Birds, weather, and wind farms
A radar’s view on bird flight in a changing seascape
van Erp, J.A.

Publication date
2024
Document Version
Final published version

Link to publication

Citation for published version (APA):

General rights
It is not permitted to download or to forward/distribute the text or part of it without the consent of the author(s) and/or copyright holder(s), other than for strictly personal, individual use, unless the work is under an open content license (like Creative Commons).

Disclaimer/Complaints regulations
If you believe that digital publication of certain material infringes any of your rights or (privacy) interests, please let the Library know, stating your reasons. In case of a legitimate complaint, the Library will make the material inaccessible and/or remove it from the website. Please Ask the Library: https://uba.uva.nl/en/contact, or a letter to: Library of the University of Amsterdam, Secretariat, Singel 425, 1012 WP Amsterdam, The Netherlands. You will be contacted as soon as possible.

UvA-DARE is a service provided by the library of the University of Amsterdam (https://dare.uva.nl)

Download date: 31 Jul 2024
Birds, weather, and wind farms
A radar’s view on bird flight in a changing seascape

Jens Auke van Erp
Birds, weather, and wind farms
A radar’s view on bird flight in a changing seascape

by
Jens Auke van Erp
Birds, weather, and wind farms
A radar’s view on bird flight in a changing seascape

ACADEMISCH PROEFSCHRIFT

ter verkrijging van de graad van doctor
aan de Universiteit van Amsterdam
op gezag van de Rector Magnificus
prof. dr. ir. P.P.C.C. Verbeek
ten overstaan van een door het College voor Promoties ingestelde commissie,
in het openbaar te verdedigen in de Aula der Universiteit
op vrijdag 12 april 2024, te 11.00 uur

door Jens Auke van Erp
geboren te Utrecht
Promotiecommissie

Promotor: prof. dr. J.Z. Shamoun-Baranes Universiteit van Amsterdam

Copromotor: dr. ir. E.E. van Loon Universiteit van Amsterdam

Overige leden: prof. dr. ir. D. Lentink Rijksuniversiteit Groningen
prof. dr. A.M. de Roos Universiteit van Amsterdam
prof. dr. B.A. Nolet Universiteit van Amsterdam
dr. A.I. Bijleveld Royal Netherlands Institute for Sea Research
dr. K.L. Krijsveld Wageningen University & Research
dr. B.T. Martin Universiteit van Amsterdam

Faculteit der Natuurwetenschappen, Wiskunde en Informatica
Contents

Chapter 1: General introduction 9
  1.1 The Southern North Sea: a hub of activity 10
  1.2 Moving towards a sustainable future 11
  1.3 The challenges of studying birds at sea 13
  1.4 Thesis overview 14

Chapter 2: Temporal patterns in offshore bird abundance during
the breeding season at the Dutch North Sea coast 19
  2.1 Introduction 21
  2.2 Methods 23
  2.3 Results 29
  2.4 Discussion 34
  2.5 Supplementary materials 40

Chapter 3: Thermal soaring over the North Sea and implications
for wind farm interactions 47
  3.1 Introduction 49
  3.2 Methods 51
  3.3 Results 59
  3.4 Discussion 67
  3.5 Supplementary materials 72

Chapter 4: A framework for post-processing bird tracks from
automated tracking radar systems 85
  4.1 Introduction 87
  4.2 Methods 88
  4.3 Results 101
  4.4 Discussion 105
  4.5 Supplementary materials 108
Chapter 5: Tracking birds with radar reveals that average flight properties are similar inside and outside an offshore wind farm

<table>
<thead>
<tr>
<th>Section</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>5.1 Introduction</td>
<td>117</td>
</tr>
<tr>
<td>5.2 Methods</td>
<td>119</td>
</tr>
<tr>
<td>5.3 Results</td>
<td>124</td>
</tr>
<tr>
<td>5.4 Discussion</td>
<td>129</td>
</tr>
<tr>
<td>5.5 Supplementary materials</td>
<td>133</td>
</tr>
</tbody>
</table>

Chapter 6: Synthesis

<table>
<thead>
<tr>
<th>Section</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>6.1 Consequences for offshore wind farm interactions</td>
<td>141</td>
</tr>
<tr>
<td>6.2 Bird radar to study bird flight at sea</td>
<td>144</td>
</tr>
<tr>
<td>6.3 Future outlook</td>
<td>147</td>
</tr>
<tr>
<td>6.4 Conclusion</td>
<td>149</td>
</tr>
</tbody>
</table>

References 150
Summary 162
Samenvatting 166
Author contributions 171
Author affiliations 172
Acknowledgements 173
Chapter 1

General introduction

Jens A. van Erp
1.1 The Southern North Sea: a hub of activity

The Southern North Sea (from here simply North Sea) is a temperate sea in north-west Europe nestled between Belgium, the Netherlands, the United Kingdom, Germany, and Denmark. It is a highly productive sea, characterized by a shallow depth (0 – 50m), input from several large eutrophic rivers, and strongly mixed water (ICES 2016). This productivity supports an extensive food web, including a diverse seabird community that fluctuates in composition throughout the seasons (Carter et al. 1993; ICES 2016; OSPAR 2017). In summer, this community mainly consists of species breeding on the surrounding coasts, including gulls (e.g. lesser black-backed gull *Larus fuscus*, herring gull *Larus argentatus*, and black-legged kittiwake *Rissa tridactyla*), terns (e.g. common tern *Sternula hirundo* and sandwich tern *Thalasseus sandvicensis*), alcids (e.g. common guillemot *Uria aalge* and razorbills *Alca torda*), and northern gannet *Morus bassanus*, among many others, while in winter the sea hosts large flocks of divers (e.g. red- and black-throated diver; *Gavia stellata* and *Gavia arctica*) and sea ducks (e.g. common scoter *Melanitta nigra*) as well. In addition, many migratory species, the most abundant group being passerines, fly along the coast and between mainland Europe and the UK on their seasonal journeys in spring and autumn, (Lack 1959; Bradarić et al. 2020; Brust and Hüppop 2022). Together, these birds with different life histories and flight motivations create patterns that fluctuate daily and seasonally, resulting in a mosaic of movement over the North Sea throughout the year.

Parallel to this avian activity, the countries surrounding the North Sea are heavily exploiting the sea’s natural resources. Currently, fisheries, transport for international trade, and extraction of fossil fuels form three of the main anthropogenic activities on the North Sea. In the past, the effects of these activities on nature were poorly understood and often carried out in an unsustainable manner (Roberts 2007; Rick and Erlandson 2008). Intense fisheries have had the most devastating effect, as they decimated or completely removed fish populations, while also destabilizing and impoverishing the seabed (Rick and Erlandson 2008). Maritime transport introduces invasive species, pollutes the water, can disturb marine megafauna, and dredging to maintain traffic channels displaces millions of tons of soil (ICES 2016). After the discovery of oil and gas reserves beneath the seabed in 1959, the North Sea became an important area for extraction of fossil fuels. The offshore platforms installed to extract these resources constitute the start of long-term human construction on open sea (Martins et al. 2023). These installations have a long-lasting impact on the surrounding benthos (Henry et al. 2017), and their lighting can also act as a beacon that attracts and disorients birds at night (Rebke et al. 2019). For seabirds, some of these activities also provide new opportunities. Several seabird species in the region supplement their diet with fishery discards (Camphuysen 1995; Garthe et al. 1996), and the offshore platforms provide opportunities to roost (Tasker et al. 1986) and new
foraging opportunities as artificial reefs develop around their base (Degraer et al. 2020). Whether these effects are positive or negative, the North Sea is one of the most heavily anthropogenically affected seas in the world (Halpern et al. 2008).

1.2 Moving towards a sustainable future

The way the western world approaches environmental policy has been changing since the late 20th century. Increasingly, we aim to achieve a net neutral, or even a net positive, impact on nature (UN General Assembly 2015). Fisheries are now regulated to stay below a maximum sustainable yield, most fish stocks are now stable, and seafloor abrasion is decreasing (ICES 2016). Similarly, maritime vessels are required to implement a ballast water management system (International Maritime Organization 2019). To reduce our impact on climate change, there is a global movement to achieve a carbon-neutral society through the development of renewable energy sources. The European Union is aiming to produce 60 gigawatts (GW) of offshore wind energy by 2030, expanding to 300 GW by 2050 (European Commission 2020). Accordingly, the countries surrounding the North Sea have started the development of large-scale offshore wind energy in order to meet this aspiration. In the Netherlands, 4.5 GW has already been installed and another 16.5 GW is planned (Fig. 1.1; Rijksoverheid 2022). The aim is to develop offshore wind energy in an environmentally responsible manner, through national programs such as the “Wind op zee ecologisch programma” (WOZEP) in the Netherlands (Rijksoverheid 2023). These programs aim to study the effects of large-scale offshore wind energy development in the broadest sense, including the effects on birds at sea.

Birds are affected by offshore wind farms in three ways: habitat alterations, avoidance behaviour, and collision with wind turbines (Drewitt and Langston 2006; Fox et al. 2006). The wind farm can affect the natural habitat and reduce the quality of, or accessibility to, foraging and roosting sites for some species, but also create new habitat for other species. For example, the turbines and associated service platforms can be used by seabirds to roost upon, resulting in attraction to wind farms (Dierschke et al. 2016; Vanermen et al. 2019). In contrast, birds may avoid the whole area of the wind farm, assumedly due to visual stimuli of the turbines and especially the moving rotors (Krijgsveld et al. 2011). Several species groups present on the Dutch North Sea, including razorbill, common guillemot, northern gannet and northern fulmar *Fulmarus glacialis*, structurally avoid wind farms (Krijgsveld et al. 2011; Dierschke et al. 2016), and large-scale offshore wind energy development might result in considerable habitat loss for these species. Lastly, birds that do enter the wind farm risk colliding with the moving rotor blades, which generally results in mortality. Due
to the severe consequences of collision, it has been a major focus of attention for species that are considered vulnerable, including nocturnal migrants (Desholm and Kahlert 2005; Hüppop et al. 2006) and soaring raptors (Skov et al. 2016). While collision risk can be assessed directly on land with the help of carcass counting (e.g., Krijgsved et al. 2009; Aschwanden et al. 2018), this is not feasible at sea (Desholm et al. 2006). Our current state of knowledge on all three types of effects (habitat change, avoidance, and collision) is far from satisfactory to make impact assessments, and therefore additional knowledge of bird behaviour in and around offshore wind farms is required (Cook et al. 2018).

Figure 1.1 The Netherlands and Dutch North Sea with wind farms that are operational (blue dotted polygons), under construction (turquoise dotted areas), in development (dotted polygons) and planned (empty polygons). Bird flight was observed at Gemini and Luchterduinen wind farm (top and bottom inset, respectively) with Robin Radar 3D-Fix radar systems (red dots). Map adopted from https://english.rvo.nl/sites/default/files/2023/05/Roadmap-Offshore-Wind-Energy-May-2023_0.pdf.
1.3 The challenges of studying birds at sea

Studying the interactions between birds and offshore wind farms is not straightforward. Ship based expeditions provided the first insights into bird behaviour at sea (Brewster 1912; Woodcock 1940a) and continue to be a great method to study behaviour in detail (Camphuysen 1995; Spear and Ainley 1997b), including wind farm interactions (Vanermen et al. 2015). Ship surveys are used to map bird activity at sea (Camphuysen and Dijk 1983; Camphuysen and Leopold 1994), which has more recently been complemented with airborne surveys (Camphuysen et al. 2004; Fijn et al. 2018). Unfortunately, these studies generally provide temporal snapshots, as they are time intensive and expensive to undertake. Additionally, these surveys are based on visual observations and therefore limited to daylight and good weather conditions. With the development of small biologging devices, the tracking of individual birds with electronic tags became possible (e.g., with UvA-BiTS; Bouten et al. 2013). These tags provide in-depth information like location, flight altitude, and accelerometry data at a high temporal and spatial resolution and can be used to track individuals over multiple years. The technique provides unrivalled insights into individual behaviour and has allowed researchers to study flight behaviour at sea (Weimerskirch et al. 2016; Fijn et al. 2017). From this type of information, the vulnerability of specific populations of interest to offshore wind development can be predicted by modelling the potential overlap with planned wind energy (Warwick-Evans et al. 2018), measuring the flight altitude in relation with the rotor swept zone (Thaxter et al. 2018), or studying the difference in foraging range between populations within a species (Sage 2022). However, sample sizes in these biologging studies are limited and make studying wind farm interactions difficult. For example, only two of 24 tagged individuals in Thaxter et al. (2018) had sufficient overlap with the nearby offshore wind farm to be considered for their analysis of flight altitude. Therefore, there are limitations to the use of biologging to study wind farm interactions directly.

A different approach to studying flight at sea lies in remote sensing, where the characteristics of an area are monitored remotely. Radar has been used as a remote sensing technique to monitor bird flight for close to a century, with the earliest report of birds as anomalous “angels” showing up on military radar scans in 1941 (Lack and Varley 1945). Ornithologists quickly realized they could use this technique to measure mass movements of birds in specific areas of interest, including at sea (Lack 1959; Buurma 1987). Bird monitoring by radar has come a long way since then (Shamoun-Baranes et al. 2019), and researchers have learned to utilize different radar systems, such as weather radar and tracking radar, to study bird flight across different spatial and temporal resolutions. Continental patterns of bird migration can be mapped by utilizing networks of weather radar (Dokter et al. 2018; Nilsson et al. 2019), and these networks are a key tool to
address the challenges of studying migration ecology on a global scale (Bauer et al. 2019). With tracking radars, on the other hand, specific flight behaviour can be studied across species (Horvitz et al. 2014). Most recently, radar systems have been developed that are specifically designed to identify and track birds autonomously (bird radars, e.g., Robin Radar systems (Robin Radar 2023) and MERLIN Avian Radar Systems (DeTect 2023)). When installed near an offshore wind farm, bird radars can measure flight in the surrounding area and in relation to nearby turbines. In this way, radar has been used to study mass migration (Desholm and Kahlert 2005; Plonczkier and Simms 2012; Bradarić 2022) and flight altitude distributions (Fijn et al. 2015) in relation to offshore wind farms. However, bird radars have their own inherent limitations, especially at sea. Considerable post-processing is required to distinguish birds from other features that create similar reflections, such as waves, rain, and wind turbines (Krijgsveld et al. 2015; Bradarić 2022). Nevertheless, when properly analysed, bird radar data could offer us further insights of bird flight and interactions with offshore wind farms.

1.4 Thesis overview

In this thesis, we study offshore bird flight in relation to the marine environment and offshore wind farms. We use the data from Robin Radar 3D-Fix radar systems, which are installed at two wind farms of the coast of the Netherlands (Fig. 1.1). We aim firstly to increase our understanding of bird flight at sea in relation to the environment, and secondly to use this knowledge to investigate the dynamics of when and how birds are interacting with offshore wind farms. We focus our studies on behavioural metrics that are also used to estimate collision risk, such as bird densities, flight altitude, and ground speed (Masden and Cook 2016), as this knowledge can further inform us on best practices for the responsible development of offshore wind energy. Our study system is the Dutch North Sea in late spring and early summer, during the breeding season of several common coastal seabirds. In this period the sea is dominated by several central place foragers, including the lesser black-backed gull, herring gull, and great cormorant Phalacrocorax carbo. As these species fly at low altitudes at sea (Johnston et al. 2014; Corman and Garthe 2014; Thaxter et al. 2018) and can be attracted to wind farms (Dierschke et al. 2016), they are likely to interact with the wind farms repeatedly and are thus potentially vulnerable to large scale wind energy development (Garthe and Hüppop 2004; Furness et al. 2013).

One of the most important determinants for bird-wind farm interactions is the number of birds found near the wind farm. In the breeding season, we expect central place foragers to select environmental conditions which increase their foraging efficiency at sea. Therefore,
these conditions should affect their abundance and, consequently, the amount of wind farm interactions. In Chapter 2, we study the temporal patterns of bird abundance near the wind farm in relation to three environmental conditions that we expect to affect offshore foraging for central place foragers: time of day, time in the breeding season, and tidal level. The outcome will improve our understanding of foraging behaviour in the marine environment during the breeding season, and show when and why we could expect wind farm interactions to increase.

One of the most abundant species at sea during the breeding season, the lesser black-backed gull, can increase its flight efficiency by switching to energy saving flight modes when possible (Shamoun-Baranes et al. 2016; Sage et al. 2019). Thermal soaring is an energy saving flight mode in which birds use thermal uplift to gain altitude, which allows them to glide long distances without having to use energy-expensive flapping flight. However, this altitude gain may increase the amount of time these birds spend within the rotor swept zone of turbines and increase their collision risk. In Chapter 3, we study the use of thermal soaring by birds flying offshore, the environmental conditions that allow this behaviour, and how thermal soaring might affect wind farm interactions. We apply a multi-method approach, measuring the change in flight altitude during thermal soaring with biologging of lesser black-backed gulls, while measuring the extent to which birds perform thermal soaring within wind farms with radar. To understand under what environmental conditions these birds can use thermal soaring at sea, we model the relation between marine thermal soaring and temperature difference between the air and sea surface as a proxy for thermal strength and relate the behaviour to synoptic weather conditions over the North Sea.

Throughout the first two chapters, we utilized bird radar systems to study birds flying at sea. Although radar is a powerful tool, it is not without limitations. Radar reflections from other sources can have the same reflective properties as birds, resulting in false positive observations. Alternatively, heavy reflections can obscure the weaker reflections from birds, resulting in false negatives observations. Therefore, post-processing is required to make the data reliable enough to scientifically study bird behaviour. In Chapter 4, we propose a framework to create standardized post-processing workflows for bird radar systems like the 3D-Fix used in this thesis. Our aim is to provide a method that enhances reproducibility and integration between radar studies, while allowing the flexibility to adjust the workflow to the specific study conditions.

Birds flying inside the wind farm might alter their behaviour due to the physical presence of the turbines (Fox et al. 2006) or the turbine wakes that form at higher wind speeds (Cañadillas et al. 2020). This can also affect their estimated collision risk, as this is partially
determined by flight metrics such as ground speed and angle of approach (Masden and Cook 2016). However, whether birds structurally alter their flight inside or downwind from a wind farm is unclear. In Chapter 5, we compare the flight of birds inside, outside, and downwind from a wind farm. Average ground speed, straightness, and direction relative to the wind are compared between these areas and in relation with the diurnal phase and wind conditions. This allows us to explore whether birds predictably alter their flight due to the presence of the turbines or the turbine wakes, and whether this affects their estimated collision risk.

In Chapter 6, I summarize the previous chapters and reflect on the two main aims of the thesis. The interactions between birds and wind farms are discussed in context of the three main impacts on birds: collision, avoidance, and habitat change, and when and why these interactions increase based on the results of this thesis. Furthermore, although this not our aim initially, I discuss our experience of using dedicated bird radar systems to study birds at sea, both their strengths and limitations. Finally, I identify further research opportunities to increase our understanding of bird flight at sea that could help reduce the impact of offshore wind farm development on bird life.
General introduction
Chapter 2

Temporal patterns in offshore bird abundance during the breeding season at the Dutch North Sea coast

Jens A. van Erp, E. Emiel van Loon, Kees (C.) J. Camphuysen, Judy Shamoun-Baranes

Published in Marine Biology (2021) 168:150, doi: 10.1007/s00227-021-03954-4
Chapter 2

Abstract

The expanding development of offshore wind farms brings a growing concern about the human impact on seabirds. To assess this impact a better understanding of offshore bird abundance is needed. The aim of this study was to investigate offshore bird abundance in the breeding season and model the effect of temporally predictable environmental variables. We used a bird radar, situated at the edge of a wind farm (52.427827 °N, 4.185345 °E), to record hourly aerial bird abundance at the North Sea near the Dutch coast between May 1\textsuperscript{st} and July 15\textsuperscript{th} in 2019 and 2020, of which 1879 hours (51.5 %) were analysed. The effect of sun azimuth, week in the breeding season, and astronomic tide was evaluated using generalized additive modelling. Sun azimuth and week in the breeding season had a modest and statistically significant (p < 0.001) effect on bird abundance, while astronomic tide did not. Hourly predicted abundance peaked after sunrise and before sunset, and abundance increased throughout the breeding season until the end of June, after which it decreased slightly. Though these effects were significant, a large portion of variance in hourly abundance remained unexplained. The high variability in bird abundance at scales ranging from hours up to weeks emphasizes the need for long term and continuous data which radar technology can provide.
2.1 Introduction

The Dutch Continental Shelf (DCS) of the North Sea is home to ecologically diverse avian species that fluctuate in number and composition year-round (Camphuysen and Leopold 1994; Fijn et al. 2018) and utilize the intertidal, coastal, and pelagic areas of the DCS to roost and forage. The DCS is also heavily exploited through human activities including fisheries, shipping, gas extraction, and increasingly wind farm development (Rijksoverheid 2015). As wind farm development is expanding on the North Sea, especially in coastal waters, the concern for its effect on birds utilizing the area has grown, as is seen in the growing field of research (Desholm and Kahlert 2005; Hüppop et al. 2006; Garthe et al. 2017; Thaxter et al. 2018; Vanermen et al. 2019). In spring and summer, central place foraging colonial seabirds, such as gulls and terns, commute regularly between breeding sites onshore and foraging grounds at sea (Wetterer 1989; Fryxell and Lundberg 1998). Due to this foraging strategy, coastal seabirds may have recurrent encounters with offshore wind farms by which they may be impacted (Drewitt and Langston 2006; Lindeboom et al. 2011). Additionally, a meta-analysis by Dierschke et al. (2016) on interactions between seabirds and wind farms on the North Sea identified species that appear to be generally attracted towards wind farms, including the lesser black-backed gull *Larus fuscus* and the European herring gull *Larus argentatus*, which are among the most abundant species on the DCS around this time of year (Camphuysen and Leopold 1994), further increasing concern for these species.

While it is clear birds are impacted by offshore wind farm development, the scope of this impact is difficult to assess as information on temporal fluctuations of offshore bird abundance is lacking due to inherent limitations of various monitoring techniques. On the North Sea, visual observations through ship surveys (Camphuysen and Leopold 1994), airplane surveys (Fijn et al. 2018), and stations along the coast (Camphuysen and Dijk 1983) have been used to determine bird species distribution and abundance year-round. This provides information on a broad range of species active during daylight hours and this information has been combined into global species distribution maps (Halpin et al. 2009). However, due to the often-high logistic costs of ship and aerial surveys, and the obvious geographical constraints of coastal bird monitoring, large temporal and/or spatial gaps exist that can make accurate offshore distribution estimations difficult. Radar is a remote sensing technology which has been applied to monitor avian abundance and flight characteristics at sea (Lack 1959; Hüppop et al. 2006; Plonczkier and Simms 2012; Fijn et al. 2015). Although limited in range, bird radar can monitor bird abundance and flight characteristics within an observation area at a high spatio-temporal resolution for extended periods of time, enabling research on factors that influence both short- and long-term temporal patterns in offshore abundance. In particular, the effect of highly
predictable external variables on bird abundance is of interest, as their predictable nature can structurally affect bird behaviour and can be taken into account when assessing bird-wind farm interactions.

Three external variables that are highly predictable and have been noted to affect the behaviour of coastal seabirds are daylight availability, the time of year, and the tide. Daylight availability is important for visual foragers and the daily rhythm of animals, including central place foragers such as seabirds (Fryxell and Lundberg 1998; Shealer 2002). The time of year affects the breeding stage of animals. During the different breeding stages these species may adjust their foraging effort and behaviour. For example, lesser black-backed gulls from coastal breeding colonies in the Netherlands (Camphuysen et al. 2015) and the UK (Thaxter et al. 2015) have been found to increase the proportion of time spent at sea during chick rearing, and some herring gulls on Texel switch to marine diets during chick rearing (van Donk et al. 2017). Lastly, the tide impacts the sea currents and can create foraging opportunities at sea through upwelling. For example, the common tern *Sterna hirundo* and roseate tern *Sterna dougallii* use upwelling caused by tidal currents to access prey (Urmy and Warren 2018).

The aim of this study is to investigate hourly fluctuations in non-migratory aerial bird abundance (henceforth: bird abundance) near an offshore wind farm and analyse the effect of the aforementioned external variables with predictable temporal variation on this abundance (daylight availability, time of year, and tide). Particularly, we are interested in local movements of birds at sea during the breeding season, when colonial seabirds forage and commute between their colonies and the feeding areas at sea. We use a bird radar system positioned at the edge of Luchterduinen offshore wind farm to measure hourly bird abundance and model the effect of sun position, week in the breeding season, and astronomic tide. We have the following expectations, based on the existing literature (see previous references): i) offshore bird abundance will be higher during daylight hours than during night, ii) abundance will be higher in the later stages of breeding than at the start of breeding, and iii) abundance will be higher between low and high tide, when the tidal current is strongest and might create foraging opportunities through increased upwelling. The external variables are all highly regular and could be used to better predict offshore bird abundance on the North Sea during the breeding season if found to have a significant impact on bird abundance.
2.2 Methods

Radar measurements

Bird flight was monitored by a bird radar system (Robin Radar 3D-Fix) consisting of a vertically rotating X-band antenna (25 kW, Furuno Marine) and horizontally rotating S-band antenna (60 kW, Furuno Marine) both rotating at 0.75 rotations s\(^{-1}\). The system was mounted on the service platform of turbine 42 (52.427827 °N, 4.185345 °E) situated at the edge of Luchterduinen, 25 km from the coast near IJmuiden (Fig. 2.1).

![Figure 2.1 Overview of the sample area and Luchterduinen offshore wind farm (box) and the position of the radar in relation to the coast of the Netherlands (map). Map: tidal water height was measured at Hoorn platform (blue dot, 52.92464 °N, 4.15 °E), ERA5 data was sampled from the nearest grid cell between 52.375 °N – 52.625 °N and 4.125 °E – 4.375 °E (blue dotted square), and ESAS 5.0 species observation data was sampled between 51.8 °N – 53 °N and 3.7 °E – 4.7 °E (dashed black square). Box: black dots show the individual turbines, the red dot shows the turbine that has the radar-system installed (52.42783 °N, 4.18535 °E). The 1 km\(^2\) area of interest is shown in red with black lining; it is delimited by the 1000 and 2000m ranges and the 22.5 ° and 60.7 ° azimuth angles from the radar.](image-url)

The measurements of the radar system were automatically processed to create tracks of birds using proprietary software developed by Robin Radar. The radar software had clutter filters to reduce the probability of non-avian scatters being erroneously tracked as birds. These filters were applied dynamically in each radar image to remove unwanted reflections caused by landscape features, waves or rain, and information on filtering was stored per
image. Each track was classified by the software based on its properties: tracks with a maximum airspeed of 36.1 ms\(^{-1}\) and a signal-to-noise ratio typical for birds (between -10 and 65) were categorised as birds. Airspeed was calculated by the proprietary software using wind speed and direction measured at the radar (AIRMAR 150WX WeatherStation). In situations where multiple birds fly closely together in a flock, the radar was not able to distinguish and track individual birds. In this case, the group of birds was tracked as a single object and given a tag to indicate the object consists of a flock of birds. It was impossible to find out the number of birds belonging to these flocks, and therefore tracks with a flock tag were treated as single observations in this study. The resulting tracks were stored in a centralized spatial database.

Radar data was collected in the years 2019 and 2020. The relevant period within these years was chosen to match the breeding period(s) of the most abundant species. Based on species observation data taken from the European Seabird at Sea database (ESAS 5.0, accessed 16-02-2021, Reid and Camphuysen 1998; Camphuysen et al. 2004) near the wind farm (51.8 °N – 53 °N, 3.7 °E – 4.7 °E, Fig. 2.1) in the months of May, June and July, the lesser black-backed gull was found to be the most prevalent species by far in this part of the North Sea (56.8 % of observations, Sup. Mat. 1). This was also confirmed by species observation reports made at the nearby OWEZ wind farm (Krijgsveeld et al. 2011) before construction of Luchterduinen (Gyimesi et al. 2019) during spring and summer. The lesser black-backed gull was therefore designated as the key species for deciding our period of interest. Based on field observations of egg laying and fledging at colonies along the North Sea coast (Camphuysen and Gronert 2010; Cottaar et al. 2018, 2020) we selected the period of May 1\(^{st}\) to July 15\(^{th}\) as the breeding season.

The bird detection probability of the radar is not equal over the whole radar observation window. The reflective size of a bird and thus its detection probability changes with range to the radar and position within the radar beam (Schmid et al. 2019). To account for this, data was selected from an area in which detection probability would be more or less homogeneous based on the properties of the radar and the position of the radar system relative to the wind farm. To account for detection loss occurring because of a decrease in radar beam power with range, the maximum range from the radar was set at 2000 m. Beyond this range the detection probability for small birds (< 62.5 g) drops below 80 % at certain scanning altitudes (Sup. Mat. 2). On the other hand, the high power of the radar beam at close range can produce false positive bird tracks caused by other features reflecting the radar beam. Therefore, the minimum range for track inclusion was set at 1000 m. Detection rate at different azimuth angles (scanning angle of the horizontal radar) differed because of turbine placement of the wind farm. As the radar itself was installed on the service platform of a wind turbine, the radar beam was blocked by the turbine
Temporal patterns in offshore bird abundance during the breeding season at the Dutch North Sea coast

between 275 ° to 346 ° degrees. Additionally, the other turbines in the wind farm were situated roughly between 80 ° to 260 °, creating a zone in which bird detection is impaired around each turbine. To avoid detection bias in these regions, data was sampled from an azimuth angle between 22.5 ° and 60.7 ° from 1000 – 2000 m from the radar, resulting in a 1 km² area of open sea in the North-East section of the radar range (Fig. 2.1). Only tracks which occurred (partially or entirely) within this area were analysed in this study. The radar detects birds reliably up to an altitude of 300m for small birds (< 62.5g) and up to an altitude of 600m for larger birds (500 g, Sup. Mat. 2). The radar system only measures birds in flight, leaving birds floating on the water unseen. Note that detection probability can also change with the aspect and shape of tracked birds (Bruderer 1997); however, there is no way to account for this in the data as we cannot quantify the aspect of the targets.

Environmental data

Astronomic tide was retrieved from the nearest observation station at Hoorn Platform (52.92064 °N, 4.09822 °E, approximately 55 km North-West of the study site, Fig. 2.1) from the Rijkswaterstaat public database (Rijkswaterstaat 2020, accessed 19 October 2020), which contains astronomic tide acquired through harmonic analysis as water height in centimetres above Mean Sea Level (cm - MSL). Tidal information was retrieved at the half-hour mark each hour (xx30 hr) to best reflect average tidal height for each hour (xx00-xx59 hr).

For data filtering purposes, we extracted wind data to independently calculate airspeed of the radar tracks (see radar data processing). Hourly wind data was acquired from the ECMWF (European Centre for Medium-Range Weather Forecasts) ERA5 reanalysis data (Hersbach et al. 2018, 2020, accessed 15 September 2020). Wind conditions are described by u- and v-components (both in ms⁻¹), where the u-component is the zonal wind (wind from the west is positive) and the v-component is the meridional wind (wind from south is positive). The u- and v-components have a temporal resolution of 1 hour and spatial resolution of 0.25° latitude and longitude and were sampled from the grid cell closest to the study area (52.375 °N – 52.625 °N and 4.125 °E – 4.375 °E, Fig. 2.1). Wind components were selected from the lowest atmospheric layer, 10 m above the sea surface, to match both the properties of the radar observations and known flight heights of the relevant bird species: we expected flight altitudes of most species to be close to the sea surface during local movements (Johnston et al. 2014; Corman and Garthe 2014; Ross-Smith et al. 2016; Borkenhagen et al. 2017).
Radar data processing

Each track created by the radar software included at least five track points and several track properties: geolocation plus timestamp (UTC) per track point and track direction based on a vector drawn from the starting point to the end point of the track (radians). Per track, straight line displacement (m) was calculated as the great circle distance between the first and last track point, and the track length (m) was calculated as the sum of the great circle distance between consecutive track points. Ground speed per track was calculated as track length divided by track duration (ms\(^{-1}\)). Airspeed per track was calculated using ground speed, track direction and hourly u- and v-wind components nearest to the first timestamp of the track according to Shamoun-Baranes et al. (2007). Track straightness was calculated by dividing the straight-line displacement by the track length. Tracks with airspeed < 5 ms\(^{-1}\) were removed as nearly all seabird species fly at higher airspeeds (Spear and Ainley 1997b; Alerstam et al. 2007; Shamoun-Baranes et al. 2016). Additionally, manual data exploration indicated static reflections from nearby vessels or structures created stationary, long-lasting, false positive bird tracks. To identify these clutter tracks, we calculated the displacement over time (ms\(^{-1}\)) by dividing straight line displacement by the track duration. Through visual inspection the tracks falling in the 0.1st percentile of displacement over time (0.08 ms\(^{-1}\)) were identified as clutter and removed.

To analyse bird abundance throughout the breeding season, we calculated the total number of tracks occurring in the area of interest per hour (from here on reported as birds h\(^{-1}\)). All tracks occurring between xx:00 – xx:59 hr were included in hour xx. Sun position (azimuth angle, extracted using the suncalc package v0.5.0; Thieurmel and Elmarhraoui 2019) and astronomic tide (cm - MSL) were collected at the half-hour mark (xx:30 hr) to reflect the average conditions within that hour. During the study period the radar was occasionally not operational and hours in which the radar was (partially) offline were not included in the analysis. Furthermore, during exploratory analysis it became clear that birds were no longer detected by the radar when the clutter filter of the radar was highly active. Therefore, to reduce the chance of analysing artificial lows in bird abundance caused by high filter activity, we removed all hours with an average filter activity above a set threshold of 0.240 (elaboration available in Sup. Mat. 3).

Though we designated a sampling period (May 1st to July 15th) in which we expected to observe predominantly local movements of species that breed in the region, migration might still occur. These events fall outside the scope of this research and could strongly impact measured hourly abundance. Therefore, we chose to remove these occurrences. We identified moments of migration in our dataset by looking at the hourly average flight characteristics. We first calculated the mean hourly track direction (radians), the hourly mean of track straightness (0 – 1), and the circular uniformity of hourly track direction (0 –
This last characteristic was calculated by treating the flight direction of each observation as a unit vector, calculating the resultant vector of all vectors in the hour combined, and dividing the resultant vector by the number of observations using the circular package (v0.4-93; Lund and Agostinelli 2017). We identified migration events as hours of relatively high bird abundance and with relatively high directional uniformity compared to the total data sample, and with straight flight paths on average. The following criteria were used to identify migration hours: hourly abundance > mean of data (114 birds h⁻¹), uniformity of hourly flight direction > 90th percentile of data (0.60), and mean track straightness > median of data (0.78). Within these migration hours, tracks with straightness > 0.78 and a track direction within a 45° window around the hourly mean track direction were removed from these hours.

After applying the aforementioned selection criteria, 1879 hourly values of bird abundance remained (based on 208372 tracks). This data formed the basis for further analysis. In general data availability was slightly higher from 22:00 to 8:00 local time (55.6 % of hours available) than between 08:00 and 22:00 (48.5 % of hours). Hourly abundance was available for 123 of 152 observations days, with 29 days that were completely observed (24 observation hours d⁻¹). Over the breeding season of 1824 observation hours per year, 417 hours were not covered in either season (overview available in Sup. Mat. 4), in particular week 2 (May 8th – 14th), week 3 (May 15th – 22nd), and week 9 (June 26th – July 2nd) missed more than a third of the observation hours (80, 60, and 96 observation hours of 168 hours respectively). Together with the hours the radar was offline, in total 48.5 % of the hours were excluded from the analysis. For a summary of data retained after each selection step and the total number of tracks per season see Table 2.1.
Table 2.1 Overview of bird tracks measured by radar during the study period in 2019 and 2020, the amount of tracks removed per processing step, the remaining tracks, including an overview of the number of measurement hours per season, the hours the radar was offline or the filter threshold was exceeded, and the final number of hours from which were analysed further. Processing steps are listed in order of processing. Percentages are based on number of raw tracks or total hours per year.

<table>
<thead>
<tr>
<th></th>
<th>2019 Tracks (#)</th>
<th>Percentage of total (%)</th>
<th>2020 Tracks (#)</th>
<th>Percentage of total (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total tracks</td>
<td>109641</td>
<td>100</td>
<td>119766</td>
<td>100</td>
</tr>
<tr>
<td>Non-bird tracks</td>
<td>4492</td>
<td>4.1</td>
<td>2797</td>
<td>2.3</td>
</tr>
<tr>
<td>(airspeed &lt; 5 ms(^{-1}) or in 0.1(^{st}) perc. displacement over time)</td>
<td>(airspeed &lt; 5 ms(^{-1}) or in 0.1(^{st}) perc. displacement over time)</td>
<td>(airspeed &lt; 5 ms(^{-1}) or in 0.1(^{st}) perc. displacement over time)</td>
<td>(airspeed &lt; 5 ms(^{-1}) or in 0.1(^{st}) perc. displacement over time)</td>
<td></td>
</tr>
<tr>
<td>Tracks during offline hours</td>
<td>2742</td>
<td>2.5</td>
<td>46</td>
<td>&lt;0.1</td>
</tr>
<tr>
<td>Tracks during hours of high filter activity</td>
<td>4330</td>
<td>3.9</td>
<td>3999</td>
<td>3.3</td>
</tr>
<tr>
<td>Migration tracks</td>
<td>846</td>
<td>0.8</td>
<td>1783</td>
<td>1.5</td>
</tr>
<tr>
<td>Remaining tracks</td>
<td>97231</td>
<td>88.7</td>
<td>111179</td>
<td>92.8</td>
</tr>
<tr>
<td>Total hours</td>
<td>1824</td>
<td>100</td>
<td>1824</td>
<td>100</td>
</tr>
<tr>
<td>Radar offline</td>
<td>227</td>
<td>12.4</td>
<td>340</td>
<td>18.6</td>
</tr>
<tr>
<td>Filter activity above threshold</td>
<td>598</td>
<td>32.9</td>
<td>604</td>
<td>33.1</td>
</tr>
<tr>
<td>Remaining hours</td>
<td>999</td>
<td>54.8</td>
<td>880</td>
<td>48.3</td>
</tr>
</tbody>
</table>

Data analysis

To model the effects of the environmental variables on hourly bird abundance and test for significance of these effects, generalized additive models were fitted to the data using the mgcv package (v1.8-32; Wood 2020). Hourly bird abundance (birds h\(^{-1}\)) was used as the dependent variable, with predictors sun azimuth (cyclic P-spline smoother, k = 9 to prevent overfitting), week in the breeding season (thin plate regression spline smoother) and tidal water height (thin plate regression spline smoother), and year as a random effect (model A). Collinearity among predictors was calculated using the Pearson product-moment correlation coefficient to verify no interaction between the predictors existed and they could be added as individual effects. We assumed a quasi-Poisson distribution for the model error, which was verified with the model residuals after fitting the model and did not require any adjustment. As we used abundance data collected over time, we tested for temporal autocorrelation of the model residuals. Model residuals were highly autocorrelated and thus a new model was fit including the previous hourly abundance added as an autoregressive term (thin plate regression spline smoother, k = 4 to prevent overfitting) to account for temporal autocorrelation (model B). 103 hours of data without known previous hourly abundance (due to gaps in the data) were excluded from model B. We checked whether each predictor contributed to the models by creating sub-models with one predictor removed and comparing for lowest AIC-scores (Burnham and Anderson
Temporal patterns in offshore bird abundance during the breeding season at the Dutch North Sea coast

2004). If a sub-model scored better, we would use this model instead of the complete model and tested whether further model-reduction would be warranted by repeating the process. The modelling outputs of both model A and B were explored further for the individual predictor effects, which were approximated by subtracting the explained deviance from the sub-model without the predictor from the deviance explained by the complete model. Due to a large observed decrease in effect size of all environmental predictors with the addition of the autoregressive term in model B, we sampled and analysed 10000 random subsamples of the data (n = 300) where all data points were at least 5 hours apart and modelled the effect of environmental predictors (same as model A) on these subsamples. We inspected the mean and standard deviation of the model outputs as well as remaining autocorrelation to confirm temporal autocorrelation for these models was highly reduced. All analyses were performed in R version 4.0.0 (R Core Team 2020).

2.3 Results

Hourly bird abundance

Hourly bird abundance varied between 0 and 1423 birds h\(^{-1}\) in 2019 (Fig. 2.2) and 0 and 840 birds h\(^{-1}\) in 2020 (Fig. 2.3). Mean hourly abundance in 2019 was 99 birds h\(^{-1}\) (95 % confidence interval = 93 – 107 birds h\(^{-1}\)) and 129 birds h\(^{-1}\) (95 % confidence interval = 119 – 136 birds h\(^{-1}\)) in 2020.

Effect of external variables

Collinearity among environmental predictors was low (Pearson product-moment correlation coefficients: sun azimuth and week in the breeding season = 0.028, sun azimuth and tidal water height = 0.075, week of the breeding season and tidal water height = 0.002) and no interactions were assumed. Model A showed a high amount of temporal autocorrelation in the residuals, which was removed in model B. For both model A and B, the full model scored the best (lowest AIC score). Model A is described further in Sup. Mat. 5. Model B is described further below (Table 2.2), with a focus on the environmental predictor effects that were significant. Bird abundance was significantly related to sun azimuth (p < 0.001) and week of the breeding season (p < 0.001), but not to astronomic tide (p = 0.576). The complete model explained 52.1 % of data deviance (R\(^2\) = 0.48). Of the three environmental predictors, sun azimuth had the strongest estimated effect on hourly bird abundance (1.1 % of deviance), followed by week of the breeding season (0.7 %), and tide (< 0.1 %, non-significant). Year as a random effect was not significant and accounted only for 0.9 % of deviance. Previous hourly abundance to account for temporal autocorrelation was...
highly significant, with an estimated effect of 33.8% of deviance. The effect size estimate and confidence intervals (2*standard error) of the significant environmental predictor effects are visualized in Fig. 2.4. The effect of sun azimuth (Fig. 2.4A) showed two peaks in predicted number of birds h⁻¹ during the day, one in the morning after sunrise (129 birds h⁻¹) and a second, smaller peak in the afternoon (115 birds h⁻¹) and lowest predicted abundance after sunset (93 birds h⁻¹). The effect of week of the breeding season (Fig. 2.4B) showed a slight increase in mean predicted bird abundance from the last weeks of May to late June (week of June 19th), rising from 85 birds h⁻¹ to 108 birds h⁻¹. After this peak hourly abundance dropped to a mean predicted 100 birds h⁻¹ in the last week of July.

**Table 2.2** Overview of the generalized additive model output for model B, including parameter estimates for the intercept and random effect (year), and the estimated degrees of freedom (edf) and estimated deviance explained for the environmental predictors and autoregressive term (previous hourly abundance), (n = 1776).

<table>
<thead>
<tr>
<th>Parametric coefficients</th>
<th>estimate</th>
<th>edf</th>
<th>est. dev. explained</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>4.534</td>
<td></td>
<td></td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Year = 2020</td>
<td>0.024</td>
<td>0.9</td>
<td>0.503</td>
<td></td>
</tr>
<tr>
<td>Smooth terms</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sun azimuth</td>
<td>4.927</td>
<td>1.1</td>
<td>&lt;0.001</td>
<td></td>
</tr>
<tr>
<td>Week of the breeding season</td>
<td>3.416</td>
<td>0.7</td>
<td>&lt;0.001</td>
<td></td>
</tr>
<tr>
<td>Tidal water height</td>
<td>1.297</td>
<td>&lt;0.1</td>
<td>0.576</td>
<td></td>
</tr>
<tr>
<td>Previous hourly abundance</td>
<td>2.976</td>
<td>33.8</td>
<td>&lt;0.001</td>
<td></td>
</tr>
</tbody>
</table>

**Table 2.3** Overview of the generalized additive model output for the subsample models (subsamples = 10000, observations per subsample = 300), including parameter estimates for the intercept and random effect (year), and the estimated degrees of freedom (edf) and estimated deviance explained for the environmental predictors (mean ± standard deviation). Note that the standard deviation on estimated deviance explained is the same for all terms, as this dependent on a single variable (the deviance explained by the full model).

<table>
<thead>
<tr>
<th>Parametric coefficients</th>
<th>estimate</th>
<th>edf</th>
<th>est. dev. explained</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>4.555 ± 0.063</td>
<td>4.2 ± 0.001</td>
<td>&lt;0.001 ± 0.001</td>
<td></td>
</tr>
<tr>
<td>Year = 2020</td>
<td>0.015 ± 0.081</td>
<td>12.3 ± 0.004</td>
<td>0.265 ± 0.028</td>
<td></td>
</tr>
<tr>
<td>Smooth terms</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sun azimuth</td>
<td>4.033 ± 1.154</td>
<td>9.0 ± 0.018</td>
<td>0.004 ± 0.018</td>
<td></td>
</tr>
<tr>
<td>Week of the breeding season</td>
<td>3.464</td>
<td>12.3 ± 0.012</td>
<td>0.001 ± 0.004</td>
<td></td>
</tr>
<tr>
<td>Tidal water height</td>
<td>2.051 ± 1.599</td>
<td>4.0 ± 0.037</td>
<td>0.380 ± 0.027</td>
<td></td>
</tr>
</tbody>
</table>
Figure 2.2 Overview of hourly bird abundance in 2019 (in dark red) per month, with kernel density distribution of the data (bottom-right corner). Grey columns show hours in which filter activity was too high for accurate recordings, while black columns show hours the radar was offline. The y-axis of all figures is limited to 800 birds h⁻¹ for better interpretation; one outlier (2019-06-14 16:00, 1423 birds) is therefore capped to 800 birds. The horizontal black lines in the density distribution graph show the mean (black line) and 90th percentile (dashed black line) of the distribution.
Figure 2.3 Overview of hourly bird abundance in 2020 (in dark blue) per month, with kernel density distribution of the data (bottom-right corner). Grey columns show hours in which filter activity was too high for accurate recordings, while black columns show hours the radar was offline. The y-axis of all figures is limited to 800 birds h\(^{-1}\) for better interpretation; two outliers (2020-06-10 05:00, 810 birds; 2020-06-20 09:00, 840 birds) are therefore capped to 800 birds. The horizontal black lines in the density distribution graph show the mean (black line) and 90th percentile (dashed black line) of the distribution.
Temporal patterns in offshore bird abundance during the breeding season at the Dutch North Sea coast

Figure 2.4 Smoothed effects of the significant individual predictors in the hourly abundance model B (n = 1776). Left y-axis shows hourly bird count (black dots / boxplots), whereas the right y-axis shows predicted hourly bird count (purple line = mean, area = mean ± 2 × se). A: Effect of sun azimuth, in radians from South (x-axis). Sunrise occurs between Azimuth = -.73π to -.64π, sunset between Azimuth = .64π to .73π, indicated by the grey areas. B: Effect of week in the breeding season, date indicates the first day of each week (x-axis).
The range of generalized additive model output for the sub-sample models is depicted in Table 2.3. The sub-sample models explained (22.0 ± 3.7 %) of deviance in the data ($R^2 = 0.18 ± 0.04$), while temporal autocorrelation was strongly reduced (ACF = 0 for time lag 1-4 hours, ACF = 0.14 ± 0.10 for time lag = 5 hours). The distribution of the size and significance per individual effect for the environmental predictors was similar to model A (Sup. Mat. 5).

2.4 Discussion

In this study we show that hourly bird abundance near an offshore wind farm can strongly fluctuate, and a portion of variance is explained by daylight availability (operationalized by sun azimuth) and time of the year (operationalized by week in breeding season), but not by astronomic tide. The results support our expectation that observed patterns of offshore bird abundance reflect both diurnal and seasonal processes throughout the breeding season, though most variability could not be explained by the temporally predictable environmental variables explored.

We expect the most abundant species near Luchterduinen are central place foragers (namely lesser black-backed gull, herring gull, and great cormorant Phalacrocorax carbo, Sup. Mat. 1) and our results support our expectation that these birds mainly undertake their foraging bouts after sunrise when daylight can aid them in their foraging. The drop in bird abundance throughout the day might indicate some birds return to their colony earlier than others. Indeed, offshore foraging trip duration of several seabird species common in the breeding season varies greatly: lesser black-backed gull 8.0 ± 6.3 h (Garthe et al. 2016) and 8.3 ± 10.2 h / 6.9 ± 11.9 h (long trips for males/females, Camphuysen et al. 2015), Sandwich tern 2.3 ± 1.1 h (Fijn et al. 2017). If most birds fly out from their colony around sunrise to undertake foraging bouts of several hours at sea, a decrease in their abundance throughout the day would be expected. The second peak in abundance before sunset might be caused by an increase in the flux of birds returning to the coast from farther at sea, or by birds also foraging in the evening which is supported by Schwemmer and Garthe (2005) who found a higher proportion of foraging lesser black-backed gull over the North Sea both in the morning and evening hours. Though we considered the breeding birds on the Dutch coast to be diurnal, with peaks in offshore activity during the day, there was activity recorded during the night as well. Several gull species such as the lesser black-backed gull and herring gull are known to be out at sea during the night (Camphuysen et al. 2015) and forage on fishery discards during the night (Garthe and Hüppop 1996; Garthe et al. 2016). We note that these studies are species specific, whereas our results depict a general trend in bird abundance, reflecting a combined activity pattern for all species observed in the study area.
In some species breeding stage can affect foraging behaviour (e.g., Sandwich tern, Fijn et al. 2017 and lesser black-backed gulls, Thaxter et al. 2015). However, whether these changes affect the overall distribution of birds offshore has not been confirmed by observations and remained unclear. Our results show that after a period of relatively low hourly abundance in May, offshore bird abundance increases from the end of May to the end of June (Fig. 2.4B, Sup. Mat. 5). This aligns with our expectations that offshore bird abundance increases throughout the breeding season, based on the assumption that coastal seabirds breeding in the region shift to a more marine diet during the chick rearing period (Spaans 1971; Annett and Pierotti 1989), which for lesser black-backed gulls begins around the end of May (Camphuysen and Gronert 2010; Cottaar et al. 2018, 2020). We expected offshore bird abundance to increase further throughout July, yet we observed a decrease in abundance from the end of June (Fig. 2.4B). The decrease sets in before we would expect to see an effect from the first fledglings in nearby colonies, which starts in the second week of July (Camphuysen and Gronert 2010). It is possible there is a decrease in foraging effort within colonies as more breeding pairs experience breeding failure. In the lesser black-backed gull colony on Texel on average 70.3 % of eggs hatch per season while only 23.7 % of the hatchlings fledge (Camphuysen and Gronert 2010, updated to 2020, unpublished data, Sup. Mat. 1), and failed breeders might spend less time foraging due to a decrease in energy demands. An alternative explanation for the seasonal patterns observed in this study may be a seasonal fluctuation in offshore food availability. Herring gulls and lesser black backed gulls in the region forage on fishery discards during the breeding season (Camphuysen 1995; Tyson et al. 2015; van Donk et al. 2017) and temporal and spatial fluctuations in fishery activity may influence bird abundance at sea. In lesser black-backed gulls on a colony in Texel, foraging trips differ between the period of incubation of the eggs, and chick rearing (Camphuysen et al. 2015): foraging trip duration decreased during chick rearing compared to egg incubation, while the trip range increased as well as proportion of time spent at sea. The start of the increase in abundance modelled in this study roughly aligns with the median hatching date of lesser black-backed gulls recorded on Texel (Camphuysen and Gronert 2010; Camphuysen et al. 2015) and might be caused by this shift in behaviour.

Opposed to our expectation, we found no effect on tide on offshore bird abundance. We expected bird abundance to be highest between low and high tide, when the tidal current might cause increased turbulent mixing in the wake of the wind farm (Schultze et al. 2020) and provide temporary foraging opportunities. Our results indicate that if this effect is present, it did not affect foraging opportunities enough to significantly affect bird abundance, nor was there any other effect of tidal water height found. For this study we used astronomic tide measured 55 km from the study site (Fig. 2.1) which was the closest offshore location for which this information was available. Given the dynamic tidal current patterns in the North Sea (Sündermann and Pohlmann 2011), this information will not
represent the situation at the study site perfectly. Local tidal information was not available for this study, so there is room for improvement in investigating the relation between the tide and bird abundance offshore.

When working with count data in ecology, temporal autocorrelation is a common phenomenon when sampling counts at a high temporal resolution and was also found in our initial model (model A). Accounting for temporal autocorrelation in the residuals is generally considered preferable, as otherwise the model effects might be inflated. In model B, the autoregressive term (previous hourly bird abundance) had the greatest effect in predicting hourly abundance by far, at an estimated 32.5 % of deviance explained. Though this model was successful in removing temporal autocorrelation in the residuals, we believe the addition of this autoregressive term in the model may have deflated the effect of our environmental predictors (Table 2.2) which were much lower than in model A (Sup. Mat. 5). As we investigate temporally varying predictor variables (which are themselves autocorrelated beyond the hourly scale), disentangling the relation between these and the autoregressive term is not straightforward. Temporal autocorrelation can also be negated by sub-sampling the data so that temporal autocorrelation decreases severely, however this decreases data availability for the model, and therefore the output becomes less reliable. By re-sampling the data many times and investigating the range of the model outputs, we believe we can still get close to the actual relationship between hourly abundance and the environmental predictors, while accounting for temporal autocorrelation. The outcome (Table 2.3) shows that both sun azimuth and week of the breeding season have clear significant effects and tide does not, and the effect size is close to the original model (model A, Sup. Mat. 5). Therefore, we expect the actual size of the effect of the predictors on bird abundance will probably lie closer to model A presented in Sup. Mat. 5 than model B (Table 2.2, Fig. 2.4). Note that though the size of the effects of model A and B differs, the pattern of the effects is very similar, and we believe these to be accurate for both significant predictors.

The bird observations used in this study were captured by a radar system installed near the Dutch West coast. Compared to the size of the North Sea, the sampling area for the dataset was small (Fig. 2.1), and thus our findings may also be limited to a specific area on the North Sea. The foraging range of coastal seabirds can differ between (Thaxter et al. 2012) and within species (Redfern and Bevan 2014), and spatial preference can even differ per year within the same colony, as seen in Sandwich terns (Fijn et al. 2017). Therefore, temporal patterns in bird abundance offshore may differ spatially in relation to distance to nearby breeding colonies, the foraging strategies prevalent within those colonies, and per year. The difference in the average seasonal abundance between the years 2019 and 2020 was large (103 birds h⁻¹ in 2019 and 134 birds h⁻¹ in 2020), and the effect of year as a
random effect in the model was significant in the model A (Sup. Mat. 5), but not in model B, which had an autoregressive term to account for temporal autocorrelation (Table 2.2). The significance had a widespread in the models of the sub-samples ($0.265 \pm 0.248$, Table 2.3) indicating a high level of uncertainty on the impact of this factor. Additionally, gaps in the data can cause increased uncertainty in the models if data is unavailable for one or both years. To separate yearly variability from repeating seasonal patterns and cover the full study period despite the gapped data, multiple years of continuous monitoring are required to illuminate underlying patterns and mechanisms in bird distribution offshore. This shows long-term monitoring is vital to understanding the variability in bird abundance offshore, as has been noted before for tracking studies (Thaxter et al. 2015). Additionally, the question remains whether the findings in this study reflect patterns and processes in other parts of the North Sea. The inclusion of abundance data from different regions of the North Sea might reveal spatial components affecting the temporal patterns of birds offshore and further reveal the underlying processes that lead to observed patterns. For example, central foragers have a foraging range around their colony (Camphuysen et al. 2015; Garthe et al. 2016), and we suspect the daily observed abundance will differ with distance to shore and/or distance to nearest seabird colonies. Ideally these data should cover long periods of time as well, and bird radars could fulfil a role here to acquire year-round abundance patterns in multiple locations. Finally, the integration of the measured abundance from bird radar with the intricate biological information which can be gained from biologging data would strengthen our capacity to understand the underlying processes influencing bird flight behaviour and distributions offshore (Bauer et al. 2019), also in relation to solving potential conflicts including wind energy and aviation safety (Shamoun-Baranes et al. 2018), and merits future exploration.

The radar used in this study dynamically applies a filter over its observed area to prevent clutter (caused by e.g., rainfall or high waves) from contaminating bird measurements, and therefore birds flying in range of the radar might be filtered out during periods of high filter activity. In our study period, 33 % of all hours could not be studied because filtering activity was estimated to be too high to yield accurate results (Table 2.1, additional elaboration in Sup. Mat. 3). In general, these filters become increasingly active as sea state increases or precipitation occurs, thus our results do not reflect bird abundance when sea state is high and during precipitation. Even when filter activity is low, some birds could still be filtered out by the radar software and cause an underestimation of observed bird abundance. Improvements in post-processing of the radar data could allow us to include data from a wider array of circumstances, including a larger sampling area and sampling during high filter activity.
Understanding temporal variation in bird abundance at sea can have important implications for wildlife management and estimating the impact of anthropogenic development in an area such as wind farm development and can improve species distribution estimations at sea. On the DCS the Dutch government plans to produce 11.5GW of offshore wind energy by the end of 2030 (Rijksoverheid 2019) and the cumulative effect of this development on offshore birdlife is difficult to predict. A commonly used method to analyse the impact of wind farms is to determine collision risk through modelling (Masden and Cook 2016). These models incorporate turbine measurements, weather conditions, bird morphometrics, flight speed and altitude, and bird abundance estimations to calculate collision risk for a specific wind farm. The specific methods these models employ can differ, but the majority assumes a linear relationship between bird abundance and collision risk. Our data shows bird abundance can fluctuate greatly on both an hourly and seasonal scale, and both spatial planning and impact assessments should address temporal variation in bird occurrence. Long term monitoring to provide wide temporal coverage is therefore needed to understand the range and causes of these fluctuations in bird abundance, which can improve the temporal accuracy of collision risk models to better inform policy makers. For example, predictions of collision risk can be used to initiate temporary shutdown of turbine during periods of high collision risk and with better temporal bird abundance estimations wind farm uptime can be maximized without endangering large numbers of birds.

This study shows that two of the three predictable external variables evaluated in this study, sun azimuth and week, affect bird abundance on the North Sea during the breeding season. The third variable, astronomic tide, appears to have no effect. The diurnal pattern in bird abundance shows a distinctive peak in the morning another lower peak later in the afternoon before sunset while it is constantly low during night. The pattern over the breeding season shows an increasing trend until the end of June, after which bird abundance decreases. Most of the observed variance in hourly bird abundance could not be explained by our investigated environmental variables, and thus other factors have to be considered such as indicators of resource availability or weather conditions. Due to its capability to monitor bird movements in an area for extended periods of time, bird radar monitoring can allow us to discover general patterns in bird movement and, when accounting for its limits, bird radar can continue to play a role in improving our knowledge of the spatial and temporal distribution of birds offshore.
Acknowledgements

We thank Rijkswaterstaat (Zee & Delta and Centrale Informatievoorziening) for providing the radar data and Robin Radar for providing details on the radar system. We thank Bureau Waardenburg for sharing their expertise with bird radar and observational data on birds flying in the wind farm. This work was carried out on the Dutch national e-infrastructure with the support of SURF Cooperative. The ESAS 5.0 database was queried as a database contributor (C.J. Camphuysen). We also thank Maja Bradarić for the extensive and fruitful discussion on working with bird radar data and Johannes de Groeve for his support on data querying. We thank the anonymous reviewers for the constructive feedback on the manuscript.
2.5 Supplementary materials

Supplementary material 1; ESAS 5.0 Data

The ESAS 5.0 (European Seabirds at Sea) database is a ship survey database (Reid and Camphuysen 1998) that incorporates all observational data made through a standardized protocol (Camphuysen et al. 2004) and is maintained by the NWO-NIOZ Royal Netherlands Institute for Sea Research. The database was queried for all bird species observed in the months of May, June, and July since the year 2000 in the area between 51.8 °N – 53 °N, 3.7 °E – 4.7 °E, which describes a rectangular area around the radar location (52.427827 °N, 4.185345 °E) near the Dutch coast (Table 2.S.1). For readability, all species with an observation rate below 0.1 % have been omitted from the table.

Table 2.S.1 Number of birds observed and percentage of total per species in the months of May, June, and July from 2000 to 2020 in the area between 51.8 °N – 53 °N, 3.7 °E – 4.7 °E. Data was queried on 16 February 2021. For readability, all species with an observation rate below 0.1 % have been omitted.

<table>
<thead>
<tr>
<th>Species name</th>
<th>Scientific name</th>
<th>Birds (#)</th>
<th>Percentage of total (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lesser black-backed gull</td>
<td>Larus fuscus</td>
<td>64870</td>
<td>56.8</td>
</tr>
<tr>
<td>Herring gull</td>
<td>Larus argentatus</td>
<td>18051</td>
<td>15.8</td>
</tr>
<tr>
<td>Great cormorant</td>
<td>Phalacrocorax carbo</td>
<td>10982</td>
<td>9.6</td>
</tr>
<tr>
<td>Large gull (unknown species)</td>
<td></td>
<td>7012</td>
<td>6.1</td>
</tr>
<tr>
<td>Herring / lesser black-backed gull</td>
<td></td>
<td>2076</td>
<td>1.8</td>
</tr>
<tr>
<td>Gull (unknown species)</td>
<td></td>
<td>1372</td>
<td>1.2</td>
</tr>
<tr>
<td>Common tern</td>
<td>Sterna hirundo</td>
<td>1265</td>
<td>1.1</td>
</tr>
<tr>
<td>Sandwich tern</td>
<td>Thalasseus sandvicensis</td>
<td>1178</td>
<td>1.0</td>
</tr>
<tr>
<td>Northern fulmar</td>
<td>Fulmaris glacialis</td>
<td>1024</td>
<td>0.9</td>
</tr>
<tr>
<td>Common scoter</td>
<td>Melanitta nigra</td>
<td>977</td>
<td>0.9</td>
</tr>
<tr>
<td>Black-headed gull</td>
<td>Chroicocephalus ridibundus</td>
<td>946</td>
<td>0.8</td>
</tr>
<tr>
<td>Common gull</td>
<td>Larus canus</td>
<td>891</td>
<td>0.8</td>
</tr>
<tr>
<td>Great black-backed gull</td>
<td>Larus marinus</td>
<td>827</td>
<td>0.7</td>
</tr>
<tr>
<td>Northern gannet</td>
<td>Morus bassanus</td>
<td>694</td>
<td>0.6</td>
</tr>
<tr>
<td>Black-legged kittiwake</td>
<td>Rissa tridactyla</td>
<td>578</td>
<td>0.5</td>
</tr>
<tr>
<td>Common / Arctic tern</td>
<td></td>
<td>249</td>
<td>0.2</td>
</tr>
<tr>
<td>Black tern</td>
<td>Chlidonias niger</td>
<td>197</td>
<td>0.2</td>
</tr>
<tr>
<td>Common shelduck</td>
<td>Tadorna tadorna</td>
<td>166</td>
<td>0.1</td>
</tr>
<tr>
<td>Common swift</td>
<td>Apus opus</td>
<td>130</td>
<td>0.1</td>
</tr>
<tr>
<td>Arctic tern</td>
<td>Sterna paradotasa</td>
<td>108</td>
<td>0.1</td>
</tr>
<tr>
<td>Whimbrel</td>
<td>Numenius phaeopus</td>
<td>87</td>
<td>0.1</td>
</tr>
<tr>
<td>Common starling</td>
<td>Sturnus vulgaris</td>
<td>58</td>
<td>0.1</td>
</tr>
</tbody>
</table>
Supplementary material 2; Robin Radar detection probability at different range and heights

Fig. 2.S.1 shows the range and altitude form the radar at which the probability of detection for an object of 1 standard avian target (SAT, Fig. 2.S.1A) and 0.125 SAT (Fig. 2.S.1B) by the horizontal S-band antenna of the Robin Radar 3D-Fix system is > 80 %. A standard avian target is a theoretical object used as a standard for evaluating the performance of avian radar systems and approximates the physical features of a carrion crow *Corvus corone* with a radar cross section (RCS) of -16 dB m⁻² and a mass of 500 g. A 0.125 SAT object correlates to an RCS of -25 dB m⁻² and a mass of 62.5 g. Based on these figures the maximum range of the area of interest was set at 2000m, as from that point the probability of detection drops below 80 % for small birds (RCS = -25 dB m⁻²) with increasing range.

Figure 2.S.1 Probability of detection by the Horizontal S-band antenna of the Robin Radar 3D-Fix at different ground range and altitude from the radar position (0,0 on the axes). A: The area shows the range/altitude combinations at which the probability of detection > 80 %. Probability of detecting a target of size 1 SAT. B: Probability of detecting a target of size 0.125 SAT. Figures provided by Robin Radar.
Supplementary material 3; Accounting for detection bias caused by dynamic radar filtering

The dynamic filter activity in each radar image directly affected detection probability of birds by increasing the threshold at which objects are detected. The filter is always online, ranging from 0 (no filtering) to 1 (complete filtering). Observation hours in which the filter activity was so high that no birds were recorded could have been misinterpreted as hours in which bird abundance was zero (false negative observations, Fig. 2.S.2A). To prevent this data from being analysed, we excluded hours with an average filter activity that resulted in more hours without bird observations than “regular” hours with at least a single observation. To find the threshold of filter activity where this was the case, average hourly filter activity and bird abundance (birds h⁻¹) was calculated for the whole study period. For each incremental filter activity step (step size = 0.005) the number of hours with that average activity was counted, differentiating between hours in which birds were measured (“Normal hours”) and hours without a single bird measurement (“0-track hours”, Fig. 2.S.2B). The threshold for data exclusion was set on the first filter activity bin (moving from 0 to 1) at which there were more hours without bird measurements. This threshold was 0.240 (orange vertical line, Fig. 2.S.2); observation hours in which filter activity was higher than the threshold were excluded from further analysis. Due to the high correlation between wind speed / sea state and filter activity this means generally only data from low wind / sea state is included in the research.

Figure 2.S.2 The relation between hourly bird counts and radar filter activity. A: Hourly bird counts (y-axis) at different filter activities (x-axis). The orange horizontal line shows the filter activity exclusion threshold (see text). B: Number of measurement hours (y-axis) for different filter activity intensities (x-axis, 0.005 bins), hour types are stacked. Blue shows the number of hours with bird observations (“Normal hours”), red shows number of hours without a single observation (“0-track hours”). The black line shows the difference between the two types (Normal hours - 0-track hours), the exclusion threshold was set at the point the difference becomes negative (orange horizontal line, filter activity = 0.240).
Supplementary material 4; Missing observations hours

In total, the study period in 2019 and 2020 contained 3648 observation hours, of which 1769 hours were removed from the final dataset due to high radar filtering or the radar being offline (see Methods). These missing observation hours were not distributed equally over time and created larger gaps of missing data in some weeks than in others. Table 2.5.2 shows the number of missed observation hours per week in the breeding season for the individual seasons (2019 and 2020) and the number of hours in which a gap exists in both seasons for a specific day and hour. In particular, weeks 2, 3, and 9 have a large number of missing data (more than a third of total observation hours per week missing in both seasons).

Table 2.5.2 Number of missing hours per week in the breeding season for both seasons (2019 and 2020), and the number of missing hours that overlap in both seasons.

<table>
<thead>
<tr>
<th>Week</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>11</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>2019</td>
<td>83</td>
<td>81</td>
<td>84</td>
<td>50</td>
<td>45</td>
<td>80</td>
<td>80</td>
<td>74</td>
<td>128</td>
<td>48</td>
<td>72</td>
<td>825</td>
</tr>
<tr>
<td>2020</td>
<td>114</td>
<td>160</td>
<td>90</td>
<td>102</td>
<td>63</td>
<td>99</td>
<td>18</td>
<td>16</td>
<td>129</td>
<td>122</td>
<td>31</td>
<td>944</td>
</tr>
<tr>
<td>Overlap</td>
<td>41</td>
<td>80</td>
<td>60</td>
<td>11</td>
<td>24</td>
<td>52</td>
<td>7</td>
<td>6</td>
<td>96</td>
<td>20</td>
<td>20</td>
<td>417</td>
</tr>
</tbody>
</table>
Supplementary material 5; GAM without accounting for temporal autocorrelation

Here we explore further the output of model A (Table 2.S.3), without added autoregressive term to account for temporal autocorrelation, following a similar structure as the main result. Bird abundance was significantly related to sun azimuth (p < 0.001) and week of the breeding season (p < 0.001), but not to astronomic tide (p = 0.167). The complete model explained 18.3 % of data deviance ($R^2 = 0.17$). Of the three predictors, week of the breeding season had the strongest estimated effect on bird abundance (8.5 % of deviance), followed by sun azimuth (5.3 %), and tide (0.3 %, non-significant). Year as a random effect was significant (p < 0.001) and accounted for 0.5 % of deviance. The effect size estimate and confidence intervals (2 x standard error) of the significant predictor effects are visualized in Fig. 2.S.3. The effect of sun azimuth (Fig. 2.S.3A) shows two peaks in predicted number of birds h$^{-1}$ during the day, one in the morning after sunrise (169 birds h$^{-1}$) and a second, smaller peak in the afternoon (130 birds h$^{-1}$) and lowest predicted abundance after sunset (77 birds h$^{-1}$). The effect of week of the breeding season (Fig. 2.S.3B) shows an increase in mean predicted bird abundance from the last weeks of May to late June (week of June 19th), rising from 76 birds h$^{-1}$ to 169 birds h$^{-1}$. After this peak hourly abundance dropped to a mean predicted 120 birds h$^{-1}$ in the last week of July.

Table 2.S.3 Overview of the generalized additive model output for model B, including parameter estimates for the intercept and random effect (year), and the estimated degrees of freedom (edf) and estimated deviance explained for the environmental predictors, (n = 1879).

<table>
<thead>
<tr>
<th>Parametric coefficients</th>
<th>estimate</th>
<th>edf</th>
<th>est. dev. explained</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>4.585</td>
<td></td>
<td></td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Year = 2020</td>
<td>0.154</td>
<td>0.5</td>
<td></td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Smooth terms</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sun azimuth</td>
<td>5.002</td>
<td>5.3</td>
<td></td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Week of the breeding season</td>
<td>4.433</td>
<td>8.5</td>
<td></td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Tidal water height</td>
<td>1.774</td>
<td>0.3</td>
<td></td>
<td>0.125</td>
</tr>
</tbody>
</table>
Temporal patterns in offshore bird abundance during the breeding season at the Dutch North Sea coast

Figure 2.S.3 Smoothed effects of the significant individual predictors in the hourly abundance model A (n = 1879). Left y-axis shows hourly bird count (black dots / boxplots), whereas the right y-axis shows predicted hourly bird count (purple line = effect size, area = effect size ± 2 × se). A: Effect of sun azimuth, in radians from South (x-axis). Sunrise occurs between Azimuth = −.73π to −.64π, sunset between Azimuth = .64π to .73π, indicated by the grey areas. B: Effect of week in the breeding season, date indicates the first day of each week (x-axis).
Chapter 3

Thermal soaring over the North Sea and implications for wind farm interactions

Jens A. van Erp*, Elspeth Sage*, Willem Bouten, E. Emiel van Loon, Kees (C.) J. Camphuysen, Judy Shamoun-Baranes
*Joint first authors

Published in Marine Ecology Progress Series (2023) 723:185–200, doi: 10.3354/meps14315
Chapter 3

Abstract

Seabirds use several flight modes at sea, including thermal soaring, in which thermal uplift is used to gain altitude and save energy. An increase in flight altitude may have consequences for wind farm interactions if it results in birds spending more time within the rotor swept zone (RSZ). To understand conditions under which thermal soaring occurs and potential implications for wind farms interactions, we investigated thermal soaring of seabirds in relation to atmospheric conditions in June and July at two study areas on the North Sea, west and north of the Dutch coast. We developed algorithms that identified thermal soaring in GPS tracks of lesser black-backed gulls and radar tracks of seabirds. By combining species-specific three-dimensional information on flight behaviour from biologging with the continuous spatiotemporal coverage of radar positioned at wind farms we obtained a more comprehensive overview of thermal soaring at sea than either method would obtain alone. Our results showed that birds flew at higher altitudes during thermal soaring than non-soaring flight, increasing the proportion of flight time within the RSZ. Thermal soaring occurred inside offshore wind farms to a similar degree as outside. Thermal soaring was positively correlated with positive temperature differences (ΔT) between sea surface and air (at 2 m above sea level), and north and north-westerly winds. We show that the probability of thermal soaring over the North Sea, inside and outside wind farms, increases with larger temperature differences, resulting in increased time spent within the RSZ and an increased collision risk for seabirds.
3.1 Introduction

Marine environments are undergoing extensive change as a result of human activities, including large infrastructure developments such as rapid growth of offshore wind industry (Esteban and Leary 2012). Seabirds already face multiple conservation threats (Croxall et al. 2012) and wind farms may place additional pressures on their survival through a range of direct and indirect effects (Perrow 2019). One of these effects is the collision of birds with wind turbines, which can increase mortality (Marques et al. 2014). Estimates of collision partially depend on the spatial overlap between the birds and the turbine rotors, which is mostly determined by two key metrics: the flight altitude distribution and some measure of bird density in the area (Band 2012; Kleyheeg-Hartman et al. 2018). Generally, seabird flight altitude offshore is low (Johnston et al. 2014; Ross-Smith et al. 2016), but seabirds gain altitude when performing thermal soaring (Woodcock 1940b, 1975; Pennycuick 1983; Weimerskirch et al. 2003), an energy saving flight mode (Nourani and Yamaguchi 2017), which could increase the probability of flying through the rotor swept zone (RSZ) of wind turbines. Thermal soaring flight is therefore especially relevant when considering interactions with wind turbines and such interactions have been studied among soaring birds on land (Péron et al. 2017; Hanssen et al. 2020), but not at sea.

The influence of atmospheric conditions on thermal soaring has mainly been studied on land (Nourani and Yamaguchi 2017), but comparable interactions also take place at sea. When cooler air overlies a warmer sea surface, the air warms up and expands, destabilising the lower atmosphere and creating vertical movement of the warm air as thermals. The difference between sea surface temperature (SST) and air temperature (Ta) as (SST- Ta, or ΔT) is a suitable proxy for thermal uplift (Woodcock 1940b; Haney and Lee 1994) and important in facilitating sea crossings in raptors around the world (Nourani et al. 2021). Changes in the altitude profile of birds during thermal soaring depend, among other factors, on both the strength of available thermals, as well as species morphology and behaviour (Pennycuick 2008). Thermal soaring at sea is well described in tropic latitudes, where occurrence of thermals is predictable enough that frigatebirds have developed a flight specialisation enabling them to use thermal soaring flight to stay aloft for weeks on open water (Weimerskirch et al. 2016). However, raptors have also been shown to use thermal soaring in sea crossings at higher latitudes during migration, and it is possible that thermal soaring is used more widely in temperate waters than past research indicates.

One of the most important areas for offshore wind energy production in Europe is the North Sea, a shallow shelf sea located in North-Western Europe. Here offshore wind development has been growing at an accelerating pace and is projected to grow considerably in the future (Rijksoverheid 2019; European Commission 2020). As a result, considerable effort
has gone into measuring seabird behaviour, including studies of flight paths, flight altitude and turbine avoidance behaviour (Krijgsveld et al. 2011; Johnston et al. 2014; Ross-Smith et al. 2016), all of which aim to improve the understanding of how wind farm developments may impact seabirds (Marques et al. 2014; Thaxter et al. 2019). Thermal soaring, however, has never been examined empirically over the North Sea, although several seabird species present on the North Sea can utilise thermals. In particular, larids such as lesser black-backed gulls *Larus fuscus* and herring gulls *Larus argentatus* are flight generalists that commonly use flapping flight (Ainley et al. 2015; Shamoun-Baranes et al. 2016), but their morphology allows them to take advantage of thermal updrafts to support soaring flight (Lindhe Norberg 2002; Sage et al. 2022). Herring gulls have been observed thermal soaring in tropical and lower mid-latitudes on the western Atlantic Ocean (Woodcock 1940a) and lesser black-backed gulls are able to use thermal soaring and orographic soaring over land (Shamoun-Baranes et al. 2016; Sage et al. 2019) and use soaring flight over sea (Shamoun-Baranes et al. 2016). Thus, under suitable environmental conditions they may utilise thermal soaring in temperate marine environments such as the North Sea.

The aims of this paper are to determine how thermal soaring at sea influences the flight altitude distributions of birds, to identify whether thermal soaring occurs within wind farm areas, and to better understand how weather conditions promote thermal soaring at sea, all in the context of collision risk assessments for wind farms. To achieve our aims, we combine two tracking techniques which provide complementary information. We use biologging data (GPS and accelerometry) to study the 3D flight behaviour at sea of lesser black-backed gulls from two coastal populations situated 24 and 60 km from two offshore wind farms (Luchterduinen and Gemini wind park respectively). However, obtaining a large enough sample size for data analysis within offshore wind farms is challenging. We therefore combine analysis from radars, positioned at both offshore wind farms, which provide continuous coverage of flight behaviour of all birds in the vicinity, but lack altitude and species-specific information. Additionally, both datasets are used to investigate the influence of ΔT and wind direction on thermal soaring in order to understand the atmospheric conditions facilitating thermal soaring at sea. We expect higher flight altitudes and an increased proportion of flight time spent within the RSZ during thermal soaring. We have no clear expectation as to whether thermal soaring occurrence within wind farms will differ from occurrence outside, as it is unclear how thermal uplift and intrinsic motivation for thermal soaring is affected by the wind farm. Furthermore, we expect positive ΔT to promote thermal soaring and that these conditions mainly develop when winds from higher latitudes cause a decrease in *T*<sub>a</sub>. For additional insight into the conditions promoting thermal uplift, we describe the synoptic weather system during one particular time period of intense thermal soaring activity, thereby linking broad-scale weather patterns to fine-scale flight behaviour. Finally, we discuss the effect of thermal soaring
Thermal soaring over the orth ea and implications for wind farm interactions

3.2 Methods

Study area and study period

The study was conducted over the southern North Sea (Fig. 3.1) between 52 ° and 55 ° latitude, a temperate area characterised by shallow sea depths < 40 m (NOAH 2022). GPS and radar measurements were taken at two study areas, to the west and north of the Dutch coast (Fig. 3.1). We refer to the two study areas as the west and north area. To get an overview of the species flying in these areas and relate them to the radar data (which is non-species specific) we gathered species counts from ESAS 5.0 ship survey data (European Seabirds at Sea, Reid and Camphuysen 1998) which is reported in Tables 2.5.1 and 2.5.1 (Sup. Mat. 1). The study was conducted from June through July in 2019 and 2020. SST ranged from 280 – 297 °K (average 290.0 °K in the west area and 288.9 °K in the north area) and $T_a$ ranged from 281 – 302 °K (average 289.6 °K in the west area and 288.6 °K in the north area) (based on ERA5, see section 2.4).

Lesser black-backed gull tracking data and analysis

GPS and accelerometer data were used to identify thermal soaring at sea in individual lesser black-backed gulls and to examine the altitude profile of thermal soaring flight in comparison to flapping flight. This data was gathered using UvA-BiTS trackers (Bouten et al. 2013) fitted to individual lesser black-backed gulls at two breeding colonies in the west and north study area (Forteiland and Schiermonnikoog respectively, Fig. 3.1) as part of long-term monitoring efforts. Individuals were tagged in 2017 and 2018 on Schiermonnikoog island (53.499 °N, 6.261 °E) and in 2019 and 2020 on Forteiland (4.575 °N, 52.465 °E), situated near IJmuiden on the mainland. Catching protocol followed previous protocols used for lesser black-backed gulls at Dutch study sites, (Shamoun-Baranes et al. 2016), where birds were captured during incubation, fitted with trackers using a wing harness made of a Teflon ribbon threaded with a nylon string, and released within 20 minutes of capture following tagging. All tagging was carried out in accordance with the Dutch ethics committee on animal experiments (DEC) of the Royal Netherlands Academy of Arts and Sciences (KNAW), and with permission by land managers PBN (IJmuiden) and Natuurmonumenten (Schiermonnikoog). The data acquisition program was set up to maximise high-resolution (3 second interval) measurements at sea by using a geographical fence for each colony. The fence covered the majority of the local marine foraging area per
colony and triggered the high-resolution measurement protocol when a tagged individual moved inside (Fig. 3.1). GPS data collected within these two fences in the north and west area during June and July in 2019 and 2020 were used in this study. The trackers also collected tri-axial acceleration data at 20 Hz for 1 second following each GPS measurement. Acceleration measurements were used for behaviour classification using a random forest classifier described by Shamoun-Baranes et al. (2016), which identifies 11 different flight and non-flight behaviours. In this study the main purpose of the behavioural classifier was to identify flight behaviour and distinguish flapping and soaring flight, where soaring is defined as a bird in flight and not flapping its wings (which may encompass climbing or gliding).

In order to identify thermal soaring in lesser black-backed gulls, high-resolution flight trajectories with reliable altitude measurements were required, which could resolve circular movement patterns and fine-scale altitude changes. Due to the use of a geographical fence, nearly all data was collected at high-resolution. However, in some instances lower resolution data can be captured within the fence (e.g., if device battery voltage is low) so point-to-point interval was calculated between every location (annotated to the second location) and any location with an interval ≥ 10 seconds was removed. Under the high-resolution measurement protocol, altitude errors of the UvA-BiTS trackers are relatively low with a mean measurement accuracy of 1.42 – 2.77 m at a measurement interval of 6 s (Bouten et al. 2013). Nevertheless, to minimise the effect of any anomalous altitudes, three-dimensional point to point velocity was calculated between subsequent points, and where this velocity exceeded 50 m s\(^{-1}\) the altitude was recalculated as the average of the altitudes to either side of the point. Measurements of altitude above sea level (ASL) can also be systematically biased on a regional scale by the ellipsoid model for the Earth’s surface upon which altitude ASL is calculated. To estimate this bias, we investigated the altitude measurements of all GPS points with classified behaviour “floating”, indicating positions at sea level. The mean altitude of all floating-point measurements (99137 points) was -4.36 m, which was considered an approximation of the systematic error caused by the ellipsoid model. To correct for the error, this value was added to all GPS altitude measurements. To remove anomalous positional fixes, the point-to-point ground speed between locations was calculated using point-to-point distance and time interval. 3117 points (0.028 % of total) for which two-dimensional ground speed exceeded 50 m s\(^{-1}\) were considered unrealistic anomalies and removed. Following this filtering, data considered for further analysis consisted of 603.4 hours of recorded flight time across 148 days and 18 individuals from the west area, with a mean time interval of 5 ± 0.2 s and 357.6 hours across 103 days and 12 individuals from the north area, with a mean time interval of 4.4 ± 1 s.
Figure 3.1 Overview of the two study areas (west and north, relative to the Dutch coast). Blue dots show the lesser black-backed gull colonies at IJmuiden (west) and Schiermonnikoog (north) and dotted squares show the geographical fence for high resolution GPS capture. Small black squares show the location of Luchterduinen (west) and Gemini (north) wind farms. Close up windows of the two wind farms show individual turbines (black dots) within the defined wind farm area (red lined area), radar location (purple square) and spatial measurement range of the radars (grey shaded area). Black gridded dots across the sea area show corners of ERA5 grid cells.

High-resolution GPS data was used to identify individual moments of thermal soaring in lesser black-backed gulls based on flight behaviour, flight speed and altitude gain. Interruptions occurred in the time series of high-resolution data whenever a bird left then re-entered the high-resolution fence area. All points were therefore grouped into periods of uninterrupted high-resolution data, deemed “bouts”. Bouts were classified by ascribing unique ascending ID numbers to every measurement (including the non-high-resolution data), then identifying breaks in subsequent measurements based on the ID
numbers. Where interruptions of more than 4 subsequent measurements occurred in the high-resolution data (usually because a bird left the geographical fence area) this was deemed a break in uninterrupted high-resolution data, ending a bout. Within a bout, points were assigned 1 of 3 classifications: circling, i.e., periods of circling flight with a gain in altitude, gliding: i.e., periods of directional flight without flapping and with a loss or maintenance of altitude, and other, i.e., neither of these behaviours were identified. To determine these classifications, a moving average approach was used. For each location, a three-point (the location and one point to either side) moving average of climb rate (ms\(^{-1}\)), angular velocity (\(^{\circ}\)s\(^{-1}\)), ground speed (ms\(^{-1}\)), and proportion of time spent soaring (as defined by accelerometer behavioural classification) was calculated. Where climb rate was > 0 ms\(^{-1}\), angular velocity was > 10 \(^{\circ}\)s\(^{-1}\), ground speed > 5 ms\(^{-1}\), and proportion of time spent soaring was ≥ 0.6, a point was defined as circling. This soaring proportion limit was chosen to allow for incidental flapping during soaring dominant behaviours, which was commonly found in the data and is expected in gulls. Where climb rate was ≤ 0 ms\(^{-1}\), ground speed was > 5 ms\(^{-1}\) and proportion of time spent soaring was ≥ 0.6, a location was defined as gliding. Any series of gliding points which was not preceded by at least one circling point within a bout was re-classified as “other”, as there was no evidence of this gliding being connected to thermal soaring behaviour. Consecutive circling points were considered a circling bout, consecutive gliding points were considered a gliding bout, and a circling bout with its directly subsequent gliding bout was considered a thermal soaring bout. Thermal soaring bouts were identified in 26 individuals (all 18 individuals from the west area and 11 individuals from the north area).

To gain insight into the amount of time gulls spent in different flight modes and at different altitudes, time proportion metrics were calculated (such as the overall proportion of flight time spent in thermal soaring flight). The proportion of different flight behaviours taking place within the RSZ were also calculated. The RSZ altitude range was set at 25 – 150 m ASL and chosen as a broadly representative RSZ for the two wind farms in this study, (Luchterduinen, 25 – 137 m and Gemini, 23.5 – 153.5 m ASL). To account for the GPS altitude accuracy, confidence bounds for these values were also calculated based on adding or subtracting 3 m (rounded up from the mean accuracy reported by Bouten et al. (2013) to either limit of the RSZ: a 22 – 28 m lower range and a 147 – 153 m upper range)

In order to compare the proportion of soaring with environmental conditions experienced, the hourly proportion of flight time spent in circling flight was calculated (circling time proportion). Here only circling flight was considered, rather than circling and gliding, as the occurrence of circling flight is expected to be most directly related to environmental conditions generating thermals. The final GPS data set consisted of data from the west area amounting to 938 covered hours across 115 days and data from the north area amounting
to 586 covered hours across 82 days. In the west area two individuals contributed data in both 2019 and 2020, whilst five individuals contributed data in both years in the north area. An overview of data counts per individual per year is presented in Table 2.S.3 (Sup. Mat. 2).

Radar data and analysis

Radar data was used to identify and examine the extent of thermal soaring in two locations partly overlapping with offshore wind farms. Bird flight was monitored by two bird radar systems with a tracking algorithm (Robin Radar 3D Fix). One system was mounted on the service platform of turbine 42 situated at the edge of the Luchterduinen wind farm (52.4278 °N, 4.1853 °E, 21.8 m above ASL), 23 km from the coast (west area, Fig. 3.1). A second system was mounted on the offshore power station of Gemini wind farm (54.0370 °N, 6.0417 °E, 31 m above ASL), situated 60 km north of Schiermonnikoog (north area, Fig. 3.1). The radar systems consisted of a vertically rotating X-band antenna (25 kW, Furuno Marine) and horizontally rotating S-band antenna (60 kW, Furuno Marine) both rotating at 0.75 rotations s⁻¹. For this study, only data captured by the horizontal antenna were used.

Radar measurements were automatically processed to create tracks of birds using proprietary software developed by Robin Radar and further post-processed to provide reliable observations as described in Chapter 2. Radar data was collected during June and July in 2019 and 2020 for the west area and in 2020 for the north area (as the north radar was not operational until 2020). The bird detection probability of the radar is not equal over the whole radar observation window; therefore, data were sampled at 1000 – 2500 m from the radar, minus the area blocked by the structure the radar was installed on and the area overlapping with the vertical antenna (between 287 ° – 30 ° and 115 ° – 135 ° in the west area and between 119 ° – 247 ° and 47 ° – 67 ° in the north area, see Fig. 3.1). The radar system only measures birds in flight, detecting birds reliably up to an altitude of 300 m for small birds (< 62.5 g) and up to an altitude of 600 m for larger birds (500 g, see Fig. 3.S.1 in Sup. Mat. 3).

Each track created by the radar software included at least five track points and several track properties: geolocation plus timestamp (UTC) per track point and track direction calculated between the first and last track point (radians). Track length (m) was calculated as the sum of the great circle distance between consecutive track points. Average ground speed (ms⁻¹) was calculated as track length divided by track duration (last timestamp - first timestamp, s). Average airspeed was calculated according to Shamoun-Baranes et al. (2007) using ground speed, track direction, and hourly u- and v-wind components (at 10 m ASL) retrieved from the ERA5 reanalysis dataset (see Environmental Conditions). Wind components were annotated to the tracks based on nearest hour to the calculated
midpoint timestamp of the track (first timestamp + ½ track duration). Only tracks with an 
average airspeed between 5 ms\(^{-1}\) and 30 ms\(^{-1}\) were included as nearly all seabird species fly 
within this airspeed range (Spear and Ainley 1997b; Alerstam et al. 2007; Shamoun-Baranes et al. 2016). Additionally, manual data exploration indicated static reflections from nearby 
vessels or structures created stationary, long-lasting, false positive bird tracks, which can 
differ per radar due to different surroundings and placement height ASL. To automatically 
identify these clutter tracks, we calculated the displacement over time (ms\(^{-1}\)) by dividing the 
great circle distance between the first and last track point by the track duration. Through 
visual inspection the tracks falling in the 1\(^{st}\) percentile of displacement over time (0.66 
ms\(^{-1}\)) and the 10\(^{th}\) percentile of displacement over time (3.72 ms\(^{-1}\)) in the west and north 
datasets, respectively, were identified as clutter and removed. Additionally, to remove false 
positive bird tracks caused by reflections of the turbines in the nearby wind farm, any track 
with > 80\% of the positions occurring within 100 m radius of a turbine was also removed.

During the study period the radar was occasionally not operational and hours in which 
the radar was fully offline were not included in the analysis. Furthermore, exploratory 
analysis revealed that birds were no longer detected by the radar when the clutter filter 
of the radar was highly active. Therefore, to reduce the chance of analysing artificial 
lows in bird abundance caused by high filter activity, we removed all hours with an 
average filter activity above a set threshold of 0.327 for the west area and 0.311 for the 
north area (further explanation available in Fig. 3.S.2 in Sup. Mat. 4). After applying the 
aforementioned selection criteria, 2265 hours of data (2379356 tracks) remained for the 
west area over 113 days in 2019-2020, and 866 hours of data (413208 tracks) remained 
for the north area over 49 days in 2020.

In order to identify thermal soaring in the radar tracks, a method was developed to identify 
thermal soaring flight from information extracted from the 2D trajectory data collected by 
the radar. Point-to-point heading (flight direction relative to the air) was calculated based 
on hourly u- and v-wind components nearest to the point timestamp, point-to-point ground 
speed and bearing (flight direction relative to the ground). From this, angular velocity was 
calculated per point as the change between subsequent point-to-point headings divided 
by point-to-point time steps. Circling flight was identified as a continuously turning track 
section (3-point average of angular velocity between 10 – 60 °s\(^{-1}\)) for a minimum of two 
full circles (720 °). Other tortuous behaviours, such as foraging, could also be identified as 
circling this way. As thermals are advected by wind, the net direction of circling flight within 
a thermal is expected to align with the wind direction (Treep et al. 2016; Weinzierl et al. 2016). Therefore, when wind speed was estimated high enough to cause advection which 
would distinguish thermal circling from other tortuous flight (wind speeds > 2 ms\(^{-1}\)), the 
net direction of circling flight had to align within a 90-degree window of the wind direction
Thermal soaring over the North Sea and implications for wind farm interactions

(45-degree clock- and counter-clockwise) to be considered thermal soaring. Circling flight was identified in 10676 of 2379356 (0.0045 %) tracks in the west area (2019 and 2020), and in 580 of 413208 tracks (0.0014 %) in the north study area (2020).

To assess the extent of thermal soaring in offshore wind farms, circling tracks were counted both within and outside the wind farm area. A geometric box was drawn around the outer turbines of the wind farm plus a 100 m buffer (Fig. 3.1, red area). The area where the wind farm overlapped with the study area (Fig. 3.1, grey area) was considered inside the wind farm (west area 4.7 km², north area 9.0 km²); the rest of the study area was considered outside the wind farm (west area 6.1 km², north area 0.7 km²). Tracks were annotated by occurrence of circling in or outside the wind farm area. If circling occurred both inside and outside within a single track, the track was considered for both categories. Circling density (circling tracks per km²) per day was calculated for both areas by dividing the number of circling tracks observed per day, per area, by the area size (km²).

To analyse the relation between thermal soaring occurrence and the associated environmental conditions, we calculated hourly proportion of circling tracks (circling track proportion) by dividing the number of circling tracks per hour by the total number of tracks per hour occurring in the area of interest. All tracks occurring between xx-1:30:00 and xx:29:29 were included in hour xx. Note that for GPS we consider circling time proportion, where for radar we consider circling track proportion, which are similar but not completely equal measurements of thermal soaring. Where both data sets are considered, we simply refer to the data as “circling proportions”.

Environmental conditions

In order to calculate wind-dependent track properties and to investigate the environmental conditions under which thermal soaring occurs, hourly measures of thermal soaring from GPS and radar were annotated with atmospheric and sea surface parameters. These parameters were acquired from the European Centre for Medium-Range Weather Forecast (ECMWF) ERA5 reanalysis, providing data on a regular latitude-longitude grid at 0.25 ° x 0.25 ° spatial resolution and hourly temporal resolution (Hersbach et al. 2020, 2023). Data was retrieved for the latitude-longitude box with coordinates 51 ° – 54.25 °N and 3.25 ° – 7 °E. The parameters extracted from ERA5 data were $T_a$ at 2 m above surface (°K), SST (°K), and u- and v-wind components at 10 m above surface (ms⁻¹). $\Delta T$ was calculated as SST - $T_a$.

Environmental variables (SST, $T_a$, $\Delta T$, and u- and v- components) were annotated to GPS points and radar tracks according to the nearest neighbour in time and space. SST and $T_a$ were also examined independently of $\Delta T$ in order to investigate how their individual
dynamics influence $\Delta T$, particularly in the context of synoptic weather conditions. To provide insight into the synoptic scale conditions that may lead to positive $\Delta T$, weather charts from the Royal Netherlands Meteorological Institute (Koninklijk Nederlands Meteorologisch Instituut) and time series of environmental variables from ERA5 (SST, $T_a$, wind speed) were examined throughout a specific thermal soaring peak (19th – 23rd July 2020) and are presented in Fig. 3.S.3 and 3.S.4 (Sup. Mat. 5).

**Statistical Analysis**

All analyses were carried out in R (R Core Team 2022). To assess the extent to which the circling time proportion (GPS) and circling track proportion (radar) complemented each other per study area we visualised the data temporally on a daily scale and calculated the Pearson correlation coefficient. To examine whether thermal soaring flight increases the chance of flying within the RSZ, GPS measurements were grouped based on flight mode (thermal soaring or non-thermal soaring) and altitude range (within RSZ altitude range or outside RSZ altitude range). A binomial logistic regression model was then fitted to the GPS data per study area (formula = altitude range ~ flight mode) where “within RSZ” was considered presence and “outside RSZ” absence, with individual as random effect, and evaluated for significant effects of flight mode on altitude range. Thermal soaring occurrence within and outside the wind farm areas was compared by calculating the daily difference between soaring density inside and outside the wind farm (removing days with no observed soaring to prevent zero-inflation of the data) and performing a two-sided T-test (alternate hypothesis = mean is not equal to 0). To test if thermal soaring occurs more with positive $\Delta T$, binomial logistic regression models were fitted to the data per measurement technique (formula = circling proportion ~ $\Delta T$), with year as random factor and weighted (by number of observations per hour for radar data, by total measured flight time per hour for GPS), and with a first order autoregressive covariance structure to account for temporal autocorrelation. To relate thermal soaring occurrence to wind conditions, binomial logistic regression models were fitted to the data per measurement technique (formula = circling proportion ~ wind $u \times$ wind $v$) with year as random factor and weighted (by number of observations per hour for radar data, by total measured flight time per hour for GPS), and with a first order autoregressive covariance structure to account for temporal autocorrelation. The binomial logistic regression models were implemented as glmm using the R-package MASS (Venables and Ripley 2002) and evaluated through the $R^2_{\text{glmm}}$ (Nakagawa et al. 2017) using R-package MuMIn (Burnham and Anderson 2004) which reports the marginal ($mR^2_{\text{glmm}}$) and conditional ($cR^2_{\text{glmm}}$) pseudo-$R^2$. 
3.3 Results

Proportions of circling were generally low, but varied among days, with some time periods having little or no soaring flight and other periods having large peaks that could last more than a day (Fig. 3.2). Some of these peaks occurred at the same time in both regions (e.g., around 08-06-2020 and 20-07-2020). In the west area circling proportions were higher in July than in June for both years. Peaks in circling were less pronounced in the north radar circling track proportions during 2020, compared to other data. Note that in the north areas, no radar data was available during the entire period in 2019 and no GPS data was available in July 2019.

Figure 3.2 Timeline of measured thermal soaring and associated environmental conditions. Daily circling time proportion for lesser black-backed gulls (GPS, red bars) and circling track proportion of all observed birds (radar, blue bars) are shown for the west area in 2019 (A) and 2020 (B) and for the north area in 2019 (C, GPS data only) and 2020 (D). Dark red bars indicate the overlap between circling time and circling ratio. Hourly sea surface temperature (SST, red) and air temperature at 2m ASL ($T_a$, black) from the ERA5 reanalysis grid cell nearest to the respective radar locations are shown as line-graphs above each daily occurrence graph. Days without soaring data available are depicted by an asterisk below the x-axis (red, blue, and black depict missing GPS, radar and both data respectively).
Correlation of circling time proportion and circling track proportion was 0.664 for the west coast data, and 0.153 for the north coast (2020 only), indicating an overlap in thermal soaring behaviour observed in lesser-black backed gulls measured with GPS and all birds measured with radar in the west area but not in the north.

Thermal soaring of lesser black-backed gulls measured with GPS tracking

The median proportion of time spent in flight across all individuals was 0.86 (IQR: 0.79 – 0.90) in the west area and 0.83 (IQR: 0.68 – 0.91) in the north area. The altitude distributions of non-thermal soaring flight and of thermal soaring flight followed a skewed distribution with a tail at greater altitudes (Fig. 3.3). The probability to fly within the RSZ increased during thermal soaring in both areas (binomial logistic regression; size estimate 1.815, p < 0.001, $\text{mR}^2_{\text{glimm}} = 0.024$, $\text{cR}^2_{\text{glimm}} = 0.122$, and 2.850, p < 0.001, $\text{mR}^2_{\text{glimm}} = 0.032$, $\text{cR}^2_{\text{glimm}} = 0.177$ for the west and north area respectively). A summary of measured altitudes in non-thermal-soaring flight and thermal soaring flight, alongside summaries of the proportion of time spent in non-thermal-soaring and thermal soaring flight within the RSZ is reported in Table 3.1.

Table 3.1 Summary of GPS data and key derived metrics relating to altitude and relative time spent in rotor swept zone (RSZ) for thermal soaring and non-thermal-soaring flight. Median values are presented with interquartile ranges (IQR) in brackets. Values relating to the proportion of time within the RSZ are presented with confidence bounds accounting for the GPS altitude accuracy in brackets.

<table>
<thead>
<tr>
<th></th>
<th>West</th>
<th>North</th>
</tr>
</thead>
<tbody>
<tr>
<td>GPS measurements (#)</td>
<td>367668</td>
<td>256954</td>
</tr>
<tr>
<td>Individuals (#)</td>
<td>18</td>
<td>12</td>
</tr>
<tr>
<td>Hours of data (#)</td>
<td>511</td>
<td>311</td>
</tr>
<tr>
<td>Covered days (#)</td>
<td>115</td>
<td>82</td>
</tr>
<tr>
<td>Median altitude (m)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(non-thermal-soaring flight)</td>
<td>22.4 (IQR: 11.4 – 33.4)</td>
<td>12.4 (IQR: 2.4 - 26.4)</td>
</tr>
<tr>
<td>Median altitude (m)</td>
<td>82.4 (IQR: 56.4 – 124.4)</td>
<td>70.37 (IQR: 45.4 – 112.4)</td>
</tr>
<tr>
<td>Proportion of all flight time within RSZ</td>
<td>0.44 (0.37 – 0.52)</td>
<td>0.28 (0.24 – 0.33)</td>
</tr>
<tr>
<td>Proportion of non-thermal-soaring flight time in RSZ</td>
<td>0.36 (0.30 -0.43)</td>
<td>0.20(0.17 – 0.23)</td>
</tr>
<tr>
<td>Proportion of thermal soaring flight time in RSZ</td>
<td>0.80 (0.79 – 0.81)</td>
<td>0.78 (0.76 – 0.80)</td>
</tr>
<tr>
<td>Proportion of total flight time defined as thermal soaring</td>
<td>0.034</td>
<td>0.022</td>
</tr>
<tr>
<td>Proportion of total flight time in RSZ defined as thermal soaring</td>
<td>0.062(0.054 – 0.072)</td>
<td>0.061 (0.054 – 0.071)</td>
</tr>
</tbody>
</table>
Thermal soaring over the North Sea and implications for wind farm interactions

Figure 3.3 Altitude distribution of (A, C) non-thermal soaring flight (all flight excluding thermal soaring bouts) and (B, D) thermal soaring flight for lesser black-backed gulls tracked in the (A, B) west and (C, D) north study areas across 2019 and 2020. Red dashed lines indicate typical minimum and maximum rotor swept zone (RSZ) heights of turbines in the study area. Note that the range of the x-axes differs between non-thermal soaring flight (0 – 200000 s) and thermal soaring flight (0 – 2500 s).

Thermal soaring measured through radar tracking

Observed circling density did not differ significantly between inside and outside the wind farm for the west area in both years (one sample two-sided t-test; 2019: n = 52, p = 0.876; 2020: n = 44, p = 0.714). In the north area circling density was different between inside and outside the wind farm (one sample two-sided t-test; n = 20, p = 0.022) with a mean difference below 0 (-0.768) indicating decreased thermal soaring inside the wind farm. Visualizations of circling densities show a patchy distribution in both areas (Fig. 3.4). In the west area the highest circling density was observed closer to the radar and between the turbines, and lowest around the turbine locations and the edges of the sampling area. In the north area the distribution was somewhat fragmented due to the smaller data set, nonetheless circling was found throughout the area, including the small section outside the wind farm. A summary of radar tracking data and observed circling count and density is reported in Table 3.2.
Figure 3.4 Spatial distribution of circling density for the west (A) and north (B) radar area (100 × 100 m cells). Density (light- to dark blue) scales differently per area to increase visual clarity, cells without observed circling are transparent. The west area shows the averaged density distribution for 2019 and 2020, the north area shows the distribution for 2020. The radar sampling area is outlined in black, with the turbine locations as black dots and the radar location as purple square. The wind farm area is outlined in red.

Table 3.2 Summary of radar tracking data and an overview of circling track count and density (tracks km⁻²) identified for the west and north study areas. Tracks with circling identified both inside and outside the wind farm were counted for both categories (inside and outside).

<table>
<thead>
<tr>
<th></th>
<th>West 2019</th>
<th>West 2020</th>
<th>North 2020</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tracks (#)</td>
<td>1209312</td>
<td>1170044</td>
<td>413208</td>
</tr>
<tr>
<td>Hours of data (#)</td>
<td>1166</td>
<td>1099</td>
<td>866</td>
</tr>
<tr>
<td>Covered days (#)</td>
<td>57</td>
<td>56</td>
<td>49</td>
</tr>
<tr>
<td></td>
<td>Inside</td>
<td>Outside</td>
<td>Inside</td>
</tr>
<tr>
<td>Circling tracks (#)</td>
<td>1291</td>
<td>1714</td>
<td>3488</td>
</tr>
<tr>
<td>Surface area (km²)</td>
<td>4.7</td>
<td>6.1</td>
<td>4.7</td>
</tr>
<tr>
<td>Circling density (# km⁻²)</td>
<td>274</td>
<td>279</td>
<td>740</td>
</tr>
</tbody>
</table>
Thermal soaring and environmental conditions

SST increased slightly throughout the season (Fig. 3.2), whilst $T_a$ fluctuated more throughout the season in response to diurnal variation and synoptic weather patterns (Sup. Mat. A.5). Peaks in circling proportion typically occurred during periods when SST temperature was higher than $T_a$ ($\Delta T$ positive), especially for periods longer than one day (Fig. 3.2A – B). One such period can be seen following 8 June 2020, where a peak in soaring is observable in the west area (Fig. 3.2B) as well as the north area for GPS tracked gulls (red bars, Fig. 3.2D). These peaks align with a period during which $T_a$ has dropped below SST for approximately 3 days. Similar alignments of thermal soaring peaks with positive $\Delta T$ are also noticeable in July 2020, with a particularly large peak observable in west area based on GPS tracking and radar monitoring and north area based on GPS around 20 July. This peak is due the passage of a cold front followed by a trough over the North Sea resulting in $T_a$ dropping and remaining below SST for several days (Sup. Mat. 5, Fig. 3.5.3 and 3.5.4, Video 3.5.1).

The relation between circling proportion and environmental conditions was consistent across the GPS data and west radar data (Fig. 3.5, Table 3.3). $\Delta T$ had a significant positive effect on circling proportion (binomial logistic regression; west GPS: size estimate = 0.841, $p < 0.001$, $mR^2_{glimm} = 0.483$, $cR^2_{glimm} = 0.494$, north GPS: size estimate = 0.819, $p = 0.006$, $mR^2_{glimm} = 0.403$, $cR^2_{glimm} = 0.403$, west radar: size estimate = 0.557, $p < 0.001$, $mR^2_{glimm} = 0.207$, $cR^2_{glimm} = 0.236$), showing thermal soaring increases with increasing $\Delta T$. Wind $v$-components had a negative effect on circling proportion (binomial logistic regression; west GPS: size estimate = -0.272, $p < 0.001$, $mR^2_{glimm} = 0.255$, $cR^2_{glimm} = 0.275$, north GPS: size estimate = -0.174, $p = 0.001$, $mR^2_{glimm} = 0.170$, $cR^2_{glimm} = 0.181$, west radar: size estimate = -0.088, $p = 0.001$, $mR^2_{glimm} = 0.038$, $cR^2_{glimm} = 0.092$), indicating thermal soaring increases with northerly winds. Additionally, wind $u$-component had a positive effect on circling proportion for the west area (binomial logistic regression; GPS: size estimate = 0.111, $p = 0.004$, radar: size estimate of 0.046, $p = 0.025$), indicating thermal soaring increases with westerly winds as well.
Figure 3.5 Overview of hourly circling track proportion (radar; west = 2265 hours, north = 866 hours) and circling time proportion (GPS; west = 938 hours, north = 586 hours) and the local temperature difference between sea surface and air at 2 m ASL (ΔT) in the same hour. The vertical line highlights the divide between negative and positive ΔT.
Figure 3.6 Average hourly circling track proportion for radar (rCTP) and circling time proportion for GPS (gCTP) binned according to local u- and v-wind component at 10 m ASL (black dots), superimposed on the associated mean ΔT for the same binned wind conditions (coloured tiles). Wind components describe where the winds blow towards, e.g., a positive u and negative v component translates to north-westerly winds. Average circling proportion (Avg. CP) and average temperature difference between sea surface and air at 2 m ASL (Avg. ΔT) per wind quadrant is displayed in the outer corners.
On average, circling proportion and $\Delta T$ were highest with positive $u$- and negative $v$-wind components, corresponding to north-westerly winds (Fig. 3.6A – C). Although the first order autoregressive covariance structure reduced temporal autocorrelation in the residuals of the models, it could not be completely removed for the west radar (Sup. Mat. 6), and more complex covariance structures provided no improvement. For the north area, no significant effects were found on hourly circling track proportion measured by radar.

**Table 3.3** Overview of the logistic regression model parameters for the hourly circling time proportion and hourly circling track proportion measured by GPS and radar respectively. For each model, estimate and corresponding p-value of model parameters is reported. Models were evaluated with the marginal and conditional $R^2_{\text{glm}}$.

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Estimate</th>
<th>p-value</th>
<th>Marginal $R^2_{\text{glm}}$</th>
<th>Conditional $R^2_{\text{glm}}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>West radar (n = 2265)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intercept</td>
<td>-6.012</td>
<td>&lt;0.001</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Temp. difference</td>
<td>0.557</td>
<td>&lt;0.001</td>
<td>0.207</td>
<td>0.236</td>
</tr>
<tr>
<td>West GPS (n = 938)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intercept</td>
<td>-4.956</td>
<td>&lt;0.001</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Temp. difference</td>
<td>0.841</td>
<td>&lt;0.001</td>
<td>0.483</td>
<td>0.494</td>
</tr>
<tr>
<td>North radar (n = 866)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intercept</td>
<td>-6.625</td>
<td>&lt;0.001</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Temp. difference</td>
<td>0.112</td>
<td>0.127</td>
<td>0.006</td>
<td>0.006</td>
</tr>
<tr>
<td>West radar (n = 2265)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intercept</td>
<td>-5.713</td>
<td>&lt;0.001</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wind u-comp.</td>
<td>0.046</td>
<td>0.022</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wind v-comp.</td>
<td>-0.088</td>
<td>&lt;0.001</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wind $u \times$ wind $v$-comp.</td>
<td>-0.002</td>
<td>0.746</td>
<td></td>
<td></td>
</tr>
<tr>
<td>West GPS (n = 938)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intercept</td>
<td>-4.657</td>
<td>&lt;0.001</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wind u-comp.</td>
<td>0.111</td>
<td>0.004</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wind v-comp.</td>
<td>-0.272</td>
<td>&lt;0.001</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wind $u \times$ wind $v$-comp.</td>
<td>0.004</td>
<td>0.685</td>
<td></td>
<td></td>
</tr>
<tr>
<td>North radar (n = 866)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intercept</td>
<td>-6.561</td>
<td>&lt;0.001</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wind u-comp.</td>
<td>0.022</td>
<td>0.310</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wind v-comp.</td>
<td>0.049</td>
<td>0.059</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wind $u \times$ wind $v$-comp.</td>
<td>-0.011</td>
<td>0.197</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
### 3.4 Discussion

This study shows that thermal soaring occurs over the North Sea, as measured by GPS tracking and radar in two areas during June and July. Flight altitudes were higher in lesser black-backed gulls during thermal soaring, resulting in a higher proportion of flight time spent within the RSZ, and thermal soaring occurred inside wind farms to a similar extent as outside. Together these results indicate thermal soaring behaviour increases collision risk with offshore wind farms. Thermal soaring is uncommon relative to the total amount of flight observed, but the propensity for birds to use thermal soaring varies between days and high peaks in thermal soaring were observed. The correlations between thermal soaring and ΔT and wind components indicate northerly and north-westerly winds bring in cold air from higher latitudes which increases ΔT and create opportunities for thermal soaring at sea. This information can be used to predict increased thermal soaring occurrence which affects collision risk.

Flight altitudes measured in this study agree with previous expectations of gull flight altitude at sea in lesser black-backed gulls (Corman and Garthe 2014; Ross-Smith et al. 2016; Thaxter et al. 2018) and with rates of flight occurring within the RSZ (Ross-Smith et al. 2016). Lesser black-backed gulls using thermal soaring on land at similar latitudes reach much higher altitudes (Sage et al. 2022), which reflects the expected greater strength of thermal uplift on land. Herring gulls have been observed thermal soaring over sea from 45 m above sea level to altitudes greater than 620 m (Woodcock 1940b; Haney and Lee 1994) and whilst altitudes this high were not observed in our study, they did regularly exceed 100 m and even occasionally 300 m. Considering the lower range of ΔT observed on the North Sea compared to the ΔT range studied by Woodcock (1940b), this is not surprising as higher ΔT leads to increased uplift (Nourani et al. 2021) and the vertical extent of thermal

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Estimate</th>
<th>p-value</th>
<th>Marginal $R^2_{\text{glimm}}$</th>
<th>Conditional $R^2_{\text{glimm}}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>North GPS (n = 586)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intercept</td>
<td>-5.438</td>
<td>&lt;0.001</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Temp. difference</td>
<td>0.819</td>
<td>&lt;0.001</td>
<td>0.403</td>
<td>0.403</td>
</tr>
<tr>
<td>Wind u-comp.</td>
<td>-4.524</td>
<td>&lt;0.001</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wind v-comp.</td>
<td>0.0195</td>
<td>0.581</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wind u- x wind v-comp.</td>
<td>-0.174</td>
<td>&lt;0.001</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>-0.021</td>
<td>0.054</td>
<td>0.170</td>
<td>0.181</td>
</tr>
</tbody>
</table>
soaring typically increases with thermal strength and boundary layer depth (Shannon et al. 2002; Shamoun-Baranes et al. 2003).

Studies into the airflow structure within wind farms show the amount of turbulence instigated by wind farms (depending, e.g., on wind speed, turbine properties and turbine array layout) can be non-trivial (Stevens and Meneveau 2017), affecting the atmospheric boundary layer and probably thermal uplift. Additionally, soaring birds may adjust their flight behaviour or propensity to use thermals in response to the presence of turbines as they present obstacles. We found no difference in the probability of thermal soaring within and outside the wind farm in the west, whereas less thermal soaring was detected within the wind farm in the north. However, we note that the mean difference found in the north area was less than 1 bird per square kilometre, and the p-value passes only the most lenient test of significance (p < 0.05). Based on these results it seems that seabirds are not significantly deterred from thermal soaring within wind farms, and we show that thermal uplift within both wind farms was sufficient to soaring flight. Although it is clear thermal soaring occurs within wind farms further research is required to uncover the mechanisms and interactions between thermal uplift and thermal soaring within wind farms.

Circling time proportion of lesser black-backed gulls in both study areas and circling track proportion in the radar data of the west area were positively correlated with \( \Delta T \) and mainly occurred when \( \Delta T \) was positive. This is consistent with previous findings in gulls at sea (Woodcock 1940b, 1975; Agee and Sheu 1978; Haney and Lee 1994) as well as for migrating raptors and storks observed soaring over sea (Becciu et al. 2020; Nourani et al. 2021). Despite being a temperate sea, positive \( \Delta T \) conducive to thermal soaring occurred regularly in summer on the southern North Sea, driven by fluctuations in \( T_a \). Most winds (from west, south, and east) carry in warm air from the surrounding land masses (Coelingh et al. 1998), but north-westerly winds carry in cold air from higher latitudes, which increases \( \Delta T \) and creates conditions suitable for thermal soaring. This is confirmed in our results, where thermal soaring probability was highest with northerly and north-westerly winds. The temporal variation of thermal soaring in relation to synoptic conditions demonstrates the important links between synoptic weather patterns and fine-scale flight behaviour. For example, the peaks in thermal soaring activity observed between 20-07-2020 – 22-07-2020 (Fig. 3.2) were most likely caused by a cold front passing over the Dutch coast. A trough of low atmospheric pressure followed, bringing in cold air from the north (Sup. Mat. 5) which decreased \( T_a \) and ultimately created favourable conditions for thermal soaring.

Our hypothesis that thermal soaring occurs with positive \( \Delta T \) was confirmed by the GPS tracking data and the radar data from the west area; however, the north area radar observed very low thermal soaring occurrence and no significant effect of environmental
variables was found. We think limitations of data sampling at the north radar are the main cause for the lack of correlation between $\Delta T$ and thermal soaring, rather than a difference in the environmental and behavioural drivers of thermal soaring in the north area. While the west area radar is situated only 24 km from the mainland, the north area radar is situated 60 km from the nearest land area (Schiermonnikoog). Lesser black-backed gulls rarely travel that far out to sea (Sage 2022), which is also reflected in the low correlation we found between the north GPS and radar data. Additionally, the increased distance from shore means sea state is higher and increased filtering is required to remove clutter from the radar data, which further results in lower track counts. Finally, there are limits to the accuracy of environmental data such as SST which are sensitive to the coupling of the surface and atmosphere (Hristov et al. 2003) and to the influence of land mass in coastal regions (Yao et al. 2021), neither of which are fully accounted for in large reanalysis datasets such as ERA5. Several mismatches where a high circling proportion is measured at relatively low $\Delta T$ were observed in the north radar, which is unexpected and could indicate a mismatch between modelled $\Delta T$ and local conditions.

As lesser black-backed gulls are the predominant species in both study areas we attribute most thermal soaring observed by radar to them. Herring gulls are also regularly observed in the west area and known to use thermal soaring over sea (Woodcock 1940a) and over land (Sage et al. 2022). Other species observed in the study areas, such as great cormorant *Phalacrocorax carbo* (west area) and black legged kittiwake *Rissa tridactyla* (north area) are not established in the literature to use thermal soaring, although they may have the capacity to do so (Rayner 1988). Discrepancies between circling proportions in GPS and radar on the same day might indicate presence of other species capable of thermal soaring. Other factors influencing thermal soaring occurrence can be the daily fluctuation in bird abundance at sea (Chapter 2) and behavioural factors not accounted for in this study.

The energy saving benefits of thermal soaring may be more important for gulls during commuting flight or when searching for aggregations of birds or boats which may signal distant foraging opportunities (Camphuysen 1995), than when foraging on natural prey at the sea surface. Changes in flight motivation may explain why there are many hours with positive $\Delta T$ but a low proportion of circling tracks. Future studies of thermal soaring at sea should therefore also seek to incorporate different at-sea behaviours. By integrating knowledge on environmental drivers and intrinsic motivation over multiple seasons it will become more feasible to predict peaks in thermal soaring and assess the conservation implications, such as the potential influence on collision risk.

Thermal soaring is an important behaviour to study when assessing bird-wind farm interactions. Models of thermal uplift have been used to inform onshore turbine siting decisions on land (Hanssen et al. 2020) and may at some point be appropriate to apply at
sea as more knowledge is gathered regarding the spatio-temporal dynamics of thermal soaring offshore. Overall, occurrence of thermal soaring is low relative to total bird flight in our study area in summer. However, we show that specific weather conditions can result in days in which thermal soaring occurrence increases by up to ten times and flight altitudes increasingly overlap with the RSZ. On 20-07-2020, a peak thermal soaring day, the overall proportion of flight within the RSZ increased to around double the values presented in Table 3.1 in both north and west areas. Such an increase in flight in the RSZ results in an increased collision risk as estimated by prominent models (Band 2012). The results in this study indicate peak thermal soaring days can be predicted based on the weather forecast of the region. The increase in thermal soaring proportion and the attributed increase in flight in the RSZ can feed into these models and quantify the increase in collision risk on peak thermal soaring days. Further research should explore the propensity for thermal soaring in a broader range of environments and at different times of the year. Our results indicate thermal soaring at sea occurs rarely, but should environments and periods be identified in which time spent in the RSZ is consistently high as a result of supporting thermal soaring conditions, then marine spatial planning for the region should take this into account.

Combining different information sources to gain a deeper understanding of intricate behavioural patterns and their drivers has been advocated previously (Bauer et al. 2019). There are further strengths of both biologging and radar that have not been utilised in this study but could be incorporated into future research. For example, this study only focuses on a two-month long summer period, but radar can be used to identify changes in thermal soaring within wind farms throughout the annual cycle, as previous studies indicate thermal soaring support can be high in autumn and winter as well (Woodcock 1940b; Haney and Lee 1994). Meanwhile, GPS can be used to examine how individuals incorporate thermal soaring into their daily movement and energy budgets to better understand the ecological impact of thermal soaring. Processing different information sources requires additional expertise and time. Additionally, finding mutual connections by which diverse data sources can be combined (spatially or temporally) is rarely straightforward. However, by combining the strengths of each measurement technique in a novel approach we can gain more insight into animal behaviour at a wider spatiotemporal scale, as in this study we gain a better understanding of thermal soaring in remote marine areas and its implication for collision risk than we could have gained through each individual technique.
Acknowledgements

We would like to thank Kees Oosterbeek and the IJmuiden team (Fred Cottaar, Jose Verbeek, Maarten van Kleinwee) for their support on the GPS tagging and tracking measurements at Schiermonnikoog and IJmuiden. We thank PBN and Natuurmonumenten for permission to access the colonies on IJmuiden and Schiermonnikoog, respectively. We thank Rijkswaterstaat (Zee & Delta and Centrale Informatievoorziening) and Gemini wind park for providing the radar data and Robin Radar for providing details on the radar system. The ESAS 5.0 database was queried as a database contributor (C.J. Camphuysen). Special thanks to Johannes de Groeve, Berend Wijers, and Bart Kranstauber for computational help throughout radar data processing, and to Leonardo Porcacchia for supporting the processing and interpretation of meteorological data. Radar and GPS data analyses were carried out on the Dutch national e-infrastructure with the support of SURF Cooperative.
3.5 Supplementary materials

Supplementary material 1: Species distribution in study area

The ESAS 5.0 (European Seabirds at Sea) database is a ship survey database (Reid and Camphuysen 1998) that incorporates all observational data made through a standardized protocol (Camphuysen et al. 2004) and is maintained by the NWO-NIOZ Royal Netherlands Institute for Sea Research. The database was queried on 4 January 2022 for all bird species observed in flight in the months of June and July in the area near Luchterduinen radar (Table 3.S.1) and Gemini radar (Table 3.S.2). For Luchterduinen, data was sampled between 52.15 – 52.65 °N, 3.5 – 4.5 °E, which describes a rectangular area around the radar (52.427827 °N, 4.185345 °E). For Gemini, data was sampled between 53.75 – 54.25 °N, 5 – 7 °E, which describes a rectangular area around the radar (54.036983 °N, 6.041655 °E). For readability, all species with an observation rate below 0.1 % have been omitted from the table. Luchterduinen has 1607 km² surveyed (5354 km steamed on effort), with data collected between 1987 and 2012. Gemini has 657 km² surveyed (2237 km steamed on effort), with data originating from the same period.

Table 3.S.1 Number of birds observed in flight and percentage of total per species in the months of June and July from 1987 – 2012 in the area near wind farm Luchterduinen between 52.15 – 52.65 °N, 3.5 – 4.5 °E. Data was queried on 4 January 2022. For readability, all species with an observation rate below 0.1 % have been omitted.

<table>
<thead>
<tr>
<th>Species ID</th>
<th>Species name</th>
<th>Scientific name</th>
<th>Birds (#)</th>
<th>Percentage of total (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>5910</td>
<td>Lesser black-backed gull</td>
<td><em>Larus fuscus</em></td>
<td>10818</td>
<td>65</td>
</tr>
<tr>
<td>720</td>
<td>Great cormorant</td>
<td><em>Phalacrocorax carbo</em></td>
<td>1551</td>
<td>9.4</td>
</tr>
<tr>
<td>5920</td>
<td>Herring gull</td>
<td><em>Larus argentatus</em></td>
<td>1297</td>
<td>7.9</td>
</tr>
<tr>
<td>5919</td>
<td>Herring gull / Lesser black-backed gull</td>
<td><em>Larus argentatus / Larus fuscus</em></td>
<td>901</td>
<td>5.5</td>
</tr>
<tr>
<td>6005</td>
<td>Large gull</td>
<td><em>Larus spec.</em></td>
<td>369</td>
<td>2.2</td>
</tr>
<tr>
<td>2130</td>
<td>Black scoter</td>
<td><em>Melanitta nigra</em></td>
<td>270</td>
<td>1.6</td>
</tr>
<tr>
<td>220</td>
<td>Northern fulmar</td>
<td><em>Fulmarus glacialis</em></td>
<td>228</td>
<td>1.4</td>
</tr>
<tr>
<td>710</td>
<td>Northern gannet</td>
<td><em>Sula bassana</em></td>
<td>170</td>
<td>1.0</td>
</tr>
<tr>
<td>6020</td>
<td>Black-legged kittiwake</td>
<td><em>Rissa tridactyla</em></td>
<td>170</td>
<td>1.0</td>
</tr>
<tr>
<td>6000</td>
<td>Great black-backed gull</td>
<td><em>Larus marinus</em></td>
<td>133</td>
<td>0.8</td>
</tr>
<tr>
<td>5820</td>
<td>Black-headed gull</td>
<td><em>Larus ridibundus</em></td>
<td>116</td>
<td>0.7</td>
</tr>
<tr>
<td>6110</td>
<td>Sandwich tern</td>
<td><em>Sterna sandvicensis</em></td>
<td>112</td>
<td>0.7</td>
</tr>
<tr>
<td>5900</td>
<td>Common gull</td>
<td><em>Larus canus</em></td>
<td>88</td>
<td>0.5</td>
</tr>
<tr>
<td>7950</td>
<td>Common swift</td>
<td><em>Apus apus</em></td>
<td>55</td>
<td>0.3</td>
</tr>
<tr>
<td>15820</td>
<td>Common starling</td>
<td><em>Sturnus vulgaris</em></td>
<td>49</td>
<td>0.3</td>
</tr>
<tr>
<td>6150</td>
<td>Common tern</td>
<td><em>Sterna hirundo</em></td>
<td>35</td>
<td>0.2</td>
</tr>
</tbody>
</table>
### Table 3.5.2

Number of birds observed in flight and percentage of total per species in the months of June and July from 1987 – 2012 in the area near Gemini wind park between 53.75 – 54.25 °N, 5 – 7 °E. Data was queried on 04 January 2022. For readability, all species with an observation rate below 0.1 % have been omitted.

<table>
<thead>
<tr>
<th>Species ID</th>
<th>Species name</th>
<th>Scientific name</th>
<th>Birds (#)</th>
<th>Percentage of total (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>5910</td>
<td>Lesser black-backed gull</td>
<td>Larus fuscus</td>
<td>1426</td>
<td>76.7</td>
</tr>
<tr>
<td>6020</td>
<td>Black-legged kittiwake</td>
<td>Rissa tridactyla</td>
<td>157</td>
<td>8.4</td>
</tr>
<tr>
<td>710</td>
<td>Northern gannet</td>
<td>Sula bassana</td>
<td>77</td>
<td>4.1</td>
</tr>
<tr>
<td>220</td>
<td>Northern fulmar</td>
<td>Fulmarus glacialis</td>
<td>47</td>
<td>2.5</td>
</tr>
<tr>
<td>2130</td>
<td>Black scoter</td>
<td>Melanitta nigra</td>
<td>37</td>
<td>2.0</td>
</tr>
<tr>
<td>6160</td>
<td>Arctic tern</td>
<td>Sterna paradisaea</td>
<td>19</td>
<td>1.0</td>
</tr>
<tr>
<td>7950</td>
<td>Common swift</td>
<td>Apus apus</td>
<td>19</td>
<td>1.0</td>
</tr>
<tr>
<td>6340</td>
<td>Common guillemot</td>
<td>Uria aalge</td>
<td>15</td>
<td>0.8</td>
</tr>
<tr>
<td>5820</td>
<td>Black-headed gull</td>
<td>Larus ridibundus</td>
<td>12</td>
<td>0.6</td>
</tr>
<tr>
<td>6110</td>
<td>Sandwich tern</td>
<td>Sterna sandvicensis</td>
<td>9</td>
<td>0.5</td>
</tr>
<tr>
<td>5690</td>
<td>Great skua</td>
<td>Stercorarius skua</td>
<td>7</td>
<td>0.4</td>
</tr>
<tr>
<td>5900</td>
<td>Common gull</td>
<td>Larus canus</td>
<td>5</td>
<td>0.3</td>
</tr>
<tr>
<td>5920</td>
<td>Herring gull</td>
<td>Larus argentatus</td>
<td>5</td>
<td>0.3</td>
</tr>
<tr>
<td>6000</td>
<td>Great black-backed gull</td>
<td>Larus marinus</td>
<td>5</td>
<td>0.3</td>
</tr>
<tr>
<td>15820</td>
<td>Common starling</td>
<td>Sturnus vulgaris</td>
<td>3</td>
<td>0.2</td>
</tr>
<tr>
<td>5610</td>
<td>Ruddy turnstone</td>
<td>Arenaria interpres</td>
<td>2</td>
<td>0.1</td>
</tr>
<tr>
<td>5670</td>
<td>Arctic skua</td>
<td>Stercorarius parasiticus</td>
<td>2</td>
<td>0.1</td>
</tr>
<tr>
<td>460</td>
<td>Manx shearwater</td>
<td>Puffinus puffinus</td>
<td>1</td>
<td>0.1</td>
</tr>
<tr>
<td>720</td>
<td>Great cormorant</td>
<td>Phalacrocorax carbo</td>
<td>1</td>
<td>0.1</td>
</tr>
<tr>
<td>1220</td>
<td>Grey heron</td>
<td>Ardea cinerea</td>
<td>1</td>
<td>0.1</td>
</tr>
</tbody>
</table>
Supplementary material 2; Overview of UvA-BiTS logger data per individual per year

Table 3.5.3 Summary table of data collected for each tagged lesser black-backed gull per year. The same individual number over a different year indicates a returned individual. Total time indicates the sum of all time intervals for the recorded GPS measurements.

<table>
<thead>
<tr>
<th>Colony</th>
<th>Individual</th>
<th>Year</th>
<th>GPS measurements (#)</th>
<th>Total time (h)</th>
</tr>
</thead>
<tbody>
<tr>
<td>IJmuiden</td>
<td>5963</td>
<td>2019</td>
<td>16024</td>
<td>22.33</td>
</tr>
<tr>
<td>IJmuiden</td>
<td>5962</td>
<td>2019</td>
<td>24696</td>
<td>34.36</td>
</tr>
<tr>
<td>IJmuiden</td>
<td>5861</td>
<td>2019</td>
<td>28130</td>
<td>39.27</td>
</tr>
<tr>
<td>IJmuiden</td>
<td>5584</td>
<td>2019</td>
<td>16264</td>
<td>22.62</td>
</tr>
<tr>
<td>IJmuiden</td>
<td>5579</td>
<td>2019</td>
<td>45615</td>
<td>63.47</td>
</tr>
<tr>
<td>IJmuiden</td>
<td>5565</td>
<td>2019</td>
<td>15698</td>
<td>21.86</td>
</tr>
<tr>
<td>IJmuiden</td>
<td>5491</td>
<td>2019</td>
<td>25792</td>
<td>35.86</td>
</tr>
<tr>
<td>IJmuiden</td>
<td>5441</td>
<td>2019</td>
<td>39738</td>
<td>55.28</td>
</tr>
<tr>
<td>IJmuiden</td>
<td>5433</td>
<td>2019</td>
<td>20796</td>
<td>28.98</td>
</tr>
<tr>
<td>IJmuiden</td>
<td>5369</td>
<td>2019</td>
<td>24938</td>
<td>34.68</td>
</tr>
<tr>
<td>Schiermonnikoog</td>
<td>5709</td>
<td>2019</td>
<td>1063</td>
<td>1.8</td>
</tr>
<tr>
<td>Schiermonnikoog</td>
<td>5561</td>
<td>2019</td>
<td>1731</td>
<td>2.26</td>
</tr>
<tr>
<td>Schiermonnikoog</td>
<td>5560</td>
<td>2019</td>
<td>3059</td>
<td>4.06</td>
</tr>
<tr>
<td>Schiermonnikoog</td>
<td>5555</td>
<td>2019</td>
<td>3155</td>
<td>3.9</td>
</tr>
<tr>
<td>Schiermonnikoog</td>
<td>5554</td>
<td>2019</td>
<td>5866</td>
<td>7.4</td>
</tr>
<tr>
<td>Schiermonnikoog</td>
<td>5532</td>
<td>2019</td>
<td>26745</td>
<td>33.98</td>
</tr>
<tr>
<td>Schiermonnikoog</td>
<td>5525</td>
<td>2019</td>
<td>25368</td>
<td>30.97</td>
</tr>
<tr>
<td>Schiermonnikoog</td>
<td>5524</td>
<td>2019</td>
<td>16583</td>
<td>20.62</td>
</tr>
<tr>
<td>IJmuiden</td>
<td>5983</td>
<td>2020</td>
<td>19152</td>
<td>26.65</td>
</tr>
<tr>
<td>IJmuiden</td>
<td>5979</td>
<td>2020</td>
<td>4693</td>
<td>6.53</td>
</tr>
<tr>
<td>IJmuiden</td>
<td>5977</td>
<td>2020</td>
<td>10561</td>
<td>14.72</td>
</tr>
<tr>
<td>IJmuiden</td>
<td>5971</td>
<td>2020</td>
<td>4655</td>
<td>6.47</td>
</tr>
<tr>
<td>IJmuiden</td>
<td>5967</td>
<td>2020</td>
<td>2048</td>
<td>2.85</td>
</tr>
<tr>
<td>IJmuiden</td>
<td>5964</td>
<td>2020</td>
<td>2010</td>
<td>2.8</td>
</tr>
<tr>
<td>IJmuiden</td>
<td>5861</td>
<td>2020</td>
<td>1216</td>
<td>1.69</td>
</tr>
<tr>
<td>IJmuiden</td>
<td>5579</td>
<td>2020</td>
<td>34928</td>
<td>48.6</td>
</tr>
<tr>
<td>IJmuiden</td>
<td>5576</td>
<td>2020</td>
<td>10671</td>
<td>14.89</td>
</tr>
<tr>
<td>IJmuiden</td>
<td>5557</td>
<td>2020</td>
<td>20043</td>
<td>27.88</td>
</tr>
<tr>
<td>Schiermonnikoog</td>
<td>5780</td>
<td>2020</td>
<td>11143</td>
<td>18.91</td>
</tr>
<tr>
<td>Schiermonnikoog</td>
<td>5709</td>
<td>2020</td>
<td>2016</td>
<td>3.41</td>
</tr>
<tr>
<td>Schiermonnikoog</td>
<td>5560</td>
<td>2020</td>
<td>16624</td>
<td>19</td>
</tr>
<tr>
<td>Schiermonnikoog</td>
<td>5554</td>
<td>2020</td>
<td>41071</td>
<td>47.02</td>
</tr>
<tr>
<td>Schiermonnikoog</td>
<td>5533</td>
<td>2020</td>
<td>11765</td>
<td>13.57</td>
</tr>
<tr>
<td>Colony</td>
<td>Individual</td>
<td>Year</td>
<td>GPS measurements (#)</td>
<td>Total time (h)</td>
</tr>
<tr>
<td>-------------</td>
<td>------------</td>
<td>------</td>
<td>----------------------</td>
<td>----------------</td>
</tr>
<tr>
<td>Schiermonnikoog</td>
<td>5532</td>
<td>2020</td>
<td>72671</td>
<td>83.45</td>
</tr>
<tr>
<td>Schiermonnikoog</td>
<td>5527</td>
<td>2020</td>
<td>7814</td>
<td>9.16</td>
</tr>
<tr>
<td>Schiermonnikoog</td>
<td>5526</td>
<td>2020</td>
<td>228</td>
<td>0.26</td>
</tr>
<tr>
<td>Schiermonnikoog</td>
<td>5524</td>
<td>2020</td>
<td>10052</td>
<td>11.62</td>
</tr>
</tbody>
</table>
Supplementary material 3; Robin Radar 3D-Fix detection probability at different range and heights

Fig. 3.S.1 shows the range and altitude from the radar at which the probability of detection for an object of 1 standard avian target (SAT, Fig. 3.S.1A) and 0.125 SAT (Fig. 3.S.1B) by the horizontal S-band antenna of the Robin Radar 3D-Fix system is > 80 %. A SAT is a theoretical object used as a standard for evaluating the performance of avian radar systems and approximates the physical features of a carrion crow *Corvus corone* with a radar cross section (RCS) of -16 dB m$^2$ and a mass of 500 g. A 0.125 SAT object correlates to an RCS of -25 dB m$^2$ and a mass of 62.5 g, the size of a song thrush *Turdus philomelos*.

**Figure 3.5.1** Probability of detection by the horizontal S-band antenna of the Robin Radar 3D-Fix at different ground range and altitude from the radar position (0,0 on the axes). A: The area shows the range/altitude combinations at which the probability of detection > 80 %. Probability of detecting a target of size 1 SAT. B: Probability of detecting a target of size 0.125 SAT. Colour scale shows theoretical detection probability ranging from 100 % (purple) to 80 % (blue). Figures provided by Robin Radar.
Supplementary material 4; Accounting for detection bias caused by dynamic radar filtering

The dynamic filter activity in each radar image directly affected detection probability of birds by increasing the threshold at which objects are detected. The filter is always active, ranging from 0 (no filtering) to 1 (complete filtering). The number of bird observations per hour is negatively related to the filter activity (black dots, Fig. 3.S.2) and could affect the outcome of modelling efforts through inclusion of unreliable observation hours. Firstly, the estimated effect of the hourly averaged dynamic filtering on bird observations was modelled through Generalized Additive Modelling (GAM). Hourly bird count was used as the dependent variable, with hourly average filter activity as predictor (thin plate regression spline smoother, k = 5 to prevent overfitting), and assuming a Gaussian distribution of the model error. The estimated effect showed a decrease in bird count around filter activity = 0.1 (blue line, Fig. 3.S.2), which levelled out around filter activity = 0.35. The filter activity at which this levelling out process starts was taken as the threshold above which hourly bird counts were considered highly affected. This value was found by calculating the second derivative over the estimated effect (red line, Fig. 3.S.2) and finding the filter activity at the maximum of the curve (red dashed line, Fig. 3.S.2). This threshold was 0.327 for Luchterduinen radar and 0.311 for Gemini radar; observation hours in which the average filter activity was higher than the threshold were excluded from further analysis.

Figure 3.S.2 The relation between hourly bird counts and radar filter activity in Luchterduinen radar. Hourly bird counts (left y-axis) at different filter activities (x-axis). Black dots depict all observation hours available. The blue line shows the estimated effect of average hourly filter activity on hourly bird counts (GAM). The red line shows the second derivative of this estimated effect (right y-axis), with the dashed red line depicting the value at which the second derivative was at its maximum, which was used to find the filter activity threshold for data exclusion.
Supplementary material 5; Overview of synoptic conditions in North Sea areas surrounding Luchterduinen and Gemini wind farm in support of thermal soaring

Soaring has been observed in both radar and GPS data on some specific days during the summer of 2019 and 2020. In the period 20-07-2020 – 22-07-2020 high a peak in thermal soaring activity occurred in the west and north study areas around the Dutch coast (Fig. 3.2, main text). To explore the synoptic conditions preceding, during and after this event (18-07-2020 – 23-07-2020) we examined synoptic weather charts showing surface pressure and synoptic weather patterns for Europe at 6-hour temporal resolution, downloaded from the KNMI data centre (https://www.knmi.nl/nederland-nu/klimatologie/daggegevens/weerkaarten), and the time series of sea surface temperature, air temperature (2 m) and wind speed (10 m) extracted from ERA5 for the two locations. Synoptic weather charts are presented in Fig. 3.S.3 (taken at 12:00 UTC), and all weather charts for the period are presented in supplementary video 3.S.3.

On 18-07-2020 a stationary front is present over the North Sea. By the end of 19-07-2020 a cold front has formed along the Dutch coastline. The cold front leaves behind a trough of low atmospheric pressure at the end of the day and into the following days (solid blue lines), which brings cold maritime wet air from the northwest. The presence of such cold air creates suitable conditions for the development of thermals near the Dutch coast; the air temperature drops and remains below the sea surface temperature for several days (Fig. 3.S.4A – B), which drives a flux of sensible heat from the sea to the atmosphere (Markowski and Richardson 2010). Note that during these days the wind speed is not particularly high (Fig. 3.S.4C), which provides beneficial conditions for thermal soaring as it reduces the likelihood of thermal disturbance and break up.
Figure 3.S.3 KNMI synoptic weather charts between 18-07-20 – 23-07-20, taken at 12:00 UTC.

Figure 3.5.4 Sea surface temperature (SST) and air temperature at 2 m above surface ($T_a$) between 16-07-2020 – 27-07-2020 in west study area (A) and north study area (B). Wind speed at 10 m ASL between 16-07-2020 – 27-07-2020 in west and north study areas (C).
Supplementary material 6; Remaining temporal autocorrelation in the logistic regression model residuals

Temporal autocorrelation in the model residuals of the proportion of thermal soaring per hour as function of temperature difference, and u- and v-wind components was addressed through a first order autoregressive covariance structure. However, this covariance structure could not completely resolve temporal autocorrelation in the models for the west area radar data. More complex covariance structures (second-/ third order autoregressive and moving average autoregressive) did not improve the residuals further. Below is the remaining temporal autocorrelation plot for the west area radar logistic regression models.

Figure 3.S.5 Autocorrelation function for the logistic regression model of proportion of circling tracks as a function of temperature difference between sea surface and air in the west area radar data. The x-axis shows the lag in hours from the observation, the y-axis shows the autocorrelation function. Autocorrelation is present for lag 1 – 6 and lag 20.
Figure 3.5.6 Autocorrelation function for the logistic regression model of proportion of circling tracks as a function of temperature difference between sea surface and air in the west area radar data. The x-axis shows the lag in hours from the observation, the y-axis shows the autocorrelation function. Autocorrelation is present for lag 1 – 27, with severe autocorrelation for lag 1 – 9.
Thermal soaring over the North Sea and implications for wind farm interactions
Chapter 4

A framework for post-processing bird tracks from automated tracking radar systems

Jens A. van Erp, E. Emiel van Loon, Johannes De Groeve, Maja Bradarić, Judy Shamoun-Baranes

Chapter 4

Abstract

Radar is an effective tool for continuous monitoring and quantification of aerial bird movement and used to study migration and local flight behaviour. However, systems with automated tracking algorithms do not provide the level of processing sufficient to guarantee reliable data. Therefore, post-processing such radar data is required but often non-trivial, especially in challenging environments such as open sea. We present a post-processing framework that implements knowledge of the radar system and bird biology to filter the data and retrieve reliable, high-quality tracking data. The framework is split into three modules, each with a specific aim: (I) sub-setting based on prior knowledge of the radar system and bird flight, (II) improving bird track quality and (III) detecting and removing spatio-temporal sections of data that have a clear bias for false observations. The effectiveness of the framework is demonstrated with a case study comparing track densities inside and outside an offshore wind farm, and by applying the workflow to a dataset of visually validated radar tracks. Application of Module I resulted in a dataset of 520894 bird tracks (19.5 % of total data) within a 10.4 km² area. Additionally, 18734 tracks were corrected for geometric errors in Module II, and Module III identified 236 of 719 observation hours and an area of 1.55 km² as unreliable for spatio-temporal analysis. No difference in track densities was found between the area inside and outside the wind farm when using the post-processed data, whereas using the unprocessed bird tracks, lower track densities were observed outside the wind farm. Of the visually validated radar tracks, the framework removed 85 % of false positive bird tracks, while retaining 80 % of true positive bird tracks. The framework provides a logical workflow to increase the reliability and quality of a bird radar dataset while being adaptable to the radar system and its surroundings. This is a first step towards standardising the post-processing methodology for automated bird radar systems, which can facilitate comparative analyses of bird movement in space and time and improve the quality of ecological impact assessments.
4.1 Introduction

Radar is a remote sensing technique which has been used for decades to quantify different aspects of avian flight and monitor biomass flows and has great potential for ecological research and diverse applications (Bauer et al. 2019; Shamoun-Baranes et al. 2019). It is the only non-invasive technique for quantifying avian flight that can measure aerial movement across a broad range of avian masses and be deployed for continuous measurements in diverse habitats. Radar has been adopted as one of the main tools in aeroecology (Gürbüz et al. 2015; Shamoun-Baranes et al. 2019), and different radar systems have been used to study migration (Bruderer 1997; Dokter et al. 2018; Bradarić et al. 2020), flight behaviour at sea (Assali et al. 2017; Chapter 2 and 3), and the flight response to anthropogenic activities and structures (Desholm and Kahlert 2005; Van Doren et al. 2017; Aschwanden et al. 2018). Additionally, radar is also used for environmental impact assessments, long-term monitoring and forecasting bird movements for applications such as aviation safety and wind energy (Shamoun-Baranes et al. 2018; van Gasteren et al. 2019).

Currently, several dedicated bird monitoring radar systems are commercially available and designed to be used "off the shelf", such as the Robin Radar systems (Robin Radar, 2023) and MERLIN Avian Radar System (DeTect, 2023) among others (Accipiter, 2023; AscendXYZ, 2023; Miltronix, 2023). These systems (from here “bird radars”) have been used to study local (Chapter 2 and 3) and migratory (Fijn et al. 2015; Bradarić et al. 2020) flight patterns in remote areas in relation to wind energy developments. They scan the horizontal and vertical plane and contain processing software on board for automated identification and tracking of bird targets from raw radar scans. Although this automated process is time- and storage-efficient in generating biological data, these data may still contain a considerable amount of false positive (reflections erroneously identified as birds) and false negative observations. This is problematic for answering ecological questions (Guillera-Arroita et al. 2017; Rempel et al. 2019), and therefore, post-processing is required before data can be interpreted adequately. Several aspects of bird radar systems, including radar image processing (Stepanian et al. 2014), target detection (Urmy and Warren 2017; May et al. 2017) and automated tracking (Urmy and Warren 2020), have been addressed in literature, however post-processing has not received the same attention. To date, this is done ad-hoc, as radar system performance can vary between locations, weather conditions, radar software and hardware configurations. This difficulty of radar data processing can hinder data standardisation and harmonisation between radar systems (Liechti et al. 2019).

In this paper we provide a modular framework to create workflows for processing horizontal bird tracks gathered from bird radars. We focus on automated systems; however, several processing steps can also be applied to radar studies where birds are tracked manually.
or using external software (e.g., Capotosti et al. 2019). The workflows can be tailored to different circumstances and systems, resulting in more reliable and standardised datasets for studying bird flight quantitatively, and facilitating reproducibility and interoperability.

The framework consists of three modules, each with a separate aim. To demonstrate the implementation and consequences of each module regarding data reduction and quality, we create a workflow for a subset of tracks observed by a radar positioned in an offshore wind farm and perform a comparative study of track densities inside and outside the wind farm using both the unprocessed and post-processed bird tracks. Additionally, we apply the workflow to a dataset of radar tracks visually validated with field observations to verify the accuracy of the framework. Offshore wind farms provide a strong testing ground as they are challenging environments for deploying radar due to high reflectivity that can be caused by waves and wind turbines.

4.2 Methods

The modules are ordered so that the first steps require only basic knowledge of the system, are computationally simple, and result in a major data reduction to facilitate more complex subsequent processing steps (Fig. 4.1). To ensure applicability of the framework to most bird radar systems, only locations and corresponding timestamps of bird trajectories are required. Required weather data can be acquired from the ECMWF ERA5 reanalysis (Hersbach et al. 2020) which is freely available and has global coverage. Module I removes data from areas with low observation reliability and identifies false positive observations. Module II improves the quality of the remaining tracks by removing false points within the track geometries. Module III removes remaining spatial and temporal sections with low reliability due to increased occurrence of false positive or false negative observations. Bird radar data processing is an iterative process because the consequences of processing steps often cannot be assessed beforehand. Hence, parameter choices need to be evaluated and visual verification of processing results is indispensable. Besides being the primary tool for finding the right parameter values, it also functions as confirmation on the adequate performance of the modules.
A framework for post-processing bird tracks from automated tracking radar systems

Each processing step will be applied to a case study to create a workflow and show its effect on data quality and quantity. Data processing was carried out in R (R Core Team 2022), using the birdR package (De Groeve and van Erp 2023) that was specifically developed for this task. We used a subset of the data from a study of thermal soaring behaviour in seabirds at sea (Chapter 3), namely the data from the bird radar (Robin Radar 3D-Fix) positioned at the Luchterduinen Offshore Wind Farm (52.427827 °N, 4.185345 °E) collected from 1 to 30 June 2020 (2668345 bird tracks). The 3D-Fix has two antennae (one horizontal, maximum range = 10 km, and one vertical, maximum range = 6 km) to capture horizontal and vertical information of birds crossing the respective beams. However only data acquired exclusively by the horizontal antenna were used in the study (Chapter 3) and, consequently, here as well.

Module I: Sub-setting based on prior knowledge

The first module removes tracks from areas that have a low reliability for observing birds (step 1) and tracks that are likely to be false positive observations (step 2). The data reduction also facilitates more complex subsequent analyses. These steps only require basic knowledge of the bird radar and the least computational effort per track.
1 Spatial filtering based on a defined inclusion area

Several factors affect what area within the radar window is reliable for observing bird flight. Firstly, there is a minimum and maximum distance from the radar at which birds can be reliably detected. Additionally, nearby large features might disrupt bird detection in the area around them or block the radar beam. Together these factors should be used to determine the radar area of inclusion (AoI, Fig. 4.2) in which bird flight can reliably be measured. The first step is to estimate the AoI based on the properties of the bird radar and apply it as a spatial mask to the data.

At small distances the radar beam is powerful enough to reflect on many unwanted features in the landscape (Rinehart 1991) and create clutter, partly because of the side lobes of the radar beam (Fig. 4.2B). Due to increased clutter, the number of false positive observations increases and this structural increase at small distances leads to a positive bias in bird observations (positive observation bias, or POB). Therefore, it is necessary to set a minimum distance (MiD) from the radar for data inclusion. The MiD depends on the power of the radar antenna and, to a lesser extent, the radar placement height, where a more powerful beam and higher placed radar results in a larger MiD.

With increasing distance from the radar, a bird's theoretical detection probability (TDP) decreases (Bruderer 1997; Schmid et al. 2019). Given uniform bird abundance and size distribution over the radar window, the observed number of birds will be lower at larger distances, leading to negative observation bias (NOB). To reduce the impact of reduced TDP and limit NOB, a maximum distance (MaD) for data inclusion should be set at a distance where the TDP for the smallest bird of interest is still high. We recommend setting the MaD to a distance at which the TDP is at least 80 % (Fig. 4.2C). Note that using a MaD limits the maximum bias in the collected data, but does not correct for the decline in TDP with distance below the MaD.

In the area between the MiD and MaD, there can be locations where birds cannot be detected due to static terrain features (typically structures or elevated terrain). Such features may impact bird detection in opposite ways: by creating false positive observations or false negative observations. False positive observations occur through the interaction between the radar beam and a feature, leading to clutter. An example is the clutter caused by turbine rotors (dashed black box in Fig. 4.2D). False negative observations occur when features block sections of the radar window or create increased background scatter. The structure on which the radar is placed can itself be a feature that obstructs the radar beam at certain angles (dashed purple box in Fig. 4.2D). If the location of these features is known in advance, the areas surrounding them should be excluded from the AoI. These areas should consist of the geographic position of the features plus a buffer, or if the
feature blocks the radar beam entirely, the angles at which the beam is blocked should be removed. The buffer should be set based on the estimated arc length of the radar beam at the location of the feature or the pulse length (whichever is largest), as these parameters define the distance from a feature at which it reflects the radar beam. The arc length at the location of the feature can be estimated if the beam width is known using the circumference formula for circles:

\[ s = \frac{\pi \theta}{180} r \]  

Where \( s \) is the arc length, \( \theta \) is the beam width (°), and \( r \) (m) is the distance between the radar and a blocking feature. One would thus define smaller buffers around features nearby the radar than further away. However, applying identical buffers for all features would simplify things. This can be done by taking the MaD as a value for \( r \) in equation 1, which comes at the cost of slightly larger buffers for some features than is strictly necessary.

The definition of the AoI may also account for spatial constraints resulting from the research aim. For example, in Chapter 2 bird flight over the open sea was studied, which required excluding the area enclosing a wind farm. Although such considerations seem obvious, this spatial sub-setting can tremendously decrease the data volume and should therefore be included as a first analysis step. Once the AoI is set, it is applied as spatial mask and radar bird tracks occurring completely outside the AoI are removed.
Figure 4.2 A: Area of inclusion (AoI, grey area) for the 3D-Fix (red dot) at Luchterduinen Offshore Wind Farm that was used in the case study. The AoI is determined by a minimum and maximum distance from the radar (1000 - 2500 m), two angles at which the radar beam is blocked, or data is unavailable (between 287 ° - 30 ° and 115 ° – 135 ° relative to Geographic North respectively), and the area within 100 m radius of each wind turbine (black dots). B: Theoretical detection probability (TDP) plot for large bird targets (-13 dB m⁻²); colour hue depicts TDP from 100 % (purple) to 80 % (blue). Close to the radar (< 1000 m, blue line) the radar beam and side lobes hit the terrain with enough power that there is a high chance for false positive bird observations. C: TDP plot for small bird targets (-25 dB m⁻²); colour hue depicts TDP from 100 % (purple) to 80 % (blue). At large distances (> 2500 m, red line), the TDP for birds drops to the extent that small bird tracking becomes less reliable. D: Terrain features within the radar window (nearby wind turbines, dashed black box) can cause increased false positive bird observations or increase the background scatter so that birds cannot be detected (leading to false negative observations). Large or nearby features (such as the turbine at which the radar system is installed, dashed purple box) can block the radar beam at certain angles (here between 287 ° – 30 °).

Case study
Based on the TDP for large bird targets (-13 dB m⁻², Fig. 4.2B) the MiD was set at 1000 m and based on the TDP for small bird targets (-25 dB m⁻², Fig. 4.2C) the MaD was set at 2500 m. The radar system was installed on the service platform of one of the wind farm turbines (dashed purple box in Fig. 4.2D), which blocked the radar beam between 287 ° – 30 ° (relative to Geographic North). The dataset only included bird tracks observed by the horizontal antenna of the radar system; tracks containing both horizontal and vertical information were excluded. Consequently, the area where the two antennae overlapped (between 115 ° – 135 °) would suffer from NOB and was therefore excluded as well.
Lastly, the other turbines in the wind farm have a negative impact on bird detection in their proximity (dashed black box in Fig. 4.2D). Using the pulse width of the 3D-Fix (30 m) and formula [1], the spatial resolution of the radar at MaD (2500 m) was calculated to be 78.5 m. Therefore, a conservative 100 m radius exclusion zone was applied around their locations. Together, these limits created the AoI for the case study (Fig. 4.2A). Tracks occurring completely outside the AoI were identified through a spatial intersection and a sub-sample was visualised to verify the identification was successful in Fig. 4.5.1 (Sup. Mat. 1). The tracks outside the AoI (2092252) were removed; 576093 radar tracks (21.6 % of total) were retained (Table 4.1).

2 Removing non-bird movement

After the spatial filter, false positive bird tracks are identified by two methods. Firstly, their average airspeed is evaluated. Empirical measurements show that the average cruising airspeed of a wide range of bird species ranges between 8 to 23 m s\(^{-1}\) (Alerstam et al. 2007). Alternatively, aerodynamic theory and scaling laws can be used to estimate a range of realistic airspeeds during flight (Pennycuick 1975). Including a margin for deviation from average airspeeds and different flight modes and conditions, see for example Spear and Ainley (1997), we recommend setting the range of acceptable airspeeds to 5 – 30 m s\(^{-1}\). If observing a certain bird species or species group, the minimum and maximum airspeed could be further limited to reflect a species’ observed or theoretical airspeeds.

A second filter can be applied to identify false positive bird tracks from features unaccounted for with the AoI. Examples of such features are objects which have variable reflectivity and are misidentified as birds under certain conditions (high wind speeds causing trees to move) or features that only exist temporarily within the AoI (e.g., an anchored ship). As these features are fixed, the false positive tracks obtained from these clutter sources can be distinguished from bird targets by their net spatial displacement (the Euclidian distance between the start- and endpoint), which will be close to zero. In contrast, the net displacement for birds tracked within the radar window tends to increase the longer they are tracked. By calculating the displacement divided by the duration of the track (displacement over time, DoT, m s\(^{-1}\)), clutter tracks can be identified as the data with the lowest DoT. As clutter tracks are also often visually distinctive from bird tracks (Fig. 4.3A), the data can be split in percentiles of DoT and visualised to find a DoT value where clutter tracks are visually absent (Fig. 4.3B). This value depends greatly on the dataset and in previous studies was established between the 0.1\(^{st}\) and 10\(^{th}\) percentile (Chapters 2 and 3). Bird tracks with a DoT below the selected threshold value should be removed, as they have a high chance of being clutter tracks.
Case study

Average airspeed was calculated for the 576093 tracks retained after the spatial mask using average ground speed, average track direction (direction between start and end location) and wind components according to Shamoun-Baranes et al. (2007). Average ground speed (ms⁻¹) per track was calculated by dividing track length (cumulative point-to-point distance, m) by track duration (time length between start point and end point, s). Hourly u- and v-wind components at 10 m ASL (ms⁻¹) were collected from the European Centre for Medium-Range Weather Forecast ERA5 reanalysis, providing weather data on a regular latitude-longitude grid at 0.25 ° x 0.25 ° spatial resolution and hourly temporal resolution (Hersbach et al. 2020, 2023). Wind components were annotated to the tracks according to the nearest neighbour in time and space, and average airspeed was calculated. As the data of this case study concerns predominantly seabirds (Chapter 3), tracks with an average airspeed below 5 ms⁻¹ and above 30 ms⁻¹ (Spear and Ainley 1997b) were removed. Success was verified with an overview of the average airspeed of removed and remaining tracks in Fig. 4.S.2 (Sup. Mat. 2). Next, DoT was calculated for all remaining tracks, and the 0.2nd to 2nd percentiles of data were extracted in increments of .2 percent and visualised (Fig. 4.3). A distinct pattern of clutter tracks caused by the turbines was visible in the 0.2nd to 0.8th percentile (Fig. 4.3A). The clutter pattern could not be clearly distinguished after the 1st percentile (Fig. 4.3B). Based on these visualisations, the threshold for track removal was set at the 1st percentile (DoT = 1.15 ms⁻¹). The two filters removed 21485 tracks (0.8 % of total, Table 4.1). After Module I, 554608 of 2668345 tracks were considered true bird tracks (20.8 % of bird tracks, Table 4.1).

Figure 4.3 Bird tracks (black) included in the 0 - 0.2nd percentile (A) and 1st - 1.2nd percentile (B) of displacement over time (DoT). Turbines of Luchterduinen wind farm are indicated as red dots. Within the green rectangles in panel (A) clear patterns of clutter tracks can be distinguished, which are absent in panel (B).
Module II: Improving the quality of bird tracks

Module II improves the quality of the true bird tracks identified in Module I to make them suitable for fine-scale behavioural analyses of track properties. Observation errors within the tracks can occur due to anomalies or bugs in the radar tracking software. This can lead to isolated cases of extremely small time intervals between consecutive points and influence the classification of flight behaviour dependent on this information, such as thermal soaring (Chapter 3). Even if there are no clear indications of errors being present, it is good practice to verify the data quality before performing more in-depth behavioural analysis. Errors can be identified by determining the time interval between consecutive points in a track. Intervals that are considerably lower than the sampling frequency of the antenna likely indicate false observations. For example, an observation frequency of 0.5 Hz results in an approximate observation interval of 2 s for a flying bird. By setting the threshold for a false observation to 10% of this interval (0.2 s), we allow for considerable deviation from the 2 s interval due to bird movements, but still identify (near) instantaneous time intervals. Erroneous time intervals are linked to two observations; as there is no straightforward way to verify which was false, both points should be removed from the track.

Case study

The time interval between consecutive points of each true bird track was calculated. The threshold for false observations was set at 0.12 s, 10% of the observation interval for static objects (rotational speed of the 3D-Fix horizontal antenna = 1.2 s per rotation). 18734 of the 554608 true bird tracks (3.4%) had one or multiple false observation points identified (20653 points of the total 1230214 points in the identified tracks, or 1.7%). These tracks were corrected by removing the two points with the time interval below the 0.12 s threshold. After correcting the tracks, all averaged track properties for those clean bird tracks were re-calculated (track length, track duration, average ground speed, average airspeed).

Module III: Removing data sections with observation bias

Subsets of the remaining data could still suffer from observation bias due to external conditions or poor radar performance. Module III is split into two processing steps: one dedicated to identifying temporal NOB in which the whole AoI is affected temporarily and one dedicated to identifying spatial observation bias in which an area within the AoI is affected constantly. Identifying these data sections requires intensive processing and is therefore done after reducing the data volume in Module I.
1 Detecting temporal negative observation bias

Temporal NOB can occur due to weather conditions affecting measured reflection, such as rainfall or high waves at sea, as well as system malfunctioning or maintenance. Periods when the system is not working appropriately should be identified to distinguish between no birds being observed (true zeros) and no observations (no data). Depending on the operating system, system malfunctions or shutdown, can be detected in the event logs or the absence of event logs of the radar system. Weather conditions have an indirect effect on bird detection, and an analytic approach is needed to determine the time periods over which the data is suffering from unacceptable levels of NOB. Note that we only consider NOB here, as radar tracking software generally responds to a temporary increase in reflections by increasing the threshold for object detection to avoid the tracking of clutter. However, the following step can also be applied to detect periods with POB if required.

During bad weather, for example, in case of a rough sea or precipitation, large sections of the radar window can show increased reflectivity. The radar software takes measures to reduce false positive observations, either by temporarily increasing the threshold for target detection or masking areas of the radar window completely. This leads to NOB for the periods when these measures are active, and these periods can be identified with the following steps. First the number of true bird tracks measured by the radar is calculated over time. We advise an hourly time scale, as this resolution is sufficiently fine to capture changes in weather phenomena while being sufficiently coarse to contain suitable sample sizes. This time series is then annotated with the variable that is expected to introduce NOB in the data and visualised (Fig. 4.4A). Either the weather variable causing NOB can be used, or the diagnostic information from the radar system like the detection threshold or masking intensity. The effect of the independent variable is modelled with a general additive model (GAM, Wood 2020), as the relation is often non-linear (Fig. 4.4B). If negative bias is confirmed visually, a threshold to distinguish between reliable and unreliable periods can be set based on the trend line of the independent variable. For example, the first derivative of the GAM curve can be used to determine the value of the independent variable where the negative effect starts (1st derivative is larger than 0) or the effect is the strongest (1st derivative is at its maximum). Tracks occurring completely within periods where the independent variable exceeds the threshold are removed from the dataset.
A framework for post-processing bird tracks from automated tracking radar systems

Figure 4.4 A: Temporal overview (hourly scale) of bird radar data (Luchterduinen Offshore Wind Farm, 3D-Fix) captured between 8 – 15 June 2020. Grey bars depict clean bird track count per hour (left y-axis) and average masking intensity per hour is shown as a black line (right y-axis). A clear indication of negative observation bias (NOB), caused by increased masking intensity, is seen on June 8. B: A scatter plot of hourly clean bird count against masking intensity shows declining bird counts with increasing masking intensity, hence NOB at higher values. This relation is estimated by a GAM (blue line). The 1\textsuperscript{st} derivative of the trend line (red line) is used to set the threshold when the bias is considered too large (minimum of 1\textsuperscript{st} derivative at 0.243, red dashed line). C: The same temporal overview as panel A, now with the threshold for NOB shown (red dashed line, 0.243). Red bars show time periods where masking intensity is above the established threshold and the unreliable data is removed.
Case study
The 3D-Fix uses a spatial mask to prevent observations in areas with increased reflections and stores the intensity of this mask in the variable ‘landmask’. This variable is recorded any time that the radar is operational. Hence, time periods without entries for the landmask variable denote moments that the radar was not operational, which in our case study was one hour (12:00 – 13:00, 03 June 2020). The data was coerced to a temporal dataset; for each hour (except the hour the radar was offline) the number of clean bird tracks was counted, the average hourly landmask intensity was calculated and labelled as masking intensity. The time series of bird counts and masking intensity showed an inverse relationship (see Fig. 4.4A). The relation was modelled by a GAM (formula = clean bird count ~ masking intensity) and visualised over the data together with the first derivative (Fig. 4.4B). A decrease in hourly bird count is seen around a landmask value of 0.2, a decline which continues until most of the data show near-zero birds (landmask = 0.3). We calculated the landmask value where the 1st derivative was at its maximum to find the value where the decrease was largest and used this as the threshold for data exclusion (landmask = 0.243). We considered the hours where this landmask threshold was exceeded to have unacceptable NOB (Fig. 4.4C), and these hours were therefore removed from the final dataset (236 of 719 observation hours). A total of 12309 clean bird tracks occurred completely within these hours and were removed.

2 Detecting spatial observation bias
Spatial observation bias can still be present in the data if it is caused by features not known a priori and is, therefore, unaccounted for in Module I. In this processing step additional areas where observation bias occurs are identified. This is done by assuming total bird abundance over the AoI is only affected by distance from the radar due to decreasing TDP (Fig. 4.2B – C) and looking for outliers of this assumption. Note that using data covering a considerable time period or from events in which bird flight is assumed to be homogenous (such as mass migration) will greatly improve this step as the data will better match this assumption. By creating a spatial raster covering the AoI, the number of tracks per raster cell can be counted to show bird detection within the AoI (Fig. 4.5A). The resolution of the raster should be fine enough to distinguish spatial patterns in detection rate, but coarse enough that the sample size per cell stays large enough. Additionally, the minimum cell size is limited by the spatial resolution of the radar system. The relation between bird counts and distance from the radar per cell can be estimated by a GAM (Fig. 4.5B). Cells showing unusually low bird counts (i.e., far below the mean value of the GAM trend line), may be the result of nearby features reducing bird detectability or because these cells occur near the border of the AoI. For cells showing unusually high bird counts, visualisation of the bird tracks occurring in these cells is advised to determine whether the large number of tracks is due to clutter missed in Module I, causing POB, or due to high local bird flight
activity. Cells showing observation bias can be identified by determining an upper and/or lower threshold relative to the trend line (Fig. 4.5C). Tracks completely occurring within unreliable cells are then removed from the dataset.

Figure 4.5 A: Spatial overview of number of birds per 100 × 100 m cell (blue to orange hue). The black outline depicts the AoI, black dots depict the individual turbines of Luchterduinen Offshore Wind Farm, the red dot indicates the location of the radar. B: Scatter plot of bird count against distance from the radar for each cell. The trend is estimated with a GAM (middle dashed purple line). The purple area shows data lying within the predicted bird count ± 10 times the standard error of the prediction. The lower limit of this area (solid purple line) was used as lower threshold for detecting cells with negative observation bias. C: The same overview as (A), but now the cells identified as having negative observation bias are removed. Removed cells were located around the wind farm turbines and along the edges of the AoI.
Case study

The lowest spatial resolution of the radar system within the AoI can be estimated with the arc length at MaD (78.5 m, see Module I) and the pulse length (30 m) which is consistent over distance from the radar. Given the size of the turbines and accounting for the spatial resolution of the radar, a cell size of 100 x 100 m was chosen. A grid was created spanning the complete AoI and the number of tracks within each cell was counted (Fig. 4.5A). Cells were annotated with the distance between their centre and the radar location. The relationship between the number of birds per cell and distance from the radar was estimated by fitting a GAM to the data and visualised on top of a scatter plot of bird count against distance from radar to see if observation bias occurred (Fig. 4.5B). Several cells showed low bird counts (0 – 300 tracks per cell) relative to the trend, mostly within the wind farm and near the borders of the AoI (Fig. 4.5A). Relatively high bird counts were observed near the north-eastern wind turbine (52.431 °N, 4.205 °E). Upon inspection, this did not seem to be due to increased false positive observations, as the trajectories in this area did not show a clear sign of increased clutter tracks in Fig. 4.5.3 (Sup. Mat. 3). Therefore, only a threshold for NOB detection was set. The predicted value minus 10 times the standard error was chosen as the threshold for identifying cells with NOB (Fig. 4.5B), which marked 148 of the 973 cells (Fig. 4.5C). These cells were excluded from the final dataset and 9814 clean bird tracks which occurred completely within the area of those cells were removed from the dataset (verified with Fig. 4.5.4 in Sup. Mat. 4).

Case study analysis: track densities inside and outside an offshore wind farm

To provide an example of the qualitative and quantitative effects of the post-processing framework in an ecological context, we analysed the estimated track densities inside and outside the wind farm. Track densities, as approximation of bird densities, are relevant for collision risk estimates (Cook et al. 2018) and the relation between track densities within and outside a wind farm can indicate avoidance or attraction behaviour (May 2015). To estimate track densities in these two areas we apply a similar method as described in Chapter 3. Tracks of the unprocessed dataset (n = 2668345) and the post-processed dataset (n = 520894) were annotated by occurrence inside or outside the wind farm area. For the unprocessed dataset, the wind farm area was considered as the geometric box drawn around the outer turbines of the wind farm plus a 100 m buffer (17.3 km²). The area within 10 km from the radar minus the wind farm area was set as the area outside the wind farm (295.7 km²). For the post-processed data, the overlap of the area of inclusion (Fig. 4.2A) and the complete wind farm area was considered as the relevant wind farm area (4.3 km²) and the difference between the area of inclusion and the complete wind farm area was considered as the area outside the wind farm (6.1 km²). If a track occurred both inside and outside the wind farm area it was considered for both categories. Average track density
per day (\# km\(^2\) day\(^{-1}\)) was calculated for both areas by dividing the number of tracks per area by the number of observation days and area size. Additionally, track density for the unprocessed data was visualized on a 100m x 100 m raster similar to the spatial overview in Fig. 4.5 for comparison with the processed data.

Post-processing of visually validated radar tracks

The classification and tracking of the bird radar at Luchterduinen was validated by Waardenburg Ecology through visual observations of the radar tracks between 2019 and 2021 (Leemans et al. 2022). Over this time 675 tracks measured by the horizontal antenna were validated and classified as true positive (tracks identified as birds both by the bird radar and by observers, 583) or false positive (tracks identified as bird by the bird radar, but as another object/feature by the observers, 92). To verify the accuracy of the framework, these tracks were post-processed with the workflow established in the case study.

4.3 Results

Implementing all modules in the workflow removed 2147451 of the 2668345 (80.5 \%) radar bird tracks and improved 18734 true bird tracks to provide a dataset of 520894 clean bird tracks. Additionally, Module III identified 236 of 719 hours (33 \%) and 155 of 993 100 × 100m cells (1.55 km\(^2\), 15.6 \%) as being unreliable. The largest proportion of data was removed in the first step of Module I, reducing the data volume by 78.4 \% (Table 4.1). The workflow applied 13 different parameters to process the data (Table 4.2). Ten of these were specified \textit{a priori} and three were specified interactively using visual inspection.

Track densities inside and outside an offshore wind farm

When using the unprocessed bird radar tracks, average track densities per day inside and outside the wind farm were 1397 and 241 birds per km\(^2\), respectively. The number of recorded tracks was extremely high near the radar (distance < 500 m) and dropped close to 0 further from the radar (Fig. 4.6). Using the post-processed bird tracks, average track densities per day within and outside the wind farm were 2116 and 2350 birds per km\(^2\), respectively. The number of recorded tracks was similar inside and outside the wind farm, with slightly higher numbers near the north-eastern-most turbine and close to the radar (Fig. 4.5C). The increase in track densities for the post-processed data is the result of a large reduction in the considered area relative to the unprocessed data (97.9 \% outside, 75.1 \% inside) which showed very low track numbers (Fig. 4.6A), resulting in a proportionally
large decrease in considered area relative to the decrease in track numbers. Additionally, the tracks of the post-processed data are on average longer in length (607 m) than the unprocessed data (412 m), and these longer tracks are more likely to cross both areas (inside and outside) in their lifetime and contribute to both density estimations.

![Figure 4.6 A: Spatial overview of number of birds per 100 × 100 m cell (blue to orange hue) for the unprocessed radar data. The black dots depict the individual turbines of Luchterduinen Offshore Wind Farm, the red dot indicates the location of the radar. B: The same spatial overview, zoomed in for comparison with the spatial overview of the post-processed data (Fig. 4.5). The black outline shows the area of inclusion as applied for post-processing in Module I, step 1.]

**Visually validated radar tracks**

Of the 675 validated radar tracks, the workflow identified 192 (28 %) as unreliable. Approximately 20 % of the true positive bird tracks (115 of 583 tracks) were removed (Table 4.1). The largest proportion were identified in Module I because they were located within 1000 m of the radar (78 tracks, Fig. 4.5.5) or had an airspeed < 5 ms⁻¹ (23 tracks). Of the false positive tracks, 85 % (78 of 92 tracks) were removed during post-processing. Step 1 of Module I removed 77 tracks, and one track was removed in step 2 of Module I.
A framework for post-processing bird tracks from automated tracking radar systems

Table 4.1 Overview of modules and processing steps and the effect of each processing step on data volume (number of tracks and percentage of tracks removed/processed) for the case study dataset and the true positive tracks of the validated dataset.

<table>
<thead>
<tr>
<th>Module</th>
<th>Processing step</th>
<th>Case study (n = 2,668,345)</th>
<th>Validated true positive tracks (n = 583)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Number of tracks removed / processed (#)</td>
<td>Number of tracks remaining</td>
<td>Percentage of tracks removed / processed (%)</td>
</tr>
<tr>
<td>(I) Sub-setting based on prior knowledge</td>
<td>Spatial filtering based on a defined area of inclusion</td>
<td>2092252</td>
<td>576093</td>
</tr>
<tr>
<td></td>
<td>Removing non-bird movement</td>
<td>21485</td>
<td>554608</td>
</tr>
<tr>
<td>(II) Improving the quality of bird tracks</td>
<td>Identify and remove false observation points</td>
<td>18734</td>
<td>554608</td>
</tr>
<tr>
<td>(III) Removing data sections with observation bias</td>
<td>Identify and remove temporal observation bias</td>
<td>12309</td>
<td>542299</td>
</tr>
<tr>
<td></td>
<td>Identify and remove spatial observation bias</td>
<td>21405</td>
<td>520894</td>
</tr>
</tbody>
</table>
Table 4.2 Overview of all parameters and recommendations for choosing the parameter value. Parameters with an asterisk are set during data processing based on visualisations and analysis of the data.

<table>
<thead>
<tr>
<th>Module</th>
<th>Processing step</th>
<th>Parameter</th>
<th>Recommendation</th>
</tr>
</thead>
<tbody>
<tr>
<td>(I) Sub-setting based on prior knowledge</td>
<td>(1) Spatial filtering based on a defined area of inclusion (AoI)</td>
<td>Minimum distance (MiD)</td>
<td>Based on power of antenna and size of side-lobes</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Maximum distance (MaD)</td>
<td>Based on a minimum theoretical detection probability (TDP) of 80% of the smallest bird target of interest</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Locations of features interfering with bird tracking</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Buffer size around interfering features</td>
<td>Based on pulse width and arc length of the radar beam at maximum distance; take the highest value</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Angles of the radar window where the radar beam is blocked by features</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2) Removing non-bird movement</td>
<td>Minimum average airspeed</td>
<td>5 m s(^{-1}) for general purposes, can be further specified based on species of interest</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Maximum average airspeed</td>
<td>30 m s(^{-1}) for general purposes, can be further specified based on species of interest</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Minimum displacement over time (DoT) *</td>
<td>Based on visualisations of the lowest percentiles of DoT tracks. Set at point where no clear occurrence of clutter is present</td>
</tr>
<tr>
<td>(II) Improving the quality of bird tracks</td>
<td>(3) Identify and remove false observation points</td>
<td>Minimum time interval between consecutive observation points</td>
<td>10% of observation frequency of static targets</td>
</tr>
<tr>
<td>(III) Removing data sections with observation bias</td>
<td>(4) Identify and remove temporal observation bias</td>
<td>Temporal resolution</td>
<td>Hourly resolution</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Exclusion threshold(s) *</td>
<td>Based on data visualisation and the relation between track counts per time and the independent variable causing observation bias.</td>
</tr>
<tr>
<td></td>
<td>(5) Identify and remove spatial observation bias</td>
<td>Spatial resolution</td>
<td>Based on pulse width and arc length of the radar beam at maximum distance; take the highest value</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Exclusion threshold *</td>
<td>Based on data visualisation and the relation between track counts per cell and distance from the radar.</td>
</tr>
</tbody>
</table>
4.4 Discussion

We provide a post-processing framework to standardise methodology and improve the reliability and quality of biological data extracted from bird radars. The associated R-package birdR (De Groeve and van Erp 2023) makes the application of this framework accessible for users with a range of goals and data processing experience. We demonstrated the framework by implementing a workflow for data from a radar system installed at an offshore wind farm. This environment is extremely challenging due to the dynamic reflectivity of the sea surface and the nearby wind turbines. The application of the workflow resulted in a significant reduction of data in the case study and limited the area covered by the radar to the most reliable region. This led to a different outcome in the comparative analysis of track densities inside and outside the wind farm and shows that post-processing can have important implications for ecological inference. Furthermore, by applying the workflow to a dataset of visually validated radar tracks, we demonstrate that the majority of true positive bird tracks are maintained during post-processing, while a large proportion of false positives is removed.

The three modules prepare the data for distinct types of analyses. Module I can be implemented based on *a priori* knowledge and improves the data to allow for reliable exploratory analysis and summary overviews. This module can be readily applied to other bird radar systems and could be used in near-real time applications such as air traffic safety warnings (van Gasteren et al. 2019; Colón and Long 2023). Additionally, the data reduction in Module I reduces the computational demand for in-depth analysis and is therefore critical to making the data workable. In contrast, Module II improves the quality of bird tracks by correcting their geometries. This makes identifying fine-scale flight behaviour possible and provides new possibilities for utilizing bird radar data, such as studying offshore thermal soaring (Chapter 3). Lastly, Module III removes spatial and temporal data sections of lower reliability due to environmental factors. It is, therefore, vital for users interested in studying time series or spatial patterns in bird flight in cluttered environments. In our case study, which used data from a challenging environment for radar monitoring, a considerable number of observation hours and grid cells with low reliability (33 % and 15 % respectively) were removed. After post-processing the data, the outcome of a comparative analysis of track densities inside and outside the wind farm changed from a clear difference (1397 birds per km² per day inside and 241 birds per km² per day outside)}
to higher densities that were similar between the two areas (2116 birds per km² per day inside and 2350 birds per km² per day outside). The difference in measurements can have major implications for environmental impact assessments, as they affect estimation of collision risk (Cook et al. 2018) and can indicate the measure of avoidance to the wind farm (May et al. 2017).

The framework is designed to facilitate verification and iteration within and between processing steps with the help of data visualisations. Data visualisations are vital to verify whether the intended result is reached, and the framework’s modularity facilitates iteration if the results are unsatisfactory. Reiterating previous post-processing steps can improve the reliability of data and subsequent research results. However, it is also important to realise that often “good enough” practices should be adopted, as perfecting the post-processing methodology for these data is close to impossible. This is in part the case because considerations for post-processing are often at odds with each other, e.g., the wish to remove any less-than-ideal data versus the need to keep enough data for good spatio-temporal coverage. This is exemplified by the visually validated radar tracks: a proportion of true positive bird tracks (20 %) is removed during post-processing, but the data reliability is increased, as a much larger proportion of false positives (85 %) is removed.

The outcome of a processing step might also provide new insights into the radar system and surrounding environment that can be utilised. For example, knowledge gained on spatial observation bias in Module III can inform the user on how to improve the definition of the AoI in Module I and aid subsequent analyses. Our case study showed that bird observations become difficult where the signal is blocked by several rows of wind turbines, limiting the distance to which bird flight can be measured reliable inside the wind farm. Alternatively, this information can improve the future positioning of radar systems, especially in cluttered environments. For example, for comparisons of flight behaviour inside and outside wind farms the radar should be positioned at the edge to provide an unrestricted view outside the wind farm.

Despite the proprietary algorithms and slight differences in characteristics, bird radar systems all record target position and time to track birds. By focusing on the utilization of this information, our framework is applicable to a wide variety of different radar datasets. Furthermore, the modularity of the framework makes it straight-forward for slight adjustments depending on the research question and data structure. Nevertheless, post-processing parameterisation might differ between radar systems and environments (e.g., see Chapter 3 for two radar locations). To further facilitate comparison of results among studies or different radar systems, workflows should be shared and well-documented. Studies where different radars are validated and cross-calibrated to try and harmonise
their observations (Nilsson et al. 2018; Liechti et al. 2019), should also be extended to also include the post-processing workflows.

Bird radar is a powerful remote sensing technology to study bird flight. The unique combination of properties makes it an important tool to obtain high resolution tracking data of multiple birds flying in remote areas of interest, for example, to assess the impact of offshore wind farm developments on bird life. Given the increasing demand for continuous and large-scale biodiversity monitoring (Schmeller et al. 2017), we believe bird radars will see increased usage and continued development. However, the cumbersome data and clutter issues can turn potential users of radar systems away. This framework aims to address these issues. It allows users to standardise where possible (e.g., the definition of concepts, the ordering of the modules and processing steps within them) while allowing for flexibility where required (e.g., the specific parameter settings and model choices to filter the data). Due to its modular nature, new processing steps can be added, or redundant steps removed to account for future developments. We believe the framework will increase the quality of future bird radar studies, broaden the range of possible applications, and encourage more scientists to use bird radars in their research.

Acknowledgements

We thank Rijkswaterstaat (Zee & Delta and Centrale Informatievoorziening) for providing the radar data and Robin Radar for providing details on the radar system. We especially thank Elisa Bravo Rebolledo, Daniel Beuker, Robert Jan Jonkvorst, Jacco Leemans, Koen Kuiper, Rob van Bemmelen, Abel Gyimesi, Mark Collier, and Ruben Fijn from Waardenburg Ecology for the validation measurements. Special thanks to Willem Bouten, Bart Kranstauber, Bart Hoekstra, Robin Radar, and Waardenburg Ecology for the helpful discussion on bird radar processing. Radar data analyses were carried out on the Dutch national e-infrastructure with the support of SURF Cooperative.
Chapter 4

4.5 Supplementary materials

Supplementary material 1; Sample of removed and retained bird tracks in step 1 of Module I

Figure 4.5.1 Random sample of 1000 removed bird tracks (red) and 500 retained bird tracks (black) based on whether they occurred completely outside the area of inclusion (AoI) as set in the first processing step of Module I. The sample confirms the processing step was successful in identifying and removing tracks occurring outside the AoI.
Supplementary material 2; Average airspeed of observed birds in step 2 of Module I

Figure 4.S.2 Histogram of average airspeeds per bird track occurring within the area of inclusion used for the second processing step of Module I. The red striped lines indicate the minimum and maximum average airspeed set to identify true bird tracks (5 and 30 m s$^{-1}$ respectively). Radar bird tracks with an average airspeed below 5 m s$^{-1}$ (red columns) were removed, no tracks with an average airspeed above 30 m s$^{-1}$ were found.
Supplementary material 3; Trajectories of birds in possible POB area

Figure 4.5.3 Trajectories of bird tracks with trajectory length < 1000 m crossing the area which showed possible positive observation bias (POB; 52.43 – 52.432 °N, 4.203 – 4.207 °E) as determined in processing step 2 of Module III (see also Fig. 5). The data was subset to a trajectory length > 1000 m as this subset makes the figure readable and, if POB occurred, clutter patterns would show up in tracks with short length. Although bird counts are high in this area, the trajectories do not show a clear sign of increased false positive observations, and therefore there is no reason to remove this area from spatial analysis.
Supplementary material 4; Sample of removed and retained bird tracks in step 2 of Module III

Figure 4.S.4 Random sample of 300 removed bird tracks (red) and 1000 retained bird tracks (black) on top of the reliable spatial 100 x 100m cells (grey squares) as determined in the second processing step of Module III. The removed bird tracks (red) occur completely outside the reliable cells and retained bird tracks (black) occur at least partially inside the reliable cells. The sample confirms the processing step was successful in identifying and removing tracks occurring outside the reliable cells.
Supplementary material 5; Sample of removed and retained validated tracks in step 1 of Module I

Figure 4.5.5 A random sample of 100 removed validated tracks (red) and 100 retained validated tracks (black) based on whether they occurred completely outside the area of inclusion (grey area) as set in Module I, step 1. Most removed tracks were located within 1000 m of the radar.
A framework for post-processing bird tracks from automated tracking radar systems
Chapter 5

Tracking birds with radar reveals that average flight properties are similar inside and outside an offshore wind farm

Jens A. van Erp, E. Emiel van Loon, Judy Shamoun-Baranes

To be submitted
Abstract

The development of offshore wind energy changes the airspace above sea from virtually unobstructed to a novel environment, in which wind turbines act as physical obstructions that can also heavily alter the wind conditions downwind through their wakes. With the ongoing wind energy development on the North Sea, interactions between birds and offshore wind farms are expected to increase. If bird flight within or downwind from the wind farm is impacted by the physical presence and/or wind effects of the turbines, this might affect the risk of collision. We use a bird radar installed at an offshore wind farm to investigate the flight properties of birds flying in three domains: inside, outside, and downwind from the wind farm. Average ground speed, straightness, and flight direction relative to the wind direction were compared between these three domains for birds observed from May 1st to July 15th, reflecting the breeding season of coastal seabirds in the region. Furthermore, we took the effect of wind conditions (wind speed and wind direction) and daylight into account. Flight properties differed between environmental conditions, but not among the domains. The results suggest that birds entering the wind farm are largely unaffected by the wind turbines and turbine wakes.
5.1 Introduction

The countries surrounding the North Sea are developing large scale offshore wind farms for renewable energy. Most wind farms currently operating are situated near the shores of the surrounding countries, but a large part of the North Sea area will be utilized for wind energy in the near future (European Commission 2020). Seabirds are vulnerable to offshore wind farm impacts, as they are long-lived with low annual reproduction, and their flight behaviour at sea puts them at risk of colliding with the turbine rotors (Garthe and Hüppop 2004; Furness et al. 2013). Species that are not avoiding the wind farms or are attracted to these locations, such as the great cormorant *Phalacrocorax carbo*, herring gull *Larus argentatus*, and lesser black-backed gull *Larus fuscus* (Dierschke et al. 2016; Vanermen et al. 2019), will have to perform micro- and meso-avoidance manoeuvres to avoid collisions (May 2015). Collision risk for seabird species is often modelled in order to assess the impact of offshore wind energy on nearby populations (Masden and Cook 2016). Many of these models, including the widely implemented Band model (Band 2012), use flight properties of the species in question to quantify the probability of collision with the rotors. It is therefore paramount that these flight properties are reflective of the behaviour that birds exhibit within these wind farms.

There are several factors that make the wind farm area a distinct habitat from the open sea and that possibly affect seabird flight behaviour. Turbines form obstructions around which birds need to manoeuvre, but also provide opportunities for roosting (Vanermen et al. 2019). Foraging opportunities may also differ between wind farms and the surrounding sea. Fisheries, which attract seabirds (Camphuysen 1995, 1999; Garthe et al. 2016), may be prohibited or severely restricted inside wind farms. On the other hand, the artificial reefs developing within wind farms might provide an alternative food source (Degraer et al. 2020). If resource availability changes in the wind farm, flight behaviour and hence collision risk may also be affected. For example, flight altitude of lesser black-backed gulls (Corman and Garthe 2014) and flight speed of sandwich terns *Thalasseus sandvicensis* (Fijn and Gyimesi 2018) are lower during foraging than when commuting. Therefore, knowledge of the behaviour and flight properties of birds inside wind farms is required to make a proper assessment of collision risk. Currently however, all of these hypotheses are only supported by anecdotal information and a handful of case studies. For a more complete understanding of the flight behaviour of birds in and around offshore wind farms we need more empirical data.

One aspect of bird-wind farm interactions at sea that has received less attention is the possible effect of wind turbine wakes. The spinning of the turbine rotor together with the turbine tower cause a downwind wake, resulting in increased turbulence and decreased
wind speeds (Stevens and Meneveau 2017; Cañadillas et al. 2020). With high wind speed in stable boundary layer conditions, these wakes can extend up to 60 km (Lundquist et al. 2018). Wind turbine wakes might impact a bird’s flight, as birds change their airspeed and altitude in response to wind conditions (Spear and Ainley 1997b; Ainley et al. 2015). In turn, changes in flight can affect the probability of colliding with the turbines. Whether and how a bird responds to these micro-scale changes in wind conditions might depend on their behaviour and motivation. Seabirds such as the lesser black-backed gull, which can opportunistically adjust flight behaviour to environmental conditions (Shamoun-Baranes et al. 2016; Sage et al. 2019; Chapter 3), might dynamically alter flight behaviour in response to changing wind conditions.

The aim of this study is to explore flight properties of birds inside and downwind from an offshore wind farm and the extent to which their flight differs from outside the wind farm. To do this we track bird flight inside and around an offshore wind farm in the Dutch North Sea with a bird radar system. We focus our study on the breeding season of the lesser black-backed gull, which is the most abundant species in the area at that time (Chapter 2) and vulnerable to wind farm interactions (Furness et al. 2013). We investigate three flight properties: average ground speed, straightness, and flight direction relative to the wind, in three geographical domains: inside the wind farm (IWF), downwind from the wind farm (DWF), and the remaining area outside the wind farm (OWF). Even small differences in these properties can result in an increase in estimated collision risk or indicate a shift in behaviour. For example, a ground speed increase of 1.3 ms\(^{-1}\) results in a 7% increase in collisions in lesser black-backed gulls (Masden et al. 2021), and relative number of estimated casualties can differ by 24% between slower foraging flight (8.3 ms\(^{-1}\)) and commuting flight (10.3 ms\(^{-1}\)) in sandwich terns (Fijn and Gyimesi 2018). Flight direction relative to the wind (and therefore relative to the turbine rotors) likewise affects collision probability (Tucker 1996; Holmstrom et al. 2011). With respect to shifts in behaviour, the straightness of flight informs us on possible avoidance behaviour or responses to high turbulence.

In the IWF, we expect that wind conditions are affected by the turbines and that birds may adjust their behaviour to the altered wind conditions, and to the physical presence of turbines by performing micro- and meso-avoidance behaviour (May 2015). The DWF does not have turbines, but wind conditions may be altered due to turbine wakes, especially in wind speeds when the turbine rotors are spinning. The OWF represents the area without wind turbines and regional wind conditions. We first describe and explore the three flight properties among the three domains in relation to wind speed, experienced wind direction, and diurnal phase. Next, we test how flight properties change within individual tracks between the domains and under different environmental conditions. We expect that ground speed is higher in the IWF and DWF compared to the OWF for birds flying in
Tracking birds with radar reveals that average flight properties are similar inside and outside an offshore wind farm

headwinds, due to the decreased adverse wind speed in the former domains. Conversely, ground speed is expected to be lower in the IWF and DWF compared to the OWF for birds flying in tailwinds, as wind support is decreased. We furthermore expect these effects to be more pronounced with higher wind speeds when the rotors are spinning. We expect more tortuous tracks inside the wind farm, as birds might perform micro- and meso-avoidance, and we expect tortuosity to increase further with higher wind speeds, when turbulence downwind from the turbines increases. We also expect to see straighter tracks at night than during the day, as birds may predominantly be commuting at this time (Shealer 2002) and the limited visual stimuli might decrease the avoidance response of birds flying near the wind farm. We do not have clear expectations regarding changes between the domains in flight direction relative to the wind. Nevertheless, we investigate this property as angle of approach to the rotor can affect collision risk (Tucker 1996; Holmstrom et al. 2011).

5.2 Methods

Study area and study period

The study was conducted at Luchterduinen wind farm in the Southern North Sea, 23 km west of the Dutch coast. Luchterduinen wind farm has 43 turbines with a hub height of 81 m above mean sea level and rotor diameter of 112 m. Bird flight near the wind farm was measured with a bird radar system with a tracking algorithm (Robin Radar 3D-Fix), which was mounted on the service platform of a turbine at the edge of the wind farm (Fig. 5.1). The radar system consisted of a vertically rotating X-band antenna (25 kW, Furuno Marine) and horizontally rotating S-band antenna (60 kW, Furuno Marine) both rotating at 0.75 rotations s⁻¹. Radar measurements were automatically processed to create tracks of birds using proprietary software developed by Robin Radar. For this study, only bird tracks captured by the horizontal antenna were used, as these tracks included information on ground speed and direction. The study period was between 1 May – 15 July in 2019 to 2022. We selected this period to focus on local bird movements rather than e.g., migratory movements. The period includes predominantly large gulls such as the lesser black-backed gull *Larus fuscus*, the most abundant breeding bird observed in the area (Chapter 2).
**Figure 5.1** Luchterduinen wind farm with the area of inclusion for the radar data. The wind farm consists of 43 turbines and a service platform (black dots). The radar system is mounted on one of the turbines at the northern edge of the wind farm (red dot). Only tracks intersecting the area of inclusion (grey polygon) are included in the study. This area is limited by a minimum and maximum distance from the radar (1000 m and 2500 m, respectively), the blockage of the radar beam (between 287 ° – 30 °) by the turbine, and the area within 100 m radius of a turbine.

**Environmental data**

Wind u- and v-components (ms⁻¹) were acquired from the European Centre for Medium-Range Weather Forecast (ECMWF) ERA5 reanalysis dataset. ERA5 reanalysis provides data on a regular latitude-longitude grid at 0.25 ° × 0.25 ° spatial resolution and hourly temporal resolution (Hersbach et al. 2020, 2023). Wind components were selected at 10 m above the sea surface to match the average flight altitude of lesser black-backed gulls in the region (Chapter 3). Wind components were retrieved for the latitude-longitude grid cell closest to the radar location (between 52.375 °N – 52.625 °N and 4.125 °E – 4.375 °E) and converted to wind speed (ms⁻¹), wind direction (°, direction the wind is blowing from). Sun altitude (°, angle relative to the horizon) was retrieved from the R-package suncalc (Thieurmel and Elmarhraoui 2019) to determine diurnal phase.
Data post-processing

A workflow for post-processing the radar tracks was applied to the data according to Module I and II of the post-processing framework detailed in Chapter 4. Firstly, Module I was applied with similar settings as used for radar post-processing in Chapter 3 (Fig. 5.1). Based on the theoretical area of detection of the 3D-Fix, an area of inclusion was set between 1000 m and 2500 m from the radar. The areas blocked by the turbine on which the radar was installed and the areas within 100 m radius of the other turbines were excluded to prevent inclusion of false positive tracks caused by turbine reflections. Only tracks that intersected with the area of inclusion were included in the study. Each track created by the radar software included at least five track points made up of geolocation plus timestamp (UTC). Track length (m) was calculated as the sum of the great circle distance between consecutive track points, and average flight direction (°) was calculated between the first and last point of the track. Average ground speed (ms⁻¹) was calculated as track length divided by track duration (last timestamp - first timestamp, s). Hourly u- and v-wind components were attached to the tracks based on the nearest hour to the calculated midpoint timestamp of the track (first timestamp + ½ × track duration). Tracks were annotated with the experienced wind direction (headwinds, crosswinds, or tailwinds) by calculating flight direction relative to the wind direction as the absolute difference between average direction and wind direction (0 ° – 180 °). Note that average flight direction is described as the direction a bird moves towards, and wind direction is the direction the wind comes from. Flight direction relative to the wind direction of 0 ° – 45 ° indicated the bird flies in headwinds, 45 ° – 135 ° indicated cross winds, 135 ° – 180 ° indicated tailwinds. Lastly, average airspeed was calculated according to Shamoun-Baranes et al. (2007) using average ground speed, average flight direction, and u- and v-wind components. Only tracks with an average airspeed between 5 ms⁻¹ and 30 ms⁻¹ were included, as nearly all seabird species fly within this range (Spear and Ainley 1997b; Alerstam et al. 2007; Shamoun-Baranes et al. 2016). Additionally, manual data exploration indicated that static reflections from nearby vessels or structures created stationary, long-lasting, false positive bird tracks, which moved within a very small area. To automatically identify these clutter tracks, we calculated the area of the minimum rotated rectangle enclosing the track (km²) and the track displacement over time (ms⁻¹) by dividing the track duration by track distance (great circle distance between the first and last track point, m). Through visual inspection, the tracks falling in the 2nd percentile of displacement over time (1.89 ms⁻¹) and the 2nd percentile of minimum covered area (0.18 km²) were identified as clutter (non-bird features) and removed. Using Module II (Chapter 3), the remaining tracks were corrected for possible erroneous track points by identifying and removing sequential points with a time difference lower than 0.12 s (10 % of the rotation speed of the radar). Module III of the framework was not applied, as this study does not apply a spatio-temporal analysis (Chapter 3).
Calculating flight properties and data annotation

To investigate flight properties in relation to the presence of the turbines or their associated wake field, each track was split into segments according to occurrence within the three domains (IWF, DWF, or OWF; Fig. 5.2). The IWF was defined as the area enclosed by the edge turbines of the wind farm with a 100 m buffer, the DWF was defined as the area directly downwind from the wind farm, which was based on hourly wind direction from the ERA5 reanalysis. The DWF was assumed to be non-existent at wind speeds \(< \, 3 \, \text{ms}^{-1}\), as this is the cut-in wind speed of the turbines (Vestas 2023) and the turbine rotors were still or barely spinning below this wind speed, as was confirmed by the turbine data. The remaining area outside the wind farm was considered the OWF domain. To make sure the track segments were representative of their domain, only tracks that had a minimum overlap of 1000 m per domain (the IWF and at least one of the other two domains) were included. Each track segment was annotated with their relevant domain. Note that DWF data was limited for periods with winds coming from 150 ° – 165 °, as the DWF domain would overlap with the gap in the area of inclusion between 287 ° – 30 ° (see Fig. 5.1), this was the case in 2.7 % of the time.

Segment length (m), distance (m), duration (s), and average flight direction (°) were calculated for each of the segments in the same way as for the entire track (see description in the Data post-processing sub-section). Using these metrics, average ground speed (ms⁻¹) and straightness (distance divided by length, 0 – 1) were calculated per segment. If multiple track segments of a single track occurred within a domain (e.g., when a bird entered and exited a domain multiple times), the distance, length, and duration of these segments were summed. The average flight direction of multiple segments was calculated by vector addition, followed by determining the direction between start and endpoint.

Figure 5.2 Two examples of the three study domains with different wind conditions (black arrow): 325 ° (A and B) and 190 ° (C). Coloured areas depict the domain inside the wind farm (IWF, purple polygon), the domain downwind from the wind farm with affected wind conditions (DWF, red polygon), and the domain outside the wind farm (OWF, blue polygon). Tracks were segmented based on occurrence within these domains for the wind conditions at that time (B and C, purple: IWF, red: DWF, blue: OWF).
Track segments were annotated with wind speed and wind direction, and flight direction relative to the wind was calculated as for the entire track (see description in the Data post-processing sub-section). The sun’s angle relative to the horizon was annotated to each track based on the midpoint timestamp, and diurnal phase was determined based on nautical dawn and dusk (day: sun angle > -12 °, night: sun angle =< -12 °).

**Statistical analysis**

To describe the flight properties (average ground speed, straightness, and average flight direction relative to the wind) in our data sample, we calculated the median and the probability density distributions for average ground speed and straightness, and the largest 10 ° bin and polar histograms for average flight direction relative to the wind, per domain. We report these parameters for all data pooled, as well as disaggregated according to the different environmental conditions (diurnal phase: day and night, experienced wind direction of the entire track: headwind, crosswind and tailwind, and wind speed: below and above 3 ms⁻¹). Next, to test how the mean flight properties changed between the domains, the difference in flight property within individual tracks was modelled using linear models (LMs). The difference in flight properties between track segments (average ground speed, straightness, and average flight direction relative to the wind) was calculated for each track, with the IWF segments as reference (OWF – IWF or dOI, and DWF – IWF or dDI). Both differences (dOI and dDI) were modelled with wind speed (ms⁻¹), experienced wind direction of the entire track (0 ° – 180 °), and diurnal phase (0 = night, 1 = day) as independent variables (formula: flight property difference ~ wind speed + experienced wind direction + diurnal phase). After fitting the models, the assumption of independent and identically distributed Gaussian residuals was assessed visually using residual plots. Explanatory power of the models was assessed with the McFadden pseudo R² score (1 - residual deviance / null deviance). All analyses were carried out in R (R Core Team 2022).
5.3 Results

After the post-processing steps, 30062 tracks remained for analysis (4572, 7695, 7695, and 10281 tracks for 2019 to 2022 respectively). All tracks had an IWF segment, 8022 tracks had a DWF segment, and 22760 tracks had a segment in the OWF. Most bird flight was observed during the day (27613 of 30062 tracks), but all other conditions were well represented (Table 5.S.1 in Sup. Mat. 1).

Median ground speed was nearly equal (difference < 0.2 ms\(^{-1}\)) between domains for all flight (Fig. 5.3A) as well as during the day, in crosswinds, and with low wind speeds (Fig. 5.3B, E, and G). For all other environmental conditions medians differed slightly, up to 1.2 ms\(^{-1}\) (e.g., between DWF and OWF when flying in tailwind, Fig. 5.3G). While ground speed within the wind farm (IWF) and outside (OWF) generally had the same distribution across all environmental conditions (Fig. 5.3B – H), the DWF distributions were distinct across conditions. For example, ground speeds in headwinds were slightly lower in the DWF than in the IWF and OWF (Fig. 5.3D), whereas ground speeds in tailwinds were higher in the DWF than both other areas (Fig. 5.3F). Ground speed showed larger difference across the environmental conditions than between domains. Median ground speed was up to 2 ms\(^{-1}\) higher and ground speeds had a broader distribution at night than at day (Fig. 5.3B – C). Furthermore, median ground speed was highest in tailwinds and lowest headwinds (Fig. 5.3D – F), and higher with wind speeds \(\geq 3\) ms\(^{-1}\) (at which the rotors were spinning; Fig. 5.3H) compared to low wind speeds.

Most birds flew with (near) straight flight across all conditions and domains (lowest median straightness = 0.86 for DWF flight in headwinds, Fig. 5.4D). Median straightness was the highest outside the wind farm and lowest downwind from the wind farm across all environmental conditions (Fig. 5.4). Across all domains, flight was straighter at night than during the day (Fig. 5.4B – C) and straighter for birds flying in tailwinds than crosswinds and headwinds (Fig. 5.4D – F). In the OWF straightness was higher with wind speeds \(\geq 3\) ms\(^{-1}\), compared to lower wind speeds (Fig. 5.4G – H).
Tracking birds with radar reveals that average flight properties are similar inside and outside an offshore wind farm.

**Figure 5.3** Probability density distributions of segment ground speed (ms⁻¹) in each domain (purple: IWF, red: DWF, blue: OWF). Data is presented for: all flight (A), flight at day (B) and night (C), flight in headwind (D), crosswind (E), and tailwind (F), and when the rotors are still (wind speed < 3 ms⁻¹, G) and spinning (wind speed >= 3 ms⁻¹, H). Median ground speed is presented per domain in the top-right corner of each graph. For wind speeds < 3 ms⁻¹, we assume there is no wind farm wake, and therefore there is no data for the DWF under these conditions.
Figure 5.4 Probability density distributions of segment straightness (0 – 1) in each domain (purple: IWF, red: DWF, blue: OWF). Data is presented for: all flight (A), flight at day (B) and night (C), flight in headwind (D), crosswind (E), and tailwind (F), and when the rotors are still (wind speed < 3 ms\(^{-1}\), G) and spinning (wind speed >= 3 ms\(^{-1}\), H). Median straightness is presented per domain in the top-left corner of each graph. For wind speeds < 3 ms\(^{-1}\), we assume there is no wind farm wake, and therefore there is no data for the DWF under these conditions.
Tracking birds with radar reveals that average flight properties are similar inside and outside an offshore wind farm. There was a general tendency of birds to fly with crosswinds and tailwinds (Fig. 5.5A – C and G – H), especially at night (Fig. 5.5C). Birds in the DWF flew with crosswind directions more often than in the other domains, as indicated by the 10 ° bin with the highest count (e.g., 160 ° – 170 ° in the IWF and DWF, 150 ° – 140 ° in the DWF for all flight, Fig. 5.5A). The flight direction relative to the wind per track segment generally aligned with the flight direction relative to the wind of the entire track (Fig. 5.5D – F), indicating birds do not structurally alter their flight direction within a domain with different experienced wind directions (e.g., if birds flying in headwinds would avoid this flight direction in the IWF, the IWF data would deviate from headwind directions in Fig. 5.5D).

**Figure 5.5** Polar histograms of flight segment direction relative to the wind direction (0 ° – 180 °) in each domain (purple: IWF, red: DWF, blue: OWF). Data is presented for: all flight (A), flight at day (B) and night (C), flight in headwind (D), crosswind (E), and tailwind (F), and when the rotors are still (wind speed < 3 ms⁻¹, G) and spinning (wind speed >= 3 ms⁻¹, H). The 10 ° bin with the highest count is presented per domain in the top-left corner of each graph. For wind speeds < 3 ms⁻¹, we assume there is no wind farm wake, and therefore there is no data for the DWF under these conditions. Testing flight property differences between domains...
Table 5.1 Overview of the LM parameters for difference in flight properties between track segments inside and outside the wind farm (dOI), and inside and downwind from the wind farm (dDI). The parameter estimates and corresponding p-values are reported per model. The explanatory power of the models is expressed with the McFadden pseudo $R^2$ score ($1 - \text{residual deviance} / \text{null deviance}$). The assumption of independent and identically distributed Gaussian residuals was met for all models.

<table>
<thead>
<tr>
<th>Response variable</th>
<th>Parameter</th>
<th>Estimate</th>
<th>p-value</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ground speed</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>dOI (n = 22760)</td>
<td>Intercept</td>
<td>-0.013</td>
<td>0.790</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Wind speed</td>
<td>0.026</td>
<td>&lt;0.001</td>
<td>0.001</td>
</tr>
<tr>
<td></td>
<td>Relative wind direction</td>
<td>0.000</td>
<td>0.263</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Day</td>
<td>-0.017</td>
<td>0.448</td>
<td></td>
</tr>
<tr>
<td>dDI (n = 8022)</td>
<td>Intercept</td>
<td>0.050</td>
<td>0.707</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Wind speed</td>
<td>-0.042</td>
<td>0.059</td>
<td>0.014</td>
</tr>
<tr>
<td></td>
<td>Relative wind direction</td>
<td>0.004</td>
<td>&lt;0.001</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Day</td>
<td>-0.251</td>
<td>0.002</td>
<td></td>
</tr>
<tr>
<td>Straightness</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>dOI (n = 22760)</td>
<td>Intercept</td>
<td>-0.016</td>
<td>0.002</td>
<td>0.003</td>
</tr>
<tr>
<td></td>
<td>Wind speed</td>
<td>0.006</td>
<td>&lt;0.001</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Relative wind direction</td>
<td>0.000</td>
<td>0.004</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Day</td>
<td>0.003</td>
<td>0.481</td>
<td></td>
</tr>
<tr>
<td>dDI (n = 8022)</td>
<td>Intercept</td>
<td>-0.006</td>
<td>0.623</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Wind speed</td>
<td>0.008</td>
<td>&lt;0.001</td>
<td>0.004</td>
</tr>
<tr>
<td></td>
<td>Relative wind direction</td>
<td>0.000</td>
<td>&lt;0.001</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Day</td>
<td>-0.012</td>
<td>0.151</td>
<td></td>
</tr>
<tr>
<td>Direction</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>dOI (n = 22760)</td>
<td>Intercept</td>
<td>-2.100</td>
<td>0.011</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Wind speed</td>
<td>-0.038</td>
<td>0.759</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Relative wind direction</td>
<td>-0.005</td>
<td>0.243</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Day</td>
<td>1.621</td>
<td>0.015</td>
<td>&lt;0.001</td>
</tr>
</tbody>
</table>
Tracking birds with radar reveals that average flight properties are similar inside and outside an offshore wind farm

<table>
<thead>
<tr>
<th>Response variable</th>
<th>Parameter</th>
<th>Estimate</th>
<th>p-value</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>dDI (n = 8022)</td>
<td>Intercept</td>
<td>-4.316</td>
<td>0.039</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Wind speed</td>
<td>-0.046</td>
<td>0.899</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Relative wind direction</td>
<td>0.010</td>
<td>0.095</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Day</td>
<td>2.003</td>
<td>0.119</td>
<td>&lt;0.001</td>
</tr>
</tbody>
</table>

The linear model outcomes for the mean change in flight properties within tracks between the different domains (both for dOI and dDI) showed very small effect sizes. Across all models, parameters that contributed significantly had very small estimate values and all McFadden pseudo $R^2$ scores were below 0.02 (Table 5.1). Due to these low model parameter values, we consider these effects to be biologically irrelevant and will not describe them further. We do note that there were some tracks with large differences in average ground speed, straightness, and average flight direction between domains (Fig. 5.S.1 – 5.S.3 in Sup. Mat. 2). These tracks often showed localized foraging or thermal soaring behaviour in one of the domains (Fig. 5.S.4 in Sup. Mat. 3), however this behaviour occurred to the same extent in all domains.

5.4 Discussion

We investigated three flight properties: average ground speed, straightness, and average flight direction relative to wind, for birds flying inside, outside, and downwind from an offshore wind farm. Based on the model results, we found no evidence that birds predictably alter their mean flight properties between these areas. The tails of the difference distributions (Sup. Mat. 2) do show that some birds change their flight considerably when entering a different domain, but these alterations were not dominant in one area or another, and therefore did not affect the model results. However, flight property medians and distributions differed slightly with wind speeds over 3 ms$^{-1}$ between the three domains, when we expected wind conditions inside and downwind from the wind farm to be affected by the turbine wakes. Flight in the IWF and DWF had a lower median ground speed and was more tortuous. These results suggest that birds flying within the wake of the turbines are affected by the increased turbulence. Interestingly, birds in these domains flew with tailwind more often than birds outside the wind farm (in the OWF). This puts birds on a perpendicular path with the spinning turbine rotors and decreases their chance of colliding with the rotors (Tucker 1996), but at slightly obtuse angles the
effect can be different (Holmstrom et al. 2011). Although the increased tortuosity inside the wind farm may indicate increased alertness and avoidance behaviour in response to the spinning rotors (May 2015; Cook et al. 2018), the agreement in results between inside and downwind from the wind farm suggests there is an effect of turbulence in addition to the physical presence of the turbines.

The medians and probability density distributions of the measured flight properties also showed differences in flight under different environmental conditions. Most flight was observed during the day (Table 5.S.1), which aligns with the expected pattern of diurnal foraging flight at sea (Shealer 2002, Chapter 2). The medians of observed average ground speed in headwinds and tailwinds agree with mean ground speed previously recorded for medium and large sized gulls (Spear and Ainley 1997b), however Shamoun-Baranes et al. (2016) reported lower ground speeds for lesser black-backed gulls. Birds tended to fly with supporting wind conditions (crosswind to tailwinds), which is conflicting with what was previously reported by Spear and Ainley (1997a), who reported a preference for flight in headwinds for larids and other seabirds. They suggest the preference for headwinds might be caused by the increased difficulty to soar and locate prey near the surface in tailwinds. This would indicate that birds in our study were more commonly commuting than foraging, which aligns with the high median straightness observed in this study, especially with supporting wind conditions. The lack of foraging behaviour might be caused by decreased foraging opportunities, as a large proportion of gulls at sea feed on the discards of fisheries (Camphuysen 1995; Camphuysen et al. 2015) which is not allowed within Dutch wind farms. At night, we observed the highest median ground speed and straightness, and birds flew with tailwinds more often, indicating a further increase in proportion of commuting flight. This aligns with our expectation that most foraging would take place during the day (Shealer 2002). Contrastingly, Masden et al. (2021) reported the fastest ground speed measured by GPS tracking in lesser black-backed gulls in the middle of the day, not at night. This disparity might be attributed to differences in regional atmospheric conditions or population level foraging behaviour.

In this study, we used bird radar to address the lack of empirical data available for bird flight within and near offshore wind farms. We obtained a large number of observations to provide overviews of bird flight properties in three different study domains and across environmental conditions (see also Sup. Mat. 1). However, some limitations should be addressed for successive research using these data. To make the results readily interpretable, we implemented only linear models for the mean with additive effects. More elaborate and complex models (e.g., including interaction terms and non-linear components, as in Masden et al. 2021, Chapter 2) might have led to a better agreement with the data. However, we think the use of the chosen models is the preferred choice.
because these matched our prior hypotheses (we did not have grounded expectations about interactions or nonlinear effects) and because the analysis of the model residuals did not suggest a violation of assumptions. Moreover, it seems that the inclusion of different predictor variables would make the crucial difference rather than different statistical models with the same predictors.

Although ecologically relevant, airspeed and heading were not considered in this study. We expected wind conditions within the wind farm and downwind from the wind farm to be affected by the turbine wakes (Cañadillas et al. 2020) and these dynamics cannot be captured by global datasets such as ERA5. The conditions a bird experiences on a second-to-second basis could be approached with fine-scale wake models (Stevens and Meneveau 2017), which would allow for a much more detailed approach of flight behaviour analysis within and around the wind farm. The need for further integration of atmospheric models has been noted before when investigating the change in altitude observed for birds within wind farms (Krijgsveld et al. 2011; Skov et al. 2012; Thaxter et al. 2018). With increased computational capabilities, this approach might be feasible in the future and provide a new avenue of research of bird flight within wind farms.

The assessment of wind farm developments on seabirds generally includes collision risk modelling (Masden and Cook 2016) and these models use bird flight properties for their parameterization. Further understanding of the way birds behave in the area in and around the wind farm, and how different environmental conditions affect their behaviour, could help to address the high amount of uncertainty still surrounding their parameterization and related model outcomes (Chamberlain et al. 2006; Cook et al. 2018; Kleyheeg-Hartman et al. 2018). This study exemplifies how radar used post-construction can be a valuable tool to monitor flight within wind farms and verify if and how bird behaviour or flight changes once the wind farm is operational. Mean flight properties changed slightly between environmental conditions, indicating that birds fly with higher ground speed and straighter flight during the night and with tailwinds. However, the sizes of these effects are so small that we do not consider them to be biologically meaningful. Nonetheless, during data exploration subtle differences in observed flight properties between the different domains were shown in the group medians and full probability density distributions. These suggest that there might be wind wake effects on bird flight for specific species and under specific conditions. It will be interesting to investigate this further when adequate high-resolution wind field data in and around wind farms becomes available.
Acknowledgements

We thank Rijkswaterstaat (Zee & Delta and Centrale Informatievoorziening) and Gemini wind park for providing the radar data and Robin Radar for providing details on the radar system. We also thank Maja Bradarić and Johannes de Groeve for the continuous discussions on how to process and interpret bird radar data. Radar data analyses were carried out on the Dutch national e-infrastructure with the support of SURF Cooperative.
5.5 Supplementary materials

Supplementary material 1: Track and segment data

Table 5.5.1 Number of observed tracks and track segments in total and split by diurnal phase, experienced wind direction, and wind speed.

<table>
<thead>
<tr>
<th></th>
<th>Tracks (#)</th>
<th>Segments (#)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>IWF</td>
<td>DWF</td>
</tr>
<tr>
<td>Total</td>
<td>30062</td>
<td>30.062</td>
</tr>
<tr>
<td>Day</td>
<td>27613</td>
<td>27.613</td>
</tr>
<tr>
<td>Night</td>
<td>2449</td>
<td>2.449</td>
</tr>
<tr>
<td>Headwind</td>
<td>5457</td>
<td>5.500</td>
</tr>
<tr>
<td>Crosswind</td>
<td>14991</td>
<td>15.080</td>
</tr>
<tr>
<td>Tailwind</td>
<td>9614</td>
<td>9.482</td>
</tr>
<tr>
<td>Wind speed &lt; 3ms⁻¹</td>
<td>12760</td>
<td>12.760</td>
</tr>
<tr>
<td>Wind speed &gt;= 3ms⁻¹</td>
<td>17302</td>
<td>17.302</td>
</tr>
</tbody>
</table>
Supplementary material 2: Probability density distributions of flight property differences between segments

Figure 5.S.1 Probability density distributions of difference in average ground speed (ms\(^{-1}\)), within tracks, between segments inside and outside the wind farm (dIO), and downwind from and inside the wind farm (dDI) for: all flight (A), flight at day (B) and night (C), flight in headwind (D), crosswind (E), and tailwind (F), and when the rotors are still (wind speed < 3 ms\(^{-1}\), G) and spinning (wind speed >= 3 ms\(^{-1}\), H). A positive value indicates a higher average groundspeed inside the wind farm relative to the other domain. The vertical red line highlights 0 on the x-axis, which indicates no difference between segments.
Tracking birds with radar reveals that average flight properties are similar inside and outside an offshore wind farm.

Figure 5.S.2 Probability density distributions of difference in straightness, within tracks, between segments inside and outside the wind farm (dIO), and downwind from and inside the wind farm (dID) for: all flight (A), flight at day (B) and night (C), flight in headwind (D), crosswind (E), and tailwind (F), and when the rotors are still (wind speed < 3 ms⁻¹, G) and spinning (wind speed >= 3 ms⁻¹, H). A positive value indicates a higher straightness inside the wind farm relative to the other domain. The vertical red line highlights 0 on the x-axis, which indicates no difference between segments.
Figure 5.5.3 Probability density distributions of difference in average flight direction, within tracks, between segments inside and outside the wind farm (dIO), and downwind from and inside the wind farm (dID) for: all flight (A), flight at day (B) and night (C), flight in headwind (D), crosswind (E), and tailwind (F), and when the rotors are still (wind speed < 3 ms\(^{-1}\), G) and spinning (wind speed >= 3 ms\(^{-1}\), H). A positive value indicates the flight direction changed in a clockwise manner inside the wind farm relative to the other domain. The vertical red line highlights 0 on the x-axis, which indicates no difference between segments.
Supplementary material 3: Sample of tracks with extreme differences in track properties between domains.

Although there was no structural difference in track properties between domains, there were tails in the distribution tracks that did show a large difference in average ground speed, straightness, and flight direction between domains (see Sup. Mat. 2). Exploring these tracks further revealed these differences could be caused by the bird turning around or specific behaviour in part of the track that (e.g., thermal soaring; Fig. 5.S.4). These behaviours occurred in all domains.

Figure 5.S.4 Sample of 15 tracks crossing the wind farm area (black outline) that have a large difference in average ground speed (blue lines), straightness (red lines) or flight direction (green lines) between different domains. Thermal soaring behaviour (Chapter 3) can be observed in several tracks.
Chapter 6

Synthesis

Jens A. van Erp
The North Sea hosts a wide range of bird species, from long-lived, pelagic species that spend most of their time offshore, to migrants that cross the sea on their seasonal journeys. While the region is one of the most affected seas by anthropogenic activities globally (Halpern et al. 2008), the development of offshore wind energy is likely to further increase the disturbance of wildlife. In order to improve our ability to assess how wind energy developments will affect avian ecology we need a better understanding of bird flight and behaviour at sea in relation to wind energy. In this thesis, we aimed to increase our knowledge of bird flight at sea in relation to the environment, including offshore wind farms. We used tracking data from bird radars installed at offshore wind farms near the Dutch North Sea coast to measure bird flight in the breeding season. In Chapter 2 we found that bird abundance offshore in the breeding season follows a daily and seasonal pattern, which we suspect is determined by the foraging and breeding ecology of nearby central-place foragers. In Chapter 3, we studied offshore thermal soaring with biologging and radar, which occurs when the sea surface is warmer than the air above. This behaviour increases flight altitude, and therefore collision risk, when performed within the wind farm. The post-processing methods developed for increasing the quality and reproducibility of bird radar research during these projects were refined and described for broader use in Chapter 4. In Chapter 5, we found average ground speed, straightness, and flight direction do not predictably differ between the area inside, outside, and downwind from an offshore wind farm. Here, I will discuss these chapters in two contexts: possible consequences of bird movements for offshore wind farm interactions and the use of bird radar to study bird flight at sea and near offshore wind farms.
6.1 Consequences for offshore wind farm interactions

The impact of offshore wind farm developments on bird populations can be split in three factors: collision which results in mortality, avoidance responses, and habitat changes which can affect annual breeding output and survival (Fox et al. 2006). Seabirds can be particularly vulnerable to these effects during the breeding season, due to increased time spent at sea during foraging trips (Thaxter et al. 2019). Therefore, I will discuss these effects in the context of birds flying offshore on the North Sea during the breeding season.

Collision risk

Collision risk models are often used to assess the environmental impact of wind farms before and after construction (Masden and Cook 2016) and are especially helpful offshore, where other methods such as carcass counts are unfeasible (Desholm et al. 2006). These models are parameterized in part by flight properties of birds to quantify the probability of collision with the rotors and bird densities to estimate the number of collisions (Kleyheeg-Hartman et al. 2018), and several of these parameters were studied in this thesis. In Chapter 2, we estimated bird abundance near Luchterduinen wind farm and showed that, although a large part of the hourly number of birds varies unpredictably, the average follows a daily and seasonal pattern. Bird abundance was highest during the day and lowest at night, which was confirmed by the number of observations during day and night in Chapter 5 and earlier observations in the area (Fijn et al. 2015). Presumably, these diurnal patterns emerge because most of the birds observed in the study area are central-place foragers that follow a diurnal foraging rhythm (Fryxell and Lundberg 1998; Shealer 2002). Abundance also increased later in the breeding season, which might be caused by the increased selection of a marine diet in breeding seabirds on the nearby coast (Spaans 1971; Annett and Pierotti 1989; van Donk et al. 2019). Another important factor for collision risk is the altitude at which birds are flying, as only flight within the altitude range of the rotors can result in collision, and this has been a main focus for collision impact studies (Corman and Garthe 2014; Johnston et al. 2014; Thaxter et al. 2018). Seabirds at sea generally fly at low altitudes and below the rotor swept zone (Johnston et al. 2014; Chapter 3), although they can increase their altitude with increased wind speed (Ainley et al. 2015). Birds also gain altitude at sea during thermal soaring by utilizing thermal uplift (Pennycuick 1983; Weimerskirch et al. 2003). Seabirds and specifically lesser black-backed gulls *Larus fuscus* can use thermal soaring on the North Sea with Northern winds and the increase in flight altitude likely results in an increased collision risk under these weather conditions (Chapter 3). Following observations in soaring raptors by Nourani et al. (2021), our findings provide further evidence that this flight mode is possible in higher latitudes for a wide range of species. Next to altitude, two other flight metrics, ground speed (Masden
et al. 2021) and direction (Tucker 1996; Holmstrom et al. 2011), also effect the collision risk of a bird flying through the rotor swept zone. In Chapter 5, we found that birds flying through the wind farm most often flew with some measure of wind support and ground speed was high relative to what was previously observed in lesser black-backed gulls (Shamoun-Baranes et al. 2016), especially at night, which is in contrast with Masden et al. (2021). Altogether, we found that bird flight offshore during the breeding season is highly variable in both volume and behaviour, and consequently we expect collision rates to vary considerably as well. This is likely due to environmental factors influencing foraging efficiency and demands, resource availability, and flight efficiency at sea which affect bird flight behaviour. Therefore, like Fijn and Gyimesi (2018), we note that the dominant flight behaviour should be taken into account when assessing collision rates over time, and several environmental factors (diurnal and seasonal phase, and wind conditions) could help to predict this behaviour.

Wind farm avoidance

Although collision is a major concern due to the direct effects on survival, most studies estimate that most seabirds are able to avoid collision (Cook et al. 2018) and thus the possible implications of avoidance are just as important. Avoidance behaviour can be split in three types, based on their scale at which avoidance occurs: macro-, meso-, and micro-avoidance (May 2015). We will only discuss the first two types (macro- and meso-avoidance) as micro-avoidance, which is the avoidance of the individual rotors of the turbine, cannot be measured by radar due to the powerful reflection of the turbine that prevents nearby bird observations. Macro-avoidance concerns the avoidance of the complete wind farm area, resulting in displacement and, effectively, the loss of habitat, as well as increased flight times. This in turn can have population level consequences if it results in reduced food availability or increased energy expenditure (Fox et al. 2006). In Chapter 4 estimated bird densities were similar inside and outside the wind farm, indicating that no mass avoidance of the wind farm occurs during the breeding season. This aligns with the lack of avoidance of wind farms found in large gull species such as the lesser black-backed gull and herring gull Larus argentatus (Dierschke et al. 2016) which were most prevalent in our study area. Meso-avoidance is the avoidance of individual turbines and will likely only result in small energetic costs to the individual bird. Arguably, the radar data are best suited to study this type of avoidance, as birds can be followed throughout the wind farm area (Desholm and Kahlert 2005; Plonczkier and Simms 2012; Skov et al. 2016). Straightness measured inside wind farms in Chapter 5 was similar to flight outside the wind farm, which indicates an absence of meso-avoidance as more tortuous flight could indicate that birds are avoiding flying close to the turbines. Similarly, birds did not fly with a different direction or ground speed when inside the wind farm.
Although these results agree with Thaxter et al. (2018), Vanermen et al. (2019) showed meso-avoidance by lesser black-backed gulls might occur in a different form, where they avoid the center of the wind farm but not the outer turbine rows. Indeed, the raster maps in Chapter 4 show a density pattern within the wind farm similar to that in Vanermen et al. (2019), however this might also be caused by the decrease in bird detection over distance from the radar. Overall, we did not find any indications that birds in the breeding season avoid the offshore wind farm areas. Although this result aligns well with earlier research (Dierschke et al. 2016), avoidance behaviour is complicated and multi-facetted (May 2015) and would benefit from additional research (see “Opportunities”).

Habitat change

Whereas avoidance can result in birds not using the area, habitat changes constitute both the direct negative and positive effects of the turbines in the area (Fox et al. 2006). It includes effects to the aerial habitat, such as wind wakes (Stevens and Meneveau 2017; Cañadillas et al. 2020), and the marine habitat, such as the artificial reef effect (Degraer et al. 2020) which can result in new foraging opportunities for birds. In this thesis we compared different aspects of bird flight inside and outside the offshore wind farms that could indicate effects of habitat change. The results from these comparisons are fairly unanimous however: bird flight does not seem to differ between inside and outside the wind farm. Thermal soaring occurrence (Chapter 3), bird densities (Chapter 4) and flight properties (Chapter 5) were similar between both areas on average. These results suggest that the majority of birds that fly in close proximity to the offshore wind parks during the breeding season are not hindered in their flight by the presence of the turbines. Nevertheless, there may be species present in small numbers (see Chapter 2 and 3) that are affected. Increased bird densities were observed near the outer turbine of Luchterduinen wind farm closest to the coast (Chapter 4), with a lot of flight to and from the turbine. The attraction to this outer turbine is similar to what was observed for lesser black-backed gulls by Vanermen et al. (2019) and great cormorants *Phalacrocorax carbo* have also been observed landing on the turbines in high frequency (Leemans et al. 2022). Secondly, lower straightness downwind from the wind farm with wind speeds > 3 ms\(^{-1}\) indicates that the wind wakes of the turbines might affect bird flight with higher wind speeds. As with avoidance, the effects of habitat change on birds might be indirect and difficult to assess. Additionally, although the turbines are a static presence, their effect on the surroundings changes as underwater communities develop (Degraer et al. 2020) and governmental policies change (e.g., the implementation of shut-down procedures (Bradarić et al. 2022) or allowing fisheries within the wind farm). Even wind conditions can change how birds experience the space within and downwind from the windfarm on an hourly scale (Stevens and Meneveau 2017; Lundquist et al. 2018; Cañadillas et al. 2020).
6.2 Bird radar to study bird flight at sea

In our research we mainly used bird radar systems (Robin Radar 3D-Fix) to study bird flight in and around the offshore wind farms. Bird radars provide a unique perspective on bird flight: their ability to autonomously track multiple birds and continuously operate for extended periods of time enables them to provide the quantitative power to study bird flight in a specific location and under a wide range of conditions. This makes them especially suitable to monitor bird flight in remote areas, e.g., offshore wind farms (Plonczkier and Simms 2012; Fijn et al. 2015), where they fill a gap in our observative capability not easily covered with other tools (see Chapter 1). These characteristics allowed us to explore movement patterns over time (Chapter 2), distributions of flight properties in different environmental conditions (Chapter 5), and even enabled us to quantify a relatively rare behaviour (Chapter 3) in the context of offshore wind energy and the breeding season. Nevertheless, preparing the data to make it suitable for research was not trivial. Initially, we had the ambition to study bird movement throughout the entire year and investigate additional environmental conditions, such as in adverse weather and around precipitation. However, during the exploratory phase of the thesis this turned out to be infeasible within the available time. In this section I discuss the use of bird radar for ecological research at sea, the challenges we faced, and how these challenges have been addressed in this thesis and elsewhere.

Working with big data

One of the first challenges users encounter when working with bird radars is the data volume that needs to be handled. As bird radars function autonomously, they can gather millions of tracks over the period they are recording. Simple tasks, like exploring the data, require specific tools and functions that are able to aggregate the data into informative metrics, and analysis of larger data sets requires substantial computational power. During the data post-processing in Chapter 2, 3, and 5, for example, the data was split per month to be workable on local computers. To support this work, as well as that of Bradarić (2022) and others, an eScience infrastructure was developed by the University of Amsterdam and supported by SURFsara. This infrastructure was vital to the project as it ensured data accessibility and consistency across users, and incentivized collaborative efforts within and outside the research group.

In addition to grappling with the data size, our concerns about their reliability required us to use the data with care. As these bird radar systems are designed for live monitoring, the tracking algorithm works with limited information and processing time, which impacts their capability to distinguish birds from other objects and can lead to false
positive observations. Additionally, the offshore wind farm is a challenging environment for radar observations: the turbines produce static reflections which obscure birds, and the spinning rotors create dynamic reflections which further convolute tracking in their vicinity. Likewise, the sea itself is a dynamic, reflecting surface, and this effect is exaggerated during adverse weather conditions. All these effects accumulate in a dataset that has both false positive and false negative observations, which need to be addressed before ecological questions can be answered. The data size prevented us from performing manually selection of the tracks, making automatic post-processing the only viable option. We initially used a cautionary approach, using only data from an unobstructed area of 1 km² in Chapter 2. However, through increased experience with the data within the team of the University of Amsterdam, as well as countless collaborative discussions with the radar developers at Robin Radar and other radar users such as Waardenburg Ecology and the Royal Netherlands Air Force, we were able to develop post-processing steps which allowed us to expand our scope of research (Chapter 3 and 5). With the advancements of monitoring tools, both in quality and affordability, the challenge of working with big data is arising across the field of movement ecology (Nathan et al. 2022). Sharing not only the results of our endeavors, but also the tools we created along the way, is paramount to move forward. Chapter 4 is another piece of the puzzle in a continuously expanding toolkit (Stepanian et al. 2014; Dokter et al. 2019; Capotosti et al. 2019; Gupte et al. 2022) that will allow researchers and other users to extract ecologically meaningful data from bird radars and (possibly) other animal tracking systems.

Finding ecological context
Although autonomous bird radars are able to track all birds in their range, information about each individual target is limited. For each individual track, only the approximate size of the target and its trajectory (location, speed and direction) within the radar range is known. This lack of detail can make in-depth ecological and behavioural analysis challenging (Nathan et al. 2022), but can be addressed by using other types of ecological data (Robinson et al. 2010; Bauer et al. 2019). In this thesis, we used species distribution information from the ESAS 5.0 ship-surveys to interpret the radar data in relation to lesser black-backed gulls, herring gulls, and cormorants, which were the most prevalent bird species offshore in the breeding season (Chapter 2 and 3). On a more fundamental level, the study design often requires ecological context that cannot be determined from radar itself. For example, the breeding season as studied in Chapter 2 is based on previous research, in contrast to biologging studies, e.g., Both et al. (2016) or Brown et al. (2020), which can use the measurements themselves to discern this period. Additionally, biologging of lesser black-backed gulls from nearby onshore colonies in IJmuiden and Schiermonnikoog enabled us to identify thermal soaring in bird radar by parameterizing
the thermal soaring identification algorithm using the behaviour as observed with GPS (Chapter 3). In the same chapter, the integration of flight altitude from biologging with the spatial distribution from radar of thermal soaring allowed us to study the effect of this behaviour for offshore wind farm interactions. In some studies, radar monitoring could be linked directly to visual observations to study species of interest (Plonczkier and Simms 2012; Skov et al. 2016), but the inherent limitations of visual observations can defeat the spatio-temporal coverage radar offers if all tracks have to be visually confirmed. More often, these data are better suited for providing visual validation rather than enriched datasets for ecological research (Fijn et al. 2015; Urmy and Warren 2020, Chapter 4). The lack of these more direct comparisons is often caused by the greatly divergent scales at which each method operates: the radar operates continuously in a small area, whereas visual ship based or aerial surveys and biologging cover much greater areas but miss temporal continuity in any given area due to logistic limitations or by virtue of the partly stochastic behaviour of the tracked animals. However, this is precisely why bird radars fill an important new niche in ecological monitoring: by providing a different scale for monitoring avian biology compared to other technologies (Nathan et al. 2022).

Matching remote observations to environmental predictors
The challenge of measuring in remote locations goes beyond avian flight itself. Reliable environmental measurements are required to associate bird observations with their surroundings. In this thesis we have used both (near) local measurements and modelled data to study the relation between birds and their environment. Local measurements often have a high temporal resolution and can be matched directly with the radar data due to their vicinity in time and space. However, these measurements can also suffer from inaccuracies due the specific sensor placement. For example, wind data from the weather station associated with the bird radar system suffered from the turbulence around the turbine the radar was situated on, making these data unusable. In other situations, local measurements may not be “local” enough, as the nearest observation point might be too far from the area of interest to accurately reflect the local circumstances. In Chapter 2, we use tidal information from an observation station 60 km from the wind farm. As the tidal pattern in the North Sea is relatively dynamic, owing to the surrounding geography affecting the tidal current (Sündermann and Pohlmann 2011), these measurements might not represent the local circumstances accurately enough. When local measurements are unavailable or unreliable, another option is to use models that interpolate from point-measurements over space and time to predict environmental characteristics (Bruneel et al. 2018). The benefit of these models is that they can approximate local circumstances over a large area, which is especially useful offshore, and can also provide context on circumstances elsewhere which might affect the behaviour of observed birds (e.g., Bradarić...
et al. 2020). In this thesis we use wind data from the ERA5 reanalysis (Hersbach et al. 2020) both to calculate airspeed and assess the effect of wind on bird behaviour (Chapter 3) and bird flight (Chapter 5). The resolution of these large-scale atmospheric models can be rough (ERA5 reanalysis is modelled per hour over a global 0.25 ° longitude by 0.25 ° latitude grid) compared to the spatio-temporal resolution of the bird radar data. However, this scale allows for straightforward comparisons between locations and across measurement tools (Chapter 3), and methods based partly on atmospheric models, such as the work in Chapter 4, can be adopted elsewhere with ease. Furthermore, these models are likely to increase in resolution and accuracy as our understanding of the natural environment increases and computational power grows to allow for more advanced environmental models (Carrassi et al. 2018).

6.3 Future outlook

Several research possibilities bird radar data offers have not been explored yet due to time constraints and methodological limitations. Avoidance behaviour can be studied further, for example by assessing the average distance between birds and the closest wind turbine, and the number of birds flying into the wind farm versus the number of birds deviating from this path. With additional years of data, other seasons can be studied that were not considered in this thesis because of the limited data availability due to adverse weather conditions, such as the winter. Similarly, data from additional locations offshore can be used to discern whether the flight patterns found in this thesis hold for different sections of the North Sea and other coastal areas, or are affected by differences in avian communities, geography and oceanography, or other environmental factors. For example, the daily abundance patterns found in Chapter 2 might be similar globally during the breeding season of the local avian species, while seasonal patterns might be more dependent on the specific breeding ecology of the species.

An integral part of current and future offshore wind farm developments is monitoring wildlife pre- and post-construction (Pérez Lapeña et al. 2010). Bird radar systems are one of the tools applied to monitor avian flight, especially for post-construction monitoring (Desholm and Kahlert 2005; Plonczkier and Simms 2012; Fijn et al. 2015). However, installment of these systems should be done with care, as improper placement can result in substantial reduction of its functionality. Based on our experience with the bird radar data, there are several considerations to make optimal use of this tool. For proper in-out comparisons, a radar should be installed on the wind farm’s outer turbines. This allows for an unobstructed view of the area outside the wind farm within the optimal range.
for bird observations, which is more difficult if the radar is placed in the center of the windfarm (e.g., Gemini wind farm in Chapter 3). Additionally, the unobstructed view of the open sea provides the possibility to study bird flight outside the context of the wind farm (e.g., Chapter 2). A significant part of bird observations will be related to the nearby coast, either as it concerns foraging birds of nearby breeding colonies (e.g., Fijn et al. 2015; Chapter 2) or migrants crossing the sea (e.g., Desholm and Kahlert 2005; Skov et al. 2018; Bradarić et al. 2020). Therefore, bird radars should be placed on the coastal side to allow an unobstructed view of birds coming from the nearest coast and observe possible avoidance behaviour. Ideally, several bird radars should be placed to allow a more complete view of bird flight through the wind farm and account for detection loss due to the rows of turbines (see Chapter 4). Lastly, care should be taken to avoid turbines lining up either radially or circularly relative to the radar location. Reflections of these rows of turbines can accumulate to cause large blind zones in the radar area that limit the available area for reliable bird observations.

We used biologging and ship-survey data to address the bird radar limitations, but there are several options for data integration that have not yet been explored here. Weather radar for avian research allows for the observation of bird movements at a much larger scale. This makes the tool especially suitable to study mass movement events such as migration (Bauer et al. 2019; Nilsson et al. 2019) or responses to fireworks discharge (Shamoun-Baranes et al. 2011). However, movement is measured in terms of mass rather than individuals, and numbers have to be estimated based on average bird mass (Dokter et al. 2019). Bird radar measurements could help to better interpret the broader movements measured by weather radar by providing local context of individual flight. For example, where weather radar measures mean ground speed (Dokter et al. 2018), bird radar can provide the distribution of all measured individuals (Chapter 5). Additionally, bird radars can provide measurements for the lowest level of elevation (0 – 200 m) which is often excluded for biological research with weather radar, due to obstructions on the ground and the curvature of the earth (Nilsson et al. 2018, 2019). Further integration across localized tracking systems also could help describe individual bird movements over a broader spatial scale. Two radars were used in Chapter 3 to compare movement in two different areas on the Dutch North Sea. However, an integrated network of local observation systems could function more akin to the ATLAS system (Toledo et al. 2020), which allows them to cover a region much larger than any single receiver (Bijleveld et al. 2021). A similar coverage could be achievable when using bird radar systems with overlapping range, for example, if multiple systems are installed within an offshore wind farm. Such a network could also be used to address the reduced bird detectability further into the wind farm. Even without interconnection of tracks or direct spatial overlap, offshore bird radars could
serve as sentinels at sea for observing continental movement patterns, such as migration as observed by Nilsson et al. (2019).

6.4 Conclusion

In this thesis, we aimed to increase our knowledge of bird flight at sea in relation to the environment, and to use this knowledge to investigate how birds are interacting with offshore wind farms. We show birds abundance, behaviour, and flight properties vary under different environmental conditions, which affects their vulnerability to offshore wind farm interactions. This knowledge can help further inform offshore wind energy development and ecological monitoring policies. Although we did not find large effects of offshore wind farms on bird flight at sea, this might change as offshore wind farm development expands further to cover larger sections of the North Sea (European Commission 2020, Rijksoverheid 2022). Cumulative effects of increased collisions and how seabirds respond to the increasing change in habitat are difficult to predict (Goodale and Milman 2016; Willsteed et al. 2018) and cumulative impact assessment methods are still developing (Korpinen and Andersen 2016). Even if direct effects of offshore wind energy are found to be minor, they can accumulate on top of existing negative effects, such as disease, predation, or other anthropogenic pressures, to exacerbate them and cause populations to move past their tipping point. Continuous monitoring of bird life is therefore paramount, but as important is the ongoing cooperation between governments, wind farm owners, and researchers to consolidate these monitoring data and create a holistic view of avian biology on the North Sea. This might allow us to meet our requirements for renewable energy while accurately assessing wildlife impacts and, ideally, predict and mitigate most negative effects.
References


References


122. R Core Team (2020) R: A Language and Environment for Statistical Computing. Available from: https://cran.r-project.org/bin/windows/base/old/4.0.0/.

123. R Core Team (2022) R: A Language and Environment for Statistical Computing. Available from: https://cran.r-project.org/bin/windows/base/old/4.2.0/.


135. Rinehart RE (1991) Radar for Meteorologists or you, too, can be a radar meteorologist, part III. University of North Dakota.


Summary

The Southern North Sea (from here simply North Sea) is a highly productive area that supports a diverse ecosystem, including a large number of seabirds. A myriad of species, such as gulls and terns, breed on the surrounding coast and undertake foraging trips at sea in summer. In winter, it hosts large flocks of divers and sea ducks. Additionally, the sea is crossed by millions of migrants, mainly passerines, each spring and fall. Together, these birds form a mosaic of movement throughout the year. Simultaneously, this region is also being heavily exploited by the surrounding countries. Fisheries have had the most profound human impact in the region, devastating fish populations and greatly disrupting the seabed, to the point that the current fish stocks are a dim reflection of what they once were. Since the discovery of gas and oil deposits beneath the seabed, the area has also become an important source of fossil fuels, and the presence of humans became permanent with the installation of offshore drilling platforms. As a result of these and other human activities, the region is one of the most heavily anthropogenically affected seas in the world.

Currently, the development of offshore wind energy constitutes a new era of anthropogenic disturbance at sea. In 2030, the EU plans to produce 60 gigawatts (GW) of offshore wind energy, which should be increased to 300 GW by 2050, and a large proportion of that production will be situated in the North Sea. The countries surrounding the North Sea aim to do this in an environmentally responsible manner, and understanding how bird life at sea is impacted by offshore wind farms is an important aspect of that. Birds are expected to be affected in three ways: through habitat change, avoidance behaviour, and mortality through collision. Habitat change constitutes both the removal of free air space and the added physical presence of the turbines, and indirect effects such as changes in resource availability. Avoidance behaviour is caused by the visual stimulus of the wind farm. Some species, such as razorbills and common guillemots, avoid the wind farm entirely, which is called macro-avoidance. Other species, such as lesser black-backed gulls and herring gulls, fly through the wind farm and will have to perform avoidance manoeuvres to prevent collisions (meso- and micro-avoidance). Lastly, if birds flying through the area fail to avoid the turbine rotor, the collision usually results in mortality. Additionally, all of these effects can interact to increase or reduce the overall impact (e.g., avoidance of the wind farm leads to decreased risk of collision). To improve our understanding of these effects and how they impact avian ecology, more knowledge of their behaviour at sea and inside wind farms is required.

Unfortunately, studying the interactions between birds and wind farms at sea is not as straightforward as on land. The first insights into bird behaviour were provided by ship-based surveys. Together with aerial surveys, they are still being used to shed light on bird densities and behaviour at sea. However, the high cost of these surveys and the dependency
on visual observations makes them unsuitable for continuously monitoring bird flight over long periods. Another available technique is biologging, which involves tracking individual birds with GPS and other sensors to get a detailed understanding of the behaviour of these individuals. This technique has greatly improved our understanding of bird flight at sea, but the number of birds that can be tagged is often restricted, limiting the number of observations in and around wind farms that can be obtained over time. Therefore, their capacity to study behaviour in the context of the fast-paced offshore wind farm development is limited as well. Radar is another tool that has historically been used to study bird flight. Depending on the type of radar, individual birds or mass movements can be continuously tracked in remote regions. Recently developed bird radars automatically track all birds in an area of several kilometres around its location and are especially suitable for the monitoring of bird flight in an offshore wind farm. Nevertheless, the technique is not perfect, as reflections of other features such as wind turbines and high sea waves can hinder the detection of birds. Therefore, additional post-processing is required to study bird flight with radar.

In this thesis, we used Robin Radar 3D-Fix bird radars in two wind farms near the Dutch coast to study bird flight offshore in relation to the marine environment and offshore wind energy. We aimed to increase our understanding of bird flight at sea in relation to the environment and use this knowledge to investigate the dynamics of when and how birds are interacting with offshore wind farms. We focussed on the breeding season of several common coastal seabirds in late spring and early summer. These species, most prevalently the lesser black-backed gull, herring gull, and cormorant, do not avoid flying into offshore wind farms. Moreover, they fly at low altitudes, which makes them particularly vulnerable to collisions.

The number of birds flying near a wind farm directly affects the number of interactions and, therefore, the possibility of collisions for these birds. If bird abundance varies in a predictable way, we can anticipate when wind farm interactions are highest. In Chapter 2, we investigated offshore bird abundance in relation to three environmental conditions that we expect to affect their foraging at sea: the time of day, the time in the breeding season and the tidal phase. We measured the number of birds near a wind farm near the west Dutch coast between May 1st and July 15th and analysed the effect of these three conditions using generalized additive modelling. We show that bird abundance is affected by the time of day and the time in the breeding season but not by the tidal phase. Abundance peaks after sunrise and increases throughout the breeding season until the end of June. Even though these factors partly explain the number of birds observed offshore, a large proportion of the variability in abundance remains unexplained. This high variability in the number of birds between hours, days and weeks emphasizes the need for long-term and continuous monitoring.
Some flight modes of birds can greatly change the rate at which they might interact with nearby wind turbines. Seabirds can use several flight modes at sea, including thermal soaring, in which they use thermal uplift to gain altitude and save energy. This increase in altitude can have consequences for wind farm interactions if it results in birds spending more time within the rotor swept zone of the turbines. In Chapter 3, we investigated the potential implications of thermal soaring at sea for wind farm interactions. We studied flight altitudes during soaring and non-soaring flight and the conditions under which thermal soaring occurs. To meet this goal, we utilized two techniques that complement each other: biologging of lesser black-backed gulls and radar tracking of all birds in the vicinity of the wind farm. From the biologging data, we saw that thermal soaring increases the time gulls spend flying within the rotor swept zone, while with radar data, we proved that birds perform thermal soaring as much inside the wind farm as outside. Together, these results show that thermal soaring increases the risk of wind farm collisions for these birds. We furthermore show that birds mostly perform thermal soaring when the sea surface is warmer than the air above, and this generally happens with north and north-westerly winds.

Measuring bird movement at sea with radar is challenging. Despite technological advancements, significant post-processing is required to use bird radar data for scientific research. In Chapter 4, we used the experience gained with bird radar systems in Chapters 2 and 3 to create a post-processing framework that implements knowledge of the radar system and bird biology to filter the data and retrieve reliable, high-quality tracking data. The framework is split into three modules, each with a specific aim: (I) to remove tracks with lower reliability of being birds, based on prior knowledge of the radar system and bird flight; (II) to improve the quality of the remaining bird tracks; and (III) to identify and remove sections of data, either in specific periods or specific locations, that are less reliable. The modules are designed to facilitate early data reduction, so that the large datasets from automated tracking radars can be efficiently processed. Additionally, we put emphasis on data visualisation so that users can verify that the post-processing steps are applied successfully. We show the effect of the framework by applying it to radar tracks collected at an offshore wind farm in the North Sea in June 2020. Application of Module I resulted in a high-quality dataset of 520894 bird tracks (19.5 % of the original dataset) sampled across a 10.4 km² area around the radar. Of this dataset, 18734 tracks were corrected for geometric errors in Module II. Lastly, Module III identified 236 of 719 observation hours and an area of 1.55 km² as unreliable for spatio-temporal analysis. The framework was applied to a visually validated radar tracks and succeeded in removing most false-positive tracks while retaining most true bird tracks. Furthermore, we show that the outcomes of a comparative analysis of track densities inside and outside the wind farm differed greatly between unprocessed and processed data, and is likely more reliable after post-processing. Altogether, the framework provides a logical workflow to increase the reliability and quality of a bird radar dataset.
while being adaptable to the radar system and its surroundings. It is a first step towards standardising the post-processing methodology for automated bird radar systems, which can facilitate future comparative analyses of bird movement.

The development of offshore wind energy is changing the airspace above the sea from virtually unobstructed to a novel environment in which wind turbines act as physical obstructions that can affect bird flight. Additionally, the turbines and the spinning rotors create so-called turbine wakes that alter the wind conditions downwind from the wind farms, which could further affect birds flying inside or downwind from the wind farm. Subsequently, these changes in flight might affect the risk of colliding with the turbines. In Chapter 5, we investigate whether birds change their flight between the area inside, outside, and downwind from a wind farm. We compare average ground speed, straightness, and average flight direction relative to the wind between these three areas. We additionally investigate the effect of experienced wind conditions (wind speed and direction) and the diurnal phase on these flight properties. Although we found indications that flight properties differ among these environmental conditions on average, we observed no biologically relevant changes between the different study areas. It seems the turbine presence and turbine wakes generally do not affect the behaviour of birds entering the wind farm to the point that they significantly alter their flight.

Throughout this thesis, we have studied birds at sea in relation to offshore wind farms and showed that flight at sea is highly variable, even within the breeding season. In the context of wind energy interactions, we found bird abundance is highest during the day (Chapter 2), time spent within the rotor swept zone increases during thermal soaring (Chapter 3), and ground speed was highest at night (Chapter 5). Furthermore, we found no evidence that bird flight differs between inside and outside the windfarm (Chapter 3, 4, and 5). However, the number of birds in the air and their flight behaviour is challenging to predict. Therefore, we need to continue these lines of study to further our understanding of bird-wind farm interactions at sea. Bird radar has proven to be an important tool in this research, due to the ability to monitor flight in relation to the wind farm in different conditions and over extended periods of time. We show what role bird radars can play in investigating bird flight offshore (Chapter 2, 3, and 5), how the output can be improved for better research (Chapter 4), and how the data can be combined with other tracking techniques (Chapter 3) to increase our understanding of flight behaviour over sea in relation to wind energy. The North Sea and other coastal seas will see further wind energy development as we increase our efforts to switch to renewable energy globally. This makes further monitoring and ongoing research collaborations vital, so that we can further increase our understanding of bird behaviour offshore. In time, we will hopefully be able to accurately predict and counteract the possible adverse effects of these developments.
De zuidelijke Noordzee (vanaf hier simpelweg Noordzee) is een gebied met een hoge productiviteit dat een divers ecosysteem ondersteunt, inclusief een groot aantal zeevogels. Diverse soorten zeevogels, zoals meeuwen en sternen, broeden aan de nabijgelegen kust in de zomer, waarvandaan ze dagelijks foerageren op zee. In de winter verblijven grote groepen duikers en zee-eenden op het water. Daarnaast trekken miljoenen vogels, voornamelijk zangvogels, over de zee in de lente en herfst tijdens hun migratie. Bij elkaar vormen al deze vogels een mozaïek van bewegingen door het jaar heen. Tegelijkertijd wordt de Noordzee zwaar geëxploiteerd door de omliggende landen. Visserij heeft de grootste impact gehad op de regio door vispopulaties in te laten storten en de zeebodem te verstoren. De huidige visstand is slechts een fractie van de vroegere situatie. Met de ontdekking van gas- en olievoorraden onder de zeebodem is de Noordzee een belangrijke energiebron geworden, en met het installeren van olieplatformen werd onze aanwezigheid op open zee permanent. Door deze en andere activiteiten is de Noordzee een van de meest beïnvloede zeeën op aarde.

Met de ontwikkeling van windenergie op zee breekt een nieuw tijdperk aan van structurele verstoring. De Europese Unie wil in 2030 60 gigawatt (GW) aan windenergie op zee genereren (toenemend tot 300 GW in 2050). Hiervan zal een aanzienlijk deel op de Noordzee geproduceerd worden. De Noordzeelanden hebben afgesproken dit op een natuurvriendelijke manier te doen, waarbij het begrijpen van het effect van windenergie op zee op vogels een belangrijk onderdeel is. De verwachting is dat vogels op drie manieren worden beïnvloed door windturbines: door de verandering van hun leefgebied, door ontwijkgedrag, en door botsingen. Met het veranderen van het leefgebied door windturbines worden zowel directe effecten (het inkrimpen van het luchtruim), als indirecte effecten (zoals een verandering in het voedselaanbod) bedoeld. Ontwijkgedrag vindt plaats wanneer vogels de windturbines zien en besluiten er omheen te vliegen. Sommige soorten, zoals alken en zeekoeten, maken een wijde boog om het hele windpark heen. Andere soorten, zoals kleine mantelmeeuwen en zilvermeeuwen, vliegen het windpark in en ontwijken de individuele windturbines. Wanneer vogels de windturbines niet ontwijken, kunnen ze botsen met de draaiende wieken, nagenoeg altijd met dodelijke afloop. Al deze effecten kunnen elkaar ook versterken of juist opheffen (actieve ontwikkeling leidt bijvoorbeeld tot een kleinere kans op botsing). Om een beter beeld te krijgen van deze effecten en de impact op vogels, moeten we meer te weten komen over hun vlieggedrag op open zee en binnen windparken.

Helaas is het bestuderen van vogels in windparken op zee niet zo eenvoudig als op land. Vogeltellingen vanaf schepen gaven ons de eerste inzichten in vogelvlucht op zee. Samen
met tellingen vanuit kleine vliegtuigen is dit nog steeds een belangrijke methode om vogeldichtheden en gedrag te bepalen. Deze excursies zijn echter duur en kunnen alleen overdag met goed weer worden uitgevoerd. Daardoor zijn continue observaties over een lange tijd niet haalbaar met deze techniek. Een andere methode is het bevestigen van kleine GPS-zenders op gevangen vogels. Deze zenders kunnen de positie en het gedrag van enkele individuen nauwkeurig bepalen. Hiermee hebben we de afgelopen decennia veel kunnen leren over vogelgedrag op zee, maar omdat er maar een klein aantal vogels gevolgd kunnen worden, is het lastig om genoeg metingen in een specifiek gebied te verzamelen, zoals een windpark. Een andere mogelijkheid is het gebruik van radars, waarbij afhankelijk van het type radar individuele vogels of juist massabewegingen kunnen worden gevolgd. Het bereik van de radar maakt het mogelijk om vogels te volgen op onherbergzame plekken, zoals op zee. Recentelijk zijn er speciale vogelradars ontwikkeld die automatisch alle vogels in een straal van een aantal kilometer kunnen volgen, waardoor deze systemen uitermate geschikt zijn om vogels in windparken te bestuderen. Desalniettemin is de techniek niet perfect, omdat ook andere objecten zoals windturbines of zeegolven de radiogolven van de radar kunnen weerkaatsen en vogelmetingen kunnen verhinderen. De radardata moet verder behandeld worden voordat we er vogelvlucht mee kunnen bestuderen.

In dit proefschrift maken we gebruik van Robin Radar 3D-Fix vogelradars om vogelvlucht op de Noordzee te besturen in en om twee windparken voor de Nederlandse kust. Ons doel was om onze kennis van vogelvlucht op zee met betrekking tot hun omgeving te vergroten en te verkennen hoe vogels omgaan met windparken op zee. We richten ons op het broedseizoen van veelvoorkomende zeevogels die zich aan de kust nestelen in de lente en vroege zomer. Deze soorten, voornamelijk de kleine mantelmeeuw, de zilvermeeuw, en de aalscholver, gaan de windparken niet uit de weg. Daarbij vliegen ze op zee vaak laag over het water, waardoor ze een hoog risico lopen om te botsen met de wieken van de windturbines.

Het aantal vogels dat in de buurt van windparken op zee vliegt, staat in direct verband met het aantal interacties met de windturbines, en dus ook de mogelijkheid om te botsen met de wieken. Als het vogelaantal volgens een vast patroon fluctueert, kunnen we voorspellen wanneer het aantal interacties het hoogst is. In Hoofdstuk 2 onderzoeken we het vogelaantal op zee in verhouding tot omgevingsfactoren die naar verwachting een effect hebben op hun foerageergedrag op zee: de tijd van de dag, de tijd in het broedseizoen, en het getij. We maten het aantal vogels met een vogelradar dicht bij een windpark aan de Nederlandse kust tussen 1 mei en 15 juli en analyseerden het effect van deze drie factoren door middel van een “generalized additive model”. We toonden aan dat de tijd van de dag en het broedseizoen gedeeltelijk bepaalden hoeveel vogels er gemiddeld op zee voorkwamen, terwijl het getij hier geen effect had. Het grootste vogelaantal kwam
voor in de vroege ochtend vlak na zonsopgang en het aantal nam door het broedseizoen toe tot eind juni. Hoewel deze factoren invloed hebben op het vogelaantal, bleef een groot deel van de variatie onverklaard. Deze variatie vond plaats tussen verschillende uren, dagen, en weken in de studieperiode, en bevestigt het belang van langetermijnstudies waarin continue gemeten wordt.

De manier waarop vogels vliegen kan grote invloed hebben op hun kwetsbaarheid voor windturbines. Zeevogels gebruiken op zee verschillende methodes om te vliegen. Eén daarvan is zweven met behulp van thermiek (hierna: thermisch zweven), waarbij ze opstijgende warme lucht gebruiken om hoogte te winnen en energie te besparen. Deze techniek kan het botsgevaar met de turbinewieken vergroten als ze langere tijd op dezelfde hoogte vliegen als de wieken. In Hoofdstuk 3 kijken we naar de potentiële gevolgen van thermisch zweven voor interacties met windturbines. We bestudeerden de hoogte waarop vogels vliegen tijdens thermisch zweven en de omgevingsfactoren waaronder thermisch zweven plaatsvindt – beide ten opzichte van andere vliegtechnieken. Om dit te doen combineerden we twee soorten meetgegevens die elkaar complimenteren: gps-routes van gezenderde kleine mantelmeeuwen en radarmetingen van alle vogels in de buurt van het windpark. Met de GPS-zenders zagen we dat thermisch zweven ertoe leidt dat vogels vaker op hoogte van de turbinewieken vliegen, en met de radar data toonden we aan dat vogels dit gedrag in dezelfde mate binnen het windpark vertonen als daarbuiten. Samen laten de resultaten zien dat met thermisch zweven de kans op botsen voor vogels toeneemt. Daarnaast laten we zien dat thermisch zweven vooral plaatsvindt wanneer het zeeoppervlak warmer is dan de lucht erboven, en dat deze situatie voornamelijk voorkomt met een noordelijke en noordwestelijke wind.

Vogelvlucht op zee met een radar meten is uitdagend. Ondanks de technologische vooruitgang moet de data die door de apparatuur wordt gegenereerd nog in belangrijke mate worden nabewerkt om de vogelradar data (zogenaamde vogel tracks) effectief voor kwantitatieve analyses te kunnen gebruiken. In Hoofdstuk 4 presenteren we een raamwerk voor het nabewerken van vogelradar data, gebruikmakend van de kennis die we hebben opgedaan in Hoofdstuk 2 en 3. Het raamwerk gebruikt de kennis van het radarsysteem en de biologie van vogels om de data te filteren en betrouwbare data van hoge kwaliteit te produceren. Het raamwerk bestaat uit drie modules die elk een specifiek doel hebben: (I) het verwijderen van onbetrouwbare vogel tracks gebaseerd op voorkennis van het radarsysteem en vogelvlucht; (II) het verbeteren van de overgebleven vogel tracks; en (III) het identificeren en verwijderen van datasecties in ruimte en tijd die minder betrouwbaar zijn. De modules zijn ontworpen om de data vroeg in het proces te reduceren, zodat grote datasets van geautomatiseerde vogelradars efficiënt verwerkt kunnen worden. Daarnaast leggen we de nadruk op het visualiseren van de data zodat gebruikers na kunnen
lopen of de databewerkingen correct zijn geïmplementeerd. We toonden de kracht van
het raamwerk aan door het toe te passen op een vogelradar dataset verzameld nabij
een windpark op de Noordzee in 2020. Na Module I hielden we een dataset van hoge
kwaliteit over met 520894 vogel tracks (19.5 % van de originele dataset) over een gebied
van 10.4 km². Binnen deze dataset werden 18734 vogel tracks gecorrigeerd voor fouten
in Module II. Tenslotte identificeerde Module III 236 van de 719 observatie-uren en een
gebied van 1.55 km² als onbetrouwbare voor analyses over tijd en ruimte. Het raamwerk
werd ook toegepast op vogel tracks die door vogelspotters waren gecontroleerd, waarbij
het lukte om de meeste vals-positieve vogel tracks te verwijderen, terwijl de meeste
echt-positieve tracks behouden bleven. Als laatste lieten we zien dat het nabewerken van
vogelradardata een aanzienlijke invloed had op ecologische analyses en waarschijnlijk een
betrouwbardere uitkomst opleverde. Het raamwerk biedt als geheel een set aan logische
stappen om vogelradardata betrouwbaarder te maken, terwijl deze stappen flexibel
genoeg zijn om te worden toegepast op verschillende radarsystemen en omgevingen.
Het vormt een eerste stap om het nabewerken van dit soort data te standaardiseren, wat
vergelijkend onderzoek tussen vogelbewegingen in de toekomst kan faciliteren.

De ontwikkeling van windparken op zee verandert het luchtruim boven zee van een (voor
vogels) vrije ruimte in een nieuwe omgeving waarin windturbines als fysieke obstructies
vogelvlucht kunnen belemmeren. Bovendien kunnen de windturbines tijdens het draaien
de luchtstroom verstoren in hun zog (de windpluim achter de windturbine) wat effect kan
hebben op vliegende vogels in de luwte van het windpark. Deze effecten kunnen tot een
toename van de kans op botsingen met de wieken van de windturbines. In Hoofdstuk 5
kijken we of vogels hun vlucht veranderen tussen het gebied in, buiten, en in de luwte
van een windpark. We vergelijken de gemiddelde grondsnelheid, de rechtheid, en de
gemiddelde vliegrichting relatief tot de wind voor individuele vogel tracks tussen deze drie
gebieden. Daarnaast kijgen we naar het effect van de wind (snelheid en richting) en de
tijd van de dag op deze eigenschappen. Hoewel we indicaties vonden dat deze eigenschappen
verschillen onder verschillende omgevingsomstandigheden, zagen we geen biologisch
relevante veranderingen tussen de vergeleken gebieden. Het lijkt erop dat de turbines en
hun zog geen effect hebben op het gedrag van vogels die het windpark binnen vliegen,
tot het punt waarop ze hun vlucht aanpassen.

In dit proefschrift hebben we vogels op zee in relatie met windparken bestudeerd en
toonden we aan dat vogelvlucht op zee enorm variabel is, zelfs binnen het broedseizoen.
Wat betreft de interactie tussen vogels en windparken, zagen we dat vogeldichtheid
het hoogst is tijdens de dag (Hoofdstuk 2), dat de tijd die ze op hoogte van de wieken
vliegen toeneemt tijdens thermisch zweven (Hoofdstuk 3), en dat ze het snelst vliegen
in de nacht (Hoofdstuk 5). Daarbij vonden we geen verschil in vogelvlucht voor vogels
die binnen of buiten het windpark vlogen (Hoofdstuk 3, 4, en 5). Het aantal vogels op
zee en hun gedrag is echter lastig te voorspellen. Daarom zijn verdere studies nodig om
onze kennis van vogels en windparken op zee te vergroten. Vogelradars zijn een bewezen
hulpmiddel in deze zoektocht naar kennis; hun vermogen om over lange tijd en continue
vogelvlucht in de buurt van het windpark te meten, maakt het bestuderen van vogels onder
verschillende omstandigheden mogelijk. We laten zien waarvoor vogelradar data gebruikt
can worden (Hoofdstuk 2, 3, en 5), hoe de data verbeterd kan worden (Hoofdstuk 4) en
hoe de data gecombineerd kan worden met andere meettechnieken (Hoofdstuk 3) om
onze kennis van vogelvlucht op zee in relatie met windenergie verder te verbeteren. Door
de alsmaar toenemende vraag naar groene energie zal windenergie zich verder blijven
ontwikkelen, niet alleen op de Noordzee maar ook op andere zeeën wereldwijd. Dit maakt
het monitoren van vogels en internationale samenwerking van vitaal belang voor het
verbreden van onze kennis. Hopelijk kunnen we te zijner tijd accurate voorspellingen
maken over vogelvlucht op zee in relatie met windparken, en zo de negatieve effecten van
windenergie ontwikkelingen tegengaan.
Author contributions

Chapter 2
Study was conceived and designed by JAvE, JSB and EEvL. Data collection was performed by JAvE and CJC provided the ESAS data. Data preparation and processing was performed by JAvE. Statistical analysis was performed by JAvE and EEvL. The first draft of the manuscript was written by JAvE, and all authors contributed to subsequent versions of the manuscript. All authors read and approved the final manuscript. JSB acquired funding for and managed this project.

Chapter 3
This study was conceived and designed by ES, JAvE, JSB, WB and EEvL. Gull tracking (tagging and data collection) at IJmuiden was led by CJC and JSB and at Schiermonnikoog by JSB and ES. Data preparation and processing of radar data was carried out by JAvE, whilst data preparation and processing of GPS data was carried out by ES. Meteorological data processing and interpretation of pressure charts was carried out by JSB. JAvE and ES took equal roles in the final data analysis, supported by JSB, WB and EEvL. JAvE and ES led the written manuscript equally. All authors contributed to the writing of the manuscript and gave final approval for publication. JSB acquired funding for and managed this project.

Chapter 4
This study was conceived and designed by JAvE, JSB, and EEvL. JAvE designed the final framework, supported by JSB and EEvL. The case study was performed by JAvE. The R-package birdR was designed by JDG and JAvE. JAvE led the written manuscript, and all authors contributed to the writing of the manuscript and gave final approval for publication. JSB acquired funding for and managed this project.

Chapter 5
This study was conceived and designed by JAvE, JSB, and EEvL. Data collection, preparation and processing was performed by JAvE. Statistical analysis was performed by JAvE and EEvL. JAvE led the writing of the manuscript, and all authors contributed to the writing of the manuscript and gave their final approval for publication. JSB acquired funding for and managed this project.
Author affiliations

**Willem Bouten** Theoretical and Computational Ecology, Institute for Biodiversity and Ecosystem Dynamics, Faculty of Science, University of Amsterdam, PO Box 94240, 1090 GE Amsterdam, The Netherlands

**Maja Bradarić** Theoretical and Computational Ecology, Institute for Biodiversity and Ecosystem Dynamics, Faculty of Science, University of Amsterdam, PO Box 94240, 1090 GE Amsterdam, The Netherlands

**Kees J. Camphuysen** Royal Netherlands Institute for Sea Research (NIOZ) Texel, PO Box 59, 1790 AB Den Burg (Texel), The Netherlands

**Johannes De Groeve** Theoretical and Computational Ecology, Institute for Biodiversity and Ecosystem Dynamics, Faculty of Science, University of Amsterdam, PO Box 94240, 1090 GE Amsterdam, The Netherlands

**Jens A. van Erp** Theoretical and Computational Ecology, Institute for Biodiversity and Ecosystem Dynamics, Faculty of Science, University of Amsterdam, PO Box 94240, 1090 GE Amsterdam, The Netherlands

**E. Emiel van Loon** Theoretical and Computational Ecology, Institute for Biodiversity and Ecosystem Dynamics, Faculty of Science, University of Amsterdam, PO Box 94240, 1090 GE Amsterdam, The Netherlands

**Elspeth Sage** Theoretical and Computational Ecology, Institute for Biodiversity and Ecosystem Dynamics, Faculty of Science, University of Amsterdam, PO Box 94240, 1090 GE Amsterdam, The Netherlands

**Judy Shamoun-Baranes** Theoretical and Computational Ecology, Institute for Biodiversity and Ecosystem Dynamics, Faculty of Science, University of Amsterdam, PO Box 94240, 1090 GE Amsterdam, The Netherlands
Acknowledgements

Here we are, at the end of the road. It is the end of February 2024, and the sun has finally shown its face after an awfully "Dutch" winter. Sitting in that welcome sunshine with a glass of wine, it was time to reflect on the last four years. Naturally, a mammoth project such as this is not completed alone. Over the time I have relied on the support of many people for as many reasons. Expressing my gratitude for all of you did not come easy to me (as Iris might attest to); although I have quite the brain for (useless) facts, when it comes to past events, I am a figurative goldfish. Nevertheless, in this final chapter I have tried to convey all the thanks and love I have for the magnificent people that helped me get as far as I have and raise my glass to you all.

I will start with my promotors, who have been the cornerstones of this project. Judy and Emiel, I often viewed you as two halves of a whole. Between the two of you, I have always been confident there was someone that was able to help me out with any issues I had.

First, to Judy, for being the first halve. I still remember how I was invited to the TTW project kick-off meeting, even before my first day had begun. It was somewhat daunting to be introduced to the shareholders without knowing a first thing about radar or offshore wind (and barely anything relevant about birds), but you offered a warm welcome and immediately made me feel at home. We did not always understand each other, which could be frustrating, but I could always talk to you afterwards to resolve things and that is what counts! Thank you for always having our backs, for all the fun we had, and for being an inspiration as a scientist and leader.

To Emiel, for being the other halve. Thank you for helping me with the statistical and methodological side of the project, which would not have been as strong without you. Although teaching together could get a little chaotic, you involved me in writing a course and allowed me to teach the way I saw fit, which I really appreciated and enjoyed! But also thank you for the walks on the Veluwe, the train rides home, and for popping by or inviting me to your house to discuss work or really anything else that came up.

And to Willem as well. Although you were only involved in the initial stage of my project, I appreciated your honest and critical assessment of the project. Discussing my ideas with you was always a bit scary because of it, but I also always walked away inspired and with renewed focus. Thank you for this!

A special thanks also to all members of my thesis committee for taking the time to read and assess my work.
I was fortunate to work within a larger project about the interactions between birds and offshore windfarms. Here I met a group of amazing people that have helped me improve my work and also showed me all the different and inspirational sides of working in this field.

To Abel, Astrid, Jacco, Jonne, Ruben, Hans, and Karen, who I had the good fortune to work with throughout the project. Thank you for all the conversation about birds and radars, you helped broaden my perspective as an outsider of the field. Abel, thank you for all the work you did, your hospitality during our visits, and the fun during meetings and conferences. Karen and Hans, thank you both for sharing your expertise with me and all the insightful conversations over the time.

To Jos, Albert, Joris, Martine, Sytske, Marin and Luuk, for making all of this work possible through the TTW and Gemini projects. Thank you all for your input and questions during our meetings, which were vital to moving me forward in my research. Marin, thank you for going through that whole ordeal of getting us the wind turbine information! Luuk, thank you especially for all our conversations and your interest in everything I did. Thank you also for the added project after my PhD that allowed me to further increase my skills and develop the radar post-processing.

To René, Silvester, Rob, Wouter, Meije, and Sibylle and everyone at Robin Radar for all indulging my near-continuous stream of questions and showing me a near-endless enthusiasm for your work. Doing this research required an in-depth knowledge of radar I did not possess when I started and all of you helped me to tackle that obstacle. René, thank you for all your patience and explanations, I can only imagine how often you had to take a deep breath before opening yet another of our emails. Thank you, Meije, for your hospitality and enthusiasm to work with us to make this project a success.

Lastly, thank you Ander and later Ahmad for your support from Surf and working with us to develop IT systems that enabled us to monitor and fully utilize the data!

Of course, the support from my colleagues and friends at the University of Amsterdam cannot be understated. Both formally and informally, the university was an amazing place to work with an equally amazing group of people.

First, I want to thank the PE&RC graduate school and IBED management. To Claudius, Saskia, Tanja, Monique, Johan, Tanya, Mary, and Pascale for all the help, for the learning opportunities, and for the support in navigating the administrative side of doing a PhD.
To the people at IBED outside of the TCE department, Jacques, Nina, Naomi, Sebastiaan, Max, Lia, René, Giuditta, Rachid, Monica, Eileen, Evy and everyone else. For all the fun times organizing P(h)D events and everything we got done to improve our work life. The COVID lockdown made for a challenging situation to get anything to work, but we found ways to keep students connected and I had a lot of fun figuring these things out together!

Then to the people within TCE, Silke, Lotte, Sara, Lars, Jasper, Julian, Sietze, Zsófia, Daniel, Kenneth, Andre, Hal, Swarnendu, Bart K, Bart H, Morgan, Elspeth, Bart N, Nelleke, Kees, Ji, Iris, Leonardo, Hans, Roos, Eldar, Chiel, Fiona, Stacy and Shreyas. Thank you for all the support during office hours and all the beers outside of them! May the floating office heads of those who gone and went be multiplying forever more, and may they creep out new colleagues for years to come. I will miss all of you, and hopefully you will allow me to annoy you at Science Park from time to time, whenever I get the chance to visit.

To Elspeth, with whom I took on the (in hindsight) insane challenge to co-write a paper that combined two monitoring techniques in two regions to investigate a very rare and specific behaviour. We had so many laughs and even more cries to get it to work, and I’m proud of us for sticking with it. Thank you for all the crazy fun along the way.

Op Johannes, voor al je hulp met de radar data. Mijn verzoeken begonnen simpel, maar uiteindelijk schreven we pagina lange SQL-query’s en hebben we een eigen R-package gemaakt: birdR. Zonder jou was me dat nooit gelukt!

Op Berend, voor al het geouwehoer in de wandelgangen en erbuiten. Het is misschien maar goed dat we samen nooit iets opgepakt hebben, dan was er nooit een einde aan gekomen. It wie foar my mei nocht en wille, ymport-Fries!

And lastly to Maja, my partner in radar-crime. I cannot imagine this thesis without your involvement, I might need to hang a picture of your face somewhere so I can keep exchanging frustrated looks with you, which became a staple of any day at the office. Thank you for the hikes, the beer drinking, the “sauning”, the dancing and singing, and maybe most importantly the rants. We know what it takes to take something to the next level, whether it is PE&RC karaoke or going to conferences, and it made for some of the best moments of my PhD. Also, thank you for also being my mermaid on the day of my defence; you can braid my hair any day (except maybe that day).

Apart from all the people I have met over the last five years, there are older friends and family that were equally important during this time. Whether it was daily or yearly, these people made sure I spend some time on other things than birds and radars.
Acknowledgements

Op alle “Wageningers”, de jaarclub en het Dispuut. Bedankt dat ik altijd op het laatste moment toch nog aan kon haken en met jullie kon lachen. In het bijzonder, Nick, op jou! Ik weet het, ik ben twee handen vol, maar ik hoop dat je weet dat ik jouw energie en input door de jaren heen enorm waardeer. Bedankt dat je opnieuw een beetje voor me wil zorgen als paranimf, en op nog meer bizarre avonturen samen!

To the gamers, Mark, Inge, Time, Timo, Bob, Freek, Max, Sander, Elena, and Ruben. Whether online or offline, I always looked forward to our shenanigans. Nothing really compares to the madness of rearranging furniture throughout the whole apartment or house to host everybody for a weekend. During the lockdown our sessions were a welcome reprieve from isolation that made working from home bearable. Thank you for so many hours of hype, fun and memes.

A second time to the Zeelanders, Max, Sander, and Elena in particular, for offering a way to easily escape a weekend to “het buitenland”. Elena, your care and hospitality has always made your house a second home, and your willingness to endure our gaming bullshit throughout the years is nothing short of amazing. Sander, it has been years since Max introduced us and I now consider travelling to Zeeland as much for you as for him. Finally Max, where to even begin. We have done it all and more, and I cannot overstate how much I appreciate our friendship. I am confident we will still find new excuses to visit and new games to play even when we are old and wrinkly.

Op Bob, Tim, Freek en Timo, de meest belachelijke groep associates die ik ooit heb meegemaakt. De weekenden en vakanties zijn touwtrekkers geweest, waar het weer even “back to basic” was. Bob, ooit op een dag gaan we echt wel een keer uit in Ede en wordt het legendarisch. Tim, bedankt voor alle chille boulder en Dark Souls sessies, ooit gaat het ons lukken langs de Smelter Demon te komen. Freek, de urenlange lore deep-dived of theory-crafts over hoe we het dode lijk dat onze guild is door de volgende raid konden sjouwen waren een welkome afleiding. En natuurlijk Timo, bedankt voor alles. Op veel manieren begon mijn wetenschappelijke loopbaan schouder aan schouder met jou in dat kleine hok bij EZO. Samen vloeken op onze eigen code en ouwehoeren over hoe we het best zee-egels over krachtsensoren moesten laten lopen en malariamuggen voor camera’s konden krijgen. Wij hebben elkaar altijd helemaal begrepen of helemaal niet, en ik weet nog steeds niet wat meer chaos oplevert. Bedankt voor alle memes boys.

Op mijn familie. Joris, wanneer ik dit schrijf, zitten jij en Ashley te wachten op de komst van Kikker (die tegen de tijd dat je dit leest hopelijk een betere naam heeft gekregen!) En Dirk, jij bent met Justine aan de andere kant van de wereld van je vrijheid aan het genieten, waarschijnlijk met een stuk beter weer dan een Nederlandse winter. Sinds we
Raerd verlaten hebben, zien we elkaar minder en gaan we onze eigen weg, maar het was fantastisch om elkaar terug te vinden op het water en in de bergen. Marathons lopen in de bergen was een heerlijke afleiding van de stress op werk en een van de hoogtepunten van de afgelopen jaren (volgende keer ben ik echt fit, beloofd). Daarnaast maakten jullie samen met pap en mam Raerd tot een oase van rust wanneer we daar samenkwaamen. Pap, er zijn te veel dingen om te noemen dus ik begin simpelweg met: bedankt voor alles. De energie die jij hebt voor alles wat je onderneemt is een inspiratie voor iedereen om je heen. Een marathon in de bergen, een meerweekse bergtocht in je eentje, het bouwen van een huis, alles wordt gedaan met een kracht waar twintigers jaloers op zouden zijn. Bedankt voor je advies wanneer ik erom vroeg (en niet), je hulp wanneer ik dit nodig had (en niet), en de mogelijkheid om me suf te werken in de tuin wanneer het uitkwam (en niet). Mam, bedankt dat jij jij bent. Ik snap nog steeds niet hoe je het hebt gedaan, drie kwajongens opvoeden en voor een vierde zorgen (dat ben jij pap), en ook nog de tijd hebben om je eigen bedrijf te starten en door Europa te trekken naar Santiago. Je oneindige geduld en steun voor alles wat wij ondernemen, zij het met een gezonde dosis bezorgdheid, is wat ons in staat stelt onszelf te zijn en ons eigen pad te bewandelen. Lieve ouders en broertjes, ik hou van jullie en bedankt voor alles.

Last but not least, Iris, op jou. Ik denk dat jij beter dan wie dan ook weet hoe zwaar deze laatste 4.5 jaren soms waren. Ik kan met zekerheid zeggen dat ik het niet gered zou hebben als jij er niet was geweest om van tijd tot tijd de puinhoop op de ruimen, of me er om 3 uur aan te herinneren dat ik nog moest lunchen. Jouw zorg en liefde maakte dat ons huis een thuis was waar ik de nodige rust kon vinden. Daarnaast zorgde je lust voor avontuur ervoor dat ik nog buiten kwam zo nu en dan, in het klein op de Veluwe en in het groot op vakantie. De stress was soms zwaar voor ons beide, maar ik denk ook dat we er sterker door zijn geworden en een beter team dan ooit. In zekere zin is dit werk niet van mij, maar van ons, en dat bedoel ik niet alleen figuurlijk. Jouw schilderkunst is de cherry on top, en ik ben zo blij en trots op het resultaat! Bedankt voor alles wat je doet en bent baab, ik hou van je.