from global mean (m)