

RESEARCH ARTICLE

The Global Energy Transition: Ecological Impact, Mitigation and Restoration

Forecasting nocturnal bird migration for dynamic aeroconservation: The value of short-term datasets

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Abstract

1. Placing wind turbines within large migration flyways, such as the North Sea basin, can contribute to the decline of vulnerable migratory bird populations by increasing mortality through collisions. Curtailment of wind turbines limited to short periods with intense migration can minimize these negative impacts, and near-term bird migration forecasts can inform such decisions. Although near-term forecasts are usually created with long-term datasets, the pace of environmental alteration due to wind energy calls for the urgent development of conservation measures that rely on existing data, even when it does not have long temporal coverage.
2. Here, we use 5 years of tracking bird radar data collected off the western Dutch coast, weather and phenological variables to develop seasonal near-term forecasts of low-altitude nocturnal bird migration over the southern North Sea.
3. Overall, the models explained 71% of the variance and correctly predicted migration intensity above or below a threshold for intense hourly migration in more than 80% of hours in both seasons. However, the percentage of correctly predicted intense migration hours (top 5% of hours with the most intense migration) was low, likely due to the short-term dataset and their rare occurrence. We, therefore, advise careful consideration of a curtailment threshold to achieve optimal results.
4. *Synthesis and applications:* Near-term forecasts of migration fluxes evaluated against measurements can be used to define curtailment thresholds for offshore wind energy. We show that to minimize collision risk for 50% of migrants, if predicted correctly, curtailments should be applied during 18h in spring and 26 in autumn in the focal year of model assessments, resulting in an estimated annual wind energy loss of 0.12%. Drawing from the Dutch curtailment framework, which pioneered the 'international first' offshore curtailment, we argue that using forecasts developed from limited temporal datasets alongside expert insight and data-driven policies can expedite conservation efforts in a rapidly changing world. This approach is particularly valuable in light of increasing interannual variability in weather conditions.

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KEYWORDS

collision risk, curtailment, mitigation, radar, seasonal, the North Sea, wind energy, wind turbines

1 | INTRODUCTION

As the world is transitioning towards sustainable energy production to meet climate targets, the airspace is bound to become riskier for flying organisms (Davy et al., 2017) due to increased wind energy production. In many countries, the expansion of wind turbines is concentrated offshore (Leung & Yang, 2012). These turbines pose a risk for migratory birds through collisions (Marques et al., 2014), habitat change and barrier effects (Drewitt & Langston, 2006). In the southern North Sea, the currently installed amount of wind power will increase fourfold 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 United Kingdom and between Northwestern Europe and Africa, mainly during the night (Dierschke, 2003; Hüppop et al., 2006; Lack, 1959).

To minimize the above-mentioned 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 (Gauld et al., 2022; Murgatroyd et al., 2021). Institutions, such as wind energy companies, which are developing infrastructure, are bound by national and international laws to comply with the mitigation hierarchy. When the first step of 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 (Bennett et al., 2022; McClure et al., 2021; Singh et al., 2015). Currently, curtailments in wind farms to protect birds have been applied in real-time and on a small scale, focusing on specific species. However, in large migratory flyways with extensive wind energy development, curtailments across multiple wind farms are needed for safe bird passage. This requires coordination among stakeholders to keep the energy grid stable and minimize the financial cost of shutdowns, and cannot be accomplished in real-time. Predicting bird arrival in risk areas using near-term forecasts is therefore suggested to be a cost-effective way to minimize impacts on bird populations (Shamoun-Baranes et al., 2017).

Near-term forecasts of bird migration that use phenological descriptors and weather conditions as predictor variables, and migration data collected by military and weather radars are already in use to minimize collisions between birds and aircraft (Kranstauber et al., 2022; van Belle et al., 2007; van Gasteren et al., 2019) and for turning off lights on high buildings to decrease the impact of artificial light on migratory birds in urban areas (BirdCast, 2022; van Doren et al., 2017; van Doren & Horton, 2018). While weather radars can

be a suitable tool to develop near-term forecasts for wind turbine curtailments on land (Cohen et al., 2022), due to their insufficient coverage at sea, they are not ideal for predicting migration to inform offshore wind turbine shutdowns. Additionally, the migratory behaviour of landbirds may differ over the sea, as seas may be perceived as ecological barriers for many species, hence influencing their departure decisions, routes and flight altitudes (Archibald et al., 2017; Deppe et al., 2015). It is, therefore, essential to develop forecast models for migration occurring over offshore wind parks with data collected at sea.

In the case of the contiguous United States, 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) since most migratory birds select nights with specific weather conditions for migration (Bradarić et al., 2020; Erni et al., 2002). Focusing shutdowns on short periods with the most intense migration maximizes conservation effects while minimizing the impact on energy production. 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), the pace of the environmental alteration requires swift conservation actions, which include wind turbine curtailment informed by near-term ecological forecasts developed using data of shorter temporal coverage, and while improving models 'on the go' (Dietze et al., 2018).

Here, we develop seasonal forecast models of low-altitude nocturnal migration at sea using a five-year dataset collected by a tracking radar positioned off the western Dutch coast. With forecasts, we provide decision-makers with a tool to coordinate wind turbine curtailments on intense migration nights in the Dutch North Sea as part of a framework for reducing avian mortality. We also use the models to study the importance of different environmental variables in shaping seasonal migration dynamics in the North Sea basin. As model input, we use the day of year and time of day to describe migratory birds' mean circannual and circadian dynamics (Gwinner & Helm, 2003; Kranstauber et al., 2023). Furthermore, we include wind assistance, air pressure, temperature and precipitation from the radar location at sea as well as from inferred departure locations on land, all of which have been observed to influence migration intensity (Bradarić et al., 2020; Kemp et al., 2013; Richardson, 1990). We create confusion matrices based on different migration intensity thresholds and discuss the effect of different thresholds on the curtailment procedure's efficiency. 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 wind energy loss in relation to the percentage of migratory birds protected. Migration intensity predictions, created 48 h ahead with these models and

weather forecasts, are used in the decision-making framework of the Dutch government to determine when turbine curtailments are necessary during spring and autumn.

2 | MATERIALS AND METHODS

2.1 | The radar system, location and study period

We used data collected by a tracking radar (Robin Radar 3D fix, Robin Radar Systems BV, the Hague, Netherlands) positioned within the operational offshore wind farm Luchterduinen (52.25 N, 4.10 E), ca. 23 km from the western Dutch coast. Given that radar operates as a remote sensing tool, our study did not require ethical approval. The radar has been continuously collecting data since 2018. We consider the full migration seasons from 15 February to 31 May in spring and 15 August to 30 November in autumn (Kranstauber et al., 2022). As the focus for wind energy curtailment is to predict hours of intense migration, we selected a restrictive period of the migratory season, which covers the most intense migration hours between 2019 and 2023, based on all-time seasonal 95th percentile of migration intensity (see Appendix S.1 in Supporting Information). This means that the months of May, August and September were excluded from our analysis. As we focus on nocturnal migration, our study uses data between sunset and sunrise.

The radar system consists of two antennae (Furuno Marine). 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 500 m 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 these data cover the altitudes of interest and contain more information about individual tracks (van Erp et al., 2024 and the supplementary information therein).

The radar tracks are created by a proprietary tracking algorithm, and the clutter is automatically discarded before entering a centralized database. Furthermore, we apply post-processing as tracks from various types of clutter entering the database despite the automated clutter filters. Detailed information on radar data processing and post-processing can be found in Appendix S.2 and van Erp et al., 2024. To estimate the hourly number of birds passing through an area of interest, we calculated the mean traffic rate of migration (MTR), which is expressed as the number of birds (#) per kilometre (km) per hour (h). Detailed calculations can be found in Appendix S.3.

2.2 | Weather data

Weather data were obtained 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-h temporal resolution. Hourly weather variables for the radar location were extracted from the closest grid cell, 52.25 N 4.00 E. Back trajectory analysis of migration data collected offshore revealed potential departure locations in the Eastern United Kingdom and Northwestern France in spring and north of the Netherlands, Northwestern Germany and central Denmark in autumn (Bradarić et al., 2020). Data from these regions were averaged over multiple grid cells (bounding boxes in Figure 1) and the first 2 h after sunset, as that is the time when most birds are expected to depart (Sjöberg et al., 2017). We extracted total precipitation (TP, m), mean sea level pressure (MSLP, Pa) and wind components at 100 m above the earth's surface 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 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. Altitudes for pressure levels were calculated by dividing the geopotential height of a pressure level by the gravitation acceleration. The air temperature was extracted from multiple pressure levels and averaged over those corresponding to the altitudes of interest (100–300 m). 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. 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) using known migration directions of 90° in spring and 220° in autumn (Bradarić et al., 2020) and included as a predictor in the model. When weather conditions are not favourable for migration for a few days, birds that would otherwise depart may accumulate in large numbers and depart simultaneously once weather conditions improve. This effect is particularly evident at the coast before birds cross ecological barriers, such as large water bodies (Biebach et al., 2000; Lowery, 1945). To capture accumulation dynamics, we calculated accumulation factors following Erni et al., 2002 and included them as predictors in our models. Details on wind assistance and accumulation calculations can be found in Appendices S.4 and S.5.

2.3 | Seasonal and diurnal phenology

To capture the mean circannual and circadian migration dynamics at the radar location, similar to Kranstauber et al., 2022, 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 dataset using the loess function of the 'base' R package (R Core Team, 2022), and the fitted

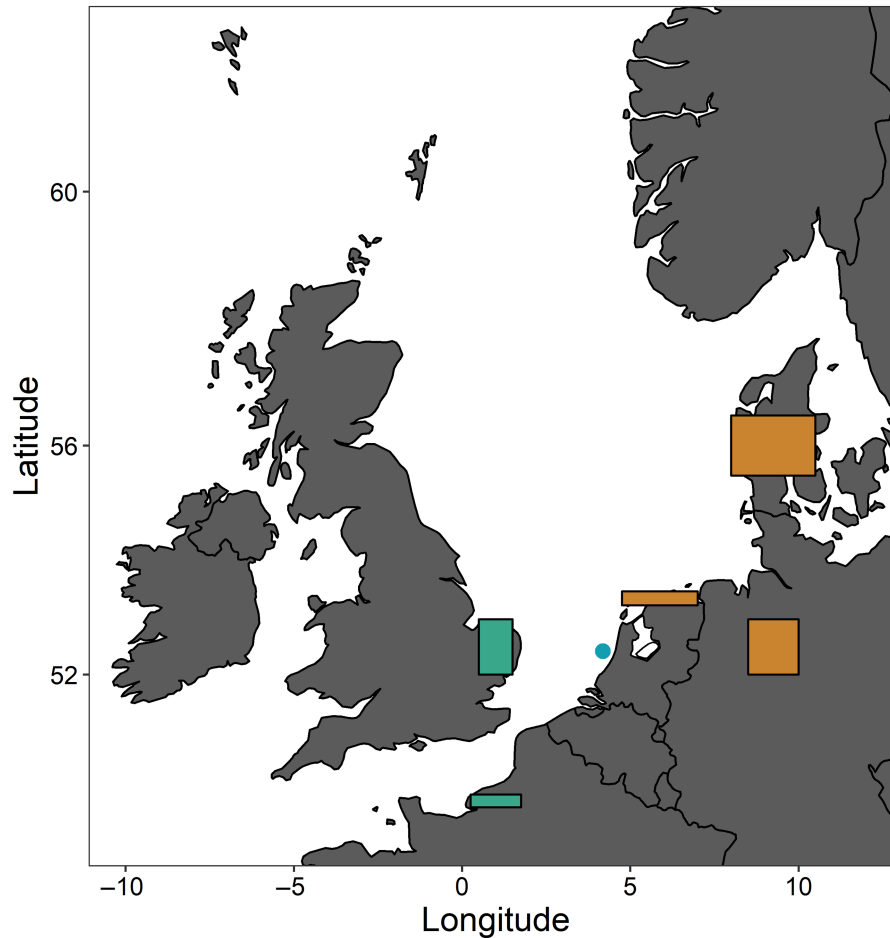


FIGURE 1 The North Sea area with the radar location within Luchterduinen wind farm (blue dot) and bounding boxes of ERA5 weather data grid cells at departure locations (Bradarić et al., 2020) in spring (green) and autumn (yellow).

MTR values were included in the models as predictors. Figures can be found in Appendix S.6.

2.4 | Predictive model

We trained random forest models using the R package 'ranger' (Wright & Ziegler, 2017) to predict migration in spring and autumn separately. Having 5 years of data for spring and 4 years for autumn, we always used 1 year of data as a testing dataset to further avoid overfitting, while the rest was used for the model training. This data division corresponds to a 70:30 ratio of training versus testing datasets usually used in random forest setups (Nguyen et al., 2021). 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 1. Before running the models, we generated correlation matrices (Appendix S.7) using Spearman's rank correlation coefficient 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). The full list of the

highly correlated seasonal variables that were removed from further analysis is given in Table S1.

The data used for the model training were imbalanced, as the number of hours with high MTRs representing intense bird migration was much lower than those with low MTRs (Appendix S.1). Imbalanced data cause 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 this paper aimed primarily to predict intense bird migration, we applied stratified sampling to balance our data (see Appendix S.8 for details).

Before training the models, we performed hyperparameter tuning by running the models with a range of different hyperparameters. We chose a combination that led to the lowest out-of-bag (OOB) RMSE (Probst et al., 2019). 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 five observations in both seasons. In spring, we used a mtry of 9; in autumn, we used a mtry of 21.

TABLE 1 Overview of variables used as model predictors.

Description	Unit	Season	Location
Wind assistance towards W	m/s	Autumn	Radar and Northwestern Germany
Wind assistance towards SW	m/s	Autumn	Radar, Northern Netherlands and Denmark
Wind assistance towards E	m/s	Spring	Radar and the United Kingdom
Wind assistance towards NE	m/s	Spring	Radar and Northwestern France
Total precipitation	mm	Both	Radar and departure locations
Temperature	°C	Both	Radar and departure locations
Mean sea level pressure	hPa	Both	Radar and departure locations
The nightly difference in mean sea level pressure	hPa	Both	Departure locations
Accumulation due to wind assistance	—	Both	Departure locations
The nightly difference in accumulation due to wind assistance	—	Both	Departure locations
Accumulation due to total precipitation	—	Both	Departure locations
The nightly difference in accumulation due to precipitation	—	Both	Departure locations
Diurnal phenology	—	Both	—
Seasonal phenology	—	Both	—

2.5 | Model evaluation

We report OOB R^2 for both seasons to indicate how much variance each model explains (Louppe, 2014). However, we are mainly interested in how the model predicts hours with high MTRs, as those are the moments relevant for offshore wind turbine curtailments. Therefore, we focused on other metrics. We create confusion matrices using a seasonal 95th percentile of observed MTR using all years of data (126.6 birds/km/h in spring and 273 birds/km/h in autumn). To show the model's predictive performance when using different thresholds, we first created receiver operating characteristic (ROC) curves based on the seasonal 95th percentile (Liu et al., 2005). Then, we created confusion matrices using three different thresholds: seasonal 95th percentile and the two top thresholds extracted from ROC curves. 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. With this, we aimed to demonstrate how the threshold choice in the operational phase of the conservation framework can contribute to the effectiveness of aeroconservation actions.

We calculated the cumulative percentage of migration intensity to (1) estimate the minimum number of hours needed for wind energy curtailment to protect a selected proportion of passing birds and (2) evaluate the accuracy and effectiveness of curtailment based on predictions. Observed and predicted hourly MTR values were ranked in descending order, and for each ordinal hour, the radar-observed cumulative MTR values were plotted. If predictions are ideal, the curves of cumulative percentages would completely overlap.

Finally, we created curves of yearly cumulative wind energy production ranked by nocturnal hourly MTR in descending order. The yearly 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) and the hourly 100-m wind speed data from the radar location. These curves were created to estimate the yearly percentage of wind energy loss if the curtailments are performed during intense migration hours.

3 | RESULTS

Here, we present the model results based on testing with 2022 in the spring and 2020 in the autumn. Other training and testing year combinations and additional information on years presented here are available in Appendices S.9–S.13.

The most important variables for predicting MTR in spring are seasonal phenology, followed by wind assistance towards NE and E at the radar location (Figure 2a), and this was consistent throughout years (Appendix S.10). Migration intensity is the highest when the seasonal phenology proxy is above 75, which corresponds to late February and March and when wind assistance towards NE at the radar location was between 0 and 2 m/s and the wind assistance towards E was above 8 m/s (Appendix S.9).

Wind assistance at departure in Denmark and towards SW at the radar location, as well as diurnal phenology, were the most important variables for predicting MTR in autumn (Figure 2b). Migration intensity is the highest when the accumulation of migrants due to negative wind assistance at departure in Denmark is above 0.75, wind assistance towards SW is above 0 m/s, and the diurnal phenology proxy is above 40, which corresponds to the first few hours after sunset, indicative of the departure of migrants from the nearby coast around sunset (Appendix S.9). To see variable importance for other combinations, see Appendix S.10.

In spring, peaks of migration intensity (nights with MTR higher than the seasonal 95 percentile) 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 3, Appendix S.1). Spring peaks generally tend to be of lower magnitude than autumn peaks, except for the peak on 15 March 2022 (Figure 3, Appendix S.1).

The OOB R^2 showed that the models explained 71% of the variance for both seasons (see Appendix S.10 for other years). In spring, confusion matrices (Figure 4) were created with 706 (out

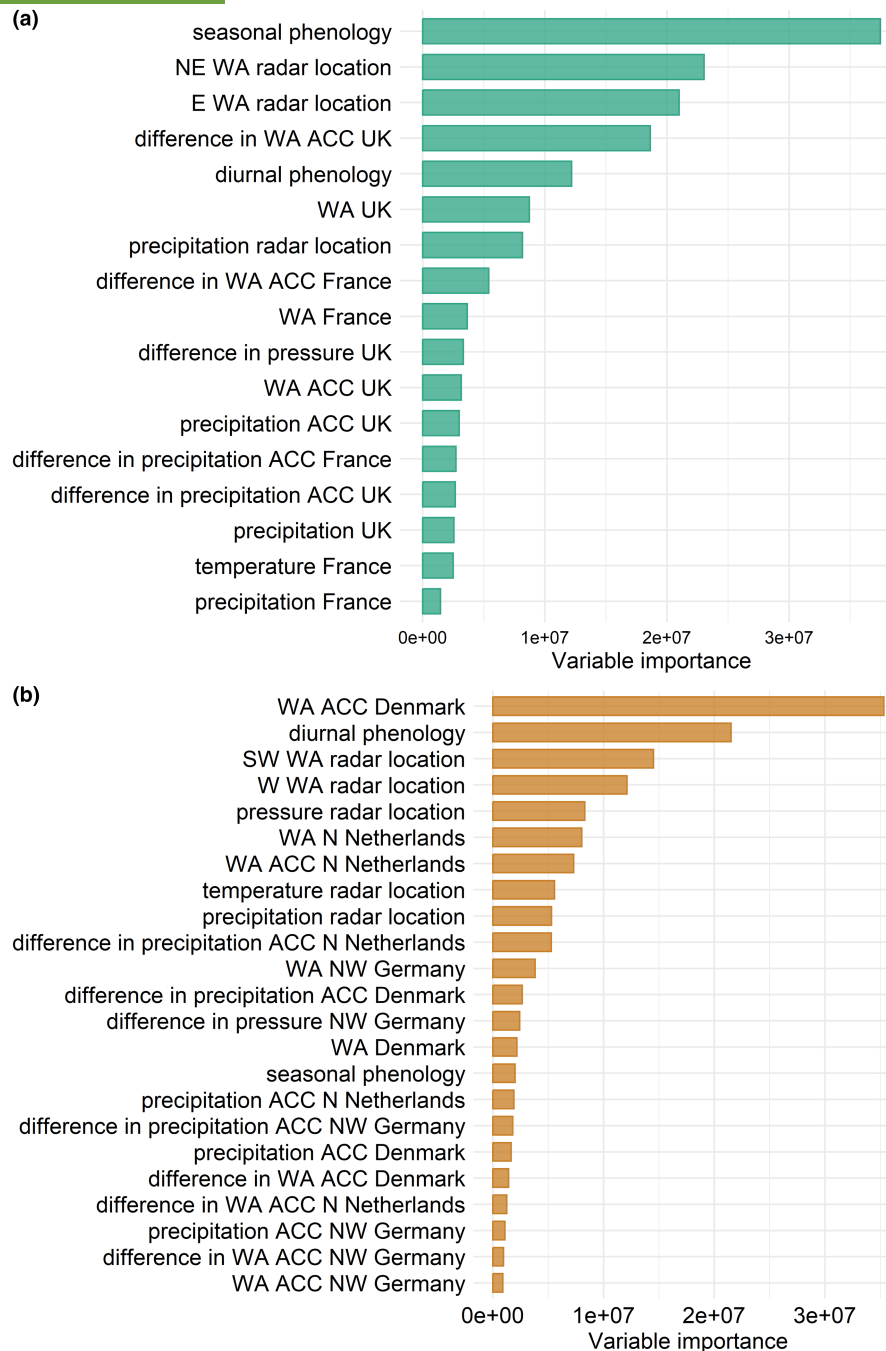


FIGURE 2 Variable importance in predicting spring (a) and autumn (b) low-altitude migration intensity based on the variance of all other variables when one of the variables was removed from the RF model.

of a total of 941) hourly data points for which the reference data were 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). The thresholds used for creating the confusion matrices were seasonal 95th percentiles and the two top thresholds from ROC curves (Appendix S.11), and they were lower in spring than in autumn (Figure 3). The model generally performs well in predicting true negatives with all threshold values in both seasons (Figure 4). The true positive fractions, which relate to hours with intense

migration, 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, we show the minimum number of hours needed in spring 2022 and autumn 2020 for wind energy curtailment to protect a proportion of passing migrants and the efficacy of the model predictions. Observed hourly MTRs are plotted as a cumulative seasonal percentage ranked by hourly migration intensity in descending order (highest MTR values left on the x-axis). The ranking (x-axis) is

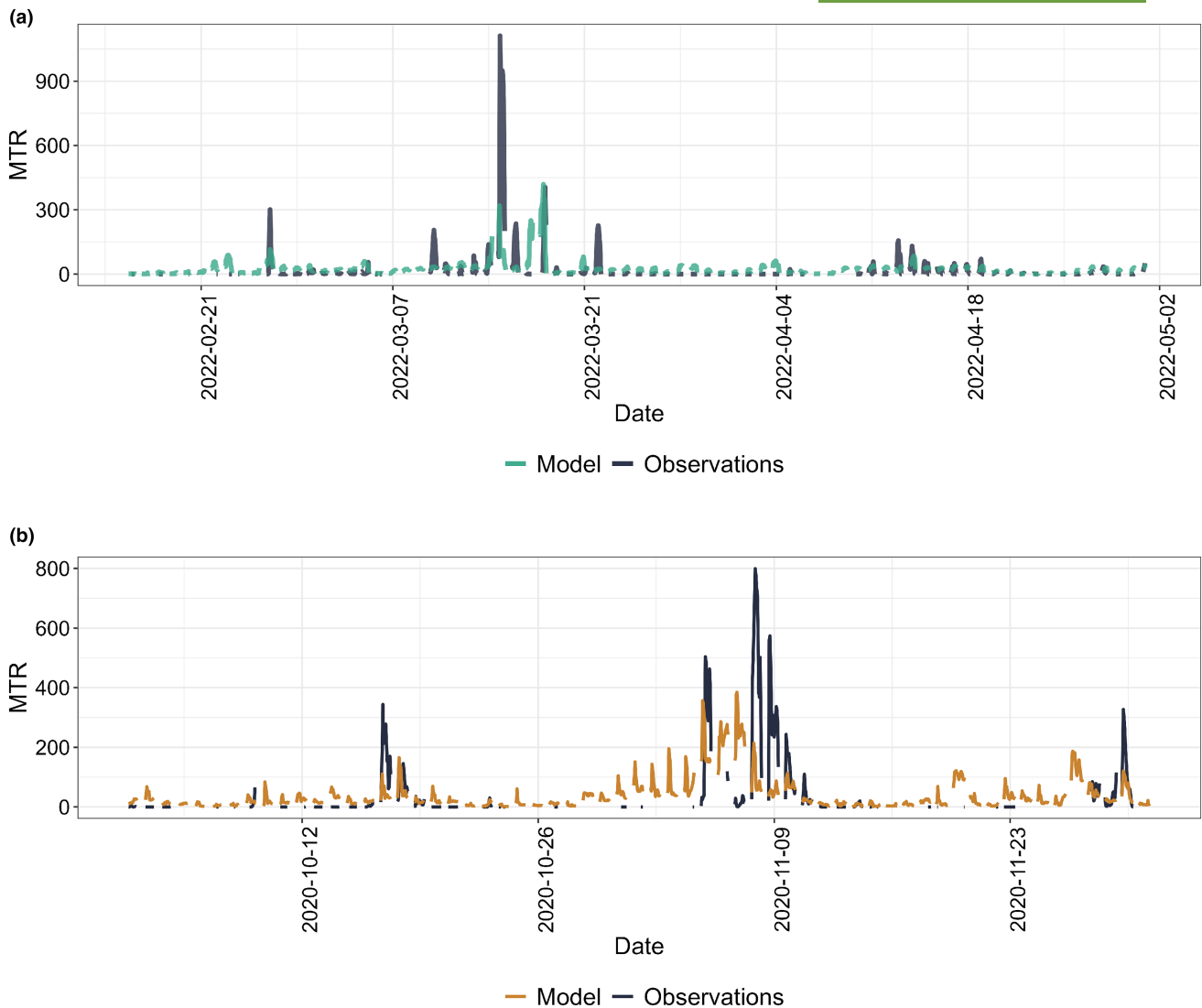


FIGURE 3 Spring 2022 (a) and autumn 2020 (b) time series of mean traffic rate (MTR; birds/km/hr) used to test the performance of the model. Model predictions of MTRs are shown in green (spring) and yellow (autumn), while the observations are in dark blue.

based on observations by the radar (dark blue line) or predictions by the model (coloured line) with radar-observed cumulative MTR on the y-axis. For a given number of hours (x-axis), the cumulative percentage of birds passed (y-axis) can be determined. For example, in spring 2022, 50% of all observed migration occurred during only 18 h (2.5% of hours in the study period). Based on the spring model, 50% of migration would happen in 37 h, with the highest MTRs (6.4% of hours in the study period). The difference between observed and predicted migration intensity is higher in autumn. In autumn 2020, 50% of all recorded migration occurred within 26 h, with the highest MTRs (5.5% of hours in the study period), while the model predicted that 50% of migration would happen within 83 h (17.7% of hours in the study period). Fifty per cent of migration equals about 10^4 birds/km in spring and 1.3×10^4 birds/km in autumn.

Figure 6 shows measured MTRs plotted as a cumulative seasonal percentage versus cumulative yearly percentage of the wind energy production ranked by hourly migration intensity in descending order

(highest MTRs values left on the x-axis). Reading the x and y coordinates of points belonging to the line, we can determine the percentage of wind 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 to conserve 50% of the birds passing, the amount of wind energy lost is 0.05% of the total yearly wind energy production. In autumn 2020, this amount was 0.07% of the total. Wind energy production curves for other years are available in Appendix S.13.

4 | DISCUSSION

Despite the temporally limited dataset of bird migration intensity and interannual differences in model performance (Appendices S.10 and S.12), we demonstrate that, overall, spring and autumn models of low-altitude nocturnal migration can

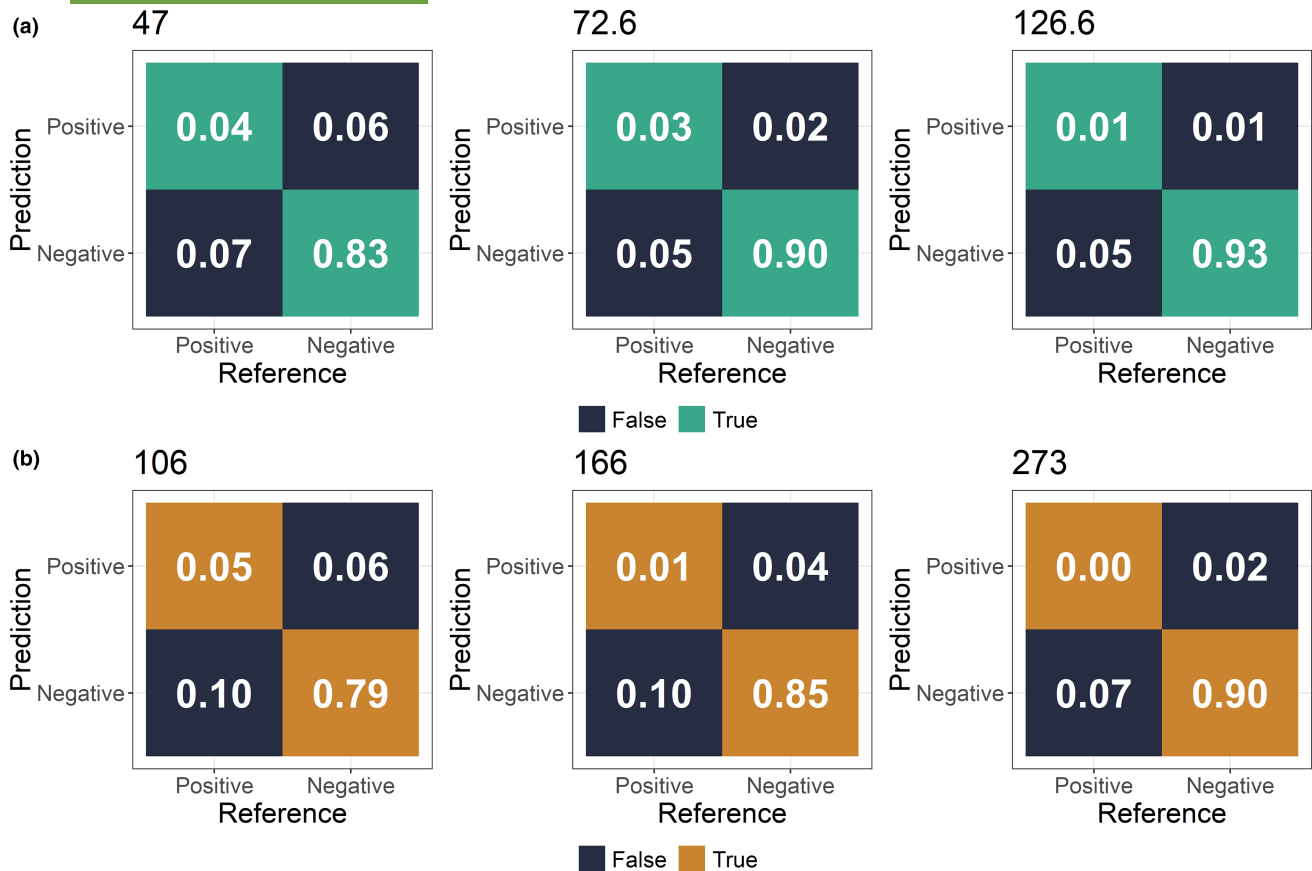


FIGURE 4 Confusion matrices for spring (a) and autumn (b) created with different mean traffic rate thresholds (given in the titles of each confusion matrix, birds/km/h). Confusion matrix tiles coloured in green (spring) and yellow (autumn) show true positives (upper left tile) and true negatives (lower right tile). Dark blue tiles 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 were available was 706 for spring 2022 and 467 for autumn 2020.

capture migration intensity dynamics well, and OOB R^2 values indicate that both models explain a large portion of the variance in migration intensity over the southern North Sea. We 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 (Figure 4). As expected, phenology proxies and wind assistance were the most important drivers of migration intensity in both spring and autumn.

Migratory movement from the United Kingdom towards the Netherlands observed in spring generally has supportive wind conditions for migration (Bradarić et al., 2020; Kemp et al., 2010), and high importance of seasonal phenology indicates that circannual rhythm is more important in influencing migration intensities in spring than wind conditions. Nevertheless, the high importance of wind assistance at the radar location shows that birds still rely on winds and increased wind assistance to cross the North Sea faster, sometimes exploiting higher wind speeds at higher altitudes (Kemp et al., 2013). In autumn, the high importance of diurnal phenology might reflect 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, as also shown for other coastal areas around Europe (Kranstauber et al., 2023). The other cohort is migrants from Scandinavia and Northwestern Germany (Bradarić et al., 2020), whose timing may vary depending on wind conditions experienced en route. The high importance of wind assistance at the radar location and the 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., 2020). Migration intensity in autumn is also strongly influenced by the accumulation of birds due to the lack of wind assistance at the departure location in Denmark. Previous studies have shown that, especially around ecological barriers, birds tend to accumulate when weather conditions are not good for migration and depart in large numbers after weather changes (Biebach et al., 2000; Lowery, 1945).

Even though the model largely explained the 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 4). 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

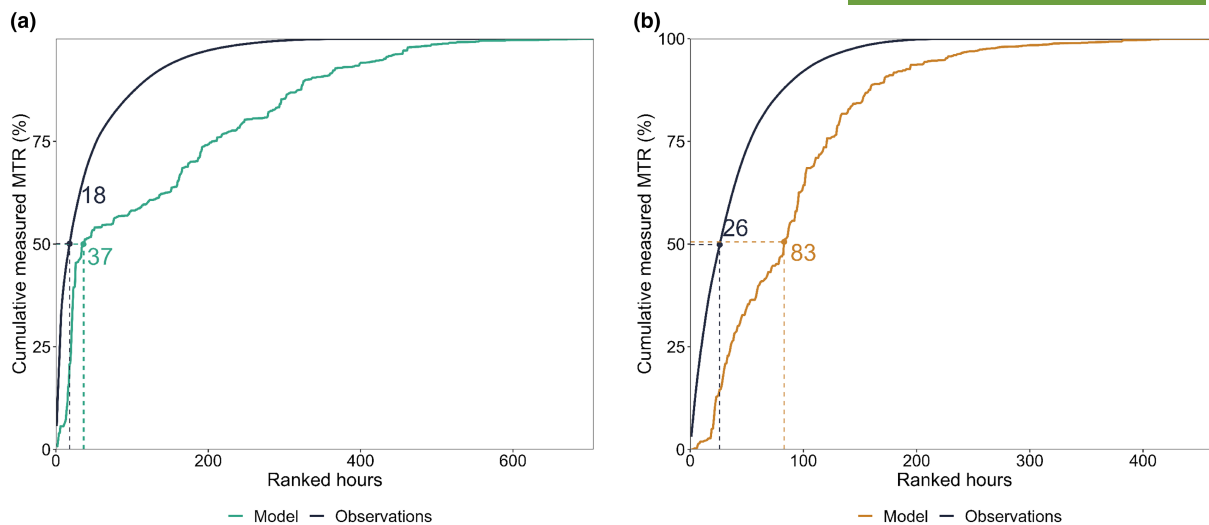


FIGURE 5 Cumulative percentage of measured mean traffic rate (MTRs) (birds/km/h) for the testing year of 2022 in spring (a) and the testing year 2020 in autumn (b) for hours ranked by MTRs in descending order based on radar observations (dark blue line) and model predictions (green in spring and yellow in autumn). Hourly migration intensity decreases from left to right of the x-axis.

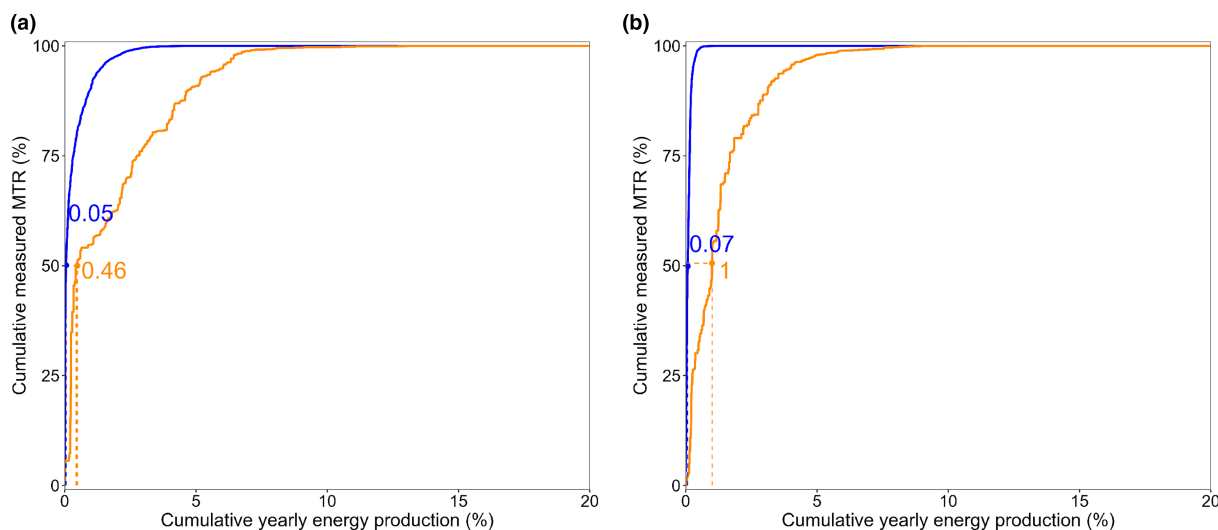


FIGURE 6 Cumulative measured mean traffic rate (MTR; y-axis) versus cumulative percentage of wind energy production (x-axis) for the testing year of 2022 during the measurement period in spring (a) and 2020 in autumn (b). The observations are ranked by hourly MTRs in descending order (higher MTR values on the right side of the graphs).

migration nights entered our training dataset, as they generally occur only a few times during the migration season (Appendix S.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., 2020). This makes it hard for the model to identify general characteristics of such cases in the training procedure, even when applying methods for balancing the data, such as stratified sampling. A second complementary explanation is the missing data due to radar issues, bad weather conditions under which the radar does not collect reliable information and further ‘shortening’ of the available dataset through rigorous but necessary filtering procedures. Often, gaps in the observed data occur when the model

predicts intense migration, especially in autumn (Figure 3). Until more data are available for model training, the optimal selection of the curtailment threshold is crucial in maximizing the proportion of accurately predicted intense migration hours while balancing false positives and negatives. In subsequent sections, we mention extra steps that can be taken to maximize the correct prediction of intense migration hours.

Intense migration nights are the highest priority for offshore wind turbine curtailments, as they provide opportunities to minimize collision risk for most migrants with minimal wind energy loss. While we show that to protect 50% of migrants, wind turbine curtailments have to be performed on a limited number of hours, due to the inaccuracy of the model predictions, the number

of hours needed to protect half of the migrants in practice will be higher (Figure 5). Since the model was trained with reanalysis weather data and the predictions used for curtailments will be based on weather forecasts, we can expect an additional prediction error due to discrepancies between weather forecasts and reanalysis data. However, when more radar measurements are available, the models will be recalibrated with the new data, improving the model performance.

When discussing curtailments, it is important to mention their consequences on the energy grid in terms of wind energy loss. Most intense migration occurs at times when wind speeds are too low to have a major impact on energy production (Appendix S.9). As a result, even when taking into account the non-optimal performance of the current model, a curtailment to protect 50% of the migrants would lead to a wind energy loss of less than 1% of the yearly production in either of the seasons. As our model improves and more observations become available, the yearly wind energy loss due to curtailments will be further reduced towards 0.05% in spring and 0.07% if the optimal model correctly predicts the observations. These numbers indicate that achieving a balance between safe passage and minimal wind energy loss is possible; this is especially important when extrapolating the bird counts from our study area to encompass the entire North Sea, where millions of birds cross during migration (Dierschke, 2003).

Graphs shown in Figures 5 and 6 can further be used to define thresholds while balancing wind energy production, wind energy loss, model performance and the percentage of birds that would have a safe passage. For example, if the goal is to allow safe passage for 50% of migrants, the graphs can inform on the number of curtailment hours that would be needed to achieve this and can provide the MTR threshold value, which, if reached or exceeded, would initiate the curtailment process. If, on the other hand, a decision has been made that curtailments are possible for 20h in each season, the graphs can show how many birds would, in this case, have a safe passage and what MTR threshold should be aimed for. It is important to note that these graphs could and should be used dynamically to periodically adjust thresholds if the conservation goals, energy sector limitations or model performance have changed.

To keep pace with the rapid anthropogenic alteration of the environment, it may be necessary to start creating conservation measures with short-term datasets and carefully tailored political decisions (Dietze et al., 2018) while concomitantly conducting long-term research to better understand the systems we are trying to protect. In the current framework for a start/stop procedure created by the Dutch government, at least for the initial stages of wind turbine curtailments, shutdown decisions are made by a multi-step process which includes model predictions, evaluation of predictions made by an expert committee and the assessment of wind conditions and the energy grid stability. While model predictions for intense migration nights could be improved by training the models with longer time series of radar data, we show that they can already help initiate curtailments during critical hours, especially in spring (Figure 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 model development. With the example from the Netherlands, we want to encourage dynamically applied conservation to further deal with high interannual differences in both weather and migration patterns in the region (Manola et al., 2020) and increased occurrence of extreme weather conditions (Kautz et al., 2022). We propose that the framework in which prediction models are used together with the assessments of experts in the relevant field is a valuable intermediate stage while the predictive performance is optimized to help minimize the negative effect of energy transition on wildlife.

AUTHOR CONTRIBUTIONS

All authors conceived the study. Maja Bradarić led the data filtering, analysis and model development, supported by Bart Kranstauber and input from Willem Bouten and Judy Shamoun-Baranes. Maja Bradarić led the manuscript writing and all authors provided feedback on manuscript versions. Judy Shamoun-Baranes was responsible for funding acquisition for projects leading to this manuscript.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

Data are available via the Dryad Digital Repository <https://doi.org/10.5061/dryad.8gtht76x0> (Bradarić et al., 2024).

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

Appendix S.1. Time series with migration data from the full observation periods.

Appendix S.2. Radar data processing and post-processing.

Appendix S.3. Mean traffic rate (MTR).

Appendix S.4. Wind assistance.

Appendix S.5. Accumulations.

Appendix S.6. Seasonal and diurnal phenology.

Appendix S.7. Correlation matrices for all predictors in spring and autumn.

Appendix S.8. Stratified sampling.

Appendix S.9. Partial dependence plots.

Appendix S.10. Model performance in different years.

Appendix S.11. ROC curves.

Appendix S.12. Cumulative percentage plots.

Appendix S.13. Wind energy loss plots.

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