The Aeronautical Journal (2024), **128**, pp. 2815–2831
doi:10.1017/aer.2024.57

ROYAL AERONAUTICAL SOCIETY

RESEARCH ARTICLE

Bird behaviour characterisation and environment dependence modelling in airport airspace based on radar datasets

Q. Xu[1], J. Liu[2], M. Su[3] and W.S. Chen[4]

[1]Research Institute of Civil Aviation Law Regulation and Standardization, China Academy of Civil Aviation Science and Technology, Beijing, China
[2]School of Electronic Information Engineering, BeiHang University, Beijing, China
[3]School of Electronic and Information Engineering, GuangXi Normal University, Guilin, China
[4]Airport Research Institute, China Academy of Civil Aviation Science and Technology, Beijing, China
Corresponding author: J. Liu; Email: bobmp5@163.com

Received: 3 December 2023; **Revised:** 14 May 2024; **Accepted:** 23 May 2024

Keywords: bird strike; remote sensing; radar data mining; aviation safety; wildlife management

Abstract
Bird strike accidents are critical threats for aviation safety especially in airport airspaces. Environment friendly solutions are preferred for wildlife managements to achieve harmonic coexistence between airports and surrounding environments. Avian radar systems are the most effective remote sensing approach for long-range and all-weather birds monitoring. Massive historical avian radar datasets and other data sources provide an opportunity to explore relevance between bird behaviour and environments. This paper proposes a bird behaviour characterisation and prediction method to reveal bird behaviour dependency with weather parameters. Bird behaviours are modelled as indices and grades from selected avian radar datasets. Weather dependence are studied from single parameter to multivariable parameters. The random forest model is selected as a behaviour grade prediction model taking four weather parameters as system inputs. Radar datasets for diurnal and nocturnal birds are constructed to validate their behaviour characters and prediction performance, respectively. Experiment results verify the feasibility of bird behaviour prediction using weather parameters, but also reflect some insufficiencies within the proposed method. Data sufficiency and severe weather considerations are also discussed to analyse their impact on prediction accuracy. A more comprehensive prediction model with standardised avian radar data quality and enhanced weather information accuracy is promising to further elevate the application significance of the proposed method.

Nomenclature

α:	kernel parameter for α quadratic entropy definition
σ:	conditional parameter defined for bird track information filtering
B:	bird behaviour index
d:	parameter defining a specific date for database construction
h:	hourly interval defined for hourly track count computation
γ:	smoothing parameter
$\boldsymbol{l}$:	all tracks spatial coordinate information within a specific grid
F:	feature vector containing temperature, humidity, wind speed and wind direction parameters
E_n:	alpha quadratic entropy
P:	probability of bird existence at specific hour and date
N:	track numbers corresponding to the specific date and conditional parameter
N:	track count database integrating all track count information
G:	grade database constructed from database $\boldsymbol{N}$

https://doi.org/10.1017/aer.2024.57 Published online by Cambridge University Press

I:	bird activity intensity database constructed through normalisation from database ***N***
T_e:	entropy threshold value defined for weighing factor computation
w:	weighing factor defined for integrating intensity and uncertainty information of bird activities
CAST:	China academy of Civil Aviation Science and Technology
UAV:	unmanned aerial vehicle
PCA:	principal component analysis
LDA:	linear discrimination algorithm

1.0 Introduction

Interactions between aviation vehicles and flying birds are significant concerns in aviation safety. Bird strikes accidents have caused nonnegligible economy and life loss in past a few years [1, 2]. Besides structure and component design on aircrafts to reduce bird strike damages [3, 4], ecological solutions are also necessary to manage the coexistence with bird interferences especially in airport airspaces. Timely and effective remote sensing solutions for birds are highly desired to support wildlife surveillance and managements. Avian radar systems are good options for their advantages of long-range and all-weather surveillance capabilities on birds. Their performance for various flying birds are validated in many airports for years [5–8]. Existing avian radar systems could detect and track various bird targets with satisfied accuracy [9, 10].

However, these systems are biased on short term temporal functionalities by providing real-time bird detection and tracking information as well as bird strike risk evaluation [11, 12]. It also indicates historical datasets are useless. However, this functionality shortage results in bird behaviour ambiguity in spatial and temporal domains. The information loss of bird behaviour characters and their distributions limits the airport bird situation understanding, and could hardly provide useful references for ecological managements to reduce bird strike risks [13, 14]. Moreover, the interference pattern between bird behaviours and environments is also ambiguous without sufficient data supports. Therefore, historical avian radar datasets have significant potentials for mining and proper radar data modelling with bird behaviour characterisation solutions are necessary. Historical observation records reveal the close relevance between bird behaviours and environmental factors [15]. Reference (16) demonstrates avian activity index dependence on different meteorological factors, and indicate that avian activity index characters are comprehensive consequences of bird species, time, location and meteorological factors. Reference (17) introduces a bird migration forecasting framework using meteorological information and weather radar systems. Relative works reveal the feasibility of forecasting bird activities using weather information. However, works in Ref. (11) only studies avian activity index relevance with single meteorological factors and does not provide a forecasting solution. The migration forecasting framework in Ref. (17) is applicable for large spatial scale based on bird surveillance information from weather radar systems. Therefore, a bird behaviour interpretation model based on multiple meteorological factors is desired to achieve bird behaviour prediction within airspace covered by avian radar systems. Historical avian radar datasets provide solid data support for bird distribution modelling in spatial-temporal domain, and quantitative behaviour characterisation. The integration with airport weather records provides the condition to build bird behaviour prediction models.

The fast development of machine learning techniques enables the bird detection using radar [18] and predict bird behaviours with proper modelling strategy [19]. This paper utilises a machine learning model to build the relevance between bird behaviours and weather parameters. Original avian radar datasets are transformed by introducing a bird behaviour characterisation model. Bird behaviour indices are firstly utilised to study relevance with single weather parameters. Behaviour dependence on multivariable weather parameters is constructed with a random forest model. Bird behaviour grades are predicted according to four weather parameters. The proposed method is verified using avian radar datasets from four years field observation experiments. Prediction results verify the feasibility of predicting bird behaviour grades according to weather information. However, some problems that influence prediction accuracy are also discussed as future works.

https://doi.org/10.1017/aer.2024.57 Published online by Cambridge University Press

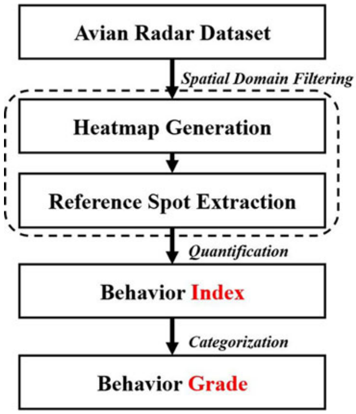


Figure 1. *Framework of bird behaviour characterisation using avian radar data.*

This paper is organised as follows. Section 2 introduces the radar data modelling and bird behaviour characterisation methods. Section 3 firstly studies bird behaviour relevance with single weather parameters, then extends to multivariable weather parameter study using learning machine model. Experiment setup, analysis results and discussions are given in Section 4. Section 5 draws the conclusion.

2.0 Data modelling and behaviour characterisation

The technique framework of bird behaviour characterisation is presented in Fig. 1. Avian radar datasets are processed in the spatial domain by generating density heatmaps. Extracted reference spots mark significant bird distribution areas. Behaviour characters are modelled within each reference spot to guarantee accuracy. The behaviour index is defined by processing filtered radar data from each reference spot as a quantitative descriptor. Behaviour grades transform indices into qualitative labels for the convenience of prediction. Details are presented in following sections.

2.1 Data modelling in spatial domain

According to historical records, birds might visit some places more frequently for roosting, food hunting or migration. This frequent visitation results in large bird track densities within specific areas. Density heatmaps depict bird distributions in spatial domain, but they are not comprehensive for more accurate description. This paper adopts the concept of reference spots, which are defined as regions with higher visiting frequencies than others [20, 21]. The first step of spots extraction is meshing radar surveillance airspaces into two-dimensional uniform grids as in Fig. 2. Reasons that airspaces are not meshed into three-dimensional grids are based on two considerations. The first one is the low altitude resolution of avian radar systems. Beamwidth in elevation angle dimension must be large enough to guarantee beam coverage. This makes avian radar systems still could hardly generate accurate bird altitude information as in range and azimuth dimensions. The other consideration is about the data sufficiency. The existing two-dimensional discretisation strategy could guarantee sufficient bird track samples for density computation. If each grid is further decomposed in the altitude dimension, insufficient data support might result in deviations with practical bird spatial distributions.

For a spatial gird at $\boldsymbol{c}$, its density is evaluated using the kernel density algorithm [22]:

$$f(\boldsymbol{c}) = \frac{1}{n\gamma^2} \sum\nolimits_{i=1}^{n} \frac{1}{2\pi} \exp\left(-\frac{|\boldsymbol{c} - \boldsymbol{l}(i)|}{2\gamma^2}\right) \tag{1}$$

https://doi.org/10.1017/aer.2024.57 Published online by Cambridge University Press

Figure 2. *Spatial grid discretisation within radar surveillance airspace.*

in which $\boldsymbol{l}$ indicates all tracks location information within the grid, $|\boldsymbol{c} - \boldsymbol{l}(i)|$ indicates the distance between $\boldsymbol{c}$ and $\boldsymbol{l}(i)$. The term γ is a smoothing parameter:

$$\gamma = \frac{1}{2}\left(\delta_x^2 + \delta_y^2\right)^{\frac{1}{2}} n^{-\frac{1}{6}} \tag{2}$$

Parameters σ_x and σ_y are standard deviations of track coordinates in longitudinal and latitudinal dimensions from n track locations.

Density heat maps are generated by calculating densities for all grids. The number of grids, total grid extent as well as a parameter p are adjusted to create landscape configurations for reference spots extraction. The parameter p denotes the percentage of largest densities. Parameters are adjusted to meet the criterion that largest density areas are depicted with discrete polygons. Considering the property that bird tracks distribute within continuous landscapes rather than discrete spots, a range of flexible landscape scenarios should be explored.

To select proper reference spots, three meshing configurations of 75×75, 100×100, 125×125 are constructed, and the parameter p ranges from 0.01% to 25%. The quality of extracted reference spots is evaluated artificially. A larger p value usually generates more reference spots, which might not be the optimal solution. The optimised p value should be the one which generates discrete reference spots over landscapes without extra landscape painting. This paper selected the parameter p as 8% rather than the conventional 15% value [20] to accommodate avian radar data properties. Figure 3 presents a distribution of reference spots. Spots I and II are mostly distributed with diurnal bird activities. In contrast, most bird activities within spots III and IV are within nocturnal hours. The yellow arrow indicates the dominant flight directions deduced from massive track information, which indicates migratory activities of nocturnal birds. In following analysis, avian radar datasets are extracted from grids in these four reference spots to provide sufficient samples.

2.2 Bird behaviour characterisation

The behaviour characterisation is composed of two steps. The first step extracts radar data under specific filtering conditions. Bird behaviour characters have close relevance with seasonal and weather conditions. Birds under extreme weather like precipitation, gust, fogs and hails present completely

https://doi.org/10.1017/aer.2024.57 Published online by Cambridge University Press

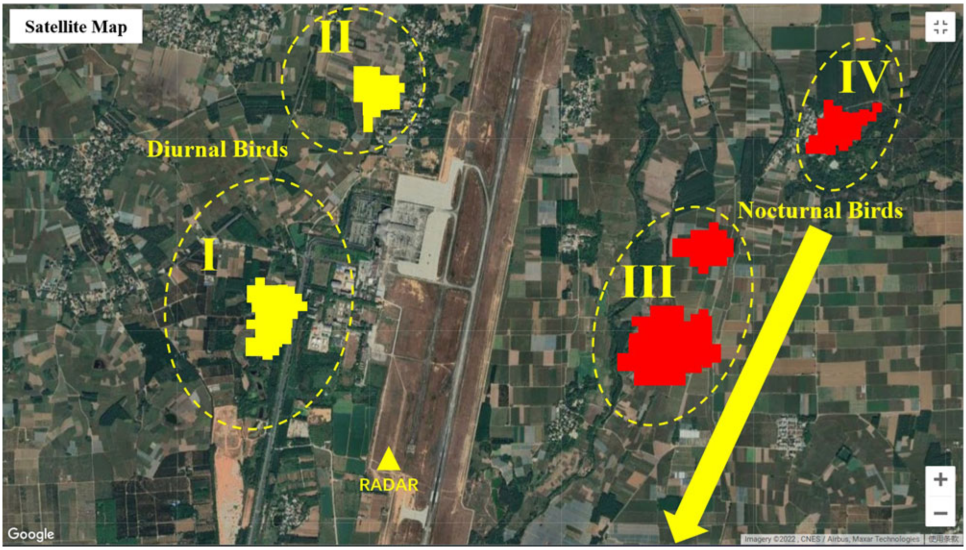


Figure 3. *Reference spots distribution within airport airspaces.*

different behaviour characters compared with normal weather conditions. Therefore, data groupings according to weather conditions is necessary to elevate data quality. This paper defines normal and adverse weather conditions $\boldsymbol{\sigma}$ based on historical observation records. Selected datasets are denoted as $\boldsymbol{N} = \{N(d_1|\boldsymbol{\sigma}), N(d_2|\boldsymbol{\sigma}), \cdots, N(d_K|\boldsymbol{\sigma})\}$, in which K indicates selected date number. The term $N(d_k|\boldsymbol{\sigma})$ indicates track number at date d_k under $\boldsymbol{\sigma}$.

The number of tracks is a straightforward bird situation indicator, but has many limitations as a behaviour descriptor. The first one is due to blind zones of avian radar systems, which result in bird quantity deviations between reality and radar detection. The incapability of avian radar systems to distinguish a single or flock birds also confines its track number accuracy. The second limitation comes from the large track number fluctuation in temporal domain. This confines bird situation integration under other spatial-temporal windows. The third reason is the ambiguous relevance between bird track count and bird strike risks. Moreover, the bird track count prediction using weather information is not feasible with little application significance. Therefore, this paper proposes a behaviour index for bird behaviour characterisation. Its computation is composed of four steps:

Step 1: Normalised intensity calculation. This intensity is extracted from the number of tracks within one hour. For a date d_k, the normalised intensity for one day composes a vector $\boldsymbol{I} = \{I(1|d_k), I(2|d_k), \cdots, I(24|d_k)\}$, the term $I(i|d_k)$ denotes the intensity between hour i-1 and i. The numerical range of normalisation is [20,100]. The lower bound is 20 rather 0 because it is unreasonable to indicate the minimum number of tracks as no bird activity.

Step 2: Intensity transformation. The intensity vector is integrated by involving data from more selected dates. Denote all selected dates as an vector $\mathbf{d}$, the corresponding dataset for hour h_k is $\mathbf{I}(h_k,\mathbf{d})$. Track count variations might result in intensity fluctuations, which is misleading for behaviour interpretation. To reduce the interference from intensity fluctuation, normalised intensities are transformed into 10 levels according to the mapping principle in Table 1. A new dataset containing all level information is $\mathbf{G}(h_k, \mathbf{d})$.

Step 3: Uncertainty modelling. The behaviour uncertainty is an important behaviour indicator. The α-quadratic entropy [23] quantifies behaviour uncertainty as:

$$En^{\alpha}(\boldsymbol{G}(h,\boldsymbol{d})) = \frac{1}{2^{-2\alpha}} \sum\nolimits_{j=1}^{10} \left(P^j(\boldsymbol{G}(h,\boldsymbol{d}))\right)^{\alpha} \cdot \left(1 - P^j(\boldsymbol{G}(h,\boldsymbol{d}))\right)^{\alpha} \tag{3}$$

https://doi.org/10.1017/aer.2024.57 Published online by Cambridge University Press

Table 1. *Mapping between normalised intensities and levels*

Level	Intensity	Level	Intensity
1	20–28	6	61–68
2	29–36	7	69–76
3	37–44	8	77–84
4	45–52	9	85–92
5	53–60	10	93–100

The term $P^j(\boldsymbol{G}(h, \boldsymbol{d}))$ represents the probability of $\boldsymbol{G}(h, \boldsymbol{d})$ at level j. The enlargement parameter α quantifies the uncertainty sensitivity [21, 22]. This paper selects α as 0.7 since the recommend 0.5 is considered insufficient to quantify behaviour uncertainties. To choose the proper α, the airport staff with rich avian radar observation experience is invited to visually categorise 200 groups of datasets into ‘smaller uncertainties’ and ‘larger uncertainties’. The behaviour characterisation model is adopted to calculate their weighing factors as defined in (4) by increasing α gradually from 0.5. When over 90% of ‘larger uncertainties’ datasets have their weighing factors larger than 1.2, the corresponding α is considered as the selected one.

Step 4: Uncertainty weighing. The bird behaviour character is modelled as an integration of intensity and uncertainty. A weighing factor is proposed to quantify behaviour uncertainty as [24]:

$$w(En^{\alpha}(h, \boldsymbol{d})) = 1 + \left(2^{-2\alpha}\right) \cdot exp(En^{\alpha}(h, \boldsymbol{d}) - T_e) \tag{4}$$

The definition in (4) indicates the uncertainty descriptor is an extra enlargement of intensity. The threshold T_e determines the enlargement pattern. Its selection is based on the entropy value of behaviour datasets which are artificially decomposed into large and small variations. The selected threshold minimises the overlapping probability between entropy histograms of large and small variations. Adopted datasets result in the threshold T_e as 1.63.

Step 5: Behaviour index calculation. The bird behaviour index is modelled as an integration of intensity and uncertainty. For an hour window h, its behaviour index is:

$$B(h) = I_{avg}(h, \boldsymbol{d}) \times w(En^{\alpha}(\boldsymbol{G}(h, \boldsymbol{d}))) \tag{5}$$

The term $I_{avg}(h, \boldsymbol{d})$ represents an averaged value of all intensity indicators within temporal window $(h, \boldsymbol{d})$. The overall framework is demonstrated in Fig. 4.

Technically behaviour indices could be adopted as a behaviour prediction indicator. A proper regression model possesses the feasibility to achieve this functionality. However, this is not adopted in our work since its application significance and regression accuracy are problematic. Behaviour indices indicate a complicated weather dependency. Existing weather measurement systems could hardly guarantee a high quality of parameter accuracy. The constructed regression model based on inaccurate weather parameters also generates in controversy results. Moreover, airport managers prefer more intuitive bird situation information for wildlife management or air traffic control, precise numerical indicators are not mandatory. A more reasonable activity categorisation strategy is useful to facilitate bird strike risk evaluation and air traffic control. Therefore, the precise regression modelling to predict bird behaviour index could not bring extra bird situation awareness, but might elevate bird situation complexity or misleading due to inaccurate regression model and weather information deviation. This paper transforms the bird behaviour prediction from a regression problem into a classification problem by denoting bird behaviours as different grades. The mapping between behaviour index and grade is defined in Table 2.

Another concern motivates the problem transformation from regression classification. Existing avian radar systems could not guarantee a 100% detection accuracy. False alarms and environmental clutters like precipitation might generate non-bird target tracks as interferences. These factors lead to avian radar data credibility and quantity uncertainty. It is possible to build a well-trained regression model with high accuracy, but its construction is based on ‘polluted’ data. Therefore, the proposed method could alleviate the data quality problem and simplify the prediction problem.

https://doi.org/10.1017/aer.2024.57 Published online by Cambridge University Press

Table 2. *Mapping between behaviour index and grade*

Behaviour Grade	Low	Medium	High
Behaviour Index	20–39	40–69	70+

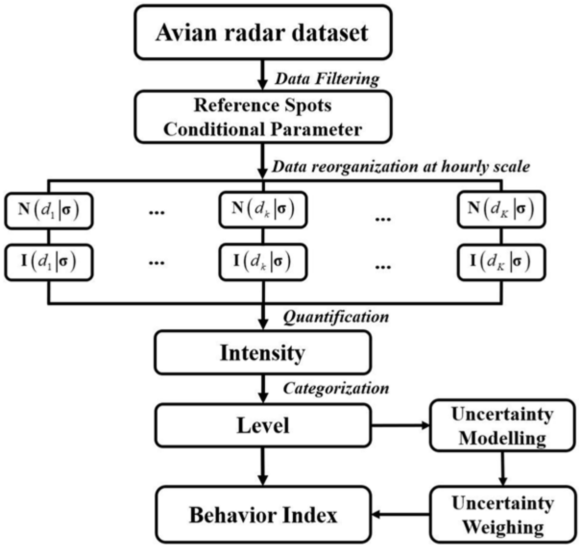


Figure 4. *Framework of behaviour index extraction.*

3.0 Behaviour dependence study with weather parameters

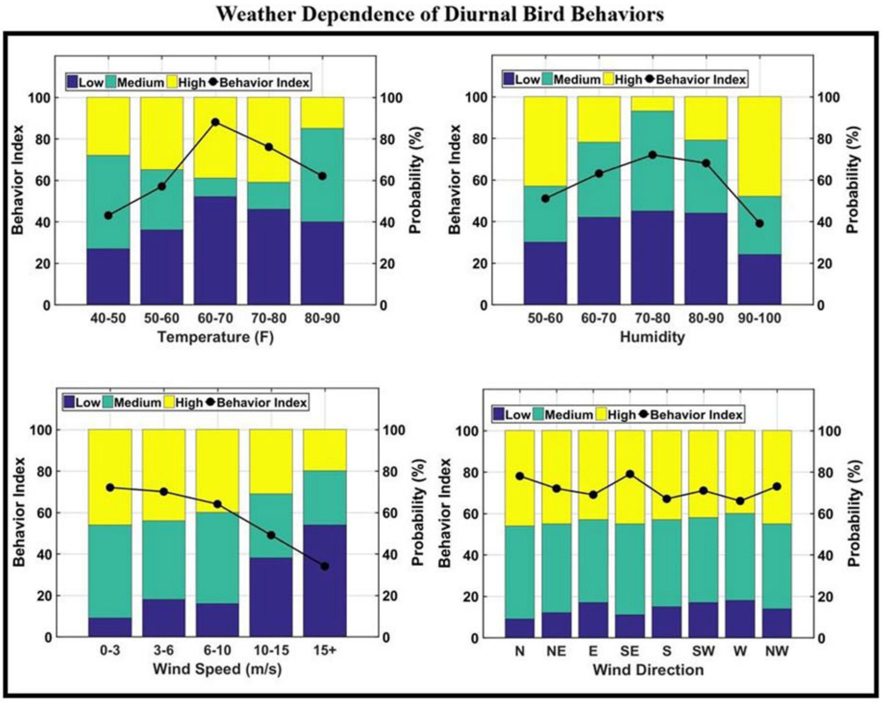
3.1 Single weather parameter

Existing avian radar datasets are categorised into diurnal local birds and nocturnal migratory birds. Two types of birds cluster within reference spots {I,II} and {III,IV}, respectively. The behaviour relevance study on a single weather parameter is fundamental to explore weather dependence characters of different bird types. Temperature, humidity, wind speed and wind direction are adopted as dominant impact factors influencing bird behaviour characters. Dependence studies are carried out for diurnal and nocturnal bird datasets, respectively. The temporal window for data extraction is from August 1 to October 31 in four years. Hour windows for diurnal and nocturnal bird data extraction are [05:00,19:00] and [17:00,06:00]. One hour is taken as the most fundamental time unit. Weather parameter information comes from historical airport weather records. Temperature, humidity and wind speed are numerical parameters. The wind direction is categorised into eight directions. Averaged behaviour index and three grades' proportions are presented at each weather parameter span. A bi-axis plotting strategy is adopted to demonstrate two indicators within one figure. A larger averaged behaviour index indicates birds are more active. The proportion of behaviour grades denotes behaviour complexity and uncertainty, which presents positive correlation relevance with medium-grade proportion.

Figure 5 presents behaviour dependence on single weather parameters for diurnal and nocturnal birds, respectively. Larger averaged grade and proportion variations indicate that temperature is the most dominant factor on bird behaviour. Like humans, birds are more active at their comfortable temperature ranges. Diurnal birds present higher behaviour intensities at the temperature span of [60,70] °F, which is consistent with artificial observation records. The most active temperature span is accompanied with smallest proportion of medium activity grade, which indicates a higher behaviour certainty. The temperature dependence of nocturnal bird is different. There is not temperature record within the span of [80,90] °F, and nocturnal temperatures are clustered within the span of [40,60] °F. The temperature relevance for nocturnal bird behaviours is not as explicit as diurnal birds. Moreover, the behaviour grade proportion

https://doi.org/10.1017/aer.2024.57 Published online by Cambridge University Press

(a)



(b)

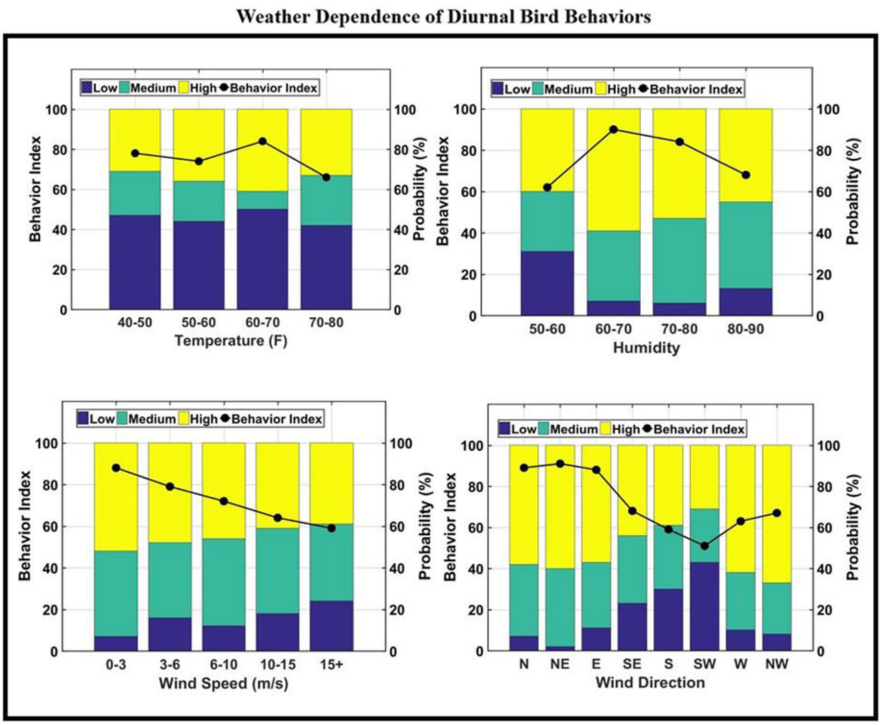


Figure 5. *Behaviour dependence on single weather parameters-(a) diurnal birds (b) nocturnal birds.*

https://doi.org/10.1017/aer.2024.57 Published online by Cambridge University Press

distribution is more uniform, indicating a lower degree of behaviour complexity. This presents a good consistency with historical analysis and understandings about migratory bird sensitivity to temperatures. The prominent behaviour intensity variation only exists for extreme temperature conditions. Moreover, this relevance ambiguity is partially contributed by measurement deviations. Compared with diurnal birds within low-altitude airspace, the averaged altitude for nocturnal bird activities is higher. According to analysis on historical datasets, over 90% of nocturnal birds distribute within the height layer of [400, 1700] meters. This is also the representative height range for migratory birds. Therefore, nocturnal birds within this height layer are extracted for following analysis. Deviations between ground measurement and real temperatures are inevitable within this airspace. The existing experiment condition could not acquire temperature information from nocturnal bird behaviour airspaces, and this accuracy could temporarily not be solved effectively.

The most preferred humidity span for diurnal birds is within [70,80]% with a larger bird behaviour complexity. Excessively dry or wet environments are not preferred by birds, their larger proportions of medium grades are also contributed by insufficient data. The humidity range in [90,100]% is usually accompanied with fogs with prominent diurnal bird behaviour reduction. Nocturnal behaviours present a similar preference on humidity ranges, grade proportion distributions present lower complexity.

Wind is important for bird activities, but wind speeds and directions have different impacts on bird behaviours. Both indicators demonstrate that stronger winds constrain bird behaviours. The larger medium grade proportion at lower speeds indicates higher behaviour complexities, this is reasonable since in this speed range wind has minor impact on birds. Nocturnal bird behaviours reflect a negative correlation pattern with wind speed. Existing understandings reveal that migratory bird activities are closely related with wind speed and directions for energy consumption considerations. Results in Fig. 5 is controversy due to wind speed information credibility. Similar to temperature and humidity, wind speed is also measured with ground equipment. The real wind speed information at migratory airspace is not clear. In contrast, wind speed has limited impacts on diurnal bird behaviours. Two indicators demonstrate uniform patterns. The larger proportion of medium grades reveals a large degree of behaviour uncertainty. This is consistent with conventional empirical ornithology understandings. In contrast, wind direction impacts on nocturnal bird behaviours are more remarkable. In Fig. 5(b), north, northeast and east directions are preferred for nocturnal birds. The track flight direction analysis reveals that the principal nocturnal migration direction within the fall season is southwest. The wind direction dependency in Fig. 5(b) indicates that birds are inclined to migrate along the wind direction for the consideration of energy consumption. Grade proportions indicate that nocturnal bird behaviour presents larger certainty at preferred wind directions. This wind direction preference might enable the deduction of bird species.

Even though bird behaviour characters are not simply dependent on a single weather parameter, this study reveals reasonability and feasibility of associating bird behaviours with weather parameters. The information deviation between ground measurement equipment and higher airspace might results in modelling error, but this technique routine is still plausible to further explore bird behaviour characters with multivariable weather parameters.

3.2 Behaviour dependence study on multivariable weather parameter

As indicated in section 2, behaviour indices are replaced by grades in the dependence study on multivariable weather parameters. This substitution transforms the bird behaviour prediction model from a regression model into a classification problem. The latter is apparently more reasonable since the behaviour index regression is unnecessary, and regression results also have credibility problems due to regression model and avian radar data uncertainties. Behaviour grades {High, Medium, Low} are used as labels for bird behaviour prediction. This prediction is a representative supervised learning problem. The input is a multivariable weather feature vector $\boldsymbol{F}$ including temperature, humidity, wind speed and wind direction parameters. Each weather parameter has its individual dimension and value ranges. Numerical renormalisation procedures are necessary to reduce feature space distortion. Eight wind directions are

https://doi.org/10.1017/aer.2024.57 Published online by Cambridge University Press

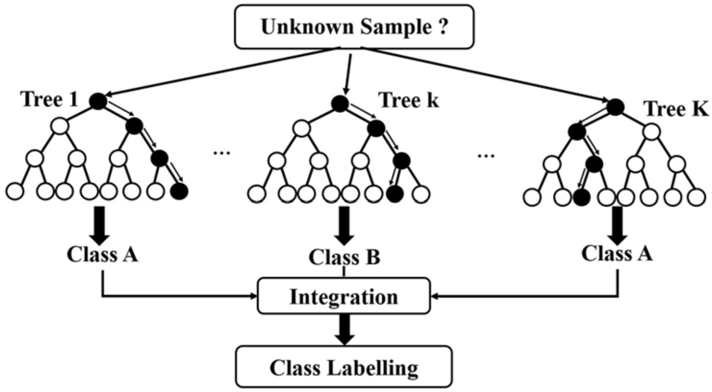


Figure 6. *Principle of random forest model.*

mapped into discrete values from 1 to 8. This paper selects the random forest as the classifier. Random forest is an ensembled classification model [25, 26] which is composed of multiple decision trees with intelligent strategy. Each decision tree within the forest selects partial features from the original feature space. Decisions among trees are independent and the final decision is a weighed integration of all trees. The random forest principle is given in Fig. 6. Compared with other popular learning machines, the random forest model possesses particular benefits to handle both numerical and non-numerical features in classification. Moreover, the random forest has a good adaptability on feature dimension inconsistency. An extra benefit of this model is its feature importance evaluation functionality using Gini index [27]. It is useful for classification problems with ambiguous feature space. The ensembled classification makes the random forest model possess better sample robustness compared with other learning machines.

To elevate samples separability among different behaviour grades, the Linear Discrimination Algorithm (LDA) [28–31] is applied on original feature vectors. LDA constructs a sample projection matrix according to training datasets to transform original feature vectors. This method has successfully applications in many radar target recognition problems [32, 33]. In this paper, weather feature vectors after LDA projection are applied on the random forest model for classifier training and behaviour grade prediction.

The overall framework of bird behaviour grade prediction using weather parameters is presented in Fig. 7. Data sources are avian radar datasets and airport weather records. Two datasets are processed by the temporal matching to generate behaviour grade and multivariable weather parameter datasets. The prediction model is evaluated using testing datasets.

4.0 Results and discussion

4.1 Experiment setup and data collection

Avian radar datasets are from an avian radar system deployed in an airport. The radar system is deployed in FuCheng airport, BeiHai in GuangXi Province of China. The system is developed by China academy of Civil Aviation Science and Technology (CAST) as in Fig. 8. The system adopts a double antenna configuration to achieve vertical and horizontal scanning modes simultaneously. The radar frequency is at S band. The horizontal scanning antenna is mounted on a platform with adjustable heights to achieve more flexible scanning coverage in horizontal dimension. Both antennas take mechanical rotation with speed of 25 revolutions per minute. Bird target detection and tracking algorithms are embedded in the system to provide real time bird situation visualisation functionality [20].

Datasets are collected from historical data measured in August, September and October from 2016 to 2019. The hour window for diurnal bird datasets is set to [05:00,09:00] according to feedbacks from artificial observation records. The hour window for nocturnal bird dataset construction is defined as

https://doi.org/10.1017/aer.2024.57 Published online by Cambridge University Press

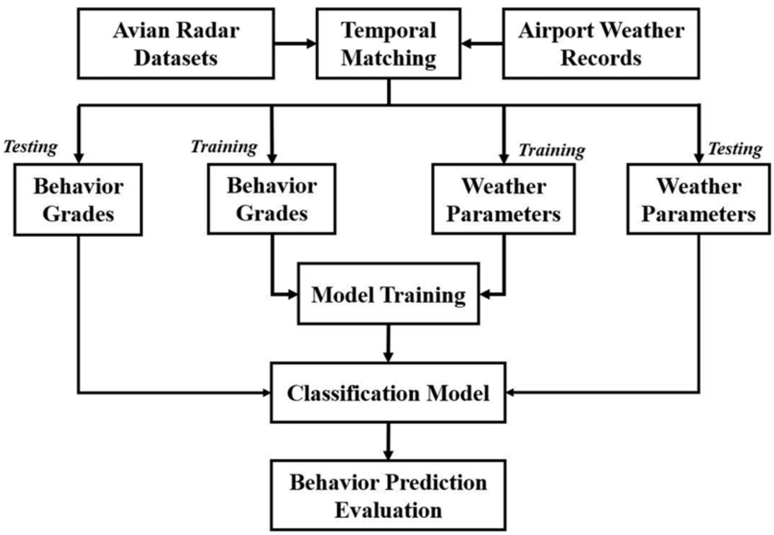


Figure 7. *Framework of bird behaviour prediction using multivariable weather parameters.*

Figure 8. *Avian radar systems developed by CAST.*

[22:00, 02:00] according to historical analysis of avian radar datasets. The conditional parameter $\boldsymbol{\sigma}$ is set to normal weather excluding weather conditions like strong gusts, precipitation, fogs and radar hardware problems. Representative weather parameters under normal weather conditions construct multiple sub-datasets. For example, a temperature sub-dataset defines its lower and upper bounds by extracting 20% and 80% percentile values. Due to weather condition difference between diurnal and nocturnal hour windows, conditional parameters are constructed, respectively. For diurnal bird behaviour analysis, numerical range in the hour window for temperature, air pressure, humidity and wind speed are [60,86] °F, [980,1030] hPa, [67,81] % and [3.2,9.1] m/s, respectively.

https://doi.org/10.1017/aer.2024.57 Published online by Cambridge University Press

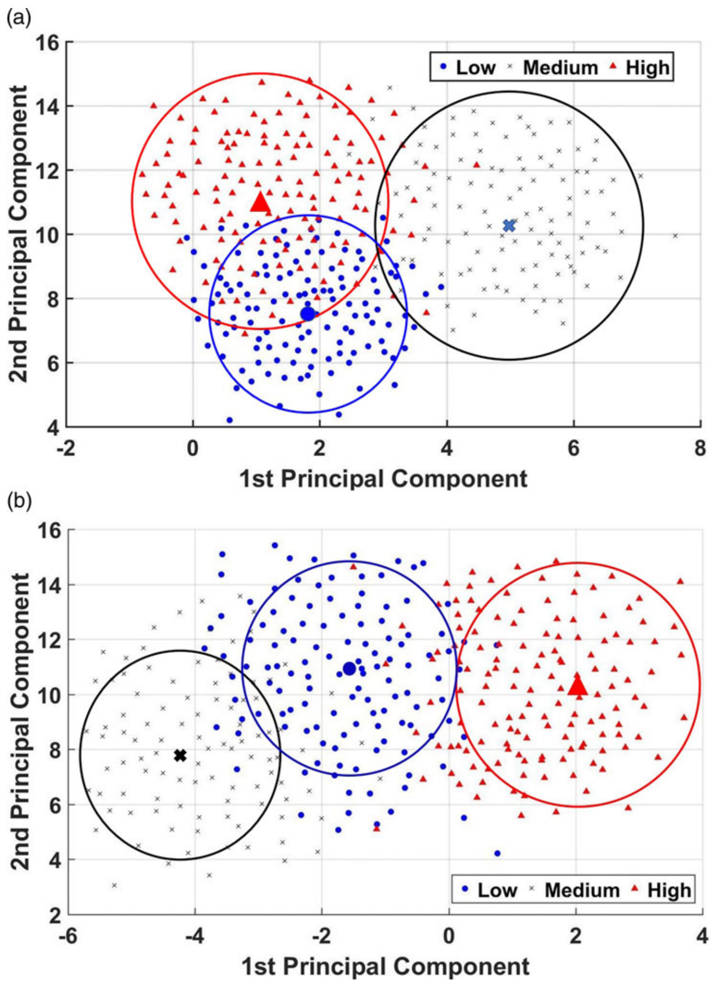


Figure 9. *Separability presentation for three activity grade samples in principle component space (a) diurnal birds (b) nocturnal birds.*

Radar data from 2016 to 2018 constructs a training dataset. The data in 2019 composes a test dataset. Numbers of training samples for diurnal and nocturnal bird studies are 545 and 671, the corresponding test sample numbers are 115 and 139, respectively.

4.2 Diurnal and nocturnal bird activity prediction

4.2.1 Feature separability analysis

To test the feasibility of feature space modelled by weather parameters, feature vectors from different behaviour grades are projected onto a two-dimensional plane for intuitive visualisation. The Principal Component Analysis (PCA) [34, 35] projection method is applied on feature vectors to extract first two principal components of feature vectors for sample separability presentation. Figure 9 illustrates principal components distributions for two types of bird data samples, which are arbitrarily selected from avian radar datasets. Both datasets present prominent sample separability, and the nocturnal bird sample separability is visually larger than that for diurnal birds. The enlarged sample separability provides confidences to build behaviour grade prediction models using multivariable weather parameters.

Table 3. *Confusion matrix of random forest self-validation for diurnal bird dataset*

	High	Medium	Low
High	86	7	7
Medium	5	89	6
Low	4	8	88

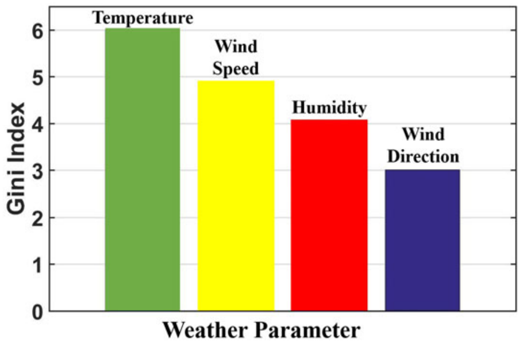


Figure 10. *Weather parameter importance ranking-diurnal birds.*

4.2.2 Diurnal bird behaviour prediction

The random forest classifier is verified through the five-fold cross validation strategy. Rates of correct and incorrect classification are presented in the confusion matrix formulation as in Table 3. The overall self-validation accuracy indicates the random forest model is theoretically qualified for behaviour grade prediction. The dataset from year 2019 is taken to test the training model quality. The rate of correct behaviour grade prediction is 77%. This prediction accuracy is obviously lower than self-validation accuracy. One possible explanation is the dataset difference in 2019. In 2019 we conducted a radar system maintenance and made slight adjustments on radar location and elevation angle. This adjustment might result in radar coverage and data difference compared with previous three years. This also indicates that bird behaviour characterisation and their weather relevance study is highly dependent on radar data quality and spatial domain characters. The behaviour characterisation model proposed in this paper attempt to regularise radar data to reduce the data variation impact, but results indicate that more data standardisation works are required to guarantee the method's universality.

Compared with other learning machine models, the random forest model possesses its particular advantages. Selected four weather parameters have their unique dimension and physical meanings. This makes the feature space have low dimension with prominent dimension inconsistency. Random forests could outperform other popular models in handling this inconsistency. The other benefit is its capability of feature importance ranking by Gini indices. Figure 10 demonstrates Gini indices of four weather parameters. The dominance property of temperature influence on diurnal bird behaviours is distinctive. The wind speed presents larger significance than wind directions. This is reasonable since diurnal birds usually present short-time flight, they are more sensitive to wind intensity. This results in the lowest rank of wind direction significance. The feature importance ranking is particularly useful for feature selection and feature space construction with ambiguous feature contributions.

4.2.3 Nocturnal bird behaviour prediction

Prediction evaluation for nocturnal bird behaviours takes a similar procedure. Five-fold cross validation results are presented in Table 4. The rate of correct prediction is 74%. Intuitive understandings believe that nocturnal migratory birds possess relatively lower behaviour complexity than diurnal birds.

https://doi.org/10.1017/aer.2024.57 Published online by Cambridge University Press

Table 4. *Confusion matrix of random forest self-validation for nocturnal birds*

	High	Medium	Low
High	82	11	7
Medium	12	83	5
Low	5	9	86

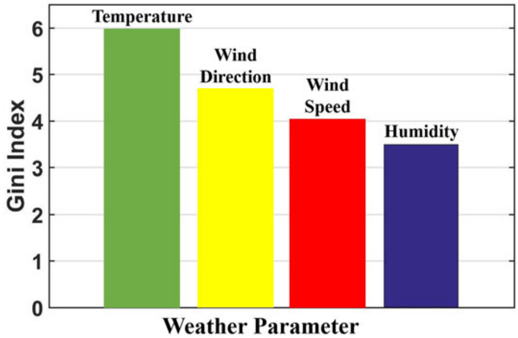


Figure 11. *Weather parameter importance ranking-nocturnal birds.*

Theoretically their behaviour grade prediction accuracy should be higher. However, both self-validation and test experiments do not reflect expected results. A probable and reasonable explanation to this problem is weather information measurement deviation. The consequence of this deviation is the prediction model quality degradation, and a lower prediction accuracy is reasonable. Besides weather information measurement deviation and data quality uncertainty, it must be admitted that actual bird behaviour characters are not merely dependent on weather parameters. Bird species, location and season also play important roles in determining bird behaviour patterns. Therefore, the prediction model introduced in this paper is not fully comprehensive for bird behaviour prediction. This might be another reason that the prediction accuracy is not satisfactory as expected.

The parameter importance ranking is presented in Fig. 11. Temperature is still the most important factor influencing nocturnal bird behaviours. The wind direction contributes more in nocturnal bird behaviour prediction. This is consistent with conventional studies since diurnal birds usually choose preferred wind conditions for energy saving during migration. The low importance ranking of humidity might be the consequence of parameter deviation between ground equipment and airspace condition.

4.3 Discussion on data sufficiency and severe weather conditions

Existing results partially validate the feasibility of the method. However, the experiment also reveals its limitations like weather information deviations. This section gives further discussion to present another two issues that have nonnegligible impact on weather dependence modelling for bird behaviours.

The first issue is about the connection between prediction accuracy and data sufficiency. Existing experiments integrates radar data from August, September and October into one dataset for training and prediction. This integration strategy is controversy in reasonability since it assumes the same weather dependence of bird behaviours for different months. A more reasonable modelling strategy is considering monthly difference in weather dependence study. However, this monthly modelling requires sufficient data supports, which is not implementable for existing datasets. As an alternative, the three months dataset for diurnal birds is divided into two parts. One dataset collects data from August 1 to September 15, the other one is composed of data from September 16 to October 31. The same training

https://doi.org/10.1017/aer.2024.57 Published online by Cambridge University Press

Table 5. *Confusion matrices of new datasets - (a) Group 1 (b) Group 2*

(a)

	High	Medium	Low
High	90	7	3
Medium	3	92	5
Low	6	4	90

(b)

	High	Medium	Low
High	90	5	5
Medium	7	89	4
Low	5	6	91

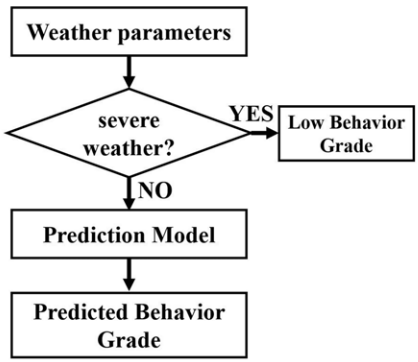


Figure 12. *Diagram of a more comprehensive bird activity prediction system.*

and testing procedures are conducted on two new datasets. Confusion matrices of self-validation results using five-fold cross validation are given in Table 5. Rates of correct prediction are 82% and 83%, respectively. Results from new datasets present prominent performance elevation, and it is promising to achieve higher accuracy based on more sufficient data supports. This experiment indicates the feasibility of prediction modelling at finer temporal scales, and it is implementable based on more sufficient data supports.

The other issue is about severe weather conditions. The existing prediction system excludes datasets under severe weathers. This limits the prediction model for practical engineering applications. According to historical artificial observation records, birds are usually inactive under severe weather conditions. This intuitive understanding needs more efforts to make quantitative modelling and predictions. Figure 12 proposes a conceptual framework based on tree structure to cover the condition of behaviour prediction under severe weather conditions. This framework could guarantee the comprehensiveness of the method, but it requires more accurate modelling for bird behaviour prediction under severe weather conditions.

5.0 Conclusion

Radar systems are proper remote sensing solutions to birds monitoring within low altitude airspace. Existing avian radar systems provide reliable bird target detection and tracking performance with

https://doi.org/10.1017/aer.2024.57 Published online by Cambridge University Press

real-time collision risk evaluation and warnings. However, these short-time functionalities are controversy in application significances. Historical avian radar datasets provide a chance to understand birds long-term behaviour characters to elevate bird situation awareness capability. This paper proposes a method to characterise bird behaviours and study their behaviour relevance with weather conditions using avian radar data. A quantitative bird behaviour modelling strategy is introduced. Weather dependency studies on single weather parameters support the feasibility of bird behaviour prediction using multivariable weather parameters. A four-dimensional feature space is constructed to build the mapping between multivariable weather parameter and bird behaviour grades. The random forest model is adopted to build the prediction system. Four years avian radar datasets are taken for validation experiment. Results indicate the feasibility of predicting diurnal and nocturnal bird behaviour characters using weather information. However, experiments also reveal some problems that limit prediction accuracy including weather information deviation, data quality uncertainty, data insufficiency and incomprehensive prediction model. Moreover, the importance of data sufficiency on prediction accuracy is addressed to indicate better prediction performance with abundant data supports. A conceptual framework for more comprehensive bird behaviour predictions is proposed to elevate its application significances, and more efforts are need to further refine the prediction accuracy under severe weather conditions. As the motivation of the proposed method is to elevate bird situation awareness capabilities within the airport, its application significance should be reflected within bird strike prevention administration. Besides behaviour prediction accuracy elevation under finer spatial-temporal scales by involving more conditional parameter, the other branch of our future work is integrating bird behaviour prediction model with air traffic control procedure. By constructing a more refined spatial-temporal bird behaviour description model, it could be applied in the fusion with aircraft's flight routine model. This fusion could provide a more accurate bird strike risk description and prediction, and the risk might be reduced by adjusting aircraft's flight plan in both spatial and temporal domains.

Acknowledgements. This paper is supported by National Natural Science Foundation of China (NSFC) under Grant 62371018 and 62361006, Guangxi Natural Science Foundation under Grant 2020GXNSFBA297119, Guangxi Science and Technology Plan Project under Grant GuiKe-AD20238025, the National Natural Science Foundation of China (NSFC) and Civil Aviation Administration of China (CAAC) (U2133216), National Key Research and Development Program (2023YFB2604103).

References

[1] Chilson, P.B., Bridge, E., Frick, W.F., Chapman, J.W. and Kelly, J.F. Radar aeroecology: Exploring the movements of aerial fauna through radio-wave remote sensing, *Biol. Lett.,* 2012, **8**, pp 698–701.

[2] Sheridan, E., Randolet, J., DeVault, T.L., Seamans, T.W., Blackwell, B.F. and Fernández-Juricic, E. The effects of radar on avian behavior: Implications for wildlife management at airports, *Appl. Anim. Behav. Sci.,* 2015, **171**, pp 241–252.

[3] Jang, J.H. and Ahn, S.H. Bird-strike damage analysis and preliminary design of composite radome structure using smoothed particle hydrodynamics, *Appl. Compos. Mater.,* 2019, **26**, pp 763–782. https://doi.org/10.1007/s10443-018-9750-9

[4] Heimbs, S. Computational methods for bird strike simulations: A review, *Comput. Struct.*, 2011, **89**, (23–24), pp 2093–2112. https://doi.org/10.1016/j.compstruc.2011.08.007

[5] Flock, W.L. Radar Echoes from Birds and their Effects on Radar Performance. *In Atmospheric Effects on Radar Target Identification and Imaging; NATO Advanced Study Institutes Series*, Volume 27, Springer, 1976, Dordrecht, The Netherlands.

[6] Moon, J.R. Effects of birds on radar tracking systems. *In Proceedings of the 2002 International Radar Conference*, 15–17 October 2002, Edinburgh, UK, pp 300–304.

[7] Cullinan, V.I., Matzner, S. and Duberstein, C.A. Classification of birds and bats using flight tracks, *Ecol. Inform.,* 2015, **27**, pp 55–63.

[8] Chen, W.S., Liu, J. and Li, J. Classification of UAV and bird target in low-altitude airspace with surveillance radar data, *Aeronaut. J.*, 2019, **123**, pp 191–211.

[9] Jun, L.I.U., Yulong, L.I., Xiancheng, Y.U., Xiaosheng, G.A.O. and Zongxing, L.I.U. Design of aircraft structures against threat of bird strikes, *Chinese J. Aeronautics,* 2018, **31**, (7), pp 1535–1558, https://doi.org/10.1016/j.cja.2018.05.004

[10] Phillips, A.C., Majumdar, S., Washburn, B.E., Mayer, D., Swearingin, R.M., Herricks, E.E., Guerrant, T.L., Beckerman, S.F. and Pullins, C.K. Efficacy of avian radar systems for tracking birds on the airfield of a large international airport, *Wildl. Soc. Bull.*, 2018, **42**, pp 467–477. https://doi.org/10.1002/wsb.910

[11] Gerringer, M.B., Lima, S.L. and DeVault, T.L. Evaluation of an avian radar system in a Midwestern landscape, *Wildl. Soc. Bull.,* 2016, **40**, pp 150–159.

[12] Dokter, A.M., Baptist, M.J., Ens, B.J., Krijgsveld, K.L. and van Loon, E.E. Bird radar validation in the field by time-referencing line-transect surveys, *PLoS ONE,* 2013, **8**, pp e74129.

[13] Nilsson, C., Dokter, A.M., Schmid, B., Scacco, M., Verlinden, L., Backman, J., Haase, G., Dell'Omo, G., Chapman, J.W., Lejinse, H., et al. Field validation of radar systems for monitoring bird migration, *J. Appl. Ecol.,* 2018, **55**, pp 2552–2564.

[14] Schmaljohann, H., Liechti, F., Bachler, E., Steuri, T. and Bruderer, B. Quantification of bird migration by radar—A detection probability problem, *Ibis,* 2008, **150**, pp 342–355.

[15] Abraham, M. Bird forecasting by radar, *Nature,* 2018, **561**, pp 314.

[16] Coates, P.S., Casazza, M.L., Halstead, B.J., Fleskes, J.P. and Laughlin, J.A. Using avian radar to examine relationships among avian activity, bird strikes, and meteorological factors, *Hum. Wildl. Interact.,* 2011, **5**, pp 249–268.

[17] Van Doren, B.M. and Horton, K.G., A continental system for forecasting bird migration, *Science*, 2018, **361**, 1115–1118. https://doi.org/10.1126/science.aat7526

[18] Chilson, C., Avery, K., McGovern, A., Bridge, E., Sheldon, D. and Kelly, J. Automated detection of bird roosts using NEXRAD radar data and Convolutional Neural Networks, *Remote Sens Ecol Conserv.*, 2019, **5**, pp 20–32. https://doi.org/10.1002/rse2.92

[19] Garcia-Quintas, A, Roy, A, Barbraud, C, Demarcq, H, Denis, D, Lanco Bertrand, S. Machine and deep learning approaches to understand and predict habitat suitability for seabird breeding, *Ecol. Evol.*, 2023, **13**, pp 9. https://doi.org/10.1002/ece3.10549

[20] Chen, W.S. Interactive processing of radar target detection and tracking, *Aircr. Eng. Aerosp. Technol.*, 2018, **90**, (9), pp 1337–1345. https://doi.org/10.1108/AEAT-07-2016-0115

[21] Li, Z., Ding, B., Han, J., Kays, R. and Nye, P. Mining Periodic Behaviors for Moving Objects, KDD'10 - Proceedings of the 16th ACM SIGKDD International Conference on Knowledge Discovery and Data, Washington, DC, 2010, pp 1099–1108.

[22] Worton, B.J. Kernel methods for estimating the utilization distribution in home-range studies, *Ecology*, 1989, **70**, (1), pp 164–168.

[23] Fauvel, M., Chanussot, J. and Benediktsson, J.A. Decision fusion for the classification of urban remote sensing images, *IEEE Trans. Geosci. Remote Sens.*, 2006, **44**, 2828–2838.

[24] Liu, J., Fang, N., Xie, Y.J. and Wang, B.F. Multi-scale feature-based fuzzy-support vector machine classification using radar range profiles, *IET Radar Sonar Navig.,* 2016, **10**, pp 370–378.

[25] Sagayaraj, M.J., Jithesh, V. and Roshani, D. Comparative Study Between Deep Learning Techniques and Random Forest Approach for HRRP Based Radar Target Classification. *In Proceedings of the 2021 International Conference on Artificial Intelligence and Smart Systems (ICAIS)*, 25–27 March 2021, Coimbatore, India, pp 385–388.

[26] Genuer, R., Poggi, J.-M. and Tuleau-Malot, C. Variable selection using Random Forests, *Pattern Recognit. Lett.,* 2010, **31**, pp 2225–2236.

[27] Menze, B.H., Kelm, B.M., Masuch, R., Himmelreich, U., Bachert, P., Petrich, W. and Hamprecht, F.A. A comparison of random forest and its Gini importance with standard chemometric methods for the feature selection and classification of spectral data, *BMC Bioinform.,* 2009, **10**, pp 213.

[28] Fu, J.S., Liao, K. and Yang, W. Radar HRRP target recognition using multi-KFD-based LDA algorithm, *Prog. Electromagn. Res.,* 2012, **30**, pp 15–26.

[29] He, L., Chen, X., Xu, C., Liu, J. and Johnson, M.T. Local Pairwise Linear Discriminant Analysis for Speaker Verification, *IEEE Signal Process. Lett.,* 2018, **25**, pp 1575–1579.

[30] Cıhan, M. and Ceylan, M. Comparison of Linear Discriminant Analysis, Support Vector Machines and Naive Bayes Methods in the Classification of Neonatal Hyperspectral Signatures. *In Proceedings of the 2021 29th Signal Processing and Communications Applications Conference*, 9–11 June 2021, Istanbul, Turkey, 2021. pp 1–4.

[31] Pan, M., Jiang, J., Kong, Q., Shi, J., Sheng, Q. and Zhou, T. Radar HRRP target recognition based on t-SNE segmentation and discriminant deep belief network. *IEEE Geosci. Remote Sens. Lett.,* 2017, **14**, pp 1609–1613.

[32] Liu, J., Fang, N., Xie, Y.J. and Wang, B.F. Scale-space theory based multi-scale features for aircraft classification using HRRP, *Electron Lett.,* 2016, **52**, pp 475–477.

[33] Lee, K.-C. and Ou, J.-S. Radar target recognition by using linear discriminant algorithm on angular-diversity RCS, J. Electromagn. Waves Appl., 2007, **21**, 2033–2048.

[34] Prasad, S. and Bruce, L.M. Limitations of principal components analysis for hyperspectral target recognition, *IEEE Geosci. Remote Sens. Lett.,* 2008, **5**, pp 625–629.

[35] Jolliffe, I.T. and Cadima, J. Principal component analysis: A review and recent developments, *Philos. Trans. R. Soc. A,* 2016, **374**, pp 20150202.

Cite this article: Xu Q., Liu J., Su M. and Chen W.S. (2024). Bird behaviour characterisation and environment dependence modelling in airport airspace based on radar datasets. *The Aeronautical Journal*, **128**, 2815–2831. https://doi.org/10.1017/aer.2024.57