RESEARCH ARTICLE

Quantifying nocturnal thrush migration using sensor data fusion between acoustics and vertical-looking radar

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Abstract

Studying nocturnal bird migration is challenging because direct visual observations are difficult during darkness. Radar has been the means of choice to study nocturnal bird migration for several decades, but provides limited taxonomic information. Here, to ascertain the feasibility of enhancing the taxonomic resolution of radar data, we combined acoustic data with vertical-looking radar measurements to quantify thrush (Family: Turdidae) migration. Acoustic recordings, collected in Helsinki between August and October of 2021–2022, were used to identify likely nights of high and low thrush migration. Then, we built a random forest classifier that used recorded radar signals from those nights to separate all migrating passerines across the autumn migration season into thrushes and non-thrushes. The classifier had a high overall accuracy (≈ 0.82), with wingbeat frequency and bird size being key for separation. The overall estimated thrush autumn migration phenology was in line with known migratory patterns and strongly correlated (Pearson correlation coefficient ≈ 0.65) with the phenology of the acoustic data. These results confirm how the joint application of acoustic and vertical-looking radar data can, under certain migratory conditions and locations, be used to quantify 'family-level' bird migration.

Introduction

Every year, billions of migratory birds travel tremendous distances in pursuit of improved feeding opportunities, safety and higher reproductive output (Bauer & Hoye, 2014). The magnitude of long-range autumn migration between Europe and Africa of passerines and near-passerines has been estimated at 2.1 billion individuals (Hahn et al., 2009). Similar or even higher numbers have been estimated for passerine migration in and out of the USA (Dokter et al., 2018), and the majority of these birds migrate at night (McLaren et al., 2018). In Finland alone, more than 22 million of them are believed to be thrushes (Weisshaupt et al., 2024).

Radar monitoring by far has been the most widely used technique to study nocturnal bird migration, with examples ranging from local (Giuntini et al., 2023; Michev et al., 2017; Shi et al., 2021; Weisshaupt et al., 2023) over regional (Farnsworth et al., 2004; Tschanz et al., 2020) to continental-scale (Dokter et al., 2018; Nussbaumer

et al., 2019) quantification. Some dedicated bird radars allow characterizing individual birds by their size and flight pattern, albeit with varying precision (Schmid et al., 2019); direction and speed of each of the flying birds are also determined (Shi et al., 2021). These radars record the signature of returned echoes from the transmitted radar pulses, i.e. the energy reflected by the bird, and its temporal variation is then used to extract several features employed for object identification. For birds, echo signatures mirror the wingbeat pattern of the individual in flight, allowing to derive several wingbeat-related measures such as the wing-beat frequency, i.e. the number of wingbeats in one flapping phase divided by its duration (Bruderer, 1997). Similarly, the radar cross-section (RCS), which refers to the size of the bird as perceived by the radar, depends not only on certain characteristics of the radar pulse itself but also on attributes of the flying animal/bird, such as its shape and reflecting properties. These and other characteristics of the radar echoes, commonly referred to as 'echo features', are used to automatically classify the echoes into broad categories or classes. These classes roughly mirror taxonomic groups such as 'passerine-type' (with regular intermittent wingbeat pattern; i.e. most passerines, excluding corvids and swallows), 'wader-type' (with continuous wingbeat pattern, e.g. waterbirds, quails, rails), 'swift-type' (with wingbeat phase irregularly interrupted by gliding phase, e.g. swifts and bee-eaters), 'large bird' (with no or irregular wingbeats, mainly raptors or storks) and 'unidentified other birds' (Schmaljohann et al., 2008). Extracting species- or family-level information using radar data only, however, remains notoriously difficult (Dokter et al., 2013; Liechti & Bruderer, 2002; Williams & Williams, 1980). Thus, to achieve better taxonomic discrimination, the radar information so far is insufficient and needs to be complemented with data from other sources such as visual or acoustic observations, an approach used with increasing frequency also in bird studies, known as 'data fusion' (Cocchi, 2019; Mirzaei et al., 2015).

Unlike radar, bioacoustic monitoring does, although sometimes not without challenge, allow for the identification of bird species (Höchst et al., 2022; Lauha et al., 2022; Van Doren et al., 2024). The detection height and volume achieved with most currently used instruments are unknown, however (Darras et al., 2018; Pérez-Granados & Traba, 2021), and can vary depending on many factors including atmospheric conditions (Sanders, 2013). Moreover, bio-acoustic monitoring is only useful to monitor migrating species that emit flight calls. And even in species known to emit flight calls, the frequency of these calls is highly variable during the night, between seasons and years (Hüppop & Hilgerloh, 2012; Weisshaupt et al., 2024) and fluctuates in response to

several environmental conditions (Horton, Stepanian, et al., 2015). For night flight calls specifically, the spectrograms from certain species are also often highly similar, adding another layer of complexity to species identification (Evans & Rosenberg, 2000).

Despite the aforementioned limitations of bioacoustic techniques, they have been used successfully to quantify nocturnal migration in certain areas (Drake & Bruderer, 2017). In North America, acoustic call data were positively correlated with birding data (Sanders & Mennill, 2014) and thermal camera monitoring (Horton, Shriver, & Buler, 2015). Sensor networks combined with automatic species recognition software have recently also enabled overcoming some of the technique's limitations, such as the limited spatial scale and the need for experts for taxonomic identification (Van Doren et al., 2023). Some fundamental challenges persist, however, to use bioacoustics to accurately quantify migratory bird flow. These include addressing the proportion of individuals emitting flight calls, understanding the specific ways in which the environment can influence call emission and precisely determining detection altitude and increasing the range of altitudinal detection to ideally several hundreds of metres. The latter is crucial, particularly because many bird species migrate at high altitudes (Able, 1970; Dokter et al., 2011). Most current acoustic setups also do not allow determining the flight direction, a crucial parameter to separate migratory from local flight.

The combined use of radar and acoustic techniques to monitor bird migration is still relatively new. Horton, Shriver, and Buler (2015) found nightly averaged data obtained from acoustics and weather radars to only be weakly correlated. Similarly, Larkin et al. (2002) and Gagnon et al. (2010) also observed weak correlations between acoustic and weather radar estimates of bird traffic, and wide variability in correlations among nights. All these studies pertain to weather radars, however, and so far no comparisons have been made with dedicated bird radars which contain information on individual birds.

Here, we combined acoustic and vertical-looking radar data, collected between August and October 2021 and 2022 in Helsinki, Finland, to test whether the taxonomic detail of echo classification in a dedicated bird radar can be refined using acoustic information. We focused our analysis on quantifying thrush (Turdidae) migration, a highly vocal and primarily nocturnal migrant family. We hypothesized that our estimates from combining radar and acoustic data would more accurately describe thrush migration compared to radar-only-based estimates. More specifically, we expected that our estimates would correlate more strongly with the frequency of calling thrushes than the 'passerine-type' phenology estimated using radar data only.

Materials and Methods

Acoustic data

Nocturnal bird calls were recorded from sunset to sunrise, from August to October in 2021 and 2022 in the city of Helsinki (Pihlajamäki District, Finland, 60.2357°N, 25.0057°E) using a Telinga PRO-X Parabolic Microphone System, coupled with a Røde NTG8 microphone pointing in a different direction. Species were identified by acoustic and visual interpretation of the sonograms using Audacity v. 2.2 software (Audacity Team, 2021). Of the 4679 total identified calls across both autumn measuring periods (1996 in 2021 and 2683 in 2022), 2653 were identified as Redwing (*Turdus iliacus*; 1212 in 2021 and 1441 in 2022), 1559 as Song thrush (*Turdus philomelos*; 603 in 2021 and 956 in 2022) and 278 as Eurasian Blackbird (*Turdus merula*; 116 in 2021 and 162 in 2022). Calls identified as Fieldfare (*Turdus pilaris*) were omitted from the dataset due to their low abundance (only 59 in 2021 and 72 in 2022). For comparison with the radar data, the calls of the three thrush species considered were summed on an hourly basis to obtain the estimated number of migrating thrushes per hour.

Radar data

A vertical-looking dedicated bird radar was, simultaneously to the acoustic measurements, operated continuously throughout the measurement period in 2021 and 2022. The radar was placed on the roof of the Finnish Meteorological Institute in Helsinki (60.2042°N, 24.9612°E), approximately 4.5 km SW of the location of the acoustic measurements. The BirdScan MR1 AVLR (manufactured by Swiss Birdradar Solutions AG, Winterthur, Switzerland) is a 25 kW X-band (9.4 GHz, 3.2 cm wavelength) marine pulse radar (Bridgemaster©) equipped with a custom-designed vertical-looking horn antenna, rotating with a 2° nutation on its vertical axis. The nominal beam width at −3 dB is approximately 17.5°. The detection range depends on the pulse duration and the size of the bird (Schmid et al., 2019). We operated the radar in short pulse mode (pulse length 65 ns, pulse rate frequency 1800 Hz, range resolution about 7.5 m), resulting in an approximate detection range from 50 m up to about 1000 m for thrushes.

An animal (or any object) flying through the radar beam produces an echo signature, i.e. a change in echo intensity over time (Bruderer, 1997; Schmid et al., 2019). From these echo signatures, a set of features (around 200) are derived, such as overall statistical properties of the signal (e.g. the standard deviation of the signature), features related to the shape of the return signal (i.e.

changes in echo intensity over time) and features derived from the frequency spectrum, calculated via the Short Time Fourier Transform. These features are then used to predict the wingbeat patterns of each animal (Schmaljohann & Liechti, 2009; Schmid et al., 2019) as well as to automatically assign the detected object to the appropriate class. For the latter, a Random Forest classifier has been trained on a dataset of annotated radar echo samples (Haest et al., 2021) to automatically classify each object to one of the following classes: 'insects' 'non-biological clutter' (i.e. precipitation and clutter), and several subgroups of birds, i.e. passerine-type, wader-type, and swift-type (Schmid et al., 2019; Zaugg et al., 2008). For this study, we only retained birds classified as 'passerines', which are characterized by a typical intermittent wingbeat pattern. These echoes should include thrushes (see Bruderer et al., 2010), and we filtered the dataset to night hours using civil twilight time, calculated using the *suntools* R package (Bivand et al., 2023) to include only nocturnal migrants. We then calculated the nightly migration traffic rates (thereafter passerine-MTR), i.e. the number of birds crossing an imaginary 1 km long aerial transect per hour (Bruderer, 1971; Lowery, 1951; Schmid et al., 2019) using the *birdscanR* R package (Haest et al., 2023).

Selection of thrush and non-thrush training data for the classification of radar objects

To build a Random Forest classifier capable of recognizing radar echoes belonging to thrush species, we built a training dataset of radar 'passerine-type' echoes classified as 'thrush' and 'non-thrush' echoes. To do so, we first selected nights that showed either high or low calling thrushes' frequency in the acoustics dataset. Nights of high/low thrush activity were defined as the nights for which the number of calling thrushes was in the upper/lower 20% of the call frequency distribution. For 2021 and 2022, the 80th percentile corresponded to days with 69 and 68 calling thrushes, respectively. The 20th percentile corresponded to 6 and 5 calling thrushes in 2021 and 2022, respectively (Figs. 1 and 2). We only considered nights from 10 September onwards for this selection because Redwings – the earliest migrants among the three species considered – start migrating around this time (Weisshaupt, Lehikoinen, et al., 2021). This first selection resulted in 22 candidate nights for both peak and low thrush migration activity. To further increase the potential for separation between thrush and non-thrush echoes using radar-derived features, we subsequently selected nights with moderate levels of passerine-MTR from the candidate nights (i.e. by selecting nights where the passerine MTR exceeded the 25th percentile but remained

below the 75th percentile). This should have helped increase the probability that most of the radar-detected birds during peak nights of calling thrushes were actually thrushes and that during bottom nights of calling thrushes, most birds were non-thrushes. This, finally, resulted in the selection of 5 nights for each class (a total of 10 nights, 6 nights in 2021 and 4 nights in 2022). All echoes of a 'thrush-night' were labelled as 'thrush', resulting in a total number of 2439 echoes. All echoes of a 'non-thrush-night' were labelled as 'non-thrush', resulting in a total number of 1926 echoes (Figs. 1 and 2).

Quantification and validation of thrush migration

To classify the 'passerine-type' echoes across the whole measurement period into either 'thrush' or 'non-thrush', we trained a Random Forest classifier on the echo-derived features using the previously identified training samples. We used 10-fold cross-validation to assess classifier performance on the training data. We used the default setting for the number of variables to consider at each split in the trees (resulting in one of 13 randomly selected variables

being used at each split), equal weights for both classes, and set the number of trees to 500. For the subsequent classification of all passerine-type radar echoes across the measurement period, we used a classifier that was trained on the eight features that were identified as the most important during the classifier training phase. We chose the first eight as they corresponded to the features with a relative importance of more than 2% compared to the first-ranked feature (in other words, the features that were no less than 50 times less important than the first). The Random Forest classification was done using the *caret* and *randomForest* R packages (Kuhn, 2008; Liaw & Wiener, 2002). Model performance was assessed using a confusion matrix, with Producer Accuracy calculated as the ratio of the number of correctly classified instances of a class (true positives) to the total number of actual instances of that class; User Accuracy calculated as the ratio of the number of correctly classified instances of a class (true positives) to the total number of instances that were classified as that class; and finally Overall Accuracy (OA) calculated as the ratio of the total number of correctly classified instances (both true positives and true negatives) to the total number of instances in the dataset (Table 3).
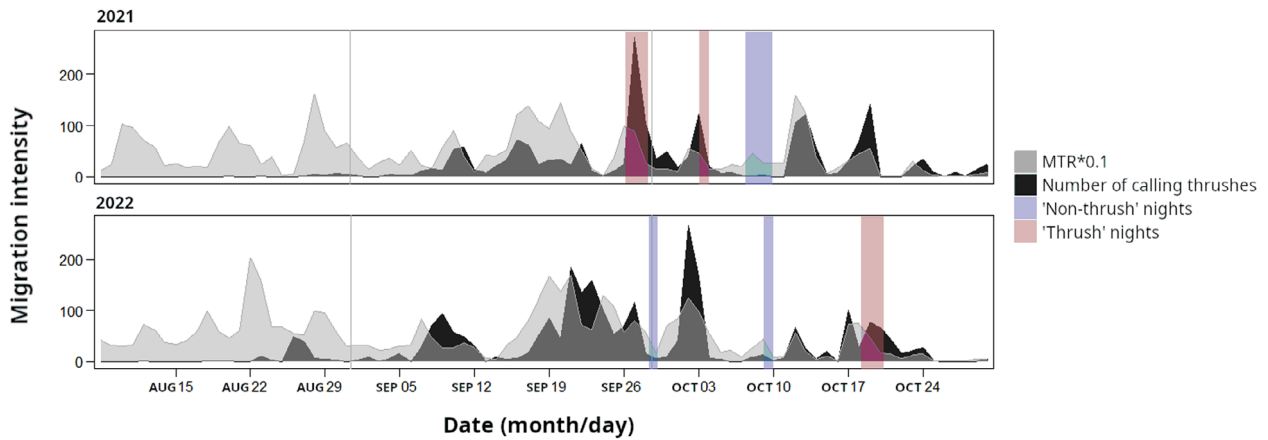
Figure 1. Autumn migration phenology for the years 2021 and 2022, measured in the city of Helsinki by radar (in grey, number of birds per hour and km) and acoustic (in black, number of calling thrushes estimated from the acoustic dataset) monitoring. The plots cover the time span from 8 August to 30 October. In black is the daily sum of calls identified as thrush, in light grey the nightly mean passerine-MTR. For visualization convenience, MTR values are divided by ten. Vertical grey lines delimit the months. The dates selected to build the classifier training dataset are highlighted in red ('thrush') and blue ('non-thrush').
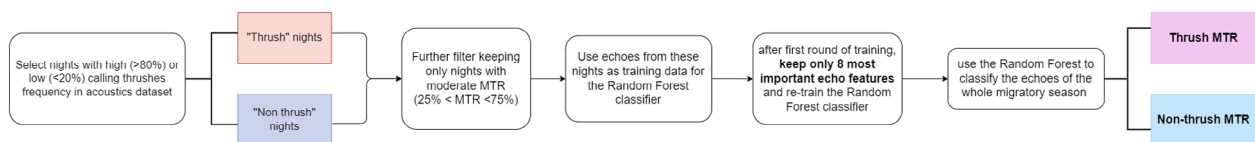
Figure 2. Workflow for the Random Forest classifier building process. The colour scheme used for 'thrush/non-thrush' nights and 'thrush/non-thrush' MTR reflects the one used in Figures 1 and 3.

After classification, we quantified 'thrush' and 'non-thrush' migration intensity across the measuring period by calculating the migration traffic rates for each class (Bruderer, 1971; Lowery, 1951), using the *birdscanR* R package (Haest et al., 2023). To assess the performance of the radar-quantified thrush migration across the entire measuring period, we calculated Pearson's correlation coefficient between the acoustic and the radar-derived MTR time series. We did this for both the original passerine-MTR and the new 'thrush/non-thrush'-MTR time series (excluding the nights used to train the classifier) to verify whether our thrush-MTR more closely matched the acoustic phenology than the passerine-MTRs.

All the analyses were done in R (version 4.0.5; R Core Team, 2021) using RStudio (version 1.4.1103; RStudio Team, 2020).

Results

Acoustic thrush and radar 'passerine' migration phenology

The frequency of calling thrushes varied greatly between successive nights (Fig. 1). Average calling frequency was strongest in September and October during the migration periods of these species (mean calling frequency in August: 0.8 calling thrushes per night in 2021 and 4.9 calling thrushes per night in 2022; in September: 35 calling thrushes per night in 2021 and 47.5 calling thrushes per night in 2022; in October: 28.7 calling thrushes per night in 2021 and 33.8 calling thrushes per night in 2022). In both years, the strongest call activity was recorded between the end of September and the beginning of October (272 calling thrushes on 27 September 2021 and 265 on 2 October 2022) (Table 1).

The radar-derived passerine-MTR also greatly varied between successive days (Fig. 1). The mean monthly passerine-MTR was slightly higher in September and August than in October (mean MTR in August: 527.9 birds per km and hour in 2021 and 662.6 per km and

hour in 2022; in September: 532.9 birds per km and hour in 2021 and 614.7 birds per km and hour in 2022, in October: 282 birds per km and hour in 2021 and 286.3 birds per km and hour in 2022). In both years, maximum daily MTR were measured in August (2021-08-28 with 1617 birds per km and hour, 2022-08-22 with 2032 birds per km and hour) (Table 1).

Passerine-MTR and the number of calling thrushes were significantly and positively correlated with Pearson's r 0.40 ($P < 0.01$) for the whole period (August 8 to October 30), and with $r = 0.59$ ($P < 0.01$) for the period known in literature as the thrush migration season (September 10 to October 30) (Table 2).

'Thrush' identification and classification

The separation of the 'passerine-type' radar echoes into 'thrush' and 'non-thrush' classes had an overall accuracy of 82% (Table 3). Producer accuracy was 83% for the 'thrush' class and 80% for the 'non-thrush' class. User accuracies were 84 and 79% for the 'thrush' and 'non-thrush' classes, respectively. The 'thrush' and 'non-thrush' training data classes showed clear differences in their value distributions for the selected radar features (Fig. 3 and Figure S1). The most important feature was related to wingbeat frequency (i.e. highest peak of the fast Fourier transform, Table 4), followed by size- and shape-related features (Fig. 3, Table 4). 'Thrushes' showed a lower wingbeat frequency, with a peak density around 11 Hz (SD = 8.76) compared to 16 Hz (SD = 8.35) for the 'non-thrushes'. The number of pause and wingbeat phases of the intermittent flight of passerine birds differed between the two groups. 'Thrushes' had comparatively fewer pauses and flapping phases. 'Thrushes' also had, on average, higher RCS values.

Although little can ultimately be said about differences in shape, as only one shape-related feature ended up in the top eight (Table 4), the importance attributed to the regression error of the polarization feature suggests a

Table 1. Average frequency of thrush calling (in italics, average number of calling thrushes per night) and average passerine-type MTR (number of birds per km and per hour) during the study periods considered.

	August Calling freq.	MTR	September Calling freq.	MTR	October Calling freq.	MTR
2021	*0.8*	527.9	*35*	532.9	*28.7*	282
2022	*4.9*	662.6	*47.5*	614.7	*33.8*	286.3

Table 2. Pearson's correlation coefficients between the number of calling thrushes and the MTR (passerine-MTR and thrush/non-thrush MTR, the latter estimated by the classifier).

	Passerine-MTR	Passerine-MTR (Thrush migration period)	Thrush-MTR	Non-thrush-MTR
2021	0.35	0.49	0.69	*0.21*
2022	0.44	0.68	0.75	0.31
Both years	0.40	0.59	0.65	0.31

The thrush migration period in column 3 refers to 10 September to 30 October, the period during which thrush migration occurs at the study site. Values in italics are not significant ($P > 0.01$).
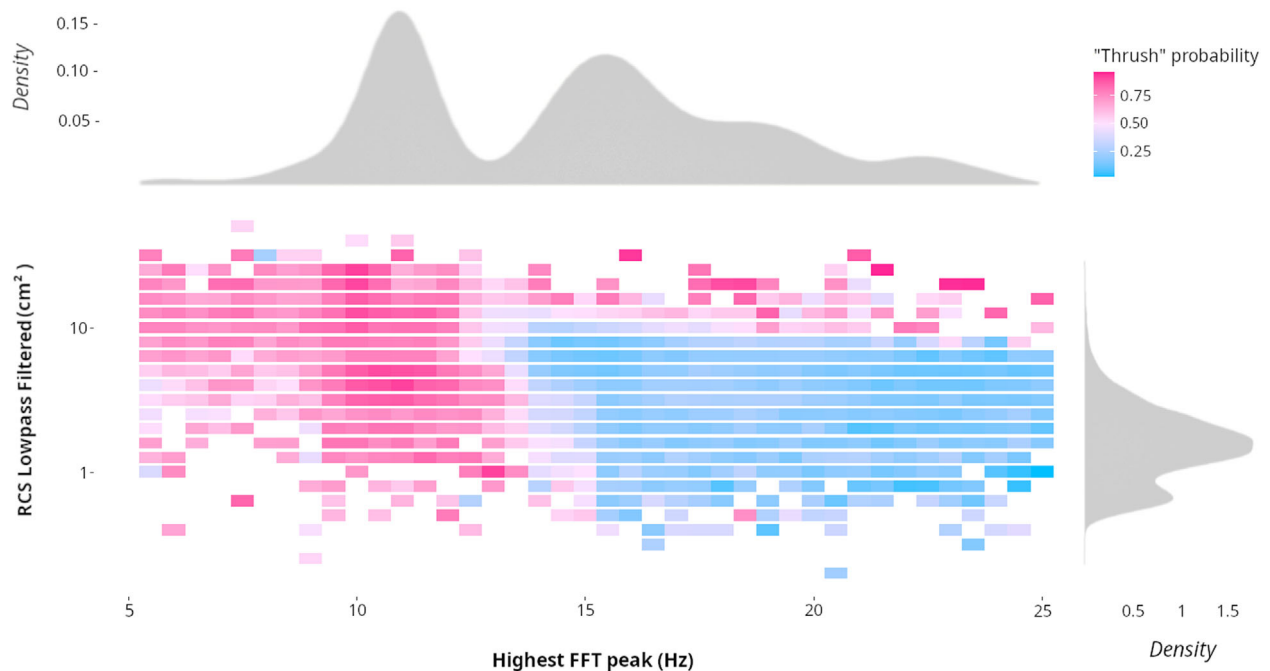
Figure 3. Raster plot depicting the probability variation of an echo being classified as 'thrush' by the Random Forest classifier, as a function of the two most important features (the highest peak of the Fast Fourier Transform, i.e. ACMaxPeakFreq, measured in Hertz; and the RCS lowpass filtered, i.e. RCS2_RCS_nearest_fea14, in square centimetres; see text for details). Cells shaded in dark pink indicate a high probability of being classified as a 'thrush', while those in blue denote a high probability of classification in the 'non-thrush' class. In grey, density plots showing the density distribution of the two features (top: ACMaxPeakFreq, RCS2_RCS_nearest_fea14, at bottom right).

difference in shape perceived by the radar between the two echo groups, since the error with which the target shape is estimated tends to be higher in 'thrushes'. Finally, the feature that describes the skewness of the band-passed signal (Table 4) tends to show higher values in 'thrushes', indicating a greater tendency of the 'thrush' signals towards higher than average values (Figure S1).

Thrush migration phenology and abundance

Across the entire measuring period, 35 925 radar echoes were ultimately classified as 'thrush' (20 862 in 2021 and 15 063 in 2022) and 32767 as 'non-thrush' (12 117 in 2021 and 20 650 in 2022). These radar-based estimates of thrush migration phenology across the autumn migration measurement period strongly correlated with the acoustic measurements ($r = 0.65$, $P < 0.01$; Table 2 and Fig. 4). This correlation persisted also when analysing the 2 years separately ($r = 0.69$ for 2021 and 0.75 for 2022, $P < 0.01$). Although the frequency of calling thrushes was also positively correlated with passerine MTR (see Results), this correlation was significantly lower (0.35 for 2021, 0.44 for 2022). The Pearson correlation between the number of calling thrushes and the non-thrush MTR was also low and, in the case of 2021, non-significant

(Table 2). In 2021, the highest thrush-MTR was recorded for 12 October (504 birds per km and hour), during which 106 calling thrushes were recorded. In 2022, the highest thrush-MTR was recorded on 21 September (400 birds km^{-1} h^{-1}), when 184 calling thrushes were recorded. In the first half of the time series (before mid-September), a time span when few thrushes are expected to migrate, the non-thrush MTR was distinctly higher than the thrush MTR (Fig. 4).

Discussion

Our results illustrate how acoustic data can refine taxonomic detail in bird radar measurements to quantify avian migration at the family level. Using acoustic recordings alone, quantification is hard (Sanders, 2013). With radar measurements only, taxonomic detail is limited (Hüppop et al., 2019). By combining both data sources, the shortcomings of both techniques can, in certain situations, be partly overcome.

The phenology of thrush migration, as evidenced by our radar data classification, aligns closely with existing literature, thereby corroborating the credibility of our model. While the classified data expose a substantial presence of thrushes from the outset of the period under consideration,

Table 3. Confusion matrix of the Random Forest classifier used for the radar dataset.

		Predicted values		
		Non-thrush	Thrush	Producer accuracy
Actual values	Non-thrush	1549	377	80%
	Thrush	409	2030	83%
	User accuracy	79%	84%	OA = 82%
				Kappa = 64%

The dataset included $n = 4365$ echoes.

Table 4. Ranking of the 8 most important features in the Random Forest classifier training (custom name appended, see Table S1 for a complete list).

Feature	Importance	Category
Highest peak of the Fast Fourier Transform ('ACMaxPeakFreq')	100	Wingbeat frequency
RCS lowpass filtered ('RCS2_RCS_nearest_fea14')	9.37	Size
RCS raw signal ('RCS2_RCS_max_rawsignal')	4.94	Size
Number intermittent pauses ('WFPf_numP_pause')	3.13	Wingbeat frequency
Number intermittent wingbeat phase ('WFPf_numP_phase')	2.97	Wingbeat frequency
Uncertainty shape feature (shapeFeatRegrErr)	2.81	Shape
Skewness broad spectrum (skw_sigBP)	2.47	Others
Estimated wingbeat frequency (WFF_predicted)	2.09	Wingbeat frequency

This measure of feature importance is computed through a permutation procedure. For each tree in the random forest model, it records how much the prediction error changes when using first only the data that the tree has not seen during training and then randomly shuffling the data for that variable. The difference between these two values is calculated for each tree and then averaged across all trees and normalized with respect to the variability of these differences. The higher the variability of the differences, the more important the feature. The measures of importance are scaled to range from 0 to 100.

especially in 2021, a significant surge in activity emerges from mid-September, culminating in peak abundance towards late September and early October. This conforms to the existing literature on the migration of these species in Finland, since it is well-documented that they typically commence migration around September (Weisshaupt, Lehikoinen, Mäkinen, & Koistinen, 2021; Weisshaupt, Lehtiniemi, & Koistinen, 2021). The thrush movements in the days leading up to the onset of migration are most likely pre-migratory movements and wandering behaviour typical of such species; also in the acoustic dataset, indeed, we detected nocturnal calls of thrushes during August.

We found the radar echoes of thrushes to be clearly distinguishable from other passerine-type birds by predominantly the wingbeat frequency, but also by additional size and shape-related features (Table S1). The average wingbeat frequencies (WBF) in the two groups (see Results) align with those given in literature: Bruderer et al. (2010) reported 10.9 Hz for *T. philomelos* and 8.9 Hz for *T. merula* during migratory flight. The 'non-thrush' echoes exhibited a higher WBF, comparable to those of small passerines (i.e. ranging from 15 to 20 Hz; Pennycuick, 2001; Bruderer et al., 2010). As such, the portion of passerine-MTR classified by our system as '-non-thrush' most likely primarily consists of small passerines, as these are indeed migrating in the study area during the study period (Weisshaupt, Lehtiniemi, & Koistinen, 2021). The European Robin *Erithacus rubecola*, for instance, is migrating in the area during the relevant period and is known to have an average WBF of 15.5 Hz (Bruderer et al., 2010). Willow Warblers *Phylloscopus trochilus* (with an average frequency of approximately 18 Hz; Bruderer et al., 2010) and Garden Warblers *Sylvia borin* (16 Hz; Bruderer et al., 2010) migrate through the area during August. On the other hand, thrushes are not the only passerines in Helsinki with relatively low WBFs. Although overall relatively few, other species migrating over Helsinki with similar WBFs include the Common Starling *Sturnus vulgaris* (around 9–10 Hz), Red-backed Shrike *Lanius collurio* (9–11 Hz), and the Bohemian waxwing *Bombycilla garrulus* (9–10 Hz estimated). It is equally true that for these species, their migration schedule does not align perfectly with that of the species under consideration: the migration of the Red-backed Shrike, for instance, is earlier; and Waxwings are mostly present from October onwards. Additionally, while starlings migrate throughout the entire migration period of thrushes, only a portion of their migratory flights is performed nocturnally (Vīgants et al., 2023). Therefore, we can assume that part of the substantial 'thrush' MTR from mid-September onwards can be attributed to these species. However, it is crucial to note that the population of Red-backed Shrikes in Helsinki is significantly smaller compared to the thrush species we considered, making their contribution likely negligible. Furthermore, it is plausible to hypothesize that also a proportion of the echoes classified as 'thrush' detected in August may be attributed to the presence of starlings, which bear a striking resemblance in both size and WBF to the species studied, and secondarily to the Red-backed Shrike. This may partially explain, for example, the presence of echoes classified as 'thrush' in August, especially in 2021. While it is less abundant than the 'non-thrush' MTR, it still exhibits a certain consistency. On the other hand, considering the outlined arguments, it remains equally reasonable to
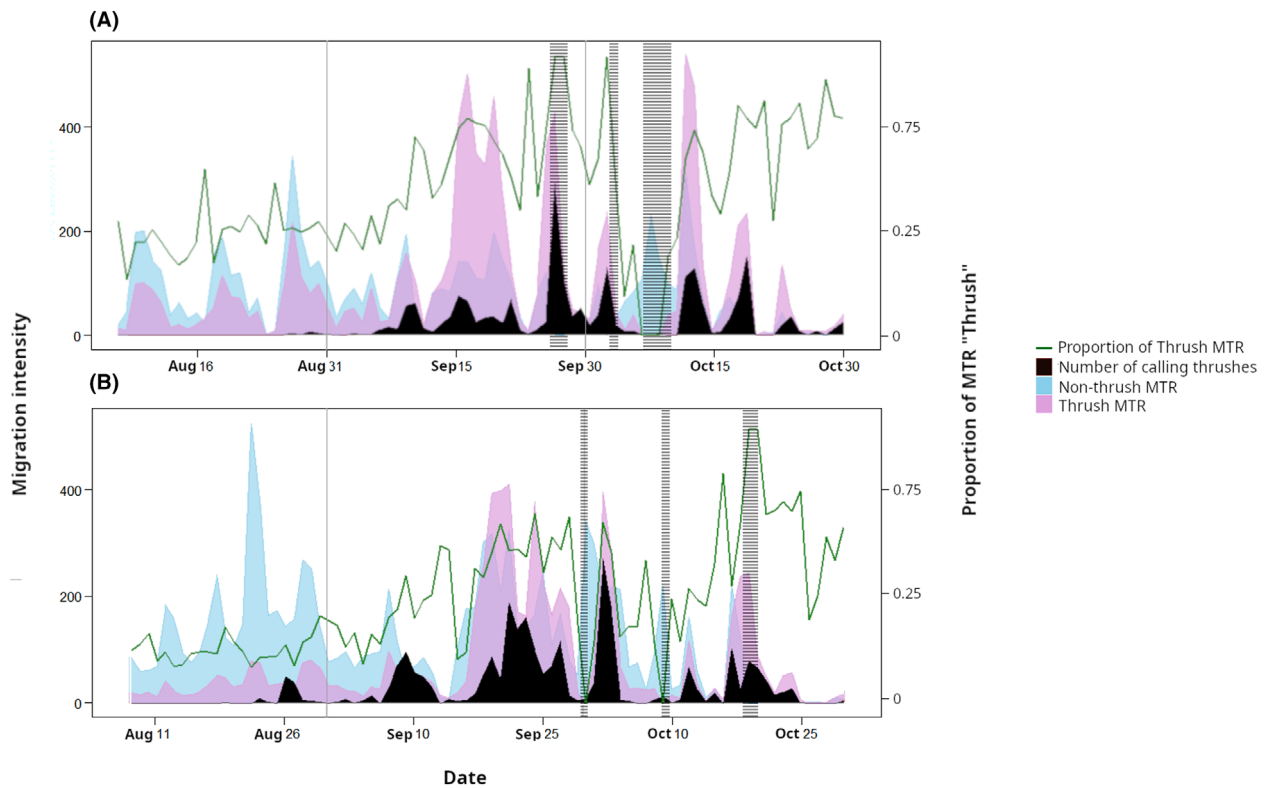
Figure 4. Comparison between thrush migration phenology measured by acoustic monitoring (in black; number of calling thrushes) and the thrush-MTR (in lilac; number of birds per hour and km) and non-thrush-MTR (in blue; number of birds per hour and km) for the years 2021 (A) and 2022 (B). The green line illustrates the proportion of the thrush-MTR to the total passerine-MTR. The plots cover the time span from 8 August to 30 October. Vertical grey lines delimit the months; horizontally striped bars cover the nights used to train the classifier.

assume that the proportion of 'thrush' MTR detected in August is indeed attributable, as already stated, to young or adult thrushes undertaking pre-migratory flights. Nonetheless, this does underline the importance of including other radar features, such as those related to size and shape, into echo classifications.

However, because of the large relative importance of the WBF-related features in our study for the separation between thrushes and non-thrushes (Table S1), our approach might not have worked had we studied a taxonomic group other than thrushes. In other words, whether a certain taxonomic group will be separable using our approach, will be strongly location-, and time-dependent. This supposition arises from the evident fact that thrushes are larger compared to other passerines (for instance, *T. merula* can be up to three times longer with double the wingspan of *P. trochilus*, Svensson, 1992) and, at the same time, most small passerines are characterized by WBFs that are roughly comparable. This makes the latter much less distinguishable from each other at the radar echo level. As for the target species, we previously mentioned how Bruderer et al. (2010) highlights a slight

difference in WBF between *T. philomelos* and *T. merula*, approximately 11 and 9 Hz, respectively, while according to existing models (Pennycuick, 1990, 2001) *T. iliacus* is expected to have a WBF averaging around 10 Hz. Given the small differences in Hz, it is, therefore, highly unlikely that thrush species can be further distinguished using similar setups, especially in light of the possible intraspecific variability in WBF (Cochran et al., 2008).

Even with our relatively rough approach of selecting all birds during certain nights as the training data for the thrush or non-thrush classes, we still obtained Pearson correlations of 0.69 for 2021 and 0.75 for 2022 (Table 2). Most likely, these correlations would have been even higher when improved on any of the shortcomings of our approach. Undoubtedly, however, certain conditions must be met to achieve similar results in different settings, e.g. location, time, or migratory bird community. The taxonomic group or species of interest must exhibit sufficient abundance to dominate the radar echo volume (sufficient sample echoes) and indicate an individual-based migration pattern (no flocks) as typically found in nocturnal migrants, such as thrushes in our study. Failure to meet

these criteria may result in the chosen training dates for the classifier being too heavily contaminated by echoes from other species and in failure to identify single echo signatures. It is furthermore crucial that the chosen species or group has distinctive morphological or behavioural traits, such as a particular flight pattern, that is recognizable at the level of radar echoes. This is essential to limit the potential confusion with echoes produced by other species. The target species or taxonomic group should also be highly vocal during nocturnal migration, so it is sufficiently registered on the acoustic recordings. If not, identifying peak migration dates becomes much more challenging, if not altogether impossible. Aside from the listed prerequisites, further work may still be necessary to use our classifier as a stand-alone tool in nocturnal migration monitoring. For instance, it would be advisable to test our classifier in a different study area to test the performance of the classifier in different regions.

As to system and spatial biases, we assume that the different detection volumes of the instruments and the distance of 4.5 km between them had no significant impact on our results. Both instruments also have different detection volumes. On the other hand, it is worth mentioning that the distance between the two instruments is quite short for migrating birds, whose migration route spans hundreds or thousands of kilometres. Moreover, the two systems are approximately positioned along the NE–SW migration direction expected for thrushes, maximizing the probability of capturing the same flux of migrants.

Our study provides the first example of combining acoustic and radar data to extract taxonomic information, enabling the quantification of family-level migration from radar data. This provides an important step towards understanding migration patterns more comprehensively. Within the wider scope of our research, the ability to identify the migratory flow of thrushes could prove valuable in ecological and conservation contexts, such as enhancing the use of radar devices to mitigate the risk of bird strikes in locations like airports, wind farms or communication towers (Kelly et al., 2007; Metz et al., 2020). In fact, thrushes constitute a substantial portion of birds most frequently involved in bird strikes in Europe (Dekker et al., 2005; Metz et al., 2022), and as evident, such incidents significantly escalate during the migratory period (EGAST, 2013). Leveraging family-level knowledge of migration can be extremely helpful in shaping conservation strategies tailored to specific taxonomic groups, particularly since radar technology allows us to gather information about migratory patterns essentially in real time.

In conclusion, the findings of this study provide a valuable contribution to the assessment of the potential of complementary techniques in migration monitoring.

Furthermore, they open up new perspectives for a more accurate understanding and quantification of migratory phenomena.

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Supporting Information

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

Figure S1. Density plots illustrating the distribution of features' values of 'Thrush' nights (in pink) and 'Non-thrush' nights (in blue) echoes we used to build the training dataset. The six features depicted in the figure are among the eight features ranked as most important and consequently used to build the classifier. The two missing features in figure (ACMaxPeakFreq and RCS2_RCS_nearest_feat14) are shown in Figure 3.

Table S1. Ranking of all features in the Random Forest classifier training. Only the eight most important ones were used to build the final classifier.