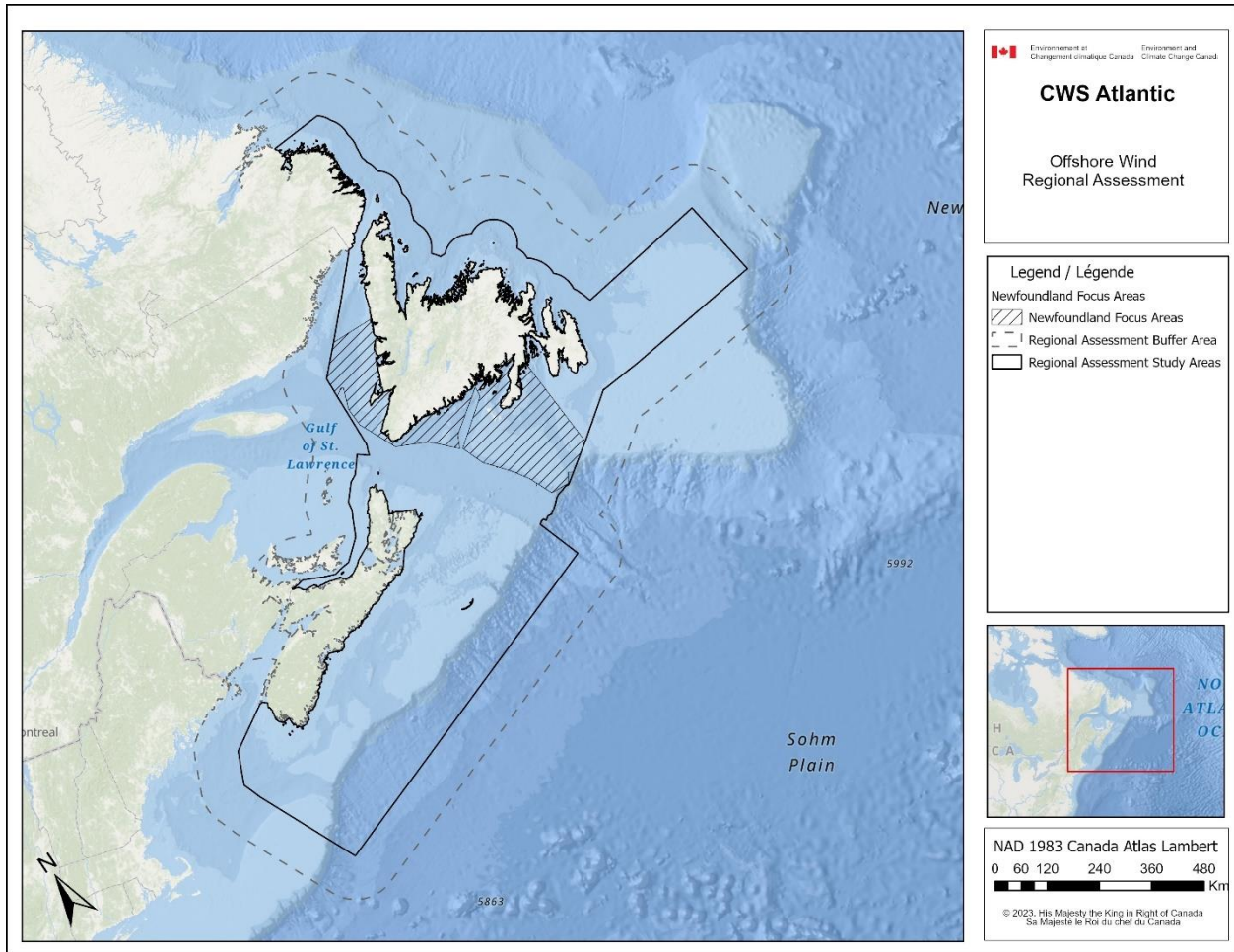


1 Avian Movement Models in Support of the Regional 2 Assessments for Offshore Wind Energy Development

3 Product Objective

4 This series of maps present movement models based on tracking data collected from birds moving
5 through the offshore region of Atlantic Canada. The goal of these products is to identify spatial and
6 temporal distributions of aerofauna in the Regional Assessment study area (Figure 1). Additionally,
7 recommendations related to technology type and study design are provided, as well as the next steps to
8 finalize products presented herein.

9 Movement and migration routes are highlighted as critical, due to the potential exposure of migrating
10 wildlife to offshore wind energy development. To identify movement corridors, ECCC reviewed and
11 analyzed tracking data for species that migrate into and out of the region or move through the region on
12 route to breeding areas beyond Atlantic Canada. Tracking data were collected using devices deployed on
13 animals that record locations over time, providing an information on where and when aerofauna are using
14 offshore areas. Multiple tracking technologies exist, each with strengths and limitations (see Appendix A
15 for a summary).



16
17 *Figure 1: Regional assessment for offshore wind energy development study areas.*

18
19 An extensive review of tracking efforts in the Atlantic Canada offshore region (Figure 1) was conducted,
20 including birds tagged at colonies within the region and tracking data for birds passing through the region.
21 Data were collected from a variety of sources including public datasets, internal ECCC data, and
22 unpublished data from researchers.

23 Movement models were created for each season to address temporal distributions. Due to variation in
24 accuracy and temporal resolution between tracking methods, different approaches were used depending
25 on the number of locations, individuals tagged, and accuracy of the tracking device (please see Appendix
26 A for information on tracking devices). Three approaches were used: plotting movement tracks,
27 calculating kernel density estimates, and creating dynamic Brownian bridge movement models (dBBMM)
28 (Figure 2). Most tracking studies do not occur throughout the whole year and are often targeted to a
29 specific period of interest. Therefore, timing plots are provided to show the temporal period covered by
30 the mapping products.

31 Further, if satellite data, either from GPS or Argos PTTs, were collected during the known migration period
32 of a species, all location data were visually examined to determine if the migration period of an individual
33 was captured. Migration tracks were then extracted from each tagged individual and plotted by species
34 for an approximation of the migration corridors used.

- 35 Products can be accessed using the following links:
- 36 • [Kernel density utilization distribution](#)
 - 37 • [Dynamic Brownian bridge movement models \(dBBMM\)](#)
 - 38 • [Migration paths](#)
 - 39 • [Tracks](#)
 - 40 • While not part of the movement models package, tracks for shorebirds provided by the Shorebird
 - 41 Collective can be found here: [Shorebird tracks](#)

43 Methodology

44 *Data Collection and Preparation*

45 An extensive review of avian tracking data in the Atlantic region was conducted, including birds tagged
 46 outside the region that pass through during migration periods. Data came from a variety of sources
 47 including:

- 48 • Public datasets (Movebank – <https://www.movebank.org> – and the Seabird Tracking Dataset –
 49 <https://www.seabirdtracking.org/>)
- 50 • Internal ECCC data
- 51 • Unpublished data from external researchers

52 In total, 2,702,347 unique locations across 42 species were collected from 73 datasets. A thorough
 53 description of all datasets is found in Appendix B. Different tracking devices were used across studies, and
 54 are described in Appendix A, along with strengths and limitations of each.

55 Since datasets came from various sources, they were pre-processed and compiled into a common format.
 56 This process included ensuring consistency in species names, date format, spatial coordinates, animal
 57 identifier, sensor type, and error associated with each location. Location error can vary between locations
 58 and was not always provided. Argos PTTs provide a location class instead of an error value, therefore,
 59 following the approach used by Spiegel et al. (2017), each error class was assigned an error value that
 60 represented the 95% error estimate of unfiltered Argos data recorded by Douglas et al. (2012). All error
 61 values are provided in Table 1. Note that some datasets provided locations estimated from a model that
 62 already considered the location error. In those cases, the error value was set as 1.

63 While GPS and GLS data were received with most erroneous data already filtered, this was not always the
 64 case with Argos data. Therefore, Argos PTT locations were filtered using a simple speed and angle filter
 65 that removes locations when the angle between three locations is too sharp or the speed between two
 66 locations is unrealistic (Freitas et al., 2008). The “argosfilter” R package v 0.7 ([https://cran.r-
 67 project.org/web/packages/argosfilter/index.html](https://cran.r-project.org/web/packages/argosfilter/index.html)) was used with a maximum speed set at 42m/sec and
 68 spikes with angles smaller than 15 and 25 degrees were removed if their extension was higher than
 69 5000m and 10000m respectively. All datasets were then compiled into a single database. Duplicates were
 70 removed to ensure there was not more than one location with the same species, sensor, timestamp, and
 71 coordinates.

72 *Table 1: Error associated with each tracking sensor. The reference column indicates the source from where values*
 73 *were extracted. A “Pers. Comm.” value indicates decisions based on discussions with subject matter experts.*

Sensor type	Error Value (m)	Reference
-------------	-----------------	-----------

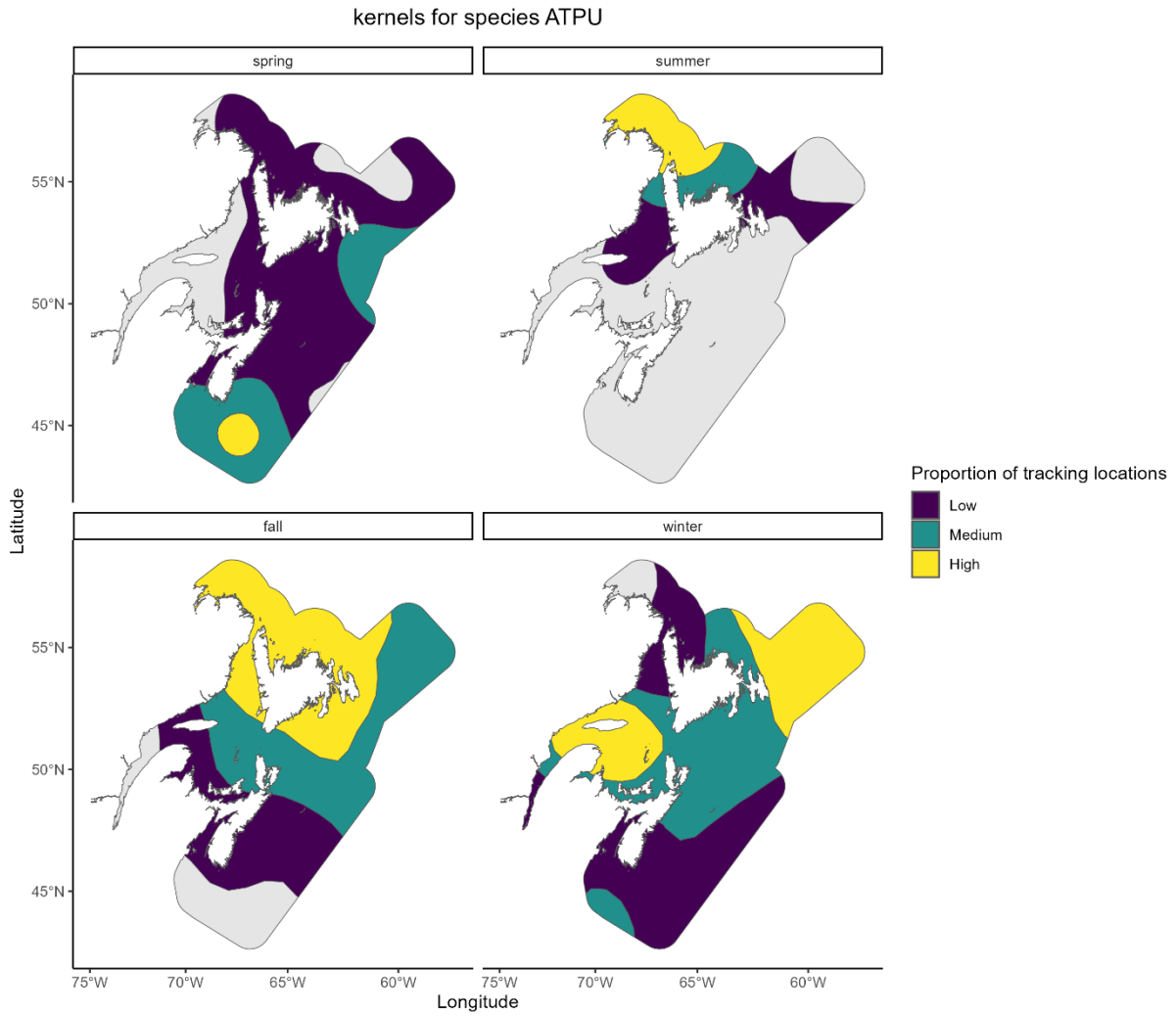
GPS / GPS-PTT		30	Spiegel et al. (2017)
Argos	LC3	1,500	Douglas et al. (2012)
	LC2	3,300	Douglas et al. (2012)
	LC1	7,600	Douglas et al. (2012)
	LC0	35,800	Douglas et al. (2012)
	LCA	59,600	Douglas et al. (2012)
	LCB	163,200	Douglas et al. (2012)
	LCZ	220,200	Douglas et al. (2012)
	LCG	Filtered out	Pers. Comm.
	No location class specified	10,000	Pers. Comm.
VHF		1,500	Upper rounding of maximum value from Zimmerman and Powell (1995)
GLS		100,000	Pers. Comm.
Modelled Locations		1	Pers. Comm.
No sensor/error provided		Filtered out	Pers. Comm.

74

75 Analyses

76 For each species, locations were first divided by season. Seasons were defined as: spring (April- May),
77 summer (June- August), fall (September- October), and winter (November- March). The analysis method
78 was selected depending on the number of locations and type of sensor. Individuals with fewer than 2
79 locations inside the study area were removed. The workflow used to select the analysis method is
80 described in Figure 2. A summary of all analyses performed by species is found in Kernel Density
81 Utilization Distribution

82 A common way to quantify space use is to calculate a utilization distribution (UD). This gives the
83 probability density that an animal is found at a given point in space. One approach to detect spatial
84 patterns are point density kernel utilization distributions, which highlight areas where multiple locations
85 are grouped together. This approach was used to process data collected using GLS sensors, due to their
86 large location error (>100km) that hampers accurate modeling. Point density kernels were created using
87 the “spatstat” R package (Baddeley and Turner 2005) using a bandwidth of 100,000m and a cell size of
88 10,000m. Kernels were calculated using all locations, even though some were not present inside the study
89 area. A species-specific mapping example created using a kernel density utilization distribution is shown in
90 Figure 3. All kernel density figures are available here: Kernel Density Figures.

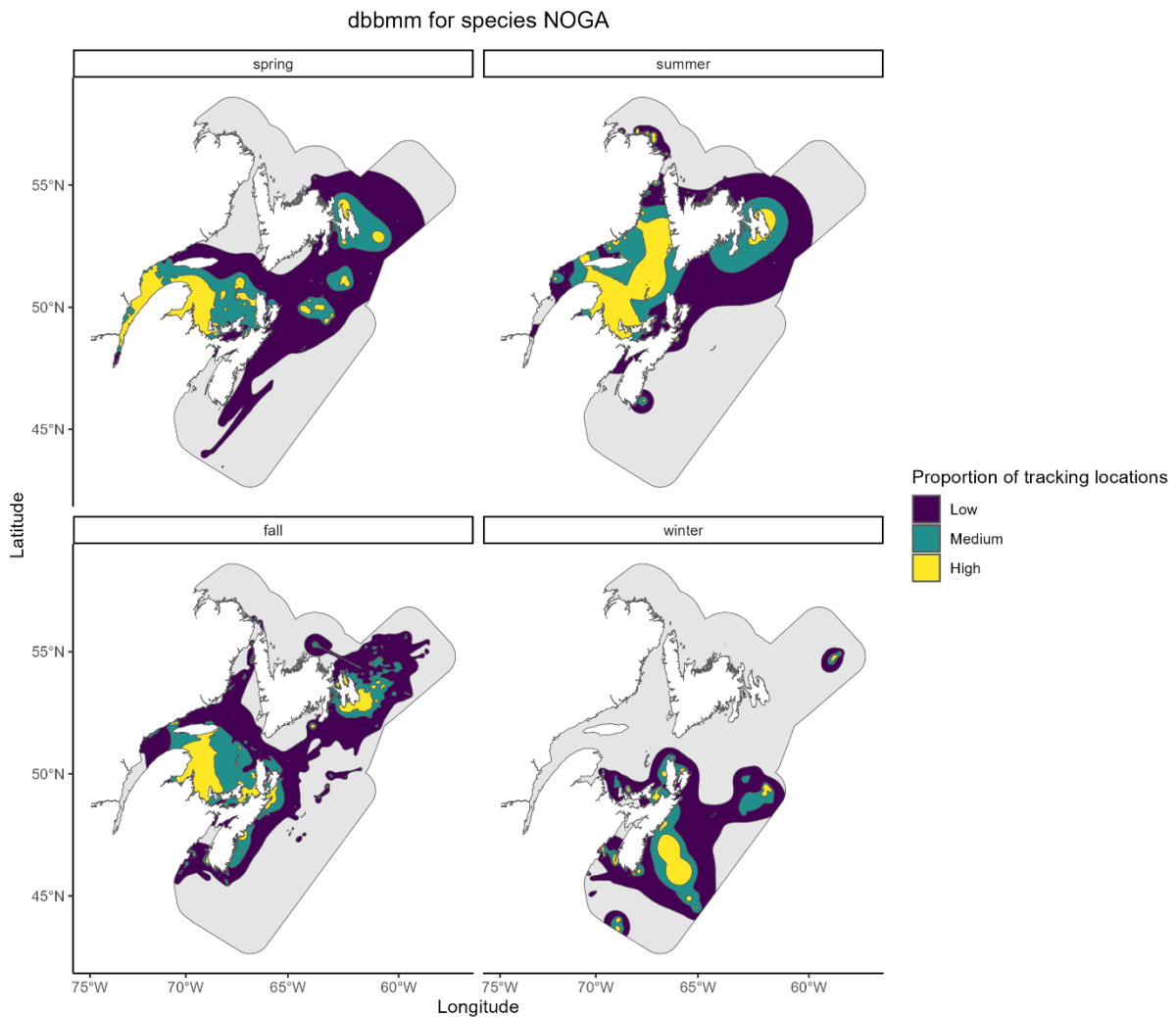


92

93 *Figure 3: Seasonal utilization distribution (UD) for Atlantic puffin (ATPU) created using a kernel density movement*
94 *model.*

95 *Dynamic Brownian Bridge Movement Models*

96 Dynamic Brownian bridge movement models (dBBMMs) were developed when species were tracked
97 using devices with higher spatial resolution, such as VHF, PTT, or GPS. dBBMMs provide more accurate
98 utilization distributions than kernel density estimates as they account for spatial and temporal
99 autocorrelation. These models are also robust to irregular sampling schedules associated with the duty
100 cycles of the transmitters, and incorporates location error estimates (Kranstauber et al. 2012; Spiegel et al.
101 2017). One movement model was conducted per individual, using a grid with a cell size of 1,000m. Only
102 individuals with at least 20 locations covering a minimum of 5 days were selected. Only locations inside
103 the study areas are used for the model. All models were composited together for each season for species
104 with at least 10 individuals. During compositing, individual rasters were weighted by the number of days
105 of tracking data per individual compared to the total number of tracking days across the species and then
106 summed. Utilization contour levels of 50%, 75%, and 95% were then calculated, representing high,
107 medium and low usage, respectively. *Figure 4* presents an example of movement maps created using
108 dBBMMs. All dBBMM figures are available here: [Dynamic Brownian Bridge Movement Models](#).

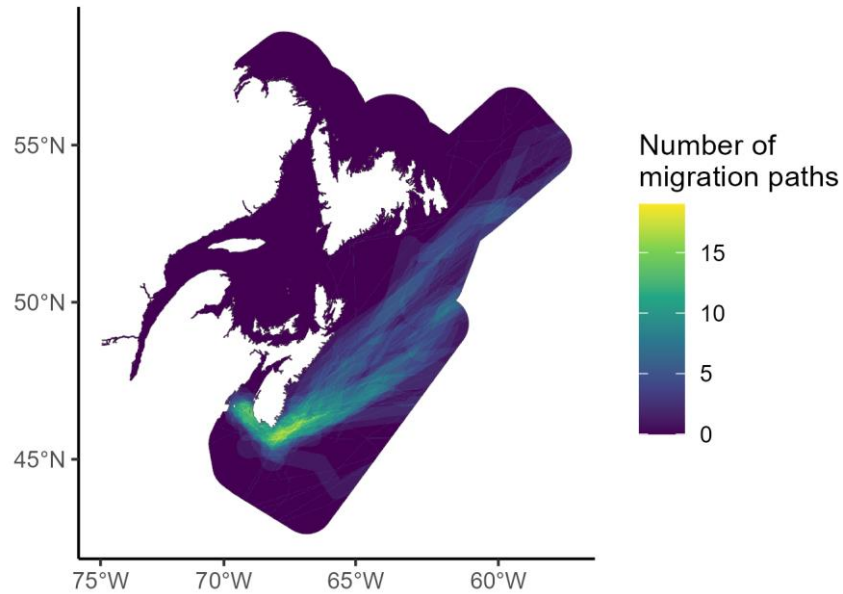


109

110 *Figure 4: Seasonal Utilization distribution (UD) maps for Northern Gannets created using dynamic Brownian Bridge*
111 *Movement Models (dBBMM).*

112 *Migration Paths*

113 When tracking data overlapping the spring or fall migration periods was available, migration dates for an
114 individual were determined by visual inspection of the tracks. Migration paths were plotted as the
115 Euclidean distance between recorded locations. A buffer corresponding to the average error of all track
116 locations for each individual was applied. All buffered tracks for a given migration period and species were
117 then summed into a single map. No GLS migration data was extracted, due to the low accuracy compared
118 to the size of the study area. An example migration path is provided in [Figure 5](#). All migration path figures
119 are available here: [Migration Path Figures](#).

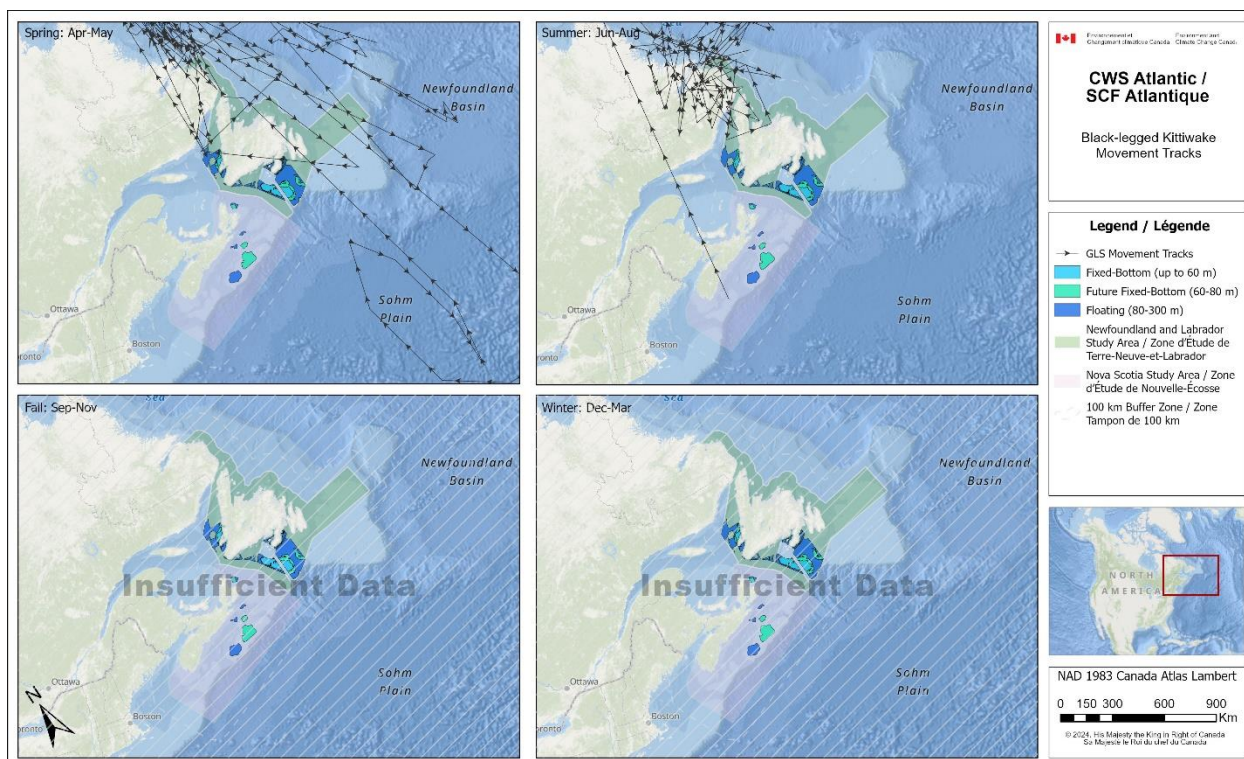


120

121 [Figure 5](#): Number of migration paths identified using movement telemetry during Fall for Great shearwater (GRSH).

122 *Tracks*

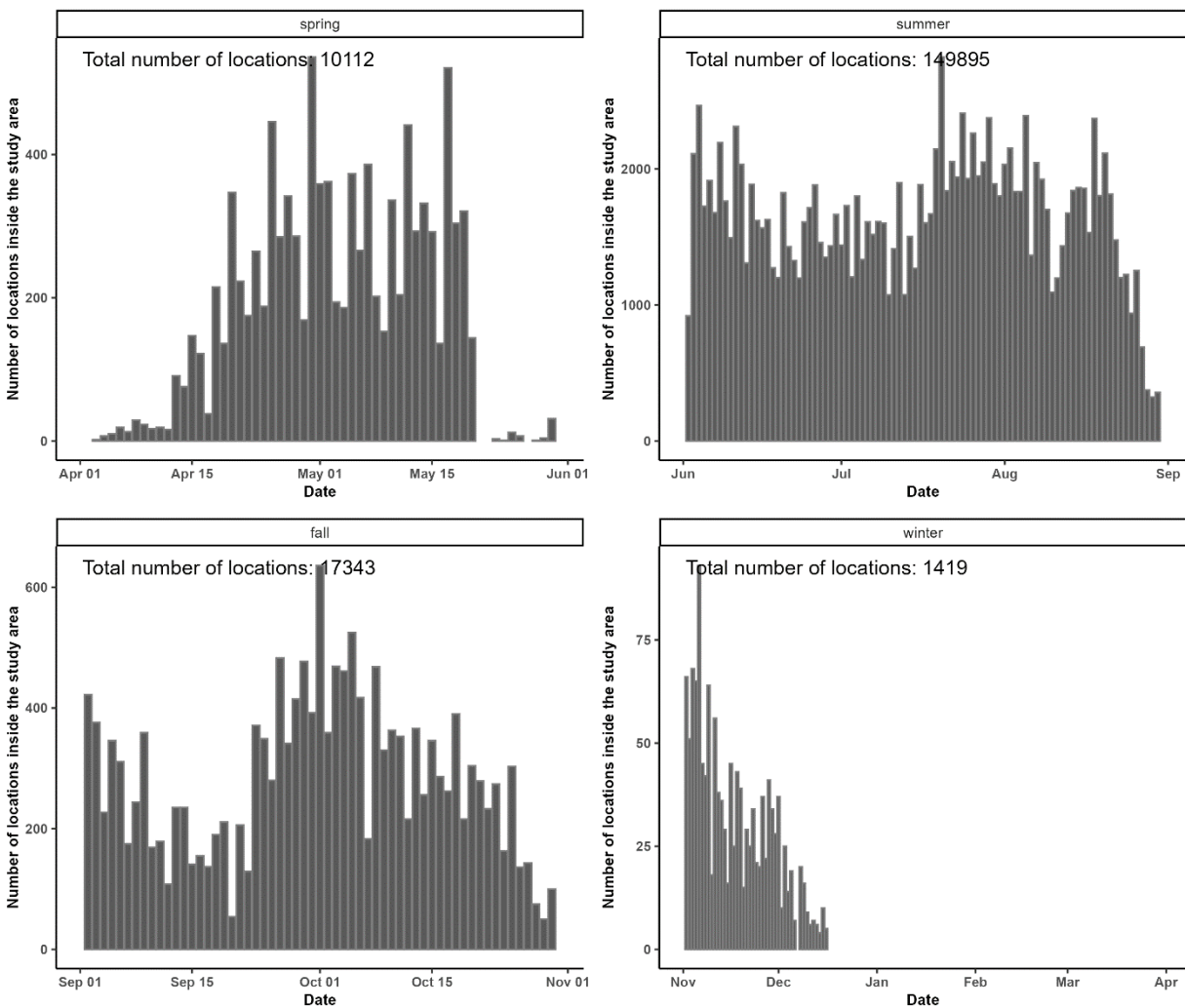
123 When not enough data were available to perform dBBMMs outside of the migration periods, individual
124 tracks (Euclidean distance between recorded locations) were mapped over the study area. Due to their
125 low accuracy compared to the size of the study area, no tracks were plotted for GLS data. Example
126 migration track maps are shown in *Figure 6*. All migration track figures are available here: Migration Track
127 Figures.



128 *Figure 6: Seasonal movement tracks for Black-legged Kittiwake (BLKI).*
129

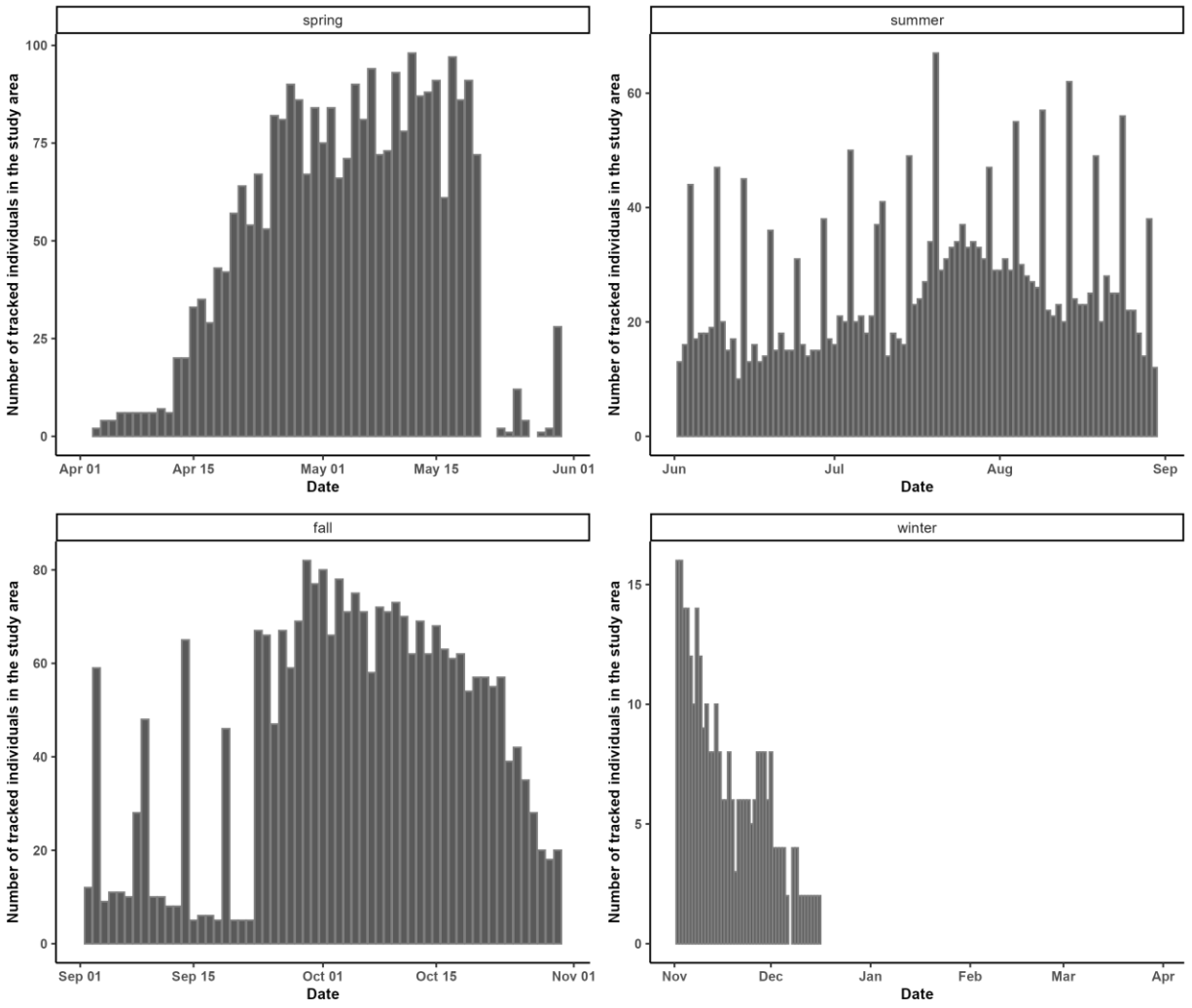
130 *Timing Plots*

131 To provide the temporal repartition of the locations within a season, additional timing plots are provided
132 for dBBMM and kernel density maps. Two sets of plots are provided. The first, using dBBMM, counts the
133 number of locations in the study area for each species and each day of a season (*Figure 7*). Only the
134 locations used in the movement models are considered. The total number of locations is also shown. All
135 dBBMM timing plots are available here: [DBBMM Timing Plots](#). The second set of timing plots, using kernel
136 density (*Figure 8: Number of tracked individuals across time whose locations were used to create the*
137 *dBBMM maps presented in Figure 4. Figure 8*), count the number of individuals tracked each day of the
138 season per species. All kernel density timing plots are available here: [Kernel Density Timing Plots](#).



139
140 *Figure 7: Temporal distribution of tracking locations used to create the dynamic Brownian Bridge*
141 *Movement Model (dBBMM) maps for Northern Gannet (NOGA), as presented in Figure 4.*

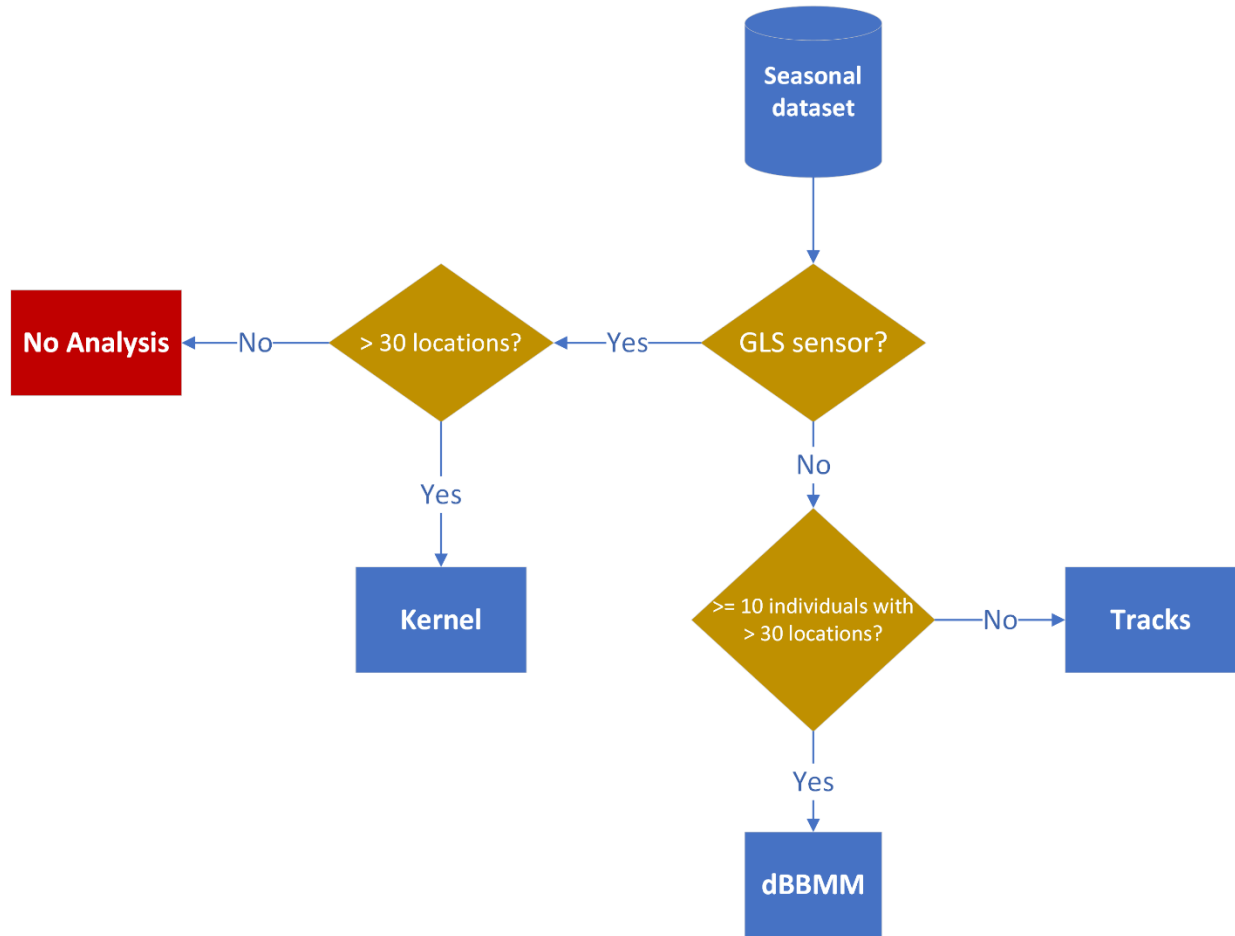
142



143

144 *Figure 8: Number of tracked individuals across time whose locations were used to create the dBMM maps presented*
 145 *in Figure 4.*

146 Table 2. Sample sizes per species, season, and tag used for each product are found in Appendix C.

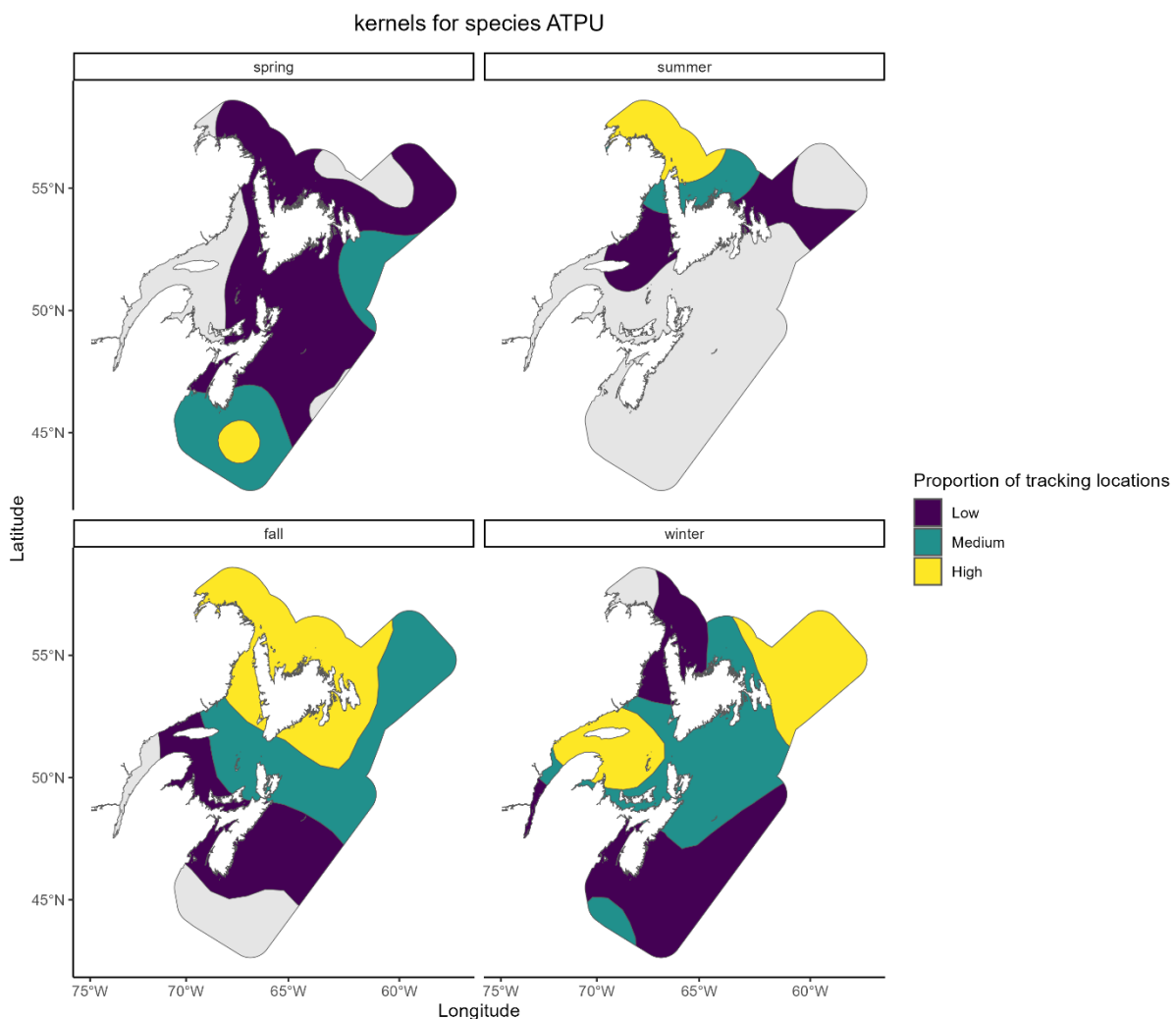


147
148 Figure 2: Workflow used to select which movement analysis to perform on seasonal data for each species.

149 *Kernel Density Utilization Distribution*

150 A common way to quantify space use is to calculate a utilization distribution (UD). This gives the
151 probability density that an animal is found at a given point in space. One approach to detect spatial
152 patterns are point density kernel utilization distributions, which highlight areas where multiple locations
153 are grouped together. This approach was used to process data collected using GLS sensors, due to their
154 large location error (>100km) that hampers accurate modeling. Point density kernels were created using
155 the “spatstat” R package (Baddeley and Turner 2005) using a bandwidth of 100,000m and a cell size of
156 10,000m. Kernels were calculated using all locations, even though some were not present inside the study
157 area. A species-specific mapping example created using a kernel density utilization distribution is shown in
158 *Figure 3*. All kernel density figures are available here: [Kernel Density Figures](#).

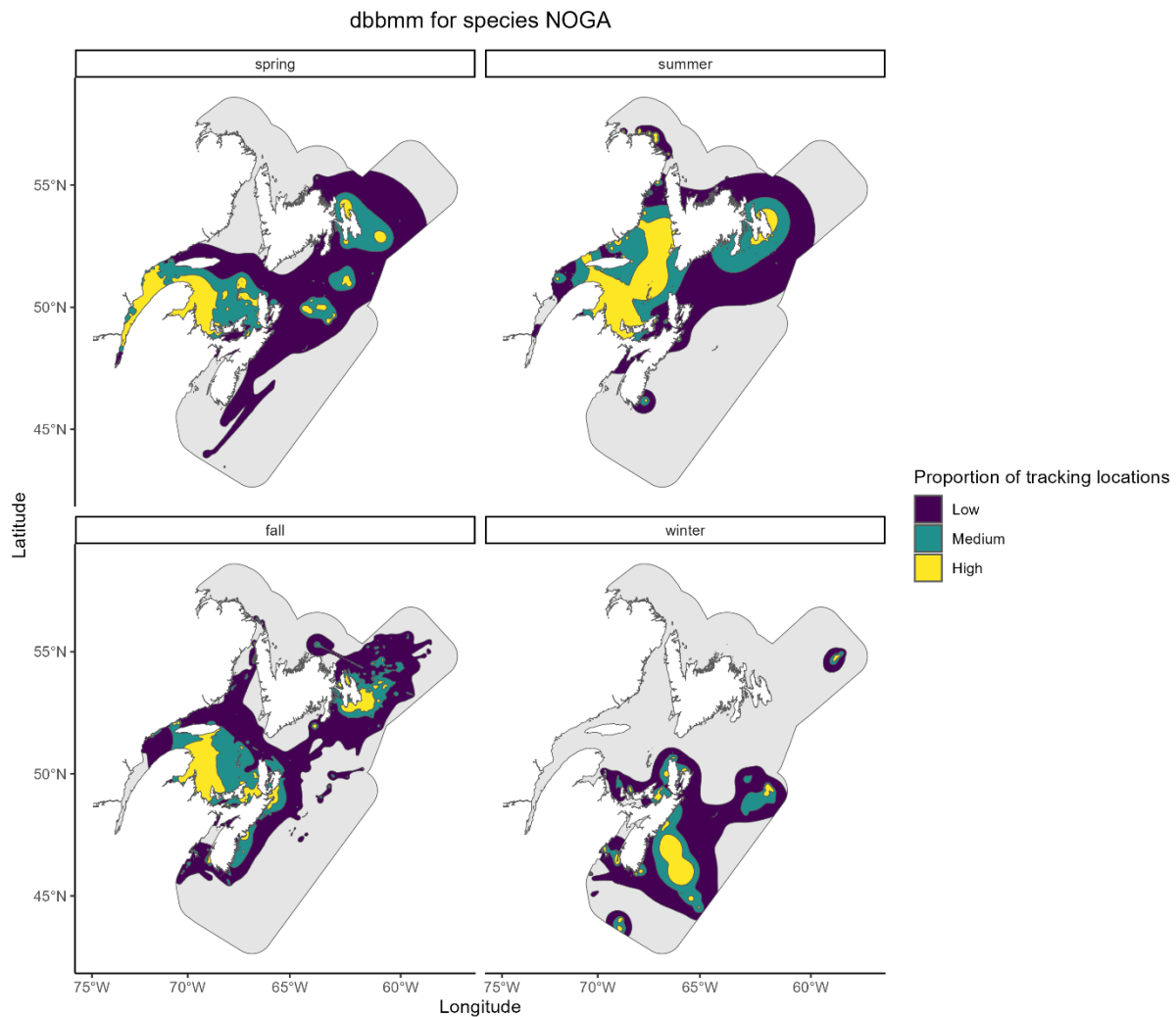
159



160
161 *Figure 3: Seasonal utilization distribution (UD) for Atlantic puffin (ATPU) created using a kernel density movement*
162 *model.*

163 *Dynamic Brownian Bridge Movement Models*

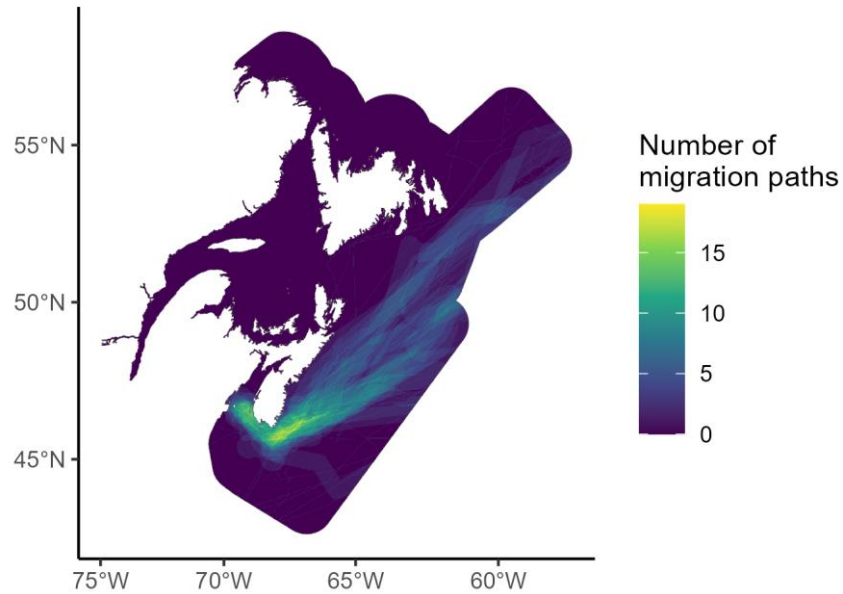
164 Dynamic Brownian bridge movement models (dBBMMs) were developed when species were tracked
165 using devices with higher spatial resolution, such as VHF, PTT, or GPS. dBBMMs provide more accurate
166 utilization distributions than kernel density estimates as they account for spatial and temporal
167 autocorrelation. These models are also robust to irregular sampling schedules associated with the duty
168 cycles of the transmitters, and incorporates location error estimates (Kranstauber et al. 2012; Spiegel et al.
169 2017). One movement model was conducted per individual, using a grid with a cell size of 1,000m. Only
170 individuals with at least 20 locations covering a minimum of 5 days were selected. Only locations inside
171 the study areas are used for the model. All models were composited together for each season for species
172 with at least 10 individuals. During compositing, individual rasters were weighted by the number of days
173 of tracking data per individual compared to the total number of tracking days across the species and then
174 summed. Utilization contour levels of 50%, 75%, and 95% were then calculated, representing high,
175 medium and low usage, respectively. *Figure 4* presents an example of movement maps created using
176 dBBMMs. All dBBMM figures are available here: [Dynamic Brownian Bridge Movement Models](#).



177
178 *Figure 4: Seasonal Utilization distribution (UD) maps for Northern Gannets created using dynamic Brownian Bridge*
179 *Movement Models (dBBMM).*

180 *Migration Paths*

181 When tracking data overlapping the spring or fall migration periods was available, migration dates for an
182 individual were determined by visual inspection of the tracks. Migration paths were plotted as the
183 Euclidean distance between recorded locations. A buffer corresponding to the average error of all track
184 locations for each individual was applied. All buffered tracks for a given migration period and species were
185 then summed into a single map. No GLS migration data was extracted, due to the low accuracy compared
186 to the size of the study area. An example migration path is provided in [Figure 5](#). All migration path figures
187 are available here: [Migration Path Figures](#).



188

189 *Figure 5: Number of migration paths identified using movement telemetry during Fall for Great shearwater (GRSH).*

190 *Tracks*

191 When not enough data were available to perform dBMMs outside of the migration periods, individual
192 tracks (Euclidean distance between recorded locations) were mapped over the study area. Due to their
193 low accuracy compared to the size of the study area, no tracks were plotted for GLS data. Example
194 migration track maps are shown in *Figure 6*. All migration track figures are available here: [Migration Track](#)
195 [Figures](#).

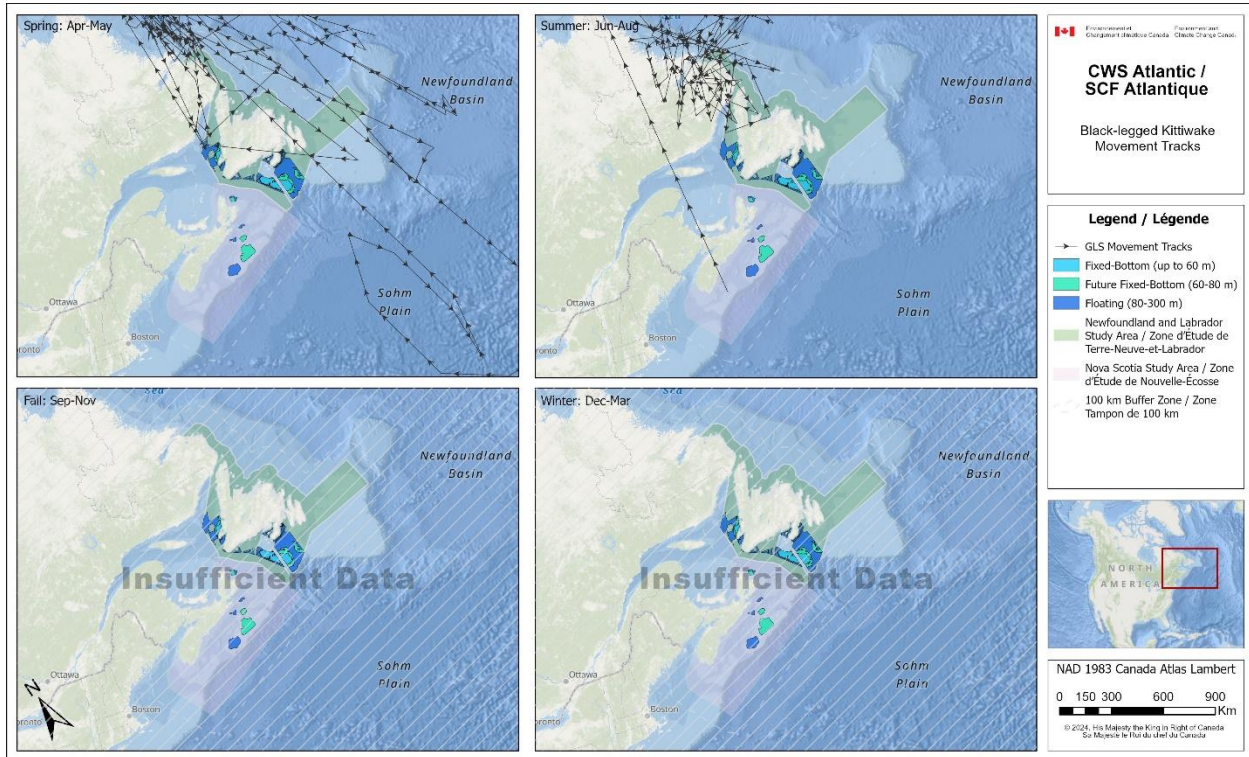
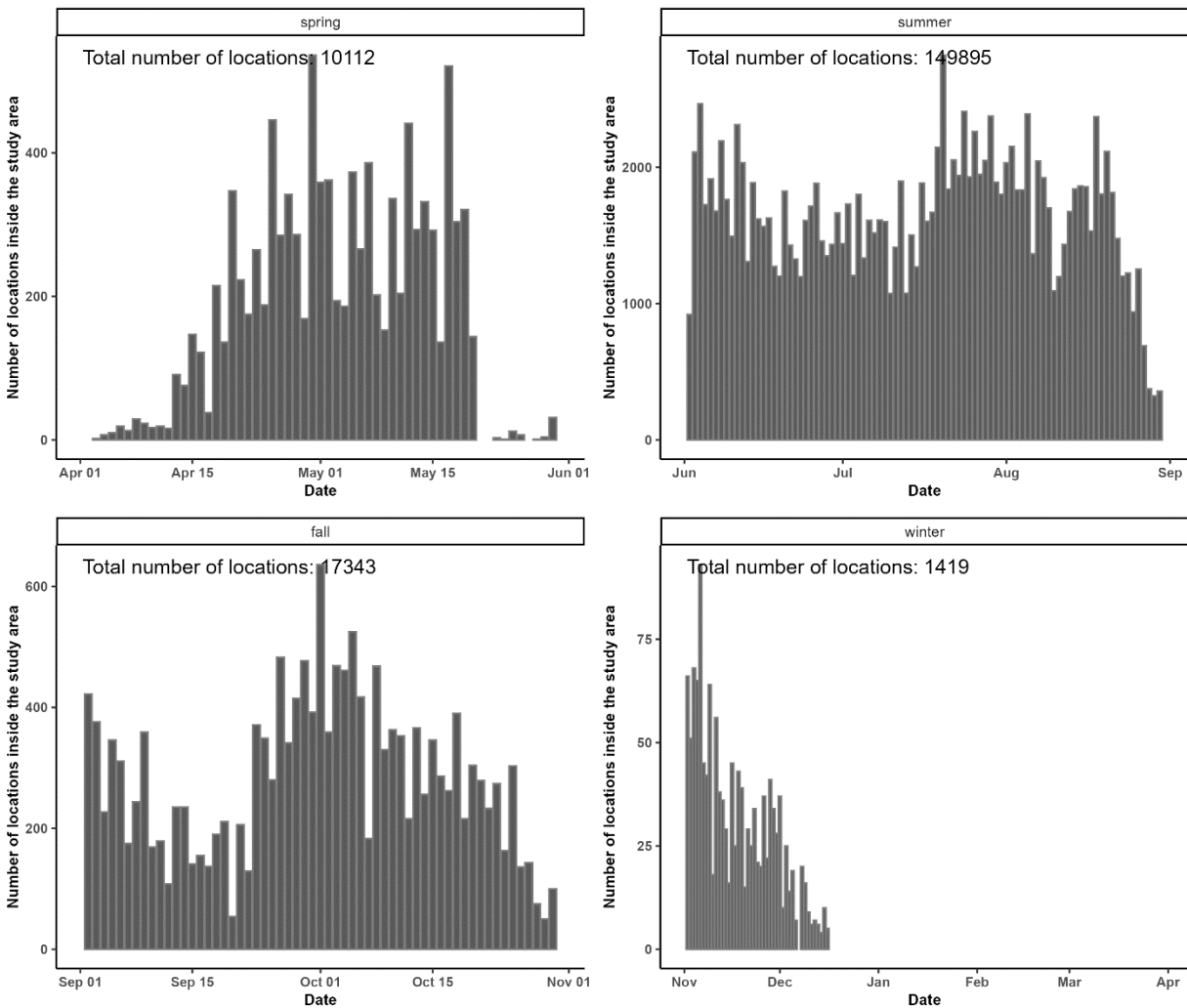


Figure 6: Seasonal movement tracks for Black-legged Kittiwake (BLKI).

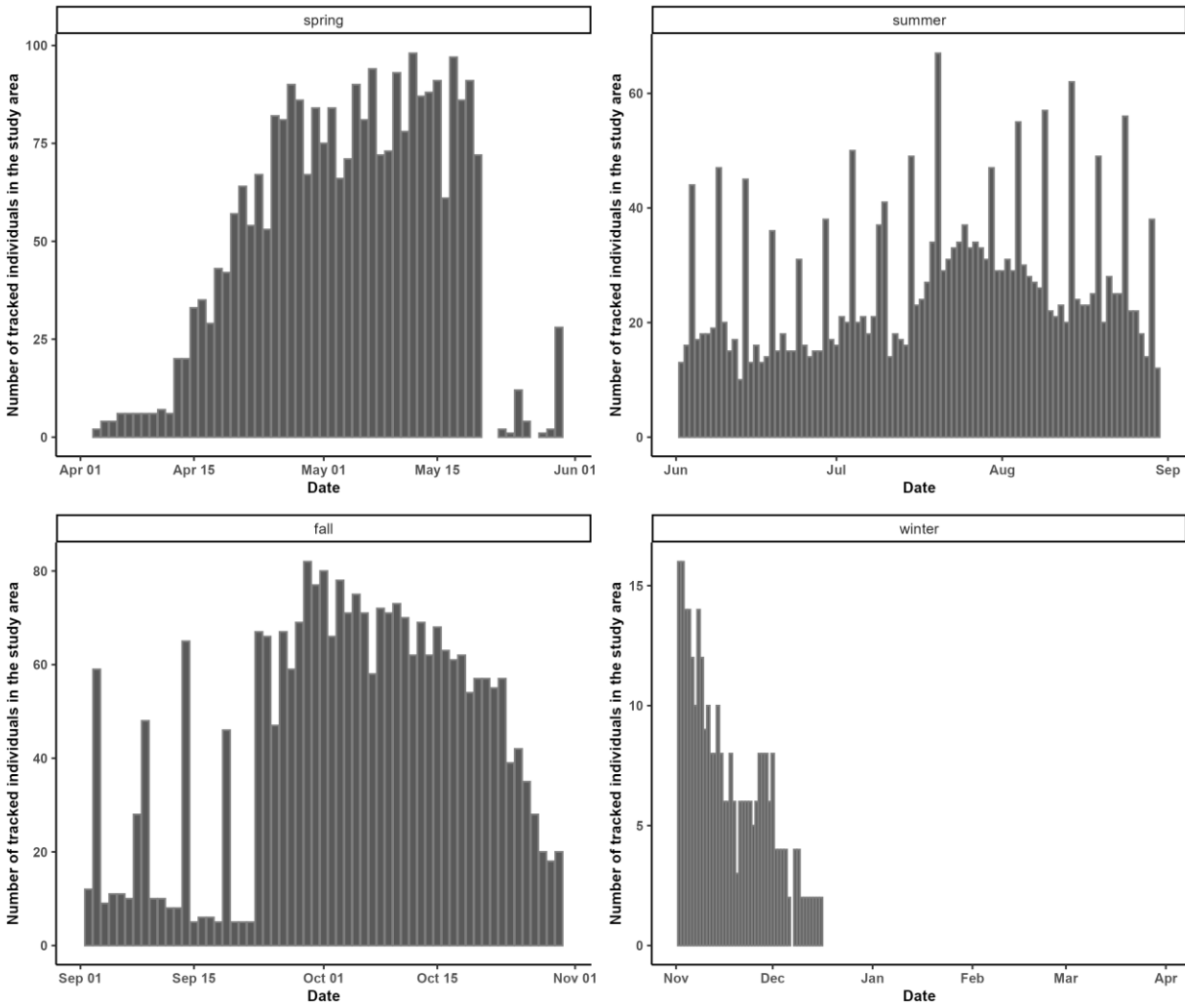
198 *Timing Plots*

199 To provide the temporal repartition of the locations within a season, additional timing plots are provided
200 for dBBMM and kernel density maps. Two sets of plots are provided. The first, using dBBMM, counts the
201 number of locations in the study area for each species and each day of a season (*Figure 7*). Only the
202 locations used in the movement models are considered. The total number of locations is also shown. All
203 dBBMM timing plots are available here: [dBBMM Timing Plots](#). The second set of timing plots, using kernel
204 density (*Figure 8: Number of tracked individuals across time whose locations were used to create the*
205 *dBBMM maps presented in Figure 4. Figure 8*), count the number of individuals tracked each day of the
206 season per species. All kernel density timing plots are available here: [Kernel Density Timing Plots](#).



207
208 *Figure 7: Temporal distribution of tracking locations used to create the dynamic Brownian Bridge*
209 *Movement Model (dBBMM) maps for Northern Gannet (NOGA), as presented in Figure 4.*

210



211

212 *Figure 8: Number of tracked individuals across time whose locations were used to create the dBMM maps presented*
213 *in Figure 4.*

214 *Table 2: List of species per product and season. Species names with an asterisk refer to kernel models created with*
 215 *fewer than 10 individuals. Four-letter codes are provided for the following species: ABDU = American Black Duck,*
 216 *AMGP = American Golden-Plover, AMWO = American Woodcock, ARTE = Arctic Tern, ATPU = Atlantic Puffin, BBPL =*
 217 *Black-bellied Plover, BLGU = Black Guillemot, BLKI = Black-legged Kittiwake, BLSC = Black Scoter, COEI = Common*
 218 *Eider, COMU = Common Murre, CORS = Cory's Shearwater, COTE = Common Tern, DOVE = Dovekie, GBBG = Great*
 219 *Black-backed Gull, GLGU = Glaucous Gull, GRSH = Great Shearwater, HERG = Herring Gull, LESP = Leach's Storm*
 220 *Petrel, LEYE = Lesser Yellowlegs, LTDU = Long-tailed Duck, LTJA = Long-tailed Jaeger, MASH = Manx Shearwater, NOFU*
 221 *= Northern Fulmar, NOGA = Northern Gannet, PAJA = Parasitic Jaeger, PESA = Pectoral Sandpiper, RAZO = Razorbill,*
 222 *RTLO = Red-throated Loon, SOSH = Sooty Shearwater, SUSC = Surf Scoter, TBMU = Thick-billed Murre, WHIM =*
 223 *Whimbrel, WWSC = White-winged Scoter, WTTR = White-tailed Tropicbird.*

Product	Spring	Summer	Fall	Winter
Tracks	BLKI, GLGU, IVGU, PAJA	BLKI, CORS, LTJA	CANG, COEI, CORS, LTJA, PAJA	GLGU, LTJA, NOFU
Dynamic Brownian Bridge Movement Models (dBBMMs)	ABDU, BLSC, HERG, LTDU, NOGA, RTLO, SUSC, WWSC	ABDU, ATPU, BLSC, COEI, COMU, GBBG, GRSH, HERG, NOGA, RAZO, ROST, SUSC, WHIM, WWSC	ABDU, GRSH, HERG, NOGA, SUSC, WWSC	ABDU, GRSH, HERG, NOGA, RTLO, SUSC, WWSC
Kernels	ATPU, BLGU*, BLKI, COMU, CORS, GLGU*, LTJA, MASH*, NOGA, PAJA*, RAZO, SOSH, TBMU	ATPU, BLGU*, BLKI, COMU, CORS, LTJA, NOGA, PAJA*, RAZO, SOSH, TBMU, WTTR	ATPU, BLGU*, BLKI, COMU, CORS, LTJA, MASH*, NOGA, PAJA*, RAZO, SOSH, TBMU, WTTR	ATPU, BLGU*, BLKI, COMU, CORS, GLGU*, LTJA, MASH*, NOGA, PAJA*, RAZO, SOSH, TBMU, WTTR
Migrations	ABDU, BLSC, GBBG, GLGU, HERG, LTDU, NOGA, PESA, RTLO, SUSC, WWSC	Not applicable	ABDU, BLSC, COEI, GRSH, HERG, LEYE, LTDU, LTJA, NOGA, PAJA, RTLO, SOSH, SUSC, WHIM	Not applicable

224

225 Interpretation

226 [Kernel density](#) and [dBBMM](#) maps present areas of potential use by avian species. They identify three
 227 areas of probable use by individuals: high, medium, and low. [Track maps](#) identify where locations were
 228 recorded, as well as an added straight line between two consecutive locations to provide a simple
 229 estimation of the path taken by the individuals. [Migration maps](#) show tracks buffered by the average error
 230 location for the migration period.

231 As the available tracking data is limited in terms of number of individuals and spatial coverage, absence
 232 should be interpreted as a gap in data collection rather than no birds being present. Similarly, high usage
 233 areas might only reflect important areas for the tagged population and not the whole population. These
 234 products provide a baseline for the species studied and should be used as an indicator of where future
 235 efforts could be directed to increase knowledge of seasonal space use.

236 Timing plots show the number of locations by season and species. These plots should be considered when
237 determining habitat use by the species. If tracking locations are lacking during a period when a species is
238 known to be present, it can be assumed that this is the result of a data gap, and that the movement
239 model does not accurately represent the spatial use of the species.

240 Limitations and Assumptions

241 While all efforts were made to be as exhaustive as possible during inventory of existing tracking data, the
242 data used to present the movement models is heterogeneous. These products include data that may vary
243 in spatial accuracy, temporal resolution, or even in the available information that is associated with the
244 tracking data. For instance, data retrieved on public datasets usually follow a defined standard so all the
245 data on the platform are similar in terms of column names, filtering process or metadata. However, these
246 same standards are not consistent with data from other sources. Some information might be missing,
247 such as the associated error in a different format, or the tagging location. The variety of tracking devices
248 used also leads to differences in the quality of products, as illustrated by the number of approaches taken
249 herein and the different resolution between methods.

250 Trade-offs between factors such as battery lifespan can lead to inconsistencies across datasets in terms of
251 accuracy, number of locations, temporal resolution, and recording period. Long-term studies typically do
252 not have the same temporal resolution as short-term studies. For instance, several datasets that included
253 records spanning several months and overlapping migration periods also had a low temporal resolution
254 (e.g., one location daily or every few days), making it difficult to identify migration routes. Conversely,
255 some studies with high temporal resolution (e.g., collecting multiple locations per day or per hour), have
256 shorter durations and tend to miss migration periods.

257 Additionally, due to the limited number of individuals tracked, these movement products should not be
258 considered as representative of the whole population of a species. Unless the number of tracking devices
259 deployed is large enough, and individuals are tagged throughout the study area, they represent only the
260 tracked individuals. Therefore, an absence of movement in an area does not indicate that no birds are
261 present, only that habitat use was not able to be determined with the tracking data available. Conversely,
262 the presence of a high usage area with a low number of tracked individuals does not mean that this area
263 is heavily used by all individuals of that species. However, this can help detect trends of habitat use that
264 can help inform follow-up studies.

265 These products focus on species that breed or forage into the Atlantic offshore region. However, some
266 species use the region only as a migratory corridor. For instance, some species of shorebirds breed in the
267 Arctic and enter the study area only during the fall migration. Those species can be under-represented, as
268 tracking data is scarce due to the logistical difficulties of deploying tracking devices in the breeding or
269 wintering areas. The movement models presented emphasise the tracking data available for a given
270 season and the known spatial use of the birds. However, these products have a coarse temporal resolution
271 and do not incorporate the biology of each presented species. Fine-scale spatial and temporal habitat use
272 will depend on the species and factors such as their foraging and breeding strategies. Habitat use will also
273 depend on population size and colony sizes. Age of birds can also influence habitat use and young
274 individuals are often considered more vulnerable.

275 Finally, the movement models presented here are limited to avian species. To our knowledge, there are no
276 tracking studies that describe the behaviour of bats and flying invertebrates (i.e., Monarch) in the

277 offshore. Due to the size and weight of recording devices, these products are limited to individuals that
278 are sufficiently large to carry the device and does not include small-bodied birds such as shorebirds.

279 Recommendations

- 280 • When possible, use high accuracy tracking device, such as GPS trackers.
- 281 • Movement data should be analysed with movement models that account for tracking error, such as
282 dynamic Brownian bridge movement models.
- 283 • Tracking devices should be programmed to record for an extended period that covers both the spring
284 and fall migration for migrants, and the whole year for residents/facultative migrants. If such a
285 deployment is not possible, consider several deployments so all life stages spent in the study area by a
286 given species are covered. A few long-term tracks can be more informative than a higher number of
287 short-term tracks (Thaxter et al. 2017).
- 288 • Ensure the number of tracking devices deployed is representative of population in the area of
289 interest. For example, between 13 and 41 birds were found to be required for Lesser Black-backed
290 Gulls (*Larus fuscus*) to accurately describe 95% of their estimated habitat use (Thaxter et al. 2017). On
291 wide-ranging species with high inter-individual variation, at least 17 to 21 devices were required to
292 minimise variations between individuals (Gutowsky et al. 2015). In both cases, increasing the number
293 of tagged individuals also increases coverage of the total habitat used (Beal et al. 2023). Based on
294 current literature, a minimum of 30 devices per species and colony should be deployed to ensure
295 adequate representation. For colonial birds, devices should be deployed across all colonies expected
296 to intersect with potential development areas. If deploying devices at all colonies that intersect an
297 area of interest is not feasible, a modelling approach using tracking data of individuals from
298 representative colonies can be used to create species predictive distributions.
- 299 • Consider deploying devices across several years, as this better describes the total habitat used (Beal et
300 al. 2023).
- 301 • Ensure there is appropriate spatial variation between tracked individuals. If multiple colonies are
302 present in or near the area of interest, distribute tracking devices on individuals across multiple
303 colonies of importance.
- 304 • Deploy devices across age classes for a species, especially if different behaviours, habitat use, or
305 migratory pathways are expected to occur.
- 306 • When possible, devices that record flight height data should be favoured, due to the lack of accurate
307 flight altitude information for several species and the importance of altitude when considering
308 collision vulnerability.

310 Next Steps

311 ECCC will continue to finalize the products presented herein, including the following:

- 312 • Update mapping products using the official ECCC-CWS template. Include timing plots within the
313 seasonal maps to identify the time coverage of the product.
- 314 • Review track products to include data not applicable to the dBMM process and ensure consistency
315 across products.
- 316 • Include Leach's Storm-petrel data.

317 References

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352

Appendix A: Devices used to collect avian movement data

Name	Description	Pros	Cons
GPS (Global Positioning System) or GPS-PTT (GPS receivers coupled with Argos Platform Transmitter Terminals)	Satellite receivers	High spatial accuracy Temporal resolution can be high (every few minutes)	Often do not cover the whole year
Argos Platform Transmitter Terminals (PTT)	Satellite emitters	Variable accuracy (250m to 10km) Temporal resolution variable (few hours to few days)	Lower accuracy than GPS Duty cycles can miss the migration phase
GLS (Global Location Sensor)	Light sensing devices. Infers position based on daylight duration	Low battery consumption Whole year coverage	Low accuracy (100km) Does not work well near the equinoxes
VHF	Radio emitters	Low impact tags, easily deployed	Only detects presence in proximity of a receiver
Modelled location (not a device)	Data that has been published after having been processed through another model	Location error has already been included inside the model	

353

354 [Appendix B: Tracking datasets used in avian movement analyses](#)

355 [ECCC Avian Tracking Datasets](#)

356

357 [Appendix C: Sample sizes used for avian movement analyses](#)

358 Sample sizes used to create kernel and dBBMM models are provided. These data can be used to identify
359 data gaps between species and/or seasons. Sample size should be used in conjunction with timing plots,
360 as a multiple locations reflect a higher recording frequency.

361 *[Kernel Density Utilization Distributions](#)*

362 The number of locations used to create the kernel density utilization distribution maps are found here:

363 [Kernels sample sizes](#)

364 Note that kernels use locations outside the study area. The number of locations found within the study
365 area are listed in column “n_locs_in_sa”. Note that only GLS data was used to create kernel density
366 utilization distributions.

367 *[Dynamic Brownian Bridge Movement Models](#)*

368 The number of locations used to create the dBBMM maps can be found here: [dBBMM sample sizes](#). Only
369 locations found within the study area were used to create dBBMM models.