Utilizing Weather Radar Data to Discover Bird Activity Hotspots in Southeast Queensland

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Abstract

Weather radars play a pivotal role in the identification of avian hotspots, a critical step toward enhancing bird conservation efforts and aviation safety. This study leverages a year's worth of data (2021) from Radar 66, strategically positioned in Southeast Queensland. Utilizing the Bio-Rad package within the R programming language framework, we successfully identified over 1.6 million birds migrating through the radar coverage area. Further, a programming script was developed to distill thousands of weather scans into a singular seasonal average by filtering and averaging pixel values, resulting in the creation of four detailed seasonal maps that highlight regions of peak bird activity. Notably, these avian hotspots include Ormeau Hills, Cedar Creek Conservation Park, Tamborine National Park, and several other key locations. Through this work, we underscore the significance of integrating technological tools and ecological data to pinpoint critical habitats, facilitating targeted conservation strategies and mitigating avian-related risks to aviation.

Keywords: weather radar, bird migration, BioRad, bird hotspots, aviation safety, conservation, Queensland

Introduction

The advancement of aviation necessitates a parallel focus on the conservation of avian species. Identifying bird hotspots in the airspace is therefore crucial for bird conservation and aviation safety. Central to this identification process are weather radars, which employ electromagnetic radiation to detect objects in the atmosphere (Kingsley and Quegan, 1999). While commonly associated with tracking precipitation, these radars also have the capability to detect a range of other objects, including insects, birds, buildings, and airplanes (Dokter et al., 2019).

The challenge lies in accurately reading and extracting biological signals from weather radar data (Dokter et al., 2019). Complexity arises due to the file formats used to store meteorological information. Specifically, this data is encapsulated in polar volumes, which are comprehensive datasets generated by weather radar systems. Polar volumes are the result of weather radars executing a series of scans across various angles of elevation (Dokter et al., 2019). Each scan captures data at a particular elevation and together, the scans form a polar volume. The polar volume methodology provides a multidimensional perspective of atmospheric conditions, yielding essential insights into weather patterns. Importantly, each radar scan captures one or several scan parameters, which are distinct types of measurements that each offer a unique view of the atmosphere's state. Fortunately, BioRad, which is a package in the R programming language, provides specialized functions and algorithms needed to extract biological signals from radar data (Dokter et al., 2019, 2011). The aim of this paper is to successfully apply the BioRad package to read one year's worth of data from a weather station to calculate aggregate data and to identify bird hotspots.

The successful mapping of identified bird hotspots will enable the development of more targeted and effective wildlife management strategies. In the context of aviation safety, bird hotspot identification may save millions of dollars in bird and aircraft collisions. The synergy between bird conservation and aviation safety creates a positive feedback loop, where actions in one area reinforce and amplify benefits in the other (Dolbeer, 2020). Aggregate data that is presented in this paper will therefore pave the way for larger research projects involving multiple weather radars and multiple years of data, providing a multidimensional impact on bird conservation and aviation safety.

This paper details related work in the field. It then describes the method used to identify and map bird hotspots. It also explains how aggregate data was calculated. Findings will then be showcased, and the results will be discussed. The full repository of findings is publicly available on GitHub for replication and further research. Finally, recommendations for future research in utilising weather radar data will be provided to contribute to existing bodies of research.

Literature Review

The BioRad package, first introduced by Dokter et al. (2019), has since been foundational in numerous ground-breaking studies. BioRad has thus facilitated a wide range of applications, particularly in the analysis of weather radar data for avian studies. Rosenberg et al. (2019) demonstrated the package's utilities on a grand scale, employing data from multiple radar stations over several decades to document a persistent decline in North American bird populations. Similarly, Nilsson et al. (2019) processed data from 84 European weather radar stations, uncovering patterns of nocturnal migration. A subsequent study by

Nilsson et al. (2021) leveraged this data to predict bird strike risks at commercial airports by estimating migration intensities. La Sorte et al. (2019) explored the impacts of climate change on bird migration, using weather radar data to forecast changes in wind assistance and its effects on migratory routes. Van Doren et al. (2023) combined weather radar data with acoustic sensors to validate migratory patterns, while Elmore et al. (2021) established a strong link between bird collision incidents in the United States and migratory variables. Gangoso et al. (2020) investigated how climatic factors affect bird populations through the lens of weather radar data. Abbott et al. (2023) utilised weather radar data to track bird migration arrival times. Additionally, Kranstauber et al. (2020) utilised 20 weather radars to delineate the spatial distribution of bird movements, while Hoekstra et al. (2024) identified the impacts of firework celebrations and bird flight. Finally, Werber et al. (2023) developed a radar classification tool to identify large scale bat migration patterns, harnessing weather radar data for their analysis. What all these papers have in common is the use of BioRad to simplify the analysis of weather radar data and the extraction of biological signals.

But the use of BioRad is not specifically mandatory in weather radar applications. Artificial Intelligence has also been used to assist in weather radar data analysis. Zewdie et al. (2019) used weather radar data and machine learning to estimate daily pollen concentration in the atmosphere. Cui et al. (2020) used deep learning to extract animal migration patterns from weather radar data. MistNet, a convolutional neural network developed by Lin et al. (2019), has been influential in discriminating precipitation from biological signals in weather radar data. These papers are not in any way the exhausted list of related works to our paper but have been selected to highlight the relevancy and application that weather radar data offers.

Method

Dataset

Radar 66 is a weather radar station ideally situated between Brisbane and the Gold Coast in Queensland, Australia. The choice of Radar 66 for our study was driven by its proximity to our research facility, making it a practical selection. This station is part of the extensive network of weather radars operated by the Australian Bureau of Meteorology. For our research, we focused on analysing data exclusively from the year 2021. A pivotal element of our research approach was the use of raw data, which led us to utilize the Level 1 dataset for 2021, as described by Soderholm et al. (2019). This dataset consists of zip files containing polar volumes of data, which are unprocessed and presented in spherical coordinates following the ODIM model, encoded in the HDF5 format. During our analysis, we noted occasional missing data for specific days within the dataset, which introduced some gaps in our findings. Nevertheless, it is crucial to emphasize that these gaps did not substantially affect our ability to identify and analyze patterns of avian hotspots and activities.

Calculating Aggregate Data

Following the recommendations of Dokter et al. (2019), our analysis focused on migration traffic (MT). Migration Traffic offers a measure of the total number of migrants passing through a specific area within a given period. To complement these metrics, we incorporated additional parameters available through BioRad, and we present our findings on GitHub. These additional metrics, while not the main focus of our current study, present avenues for future research. The visualization of these supplementary quantities underscores their potential relevance in advancing our understanding of migratory patterns.

Polar volumes were initially ingested by BioRad and promptly processed into vertical profiles leveraging the Vol2bird algorithm, as detailed by Dokter et al. (2011). We adhered strictly to the default settings for all function parameters, setting the radar cross-section to 11 cm^2 in accordance with recommendations from Dokter et al. (2019). Subsequently, these vertical profiles were organized into a chronological series, facilitating the construction of vertically integrated profiles. This step was crucial for plotting the migration traffic. Notably, the entirety of our data processing pipeline was executed using the native functions provided by BioRad, ensuring a streamlined and efficient analysis process.

Identifying Bird Hotspots

To gain a visual understanding of the geographic origins of our aggregate data, we turned to the mapping tools provided by BioRad. Advances in spatial imaging technology have introduced plan position indicators, which offer spatial representations of vertically integrated density from all radar elevation scans (Kranstauber et al., 2020). While these indicators are the preferred method for visualizing bird density, technical challenges with our dataset necessitated an alternative approach.

Instead of utilising plan position indicators, we selected the first five elevation scans from each polar volume for analysis, implementing weather filtering techniques. This selection was based on the observation that bird activity is more prevalent at lower altitudes (Scott, 2011), with chosen angles at 0.5, 0.9, 1.3, 1.8, and 2.4 degrees. For each of these scans, we measured reflectivity (DBZH) and applied a widely used filtering method to distinguish between precipitation and avian signals, setting a correlation coefficient threshold of 0.95 to exclude precipitation (Dokter et al., 2019). Despite some instances of precipitation contamination, this did not hinder our analysis.

To effectively capture bird migration patterns without overwhelming our computational resources, we adopted a strategic approach to data collection from our year-long dataset. Recognizing that analysing every polar volume, which is generated every six minutes, would be computationally intensive, we decided that taking scans every three hours would be a sufficient compromise.

Hence, for each day throughout the year, we collected scans at eight specific times: 12am, 3am, 6am, 9am, 12pm, 3pm, 6pm, and 9pm. This approach resulted in a dataset that, while streamlined, still robustly represents the patterns of bird activity across different times and seasons. With approximately 3600 scans per season, this method allowed us to project these scans onto a base map, analyzing the reflectivity at the selected angles and times.

To distil seasonal bird migration patterns from our mapped scans, we developed a Python script aimed at calculating the average DBZH values for each pixel across a season's worth of data. The script begins by defining a threshold range for DBZH values to isolate relevant data from the base map. An accumulator array is then initialized to zero, serving as a repository for summing the pixel values across all images. As the script iterates through the season's mapped scans, it adds the current image's pixel values to the accumulator. Upon completing the loop through all images, the script calculates the average pixel value by dividing the accumulated sum by the total number of images processed. These average values are then superimposed onto an empty base map, effectively condensing thousands of individual scans into a single, comprehensive map. This refined mapping enables us to pinpoint geographically where birds are most frequently found during each season, thus identifying significant avian hotspots with precision.

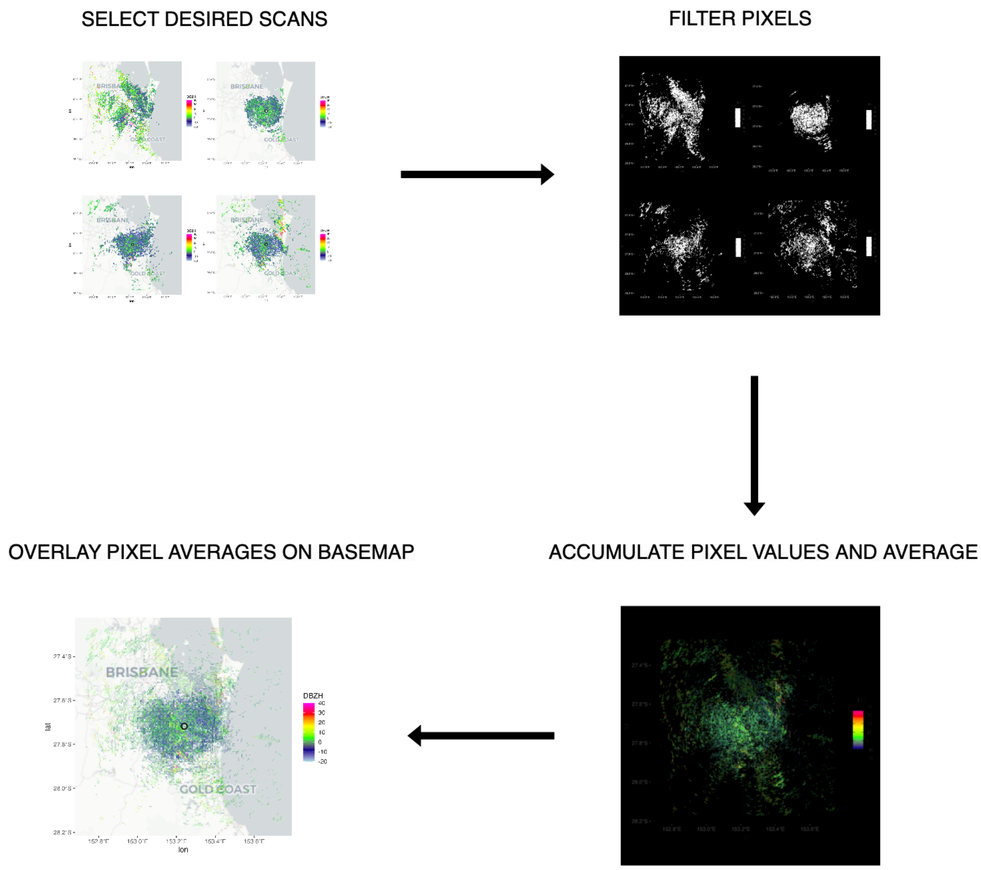

Figure 1: Process flow for aggregating avian radar scan data.

Results

The seasonal averages of bird activity over the Brisbane and Gold Coast regions depict distinct variations in migration patterns throughout the year. During the summer (Figure 2), there's a moderate level of activity, with notable concentrations around the Brisbane area. In autumn (Figure 3), the radar data shows a slight decrease in movement within the same regions. Winter (Figure 4) brings a further reduction in detections, with minimal activity. Contrastingly, spring (Figure 5) sees a resurgence in activity, with a substantial increase in detections. The data suggests a seasonal fluctuation in migration however, what remains the same are certain regions on the map containing high levels of bird activity, indicating hotspots. Over the course of the year, the number of migrants fluctuates each month, with the total number of migrants surpassing 1,600,000 at the end of the observed period.

Table 1: *Migration traffic by month.*

Month	Cumulative Migration Traffic (km)
January	68,000
February	375,000
March	235,000
April	216,000
May	115,000
June	51,000
July	45,000
August	90,000
September	190,000
October	120,000
November	72,000
December	60,000
Total	1,637,000

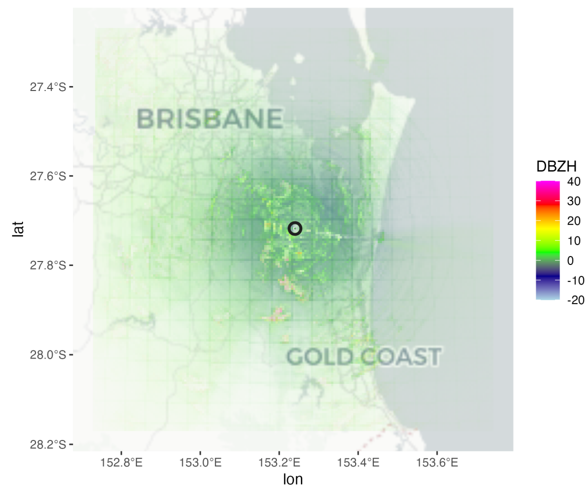

Figure 2: Summer Average

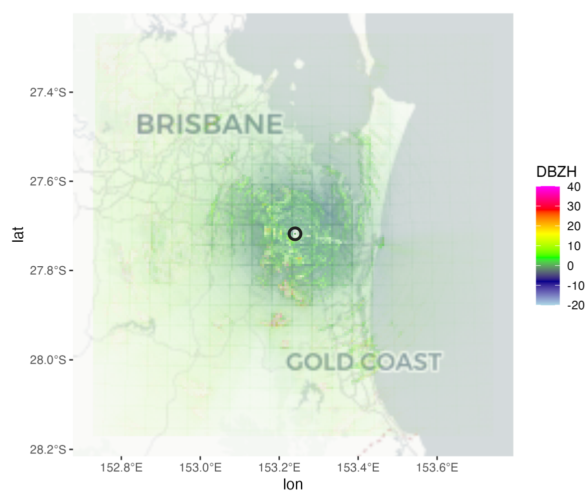

Figure 3: Autumn Average

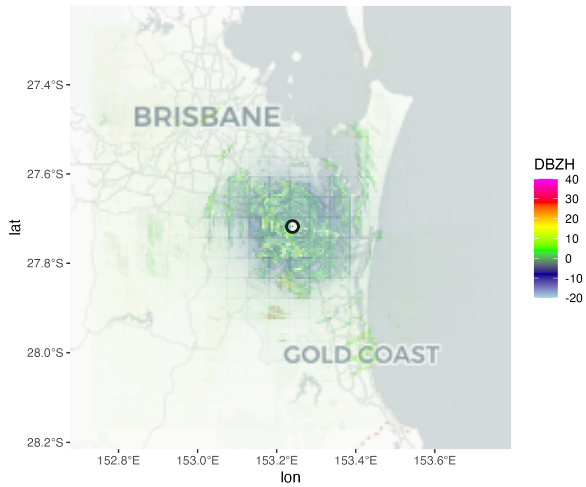

Figure 4: Winter Average

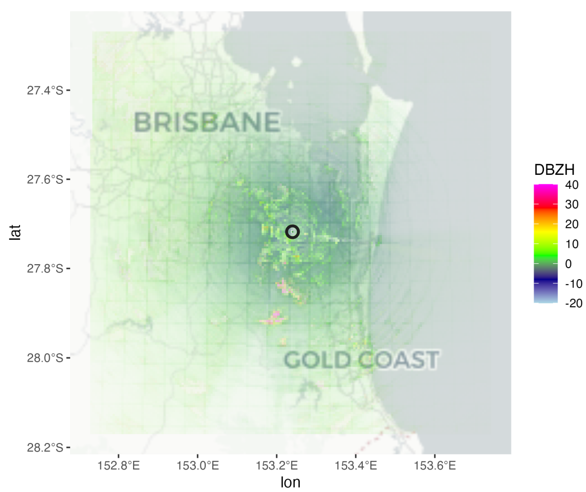

Figure 5: Spring Average

Discussion

Migration Traffic

The patterns observed in the migration traffic data presented in Table 1 align well with established understandings of avian migratory behaviors. These behaviors are influenced by a combination of factors, primarily related to evolutionary adaptations that optimize survival and reproductive success (La Sorte et al., 2016).

One of the primary reasons birds migrate is to exploit seasonal abundance of food resources. In temperate and polar regions, food availability changes drastically between seasons, prompting birds to move to areas where food is plentiful (Komal et al., 2017). Additionally, migration allows birds to take advantage of milder climates for breeding and rearing their young. During the harsh winter months, food scarcity and lower temperatures in higher latitudes drive birds towards the equator, where conditions are more favorable. Conversely, as spring arrives, birds return to higher latitudes to utilize the abundant summer resources for breeding.

In terms of aviation, bird migration poses significant risks. The data indicates peak migration traffic in late summer/early autumn and spring, coinciding with the times when birds cross flight paths of aircraft, increasing the likelihood of bird strikes. Bird strikes can cause substantial damage to aircraft and endanger the lives of passengers and crew. As a result, this data is crucial for informing flight planning and aviation safety measures. Airports and air traffic control units may use this information to adjust flight schedules, routes, and implement bird-detection radar systems to mitigate the risk of bird strikes.

For wildlife conservation, understanding migration patterns is vital for the protection of migratory bird species. The data can guide conservation efforts by identifying critical times of the year when birds are on the move, which is essential for creating and enforcing policies that protect important habitats along migration routes. Conservationists can work to ensure that key stopover sites, where birds rest and refuel during their long journeys, are preserved and managed appropriately. Additionally, this information can be used to monitor changes in migration patterns that might signal broader ecological issues, such as climate change or habitat loss, and drive initiatives to address these challenges.

Identified Hotspots

The delineation of hotspot regions in Figure 6 is corroborated by satellite imagery, revealing a convergence of avian activity within these zones. Within Figure 7, we observe a mix of urban settlements and patches of greenery, likely providing a mosaic of resources such as food, shelter, and nesting sites. This juxtaposition may be conducive to urban-adapted species that thrive at the human-nature interface. In contrast, Figure 8 showcases a more varied topography with forested areas and elevation changes near Tamborine Mountain, which might cater to a different ecological community of birds, potentially those requiring larger territories and specific habitats.

The predilection of birds for these locations may be attributed to several factors, including the availability of diverse feeding opportunities, the presence of water bodies, safe breeding areas, and migratory pathways. Additionally, the less disturbed natural environments, especially in Figure 8, offer sanctuary from urban stressors.

Leveraging this information has multiple applications. Conservation efforts can be concentrated in these hotspots to ensure the protection of avian biodiversity. Urban planners and wildlife managers can use this data to create green corridors that facilitate bird movement between urban and natural landscapes. Advancements in aviation such as drone technology, can utilise these hotspots to avoid bird striking and collisions. Furthermore, these hotspots could serve as key areas for citizen science and educational initiatives to promote birdwatching and conservation awareness. Identifying such regions also helps predict and mitigate potential human-wildlife conflicts, especially in urbanized areas. Ultimately, this knowledge can inform policy decisions and promote cohabitation strategies that balance human development with the intrinsic value of our natural co-inhabitants

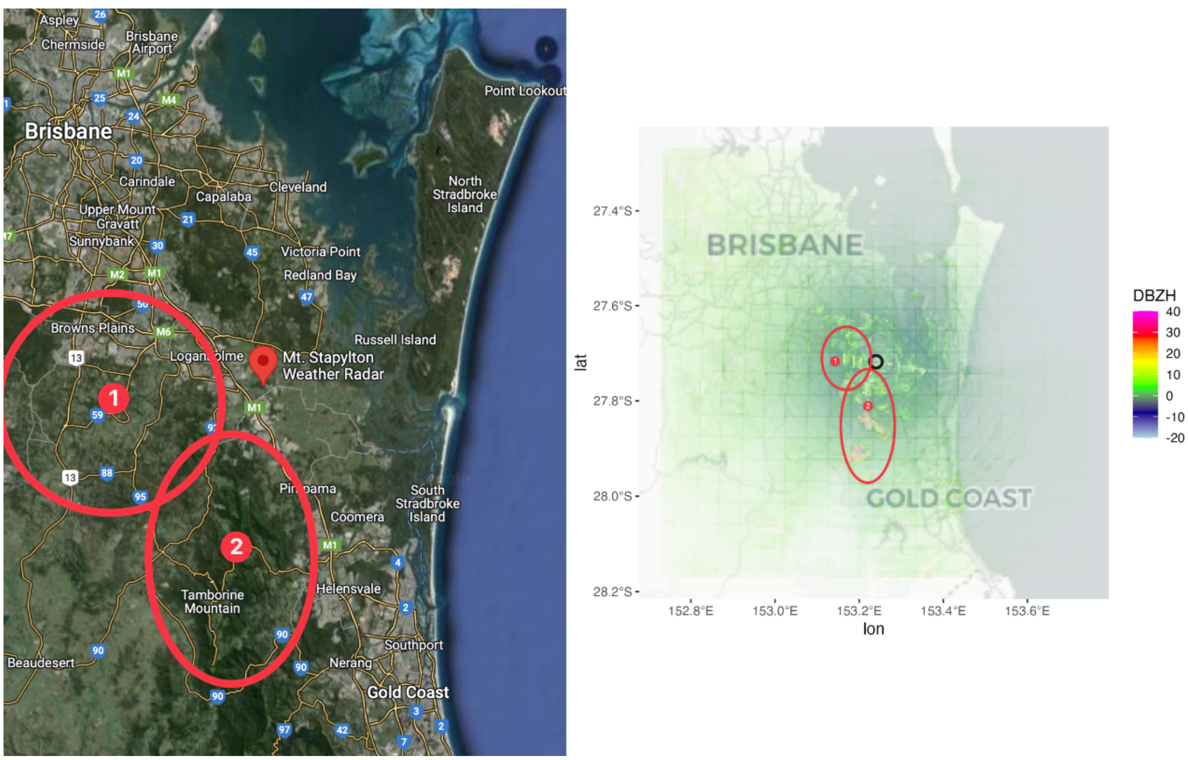

Figure 6: Identified Regions of Bird Hotspots

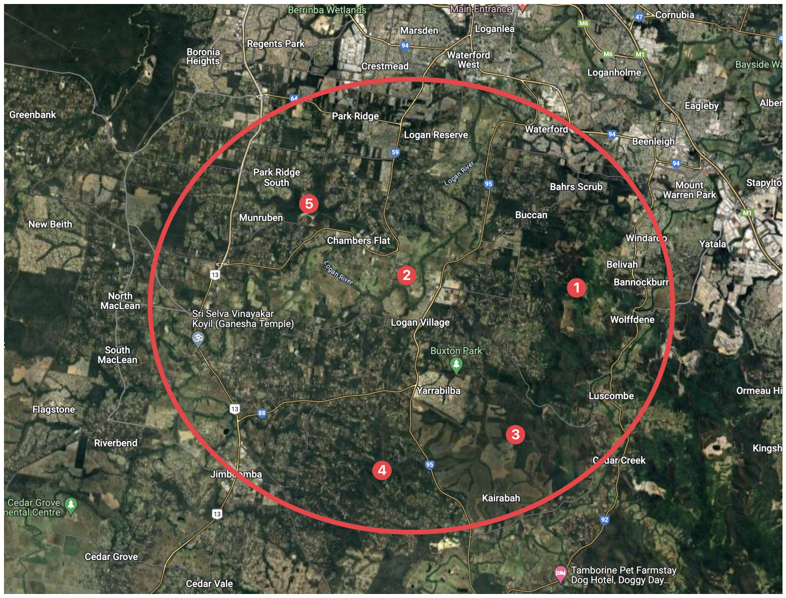

Figure 7: Likely Hotspots within Region 1

Figure 8: Likely Hotspots within Region 2

Conclusion

In conclusion, this research has elucidated the significant potential of weather radar technology in identifying avian hotspots, offering promising avenues for enhancing bird conservation strategies and aviation safety. Through the analysis of data from Radar 66, situated between Brisbane and the Gold Coast, we have mapped out critical bird migration pathways, identifying key hotspots in Ormeau Hills, Cedar Creek Conservation Park, Willow Vale, Tamborine National Park, Buccan, and the areas surrounding Logan Village. Our methodology, leveraging the BioRad package and custom Python scripting for data analysis, demonstrates the utility of combining meteorological data with biological research to reveal patterns of bird migration.

However, it is essential to acknowledge the limitations encountered in this study, notably the potential pollution of data by non-avian biological signals such as insects and bats. These findings underscore the necessity for future research to refine data processing techniques, enhancing the specificity of biological signal extraction to accurately differentiate between species. Furthermore, this research highlights the constraints imposed by limited computational resources, which curtailed the scope of analysis to a single radar station and a one-year dataset.

Looking ahead, there is a clear path for expanding this research framework to harness high-performance computing capabilities, facilitating a more comprehensive analysis across multiple radar stations and over extended periods. Such advancements could not only refine our understanding of avian migration patterns on a macro scale but also contribute significantly to the fields of ecology, conservation science, and aviation safety. By addressing the current limitations and aspiring towards a broader, more detailed exploration of ecological data, future research has the potential to uncover invaluable insights into avian population dynamics, migration routes, and their implications for conservation and human activity.

References

Abbott, A. L., Deng, Y., Badwey, K., Farnsworth, A., and Horton, K. G. (2023). Inbound arrivals: Using weather surveillance radar to quantify the diurnal timing of spring trans-gulf bird migration. *Ecography*, 2023(8):e06644.

Cui, K., Hu, C., Wang, R., Sui, Y., Mao, H., and Li, H. (2020). Deep-learning-based extraction of the animal migration patterns from weather radar images. *Science China Information Sciences*, 63:1–10.

Dokter, A. M., Desmet, P., Spaaks, J. H., van Hoey, S., Veen, L., Verlinden, L., et al. (2019). biorad: Biological analysis and visualization of weather radar data. *Ecography*, 42(5):852–860.

Dokter, A. M., Liechti, F., Stark, H., Delobbe, L., Tabary, P., and Holleman, I. (2011). Bird migration flight altitudes studied by a network of operational weather radars. *Journal of the Royal Society Interface*, 8(54):30–43.

Dolbeer, R. A. (2020). Population increases of large birds in north america pose challenges for aviation safety.

Elmore, J. A., Riding, C. S., Horton, K. G., O'Connell, T. J., Farnsworth, A., and Loss, S. R. (2021). Predicting bird-window collisions with weather radar. *Journal of Applied Ecology*, 58(8):1593–1601.

Gangoso, L., Viana, D. S., Dokter, A. M., Shamoun-Baranes, J., Figuerola, J., Barbosa, S. A., and Bouten, W. (2020). Cascading effects of climate variability on the breeding success of an edge population of an apex predator. *Journal of Animal Ecology*, 89(11):2631–2643.

Hoekstra, B., Bouten, W., Dokter, A., van Gasteren, H., van Turnhout, C., Kranstauber, B., et al. (2024). Fireworks disturbance across bird communities. *Frontiers in Ecology and the Environment*, 22(1):e2694.

Kingsley, S. and Quegan, S. (1999). *Understanding radar systems*, volume 2. SciTech Publishing.

Komal, R., Khushboo, Dwivedi, A., Vaish, V., and Rani, S. (2017). Conquering the night: Understanding nocturnal migration in birds. *Biological Rhythm Research*, 48(5):747–755.

Kranstauber, B., Bouten, W., Leijnse, H., Wijers, B. C., Verlinden, L., Shamoun-Baranes, J., and Dokter, A. M. (2020). High-resolution spatial distribution of bird movements estimated from a weather radar network. *Remote Sensing*, 12(4):635.

La Sorte, F. A., Fink, D., Hochachka, W. M., and Kelling, S. (2016). Convergence of broad-scale migration strategies in terrestrial birds. *Proceedings of the Royal Society B: Biological Sciences*, 283(1823):20152588.

La Sorte, F. A., Horton, K. G., Nilsson, C., and Dokter, A. M. (2019). Projected changes in wind assistance under climate change for nocturnally migrating bird populations. *Global Change Biology*, 25(2):589–601.

Lin, T. Y., Winner, K., Bernstein, G., Mittal, A., Dokter, A. M., Horton, K. G., et al. (2019). Mistnet: Measuring historical bird migration in the us using archived weather radar data and convolutional neural networks. *Methods in Ecology and Evolution*, 10(11):1908–1922.

Nilsson, C., Dokter, A. M., Verlinden, L., Shamoun-Baranes, J., Schmid, B., Desmet, P., et al. (2019). Revealing patterns of nocturnal migration using the european weather radar network. *Ecography*, 42(5):876–886.

Nilsson, C., La Sorte, F. A., Dokter, A., Horton, K., Van Doren, B. M., Kolodzinski, J. J., et al. (2021). Bird strikes at commercial airports explained by citizen science and weather radar data. *Journal of Applied Ecology*, 58(10):2029–2039.

Rosenberg, K. V., Dokter, A. M., Blancher, P. J., Sauer, J. R., Smith, A. C., Smith, P. A., et al. (2019). Decline of the north american avifauna. *Science*, 366(6461):120–124.

Scott, G. R. (2011). Elevated performance: The unique physiology of birds that fly at high altitudes. *Journal of Experimental Biology*, 214(15):2455–2462.

Soderholm, J., Protat, A., and Jakob, C. (2019). Australian operational weather radar level 1 dataset. Electronic dataset, National Computing Infrastructure. `https://doi.org/10.25914/508X-9A12`.

Van Doren, B. M., Lostanlen, V., Cramer, A., Salamon, J., Dokter, A., Kelling, S., et al. (2023). Automated acoustic monitoring captures timing and intensity of bird migration. *Journal of Applied Ecology*, 60(3):433–444.

Werber, Y., Sextin, H., Yovel, Y., and Sapir, N. (2023). Batscan: A radar classification tool reveals large-scale bat migration patterns. *Methods in Ecology and Evolution*, 14(7):1764–1779.

Zewdie, G. K., Lary, D. J., Liu, X., Wu, D., and Levetin, E. (2019). Estimating the daily pollen concentration in the atmosphere using machine learning and nexrad weather radar data. *Environmental Monitoring and Assessment*, 191:1–9.