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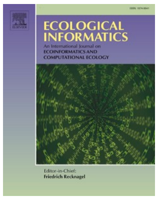

Operationalising weather surveillance radar data for use in ecological research

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ABSTRACT

Global biodiversity declines require a step change in monitoring frameworks to properly track and diagnose population trends. National weather surveillance radar (WSR) networks offer high spatial (ca. 1-10 km) and temporal (5–10 min) resolution data collected over regional and decadal scales, with well-supported infrastructure that holds great promise for the study of biodiversity. However, WSR datasets pose new challenges for ecologists due to their format, volume, and three-dimensional spatial structure. Here, we define a novel approach to the processing of WSR data to produce a product that can be used to interrogate trends in aerial biodiversity (abundance or diversity) at and across individual ground-level sites. From the full volume of WSR data collected approximately every six minutes we extract vertical columns of WSR observations above sites to compare against standardised nocturnal macro-moth monitoring data at ground level. The results show that there is strong agreement between the WSR-derived proxy of biodiversity in the air column and ground-level measurements of abundance and diversity in nocturnal moth communities. The columnar product operates on a biologically relevant scale with a diameter of 5 km, although column dimensions can easily be customised, and can be deployed at any site within a WSR's observable range. These findings have the potential to unlock past and present WSR observations for widespread application to existing and novel ecological questions and can be applied to weather radar networks around the world.

1. Introduction

Biodiversity declines represent one of the primary challenges to society in terms of the loss of ecosystem services that those natural resources represent (Díaz et al., 2019; IPBES, 2019). There is growing evidence of both species loss and abundance declines in a wide range of animal and plant taxa and yet that evidence remains – for most species – relatively weak due to spatio-temporal heterogeneity (Pilotto et al., 2020; van Klink et al., 2020; van Klink et al., 2022b). Heterogeneity in complex trends is compounded by severe biases in the practice of conservation biology. In particular, there has been an emphasis on (i) charismatic taxa (vertebrates, and particularly birds) (Bonnett et al., 2002; Leather, 2009), (ii) higher income countries (Christie et al., 2021), (iii) recent time periods rather than on historical data (McClenachan et al., 2012), and (iv) methods involving field sampling by trained researchers or citizen scientists complemented by technologies that are still at an early stage of development and validation (Berger-Tal and Lahoz-Monfort, 2018).

A particular focus of these existing studies in ecology and conservation has been the detection and listing of the presence or absence of a particular species within a community. Such presence-absence and diversity data have facilitated great advances in analytical methods such as species distribution modelling that give measures of habitat suitability or probability of presence (Outhwaite et al., 2020) and meta-

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analyses that harness extensive but heterogeneous datasets (van Klink et al., 2020). However, less attention has been given to trends in the abundance of taxa – the so-called "Prestonian shortfall" (Hortal et al., 2015). The lack of abundance data persists despite the significance of population abundances for ecosystem service delivery (Kleijn et al., 2015) and has been brought into focus in recent years by a series of long-term studies on insect biomass (most prominently by Hallmann et al., 2017; and see Müller et al., 2023 for recent interpretations based on weather). Various solutions have been proposed to fill the gap in our understanding of abundance. Standardised citizen science methods have been successful in detecting abundance trends in butterflies across Europe (Van Swaay et al., 2019) and could be used in other taxa (Bried et al., 2020). However, new schemes will be limited in their ability to make inferences for several years until trends can be perceived (e.g. recommendations of 20 year time periods over which to study phenological change, Sparks and Menzel, 2002). Technology also has a potential role to play and there has been a proliferation of novel techniques for applying new and existing technologies to the study of biodiversity (van Klink et al., 2022a).

A potential solution to at least some of the challenges outlined above may be found in existing sources of data that are not collected for biodiversity purposes but could be processed to yield useful information. Radar data are being used as a relatively minor tool in the ecology and conservation of insects despite the magnitude of the research findings that result when radars are turned on biological questions. For example, vertical-looking radars (VLRs) operate at high taxonomic resolution (Drake, 2016; Hao et al., 2020; Hu et al., 2018) and can calculate the abundance, biomass, and relative diversity of insects passing above a site (Hu et al., 2016; Smith et al., 2000; Wotton et al., 2019). VLRs operate a thin, vertically oriented beam (~10-100 m wide at typical scan altitudes, Chapman et al., 2002), and can create continuous profiles of insect movement up to an altitude of 2.5 km (Drake and Bruderer, 2017). The second primary type of radar that has been applied in ecological research is the weather surveillance radar (WSR). In contrast to VLRs, WSRs scan at multiple elevation angles around a 360° axis and record the radiation scattered by populations occupying resolution volumes (proportional to product of beamwidth with range) using either horizontally-oriented (in the case of single polarisation radar) or both horizontally- and vertically-oriented electric fields. WSRs have been harnessed to quantify migratory insect movement (Cui et al., 2019), mass emergences of lake flies (Stepanian et al., 2020), and the influence of artificial light at night (ALAN) on orthopteran swarming behaviours (Tielens et al., 2021); they have also been shown to produce quantitatively similar biodiversity measures to ground-level monitoring approaches, even at coarse scales (Lukach et al., 2022).

Importantly, WSR data are typically freely available. Those data span multiple decades in some radar networks (e.g., WSR-88D in the United States, freely available) and make observations over entire nations, and in some cases entire continents, at extremely high temporal resolution (scanning every 5–10 min). Why, then, have WSR observations not been more widely used in ecological studies of insects? Key limitations include the accurate identification of biological objects ('bioscatterers') within the radar volume, and particularly the separation of insects from birds and bats (especially at night in migration seasons) (Bauer et al., 2017), and a paucity of standardised data products capable of quantifying volant biodiversity in an ecologically intuitive, site-specific fashion. Though a growing number of studies have shown electromagnetic simulation to be an effective pathway to providing greater taxonomic resolution (Addison et al., 2022; Mirkovic et al., 2016; Mirkovic et al., 2019), and recent work indicates that machine-learning approaches may be effective in distinguishing broad classes of bioscatterers within WSR data (Gauthreaux and Diehl, 2020; Lukach et al., 2022), these advances fail to provide methods of quantifying WSR data that can provide meaningful answers to pressing ecological questions. In particular, a fundamental problem that remains for the field is to establish the taxonomic limits of WSR observations (Addison et al., 2022; Mirkovic et al., 2016; Stepanian et al., 2020).

To contribute to a solution to this final problem of access to WSR observations, we have developed a novel method for extracting information from WSR datasets that gives biologically meaningful data at the level of the ecological "site" and that could be incorporated easily into standard ecological analyses. We classify these data with a hierarchical clustering algorithm (Lukach et al., 2021) that attempts to infer the biological composition and diversity of bioscatterers in WSR observations and from which we then derive WSR-based biodiversity measures. We go on to demonstrate strong agreement between these measures and standardised monitoring of insects at a similar spatiotemporal scale at ground level.

2. Methods

2.1. Methodological summary and novelty

In earlier work, we provided a proof of concept that there were relationships between what weather radars can detect and the insect communities at ground level (Lukach et al., 2022). That study examined relationships between putative insect scattering signals across the entire radar scanning volume, which is a total area of ca. 2800km^2 centred on the radar, and observations at ground level. That initial analysis demonstrated that there was reason to believe that there were signatures of insects within the radar data based on associations at ground level. In this study, we move beyond the use of the entire scanning volume to construct custom volumes (5 km diameter, ca. 20km^2) that are relevant to ecological studies at particular locations. The construction of those volumes is far from trivial: the work requires the identification of the voxels within the scan volume that are found within the area of interest, the definition of a radius around the site of interest to balance data availability (which decreases due to beam spread further from the radar) with the specificity of the site (based on ecological processes and animal movement that often operate over a few km at most), and inter-conversion between the polar coordinate system of the radar and the Cartesian system of ground level data. As well as developing this workflow, we have produced a script to make the whole workflow reproducible by researchers and validated the approach using the same methods as in the previous paper. The new method allows researchers with access to radar data (UK Met Office radar data, for example, are freely available, although we acknowledge that there are considerable technical barriers to the use of the data) to analyse any set of sites for long term time series of aerial abundance. The methodology can be described in four main steps: selection of the set of radar volume files, extraction of the columnar vertical profiles (CVPs) for two locations, hierarchical clustering of the CVP datasets, and comparison of identified clusters to the ground-level observations. The flow of the hierarchical clustering can be found in Fig. 3 of Lukach et al. (2021).

2.2. Weather surveillance radar data selection and pre-processing

The WSR data used in this study were collected by the X-band dual-polarisation Doppler weather radar (NXPol-1) at the Chilbolton Atmospheric Observatory (CAO; 51° 8′40"N, 1°26′19.00"W) between May and July 2017. NXPol-1 is a modified version of Meteor 50DX model manufactured by Selex-Gematronik (now Leonardo Germany GmbH). The modification includes a larger 2.4 m diameter antenna without a radome that provides a 0.98° half-power beam width. The WSR is operated by the UK's National Centre for Atmospheric Science (NCAS) and its specifications can be found in Neely III et al. (2018). All technical details on the operation of NXPol-1, utilised software, and data pre-processing are described in Lukach et al. (2022). Important for this work, NXPol-1 continuously scans the atmosphere at 10 elevations in 360 azimuthal directions (1 degree resolution) and in 150 m equidistant range gates out to 150 km. This scanning geometry forms a set of voxels (volume pixels): data representing the atmosphere and everything in it around the radar location (Fig. 1). NXPol-1 scans this volume approximately every 6 min. From these scan data, we extract "vertical column" subsets that include all the voxels within a 2.5 km radius around each location (Fig. 1). The selected radius includes enough voxels to reduce statistical errors within the radar data at each time step (Kumjian and Ryzhkov, 2012), as the voxel data belonging to the same altitude layer all participate in the calculation of the mean per altitude value while also balancing the need to retain ecologically relevant spatial resolution. Columnar vertical profiles (CVPs) are formed by these mean-per-altitude-layer values for each time stamp of the WSR dataset as in Murphy et al. (2020). The number of voxels contributing to each altitude level vary depending on the presence of meaningful values in the available radar variables. The mean value for different altitudes at different timestamps might include from 1 up to 35 depending on the scanning geometry of the radar, with total of 8170 potential voxels per column of 2.5 km radius. The code for the generation of CVPs can be found at https://github.com/cemac/VP_Extraction.

For this study, we selected two "vertical column" subsets of the volume data corresponding to two permanent locations inside NXPol-1's range domain. The locations are centred on the Bentley Wood (51° 5′ 25.09″ N, 1° 38′ 24.53″ W) and Porton Down III (51° 8′ 39.78″ N, 1° 40′ 57.3672″ W) Rothamsted Insect Survey (RIS) light trap sites located in the south of England (Fig. 2). The two sites are 15 km and 17 km from the radar location at CAO, respectively, and approximately 6.7 km from each other. The azimuthal resolution of the scans is 1° and so the approximate size of voxels comprising the CVPs is 262 m (Bentley) and 296 m (Porton). At these distances from the radar, the lowest voxel centres are approximately 250 m above mean sea level. The time series of CVPs form a timeline with time on the x-axis and altitude on the y-axis. An example 40-h CVP timeline is shown in Fig. 3.

We selected sampling dates between May and July 2017. Dates were chosen based upon nights where the RIS light traps were active and excluded dates where there was a high likelihood of meteorological "clutter" on the radar scans or where either of the two light traps aggregated samples over two or more nights. A preliminary analysis of the plan positional indicator (PPI) scans for each night allowed us to check that there were no bird migrations during the study period (characterised by high reflectivity and strong, directed flight). In the UK, bats are estimated to have 18 % of the abundance of birds and bats are a small component of aerial fauna by biomass (ca. 0.16 % of the biomass of birds, Greenwood et al., 1996). As a result, while we treat the remaining bioscatterers as insects, the signals we extract may contain contamination from a mixture of birds and bats. At the Bentley Woods site, validation data from the RIS light trap were available for 33 nights: 11–14 and 31 May; 6, 14–21 and 25–27 June; and 1–11, 17–18, and 24–26 July. At the Porton Down III site, the light trap was only operational for 16 nights: 31 May; 1, 14–15, 21, and 26 June; and 3–6, 10–11, 18 and 24–26 July. This selection process resulted in 49 individual 24-h observation periods from which CVPs could be extracted from NXPol-1's dataset. From these 49 observational periods, the times between civil dusk to civil dawn were utilised as input for a hierarchical clustering algorithm with the same dual-polarisation variables as described in Lukach et al. (2021): horizontal reflectivity factor Z_H [dBZ], vertical reflectivity factor Z_V [dBZ], differential reflectivity Z_{DR} [dB], copolar correlation coefficient ρ_{HV} [unitless] and specific differential phase K_{DP} [$^\circ$ km^{-1}]. These variables describe the main characteristics of scatterers: dielectric properties, shape, orientation, their quantity and variety.

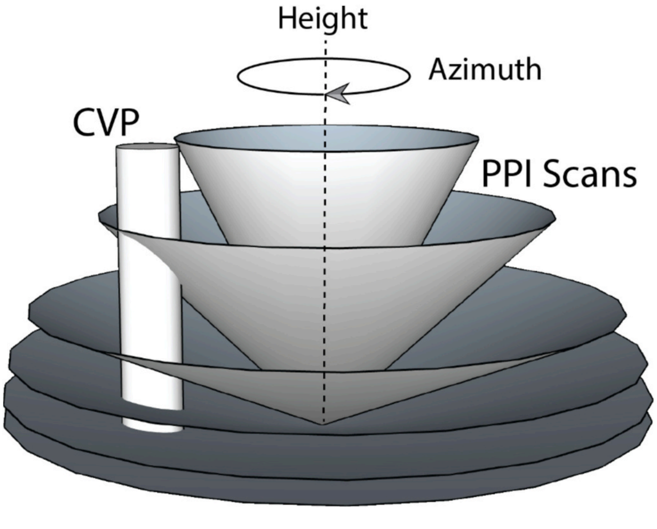

Fig. 1. A schematic depicting the geometry of the weather radar PPIs and positioning of CVP in it. To form a CVP, the voxels of data belonging to the column are averaged and resulting values are projected onto the height axis. PPI, plan position indicator; CVP, column-vertical profile.

We note that K_{DP}, the propagation differential phase, observed from the scattering of insects is effectively zero because their concentration in the radar resolution volume is extremely low compared to meteorological scatterers. Thus, when observing a voxel of insects only, NXPol-1 is observing only the system differential phase, typically constant, plus the backscatter differential phase, which can be a few tens of degrees and varies with the size and composition of the observed insect population. When the derivative of the observed total backscatter differential phase, which is the sum of all three terms, is computed to derive K_{DP}, under the assumption that most variation comes from the propagation term which is typically true for meteorological scatterers, statistical fluctuations and variations in backscatter differential phase produce an apparent $K_{DP.}$ As such the K_{DP} reported for insect-only voxels is a computational artifact and should not be interpreted with the same physical interpretation as the K_{DP} of meteorological scatterers. Some insects, notably nocturnal insects, are relatively large and when observed with an X-band radar, 3 cm wavelength, they likely produce measurable backscatter differential phase thus the values of K_{DP} reported here may have some meaning and we utilise this information for the clustering process.

2.3. *Bioscatterer classification algorithm*

The algorithm used in the study was developed for hydrometeor classification and successfully applied to nocturnal bioscatterer detection (Lukach et al., 2021; Lukach et al., 2022). In this study, we apply the bioscatterer classification version of the algorithm (BCA), described in Lukach et al. (2022), to a more localised subset of volume radar data – the CVP. The hierarchical clustering of the BCA is data-driven, and more localised input data should result in more specific classes in the final optimal set of clusters than discussed in Lukach et al. (2022). The hierarchical structure represents the splitting of clusters at each level (see example in Fig. 4) and keeps the information about the most pronounced classes and their relation to the classes of previous and subsequent levels. These levels are accessible separately for the analysis of the bioclasses represented by the clusters. The essence of the algorithm is in detecting an optimal number of clusters in multivariate data in agreement with its characteristics in a principal component space while preserving the sequence of splits in the hierarchical structure. Principal components reduce the dimensionality and pick out the strongest factors in the excessive set of input variables.

2.4. *Moth community analysis*

The following ecological analysis closely follows that in Lukach et al. (2022). We compared the BCA output to reference samples from two RIS light traps: Bentley Woods and Porton Down III. These two traps sampled 177 macro-moth species ($N = 2030$ macro-moths) in total across our chosen 49 sampling periods; with 151 species ($N = 1627$) sampled across all 33 nights by the Bentley Woods light trap, and 75 species ($N = 403$) sampled across 16 nights of the Porton Down III light trap.

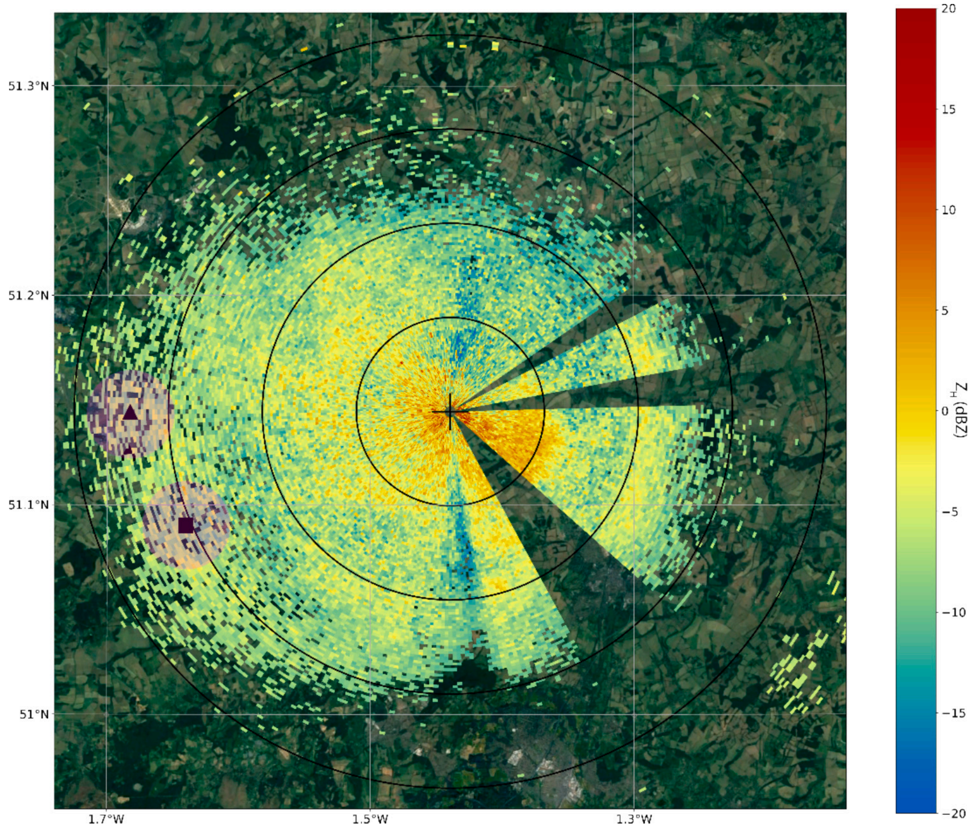

Fig. 2. Map showing the study area (with 5 km, 10 km, 15 km, and 20 km range circles) and the locations of the two CVPs above light traps (left, grey circles) and the NxPol-1 radar (in the centre with an example of one PPI horizontal reflectivity data).

Next, we explored the extent to which community-weighted mean trait values in ground-level moth communities from the light traps could explain the detection of different clusters in the radar data. Full details of the methodology can be found in Lukach et al. (2022) and raw data can be found in Dally et al. (2021). Briefly, we compiled a database of mean morphometric traits for each sampled macro-moth species, using measurements taken from specimens within the digitised collections of the Natural History Museum (NHM), London, as well as the (to-scale) colour photographic plates present in Skinner and Wilson (2009). We excluded micro-moth species from the reference data as, aside from a few common species, they are not well represented in the RIS light trap data and very few species had digitised specimens available in the NHM collections. We measured six traits: forewing length (mm), thorax length (mm), thorax width (mm), abdomen length (mm), and abdomen width (mm). A further four traits were derived from these initial measurements: fresh body mass (mg) (see Kinsella et al., 2020; Rydell and Lancaster, 2000), thorax depth (mm), the lateral aspect ratio (body length/thorax depth), and the anterior aspect ratio (thorax width/thorax depth). Using this trait database, we created a matrix of 10 mean trait values per macro-moth species per night.

2.5. Moth and bioscatterer cluster traits

We standardised the trait data and applied principal components analysis (PCA) to reduce the dimensionality of these correlated trait data. In each case, we retained the first two principal components (PCs). PC1 and PC2 cumulatively explained 93.0 % and 81.5 % of the variance in Porton and Bentley, respectively. In both datasets, PC1 is associated with weak positive scores for the 8 morphometric traits that represent linear dimensions (excluding lateral and anterior aspect ratios), indicating that this component is representative of macro-moth size. PC2, meanwhile, is associated with strong positive scores for forewing length and abdomen length, but negative scores for aspect ratios and thorax measurements, indicating that this component is representative of macro-moth shape (higher values mean larger wings, longer abdomens, smaller thoraces and relatively deep thoraces compared to body length or thorax width).

In an attempt to link moth morphometrics with bioscatterer classes, we used redundancy analysis (RDA) in the vegan package (Oksanen et al., 2020) in R, version 4.1.2 (R Core Team, 2021) to explore the relationship between the derived macro-moth community traits and the relative abundance of each BCA cluster classified by our algorithm. We performed analysis using the input from Bentley Woods where there were 4 clustering levels at level 2 of the cluster tree, and Porton Down III, where we found 2 clusters at level 1 of the cluster tree. The significance of this model, its component axes, and its terms, was then assessed via permutation tests using the *anova.cca* function in the vegan package (Oksanen et al., 2020) in R.

2.6. Diversity and abundance comparison

Finally, we tested whether the diversity and abundance of moths caught at light traps could be predicted based on the diversity and abundance of bioscatterer clusters in the radar data. The abundance of bioscatterer clusters represents the number of voxels within the radar scanning volume that were assigned to one of the bioscatterer clusters in the BCA, and so is roughly equivalent to the volume of the scanned air column that is dominated by insects. We conducted the analysis for Bentley Woods (33 nights) and Porton Down III (16 nights) separately. We calculated the Shannon diversity of the macro-moth communities using the *diversity* function in the vegan package (Oksanen et al., 2020). We then calculated an analogous metric for the radar bioscatterer communities, treating each BCA bioscatterer cluster as a separate “species”. We then calculated the total abundance of macro-moths on

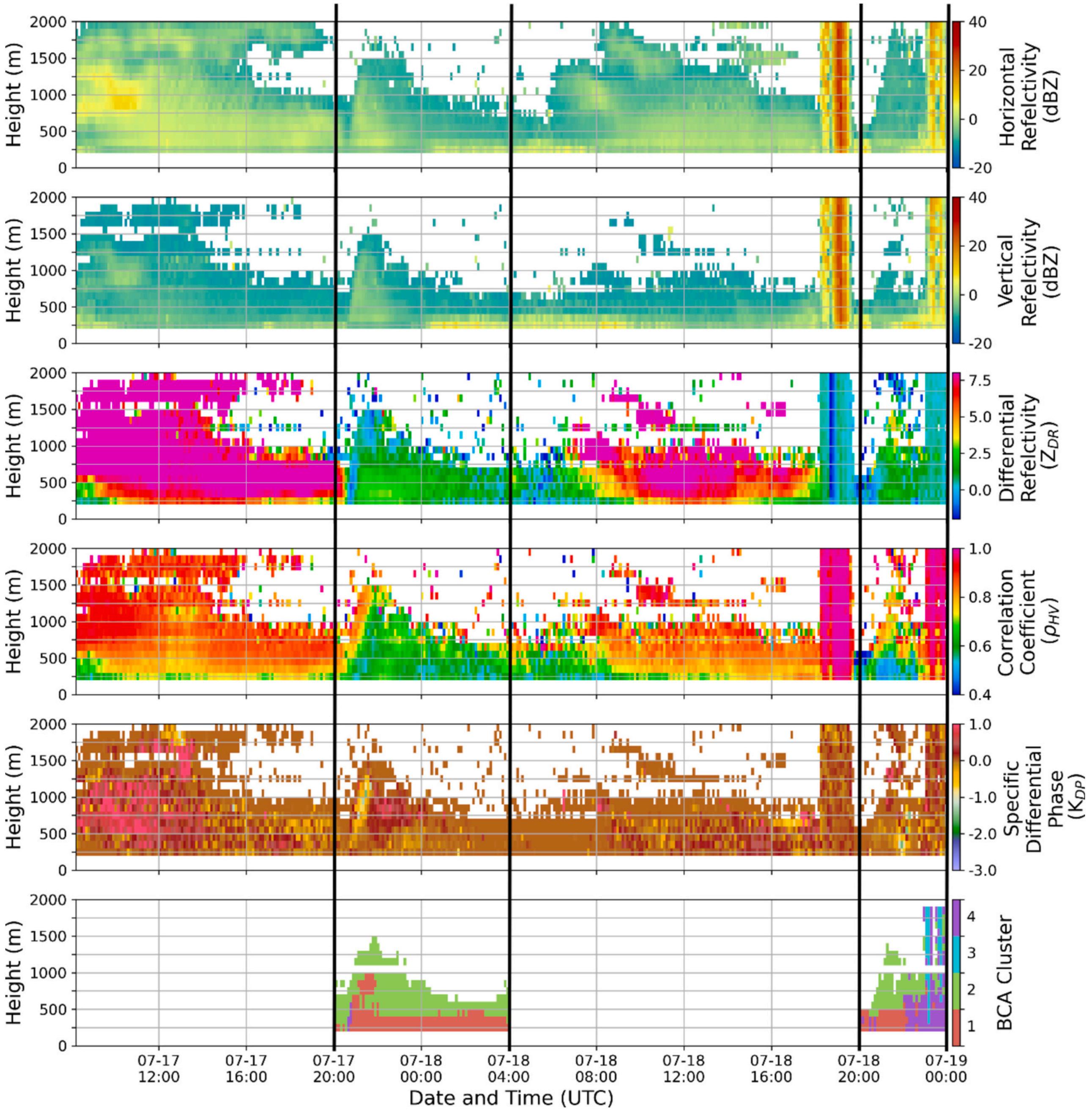

Fig. 3. An example of two days' column vertical product (CVP) observations and correspondent clustering results for the Bentley Woods location.

each night and the summed abundance of all BCA clusters per column per night. The summed abundance of BCA clusters corresponds roughly to the volume of the CVP that is dominated by insects, and we treat this value as a proxy for insect abundance within the column. Spearman's rank correlations were used to compare our measures of abundance (insect counts from traps vs. summed BCA clusters) and diversity (Shannon diversity of moth catches vs. Shannon diversity of cluster compositions) due to deviations from parametric assumptions in some cases. We conducted these correlations on the two sites separately.

3. Results

3.1. Bioscatterer classification algorithm

The application of the BCA to the Porton Down III and Bentley Woods datasets resulted in the hierarchical clustering trees shown in Fig. 4. The characteristics of the final clusters are presented in Fig. 5 as the mean and variability of the input variables. Information about the altitude and the timestamp of each voxel is kept in the data but not used by the algorithm. Fig. 5A(v) and B(v) show the mean altitudes and their variance for each cluster. The time-series of the final clusters at Bentley Woods demonstrates good connectivity of the voxels belonging to the same cluster in both sites, as might be expected if nocturnal insect communities were changing in a gradual way through the night (Fig. 3F).

The clusters detected by the BCA and their characteristics depend on the choice of the input variables and on the voxels selected for the input dataset as the algorithm is fully data-driven. Thanks to the hierarchical structure, it is easy to follow each step of the iterative process, trace the splits at each level and check the characteristics of the clusters. The first split (Fig. 4) separates the voxels with predominantly meteorological scatterers from the voxels with non-meteorological ones; according to the characteristics of the clusters at Level 1. This can be seen in the much

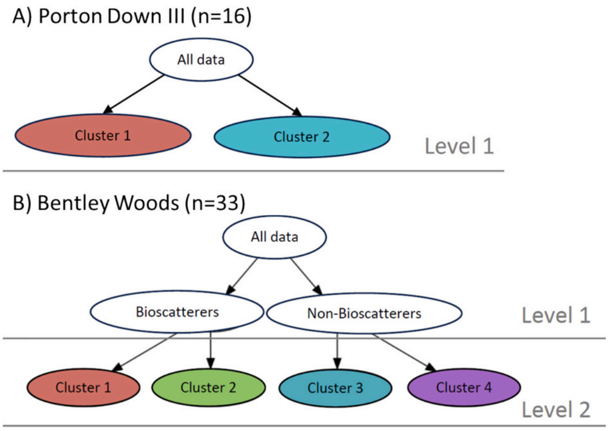

Fig. 4. Classification tree created by the application of the bioscatterer classification algorithm (BCA) to (A) 16 nights of NXPol-1 observations at Porton Down III and (B) 33 nights of observations at Bentley Woods. The Porton Down III clustering separated data only at the first level to contain what are likely to be bioscatterers and non-bioscatterers. At Bentley Woods, there were four clusters at level 2 that are likely two clusters of bioscatterers and two clusters of non-bioscatterers. The colour of the tree label of the final clusters corresponds to the colours used in the following figures.

higher copolar correlation (ρ_{HV}) values (0.9–1.0) in the meteorological clusters compared to values in the range of 0.5–0.8 in the non-meteorological clusters (Fig. 5A(iii) and B(iii)).

The Porton Down III site was not split further, remaining with two clusters. The Bentley Woods site was split again, and both meteorological and non-meteorological clusters were divided into two subclusters at Level 2 (Fig. 4B). The non-meteorological cluster was divided into one subcluster with a lower mean Z_{DR} value (1.2 dB) and a lower mean ρ_{HV} (0.56), compared to another with a mean Z_{DR} value of 1.9 dB and a slightly higher mean ρ_{HV} of 0.69. The last cluster also has lower reflectivity values (both Z_H and Z_V) which occur either with smaller sizes of the observed species or with fewer insects in the observed volume. The combination of higher mean Z_{DR} and ρ_{HV} values suggests that scatterers are more elongated and more uniform inside the observed volume.

While the outcome of the clustering varied across sites in terms of depth, the clusters are largely consistent when compared across the two sites. We explored the similarity between two clusters on the first level of the clustering analysis (Fig. 4) at Porton and Bentley (Fig. S1B,C). The two clusters show a strong similarity (Fig. S1E), suggesting that the same separation between bioscatterers and non-bioscatterers occurred at both sites. We also analysed the clustering for the two sites when pooled together and the results are similar. Clustering for the two sites combined produced three bioscatterer and two hydrometeorological clusters as a final set of clusters (see Fig. S1A). The same first two clusters arise in level 1, followed by a highly similar set of four clusters at level 2 in Bentley and the pooled dataset (Fig. S1D). For more details, see

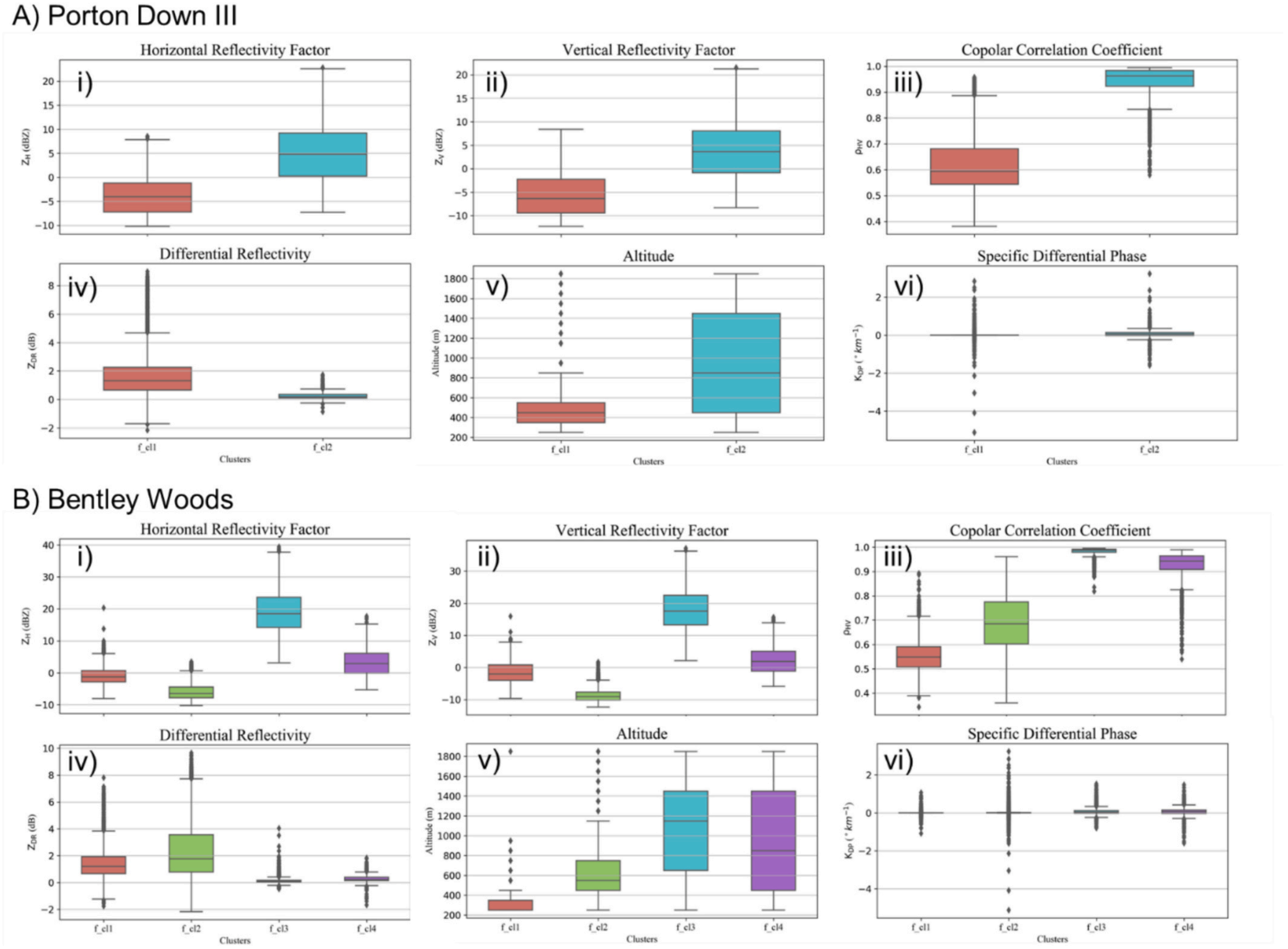

Fig. 5. Characteristics of cluster centroids in input data for (A) Porton Down III and (B) Bentley Woods, as shown in Fig. 4.

Supplementary materials analysis 1.

We further explored the similarity between the clustering achieved using the spatially-limited CVP approach and the QVP (whole domain) approach from a previous study (Lukach et al., 2022). When the medoids of the clusters in the original radar variables are compared, we find evidence for 4 out of 5 CVP clusters from the pooled data also being found in the clustering of QVP data from that earlier work (see Fig. S4). Such a finding is significant, as it suggests that the clusters are representative of regional communities that vary in relative abundance in different locations. For more details, see Supplementary materials analysis 2.

Note that each cluster is split in the principal components (PC) space, calculated from the subset of data points involved in that splitting step. Transitioning to PC space reduces dimensionality at each split, allowing us to focus on the most significant differences within each cluster. Only the first principal components which account for 70 % of the total variation in the data to be split are used. Examination of the coefficients of the PCs revealed that K_{DP} played an insignificant role in their formation whilst the other variables contributed with a varying but significant role.

3.2. Moth and bioscatterer cluster traits

Since Porton Down III only had a single bioscatterer cluster, we focused on Bentley Woods for the community analysis. When we attempted to explain the composition of bioscatterer clusters in the radar data based on Bentley Woods moth traits using RDA, we found evidence for an association between the moth trait data and the variation in cluster composition. When analysing the Level 2 clustering (two bioscatterer and two hydrometeorological clusters), we found that there was no significant association between the PC1 of community weighted mean trait values (corresponding to overall size; RDA result: F-statistic $= 1.451$, degrees of freedom $= 1{,}29$, $p = 0.250$) but that there was a significant association between bioscatterer cluster structure and PC2 (corresponding to shape; $F_{1,29} = 7.818, p = 0.003$). These results suggest that the relative abundance of the bioscatterer clusters may be related to the average shape of macro-moths sampled per night by the light traps.

3.3. Diversity and abundance comparison

There was a statistically significant positive relationship between taxonomic diversity at Bentley and an analogous measure of diversity based on the relative frequencies of BCA clusters (Spearman's $\rho = 0.486$, $p = 0.005$, Fig. 6A). We also find a statistically significant correlation between the abundance of macro-moths caught at light traps across both sites and the abundance of bioscatterer clusters classified based on the BCA (Spearman's $\rho = 0.490$, $p = 0.004$, Fig. 6B). However, the association between BCA and light trap abundance was not significant at Porton Down with a smaller sample size (Spearman's $\rho = 0.368$, $p = 0.161$, Fig. 6C). This finding suggests a degree of localisation of the phenomena described here, and the CVP approach would be most useful if the data showed differences between the light trap sites that could be explained independently by local radar data. When we compared the 15 nights for which data were available for both trapping locations, there was no significant correlation in abundance ($R = -0.088$, $p = 0.756$) but a significant correlation in diversity ($R = 0.725$, $p = 0.002$) between the two sites (Fig. S5). This result suggests that the two locations vary in abundance but have covarying diversity and that the radar-derived measures of abundance may be able to provide proxy measures of abundance in both sites. See supplementary information analysis 3 for more details.

4. Discussion

We demonstrate and validate a novel method for the analysis of weather surveillance radar data that aggregates the complex geometry of radar data within the scanning volume at scales relevant to ecological analyses. The results show that radar data can be processed using unsupervised classification algorithms to differentiate meteorological from biological scatterers. There is a statistically significant correlation between the biological radar data and patterns of abundance of insects collected at ground level, with less clear associations between diversity of insects and diversity of the bioscatterer clusters, suggesting that there are strong, biologically meaningful relationships to be derived from radar data. Importantly, by working at scales of ca. 2.5 km, WSR data can be applied to ask important ecological questions retrospectively, and at high spatial and temporal resolutions.

As an important first step, the BCA split the data into meteorological and non-meteorological clusters at the Level 1 of the hierarchical tree (Fig. 4). The BCA also showed the same behaviour processing of the QVP data in Lukach et al. (2022). The ability of the algorithm to divide these two types of scatterers in the weather radar data comes from a pronounced signature of the non-meteorological data in several polarimetric variables, such as copolar correlation coefficient and horizontal and vertical reflectivities (Gauthreaux and Diehl, 2020). While standard algorithms for the discrimination of meteorological and biological scatterers rely on thresholds of certain raw radar variables (Gauthreaux et al., 2008), our methods demonstrate an alternative approach that recovers similar classification without a priori parameterization.

The CVP approach represents an advance over the QVPs (Quasi

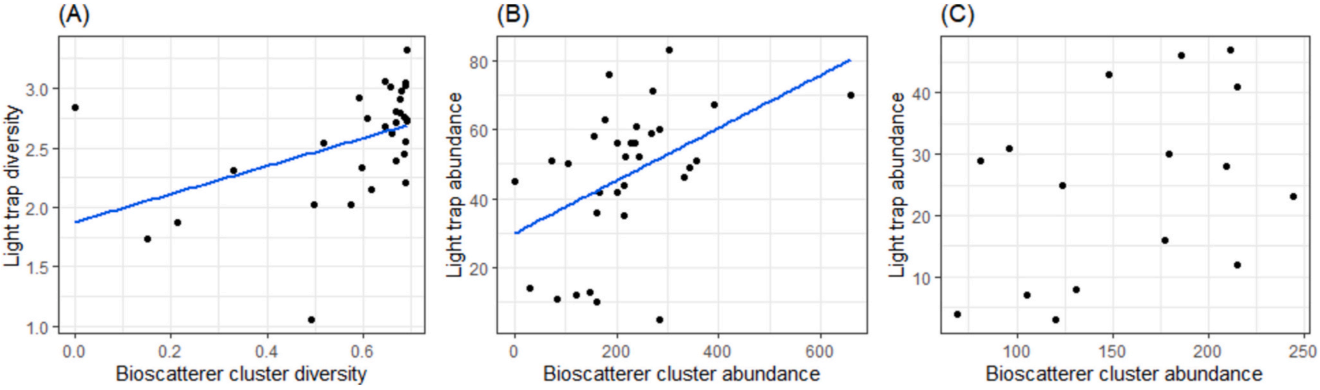

Fig. 6. Scatterplots showing the relationships between the summed abundance of BCA bioscatterer clusters, and the summed abundance of moths caught at light traps per night over (A) Bentley Woods, and (C) Porton Down III, and between Shannon diversity of both the macro-moth community and the BCA cluster community present over (B) Bentley Woods. Regression lines show significant relationships (although lines should be considered indicative of trends because non-parametric correlations were used to determine relationships). Diversity could not be calculated for the bioscatterer clusters at Porton Down III because there was only a single cluster.

Vertical Profiles) in Lukach et al. (2022). QVPs in that earlier study were generated based on data from one scan elevation and were a vertical representation of the mean values from a large scanning domain (around 60 km radius) especially at the altitudes close to 2 km. The columns of volume data used in the CVPs presented here better represent the local situation over the light traps and address issues of grain size and data quality to provide a radar product approaching site-level data (Anderson, 2018). Our analysis of the differences between the Porton Down III and Bentley Woods sites provide evidence that smaller-scale radar data analysis can yield meaningful insights into spatial heterogeneity in nocturnal insect communities. Combined with the exceptional temporal resolution of radar observations, our methods present a robust approach for the high-resolution study of aerial organisms at ecologically meaningful scales.

As in Lukach et al. (2022), we show strong evidence for positive relationships between both the diversity and the abundance of nocturnal macro-moth and aerial bioscatterer communities; indicating that bioscatterer signals generated using CVPs, as with those generated using QVPs, can be used as proxies for surface-level nocturnal insect biodiversity. Furthermore, we were able to link the relative abundance of bioscatterer clusters in the air with the prevalence of certain insect morphotypes within light trap samples, a result that we were unable to produce in previous analyses (Lukach et al., 2022). This suggests that the BCA can differentiate broad insect morphotypes using WSR outputs, but that a more localised WSR product is required to extract information concerning insect morphology and, therefore, potentially taxonomy from WSR data. Previous studies have only been able to characterise insect morphotypes using VLR data in combination with the scatterers' RCS, wing beat frequency, and/or mass (e.g., Chapman et al., 2002; Hao et al., 2020; Hu et al., 2018; e.g., Stepanian et al., 2020; Wood et al., 2006; Wood et al., 2009). There remains the possibility that the radar-derived insect communities and the ground-level light trap catches are both responding to the same environmental drivers of activity without necessarily arising from the same, shared pool of animals. However, other preliminary data suggests that the relationship between ground-level insect catches and radar-based estimates of aerial insect abundance weakens with increasing altitude (Mungee et al., in prep), which would be suggestive of direct causal links between the two data sources.

Further development of the CVP approach using a more diverse set of input data has the potential to generate a regional pool of clusters that could then be used to classify any given set of radar observations. Such a cluster dataset would act as a classification system that would give WSR a similar analytical power that could be validated against a broader range of sites in different geographical and taxonomic contexts. In particular, while we have restricted ourselves to nocturnal insects due to the availability of high quality validation data, we could also extend our current analysis to include measures of diurnal communities that may have similar functions but different species composition (e.g. Devoto et al., 2011), allowing us to assess the BCA's ability to differentiate bioscatterers from hydrometeors using data representing a much more diverse community of aerial biological scatterers. The data accumulated by the RIS suction trap network, in particular the bycatch associated with each of the traps, would allow us to look at correlations between diurnal measures of insect diversity and abundance and the equivalent data for diurnal bioscatterers generated using CVPs and evaluate correlations with long term standardised monitoring (Bell et al., 2020). Beyond the site level, one exciting possibility is to identify different types of insects in a larger extent of the PPI or volume data from the WSRs through the assignment of these voxels to the cluster centroids achieved by the BCA. Such an approach would produce a near-continuous insect community surface dataset that spanned the radar scanning range at least to the limits of where insect scatterers can be reliably detected (30-40 km by our estimation). Such an insect community dataset would provide a valuable complement to stacked species distribution models (Guisan and Rahbek, 2011), that have issues with the incorporation of biotic interactions (e.g. Gavish et al., 2017), or macroecological predictions of diversity and turnover (e.g. Hawkins et al., 2003).

In addition to expanding the spatial scale, there is also the potential to exploit the fine temporal resolution of radar observations. Pollution releases, heatwaves, and other sudden environmental changes occur on timescales that often cannot be captured by standard ecological monitoring, and therefore the attribution of ecological change is difficult (Raiter et al., 2014). However, WSRs been shown to be able to capture such phenomena, such as the responses of birds to firework displays (Shamoun-Baranes et al., 2011). Such an approach, combining site level measurements with high temporal resolution could allow for the study of pulse stressors beyond heatwaves (e.g. Harris et al., 2018) to include phenomena such as individual pesticide applications, short-term floods, or the sudden removal of habitat (e.g., tree felling). What is more, the archiving of WSR observations means that such questions can be asked in retrospect.

5. Conclusion

Here, we weave together two methodological advances – a columnar vertical product (CVP) that addresses complexities of radar data geometry and a Bayesian hierarchical classification model to extract biological meaning from radar observations – to produce an ecologically-relevant weather radar data product. We validate this product using field observations of nocturnal moths to show a significant relationship not only with abundance but also with diversity of insects. While more work needs to be done to apply the CVP approach to the full range of ecological questions, this analysis represents an important stage in the merging of radar aeroecology into the mainstream of ecological analysis and biodiversity conservation.

Author contributions

RRN, CH, WEK, ED and JWC conceived the research; ML, FIA, LB and RRN processed and analysed the radar data; TD and WE collated moth traits data; TD and CH analysed the ecological data; all authors contributed to the writing of the paper.

CRediT authorship contribution statement

Maryna Lukach: Writing – review & editing, Writing – original draft, Software, Methodology, Formal analysis, Data curation. **Thomas Dally:** Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation. **William Evans:** Formal analysis, Data curation. **Elizabeth J. Duncan:** Writing – review & editing, Conceptualization. **Lindsay Bennett:** Writing – review & editing, Formal analysis, Data curation. **Freya I. Addison:** Writing – review & editing, Formal analysis, Data curation. **William E. Kunin:** Writing – review & editing, Conceptualization. **Jason W. Chapman:** Writing – review & editing, Conceptualization. **Ryan R. Neely:** Writing – review & editing, Supervision, Project administration, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Christopher Hassall:** Writing – review & editing, Writing – original draft, Supervision, Project administration, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors have no conflicts of interest to declare.

Data availability

All radar observations from NXPol-1 used in the analyses presented in this work may be found at: Bennett (2020). The CVP calculation code is available at https://github.com/cemac/VP_Extraction. Moth morphometric data are available at https://catalogue.ceh.ac.

uk/documents/3a813bd9-59ae-476e-a170-ab83fe1587b2, with additional moth thorax measurements in Table S2 of Lukach et al. (2022). The CVP clusters counts, moth community data, and all R code associated with the analysis, along with Python code and data to produce Fig. 3 and Fig. 5, can be found on Figshare (https://doi.org/10.6084/m9.figshare.27682368).

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecoinf.2024.102901.

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