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An assessment of three survey methods on common bird species in low Arctic tundra

Comparing line transect distance sampling, repeated point counts and double observer point counts

Erik Schmidt Lindgaard

BIO-3950 Master thesis in Biology

May 2017



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Northern Populations and Ecosystems

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Cover photo: Erik Schmidt Lindgaard
Photo of field worker walking on the Siberian tundra

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Abstract

Long-term studies of bird communities in Arctic regions are rare in comparison to studies performed in temperate regions, particularly studies that takes detectability into consideration. Finding a suitable and robust method for long-term monitoring of bird populations in the low Arctic which includes a correction of imperfect detection, can contribute to increased ecological understanding and easier identification of changes over time. During two field seasons (June-July) in 2015 and 2016, the bird population on Erkuta tundra monitoring site, Yamal, Russia, was surveyed using the three different methods: distance sampling on line transects, repeated point counts and double observer point counts. The comparison between the methods was done by estimating abundances and densities of the three most common species in the area, i.e. Lapland bunting (*Calcarius lapponicus*), Red-throated pipit (*Anthus cervinus*) and Wood sandpiper (*Tringa glareola*). I found that the most plausible density estimates of the common target species were provided by the line transect distance sampling. Although all assumptions were difficult to completely fulfil in the field, the method could be improved by more exact distance measurements in the field, since the degree of overestimation is limited to the extent of which the assumptions are violated. In addition, the line transect distance sampling method have the least impact of “floaters” (non-breeders), which also makes this method more robust. Repeated point counts heavily overestimated the densities, and the models fitted poorly for Red-throated pipit. The overestimation was likely due to violation of the assumption of closed population, and could be reduced by using a model allowing for temporary emigration. Also, too short distance between points, and thus a risk of double counting, could have contributed to the overestimation. However, the double observer point counts offer an alternative approach for long-term monitoring, where the slight overestimation also can be decreased with increased distance between points. In addition, the double observer method requires less effort than the other two methods.

Keywords: survey method, distance sampling, point count, double observer, line transect, detectability, low Arctic, Lapland bunting, Red-throated pipit, Wood sandpiper

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1 Introduction

Monitoring programs are central to ecology and for assessing the impact of environmental change on ecosystems. Biological monitoring has a long tradition worldwide, and is the process of field-based empirical collecting of data about a system, e.g. communities or populations, at different times to assess the state and draw inferences about changes over time. The purpose of this is scientific by learning and developing an understanding of the system, and providing information for management purposes that can help to make well-founded and appropriate management decisions (Yoccoz et al., 2001; Lindenmayer and Likens, 2010). Recognition of the importance of long-term ecological research and monitoring has developed as a result of an acknowledgement of long-term studies as a main approach to understand ecological patterns and processes (Ims et al., 2013b). Effective management of bird populations depends heavily upon accurate estimates of trends in bird abundance (Taylor and Pollard, 2008). This allows one to identify changes and implement appropriate conservation measures if necessary. Developing suitable standardized surveys or counts with predefined method design and protocol, will contribute to better monitoring with more precise and reliable abundance and density estimates.

Bird communities need to be monitored to identify and understand trends in avian ecology and in addition they function as useful indicators of the state of environment in relation to environmental factors or direct threats (Bibby, 2000). Birds are important indicators, due to their occurrence high in the food chain, their sensitivity to both natural and anthropogenic change, and their abundance and mobility which causes them to inhabit most habitats – both terrestrial and marine. As they are relatively easy and inexpensive to monitor and identify, and have long been the focus of interest of many naturalists, long-term series exist which allow for historical perspective and trend analysis. (Gregory and van Strien, 2010).

The Arctic is currently influenced by both climate change, which is more rapid than in other parts of the world, and increased human activity such as oil and gas exploitation (Forbes et al., 2009; Liebezeit et al., 2009; Møller et al., 2013). Northern latitudes are expected to be particularly strongly influenced by climate change (Houghton et al., 2001). This includes Arctic and boreal species that are predicted to be affected by huge range reductions, providing a demand for protection of prone areas (Virkkala et al., 2008). Due to the rapidity of climate change and the anthropogenic threats to wildlife, it is especially important to monitor trends

in bird communities in the Arctic. A small proportional decline in abundance of common species might lead to large absolute losses of individuals and biomass which can disturb ecosystem structure and function (Gregory and van Strien, 2010). In particular, long-term studies of bird communities in Arctic regions are rare in comparison to studies performed in temperate regions.

This study is performed on the Erkuta tundra monitoring site on the southern part of the Yamal Peninsula, Russia. What makes the study site particularly interesting for research, is its location in the low Arctic, which is one of the first parts of Arctic to experience the consequences of climate change (Ims et al., 2013a). With southern species extending their ranges northwards, the proximity to the sub-Arctic (or forest tundra) entails possible threats like gradual homogenization of biodiversity, change of community composition and invasive species. Sokolov (2012) monitored bird communities on Erkuta to analyze bird habitat relationships and quantify habitat specialization. By using spot mapping and nest searching for abundant species, the implementation of the method is highly observer dependent and time consuming, thus difficult to apply for long-term monitoring.

Many different counting methods and approaches exist to produce abundance and density estimates, such as distance sampling, line transects, point counts, double-observer counts, migration counts, playback surveys, spot mapping, nest monitoring and capture-mark-recapture. Capture and marking of birds can be difficult to implement over large areas and can be invasive to the birds. Observational approaches like point counts and line transects are common methods to estimate population size, and is in addition minimally invasive and requires less resources to implement (Henry and Anderson, 2016). Different methods can help determine the abundance of birds in different ways depending on varying factors such as observer, study area, habitat, time, weather and behavior of the birds. To be able to choose the most appropriate survey method, several different methods need to be compared in the same area. This will make it possible to recognize weaknesses and strengths of the different methods, and to determine differences in accuracy and precision of the density estimates. The execution of the methods will also make it possible to compare the time and resources spent between the methods to increase efficiency and optimize survey methods in the future. A traditional single-observer count does not consider the birds that are present, but not detected. The assumption that captured or observed animals form the selected community can lead to missing out on an important aspect - i.e. the differences amongst individuals in the probability

of detection (Buckland et al., 2011). Individuals in a population are heterogeneously distributed in space, and behavior, camouflage, weather, habitat characteristics and proximity to observer will affect their detectability. If ignored, imperfect detection can introduce measurement error which lead to imprecise population estimates. Therefore, survey methods which includes a correction of imperfect detection, are recommended (Diefenbach et al., 2003). Specialized survey methods like repeated point counts, site occupancy sampling, distance sampling, removal sampling and double observer sampling have been developed to handle with imperfect detection. (Freckleton et al., 2006; Fiske and Chandler, 2011). This study will take a closer look at three of the methods which take these undetected birds into account, namely; distance sampling (Buckland et al., 2001), repeated point counts (Royle, 2004a) and double-observer point count (Nichols et al., 2000).

In distance sampling, the key sample data are the distances from registered individuals to a transect line or to a point. Also, the effort, that is transect length or visits to points, is recorded (Buckland et al. 2001). Collected distances are used to estimate a detection function, which is the probability that an animal is detected as a function of distance to the line (Buckland et al., 2011). The detection function compensates for the decreasing detectability with increasing distance from the observer, and make it possible to estimate density that is adjusted with respect to nondetection bias (Rosenstock et al., 2002; Royle et al., 2004b). An adequate number and random placement of transect lines allows to estimate density within the whole study area (Buckland et al., 2011). Repeated point counts, as proposed by Royle (2004a), is a method that allows for estimating of population size, corrected for imperfect detection, from temporally separated replications. The hierarchical structure of these models has been developed to separate modeling of abundance and detection probability in an attempt to reduce measurement error. Estimation of site-specific abundance is not always of specific interest since there is little ecological information to obtain from small local populations. But an estimate of average abundance over multiple locations within a region can form a basis for evaluation of change over time (Royle, 2004a; Fiske and Chandler, 2011). The double – observer method is an approach which uses two observers that permits estimation of detection probability and abundance from point counts (Nichols et al., 2000). The method has two different approaches; the dependent-observer and the independent-observer. This study uses the dependent-observer approach, where there is some communication between the observers, because it has been shown to result in higher observer-specific, species-specific and joint

detection probabilities, and lower standard errors of detection probability (Forcey et al., 2006).

The aim of this study is to compare and assess the three survey methods carried out on the Erkuta tundra monitoring site; distance sampling on line transects, repeated point counts and double observer point counts. Finding a suitable and robust method for long-term monitoring of bird populations in the low Arctic can contribute to increased ecological understanding. In this thesis, I present an evaluation of the three different survey methods with focus on estimates, accuracy and precision. In particular, I will:

- 1) Compare and assess differences in detectability, abundance and density estimates between years for three common species, and evaluate the differences between the methods.
- 2) See if, and how, covariates as habitat, wind, time, and Julian day effects detectability
- 3) Discuss which method may be best suited for monitoring the abundance of common bird species in low Arctic tundra, taking the required field effort into account.

2 Methods

2.1 Study area

The Yamal Peninsula is located in the north-western part of Siberia, Russia (Figure 1A), surrounded by the Kara Sea. It is underlain by continuous permafrost, and stretches over 700 km with a total land area of 122 000 km² (Pika and Bogoyavlensky, 1995). Due to rich deposits of oil and gas, this area is undergoing a massive industrial development for utilization of these resources. The region also has many semi-domestic reindeer herds, owned and managed by the indigenous nomads –the Nenets.

The study was carried out in the southwestern part of the Yamal Peninsula in the Erkuta tundra monitoring site (N68°13' E69°09') around 30 km from the coast (Figure 1B). This area consists of flat tundra combined with sandy hills (rising up to 40 m high). A network of lakes, rivers and wetlands divide the tundra landscape, and many low-lying areas are flooded in spring. Sandy cliffs are created along the rivers banks and around lakes. There are numerous patches of willow thickets, occasionally interspersed with areas of alder (*Alnus fruticosa*) (Ehrich et al., 2012). Long term mean temperature in the area is –24.1°C in January and 11.4°C in July, and mean annual precipitation is about 335 mm (averages for the period 1950 – 2000; downloaded from www.worldclim.org, accessed 28-04-2017). But during the last 10 years, mean temperature has increased somewhat to -20.5°C in January and 13.6 °C in July (Data from the ERA-interim reanalysis model; <http://apps.ecmwf.int/datasets/>, accessed 28-04-2017). There is a stable snow cover from early October until early June (Sokolov et al., 2012).

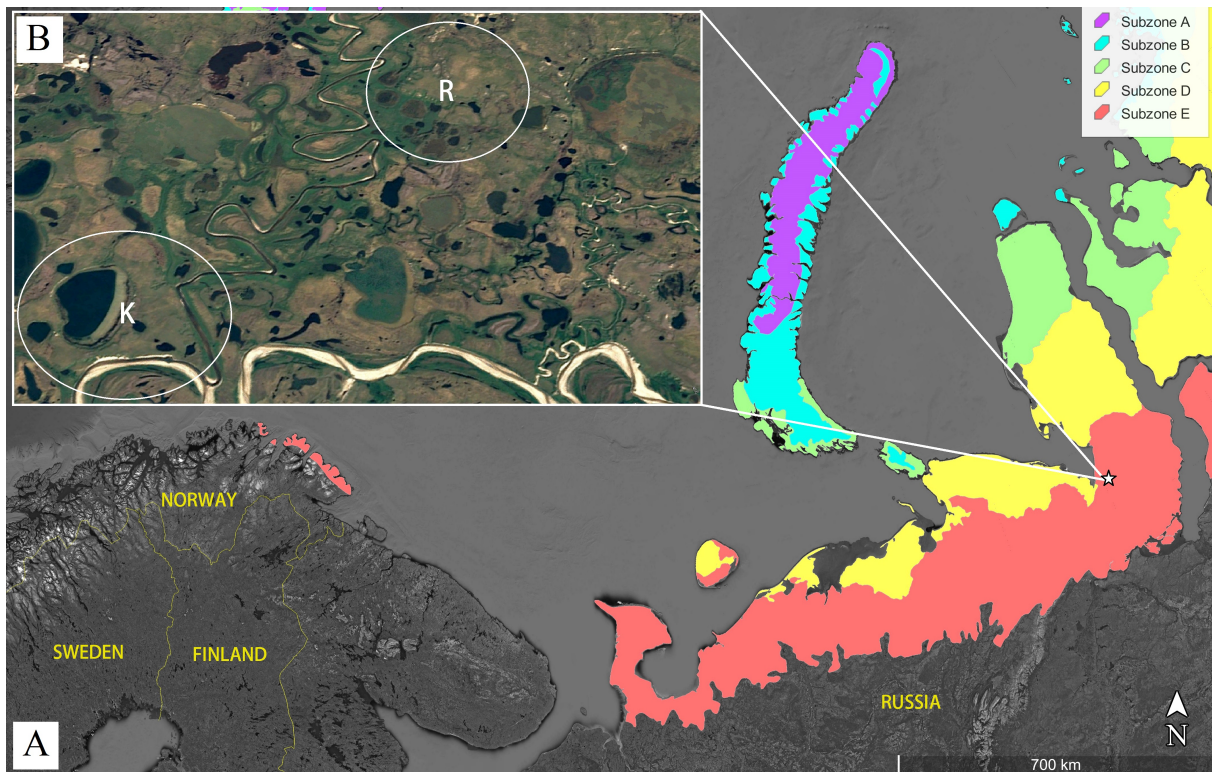


Figure 1: A) Map showing the location of the study area in southern Yamal. The colors represent the different bioclimatic subzones of the Arctic (A-E) as used by the Circumpolar Arctic Vegetation Map (Walker et al., 2005). B) Map of the study area with surveys carried out in 2 study units (K and R) separated by approximately 7 km. Map data: Google Earth.

According to the Circumpolar Arctic vegetation map (Walker et al., 2005), four of the five bioclimatic subzones are present on the Yamal Peninsula. Erkuta is located in subzone E (Figure 1A), which is the largest (36% of the Arctic), warmest and most vegetated subzone. It is characterized by an 80-100% plant cover of vascular plants, 2-3 moss layers where each layer is 5-10 cm thick, herbaceous/dwarf shrub layer 20-50 cm tall, and sometimes with low-shrub layer up to 80 cm. The study area is at the border between two vegetation zones: erect dwarf-shrub and the more common low-shrub tundra.

2.2 Fieldwork and sampling design

The study was conducted during two field seasons in 2015 (15th of June - 19th of July) and 2016 (3rd of June - 17th of July). All surveys were done in different habitats to get a better view of the overall community composition. Sokolov et al. (2012) used five specific habitat types for his study, but for this study I chose to use three main habitats which correspond to the three distinct species assemblages identified – willow thicket edges, upland tundra, and lowland shrub tundra and marshes. These habitats cover all the different structural elements, resources availabilities and breeding grounds, and represent the main landscape elements

present in the study area. The willow thicket habitat consists of dense willow thickets growing along rivers, flooded areas or in slopes (Figure 2A). The upland tundra habitat is characterized by flat open tundra on dry higher ground (Figure 2B). The lowland shrub tundra and marshes habitat is found on moist lower ground which can be flooded in spring (Figure 2C). The two open habitats, upland tundra and lowland shrub tundra and marshes, are by far the most common habitats in the area. However, due to the productivity and species richness in the rarer willow thickets, this is included to give an overall perspective of the community.

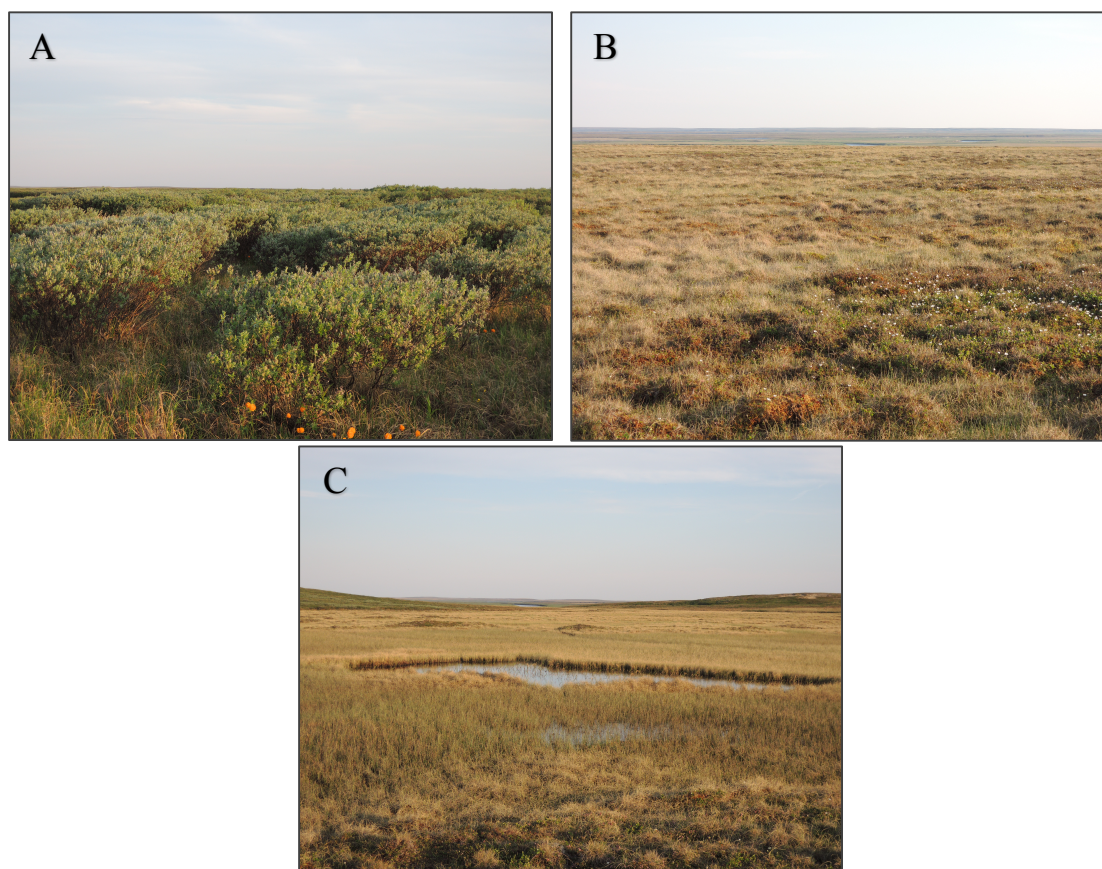


Figure 2: Photographs of the three different habitat types. **A)** Willow thicket edges, **B)** Upland tundra and **C)** Lowland shrub tundra and marshes.

For all three survey methods, passerines and waders were the main groups of birds targeted. However, other species were also registered. Recording of individuals was done by visual and/or aural detection. Date (Julian day), habitat, time, wind speed (using an anemometer in 2016, only estimating in 2015) was noted for every count (Table 1). I also noted whether the bird was territorial, and if possible, the sex. Counts were conducted at different times of the day in suitable weather without rain and wind speed not exceeding 6.0 m/s. Time of day was in the analyses divided into three categories: morning (01:30-10:00), daytime (10:00-18:00)

and evening (18:00-00:00). The wind was also divided into three categories: weak (0-2 m/s), medium (2-4 m/s), and strong (4-6 m/s). A GPS (Garmin Etrex Vista HCx) was used to record routes and points. A binocular was used on all counts, and a laser rangefinder (Nikon Forestry Pro) was used to give an accurate distance to each bird. No distance limits were used in the field to allow more opportunities for data analysis.

Table 1: For each covariate, it is given a description, the data type, the level (site or observation) and for which survey method it is included in.

Covariate	Description	Data type	Covariate level	Survey type
Habitat	Willow thicket edges, upland tundra, lowland shrub tundra and marshes	Categorical	Site-level	Distance sampling Repeated point counts
Wind	Weak (0-2 m/s), medium (2-4 m/s), strong (4-6 m/s)	Categorical	Observation-level	Distance sampling Repeated point counts
Time	Morning (01:30-10:00), daytime (10:00-18:00), evening (18:00-00:00)	Categorical	Observation-level	Distance sampling Repeated point counts
Julian Day	Julian day of count	Continuous	Observation-level	Distance sampling Repeated point counts

The study design comprised two areas (R and K) separated by approximately 7 km, called units in the following (Figure 1 and Figure 3). In each habitat in both study units, it was chosen two transect lines for the line transect distance sampling, resulting in 12 transects in total. The length of the transects ranged from 0.886 km to 1.4 km depending on the availability of suitable habitat. The location of the transects was *a priori* determined on a map, and a route was made on the GPS the first time. This route was used as a path for later repetitions. In open habitat, the lines were made straight, but some lines had to take lakes and hills into consideration. For the willow thickets, the lines followed the thicket edge. The observer followed the transect line and recorded all birds seen and heard, and measured the perpendicular distance from the line to the bird (Buckland et al., 2001).

On each of the transect lines, I randomly chose three points at least 200 m apart from each other, and more than 50 m from the border of another habitat, resulting in 36 points in total. A GPS point was made on each point the first time, and later used for repetitions. After arrival

to the point, the observer waited 2-3 minutes before recording. The observer then recorded all birds seen and heard, including the distance to the bird, within 10 minutes on each point.

The same points were used for the double observer method. It was carried out as described by Nichols et al. (2000). On each of the point, two observers were present. One was assigned the role of ‘primary observer’, and the other was the ‘secondary observer’. After arrival to the point, the observers waited 2-3 minutes before recording. The primary observer identified all birds seen and heard within 10 minutes, and told these, including direction and distance to the bird, to the secondary observer. The secondary observer noted what the primary observer registered, but also surveyed and noted own registrations of the area. The two observers alternated on being primary and secondary observer throughout the survey. As a result, the data will include the numbers of bird of each species detected by the primary observer, and numbers of birds missed by the primary observer but detected by the secondary observer for each point (Nichols et al., 2000). Double observer counts were carried out one time per year, and were in both years conducted together with experienced ornithologists. The placement of line transects and points on the two study units is showed in Figure 3. A summary of the sampling effort associated with the different survey methods is presented in Table 2.

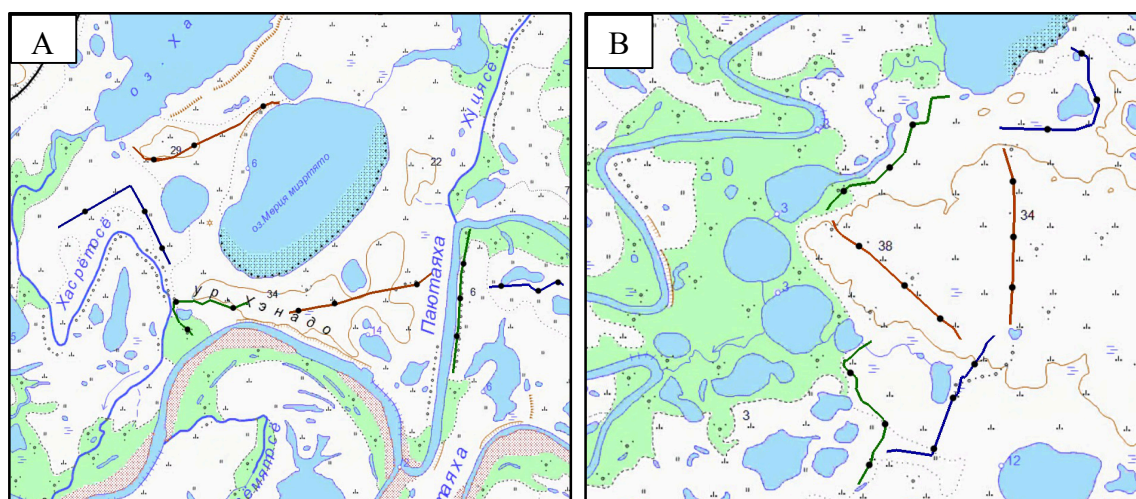


Figure 3: Detailed map of the two study units K (A) and R (B) with placement of transects (lines) and points (dots). Line color represents type of habitat; willow thicket edges (green), upland tundra (brown), and lowland shrub tundra and marshes (blue). Map data: Russian topographic maps GGC (downloaded from: loadmap.net, accessed 15-04-2017).

Table 2: *Presents sampling effort for each survey method per year.*

Survey type	Parameter	2015	2016
Line transect	No. of transects	12	12
	Repetitions	2	5*
	Cumulative distance covered	25.77 km	60.93 km
	Transect length (range)	0.886-1.4 km	0.886-1.4 km
Repeated point counts	No. of points	36	36
	Repetitions	3	5*
	Cumulative survey time	18 h	27.5 h
Double observer point counts	No. of points	30**	33**
	Repetitions	1	1
	Cumulative survey time	5.0 h	5.5 h

*with a few exceptions, due to flooded lakes

**missed some points due to flooded lakes

2.3 Statistical analysis

The data sets from both years and all three methods were inspected to find species with sufficient detections across all habitats that provided a good sample size for analyses of abundance. Buckland (2001) recommends having at least 60-80 observations to be able to fit distance sampling models. Based on this, the target species became Lapland bunting (*Calcarius lapponicus*), Red-throated pipit (*Anthus cervinus*) and Wood sandpiper (*Tringa glareola*). All three target species were analysed in the same manner to compare detectability, abundance, and density estimates between the survey methods.

2.3.1 Distance sampling

Distance sampling analysis was used to compute abundance and density estimates according to Buckland et al. (2001) using the package *Distance* (Miller, 2015) in the R software (version 3.1.2)(R Core Team, 2016). *Distance* offers a selection of candidate functions to describe the probability of detection as a function of distance, and estimates the related parameters using maximum likelihood estimation. It also allows for incorporation of covariates into the detection function. In distance sampling line transect surveys, there are three key assumptions that are important to achieve precise and reliable density estimates. The assumptions are: (1) birds on the transect line are detected with certainty, (2) birds are detected at their initial location prior to evasive movement, (3) the perpendicular measurements from the line to the bird are exact. One or more of these can be relaxed under certain circumstances (Buckland et al., 2001).

Histograms of the distance data were plotted with many intervals to investigate whether they violated some of the assumptions. The plots revealed clear heaping in the data (example in appendix A), which indicates violation of the third assumption. When identifying birds through vocalization, it can be difficult to acquire precise distance information, which often leads to grouping into discrete intervals. The perpendicular distance from the line, x , was often rounded to the nearest 10m, and is a common data issue when aural detection is used (Buckland et al., 2015). The effect of heaping was reduced by grouping the data into intervals, as recommended by Buckland (2001). The cutpoints were chosen at distances that avoided favored distances, such as 0, 12.5, 22.5, 32.5, 42.5 etc. Truncation distance, w , were set to truncate observations with distances over 110 m for Lapland bunting and Red-throated pipit, and to 180 m for Wood Sandpiper which was considered easier to detect at longer distances due to size and sound recognition. Some truncation of the data gives a more robust analysis, and allows for deletion of a few outliers that make fitting of detection function more difficult (Buckland et al., 2011; Buckland et al., 2015). Transect length, L , was used to define the area covered by the survey, $a=2wL$. When the detection probability for an individual within this area is P_a , then the estimated probability (\hat{P}_a) for detecting an individual at distance x from the line can be modelled by a detection function $g(x)$. In accordance with the first key assumption, probability of detection P_a at zero distance should be 1 (i.e. $g(0)=1$), while the detection probability is expected to decrease with increasing distance from the line. n is the number of individuals within the surveyed area. The effective strip half-width, μ , is distance from the line at which the expected number of animals detected beyond μ (but within w) equals the expected number of animals missed within a distance μ of the line. This parameter is calculated by integrating $g(x)$. The relative frequencies of observed detection distances can be modelled by fitting a probability density function, given as $f(x)=g(x)/\mu$. This leads to density, \hat{D} , being estimated by

$$\hat{D} = \frac{n}{2\hat{\mu}L} = \frac{n\hat{f}(0)}{2L} \quad (eq. 1)$$

Distance offers the three recommended models of detection functions; half-normal, hazard-rate and uniform to fit the distance data, and Akaike's Information Criterion (AIC) was used to choose the most suitable model (Buckland et al., 2001). The covariates habitat, wind, time and Julian day were then added one at a time, and in combination with each other, to the selected detection function to build candidate models to see if they affected the relation

between distance and detectability. Models with $\Delta\text{AIC} \leq 2$ relative to the best model in the candidate set, are considered strongly plausible, and the simplest of the models having $\Delta\text{AIC} \leq 2$ was chosen (Burnham and Anderson, 2003). This process was done for all the model selections in this study, and the ranking of the models with and without covariates is found in Appendix B. These models were created with grouped distance data, but to compare the differences in the abundance estimates without grouped data, the continuous distance data was tried to fit the half-normal detection function. The half-normal key-function is not as sensitive to change in the shape of the detection function, only in how quickly probability of detection falls with distance from the line (Buckland et al., 2015). This was done to quantify the effect grouping of data and inclusion of covariates have on detectability, abundance and density estimates. For the comparison to the other survey methods, the estimates derived from the models with covariates are used since they are more complex and can identify important variables affecting detectability.

The AIC of the models only indicate the relative fit, so a chi-square goodness-of-fit that measures the discrepancy between observed and expected data was used to see if the model had an adequate fit to the data. When the p-value was larger than 0.05, I did not have evidence for a discrepancy between the frequency distribution observed in the sample and the one derived from the modelling assumptions, and I concluded that the model fit was adequate (Buckland et al., 2001; Thomas et al., 2010; Buckland et al., 2015). If the model with the lowest AIC proved to have a poor fit to the data, then the model with the second-best AIC was tested and so on, until I found a model with an adequate fit. The Goodness-of-fit test rejected models with continuous distance due to heaping in the data, but showed a better fit for the grouped distance data.

2.3.2 Repeated point counts

I used, for analyses of the point count data, an N-mixture model implemented in the *pcount* function of the package *unmarked* (Royle, 2004a; Fiske and Chandler, 2011) in R, to fit separate models for each year. From replicated points counts, this function allows for calculation of detection probability and abundance. *Pcount* is used to survey populations assumed to be closed, that is, there is no recruitment, mortality or movement of individuals between the visits within a single study season. This is a reasonable assumption when breeding birds have established territories (Royle, 2004a). To obtain abundance information, M sites are visited J times, with recording of unique individuals observed at each site. It is

assumed that the abundance at a site remains constant throughout the same season, and repeated visits at a site are independent. *Pcount* implements the two-level hierarchical model for repeated point counts by Royle (2004a), where the key is to view site-specific population sizes, N_i , as an independent random variable that is modeled by Poisson distribution for abundance and by binomial distribution for detectability. Here, N_i is the unobserved total number of individuals at site i , and C_{ij} is the counted number of individuals at site i during survey j . This makes,

$$N_i \sim \text{Poisson}(\lambda_i) \text{ for } i = 1, 2, \dots, M$$

$$C_{ij} | N_i \sim \text{Binomial}(N_i, p) \text{ for } j = 1, 2, \dots, J_i,$$

where λ_i is the expected abundance at site i , and p is the per-individual detection probability. Covariates can be included in the models for both abundance and detection probability for the repeated point counts. For the abundance model, covariates are included by:

$$\log(\lambda_i) = \beta_0 + \beta_1 * x_i$$

where x_i is a site-level covariate vector, and β is a vector of their effect parameter. For the detection probability model, covariates are included by:

$$\text{logit } p_{ij} = \alpha_0 + \alpha_1 * v_{ij}$$

where v_{ij} is an observation-level covariate vector, and α is a vector of their effect parameter. The *predict* function in *unmarked* gives an estimate of expected abundance per site (λ_i), and thus the density is calculated using the following equation:

$$\hat{D} = \frac{\text{sum}(\lambda_i)}{\text{area} * i} \quad (\text{eq. 2})$$

Model selection was made based on AIC-values. Covariates were added one at a time and in combination with each other in the same manner as for distance sampling. Habitat was the only site covariate tested for, and the observational covariates was wind, time, and Julian day. Julian day was scaled to ease convergence of the models (Fiske and Chandler, 2011). The same truncation distance used for distance sampling was used as radius for the repeated point counts. Goodness-of-fit was determined using parametric bootstrapping (function *parboot* in

unmarked) which simulates, refits and creates a sampling distribution for fit-statistics used for my models. This sampling distribution is then compared to the observed statistics and evaluated using chi square goodness-of-fit test (Royle, 2004a; Fiske and Chandler, 2011; Kéry and Royle, 2015).

2.3.3 Double observer

Double observer analysis was used to estimate detection probabilities for point counts in accordance with Nichols et al. (2000) in using the program *DOBSERV* (Hines, 2000). The data input for the program consists of counts of species, individuals observed by both observers, and individuals observed by the secondary observer which were not observed by the primary observer. The same truncation distance used for distance sampling and repeated point counts were used as fixed-radius, as recommended by Nichols et al. (2000). Inclusion of covariates is not possible in *DOBSERV*. One assumption for the double observer method is that the probability of detection for all individuals of the same species is equal. Also, it is assumed that the observer's detection probability is the same whether the person is primary or secondary observer, and that detection of birds is independent between the two observers (Nichols et al., 2000; Taylor and Pollard, 2008). When starting the analysis, I specified that my data should be analyzed according to the dependent-observer approach. For the analysis, observer, bird species and species groups were possible sources of variation. *DOBSERV* summarizes the data, and creates an input code for another program *SURVIV* (White, 1983) that produce the estimates for detection probability (p) in six different models:

- P (.,.) - detection probability (p) is the same for all species and both observers.
- P (s,.) - detection probability (p) is different for each species, but equal among observers.
- P (.,i) - detection probability (p) is equal among species but different between observers.
- P (s,i) - detection probability (p) is different for each species and different between observers.

The different models were presented in ascending order according to AIC-values. The best model with the lowest AIC value was selected for the target species. Estimates of population size (N) at site i , can be written as:

$$\hat{N}_i = \frac{C_i}{\hat{p}_i}$$

where C_i denotes the count (birds seen by either of the observers), and p_i is the estimated detection probability. To acquire the standard error of the population size ($SE(N)$), *DOBSERV* recreates the *SURVIV* input file with redefined parameters, which uses overall detection probability of both observer (p'), and detection probability of the primary observer ($p1'$), instead of the detection probability of the primary ($p1'$) and secondary ($p2'$) observer. The final output produces total observations (x), detection probability (p), standard error of detection probability ($SE(p)$), estimation of population size (N), standard error of population size ($SE(N)$), and a 95 % confidence interval for the population size.

3 Results

3.1 Observations and species composition

Throughout the course of this study during all survey methods both years, 60 different species were recorded in total (full species list in Appendix F). The most common species were for both years Lapland bunting, Red-throated pipit, Wood sandpiper, Willow warbler (*Phylloscopus trochilus*) and Yellow wagtail (*Motacilla flava*). The upland tundra and lowland shrub tundra and marshes were dominated by Lapland bunting, Red-throated pipit and Wood sandpiper, and the willow thicket edges were characterized by Willow warbler, Yellow wagtail and Wood sandpiper. In both years, the highest number of species were recorded during repeated point counts, and the lowest during double observer point counts. A summary of observations and species counts is found in Table 3.

Table 3: Total number of observations, and number of different species for each survey type and year.

Survey type	Parameter	2015	2016
Line transect	No. of observations	456	1602
	No. of species	41	49
Repeated point counts	No. of observations	913	1785
	No. of species	43	50
Double observer point counts	No. of observations	283	703
	No. of species	31	44

3.2 Population density estimates

3.2.1 Distance sampling

The hazard-rate key function offered the best model of detection function to the Lapland bunting data from 2015 and 2016, and to the Red-throated pipit data from 2015. The half-normal key function provided the best fit for Red-throated pipit data in 2016, and for Wood sandpiper from both 2015 and 2016. When adding the covariates to the related key function, wind provided the best model for Lapland bunting in 2015. Detection probability (average 0.45) declined with weak wind, and increased with strong wind. In 2016, time offered the best model, where the detection probability (average 0.52), was highest in the morning. For Red-throated pipit, habitat provided the best model for the data from both 2015 and 2016, where detection probabilities (average 0.46 in 2015 and 0.40 in 2016) were highest in lowland shrub tundra and marshes. Julian day provided the best model for Wood sandpiper in 2015, and the

detection probability (average 0.44) was highest on the first count of the season. In 2016, time offered the best model, with the detection probability (average 0.80) being highest in the morning. All the fitted detection functions with inclusion of covariates are presented in Figure 4.

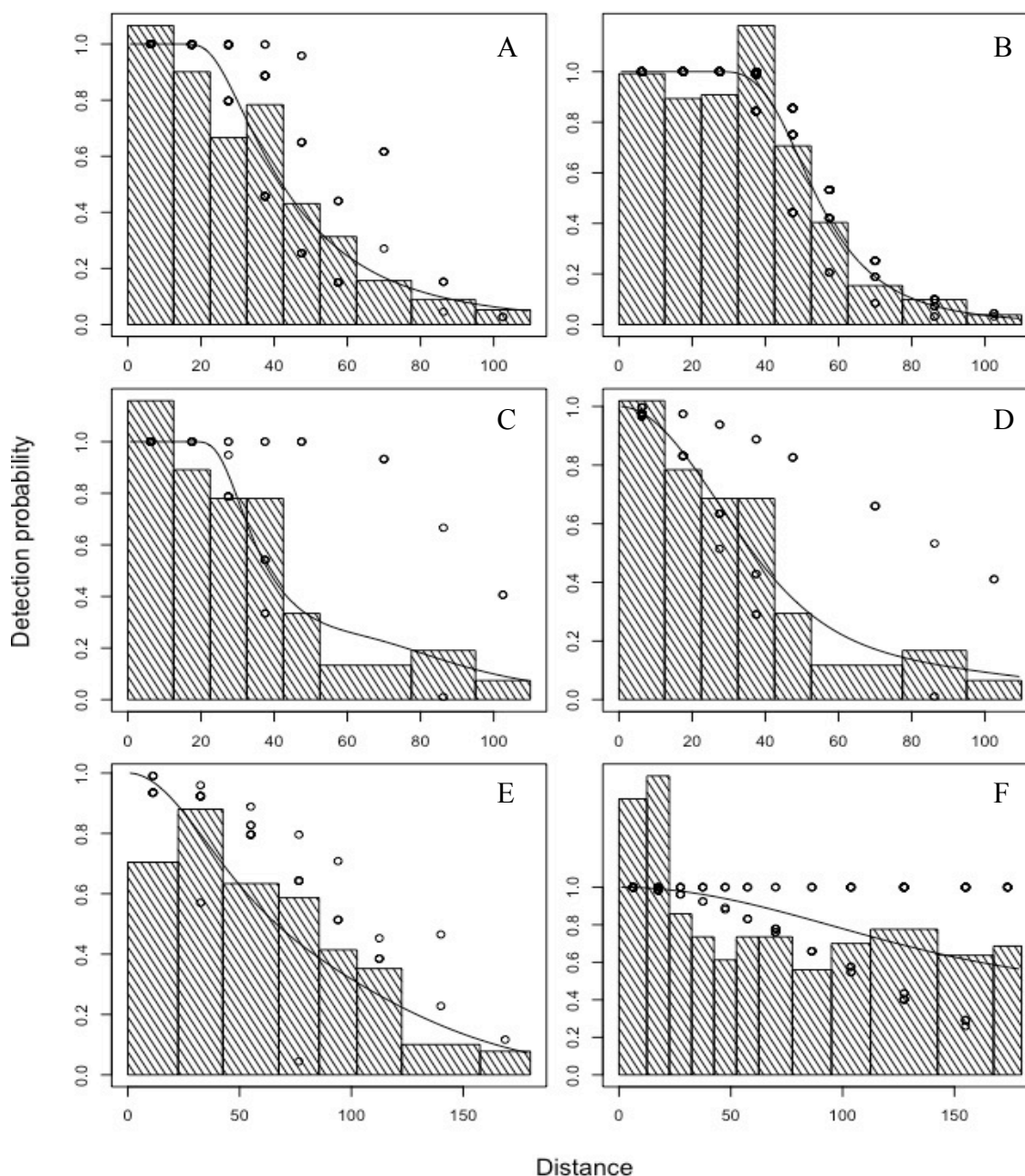


Figure 4: Fitted detection probability functions (line and dots) with covariates of distance sampling data. The histograms represent empirical distribution of the distance data. **A)** Hazard-rate detection function for Lapland bunting 2015 w/wind, **B)** Hazard-rate detection function for Lapland bunting 2016 w/time, **C)** Hazard-rate detection function for Red-throated pipit 2015 w/habitat, **D)** Half-normal detection function for Red-throated pipit 2016 w/habitat, **E)** Half-normal detection function for Wood sandpiper 2015 w/Julian day and **F)** Half-normal detection function for Wood sandpiper 2016 w/time.

The models which received most support from AIC, and that had a reasonable fit according to the goodness-of-fit test, were used to calculate abundance of individuals within the covered region. The hazard-rate model, used on Lapland bunting both years and on Wood sandpiper only in 2015, is flexible, and tries to fit the observation peak at distance zero. It is important to emphasize that the covered area differed between the years due to increased survey effort in 2016. The differences between the three estimates of N within the same species and year, ranged from 2.7 - 148.1 individuals and 0.1 - 11 ind/km² (Table 4), with the largest difference for Lapland bunting. The density estimates show an increase for the Lapland bunting from 2015 to 2016, and a decrease in density of both Red-throated pipit and Wood sandpiper. All abundances (N) in the covered region, densities (ind/km²), together best key function and covered area, are listed in Table 4. Ranking of candidate models, chi-square goodness-of-fit test results and R-output from the selected model can be found in Appendix B.

Table 4: For each target species per year, it is presented the covered area (km²), best key function, best covariate. In addition, the associated abundance (\pm SE) and density (bold) estimates with; best covariate (N_1), best covariate and half-normal key function without grouping of distances (N_2) and without covariates (N_3).

Species	Year	Covered area (km ²)	Key function	Best covariate	Abundance (N_1) and density w/covariates	Abundance (N_2) and density w/covariates and half-normal key function w/o grouping	Abundance (N_3) and density w/o covariates
Lapland bunting	2015	5.67	Hazard-rate	Wind	280.6 (\pm 31.0) 49.5	290.9 (\pm 27.0) 51.3	258.2 (\pm 26.7) 45.5
	2016	13.4	Hazard-rate	Time	763.0 (\pm 38.0) 56.9	906.1 (\pm 50.9) 67.6	758.0 (\pm 38.1) 56.5
Red-throated pipit	2015	5.67	Hazard-rate	Habitat	98.7 (\pm 17.3) 17.4	116.1 (\pm 19.9) 20.5	108.9 (\pm 24.9) 19.2
	2016	13.4	Half-normal	Habitat	112.2 (\pm 19.8) 8.4	116.1 (\pm 19.9) 8.7	125.8 (\pm 25.0) 9.4
Wood Sandpiper	2015	9.28	Half-normal	Julian day	102.2 (\pm 18.5) 11.0	106.4 (\pm 19.5) 11.5	87.5 (\pm 14.2) 9.4
	2016	21.93	Half-normal	Time	146.9 (\pm 26.7) 6.7	149.6 (\pm 26.1) 6.8	147.8 (\pm 14.8) 6.7

3.2.2 Repeated point counts

For Lapland bunting in 2015, the best AIC *pcount*-model for estimating detection contained wind as covariate. The mean detection probability was 0.51 (\pm SE 0.13) in weak wind, 0.35 (\pm 0.09) in medium wind, and 0.49 (\pm 0.12) in strong wind. The predicted abundance (λ) for the covered area was 156.3 individuals (\pm 42.7), and by using equation 2, the estimated density for the covered area was 114.2 ind/km². In 2016, the best model for estimating detection probability was without any covariates, with a mean detection probability of 0.48 (\pm 0.07), a predicted abundance of 172.6 individuals (\pm 35.6), and a density of 126.10 ind/km².

For Red-throated pipit, the best model in 2015 included wind, time and Julian day. Time and Julian day were chosen for the data from 2016. However, the goodness-of-fit test show that all models both years had an inadequate fit to the data (test statistics in appendix C).

For Wood sandpiper in 2015, the best model for estimating detection included wind, time and Julian day as covariates. In the model for Wood sandpiper from 2015, the Julian day represents the detection probability on the median Julian day. I used the detection probability on the mean Julian day in combination with wind and time. Abundance was predicted to 199.1 individuals (\pm 168.8) within the covered area, and a density of 54.3 ind/km². Of the data from 2016, the best model was without covariates, and had a mean detection probability of 0.18 (\pm 0.07). Predicted abundance was 225.6 individuals (\pm 88.7) and the density was 61.6 ind/km². All detection probabilities, abundance estimates (provided on normal scale) and densities are listed in Table 5. Ranking of candidate models, chi-square goodness-of-fit test results and R-output from the selected model can be found in Appendix C.

Table 5: Overview of best models of pcount per species and year including mean detection probability with standard errors ($\pm SE$), predicted abundance (λ) and estimated density.

Species	Year	Best model	Predicted detection probability (p)			Predicted abundance (λ)	Estimated density	
			Weak	Medium	Strong			
Lapland bunting	2015	Wind	Weak	0.51 (± 0.13)	156.3 (± 42.7)	114.2		
			Medium	0.35 (± 0.09)				
			Strong	0.49 (± 0.12)				
	2016	No covariates	0.48 (± 0.07)			172.6 (± 35.6)	126.6	
Red-throated pipit	2015	Wind + Time + Julian day	NA			NA	NA	
	2016	Julian day + Time	NA			NA	NA	
Wood sandpiper	2015	Wind + Time + Julian day	*	Weak	Medium	Strong	199.6 (± 168.8)	54.5
			Morning	0.30 (± 0.17)	0.10 (± 0.06)	0.06 (± 0.05)		
			Daytime	0.68 (± 0.23)	0.34 (± 0.20)	NA		
	Evening	NA	0.11 (± 0.08)	0.07 (± 0.06)				
	2016	No covariates	0.18 (± 0.07)			225.6 (± 88.7)	61.6	

*predicted detection probability was calculated with the median of Julian day 176.5.

3.2.3 Double observer

The model P(.,.) stating that detection probability is the same for all species and both observers, was most suitable for the data from both years, and showed an adequate fit according to the goodness-of-fit test. Ranking of candidate models and goodness-of-fit test results are presented in appendix D. All species-specific joint detection probability exceeded 0.98, and Lapland bunting and Wood sandpiper show an increase in density from 2015 to 2016. The density of Red-throated pipit was exactly the same in the two contrasting years. All detection probabilities, abundances and density estimates per species and year are listed in Table 6. Complete SURVIV-output from the analysis can be found in appendix E.

Table 6: Best model, joint detection probability (p) and abundance (N) with standard errors ($\pm SE$) each year for double observer analysis from SURVIV.

Species	Year	Best model	Detection probability (p)	Abundance (N)	Density (ind/km ²)
Lapland bunting	2015	P(.,.)	0.9895	73.8 (± 0.99)	64.7
	2016	P(.,.)	0.9984	115.2 (± 0.45)	91.8
Red-throated pipit	2015	P(.,.)	0.9895	37.4 (± 0.67)	32.8
	2016	P(.,.)	0.9984	41.1 (± 0.26)	32.8
Wood sandpiper	2015	P(.,.)	0.9895	30.3 (± 0.60)	9.9
	2016	P(.,.)	0.9984	53.1 (± 0.30)	15.8

3.2.4 Overview of obtained estimates

To make the comparison of the methods easier, I put the obtained abundance and density estimates from the survey methods in Table 7, where they can be seen in conjunction to each other. The covered area differed between years and methods, thus the abundance (N) with standard error is included to display the precision. The density (ind/km²) is included to show the difference between the methods, and can be used to assess difference between years. In the discussion part, I will evaluate the density estimates in relation to other studies performed in low Arctic to say something about the plausibility of the results.

Table 7: Overview of estimated abundance ($\pm SE$) in covered area and density (ind/km²) provided by the three survey methods. Estimates from distance sampling are provided from the best model with covariates. No model fitted for repeated point counts for Red-throated pipit. It is important to emphasize that the covered area differed between the years due to increased survey effort in 2016.

Survey method	Year	Lapland bunting		Red-throated pipit		Wood sandpiper	
		Abundance estimate ($\pm SE$)	Density estimate (ind/km ²)	Abundance estimate ($\pm SE$)	Density estimate	Abundance estimate ($\pm SE$)	Density estimate
Line transect distance sampling	2015	280.6 (± 31.0)	49.5	98.7 (± 17.3)	17.4	102.2 (± 18.5)	11.0
	2016	763.0 (± 38.0)	56.9	112.2 (± 19.8)	8.4	146.9 (± 26.7)	6.7
Repeated point counts	2015	156.3 (± 42.7)	114.2	NA	NA	199.1 (± 168.8)	54.3
	2016	172.6 (± 35.6)	126.6	NA	NA	225.6 (± 88.7)	61.6
Double observer point count	2015	73.8 (± 0.99)	64.7	37.4 (± 0.67)	32.8	30.3 (± 0.60)	9.9
	2016	115.2 (± 0.45)	91.8	41.1 (± 0.26)	32.8	53.1 (± 0.30)	15.8

4 Discussion

The aim of this study was to compare and assess different survey methods for monitoring of common bird species in the low Arctic tundra. This comparison was done by estimating abundances of the three most common species in the Erkuta tundra monitoring site through two breeding seasons using the methods; distance sampling on line transects, repeated point counts, and double observer point counts. Differences in estimates between the methods may help to identify strengths, weaknesses, suitability and feasibility of the survey methods performed. Precision, accuracy, effort, and how easy it is to get field data to meet the assumptions of the methods, can be decisive for which method is preferred. I found that line transect distance sampling provided the most plausible density estimates for all target species, with estimates closest to the expected value and to each other. Repeated point counts probably overestimated the densities to a large extent, likely due to violation of the assumption of *pcount* that the surveyed population is closed. In addition, there were not any candidate models that fitted the data for Red-throated pipit neither of the years. Inclusion of covariates improved all model fits for distance sampling, and half of the models able to fit for repeated point counts. Further, the double observer point count seemingly overestimated the densities for all species, but not to the same extent as the repeated point counts. In the following, I will first compare the obtained density estimates with other studies to assess whether they are plausible, and then discuss each method separately.

The density estimates obtained in this study can be seen in relation to other studies performed in low Arctic to say something about the plausibility of the results. However, it is important to emphasize that the density estimates from this study are from certain habitats chosen according the work of Sokolov (2012), and are not representative for the distribution of habitats in the landscape. The obtained estimates are thus best suited for comparison between years since they are carried out on the same transects/points. Also, the density estimates can be difficult to compare with each other due to spatial variation between transects and points. Further, the implementation and habitat characteristics of the compared studies differ to some degree, and can only be used as a pointer of densities for the target species. First out is the Lapland bunting. Using the spot mapping method, Sokolov (2012) found an overall density of 10.1 pairs/km² in the same study area as my surveys were conducted in. On the Ungava peninsula, Canada, in the bioclimatic subzone E, Andres (2006) used plot sampling to estimate an overall density of 30.7 ind/km². In a study area in northern Norway, on the border area to subzone E, Järvinen (1978) used the line transect method to estimate habitat-specific

densities, which ranged from 2.1 to 63.9 pairs/km². Latour (2005) used plot mapping for two areas in Creswell Bay in Nunavut, Canada, albeit in subzone C, and found overall densities of 12.8 ind/km² and 10.5 ind/km². Although the unit of density varies between pairs/km² and ind/km², they can serve as an indicator of plausibility. The density estimates obtained in this study for all habitats for Lapland bunting with line transect distance sampling (49.5 ind/km² (2015) and 56.9 ind/km² (2016)), seem reasonable in comparison with these studies. The double observer point count density estimates (64.7 ind/km² (2015) and 91.8 ind/km² (2016)) were slightly higher, and may seemingly have overestimated the density. The repeated points count density estimates (114.2 ind/km² (2015) and 126.6 ind/km² (2016)) appear clearly overestimated.

Red-throated pipit has a far smaller distribution area than the Lapland bunting, and thus less studies have estimated their densities. However, Sokolov (2012) and Järvinen (1978) have results that show, respectively, overall Red-throated pipit densities of 18.3 pair/km² and habitat-specific densities ranging from 0.2 to 9.1 pairs/km². Density estimates derived from line transect distance sampling in this study (17.4 ind/km² (2015) and 8.4 ind/km² (2016)) appear to be plausible. The double observer point count estimates (32.8 ind/km² (2015) and 32.8 ind/km² (2016)), as for the Lapland bunting, seemed somewhat overestimated. No estimates were produced for repeated point counts.

Wood sandpiper, like the Red-throated pipit, also has less distribution area than the Lapland bunting, with subsequent less studies and comparable density estimates. Sokolov (2012) estimated 4.2 pairs/km² for all habitats, and Järvinen (1978) had a habitat-specific density ranging from 2.9 to 6.9 pairs/km². Line transect distance sampling estimates (11.0 ind/km² (2015) and 6.7 ind/km² (2016)) seem plausible also with these results. As do the estimates from the double observer point counts (9.9 ind/km² (2015) and 15.8 ind/km² (2016)). The repeated points count density estimates (54.3 ind/km² (2015) and 61.6 ind/km² (2016)) appeared, as for Lapland bunting, clearly overestimated.

4.1 Distance sampling

The main problem with distance sampling was that my data showed rounding of distances (heaping), which conflicts the third assumption that perpendicular distances from the bird to the line are exact. When recording individuals of passerines and waders with aural detection in a tundra landscape like Erkuta, the birds camouflage and surroundings with tussocks or thickets, sometimes made it difficult to measure exact distances. Measurement error can have a considerable impact on the accuracy and precision of the distance sampling estimators. To reduce the effect of heaping, I grouped my data into intervals. It is shown that, compared with estimates from continuous distances, little precision is lost, and the impact of this on estimation is small. Still, some information is lost to evaluate whether the assumptions hold, and to assess the fit of the detection function (Royle et al., 2004b; Buckland et al., 2015). Ekblom (2010) showed in a simulation study that even distance data collected in two groups (close and far away) provided reasonable densities of birds. The measurement error could be reduced by, in addition to recording distance, recording the angle between the line and the bird from the observation point. By using trigonometry, one can then calculate an accurate perpendicular distance from the bird to the transect line (Ekblom, 2010). This would probably reduce some of the heaping, but still it would be difficult to estimate exact distances to birds only recognized by aural cues. If exact distance data is difficult to collect with a reasonable accuracy, then collecting distances into discrete groups is recommended. Another possible solution could be accounting for measurement error and incorporate this into the models (Borchers et al., 2010). The truncation distance has a small effect on the population estimates, so most care should be taken on distances recorded close to the transect (Ekblom, 2010).

A good model for the detection function should possess a shoulder, which means detection close to the transect line is close to one, i.e. detection of all individuals. The probability of detection should then fall away at larger distances. This is called the shape criterion, and violation of this will decrease estimation precision. The detection function for Lapland bunting 2015 (Figure 4A), Lapland bunting 2016 (Figure 4B) and Red-throated pipit 2015 (Figure 4C), used the hazard-rate key function and produced a shoulder. The detection function for Red-throated pipit 2016 (Figure 4D), Wood sandpiper 2015 (Figure 4E) and Wood sandpiper 2016 (Figure 4F) used a half-normal key function, and possessed a narrow shoulder, which decreases estimation precision. All the detection functions filled the criterion that a detection function should have a non-increasing function of distance from the line,

which means that the probability of detection at a given distance should not be larger than the probability of detection at a smaller distance (Buckland et al., 2001). However, for Wood sandpiper 2016 (Figure 4F), the detection function was not ideal with very high detection probabilities at most distances (average 0.80), and a slow decrease of detection probability with increasing distances.

For all species and years, the models were improved with inclusion of covariates. Bird detections are usually inversely correlated to wind speed (Robbins, 1981a), but the Lapland bunting in 2015 had higher detectability in strong wind than in weak wind, which contradicted both expectation and theory. This may be due to a small sample size in strong wind, or possibly a consequence of running many models. The detection probabilities from Wood sandpiper in 2015 was highest on the first day of counting, which may argue for registration in early breeding season. In 2016, the detection probabilities peaked in the morning which corresponds to the fact that most bird species have their activity peak in the morning hours during the breeding season (Robbins, 1981b).

For the Red-throated pipit, the estimate with covariates (N_1) gave the lowest abundance and density in both 2015 and 2016. The estimate with covariates and half-normal key function (N_2) without grouping of distances, provided the highest abundance for all models in comparison to the estimates with and without covariates. The overestimation was highest on the models that had the best fit with the hazard-rate key function. The abundance estimates without covariates (N_3), were for both years lower for Lapland bunting and Wood sandpiper, and gave the middle estimate for the Red-throated pipit. The standard error show that the precision of the estimates was rather consistent between the three estimates of abundance (N), with a difference ranging from ± 0.5 –12.9 individuals. According to Ekblom (2010), standard errors are generally larger when using grouped distance data, than for exact measurements. All standard error was also higher for the estimates of 2016, which was not expected due to bigger sample sizes this year. Some of the uncertainty can arise from both variability in encounter rate between the transects, and from uncertainty in the detection function (Buckland et al., 2015). As presented earlier, the overall density estimates appeared to be slightly overestimated, perhaps as a result of violation of some assumptions. An overestimation of birds detected on the transect line, an underestimation of distances, and birds undetected prior to evasive movement, causes overestimation (Ekblom, 2010). However, the degree of overestimation is limited to the extent of which the assumptions are violated.

4.2 Repeated point counts

The first key assumption when modeling repeated point count data with *pcount* in *unmarked*, is that abundance at a site remains constant throughout the same season. To meet this assumption, the data was collected during the breeding season and limited to 18 days in 2015 and 27 days in 2016. In this period, the breeding birds are assumed to have established territories so that observed birds are primarily local breeders (Royle, 2004a). When using *pcount* to estimate the detection probability for Lapland bunting in 2015, the highest detection probability was during weak wind. It was lower in medium wind, but then showed an increase again in strong wind. This may, as for the distance sampling results, be due to a small sample size in strong wind, or a consequence of running many models. For Wood sandpiper, the highest detection probability in 2015 was in weak wind at daytime. The lowest detection probabilities were in strong wind, which may suggest that the detectability of the Wood sandpiper is sensitive to wind. In 2016, the detection probabilities for Lapland bunting and Wood sandpiper was independent of any of the covariates. The precision in the detection probability estimates ranged from $\pm 0.05 - 0.23$, where both the highest and lowest were generated in the model from Wood sandpiper 2015 with all covariates included. The goodness-of-fit test show that no model had an adequate fit for the Red-throated pipit data. The reason for this is not clear, but it may indicate that the assumptions underlying the model can be inappropriate for abundance estimation of Red-throated pipit.

The predicted abundance estimates seem to be overestimated both years with high standard errors. The low precision appears for example in the 2015 data for Wood sandpiper, where the standard error it selves is almost as high as the abundance estimate. The calculated density estimates are for some more than doubled relative to the estimates from distance sampling and double observer point counts. The first reason for this is likely a violation of the assumption that the surveyed population is closed, which the other two methods do not assume. A second possible reason is too short distance (minimum 200m) between the points, and therefore a risk of a double counting of the same individual on two different points and on separate visits. The placement and extent of the bird territories is uncertain, and some of the points have probably been within the same territory, also increasing the risk for double counting. An alternative approach for the repeated point counts that would reduce the effect of these two possible sources of error, could be to increase the distance between the points, and to use the function

gpcount in *unmarked* that allows for temporary emigration, i.e. not all individuals are present for detection at every visit (Chandler et al., 2011).

4.3 Double observer

The double observer point counts were only conducted one time per point each year, and consequently had the smallest sample size of the three methods. It is important to emphasize that this method only estimates the detection probability on the current day, and do not consider repeated visits like the other methods. In line transect distance sampling and repeated point counts with a single observer, a varying proportion of birds present in the area is missed. The results from the double observer method show a high overall joint detection probability for the two observers (> 0.98), which provides basis for precise estimates. The method is preferable to use when detection probabilities are assumed to be 1, and not recommended to use when detection probabilities are below 0.40 (Nichols et al., 2000).

The assumption that the probability of detection for all individuals of the same species is equal, is not always true in field situations. For example, individuals close to the observers will be more likely to be detected than those further away. Differences in distances at which observers detect birds is also a source of bias, where some individuals at large distances in reality only can be detected by one of the observers. This variation is reduced by using fixed-radius. However, a simulation study by Taylor and Pollard (2008) showed that varying detection probabilities among individuals gave population estimates close to the estimates provided with equal detection probabilities for all individuals of the same species. Based on this, the likely violation of this assumption in the field does not have a big impact on the population estimates. The assumption that the observer role does not have an impact on detection probability were perceived to be held in the field. The last assumption about independent detection of birds between the observers was most likely not entirely fulfilled. Although the secondary observer always stood behind the primary observer, some provision of cues, like writing or looking in a certain direction, was still given away by the secondary observer when the primary observer was scanning the area. This likely violation increases the joint detectability, and can be a possible explanation for the slight overestimation of densities.

The selected model was, for both years and all species, the model where the estimates of detection probability were equal among species and observers ($P(.,.)$). The counting's were done with a different ornithologist each year, and the detection probabilities show a slight

increase in 2016. The density estimates, in accordance with the other methods, show an increase in density of Lapland bunting from 2015 to 2016. What separates these results from the other two methods, is that they show an increase in density of Wood sandpiper and an identical density of Red-throated pipit from 2015 to 2016. The estimates might, as for the repeated point counts, have been affected by the short distance between the points and the accompanying risk of double counting of individuals. The joint detection probabilities obtained with the double observer method were very high, and resulted in precise abundance estimates with low standard error ranging from 0.26 to 0.99. Approximate equally high detection probabilities, and thus low standard errors, were also estimated by Nichols et al. (2000) in his field trials.

5 Conclusions and Recommendations

Before going into the field and conducting a survey on a chosen bird community, it is essential to recognize the characteristics of both the survey method and the bird community. The detectability and abundance of the species, the characteristics of the terrain, and resources available are variables that need to be taken into consideration when deciding which survey type is better for the selected study area (Joseph et al., 2006). As mentioned earlier, studies on bird communities performed in the Arctic are not as numerous as for temperate regions, and thus is this study a step towards a broader knowledge and development of robust survey methods for such communities. Based on this study, it is possible to draw some conclusions about which survey method is best suited for long-term monitoring of the bird community on the Erkuta tundra monitoring site and in similar areas in the low Arctic. The most plausible density estimates of the common target species were provided by the line transect distance sampling. Although all assumptions are difficult to completely fulfil in the field, the method could be improved by more exact distance measurements in the field, since the degree of overestimation is limited to the extent of which the assumptions are violated. Repeated point counts heavily overestimated the densities and the models fitted poorly for Red-throated pipit. This could probably be reduced by using a model allowing for temporary emigration and increasing distance between points. However, double observer point counts offer an alternative approach for long-term monitoring, where the slight overestimation can be decreased with increased distance between points. In addition, the double observer method requires less effort than the other two methods.

This study, in accordance with for example the studies performed by Latour (2005) and Andres (2006), estimates all individuals present throughout the breeding season. This approach includes the non-breeders (i.e. non-territory holders) in the area during the breeding season, the so-called “floaters” (Penteriani et al., 2011). The extent and impact from “floaters” on density estimation of the target species and in my study area is difficult to assess. However, Nur et al. (2000) studied demographic processes in passerine birds and found out that “floaters” (classified by a single capture throughout breeding season), amounted more than half of the adult Song sparrows (*Melospiza melodia*) caught. This could argue for a possible approach to focus the surveys only on territorial males, and extrapolate the density estimate to get an estimation of number of breeding pairs. “Floaters” will to a large extent be ruled out of the counts, and this will in addition give less measurement error of

distance, since territorial males naturally have a higher aural and visual detectability. The double observer point count method only entail one visit to each point per season, which makes this method especially susceptible to influence from “floaters” in abundance estimates. The line transect distance sampling method have the least impact from “floaters”, which also can speak in favor of this method.

The target species chosen from the analysis in this study were numerous in most habitats and transects/points. A possible extension of the study could be to look further into how the methods apply on species that are not as numerous, as for example the Shore lark (*Eremophila alpestris*), or species that were particularly habitat-bound, such as the Willow warbler. The study could be extended to surveying a bird community by choosing one preferred method and use this to estimate abundance and density for several species.

When performing surveys in the Arctic, it is of great significance to consider the effort associated with different survey methods both when it comes to funding and available people. The breeding season is shorter than in temperate zones (Baker, 1939), and accommodation and travel expenses for personnel is often high. This should lead to the cumulative distance covered, time spent recording, and number of visits to be included in the assessment of method selection. The 12 transects of distance sampling analysis were repeated two to five times during a breeding season, and due to differences in transect length and encounter rate, the time spent on each transect varied. The 36 repeated point counts were visited 3-5 times, and had a cumulative registration effort of 18 h in 2015 and 27.5 h in 2016. In contrast, the double observer point count was only conducted one time per season (though with two people), with a least time-consuming cumulative survey time of 5 h in 2015 and 5.5 h in 2016. Although effort is a variable that should be considered, it is of course the accuracy, precision and plausibility of the estimates that should be the primary reason for choice of method.

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Appendix

Appendix A

Histogram showing an example of heaping in distance data (Figure B.1) and the reduced 'spikes' in the data when grouping the distance data (Figure B.2).

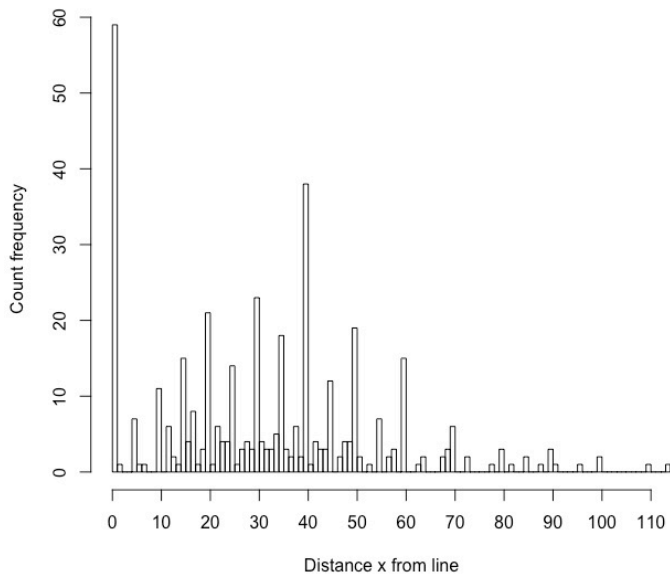


Figure B.1: Lapland bunting distance data from 2016 *without* grouping of distances.

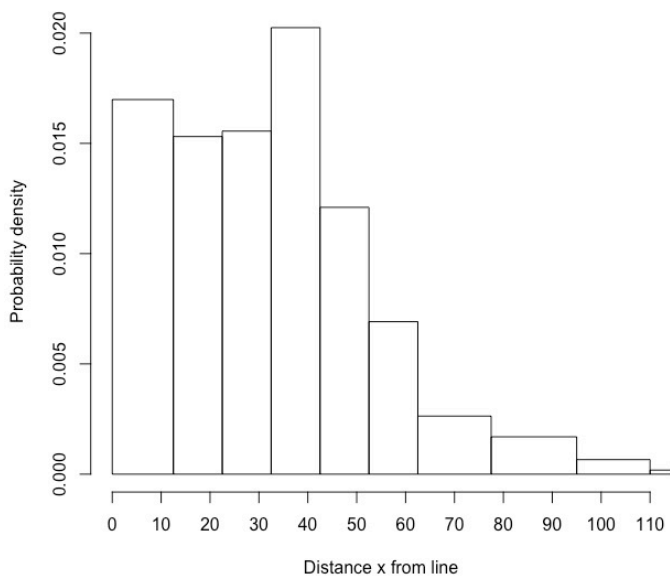


Figure B.2: Lapland bunting distance data from 2016 *with* grouping of distances. Note that the y-axis is plotted with probability density rather than count frequency, due to varying interval width.

Appendix B

This appendix contains:

- Model selection tables for the line transect distance sampling analysis with inclusion of covariates. Candidate model in bold gives an adequate fit to data, and best AIC.
- Chi-square goodness-of-fit test results from the selected model.
- R output for the selected model.

Table A.1: Comparison of different candidate models of line transect distance sampling evaluated for estimating abundance for Lapland bunting 2015 with hazard-rate detection function.

Covariates	AIC	Δ AIC
Time + Wind	485.28	0
Wind	485.66	0.38
Julian day + Time + Wind	487.16	1.88
Julian day	487.80	2.52
Time	489.75	4.48
Julian day + Time	490.69	5.41
Julian day + Wind	490.96	5.68
No covariates	492.17	6.89
Habitat	495.80	10.52

Chi-square goodness-of-fit test results for [Wind] object:

Chi-square value = 3.09

P=0.54239

```
> summary(LB15_wind)
```

Summary for distance analysis

Number of observations : 125

Distance range : 0 - 110

Model : Hazard-rate key function

AIC : 485.6598

Detection function parameters

Scale Coefficients:

	estimate	se
(Intercept)	3.8762671	0.1817068
WindcatStrong	0.3583770	0.3702791
WindcatWeak	-0.4111832	0.1995215

Shape parameters:

	estimate	se
(Intercept)	1.130598	0.2022396

	Estimate	SE	CV
Average p	0.4454086	0.0386467	0.08676686
N in covered region	280.6412211	30.9591128	0.11031563

Table A.2: Comparison of different candidate models of line transect distance sampling evaluated for estimating abundance for Lapland bunting 2016 with hazard-rate detection function.

Covariates	AIC	Δ AIC
Time + Wind	1571.44	0
Habitat + Time	1571.69	0.24
Time	1575.95	4.51
Habitat	1578.93	7.49
Habitat + Wind	1579.68	8.24
Wind	1580.62	9.18
No covariates	1581.22	9.77
Julian day	1590.14	18.70

Chi-square goodness-of-fit test results for [Time] object:

Chi-square value = 7.43

P = 0.11458

```
> summary(LB16_time)
```

Summary for distance analysis

Number of observations : 402

Distance range : 0 - 110

Model : Hazard-rate key function

AIC : 1575.948

Detection function parameters

Scale Coefficients:

	estimate	se
(Intercept)	3.99549706	0.05784177
TimecatDay	-0.06753968	0.08187329
TimecatEvening	-0.24472716	0.08330365

Shape parameters:

	estimate	se
(Intercept)	1.58586	0.1245079

	Estimate	SE	CV
Average p	0.5268698	0.01890061	0.03587339
N in covered region	762.9967989	37.96585023	0.04975886

Table A.3: Comparison of different candidate models of line transect distance sampling evaluated for estimating abundance for Red-throated pipit 2015 with hazard-rate detection function.

Covariates	AIC	Δ AIC
Habitat + Wind	171.99	0
Habitat	172.98	0.98
Habitat + Time	173.83	1.83
Habitat + Time + Wind	174.54	2.55
Time + Wind	176.34	4.34
Wind	178.02	6.02
Time	178.83	6.84
No covariates	179.86	7.86
Julian day	180.56	8.56

Chi-square goodness-of-fit test results for [Habitat] object:

Chi-square value = 4.48

P = 0.34535

```
> summary(RTP15_habitat)
```

Summary for distance analysis

Number of observations : 45

Distance range : 0 - 110

Model : Hazard-rate key function

AIC : 172.9763

Detection function parameters

Scale Coefficients:

	estimate	se
(Intercept)	3.4157546	0.2332194
HabitatUpland	0.1509885	0.3506890
HabitatWetland	1.0631858	0.3031993

Shape parameters:

	estimate	se
(Intercept)	1.460822	0.3085312

	Estimate	SE	CV
Average p	0.4558094	0.05850621	0.1283568
N in covered region	98.7254804	17.29931378	0.1752264

Table A.4: Comparison of different candidate models of line transect distance sampling evaluated for estimating abundance for Red-throated pipit 2016 with half-normal detection function.

Covariates	AIC	Δ AIC
Habitat + Time	170.68	0
Habitat	172.18	1.51
Julian day + Habitat	172.52	1.85
Time	176.31	5.63
Julian day	176.33	5.65
Wind	178.03	7.35
No covariates	181.25	10.58

Chi-square goodness-of-fit test results for [Habitat] object:

Chi-square value = 3.84

P = 0.57289

```
> summary(RTP16_habitat)
```

Summary for distance analysis

Number of observations : 45

Distance range : 0 - 110

Model : Half-normal key function

AIC : 172.1844

Detection function parameters

Scale Coefficients:

	estimate	se
(Intercept)	3.3608662	0.1253808
HabitatUpland	-0.1894198	0.3364531
HabitatWetland	0.9809140	0.4377774

	Estimate	SE	CV
Average p	0.4010044	0.05061198	0.126213
N in covered region	112.2182295	19.77464345	0.176216

Table A.5: Comparison of different candidate models of line transect distance sampling evaluated for estimating abundance for Wood sandpiper 2015 with half-normal detection function.

Covariates	AIC	Δ AIC
Julian day	171.98	0
Julian day + Habitat	173.29	1.31
Habitat	173.65	1.66
No covariates	174.22	2.23
Habitat + Time	175.29	3.31
Time	175.44	3.46
Wind	176.11	4.13

Chi-square goodness-of-fit test results for [Julian day] object:

Chi-square value = 2.56

P = 0.46497

```
> summary(WS15_day)
```

Summary for distance analysis

Number of observations : 45

Distance range : 0 - 180

Model : Half-normal key function

AIC : 171.9822

Detection function parameters

Scale Coefficients:

	estimate	se
(Intercept)	4.7287597	0.8905441
Julian.day174	-0.2360972	1.3586564
Julian.day175	-1.3059913	0.9109562
Julian.day179	-0.3291349	0.9124262

	Estimate	SE	CV
Average p	0.4401211	0.06013723	0.1366379
N in covered region	102.2445949	18.48422820	0.1807844

Table A.6: Comparison of different candidate models of line transect distance sampling evaluated for estimating abundance for Wood sandpiper 2016 with half-normal detection function.

Covariates	AIC	Δ AIC
Julian day	571.23	0
Julian day + Habitat	572.68	1.45
Time	575.48	4.25
Habitat + Time	576.27	5.04
Habitat	576.35	5.12
No covariates	578.25	7.02
Wind	580.38	9.14

Chi-square goodness-of-fit test results for [Time] object:

Chi-square value = 9.10

P = 0.33478

```

> summary(WS16_time)

Summary for distance analysis
Number of observations : 118
Distance range       : 0 - 180

Model : Half-normal key function
AIC   : 575.4842

Detection function parameters
Scale Coefficients:

              estimate    se
(Intercept)  12.490191  171.8435
TimecatDay   -7.942311  172.2671
TimecatEvening -7.897720  172.2685

              Estimate    SE    CV
Average p     0.8034056  0.1416746  0.1763426
N in covered region 146.8747599  26.7314299  0.1820015

```

Appendix C

This appendix contains:

- Model selection tables for repeated point counts with inclusion of covariates. Candidate model in bold gives an adequate fit to data and, best AIC.
- Chi-square goodness-of-fit test results with parametric bootstrapping from the selected model.
- R output for the selected model.

Table B.1: Comparison of different candidate models of pcount evaluated for estimating abundance for Lapland bunting 2015.

Covariates	AIC	Δ AIC
Wind	316.33	0
Julian day + Wind	317.69	1.36
Time + Wind	317.91	1.58
Julian day + Time + Wind	318.11	1.78
No covariates	321.6	5.28
Julian day	323.5	7.17
Time	325.28	8.95
Julian day + Time	327.08	10.76

Chi-square goodness-of-fit test results with parametric bootstrapping for [Wind] object:

Chi-square value = 99.8

P = 0.465

```

> pcount(~Wind ~Habitat, umf)

Call:
pcount(formula = ~Wind ~ Habitat, data = umf)

Abundance:
      Estimate      SE      z      P(>|z|)
(Intercept)  0.0709  0.380  0.187  8.52e-01
HabitatUpland  1.8485  0.356  5.199  2.00e-07
HabitatWetland  1.5657  0.362  4.322  1.54e-05

Detection:
      Estimate      SE      z      P(>|z|)
(Intercept) -0.640  0.394 -1.62  0.1045
WindStrong   0.613  0.328  1.87  0.0619
WindWeak     0.668  0.274  2.44  0.0148

AIC: 316.3274

```

Table B.2: Comparison of different candidate models of pcount evaluated for estimating abundance for Lapland bunting 2016.

Covariates	AIC	Δ AIC
No covariates	499.95	0.00
Time	501.12	1.17
Julian day	501.54	1.59
Julian day + Time	501.95	2.00
Wind	503.59	3.64
Time + Wind	504.48	4.53
Julian day + Wind	505.35	5.40
Julian day + Time + Wind	505.72	5.77

Chi-square goodness-of-fit test results with parametric bootstrapping for [No covariates] object:

Chi-square value = 104.1

P = 0.990

```

> pcount(~1 ~Habitat, umf)

Call:
pcount(formula = ~1 ~ Habitat, data = umf)

Abundance:
      Estimate      SE      z      P(>|z|)
(Intercept)  0.589  0.246  2.39  1.68e-02
HabitatUpland  1.318  0.267  4.94  7.89e-07
HabitatWetland  1.176  0.278  4.22  2.40e-05

Detection:
      Estimate      SE      z      P(>|z|)
-0.0691  0.285  -0.243  0.808

AIC: 499.9484

```

Table B.3: Comparison of different candidate models of *pcount* evaluated for estimating abundance for Red-throated pipit 2015. No model selected due to poor goodness-of-fit.

Covariates	AIC	Δ AIC
Julian day + Time + Wind	292.48	0.00
Julian day + Wind	296.39	3.91
Julian day + Time	297.94	5.47
Julian day	301.55	9.07
Time + Wind	308.76	16.28
Time	309.70	17.22
Wind	318.19	25.72
No covariates	318.63	26.16

All models gave very low P-values from the goodness-of-fit test with parametric bootstrapping, that rejects the null hypothesis. Thus, no model provides an adequate fit to the data. For example, the chi-square goodness-of-fit test results with parametric bootstrapping for [All covariates] object:

Chi-square value = 177.1

P = 0.000

No models provided adequate data fit

Table B.4: Comparison of different candidate models of *pcount* evaluated for estimating abundance for Red-throated pipit 2016. No model selected due to poor goodness-of-fit.

Covariates	AIC	Δ AIC
Julian day + Time	377.61	0.00
Julian day + Time + Wind	378.82	1.21
Time	381.47	3.87
Time + Wind	383.02	5.41
Julian day + Wind	403.04	25.44
Julian day	403.70	26.09
Wind	404.20	26.59
No covariates	405.34	27.73

All models gave very low P-values from the goodness-of-fit test with parametric bootstrapping, that rejects the null hypothesis. Thus, no model provides an adequate fit to the data. For example, the chi-square goodness-of-fit test results with parametric bootstrapping for [Day + Time] object:

Chi-square value = 205.8

P = 0.000

No models provided adequate data fit

Table B.5: Comparison of different candidate models of pcount evaluated for estimating abundance for Wood sandpiper 2015.

Covariates	AIC	Δ AIC
Julian day + Time + Wind	242.97	0.00
Julian day + Wind	254.65	11.67
Time + Wind	255.50	12.53
Julian day + Time	260.08	17.10
Julian day	264.06	21.09
Wind	264.12	21.15
No covariates	277.41	34.44
Time	277.76	34.79

Chi-square goodness-of-fit test results with parametric bootstrapping for [All covariates] object:

Chi-square value = 102.5

P = 0.426

```
> pcount(~Wind+Timecat+scale(Julian.day) ~Habitat, umf)
```

Call:

```
pcount(formula = ~Wind + Timecat + scale(Julian.day) ~ Habitat,
       data = umf)
```

Abundance:

	Estimate	SE	z	P(> z)
(Intercept)	1.9390	0.875	2.217	0.02663
HabitatUpland	-1.0825	0.355	-3.051	0.00228
HabitatWetland	0.0527	0.252	0.209	0.83456

Detection:

	Estimate	SE	z	P(> z)
(Intercept)	-2.5760	0.924	-2.787	5.32e-03
WindStrong	-0.4396	0.437	-1.006	3.14e-01
WindWeak	1.3640	0.350	3.900	9.61e-05
TimecatEvening	1.5154	0.467	3.245	1.18e-03
TimecatMorning	0.0803	0.336	0.239	8.11e-01
scale(Julian.day)	0.5866	0.180	3.261	1.11e-03

AIC: 242.9727

Table B.6: Comparison of different candidate models of pcount evaluated for estimating abundance for Wood sandpiper 2016.

Covariates	AIC	Δ AIC
No covariates	443.67	0.00
Julian day	445.72	2.05
Time	446.56	2.90
Wind	447.12	3.46
Julian day + Time	448.55	4.89
Julian day + Wind	449.13	5.47
Time + Wind	449.95	6.28
Julian day + Time + Wind	451.98	8.31

Chi-square goodness-of-fit test results with parametric bootstrapping for [No covariates] object:

Chi-square value = 163.9

P = 0.4554

```
> pcount(~1 ~Habitat, umf)
Call:
pcount(formula = ~1 ~ Habitat, data = umf)

Abundance:
      Estimate   SE      z    P(>|z|)
(Intercept)  1.806  0.411  4.4  1.09e-05
HabitatUpland -0.497  0.261 -1.9  5.74e-02
HabitatWetland 0.392  0.218  1.8  7.22e-02

Detection:
 Estimate   SE      z    P(>|z|)
-1.5      0.467 -3.22  0.00127

AIC: 443.6689
```

Appendix D

This appendix contains:

- Model selection tables for double observer point counts. Candidate model in bold gives an adequate fit to data and best AIC.
- Goodness-of-fit test results from the selected model.

Table C.1: Comparison of different candidate models of double observer evaluated for estimating abundance in 2015.

Model	AIC	Δ AIC
P(.,.)	24.210	0
P(G,.)	24.210	0
P(S,.)	24.708	0.498
P(S,I)	24.708	0.498
P(.,I)	26.116	1.906
P(G,I)	26.116	1.906

Goodness-of-fit p-value of selected model computed in SURVIV = 0.2185.

Table C.2: Comparison of different candidate models of double observer evaluated for estimating abundance in 2016.

Model	AIC	Δ AIC
P(.,.)	19.521	0
P(G,.)	19.521	0
P(S,.)	20.318	0.797
P(G,I)	21.519	1.998
P(.,I)	21.519	1.998
P(S,I)	24.903	5.382

Goodness-of-fit p-value of selected model computed in SURVIV= 0.7065.

Appendix E

Output from SURVIV analysis in DOBSERV program.

Table E.1: SURVIV output from best model P(.,.) from 2015 double observer data.

SPECIES	X.	P	SE(P)	N	SE(N)	CHAO 95% CONF. INT.	
						LOWER	UPPER
Lapland Bunting	73	0.9895	0.0061	73.77	0.99	73.11	- 78.36
Red-throated pipit	37	0.9895	0.0061	37.39	0.67	37.04	- 40.88
Wood Sandpiper	30	0.9895	0.0061	30.32	0.60	30.03	- 33.53

Table E.2: SURVIV output from best model P(.,.) from 2016 double observer data.

SPECIES	X.	P	SE(P)	N	SE(N)	CHAO 95% CONF. INT.	
						LOWER	UPPER
Lapland Bunting	115	0.9984	0.0012	115.18	0.45	115.01	- 117.82
Wood Sandpiper	53	0.9984	0.0012	53.08	0.30	53.00	- 54.98
Red-throated pipit	41	0.9984	0.0012	41.07	0.26	41.00	- 42.76

Appendix F

Complete list of bird species observed by the research team on Erkuta during the field seasons of 2015 and 2016. Their status is compared with registrations from 1999-2009 by V. Sokolov. Species with a change in their status have the updated status behind the slash.

B: breeder; b*: occasional or rare breeder; b: possible breeder; M: common or abundant migrant; +: transient or rare to uncommon migrant, -: new species.

Species	Status	Species	Status
Red-throated diver <i>Gavia stellata</i>	B	Hen harrier <i>Circus cyaneus</i>	b
Black-throated diver <i>Gavia arctica</i>	B	Pallid harrier <i>Circus macrourus</i>	b
Red-breasted goose <i>Branta ruficollis</i>	b*	Rough-legged Buzzard <i>Buteo lagopus</i>	B
White-fronted goose <i>Anser albifrons</i>	B	White-tailed Eagle <i>Haliaeetus albicilla</i>	M
Lesser white-fronted goose <i>Anser erythropus</i>	b*	Gyrfalcon <i>Falco rusticolus</i>	b*
Bean goose <i>Anser fabalis</i>	b*	Peregrine falcon <i>Falco peregrinus</i>	B
Bewick's swan <i>Cygnus bewickii</i>	b*	Merlin <i>Falco columbarius</i>	b*
Teal <i>Anas crecca</i>	B	Short-eared owl <i>Asio flammeus</i>	b*
Wigeon <i>Anas penelope</i>	B	Sand martin <i>Riparia riparia</i>	B
Pintail <i>Anas acuta</i>	B	Barn swallow <i>Hirundo rustica</i>	+
Shoveler <i>Anas clypeata</i>	+	Shore (horned) lark <i>Eremophila alpestris</i>	B
Tufted duck <i>Aythya fuligula</i>	+	Pechora pipit <i>Anthus gustavi</i>	B/b
Scaup <i>Aythya marila</i>	B	Meadow pipit <i>Anthus pratensis</i>	B
Long-tailed duck <i>Clangula hyemalis</i>	B	Red-throated pipit <i>Anthus cervinus</i>	B
Goldeneye <i>Bucephala clangula</i>	b	Yellow wagtail <i>Motacilla flava</i>	b*/B
King eider <i>Somateria spectabilis</i>	B/b*	Citrine wagtail <i>Motacilla citreola</i>	B
Common Scoter <i>Melanitta nigra</i>	B	Pied wagtail <i>Motacilla alba</i>	B
Velvet scoter <i>Melanitta fusca</i>	+/b*	Magpie <i>Pica pica</i>	+

Smew <i>Mergus albellus</i>	M	Hooded crow <i>Corvus cornix</i>	b/b*
Red-breasted merganser <i>Mergus serrator</i>	B	Raven <i>Corvus corax</i>	B
Waxwing <i>Bombycilla garrulus</i>	+	Black-headed gull <i>Larus ridibundus</i>	+
Siberian accentor <i>Prunella montanella</i>	b*/+	Heuglin's (siberian) gull <i>Larus heuglini</i>	M
Willow grouse <i>Lagopus lagopus</i>	B	Glaucous gull <i>Larus hyperboreus</i>	M
Grey plover <i>Pluvialis squatarola</i>	b*	Arctic tern <i>Sterna paradisaea</i>	B
Golden plover <i>Pluvialis apricaria</i>	B	Sedge warbler <i>Acrocephalus schoenobaenus</i>	B
Ringed plover <i>Charadrius hiaticula</i>	B	Willow warbler <i>Phylloscopus trochilus</i>	B
Dotterel <i>Eudromias morinellus</i>	+	Chiffchaff <i>Phylloscopus collybita</i>	B
Wood sandpiper <i>Tringa glareola</i>	B	Arctic warbler <i>Phylloscopus borealis</i>	b*
Spotted redshank <i>Tringa erythropus</i>	+	Yellow-browed warbler <i>Phylloscopus inornatus</i>	-/+
Terek sandpiper <i>Xenus cinereus</i>	b	Northern wheatear <i>Oenanthe oenanthe</i>	B
Red-necked phalarope <i>Phalaropus lobatus</i>	B	Bluethroat <i>Luscinia svecica</i>	B
Ruff <i>Philomachus pugnax</i>	B	Fieldfare <i>Turdus pilaris</i>	b*/B
Little stint <i>Calidris minuta</i>	b*	Redwing <i>Turdus iliacus</i>	B
Temminck's stint <i>Calidris temminckii</i>	B	Tree sparrow <i>Passer montanus</i>	-/+
Dunlin <i>Calidris alpina</i>	b*	Brambling <i>Fringilla montifringilla</i>	b/+
Jack snipe <i>Lymnocyptes minimus</i>	b*	Redpoll <i>Acanthis flammea</i>	B
Common snipe <i>Gallinago gallinago</i>	B	Reed bunting <i>Emberiza schoeniclus</i>	B
Pintail snipe <i>Gallinago stenura</i>	b	Little bunting <i>Emberiza pusilla</i>	B
Arctic skua <i>Stercorarius parasiticus</i>	B	Lapland bunting <i>Calcarius lapponicus</i>	B
Long-tailed skua <i>Stercorarius longicaudus</i>	B		