On the radar

*Weather, bird migration and aeroconservation over the North Sea*

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Tina, are you for real?! I've asked for that sunscreen a billion times!

I can see them flying! I will turn the wind turbines off! Do you copy? I will turn the turbines off!
Chapter 5

Forecasting nocturnal bird migration to mitigate collisions with offshore wind turbines in the southern North Sea

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To be submitted

Abstract

To meet climate targets, the world’s energy sector is transitioning to zero-carbon energy production, with a major contribution expected from the expansion of the wind energy sector. This means wind turbines will increasingly clutter airspace and can have negative direct and indirect effects on aerial wildlife. Placement of wind turbines within large migration flyways can contribute to declines of vulnerable migratory bird populations by increasing mortality through collisions and alteration of migratory routes. On-demand curtailment of wind turbines limited to short periods with peak migration can considerably minimize negative impacts on bird populations, and near-term forecasts of bird migration can inform such decisions. Here, we develop a near-term forecast of low-altitude (up to 300 m) nocturnal bird migration over the southern North Sea. We use tracking bird radar data collected off the western Dutch coast and weather and phenological variables to facilitate the curtailment of wind turbines offshore during spring and autumn migration. We demonstrate that the most important predictors of migration intensity in spring are seasonal phenology and wind assistance at an inferred departure region in the UK and at the radar location. In autumn, diurnal phenology and wind assistance were the most important predictors. We show that overall, the model classified migration hours by intensity correctly in more than 90% of cases in spring and more than 80% in autumn. However, the number of correctly predicted intense migration hours was low, likely due to the short-term dataset. We show that to minimize collision risk for 50% of migrants, if predicted correctly, curtailments should be performed during only 18 hours in spring and 26 in autumn (2.5 % of the migration period in spring and 5.5 % in autumn), but this can differ between the years. The amount of energy that would be lost due to curtailments is 0.56% in spring and 1.26% in autumn. Finally, we argue that using near-term ecological forecasts developed with limited datasets in combination with expert knowledge is necessary to speed up conservation efforts in a rapidly changing world.
5.1 Introduction

Airspace, where bird migration journeys occur, is increasingly altered by man-made structures such as wind turbines, power lines, buildings, drones and aircraft (Bauer et al. 2019; Lambertucci & Speziale 2021). These structures pose a risk for migratory birds through collisions (Marques et al. 2014; van Gasteren et al. 2019; van Doren et al. 2021), habitat change and barrier effects (Drewitt & Langston 2006; Gaultier et al. 2020). As the world is transitioning toward sustainable energy production to meet climate targets, the airspace is bound to become riskier (Davy et al. 2017) due to the energy transition relying on increased wind energy production, with many countries concentrating on expansion offshore (Leung & Yang 2012).

To minimize these and other negative impacts of environmental alterations on wildlife, a mitigation hierarchy consisting of four steps (avoid, minimize, remediate and offset) has been developed (Arlidge et al. 2018), and ways to implement these steps have been relatively well-established (Schaub et al. 2020; Serrano et al. 2020; Murgatroyd et al. 2021; Gauld et al. 2022). Institutions, such as wind energy companies, which are developing infrastructure that is cluttering the airspace, are bound by national and international laws to comply with the mitigation hierarchy. When the first step of completely avoiding new energy infrastructure in hotspots for aerial wildlife (Gauld et al. 2022) is not possible, methods such as on-demand wind turbine curtailment have been shown to minimize the adverse effects on bird and bat populations onshore (Singh et al. 2015; Hayes et al. 2019; McClure et al. 2021; Bennett et al. 2022). So far, such curtailments have mainly been performed near real-time and on a small scale, mostly focusing on specific species within individual wind farms. In regions which are experiencing extensive wind energy development and hosting large migratory flyways with broad-front bird migration of various species, turbines in multiple wind farms have to be curtailed simultaneously to allow for a safe passage. An endeavour of that magnitude requires coordination of multiple stakeholders to keep the energy grid stable and cannot be accomplished near real-time. Instead, predicting when birds will arrive in risk areas can help set up cost-effective mechanisms to minimize negative impacts on bird populations (Reynolds et al. 2017b; Shamoun–Baranes et al. 2017).

In recent decades, ecological forecasting has been highlighted as an imperative to improve and speed up conservation efforts while balancing financial and societal costs with nature benefits (Clark et al. 2001; Luo et al. 2011; Dietze et al. 2018; Horton et al. 2021). An increase in data availability and advances in data processing, statistics and computational infrastructure allow for near-term predictive models (Dietze et al. 2018). Such models can help steer environmental management when swift conservation action is needed (Luo et al. 2011; Reynolds et al. 2017b; Dietze et al. 2018), which is particularly important in today’s rapidly changing world (Clark et al. 2001; Dietze et al. 2018). They are, for example, featured as an invaluable tool for the dynamic conservation of migratory birds (Reynolds et al. 2018; Horton et al. 2021).
Near-term forecasts of bird migration with a regional extent are already in use to minimize collisions between birds and aircraft (van Belle et al. 2007; van Gasteren et al. 2019; Kranstauber et al. 2022). Forecast models with a continental extent have been developed (van Doren & Horton 2018) and are used for turning off lights on high buildings (BirdCast 2022) to decrease collisions migratory birds experience in urban areas due to attraction to light (van Doren et al., 2017). Similar types of forecasts could be used to inform wind turbine shutdowns in large wind energy production areas. Several of these models were developed using weather radar data. However, these radars have poor coverage in offshore areas, where a large proportion of new wind energy development will occur, especially at the lower altitudes relevant to wind energy. This is due to the spatial extent of weather radar that generally does not extend above sea and problems with ground clutter sensitivity, making biological information obtained at low altitudes less reliable (Dokter et al. 2009). To inform offshore wind turbine shutdowns, it is necessary to predict migration up to 300 m of altitude offshore.

In the southern North Sea, where Belgium, the UK and the Netherlands are building new wind parks, the currently installed amount of wind power will increase four-fold by 2030 (Department of Energy & Climate Change 2013; FPS Economy 2021; Rijksoverheid 2021). Concurrently, the North Sea is a migratory corridor for several hundred million birds that migrate twice a year between mainland Europe and the UK and between NW Europe and Africa, mainly during the night (Lack 1959; Dierschke 2003; Hüppop et al. 2006). Most migratory birds select nights with specific weather conditions for migration (Richardson 1978; Erni et al. 2002b; Bradarić et al. 2020; Manola et al. 2020a). In the case of the contiguous US, it has been suggested that shutting down turbines on 10% of migration nights would already allow a safe passage for 50% of migratory birds (Horton et al. 2021). Limiting wind turbine curtailment on several intense migration nights is the key to performing aerial conservation actions over large areas with minimal impact on the energy market. Near-term migration forecasts that rely on well-known drivers of migration intensity could be used to achieve that.

Phenology and weather are the two main categories of drivers generally used to predict migration intensity over land (van Belle et al., 2007; van Doren & Horton, 2018; Kranstauber et al., 2022). Many migratory species exhibit a clear circannual rhythm in their migratory activity, often considered to be triggered by seasonal changes in day length (Gwinner & Helm 2003). In addition, many species exhibit a circadian rhythm that can prompt daily migration schedules (Gwinner et al. 1997). For many landbirds migrating at night, migratory activity is often initiated around sunset (Åkesson et al. 1996), with some variation due to environmental factors and body condition (Sjöberg et al. 2017; Müller et al. 2018b). Weather, especially wind, is crucial for departure decisions (Alerstam 1990; Newton 2008). Birds fly with winds that are more supportive of migration (Bradarić et al. 2020), which helps increase their migration speed, thus reducing the time and effort spent on migration
(Liechti 2006). Besides winds, temperature (Kemp 2012; Deppe et al. 2015) and air pressure (Richardson 1990a) can trigger migratory movements. In North-western Europe, migration intensity over land in spring is high when temperatures are above zero, bringing more stable weather conditions (Kemp et al. 2013; Kranstauber et al. 2022). In both seasons, precipitation generally has an inhibiting effect on migration (Richardson 1990a; Erni et al. 2002b). Including weather variables in predictive models allows for capturing finer-scale temporal dynamics of migration, thus increasing the probability of accurately forecasting migration intensity (Kranstauber et al. 2022).

Existing bird migration forecast models currently focus on migration over land. However, the migratory behaviour of landbirds may differ over the sea, as seas may be perceived as ecological barriers. This is because large bodies of water have limited or no opportunities for landbirds to land or refuel, and it has been demonstrated that birds exhibit different departure decisions when embarking on such journeys (Alerstam 2001; Deppe et al. 2015). When crossing ecological barriers, birds become more selective of weather conditions, which influences their departure decisions (Deppe et al. 2015), routes (Diehl et al. 2012; Bruderer et al. 2018) and flight altitudes (Eastwood & Rider 1965; Archibald et al. 2016), consequently influencing migration intensity. It is, therefore, essential to understanding which factors are the main drivers of migration over the sea to provide the most accurate offshore bird migration predictions.

One of the challenges associated with developing predictive models of migration which rely on weather variables as input is having a sufficiently long time series to capture diverse weather conditions and rare peaks in migration. A minimum of two years of radar data has been suggested for the development of predictive models on land (van Belle et al. 2007), although intense migration nights with a rare set of weather conditions can be hard to predict even with 10-year datasets (Kranstauber et al. 2022). Radars that have been collecting data offshore do not yet have such a long time series. However, the pace of the environmental alteration requires swift conservation actions, which include wind turbine curtailment informed by near-term ecological forecasts with less-than-ideal data, and improving models “on the go” (Dietze et al. 2018).

Striving to allow decision-makers to make near-term decisions regarding offshore wind turbine curtailment, we demonstrate the first attempt to make seasonal forecast models of low-altitude nocturnal migration at sea and explore which environmental variables in departure regions and offshore influence migration intensity at low altitudes in the Dutch part of the southern North Sea. We train a random forest model with data collected by a tracking radar positioned offshore of the western Dutch coast. As model input, we use day of year, time of day and weather variables (wind, temperature, precipitation, air pressure) from inferred departure locations and the radar location to predict migration in spring and autumn. We expected that
seasonal and diurnal phenology, the wind and precipitation at sea and potential departure locations would be the most important factors influencing migration, with other factors considered of secondary importance. We test how accurate the forecasts are in each season by creating confusion matrices based on different thresholds and discuss the threshold effect on the curtailment procedure. We demonstrate the model performance in its current form and describe the main drivers of nocturnal bird migration over the North Sea in spring and autumn. We show the percentage of migratory birds that would have a safe passage as a function of the number of curtailment hours and demonstrate the energy loss in relation to the percentage of migratory birds protected. Migration intensity forecasts, created 48 hours ahead, with the models described in this paper and using weather forecast as an input, will be used by an expert committee in the initial stages of the decision-making process created by the Dutch government to determine whether turbine curtailments are necessary during specific periods in spring and autumn. We discuss our findings within the context of these curtailment procedures.

5.2 Materials and methods

5.2.1 The radar system, location and study period

In our study, we used data collected by a tracking radar (Robin Radar 3D fix, Robin Radar Systems BV, the Hague, Netherlands) positioned within the existing offshore wind farm Luchterduinen (52.25° N, 4.10° E), ca 23 km from the western Dutch coast. The radar has been continuously collecting data since 2018. Our study uses data between sunset and sunrise during spring (15th of February – 30th of April) and autumn (1st of October – 30th of November) seasons. This period covers the most intense migration nights between 2019 and 2022 (Figure 5.A.1).

![Figure 5.1](image)

Figure 5.1: The North Sea area with the radar location (blue dot) and bounding boxes of ERA5 weather data grid cells at departure locations (Bradarić et al. 2020) in spring (green) and autumn (yellow).

The radar system consists of two antennae. An X-band antenna with the power of 25
kW rotates vertically and collects information about bird numbers and altitudes, and an S-band antenna that rotates horizontally and collects information on numbers, flight directions and speeds of birds up to 500m altitude. Both antennae have radar beams 20 degrees wide and rotate at 45 rpm. In this study, we only use the data collected by the horizontal antenna, as this data covers the altitudes of interest and contains more information about individual tracks.

A proprietary tracking algorithm generates tracks of moving targets recorded by the radar based on target characteristics (speed, direction and radar cross-section). The radar system employs automated clutter filters to reduce the number of non-bird targets that can mistakenly be classified as bird tracks. Clutter filters are applied dynamically in each radar scan and expressed as a fraction of the total scan area in which clutter is detected. This is expressed with a value between 0 (no clutter on the radar image) and 1. Dynamic filters reduce reflections coming mostly from landscape features, waves and rain. Tracks lasting for at least eight consecutive rotations are automatically stored in a centralized database. Bird tracks include the following information used in this study: ground speed, track direction, straight-line distance (between the first and the last point of a track), track length, track centroid, and the number of individual points per track.

5.2.2 Radar data post-processing

We apply additional filtering to derive the hourly migratory track count from the radar data. Tracks originating from static clutter entered the database despite the automatic clutter filters. These tracks were characterized by low displacement over time. We calculated displacement over time by dividing the straight-line distance between the first and last track point with track duration and removed 10% of tracks with the lowest values. Due to clutter close to the radar and detection loss of small songbirds further from the radar, only tracks whose central point had a horizontal distance from the radar between 1000 and 2000 m were used in our analysis (excluding the area between 275° and 346° which was blocked by a structure the radar was mounted on). Exploratory analysis of nights of intense migration with highly uniform flight directions has shown that individual tracks have low tortuosity. We, therefore, use only straight tracks in our analysis. The straightness of a track was estimated by dividing the straight-line distance between the first and last track point by a track length. All tracks with straightness lower than 0.7 (based on the visual inspection of the data) were characterized as non-migratory and were removed from the analysis. Tracks with airspeeds ≤ 5 m/s (see section 5.2.5 for airspeed calculation) were removed from the analysis as they most likely come from insects. All hours with no biological data were included as zero measurements. Finally, all minutes in which the clutter filter activity was higher than 0.3 (van Erp et al. 2021) and all hours with ten or fewer minutes of data were excluded from the analysis to avoid including artificially-created low migration intensities due to high clutter
activity.

5.2.3 Mean traffic rate (MTR)

To estimate the hourly number of birds passing through an area of interest, we calculated the mean traffic rate of migration (MTR). MTR is expressed as the number of birds (#) per kilometre (km) per hour (h). MTRs (#/km/h) were estimated as follows:

$$MTR = d \times V_g$$  \hspace{1cm} (5.1)

where $d$ represents mean bird track density (#/km²), and $V_g$ represents mean ground speed (km/h). Mean bird track density ($d$) was expressed as

$$d = \frac{P_t}{A}$$ \hspace{1cm} (5.2)

where $A$ is the surface area of the radar sector (km²) from which we sampled our data, and $P_t$ represents the mean number of all bird track points recorded by the radar per rotation in the area and is calculated as in equation 5.3

$$P_t = \frac{\sum (P_i)}{rph}$$ \hspace{1cm} (5.3)

where $P_i$ is the number of points of each track whose central point was recorded within the area in an hour $t$, and $rph$ is the number of radar rotations per hour. All mean ground speeds were expressed as harmonic means of ground speeds (m/s) of each point of a track.

5.2.4 Weather data

Weather data was extracted from the European Centre for Medium-Range Weather Forecast ERA5 reanalysis dataset (Hersbach et al. 2020), which has a global extent, 0.25-degree grid size and 1-hour temporal resolution. Hourly weather variables for the radar location were obtained from the closest grid cell, 52.25 N 4.00 E. Data for potential departure locations in the Eastern UK and Northwestern France in spring and north of Netherlands, Northwestern Germany and central Denmark in autumn (Bradarić et al. 2020) were averaged over multiple grid cells (bounding boxes in Figure 5.1) and over the first two hours after sunset, as that is the time when most birds are expected to depart. We extracted total precipitation (TP, m), mean sea level pressure (MSLP, Pa) and wind components at 100m above the earth’s surface (ASL) that describe wind from west to east ($u$, m/s) and south to north ($v$, m/s), from the single level dataset. Air temperature ($t$, °K) and geopotential height were extracted from several pressure levels. Before doing any calculations, the weather variables units were converted as follows: mean sea level pressure was converted from Pa to hPa, total precipitation from m to mm and air temperature from °K to
°C. The air temperature was extracted from multiple pressure levels and averaged over those that correspond to the altitudes of interest (100 – 300 m). Altitudes were calculated by dividing the geopotential height of a pressure level by the gravitation acceleration. To capture the change in weather conditions from night to night, we calculated the nightly difference in mean sea level pressure by subtracting the mean sea level pressure of the current night from the mean sea level pressure of the previous night. This variable was calculated for radar and departure locations and included in the model as a predictor.

5.2.5 Wind assistance

Wind assistance (WA, m/s) is an estimate of wind support that birds experience during flight, and it was calculated using the tailwind equation (Kemp et al. 2012)

\[ WA = y \cos \theta \] (5.4)

where \( y \) is wind speed (m/s), and \( \theta \) is a difference between the direction the wind is blowing to and the preferred migration direction (PMD). Wind direction and wind speed were calculated using \( u \) and \( v \) components of the ERA5 dataset for different locations (Shamoun-Baranes et al. 2007). At the radar location, PMD was calculated from the data, 91° for spring and 214° for autumn. At the departure locations, the PMD was estimated from the literature. In spring, the PMD for departure location in the UK was 90°. Additionally, wind assistance using 30° as a PMD was calculated to capture movement from NW France towards NE. In autumn, PMD was set to 220° for N Netherlands and Denmark (Shamoun-Baranes & van Gasteren 2011; Bradarić et al. 2020). To represent sea crossings towards the UK in autumn, an additional wind assistance variable was calculated at the radar location for these birds, using 270° as PMD. PMDs and airspeeds at the radar location were calculated from track directions, groundspeed and wind data at 100 m ASL following Shamoun-Baranes et al. (2007).

5.2.6 Accumulations

When weather conditions are not favourable for migration for a few days in a row, birds that would otherwise depart may accumulate in large numbers and depart once weather conditions improve. This effect is particularly evident at the coast before birds embark on crossing ecological barriers, such as large water bodies (Lowery 1945; Biebach et al. 2000). In order to capture accumulation dynamics, we calculated accumulation factors following Erni et al. 2002 and included them as predictors in our models. We first determined a binary variable for migration accumulations based on precipitation at departure locations. We assumed birds would accumulate if hourly precipitation was more than 0.01 mm. We then calculated accumulation due to wind assistance at departure locations, assuming that birds would accumulate if wind assistance is lower than -2 m/s. The thresholds have been
identified by looking into differences in wind assistance and precipitation between the top 10% of intense migration nights and the rest of the data. An accumulation index of ¾ has been used following Kranstauber et al. 2022. This means that if wind assistance was lower or precipitation higher than the threshold above, ¾ of birds that were supposed to depart on one night would wait until the next night to start their migration. Finally, we calculated nightly differences in accumulations and included them as predictors in our models. Accumulations ranged between zero and one, one representing the highest accumulation due to unfavourable weather conditions explained above.

5.2.7 Seasonal and diurnal phenology

To capture circannual and circadian migration dynamics at the radar location, we created a proxy for seasonal and diurnal phenology by fitting local polynomial regression curves to hourly MTRs grouped by day of year and hour after sunset. Curves were fitted to the full (4-year for spring and 3-year for autumn) dataset using the `loess` function of the ‘base’ R package (R Core Team 2022) and included in the models as predictors. Figures can be found in Appendix (Figure 5.A.2).

5.2.8 Predictive model

We trained random forest models using the R package ‘ranger’ (Wright & Ziegler 2017) to predict migration in spring and autumn separately. Having four years of data for spring and three years of data for autumn, we always used one year of data as a testing dataset, while the rest was used for the model training. The main text shows the model results based on training data from 2019, 2020 and 2021 for spring and 2019 and 2021 for autumn. In spring, 2022 was used as a testing dataset for model evaluation, while 2020 was used in autumn. These combinations showed the best model results, which is why they were presented in the main text. All the other combinations of training and testing years are available in Appendix (Figure 5.A.6). This data division corresponds approximately to a 70:30 ratio of training vs testing datasets usually used in random forest setups. The models were trained with a regression setting, using MTRs as a continuous response variable and accumulations, weather and phenology variables as predictors. The full list of predictors which differed between the two migration seasons can be found in Table 5.A.1.

Before running the models, we generated correlation matrices (Figure 5.A.3) using Spearman’s rank correlation coefficient with the ‘corrplot’ package (Wei & Simko 2021) to remove the correlated predictors, as they do not explain the extra variance and can affect the ability of the model to identify variable importance (Gregorutti et al. 2017). Since the previous research on nocturnal bird migration over the North Sea showed that wind assistance drives departure decisions of migratory birds (Bradarić et al. 2020), wind assistance at the radar and departure locations were kept in the
model. All the other variables with the highest absolute correlation (above 0.7) were removed from the modelling procedure. This means that if the two variables were highly correlated, the correlation of each of those two variables with all the other variables was checked, and the variable with the highest absolute correlation was removed. The full list of the seasonal variables that were highly correlated and removed from the further analysis is given in Appendix (Figure 5.A.3).

The data used for the model training was imbalanced, as the number of hours with high MTRs representing intense bird migration was much lower than the number of hours with low MTRs (Figure 5.3, Figure 5.A.1). Imbalanced data causes imbalanced learning for the random forest algorithm. This means that due to a lack of hours with intense bird migration, the model cannot learn much about the conditions that lead to such high numbers of migrants. Since the aim of this paper was primarily to predict intense bird migration, we applied stratified sampling to balance our data (Brieuc et al. 2018).

Table 5.1 Overview of variables used as model predictors.

<table>
<thead>
<tr>
<th>Description</th>
<th>Unit</th>
<th>Season</th>
<th>Location</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wind assistance toward W</td>
<td>m/s</td>
<td>Autumn</td>
<td>Radar and NW Germany</td>
</tr>
<tr>
<td>Wind assistance toward SW</td>
<td>m/s</td>
<td>Autumn</td>
<td>Radar, N Netherlands and Denmark</td>
</tr>
<tr>
<td>Wind assistance toward E</td>
<td>m/s</td>
<td>Spring</td>
<td>Radar and the UK</td>
</tr>
<tr>
<td>Wind assistance toward NE</td>
<td>m/s</td>
<td>Spring</td>
<td>Radar and NW France</td>
</tr>
<tr>
<td>Total precipitation</td>
<td>mm</td>
<td>Both</td>
<td>Radar and departure locations</td>
</tr>
<tr>
<td>Temperature</td>
<td>°C</td>
<td>Both</td>
<td>Radar and departure locations</td>
</tr>
<tr>
<td>Mean sea level pressure</td>
<td>hPa</td>
<td>Both</td>
<td>Radar and departure locations</td>
</tr>
<tr>
<td>The nightly difference in mean sea level pressure</td>
<td>hPa</td>
<td>Both</td>
<td>Departure locations</td>
</tr>
<tr>
<td>Accumulation due to wind assistance</td>
<td></td>
<td>Both</td>
<td>Departure locations</td>
</tr>
<tr>
<td>The nightly difference in accumulation due to</td>
<td></td>
<td>Both</td>
<td>Departure locations</td>
</tr>
<tr>
<td>wind assistance</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Accumulation due to total precipitation</td>
<td></td>
<td>Both</td>
<td>Departure locations</td>
</tr>
<tr>
<td>The nightly difference in accumulation due to</td>
<td></td>
<td>Both</td>
<td>Departure locations</td>
</tr>
<tr>
<td>precipitation</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Diurnal phenology</td>
<td></td>
<td>Both</td>
<td>-</td>
</tr>
<tr>
<td>Seasonal phenology</td>
<td></td>
<td>Both</td>
<td>-</td>
</tr>
</tbody>
</table>

Stratified sampling allows for creating sub-groups of the data and including them equally in the model training procedure, despite the fact that one category is less numerous than the other. The ‘ranger’ function regulates stratified sampling with the ‘inbag’ parameter. The ‘inbag’ parameter is a list whose length corresponds to the number of trees within a random forest. Each list element consists of an array whose length corresponds to the training dataset’s number of observations. Array elements are numbers that specify how often a certain observation will be used when creating
individual trees. With each of these arrays, we specified how many times each of our observations would be used in generating each random forest tree. To determine how to set the inbag parameter to balance our data, we first divided our training dataset into low and high migration intensity observations based on the 95 percentile of the hourly MTRs. All hourly observations that were lower than this threshold were categorized as low-intensity hours, and all observations above the threshold were categorized as high-intensity hours. By dividing data in this way, we determined that the number of low-intensity hours was approximately 20 times higher than the number of high-intensity hours in both seasons. In order to balance this, we set up our random forest algorithm in such a way that all high-intensity hours were used 20 times in the creation of each tree, while low-intensity observations were used only once. Thus, for each tree, we assigned a value of one to 63.2% of random low-intensity observations and a value of 20 to 63.2% of high-intensity observations. This means that all random low-intensity observations used to build each tree will only be used once, while all random high-intensity observations will be used 20 times. The rest of the random data in each category was assigned zeroes and used for out-of-bag (OOB) calculations. 63.2% is a default fraction for randomly sampling the training data in the random forest algorithm of the ranger package.

Before training the models, we performed hyperparameter tuning by running the models with the range of different hyperparameters and chose a combination that led to the lowest out-of-bag RMSE. We varied the node size (node.size) from 5 to 50 with increments of 5 for both seasons, and the number of variables randomly sampled as candidates for each node split (mtry) from 2 to 16 in spring and from 2 to 22 in autumn over the default number of 500 trees. We used 500 trees and the minimum node size of 5 observations in both seasons. In spring we used mtry of 7 and in autumn mtry of 15.

5.2.9. Model evaluation

We report OOB $R^2$ for both seasons to indicate how much variance is explained by each model. However, we focus on other model evaluation methods, as we are mainly interested in how the model predicts hours with high MTRs, as those are the moments relevant for offshore wind turbine curtailments. We create confusion matrices using a threshold of 150 birds/km/h (95$^{th}$ percentile of MTR). All the hours with migration intensity higher or equal to the threshold can be considered hours with high migration intensity and are candidates for offshore turbine curtailments. To show the predictive performance of the model when using different thresholds, we created receiver operating characteristic (ROC) curves based on the 95$^{th}$ percentile (150 birds/km/h) and from there extracted two values which show the best model performance to use as thresholds in two additional confusion matrices. With this, we aimed to demonstrate how the threshold choice in the operational phase of the conservation framework can contribute to the effectiveness of the aeroconservation.
We calculated the cumulative percentage of migration intensity ranked by hourly MTR values in descending order over the course of a season to illustrate the number of hours needed for a certain percentage of migrants to pass, which can be used to estimate the number of hours needed for wind turbine curtailments for the most effective conservation. These calculations were performed for both observed and predicted MTR values, and their comparison can be used to evaluate the accuracy and effectiveness of curtailment based on predictions; if the predictions are ideal, the curves of cumulative percentages would completely overlap.

Finally, we create curves of cumulative energy production ranked by hourly MTR in descending order. The energy production was calculated based on the power curve for wind turbine type V112, the type used within the Luchterduinen wind farm (Bauer & Matysk, 2022). Energy production was calculated using the hourly 100 m wind speed data from the radar location. These curves are created in order to estimate the percentage of energy loss if the curtailments are performed during the intense migration hours.

### 5.3 Results

#### 5.3.1 MTR, weather variables and phenology

Hourly migration traffic rates could fluctuate between nights over several orders of magnitude and peak nights of migration are much higher in autumn than in spring (Figure 5.A.1, Figure 5.3). In spring, peaks of migration intensity occur in March and the first half of April, while the MTRs are the highest in the second half of October and the first half of November in autumn (Figure 5.3, 5.A.1). Spring peaks are generally fewer than autumn peaks and tend to be of lower magnitude, except for the peak on the 15th of March 2022 (Figure 5.3, Figure 5.A.1).

The most important variables for predicting low-altitude offshore migration in spring are seasonal phenology, followed by nightly difference in accumulation due to wind assistance at the potential departure locations in the UK and wind assistance towards NE at the radar location (Figure 5.2, upper graph). Migration intensity is the highest when the seasonal phenology proxy is above 40, which corresponds to late February and March, when the nightly difference in accumulations due to wind assistance was positive (meaning that the accumulation of birds at the departure of the previous night is higher than on the current night, i.e. conditions improved and birds depart after a period of poor conditions) and when wind assistance towards NE at the radar locations between 0 and 2 m/s (Figure 5.A.4).

In autumn, migration intensity is the highest when wind assistance towards SW at the radar location is positive but not higher than 5 m/s, when wind assistance at the departure location in the North of the Netherlands is between -3 and 0 m/s and when the diurnal phenology proxy is around 40, which corresponds to the first two
hours after sunset, which is indicative of the departure of migrants from the nearby coast around sunset (Figure 5.A.4).

5.3.2 Model predictions and evaluation

The OOB $R^2$ showed that the model explains 76% of the variance for spring and 59% for autumn. In spring, confusion matrices (Figure 5.4) were created with 706 (out of a total of 941) hourly data points for which the reference data was available (moments in which the radar was functioning and clutter filtering was not high). The number of available hourly data points in autumn was slightly lower than in spring (467 out of 944). Thresholds used for the creation of the confusion matrices were lower in spring than in autumn (Figure 5.3). The model generally performs well in predicting true negatives with all threshold values in both seasons (Figure 5.4). The true positive fractions, which relate to hours with higher values of MTRs, are low in spring and autumn. The spring model performs slightly better than the autumn one, with overall fractions of true predictions being higher and the fraction of false predictions being lower.

In Figure 5.5, MTRs are plotted as a cumulative seasonal percentage ranked by hourly migration intensity in descending order (hours with highest MTRs values first, plotted from the left side of the x-axis) as observed by the radar and compared with the cumulative seasonal percentage of MTRs as predicted by the model (Figure 5.5 shows spring of 2022 and autumn 2020, while curves for all the other years can be found in Figure 5.A.6). If the model predictions were perfect, these two lines would completely overlap. Reading the x and y coordinates of points belonging to each line, we can determine the percentage of migration (y-axis) that occurs during a certain number of hours (x-axis). For example, in spring, 50% of all recorded migration occurs during only 18 non-consecutive hours (2.5% of the total hours during the period used in this study, 1.9% of the total 2022 spring season), while the spring model predicted that 50% of total spring migration would happen in 36 non-consecutive hours with the highest MTRs (4.5% of hours in the observed period and 3.4% of the entire season). The difference between observed and predicted migration intensity is higher in autumn. In autumn, 50% of all recorded migration occurs within 26 hours with the highest MTRs (5.5% of hours in the observed period and 2.7% of the hours in the entire 2020 autumn season), while the model predicted that 50% of migration would happen within 79 hours (16.9% of hours in the observed period, 8.3% of hours for the entire season). In spring, 50% of migration ranked by MTR in descending order equals to about 10000 birds/km, while in autumn, about 13000 birds/km pass over the radar location.
Figure 5.2 Variable importance in predicting spring (upper plot) and autumn (lower plot) low-altitude migration intensity based on the variance of all other variables when one of the variables was removed from the RF model.
Figure 5.3 Spring 2022 (upper graph) and autumn 2020 (lower graph) time series used to test the performance of the model. Model predictions of MTRs (birds/km/hr) are shown in red (spring) and yellow (autumn), while the observed data is shown in dark blue.
Figure 5.4 Confusion matrices for spring (upper graph) and autumn (lower graph) created with different MTR thresholds (given in the titles of each confusion matrix). Confusion matrix tiles coloured in green (spring) and yellow (autumn) show true positives (upper left tile) and true negatives (lower right tile). Tiles coloured in dark blue show false positives (upper right tile) and false negatives (lower left tile). The numbers in the tiles represent a fraction of predicted hours (0-1) that belong to each category. The total number of hours for which the reference data was available was 706 for spring and 467 for autumn.

Figure 5.6 shows measured MTRs plotted as a cumulative seasonal percentage vs cumulative seasonal percentage of the energy production ranked by hourly migration intensity in descending order (hours with highest MTR values first, plotted from the left side of the x-axis). Reading the x and y coordinates of points belonging to the line, we can determine the percentage of energy production lost if the curtailment was performed on a certain percentage of hours with high migration intensity. For example, in spring 2022, if the curtailments are performed in order to conserve 50% of the hours with the highest migration intensity, the amount of energy that would be lost is 0.56% of the total energy that is produced in the part of the season we used for the data analysis. In autumn 2020, this amount was 1.26% of the total. Energy production curves for other years are available in Appendix (4.A.7).
Figure 5.5 Cumulative percentage of measured MTRs (birds/km/h) for the testing year of 2022 in spring (left) and the testing year 2020 in autumn (right) for hours ranked by MTRs in descending order based on radar observations (dark blue line) and model predictions (green in spring and yellow in autumn). Hourly MTR decreases going from the left to the right side of the x-axis.

Figure 5.6 Cumulative percentage of measured MTR (y-axis) vs cumulative percentage of energy production (x-axis) for the testing year of 2020 during the measurement period in spring (left) and 2022 in autumn (right). The observations are ranked by hourly MTRs (birds/km/h) in descending order (higher MTR values on the left side of the graphs).

5.4 Discussion

Despite having a limited time series of migration data from the radar location, we demonstrate that, overall, spring and autumn models of low-altitude nocturnal migration can capture migration intensity dynamics quite well, and OOB R² values indicate that both models explain a large portion of the variance in hourly migration intensity over the southern North Sea, with the spring model performing slightly better. Confusion matrices show that more than 90% of hours in spring and more than 80% in autumn were classified correctly by our models with different MTRs as thresholds. As expected, phenology proxies and wind assistance were the top three predictors of spring and autumn migration, while the expected effect of precipitation was not captured with our models.
Although similar variables were of high importance in both seasons, we show that seasonal phenology has the highest importance in spring (Figure 5.2). In this part of the world, wind generally comes from the west, which supports the dominant migratory movement from the UK towards the Netherlands observed in spring during previous studies (Kemp et al. 2010; Bradarić et al. 2020). Because of this, spring migrants have supportive wind conditions for migration most of the time. Instead, the high importance of seasonal phenology in this season reflects that the circannual rhythm may be more important in influencing migration rates in spring than wind conditions. Nevertheless, wind assistance variables were also among the top predictors of migration intensity (Figure 5.2). Therefore, we conclude that birds still rely on higher wind assistance and choose such moments to cross the North Sea faster, sometimes exploiting higher wind speeds at higher altitudes (Chapter 4; Kemp et al., 2013). In autumn, diurnal and not seasonal phenology was amongst the top predictors. This likely reflects different migration cohorts that can cross the radar in autumn. One cohort consists of birds leaving directly after sunset from the Dutch coast, ca 23 km from the radar, and thus their daily timing would be relatively predictable, while the other cohort is migrants from Scandinavia and NW Germany (Bradarić et al. 2020). The high importance of wind assistance at the radar location and more frequent occurrence of higher migration peaks indicates that birds tend to be more selective of wind conditions in autumn, which are generally not supportive of migration in this season (Bradarić et al. 2020; Manola et al. 2020a), although species differences exist and some groups of birds fly with suboptimal wind conditions (Grönroos et al. 2012).

For over-the-land migration over the contiguous US, it was estimated that 50% of total seasonal migration occurs within 10% of migration nights (Horton et al. 2021). We show that 50% of measured migration offshore occurred within 18 hours (2.5%), with the highest MTRs in spring and 26 (5.5%) in autumn (Figure 5.5). The model predicted that 50% of migration occurred during 36 hours in spring and 79 in autumn. Although such a short period in which the majority of migration occurs is partially due to the fact that we only use part of the migration season with the highest migration intensity, it also most likely illustrates that the ecological barrier affects migratory departure decisions. Studies around large water bodies have shown that birds tend to be more selective of weather conditions when making departure decisions (Newton 2008; Deppe et al. 2015), resulting in fewer occasions when large numbers of migrants make barrier crossings. The results shown in this paragraph are based on the model trained with a combination of years which showed the best model results, and the number of hours in which curtailments should be performed to preserve 50% of migration is higher for all the other combinations (Figure 5.A.6).

Even though the model explained a high percentage of variance in migration intensity in both seasons, the percentage of correctly predicted intense migration hours was low, and the percentage of false negatives was relatively high (Figure
There are several explanations for this. First, the expected issue of having only a few years for model training meant that only a small number of intense migration nights entered our training dataset, as they generally occur only a few times during the migration season (Figure 5.A.1) (Kranstauber et al. 2022). These nights can have complex weather systems passing through the region, especially in autumn and can be very different on different intense migration nights (Manola et al. 2020a). This makes it hard for the model to “learn” to recognize such cases in the training procedure, even with applying methods for balancing the data, such as stratified sampling. A second explanation is the missing data due to radar issues, bad weather conditions (which is probably why our models could not capture the expected effect of the precipitation) under which the radar does not collect reliable information and further “shortening” of the available dataset through a rigorous but necessary filtering procedure. Often, gaps in the observed data occur when the model predicts intense migration, especially in autumn (4.2). The spring model explained more variance and had a higher percentage of correct classifications than autumn. This is most likely due to more consistent weather conditions throughout the spring migration season and the longer time series used for the model training.

Intense migration nights are of the highest priority for wind turbine curtailments, as they provide opportunities to minimize collision risk for the highest number of migrants with minimal energy loss. While we show that to protect 50% of migrants, wind turbine curtailments only have to be performed for a limited number of hours (18 in spring and 26 in autumn), the model predictions showed that the number of hours needed to protect half of the migrants in the season is higher (36 in spring and 79 in autumn). This is because the model was able to correctly predict only a small portion of the intense migration nights. Considering the fact that the model was trained with the reanalysis weather data and that the predictions used for curtailments will be based on weather forecasts, we can expect an additional error in predictions due to weather forecast uncertainty. However, when more radar measurements are available, the model can be recalibrated with the new and longer time series of data, which should improve the model performance. Therefore, the number of curtailment hours needed to protect 50% of seasonal migration will have a smaller discrepancy between the model and the observed values.

In the initial stages of wind turbine curtailments, when model predictions of intense migration are not great due to the limited time series of data, setting the right curtailment thresholds is crucial for achieving the best results. Confusion matrices created with different thresholds indicate that choosing lower MTR values increases the chance of correctly predicting peak migration, but it also increases the percentage of false positives and sometimes even false negatives, which is especially pronounced in spring. For wind turbine curtailments, it is important to strike a balance between all categories. False positives can cause unnecessary shutdowns, resulting in economic loss without conservation effect. On the other hand, false negatives mean that the turbines will not be curtailed in times of intense migration.
migration offshore.

When discussing curtailments, it is important to mention the consequences they would have on the energy grid in terms of energy loss. With our results, we show that if we want to protect 50% of the migrants, the energy loss during the potential curtailment hours is minimal, being below 2% in both seasons (note that this is during the parts of the seasons in which the nights of high migration intensity occur), if the model can correctly predict them. This means that the most intense migration occurs at the times when wind speeds are too low for energy production.

In the current framework created by the Dutch government, wind turbine curtailment decisions will be made by a multi-step process which includes model predictions, evaluation of the expert committee and the assessment of wind conditions and potential energy production/loss. While model predictions for intense migration nights could be improved by training the models with longer time series of radar data, we see that they can already help to initiate curtailments during critical hours, especially in spring (Figure 5.5). When combined with carefully chosen thresholds and expert knowledge in ecology and meteorology, adequate conservation action can be performed, even in these early stages of offshore low-altitude forecast development. With the example from the Netherlands, we want to encourage action-oriented conservation, as the development of extensive research studies followed by carefully planned conservation actions usually cannot keep up with the pace of the environment alteration, and it is necessary to start creating conservation measures with short-term datasets and carefully tailored political decisions (Dietze et al. 2018). We propose that the framework in which prediction models are used with input from expert teams can yield significant results and help minimize the negative effect of various anthropogenic developments on wildlife.
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5. A Appendix for Chapter 5

Figure 5.A.1 Time series with migration data from the full observation periods
Figures below show the measured MTRs for February through May (spring 2019 – 2022) and August through November (autumn 2019 – 2021) seasons, of which only the part with the highest migration intensity has been used in our analysis (15 February to 1 May for spring and 1 October to 1 December in autumn). Note that the y-axes are different for each subplot.

Spring (2019-2022)
To capture circadian and circannual migration dynamics at the radar location, a proxy for seasonal and diurnal phenology was created by fitting local polynomial regression curves to hourly MTRs (birds/km/hr) grouped by day of year and hour after sunset. Curves were fitted to the full (4-year for spring and 3-year for autumn) datasets using the \textit{loess} function of the ‘base’ R package (R Core Team 2022) and included in the models as predictors. In the plots below, the blue line represents the values which were used as phenology proxies in our models. If the days and hours of high migration intensity occur at the same time of a year or a day, the phenology proxies will have higher values for those specific moments.
5.A.2.1 Diurnal phenology

Spring

Autumn
5.A.2.2 Seasonal phenology

Spring

Autumn
Figure 5.A.3 Correlation matrices for all predictors in spring and autumn

Spring

Autumn

*glossary available in Table 5.A.2.
Table 5.A.1 Seasonal overview of the variables that were highly correlated, therefore excluded from the model.

<table>
<thead>
<tr>
<th>Spring</th>
<th>Autumn</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean sea level pressure in the UK</td>
<td>Mean sea level pressure in Denmark</td>
</tr>
<tr>
<td>Mean sea level pressure at the radar location</td>
<td>Mean sea level pressure in the N Netherlands</td>
</tr>
<tr>
<td>Accumulation due to wind assistance in France</td>
<td>Nightly difference in mean sea level pressure in Denmark</td>
</tr>
<tr>
<td>Temperature in France</td>
<td>Mean sea level pressure in NW Germany</td>
</tr>
<tr>
<td>Nightly difference in mean sea level pressure in the UK</td>
<td>Total precipitation Denmark</td>
</tr>
<tr>
<td>Temperature in the UK</td>
<td>Temperature in NW Germany</td>
</tr>
</tbody>
</table>

| Nightly difference in mean sea level pressure in N Netherlands | Accumulation due to wind assistance in the N Netherlands |
| Temperature in N Netherlands                        | Temperature in Denmark                        |
| Temperature in Danmark                              | Total precipitation in NW Germany             |

Table 5.A.2 Glossary of abbreviations in correlation matrices

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>acc_diff</td>
<td>(nightly) difference in accumulation</td>
</tr>
<tr>
<td>tp or P</td>
<td>total precipitation</td>
</tr>
<tr>
<td>wa</td>
<td>wind assistance</td>
</tr>
<tr>
<td>t</td>
<td>temperature</td>
</tr>
<tr>
<td>msl</td>
<td>Mean sea level pressure</td>
</tr>
<tr>
<td>UK</td>
<td>United Kingdom</td>
</tr>
<tr>
<td>F</td>
<td>France</td>
</tr>
<tr>
<td>NW</td>
<td>North-west Germany</td>
</tr>
<tr>
<td>NN</td>
<td>North Netherlands</td>
</tr>
<tr>
<td>D</td>
<td>Denmark</td>
</tr>
<tr>
<td>delta</td>
<td>(nightly) difference in weather variable</td>
</tr>
<tr>
<td>Hour_p</td>
<td>Proxy for seasonal phenology</td>
</tr>
<tr>
<td>Year_p</td>
<td>Proxy for yearly phenology</td>
</tr>
</tbody>
</table>
Partial dependence plots (PDPs) below show each of the top three predictor’s relationships with the response variable (MTR) while all the other predictors remained constant. The plots below show these relationships when the model was trained with the data from 2019 – 2022 for spring and the data for 2019 and 2021 for autumn. Grey areas around lines indicate confidence intervals (0.95), and rug plots along the bottom indicate the distribution of the data. A further explanation of these relationships can be found in the main text of the paper’s Results section.
The receiver operating curves (ROC) for the spring and autumn models created with a threshold of 150 birds/km/h ($95^{\text{th}}$ percentile of MTR values in the data used in this study). These plots show the effectiveness of the model for identifying hours with the high migration intensity while at the same time having the lowest fraction of the false positive predictions. For example, with the threshold of 73.8 birds/km/h in spring, approximately 52% of hours with the migration intensity of 150 birds/km/h can be correctly predicted with the model, with only 0.03% of false positive predictions. ROC plots can be viewed as a continuous version of confusion matrices shown in Figure 5.4.
Figure 5.A.6 Cumulative percentage plots

Cumulative percentage of measured MTRs for spring (left) and autumn (right) for different testing years, which were not shown in the main text of the paper. Hours are ranked by MTRs in descending order based on radar observations (dark blue line) and model predictions (green in spring and yellow in autumn). Hourly migration intensity decreases going from the left to the right side of the x-axis.
Figure 5.A.7 Energy plots

Figures below show cumulative measured MTR (y-axis) vs cumulative energy production (x-axis) for spring (left) and autumn (right) of different years, which were not shown in the main text. The observations are ranked by hourly MTRs in descending order (higher MTR values on the right side of the graphs).