Master's Thesis of Agriculture

Wind turbine avoidance through flight behavioral change in Black-tailed Gulls *Larus crassirostris*

비행행동의 변화를 통한 괭이갈매기
*Larus crassirostris*의 풍력발전기 회피

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Abstract

The increasing need to reduce carbon emissions has led to the development of various types of renewable energy, with wind power gaining significant attention. However, the expansion of wind power infrastructure has raised concerns about its negative environmental impacts, such as habitat destruction and collisions with avian and bat species, exacerbating the biodiversity challenge. Among these impacts, birds are particularly susceptible to wind turbines due to direct effects such as habitat loss and collision risks. Therefore, it is crucial to study the behavioral changes resulting from the implementation of wind turbines. This study aimed to investigate the flight behavioral changes of Black-tailed Gulls (*Larus crassirostris*) according to the distance and assessment of avoiding wind turbines. To collect data, GPS tracking devices were attached to Black-tailed Gulls.

In order to evaluate the change in flight behavior based on distance, buffer areas were created around each wind turbine. A buffer area ranging from 50m to 100m was established to examine micro-avoidance, which refers to immediate avoidance before the collision. Another buffer area ranging from 100m to 700m was defined to assess meso-avoidance, which involves avoidance within the wind farm. After the buffer area was created, wind turbine height was categorized into 4 different categories; (below collision risk zone, lower collision risk zone, higher collision risk zone, and above collision risk zone) based on the collision risk heights that

were available from the currently installed wind turbines.

The purpose of flight behavioral change of Black-tailed Gulls aimed to avoid threats, in which case, collision. Previous research has identified three key components of flight behavioral change: flight angle change, horizontal spatial utilization, and vertical spatial utilization. Flight angle change was evaluated by using both velocity and turning angle, resulting in the identification of four distinct movement modes: low velocity/low angle, low velocity/high angle, high velocity/low angle, and high velocity/high angle. The proportions of these movement modes were calculated within the defined buffer areas. Horizontal spatial utilization was examined by connecting the coordinates to form flight paths, and the proportions of these paths within the buffer areas were determined. Lastly, vertical spatial utilization was assessed by analyzing altitude information, and the proportions of coordinates within the height category were calculated.

Behavioral change research related to wind turbines usually involved comparing data before and after the construction of wind farm. Due to the lack of available pre-construction data, simulated data were generated to represent scenarios where wind turbines were absent and random spatial utilization. The simulation data were generated by rotating observed data multiple times at random angles.

Subsequently, this study analyzed the disparity in flight behavior changes along the distance from a turbine, in terms of three components (flight angle change, horizontal spatial utilization, and vertical spatial utilization), by comparing the proportions of movement modes, paths, and altitudes between the simulated and observed data. The observed data showed a higher frequency of flights with low velocity compared to the simulated data. Among these low velocity flights, there was a higher occurrence of flights with high angles compared to those with low angles. When comparing horizontal spatial utilization, Black-tailed Gulls demonstrated reduced participation in flights within the 50m to 100m range around wind turbines, but no significant difference in spatial utilization was observed within the 100m to 700m range. In terms of vertical spatial movements, Black-tailed Gulls exhibited a preference for flying at altitudes below approximately 40m while actively avoiding heights associated with collision risks. These findings suggest that the presence of wind turbines can potentially impact the behavior of Black-tailed Gulls, influencing their flight velocity, angle, and spatial utilization both horizontally and vertically.

Investigating the behavioral changes of Black-tailed Gulls not only holds great significance as it can effectively mitigate collision risk by adjusting the height of the wind turbine but also enables predictions of avoidance behavior in response to future wind turbine installations and the assessment of potential population-level impacts through subsequent research. However, it is important to acknowledge that all the observed flight behavioral changes in Black-tailed Gulls may be influenced by environmental factors, such as freshwater resources for roosting and bathing, not solely by the presence of wind turbines. Future research should be conducted the under controlled environmental conditions such as offshore or forestry wind farms, where the presence of a forest can create a uniform condition across the wind farm

area. Also, the data collection before the wind farm construction should be conducted as well. Considering that avian movements are species-specific and influenced by various factors, it is recommended to incorporate species-specific movement patterns while accounting for environmental factors in comprehensive studies.

Keywords : Avoidance behavior, behavioral change, Black-tailed Gull, horizontal spatial utilization, vertical spatial utilization, wind turbine

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Table of Contents

List of Tables

List of Figures

1. Introduction

1.1 Background

The carbon emissions due to burning fossil fuels are the major cause of global climate change, permanently changing the earth's ecosystem and physical characteristics (He et al. 2023). The Paris Climate Agreement acknowledged the need for clean energy production to decrease carbon emissions, with 35% of emissions in 2010 resulting from burning fossil fuels, as stated in the IPCC’s 2018 report (Mello et al. 2022). Among the many options for producing renewable energy, wind power is rapidly growing since it applies to most countries without strict constraints (Pechak et al. 2011). Last decade, renewable energy development has been increasing in Europe, with wind power responsible for the second most energy-generating source in 2016. In 2021, installed wind turbines generated 837GW, with China generating 338GW, followed by the United States, generating 134GW (He et al. 2023).

However, the development of renewable energy infrastructure has the potential to undermine efforts aimed at conserving biodiversity by causing various forms of ecological damage (Rehbein et al. 2020). The increasing number of wind turbine installations has raised concerns about potential negative environmental impacts (Beston et al. 2016). These impacts may be indirect, such as habitat destruction for wild animals and cause barrier effect (Drewitt & Langston 2006; Humphreys et al. 2015), or direct, such as construction noise, and collisions with birds (Marques et al. 2020; Peschko et al. 2020). Overall, the development of renewable energy aimed to mitigate the impact of global climate change, but the extent of their impact on biodiversity remains poorly understood (Bakken et al. 2014).

Finding a balance between economic growth and biodiversity conservation has been a persistent challenge in the development of renewable energy. The impact of wind turbines on birds is a frequently studied topic (Leung & Yang, 2012). The proliferation of wind turbines poses a potential threat to bird conservation efforts. While the negative impact of wind power on birds may be relatively small compared to other anthropogenic activities such as deforestation and urbanization, (Leung & Yang, 2012) the cumulative effect of wind power cannot be overlooked. Over time, the impact of wind turbines on bird populations can become significant and have implications for biodiversity conservation.

In the context of wind energy production, studies have been conducted to optimize the generation of renewable energy while mitigating the potential negative impacts on biodiversity, with a particular focus on birds. These studies have explored various strategies, including decreasing the rotation speed of wind turbine, locating facilities away from migration routes (Popescu et al. 2020), estimating collision and mortality rates of birds and bats (De Lucas et al. 2008), change of habitat usage (Carrete et al., 2009; Madsen & Boertmann, 2008), and behavioral change as a response to wind turbines. (Everaert, 2014). Among these studies, the assessment of behavioral change holds importance in terms of conservation due to its significant implications. Behavioral change is caused by a combination of internal states, environmental factors, and evolutionary or biological constraints. Analyzing these behavioral changes is crucial as it can unveil the fundamental biological mechanisms that govern animal movement and behavior (Thiebault & Tremblay, 2013). Behavioral change exhibited by birds is considered avoidance behavior. These behaviors toward artificial structures such as wind turbines can be interpreted as an evolved anti-predator strategy aimed at mitigating perceived risk, involving an increase or decrease of flight speed, horizontally changing the flight angle, and vertically changing the flight altitude (May, 2015). Moreover, such behaviors can lead to reduced foraging time, increasing energy expenditure by avoidance maneuvers, and restricting space utilization (Frid & Dill, 2002). Therefore, understanding the specific strategies employed by birds to avoid collisions is crucial. These behaviors can take place outside of the wind farm, where wind turbines are clustered, and is called macro-avoidance. It usually involves circumventing the whole wind farm area. Avoidance taking place inside the wind farm is called meso-avoidance, and the last-second maneuver to avoid collision with an individual wind turbine is called micro-avoidance (Cook et al. 2018). Previous studies on the avoidance behavior of birds revealed that birds exhibit horizontal avoidance toward wind turbines by modifying their flight paths (Cabrera-Cruz & Villegas-Patraca, 2016a), as well as vertical avoidance through adjustments in flight altitude, preferring higher altitudes (Johnston et al. 2014), or lower altitude (Therkildsen et al. 2021).

Although much research has been conducted on raptors and migratory species, studies investigating the local species and wind turbines are necessary. The Black-tailed Gull *(Larus crassirostris*) is a predominant resident seabird species in the Republic of Korea that breeds in large colonies on remote islands (Myeong et al. 2013; Kim et al. 2017). Seabirds are a highly vulnerable bird group and effective indicators for assessing the health of the ecosystem and are at significant risk due to their susceptibility to collision with wind turbines, which is among the most concerning direct threats posed by wind farms (Dias et al. 2019). As resident birds, they may have an advantage over migratory birds due to their ability to learn and recognize artificial structures, allowing them to avoid and navigate around wind turbines (Leung & Yang 2012). Given the lack of research on the avoidance behavior of this species, it is imperative to conduct studies to elucidate the ways in which they interact with man-made structures such as wind turbines.

1.2 Research Goal

The breeding islands of Black-tailed Gulls are in close proximity to wind farms. These gulls primarily feed on coastal or epipelagic fish found near the shore (Kazama et al. 2008). Gulls need to approach the coastline, where wind turbines are located, in order to engage in foraging activities. The presence of water resources and rice fields within the wind farm area serves as resting places for these gulls, which in turn increases the likelihood of their spatial utilization within the wind farm. Moreover, the high breeding densities during the breeding season creates the potential for avoidance behaviors, particularly at the meso and micro-scale levels. The goal of this study is to analyze the flight behavioral change of Black-tailed Gulls in the vicinity of wind turbines and utilize this knowledge to develop strategies for mitigating potential negative impacts, such as collisions. Previous studies on flight behavior changes in response to wind turbines consistently observed three components of such changes: alterations in flight angles, (Cabrera-Cruz & Villegas-Patraca, 2016; Linder et al. 2022; Santos et al. 2022) adjustments in flight paths, (Therkildsen et al. 2021) and modifications in flight altitudes (Schaub et al. 2020). The objective of this study is to evaluate these three components of flight behavioral change of Black-tailed Gulls toward wind turbines. Building upon previous research, this study focuses on the following research questions;

1) How do Black-tailed Gulls change their flight speed and angle when encountering wind turbines? (Meso-scale avoidance)

2) How do Black-tailed Gulls change their flight behavior horizontally? (Meso and micro-scale avoidance, with horizontal spatial utilization)

3) How do Black-tailed Gulls change their flight behavior vertically? (Meso and micro-scale avoidance, with vertical spatial utilization)

2. Literature review

The collision of birds with artificial structures such as buildings, windows, power lines, and wind turbines is a well-documented phenomenon. The visual perception of birds differs from that of humans, and structures that are perceived as easily avoidable by humans may not be so for birds. Birds' lateral vision is more attuned to detecting food sources or predators, and therefore, they may not prioritize detecting obstacles in their flight path (Martin, 2011). Many studies revealed that the birds exhibit various avoidance behaviors toward wind turbines. This type of research usually requires the collection of data before and after wind turbine construction, or the simulation that represents before-construction conditions. Additionally, to achieve precise monitoring of bird behavior, many researchers employ advanced technological tools such as GPS tracking devices or radar.

The study conducted on Black Kites (*Milvus migrans*) using GPS tracking devices showed evidence of macro-avoidance towards wind turbines. This study revealed that the probability of birds facing wind turbines decreased as they flew closer to the turbine when the distance between turbines and birds was less than 750m (Santos et al. 2022).

Meso-avoidance was assessed by comparing before and after the construction of wind turbine data. Data from pre-construction showed that the number of flights was evenly distributed, whereas post-construction data showed that passing between turbines was found to be more than 150m away from the turbine, suggesting horizontal avoidance. Additionally, the flight frequency of collision-prone height was reduced after the wind turbine construction, which indicates vertical avoidance by altering flight height (Therkildsen et al. 2021). A similar study was conducted on migrating Golden Eagles (*Aquila chrysaetos*), exhibiting that they would be less likely to fly inside the collision-prone area during post-construction compared to pre-construction, suggesting that eagles showed detection and avoidance towards wind turbines (Johnston et al. 2014).

Along with GPS tracking, radar monitoring is another form of effective data collection method because it can cover a large area and provide accurate information on flight paths. However, radar data alone cannot identify bird species, so visual observations are necessary in conjunction with radar monitoring (Krijgsveld et al. 2011). Micro-avoidance was assessed using radar and visual observations. The comparison between the number of tracks near the turbines and the number of tracks if birds were distributed evenly revealed evidence of avoidance behavior (Krijgsveld et al. 2011).

On the other hand, before construction data are not always available. To resolve the problem, creating a null model is widely used (Connor & Simberloff, 1979; Gotelli, 2000; Roxburgh & Matsuki, 1999; Wiegand & Moloney, 2004). The null model serves the purpose of not only replicating the absence of pre-construction data but also generating alternative bird behaviors. This allows for a meaningful comparison with observed data, leading to valuable insights. Villegas-Patraca et al. 2014 developed five distinct scenarios to simulate flight trajectories based on observed flight patterns, each scenario representing alternative trajectories. By comparing the number of intersected trajectories observed in real data with the simulated trajectories, they discovered that the observed number of intersections was lower than that of the simulated trajectories, indicating avoidance behavior toward wind farms. Although the target species of this study were Turkey Vultures (*Cathartes aura*) and Swainson's Hawks (*Buteo swainsoni*), it provided valuable insights into the effectiveness of the null model approach.

In another study, a null model approach involving the horizontal rotation of original bird tracks was employed to assess the vertical avoidance behavior of Montagu's Harriers (*Circus paygargus*) (Schaub et al. 2020). By comparing the proportion of original tracks to simulated tracks, the researchers calculated avoidance rates and an avoidance index. The results showed that Montagu's Harriers exhibited a remarkable 93% avoidance at the collision risk heights. A similar methodology was used to investigate the avoidance behavior of Lesser Black-backed Gulls (*Larus fuscus*) towards wind farms (D. T. Johnston et al. 2022). This study also examined the relationship between avoidance and the distance from the wind turbine. The findings revealed that when the gulls were within the collision risk height, they displayed avoidance behavior within a range of 100 m. Overall, these studies demonstrate how the application of the null model approach can provide valuable insights into avian avoidance behaviors and their interactions with potential hazards such as wind turbines.

The presence of avoidance behavior is closely linked to collision and mortality rates. To estimate the mortality rate of birds around wind turbines, a Collision Risk Model was developed (Band, 2012) and is widely used in many studies. The model considers both macro and micro-avoidance rates to calculate the overall avoidance rate. Extensive research suggested that birds exhibit an avoidance rate of at least 98%, as concluded from various studies incorporated into the model.

While research on the impacts of wind turbines on birds has been extensively conducted in Europe and North America, there has been limited investigation in the Republic of Korea. Two recent studies have explored the relationship between wind turbines and birds in Korea, with a focus on the distribution of birds in relation to the presence of wind turbines (Kim et al. 2021), and the overall negative impacts on birds (Hong et al. 2019). However, there remains a gap in knowledge regarding the avoidance behavior of birds in the presence of wind turbines. Thus, further investigation is necessary to gain insights into how birds react to such threats in the Republic of Korea. Prior research has demonstrated that birds tend to display meso-avoidance behavior, exhibiting both horizontal and vertical avoidance, and it is anticipated that Black-tailed Gulls will also exhibit this behavior when approaching wind turbines, based on the findings of previous studies.

3. Materials and Methods

3.1 Study area and target species

The study area is located in Yeonggwang-gun, Jeollanam-do, in the Republic of Korea. There are three different wind farms composed of 76 wind turbines. These turbines are located along the rice fields, Bulgap estuary, and salt evaporation ponds. Additionally, there are two breeding islands, named Sonoindo Island and Chilsando Islands, located approximately 9-12km away from the wind farms.

Black-tailed Gulls (*Larus crassirostris*) are widely distributed in Korea, Japan, and China, with the majority of the global population estimated at around 1.1 million individuals breeding in the Republic of Korea, Japan, and Russia (Brazil, 2009). Specifically, in the Republic of Korea, there are approximately 100,000 breeding pairs (Kim et al. 2017). According to the IUCN Red List, the species has a stable population is stable with an average lifespan of 11.5 years.

Within the Republic of Korea, they are the most prevalent species of Laridae and can be observed throughout the year. Breeding colonies are located on isolated islands distant from the mainland. During the winter, these gulls display feeding behavior in wetlands and estuaries, where water is abundant.

Figure 1. Location and map of the study area. Pink and yellow dots are breeding islands (Chilsando and Sonoindo Island), and green dots are wind turbines.

Figure 2. Wind turbines in the study area

Figure 3. Black-tailed Gull (*Larus crassirostris*) with a GPS tracking device attached.

3.2 Data collection

3.2.1 GPS deployment and data filtering

A total of 99 Black-tailed Gulls were captured in 2021 from five different breeding islands (Bulmugido island, Chilsando islands, Nando island, Seomando island, and Sonoindo island). Black-tailed Gulls were captured using a spring-released type trap. The trap was designed to be foldable on one side against the ground and could be remotely triggered using a controller. The trap was placed on the gull's nest once it was ready, and as soon as the gull approached the nest, the trigger was activated to remove the tension, safely capturing the gull for the GPS attachment.

It is advisable to ensure that the mass of any tracking devices utilized for the purpose of avian species attachment does not surpass 5% of the target species' body mass (Wild et al. 2022). Data were collected from the Druid Omni 3G device manufactured by Druid Technology Co. having a weight of approximately 15g. The device was observed to be below 5% of the body weight of the Black-tailed Gull (*Larus crassirostris*), a species that typically weighs approximately 500g. This device operates through solar power and collects longitude, latitude, altitude, speed, geoid heights, number of satellites used, collecting time, transmitting time, and horizontal and vertical dilution of precision. The device has a default coordinate acquisition interval of 30 minutes, but its data collection frequency may vary between 10 seconds to 20 minutes depending on the battery level. Data collected at 30-minute intervals is referred to as "scheduled data," while data collected at intervals of 10 to 30 seconds is referred to as "flight data" due to its ability to capture the flight behavior of birds.

With the development of modern digital data collection technologies such as the Global Positioning System (GPS), researchers can now collect spatial information from such devices and assess wildlife movement with greater accuracy and precision (Lewis et al. 2007). Despite the fact that such improvements are made, spatial information collected from the GPS is not always reliable, which means that factors influencing the accuracy must be considered (Recio et al. 2011). For GPS data collection, it is recommended to use signals received from a minimum of four satellites and utilize low values of horizontal and vertical dilution of precision (DOP). DOP represents the distribution and quantity of satellites in the constellation, and a lower DOP value indicates a wider spread of satellites (Justicia et al. 2018). In some studies, used preferably below 10, as lower DOP values indicate higher confidence in data accuracy (Acácio et al. 2022; Bergen et al. 2022).

Data collection started in May 2021 and has been ongoing until the present time. The density of Black-tailed Gulls is concentrated during the breeding seasons which makes them interact with the wind turbines more frequently for foraging and mating. Therefore, the flight data from May to July in 2021 and 2022 was used in this study. To ensure data consistency, data were subjected to a uniform filtering procedure. This involved eliminating coordinates that exhibited a speed lower than 1 m per second, an altitude below 0 m, and any longitude or latitude coordinates indicating a value of 200, which is considered a GPS error. A similar study (Schaub et al. 2020) used DOP less than 4, and lower DOP indicates higher accuracy, therefore VDOP less than tha1.5 was used in this. The data were obtained from the Druid Technology website and were provided in Excel format.

3.2.2 Categorizing wind turbine heights

Wind turbines are composed of a tower, a nacelle that contains generating components, and three blades (Liu & Barlow, 2017), with the total height of the turbine being the sum of the tower height and the radius of a single blade. In the study area, 76 wind turbines were installed, and for bird collisions to occur, the birds' flight height must fall within the range of rotating blades, which corresponds to the blade diameter. Thus, it is crucial to set the collision risk zone based on currently installed wind turbines. However, given the differences in manufacturing companies, the specifications of each wind turbine were not uniform. To address this issue, the collision risk zone was calculated using the average tower height and rotor diameter that were available. This calculation method was selected as it allowed for the identification of different categories based on collision risk and ultimately provided insight into bird behavior in relation to wind turbines. The height of the turbines can be divided into three distinct categories based on the calculated collision risk zone; below collision risk zone (BCRZ), collision risk zone (CRZ), and above collision risk zone (ACRZ) (Cook et al. 2012). The collision risk zone of the study area was found to be ranged from approximately 40m to 146m. The collision risk zone was subdivided into low and high, to evaluate the difference inside the collision risk zone itself.

Therefore, the height of the turbines was segmented into four categories, having BCRZ (0~40m), lower CRZ (40~93m), higher CRZ (93m~146m), and ACRZ (146m or more).

3.2.3 Applying buffer area around the wind turbine

To evaluate the avoidance behavior in relation to the distance between gulls and wind turbines, a buffer area of a specific size was generated around each structure. In determining the appropriate buffer size, inter-turbine distances were taken into consideration to ensure the accuracy and relevance of the analysis. By applying this approach, the buffer area served as an effective indicator of the potential collision-prone area surrounding each wind turbine (McClure et al. 2021). It is crucial to establish boundaries for meso and micro-scale behaviors, as each behavior occurs in different locations. The definition of these boundaries can be based on factors such as turbine rotor diameter or the spacing between turbines within the wind farm. (Cook et al. 2014). Due to the uneven distribution of wind turbines in the study area, the distances between turbines were also found to be non-uniform. To address this issue, a maximum distance of 700m between adjacent wind turbines was chosen as the reference distance for analysis. Micro-scale behavior is anticipated to take place within 10m of the turbine blades, although this specific distance may be further refined in future studies. On the other hand, meso-scale behavior is expected to occur beyond the micro-scale and within the perimeter of the wind farm (Cook et al. 2014).

To assess the micro-avoidance behavior in proximity to each wind turbine, the buffer ranges from 50m to 100m, in increments of 10m was generated and to assess the meso-avoidance, the buffer ranges from 100m to 700m, in increments of 100m were generated around each turbine. By separating buffer areas into the ranges of 50m to 100m and 100m to 700m, it enabled a detailed examination of avoidance behavior on both micro and mesoscales.

3.2.4 Data simulation

In order to investigate the avoidance behavior towards wind turbines, it is essential to collect data from both before and after wind turbine construction. However, due to the unavailability of pre-construction data, a hypothetical scenario was created to simulate the randomized spatial utilization in the absence of wind turbines in the area. There are several methods available for simulating animal movements, such as the random walk model (Schaub et al. 2020) and the Hidden Markov model. While the random walk model is a useful tool for modeling animal movement, it has a limitation when it comes to creating movement patterns with equal area usage. In this study, the data used for Black-tailed Gulls' movement consisted of coordinates recorded at short intervals of 10-30 seconds. This data exhibits high sinuosity and short path lengths. The goal of the data simulation in this study is to create movements that equally distribute in a large area. When using a random walk model to create such a scenario, it becomes challenging to achieve equal area usage. Random walks tend to generate paths with higher sinuosity, leading to a smaller distribution and potentially biased area coverage (Bovet &

Benhamou, 1988). Therefore, in the context of this study where the focus is on achieving random distribution, the random walk model may not be the best fit.

A Hidden Markov model (HMM) is a probabilistic model used to analyze time series data. It assumes the presence of hidden states that transition between each other, as well as observable states that are directly observed. The current hidden state depends only on the previous hidden states, and the current observable state depends solely on the current hidden state. To calculate the hidden states, transition probabilities are used. As the calculations continue, the model is completed, providing a representation of the underlying hidden states based on the observed data (Rabiner & Juang, 1986; Eddy 1996). When applied to animal movement, an HMM can generate animal movement patterns based on the previous movement history. By considering the transition probabilities and observed data, the model can simulate animal movement sequences that capture the probabilistic nature of their behavior. HMM relies on the previous movement to generate the next movement in a sequential manner. However, when simulating data using observed data collected after the model's construction, there is a possibility that the animal's movement in the observed data might contain information influenced by factors such as avoiding wind turbines. As a result, the simulated data generated by the HMM may not accurately represent truly random movement patterns.

Due to the limitations of modeling methods, rotating observed data to create a random spatial usage was used. To create such scenario, a null model was created. A null model refers to a pattern-generating model that relies on the randomization of ecological data or random sampling from a known or imagined distribution (Gotelli, 2001). Through the application of randomization, an environment is created that reflects the expected conditions in the absence of a specific ecological mechanism capable of influencing animal behavior (Richard et al. 2013). To apply the randomization to the study site, the central wind turbine within the wind farm was sorted. And a buffer with a radius of approximately 9 km, which is equivalent to the distance between breeding islands and the wind farm, was applied around the central wind farm turbine, all coordinates falling within this 9 km buffer and satisfying flight conditions were collected. To generate random spatial scenarios, these coordinates within the buffer were subjected to 100 rotations, each involving a random angle. These rotations were performed around the center of the wind farm area. These simulated data were used as a control condition for comparison with the observed data collected after the construction of the wind turbines. By comparing these two datasets, it was possible to assess any avoidance behaviors exhibited after the construction of wind turbines. These rotated data were called 'simulated data' and the original data were called 'observed data'.

Initially, the three components of flight behavioral change of Black-tailed Gulls were evaluated. And simulated data were created following the above procedure. Overall, three components were segregated into observed data and simulated data, enabling a comparative analysis to evaluate the difference between these two datasets.

3.3 Methods

3.3.1 Movement modes

The locomotion of most animal species can be exhibited through multiple movement modes, and the kinematic differences associated with each movement mode can be accurately captured by GPS tracking devices, enabling precise classification of animal behavior (Conners et al. 2021). The analysis was specifically designed to evaluate the flight speed and angle adjustment of Black-tailed Gulls while actively flying. The traditional method of categorizing behavior often relies on assessing velocity and estimating turning angle behavior (Garriga et al. 2016). To distinguish turning angle behavior during flight, the Expectation Maximization Binary Clustering (EMbC) package was utilized. This package is capable of transforming data points into bivariate clusters based on the velocity and turning angle of the birds (Garriga et al. 2016). To utilize the EMbC package, flight data that included information on longitude, latitude, and time of coordinate collection was used. The time data was modified to include only the year, month, date, hour, and minutes, and any overlapping time periods were eliminated. This package achieved clustering by introducing a set of parameters known as delimiters. Delimiters represent a value that splits the range of a variable into a binary discretization. Using this technique, the range of velocity and turning angle variables were split into four movement modes, each representing a unique bird behavior. The four groups were classified as low velocity/low angle (LL), low velocity/high angle (LH), high velocity/low angle (HL), and high velocity/high angle (HH) (Figure 4). LL is a slow and straight flight which can be interpreted as resting, LH is a slow and many directional changing flights which can be interpreted as intensive search, HL is a fast and straight flight which can be interpreted as traveling, and HH is fast and many directional changing flights which can be interpreted as an extensive search (Garriga et al. 2016). Categorizing bird behavior using the EMbC package is widely used due to its ability to provide significant biological interpretations using two key input variables: speed and turning angle (Jones et al. 2018; Mendez et al. 2017). After the movement modes were separated, the preference for specific movement modes within the maximum 700m buffer area was analyzed by comparing the observed and simulated proportions using Jacobs' selectivity index. Jacobs' selectivity index (Jacobs, 1974) indicates the preference or avoidance of certain habitat or prey items by comparing the proportion of resources utilized and resources available. Through the utilization of this index, it was possible to identify the specific movement modes that Black-tailed Gulls exhibited a preference for or avoidance of when encountering wind turbines. The equation for Jacobs' selectivity index is

$$D = (r-p)/(r+p-2rp)$$

where r is resource utilization, and p is a resource available. In this study, the proportion of observed coordinates in each buffer area was r, and the proportion of simulated coordinates was p. The calculation provided a D value which ranged from -1 to 1, with a negative value indicating avoidance, and a positive value indicating preference.

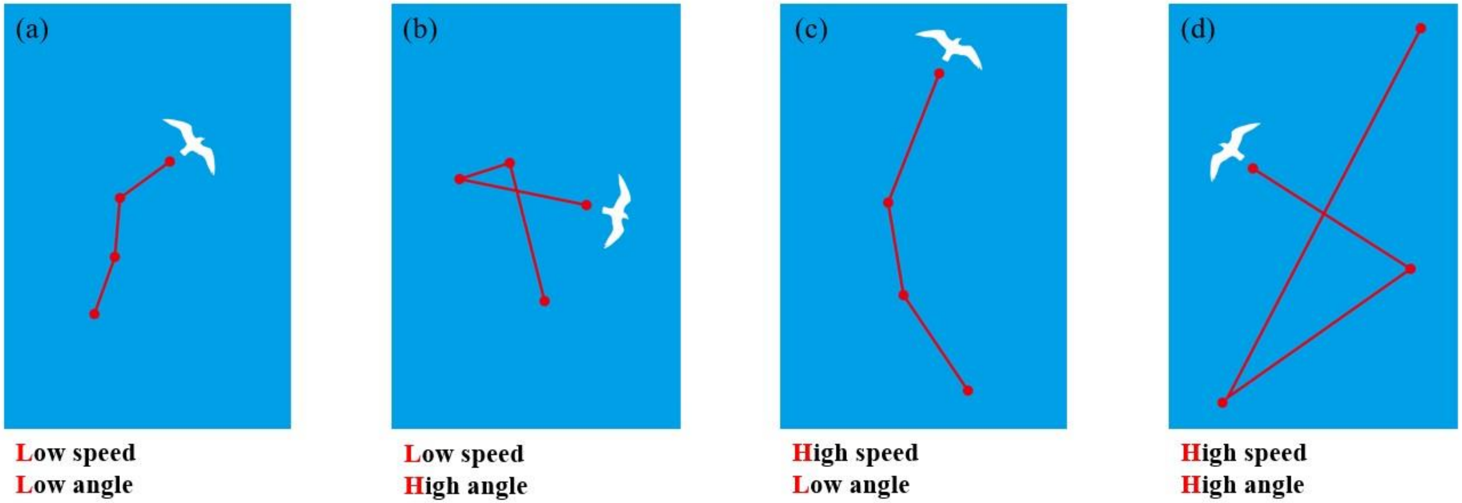


Figure 4. Example of each movement mode (Garriga et al. 2016). (a) LL: slow and straight flight, (b) LH: slow and directional changing flight, (c) HL: fast and straight flight, and (d) HH: fast and directional changing flight (Image recreated based on Garriga et al. 2016).

3.3.2 Horizontal spatial utilization

It is common for birds to alter their flight paths to avoid entire wind farms (Cabrera-Cruz & Villegas-Patraca, 2016; Santos et al. 2022). In order to assess the horizontal movement, which is horizontal spatial utilization through path adjustments, all the coordinates that fell within the buffer area were connected to form paths. From this process, 38 Black-tailed Gulls were sorted. For each Black-tailed Gull, their paths were created by connecting the coordinates both individually and on a daily basis. This process allowed to creation of continuous flight paths for each Black-tailed Gulls, representing active flights. The number of paths that were included in each buffer area was collected. It was obvious that as the buffer area increased, the number of paths that were included in the buffer increased. Consequently, the number of paths present between each buffer area was collected by each buffer area, and the proportion of paths for both observed and simulated data was compared to determine if there were any differences in proportion based on the distance from a wind turbine. The distance from a wind turbine ranged from 50m to 100m for micro-avoidance assessment and 100m to 700m for meso-avoidance assessment.

3.3.3 Vertical spatial utilization

To ensure the accuracy of analysis, it is important to sort out flight data that are actively participating in flights and interacting with wind turbines. The coordinates that demonstrated distinctive flight behavior, such as flying across the entire wind farm or flying in and outside of the wind farm were filtered out once again, 22 individual Black-tailed Gulls were selectively sorted and included in the vertical movement analysis. Another mechanism of avoidance that birds use to mitigate collisions with wind turbines is vertical movement, which involves changes in altitude. To examine the impact of wind turbines on the vertical movement of gulls, four distinct height categories were used. These categories were calculated previously and used in this analysis. By using this categorization approach, the analysis was able to evaluate the movement of birds more comprehensively in relation to wind turbines. The same flight data, simulated data, and buffer areas were used in this analysis as well. To assess the vertical movement, which would be the vertical spatial utilization within each buffer area, the number of coordinates within each buffer area and the number of coordinates falling into different height categories were collected. Subsequently, these numbers of coordinates were calculated in proportion. After collecting the coordinates from both observed and simulated data, Jacobs' selectivity index (Jacobs, 1974) was also used to identify the specific heights that gulls exhibited a preference for or avoidance of when encountering wind turbines. To estimate the variance of this index, resampling was performed 100 times through bootstrapping to each of the 4 height categories and by the buffer area. Resampling did not follow the normal distribution. Manly's selection index was also calculated, representing the probability of the next selection being the most preferred habitat (Manly et al. 2002), in this case, the height category, assuming all heights are equally available. Bonferroni confidence interval was calculated for resource utilization and selection index. All the statistical analysis was performed through R (R version 4.2.2. R Core team 2022), R package trajr (McLean & Skowron Volponi, 2018), EMbC (Garriga et al. 2016) used, and ArcMap version 10.3.1 was used for coordinates collection.

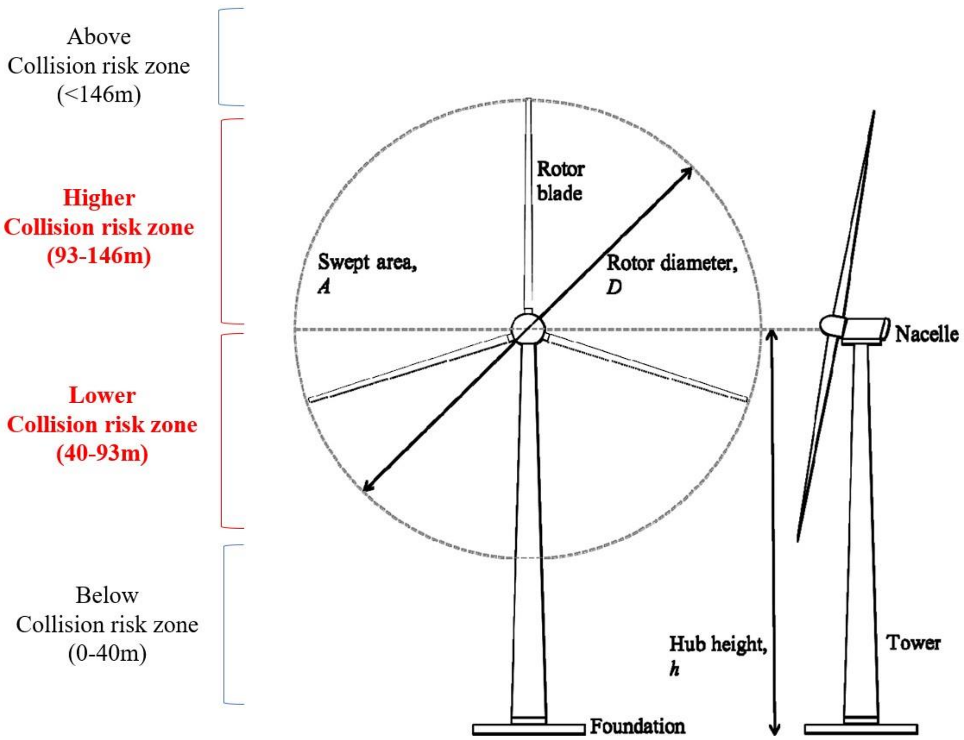
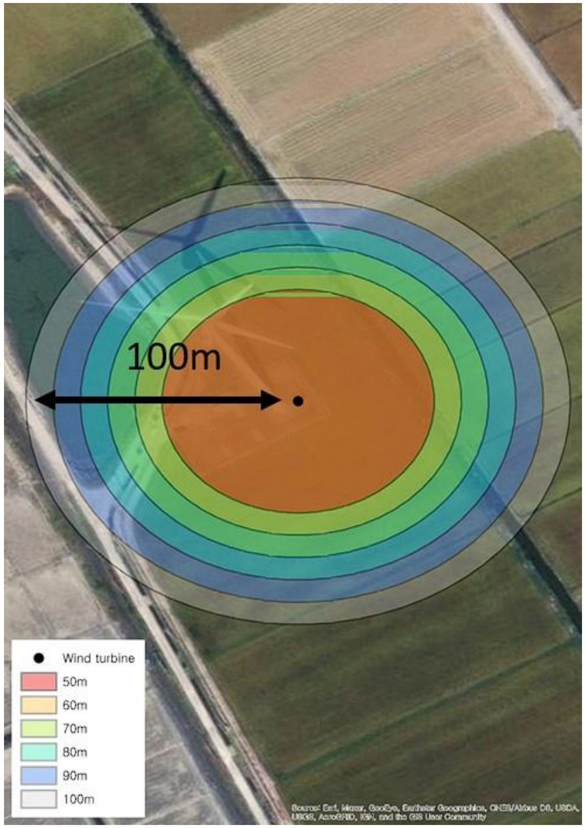


Figure 5. A wind turbine with each height category used in this study (Image recreated from Caduff et al. 2012).



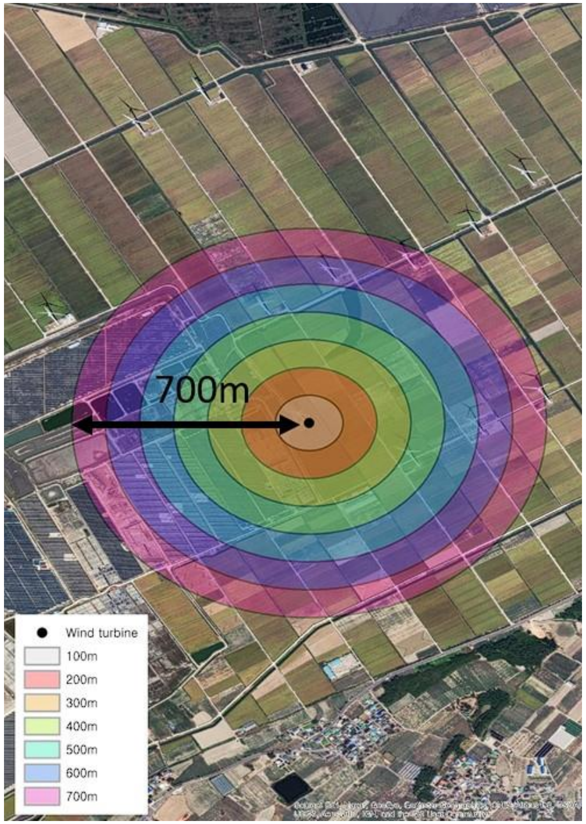


Figure 6. Micro-scale buffer (left) of the outermost (100m) and meso-scale buffer (right) of the outermost (700m) from a wind turbine (filled circle).

Figure 7. Example of an original track (black) and a randomly-rotated track (green). A black dot indicates a point of rotation.

Figure 8. A set of original tracks.

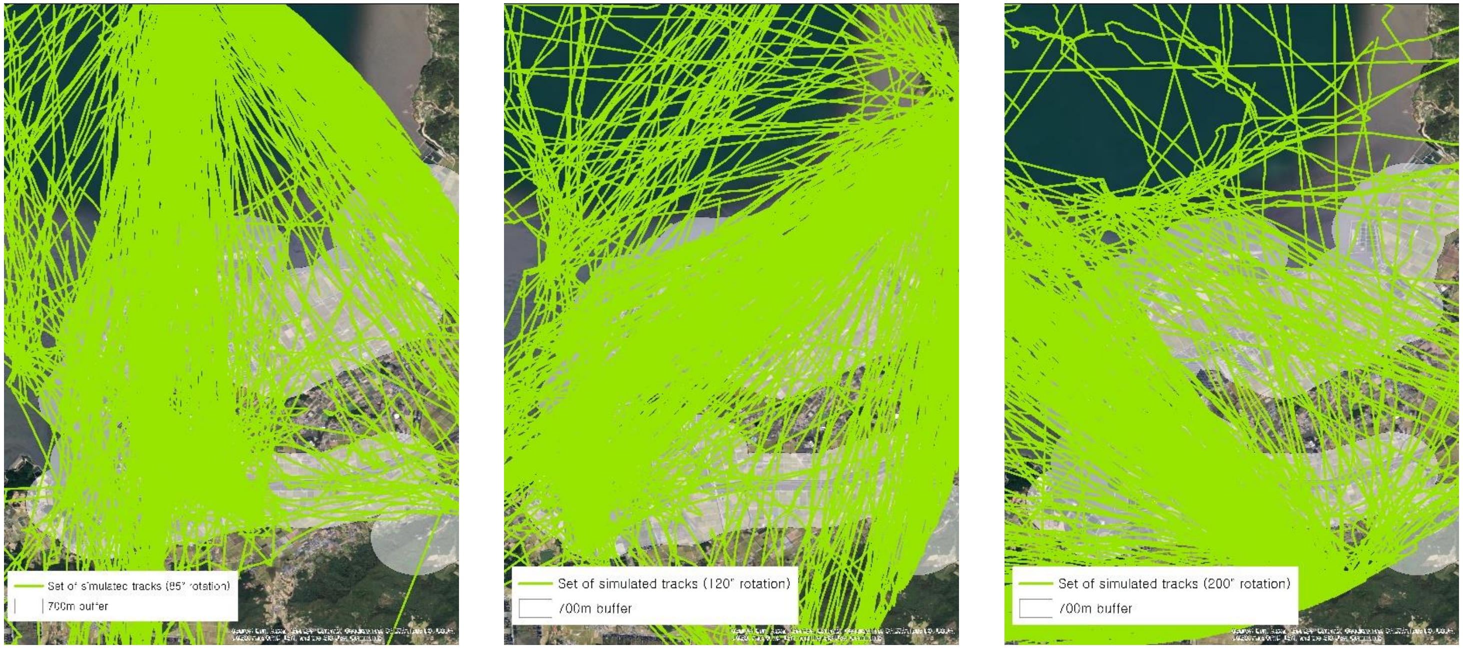


Figure 9. An example of sets of simulated tracks after a random rotation (left; 85° rotation, middle; 120° rotation, right; 200° rotation).

Figure 10. A set of final simulated tracks after random rotations used in the analysis.

4. Results

4.1 Movement modes

After the simulated data was generated, a comparison between observed data was made. In observed data, it was evident that the movement modes that utilized low velocity were responsible for almost 80% (Figure 11). Although all the other movement modes had exhibited similar distribution on both simulated and observed, only the LH movement showed a greater proportion in observed than simulated data (Figure 11). In order to determine the preferred movement modes within the maximum 700m buffer, Jacobs' selectivity index was calculated (Figure 12). A chi-square test for the observed data and simulated data for the maximum buffer area of 700m entire wind farm area had a p-value less than 0.001, indicating that there was a significant difference in proportion. (Table 1.)

Jacobs' selectivity index indicated that among all the behaviors, only LH had a positive index value, having 0.358 (Figure 12).

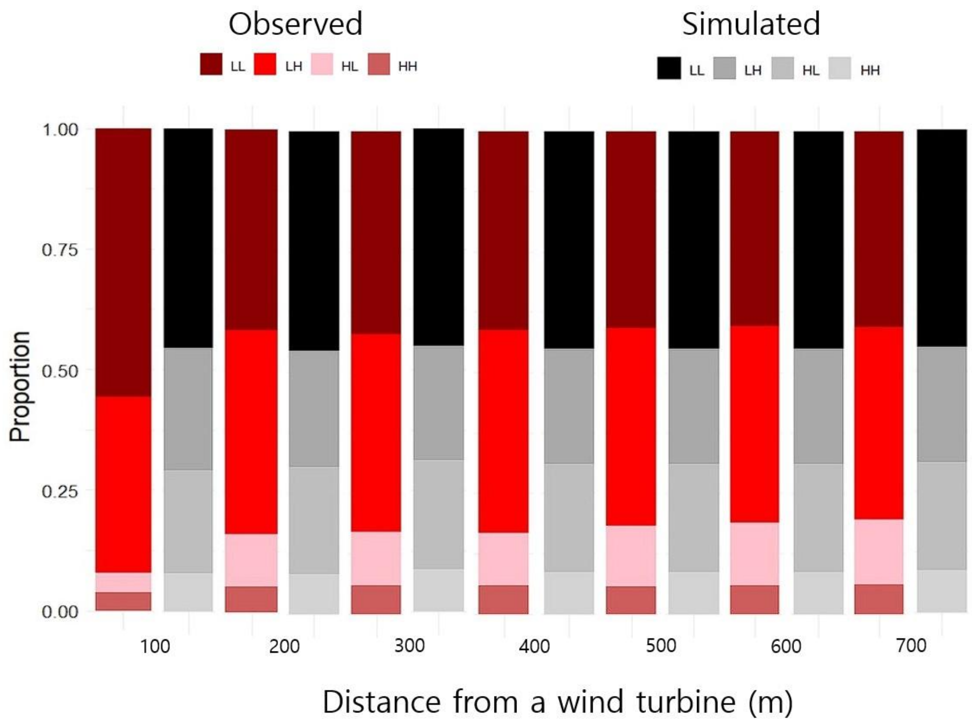


Figure 11. The proportion of the number of coordinates categorized into four different movement modes (LL, LH, HL, and HH; see Figure 4 for reference) in observed and simulated data along the buffer from a wind turbine.

Table 1. Chi-square test for observed and simulated data in a maximum buffer of 700m. See Figure 4 for reference.

	Movement modes				Chi-square	
	Low velocity/ Low angle (LL)	Low velocity/ High angle (LH)	High velocity/ Low angle (HL)	High velocity/ High angle (HH)	x^2	p-value
Observed	556 (40.60%)	553 (39.76%)	187 (13.44%)	85 (6.11%)	205.46	<0.001
Simulated	17,844 (45.41%)	9,335 (23.76%)	8,782 (22.35%)	3,334 (8.49%)		

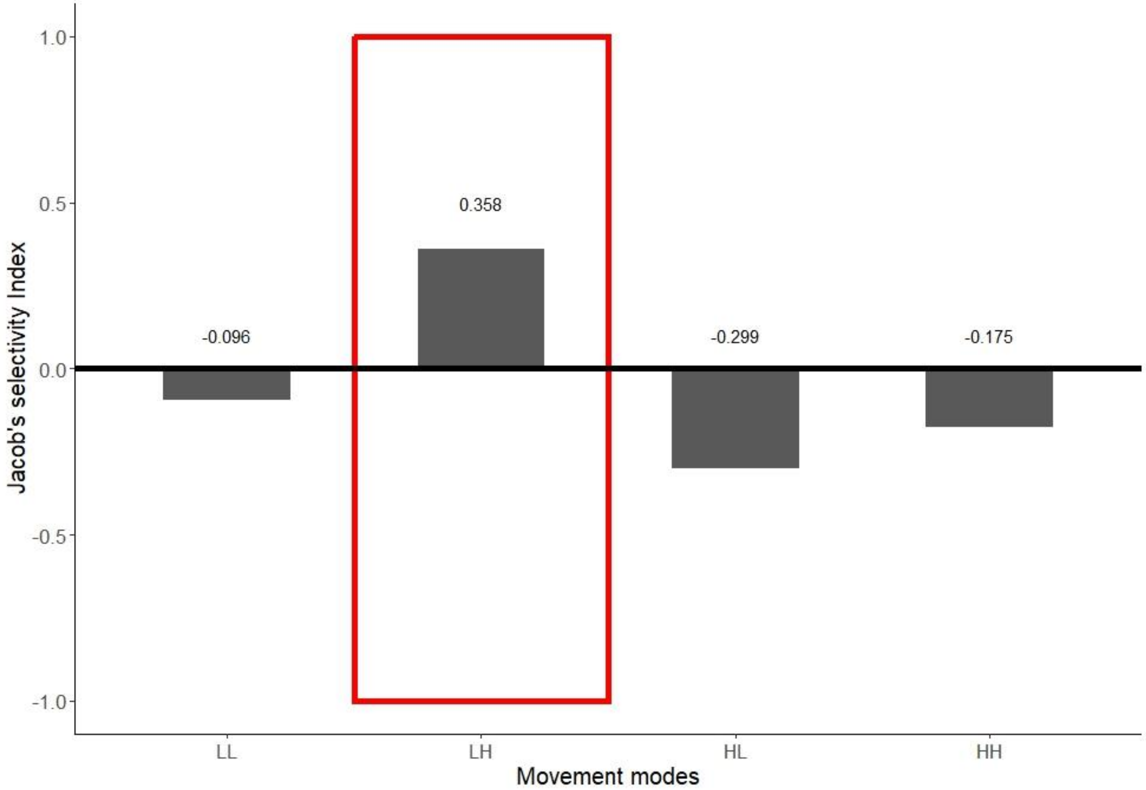


Figure 12. Jacobs' selectivity index for all the behaviors. Only LH had a positive value (0.358). See Figure 4 for reference.

4.2 Horizontal spatial utilization

The proportions of the number of observed and simulated paths within a maximum buffer distance of 700m were calculated, and a chi-square test was conducted to compare these proportions to assess the differences. The analysis revealed significant differences (p-value < 0.05) across all buffer ranges from 50m to 700m. Notably, the 700m buffer range exhibited a p-value of 0.01, which remains below the significance threshold of 0.05. To evaluate potential differences between the micro and meso-scale, a chi-square test was conducted again for each scale.

When comparing the 50m to 100m buffer range and the 100m to 700m buffer range, the chi-square test revealed that the 50m to 100m buffer had a p-value of less than 0.05 (Table 2), indicating a significant difference between the observed and simulated data. On the other hand, the p-value for the 100m to 700m buffer range was found to be 0.221 (Table 3), suggesting that there was no significant difference observed in this case. Within the micro-scale buffer, the number of observed paths increased as the distance from the wind turbine increased. However, within the meso-scale buffer, no significant pattern was observed.

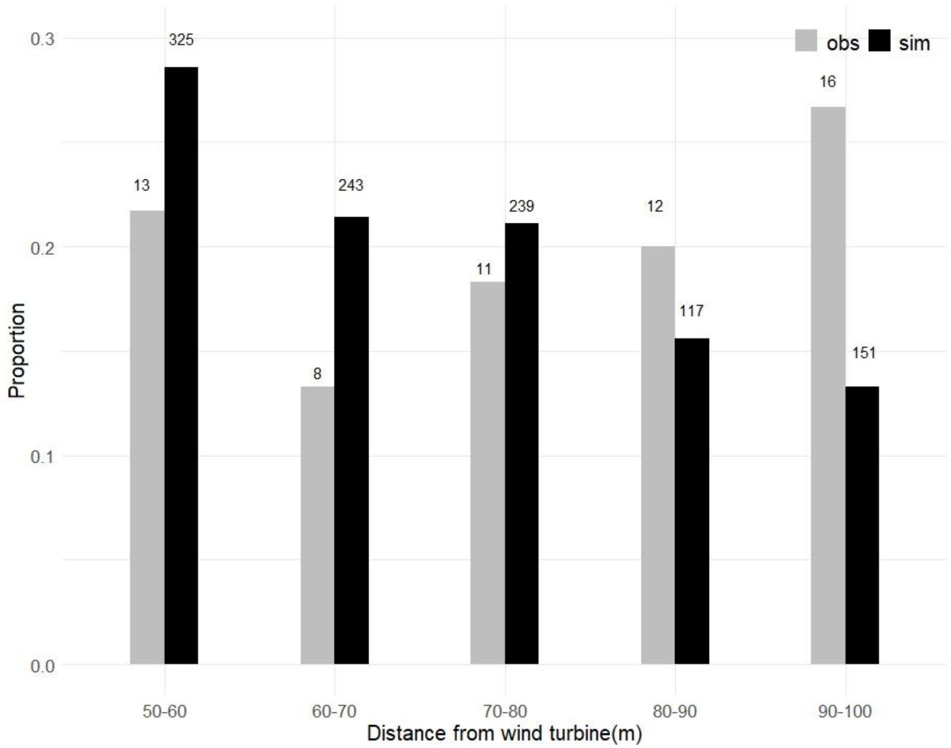


Figure 13. The proportion of the number of paths collected within each buffer area for observed and simulated data in micro-scale (50-100m). Figures above the bars denote the numbers of observed and simulated paths.

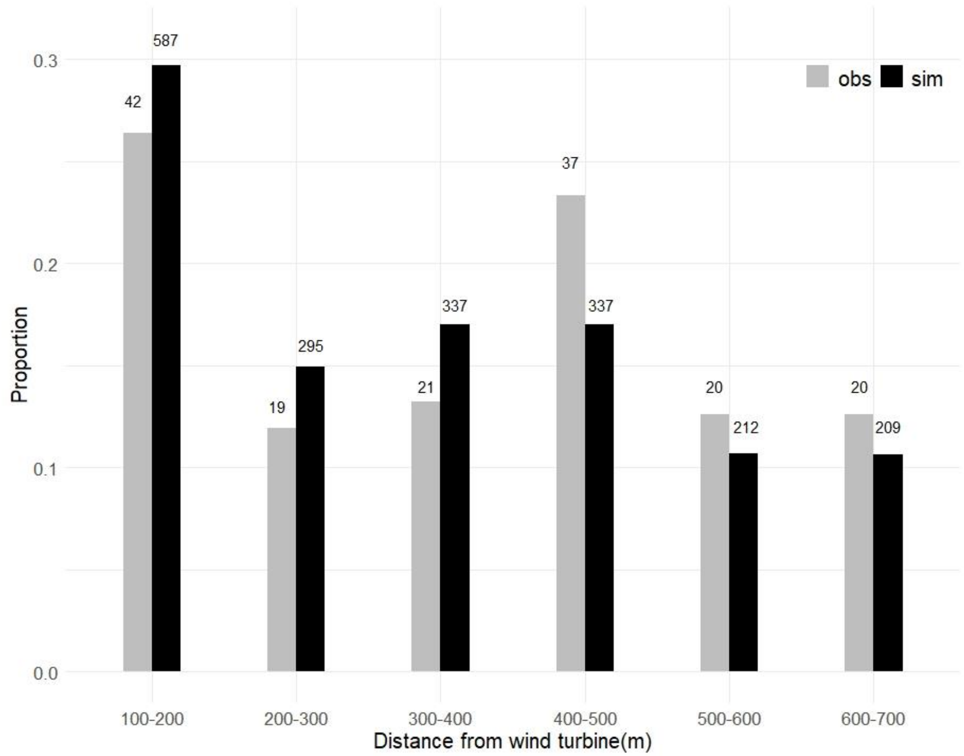


Figure 14. The proportion of the number of paths collected within each buffer area for observed and simulated data in meso-scale (100-700m). Figures above the bars denote the number of observed and simulated paths.

Table 2. The number of paths included between each buffer area (50-100m). Chi-square comparing observed and simulated data by the distance from each buffer area in micro-scale.

	Each buffer area in distance (m)					Chi-square	
	50-60	60-70	70-80	80-90	90-100	x^2	p-value
Observed	13 (21.67%)	8 (13.33%)	11 (18.33%)	12 (20%)	16 (26.67%)	14.308	0.006
Simulated	325 (28.63%)	243 (21.41%)	239 (21.06%)	117 (15.60%)	151 (13.30%)		

Table 3. The number of paths included between each buffer area. Chi-square comparing observed and simulated data by the distance from each buffer area (100-700m).

	Each buffer area in distance (m)						Chi-square	
	100-200	200-300	300-400	400-500	500-600	600-700	x^2	p-value
Observed	42 (26.42%)	19 (11.95%)	21 (13.21%)	37 (23.27%)	20 (12.58%)	20 (12.58%)	6.99	0.221
Simulated	587 (29.69%)	295 (14.92%)	337 (17.05%)	337 (17.05%)	212 (10.72%)	209 (10.57%)		

4.3 Vertical spatial utilization

The overall Jacobs' selectivity index was calculated for each height category, revealing that the below collision risk zone exhibited a positive value, indicating preference, whereas all other heights demonstrated mostly negative values, indicating avoidance (Figure 15). The calculated Jacobs' selectivity index for each height category did not follow the normal distribution ($p < 0.05$), as well as the use of bootstrapping to resample the data ($p < 0.05$). Jacobs' selectivity index was calculated for each buffer area to assess potential differences based on the distance. The results revealed a similar trend in terms of horizontal spatial utilization. Within the high collision risk area (micro-scale), Black-tailed Gulls exhibited a preference for lower altitudes while avoiding the collision risk zone (Figure 16). However, when gulls approached the wind turbine from a distance (meso-scale), no particular preference or avoidance behavior was observed (Figure 17). Manly's selection indices were also calculated for each height category, as well as the distance from a wind turbine.

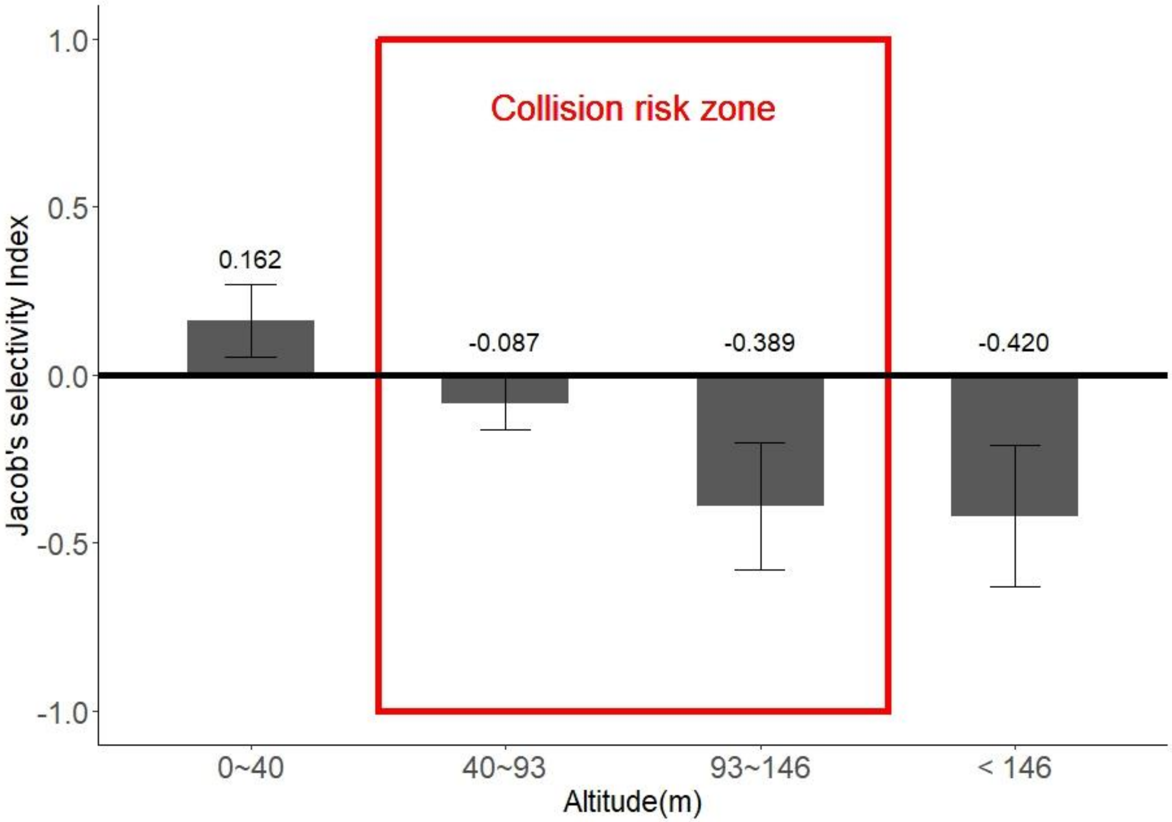


Figure 15. Resampled Jacobs' selectivity index in each height category. Negative value represents avoidance, positive value represents preference. The number and bar represent the mean preference or avoidance, while the vertical lines on bars denote 95% confidence intervals.

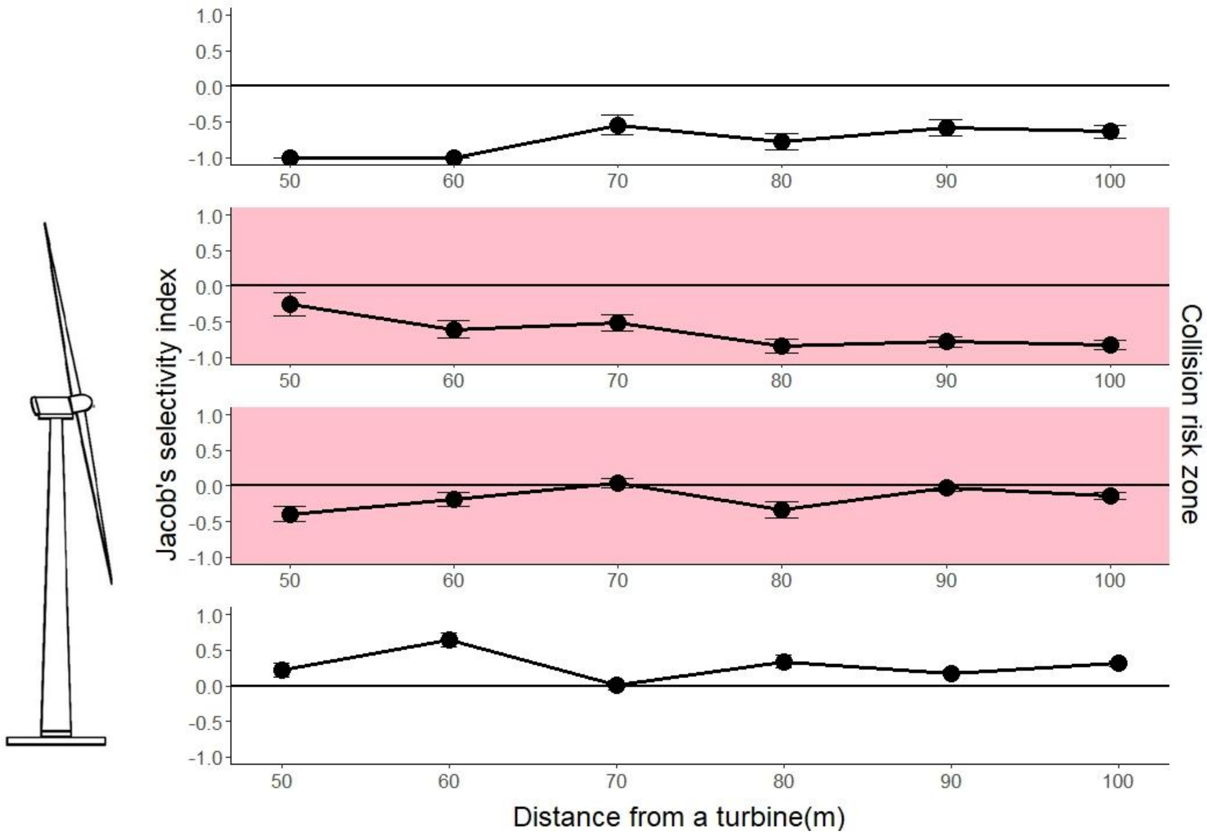


Figure 16. Resampled Jacobs' selectivity index in each height category by a buffer area in micro-scale (50-100m). Negative value represents avoidance, positive value represents preference. Colored parts in two middle panels are collision risk zones, whereas those not colored are below collision risk zone (bottom) and above collision risk zone (top) (Wind turbine image from Caduff et al. 2012).

Table 4. Estimated selection indices and Bonferroni confidence interval for below collision risk zone in micro-scale (50-100m). Values in parenthesis mean the lower and upper confidence intervals.

Distance (m)	Available		Used		Selection index With Bonferroni CI	Standardized selection index
	Count	Proportion	Count	Proportion		
50	489	0.063	7	0.048 (0.002 – 0.094)	0.760 (0.024 – 1.496)	0.127
60	672	0.086	13	0.088 (0.027 – 0.149)	1.027 (0.312 – 1.742)	0.171
70	911	0.117	17	0.116 (0.047 – 0.185)	0.991 (0.397 – 1.585)	0.165
80	1,191	0.153	27	0.184 (0.100 – 0.268)	1.204 (0.655 – 1.753)	0.201
90	1,508	0.193	32	0.218 (0.128 – 0.308)	1.127 (0.663 – 1.591)	0.188
100	3,033	0.389	51	0.347 (0.244 – 0.450)	0.893 (0.628 – 1.158)	0.149
Total	7,804		147		6.000	1.000

Table 5. Estimated selection indices and Bonferroni confidence interval for lower collision risk zone (50-100m). Values in parenthesis mean the lower and upper confidence intervals.

Distance (m)	Available		Used		Selection index With Bonferroni CI	Standardized selection index
	Count	Proportion	Count	Proportion		
50	237	0.061	4	0.027 (-0.008 – 0.062)	0.435 (-0.135 – 1.006)	0.095
60	349	0.090	10	0.067 (0.013 – 0.121)	0.739 (0.142 – 1.336)	0.161
70	466	0.120	10	0.067 (0.013 – 0.121)	0.554 (0.107 – 1.001)	0.120
80	598	0.155	14	0.093 (0.031 – 0.155)	0.604 (0.202 – 1.006)	0.131
90	750	0.194	18	0.120 (0.050 – 0.190)	0.619 (0.244 – 0.964)	0.135
100	1,469	0.380	94	0.627 (0.523 – 0.731)	1.650 (1.337 – 1.923)	0.359
Total	3,869		150		4.601	1.000

Table 6. Estimated selection indices and Bonferroni confidence interval for higher collision risk zone (50-100m). Values in parenthesis mean the lower and upper confidence intervals.

Distance (m)	Available		Used		Selection index With Bonferroni CI	Standardized selection index
	Count	Proportion	Count	Proportion		
50	64	0.061	0	0.000	-	-
60	94	0.089	1	0.200 (-0.270 – 0.670)	2.240 (-3.046 – 7.526)	0.333
70	128	0.122	1	0.200 (-0.270 – 0.670)	1.645 (-2.211 – 5.501)	0.245
80	164	0.156	1	0.200 (-0.270 – 0.670)	1.284 (-1.732 – 4.300)	0.191
90	205	0.195	1	0.200 (-0.270 – 0.670)	1.027 (-1.386 – 3.440)	0.153
100	398	0.378	1	0.200 (-0.270 – 0.670)	0.529 (-0.716 – 1.774)	0.079
Total	1,053		5		6.726	1.000

Table 7. Estimated selection indices and Bonferroni confidence interval for above collision risk zone (50-100m). Values in parenthesis mean the lower and upper confidence intervals.

Distance (m)	Available		Used		Selection index With Bonferroni CI	Standardized selection index
	Count	Proportion	Count	Proportion		
50	24	0.051	0	0.000	-	-
60	37	0.078	0	0.000	-	-
70	56	0.118	1	0.250 (-0.320 – 0.816)	2.121 (-2.692 – 6.934)	0.387
80	81	0.171	1	0.250 (-0.320 – 0.816)	1.466 (-1.855 – 4.787)	0.268
90	96	0.202	1	0.250 (-0.320 – 0.816)	1.237 (-1.574 – 4.048)	0.226
100	181	0.381	1	0.250 (-0.320 – 0.816)	0.656 (-0.835 – 2.147)	0.120
Total	475		4		5.480	1.000

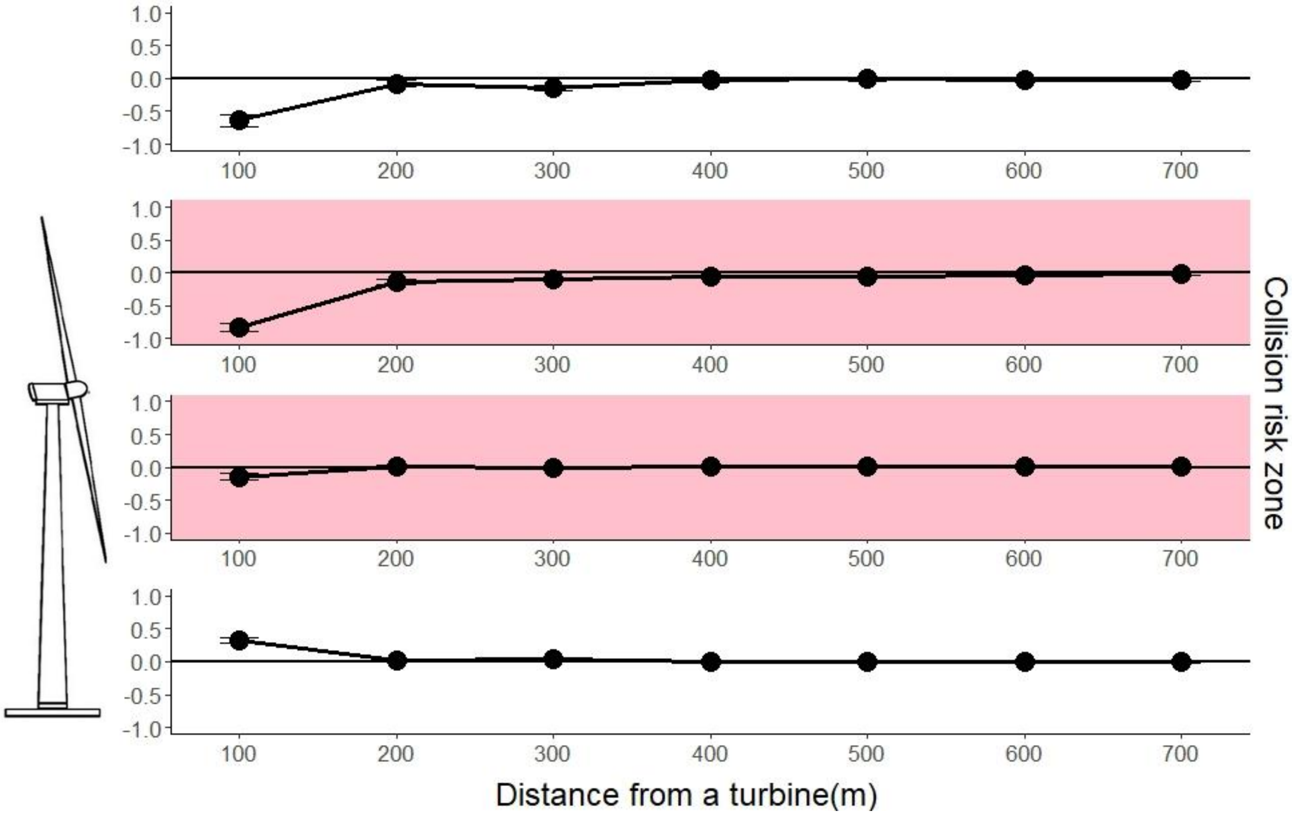


Figure 17. Resampled Jacobs' selectivity index in each height category by a buffer area in meso-scale (100-700m). Negative value represents avoidance, positive value represents preference. Colored parts in two middle panels are collision risk zones, whereas those not colored are below collision risk zone (bottom) and above collision risk zone (top) (Wind turbine image from Caduff et al. 2012).

Table 8. Estimated selection indices and Bonferroni confidence interval for below collision risk zone (100-700m). Values in parenthesis mean the lower and upper confidence intervals.

Distance (m)	Available		Used		Selection index With Bonferroni CI	Standardized selection index
	Count	Proportion	Count	Proportion		
100	3,033	0.020	51	0.016 (0.01 – 0.022)	0.799 (0.489 – 1.109)	0.117
200	10,374	0.068	202	0.063 (0.051 – 0.075)	0.925 (0.749 – 1.101)	0.136
300	17,656	0.115	388	0.121 (0.105 – 0.137)	1.044 (0.904 – 1.184)	0.153
400	23,447	0.153	513	0.159 (0.141 – 0.177)	1.039 (0.921 – 1.157)	0.153
500	28,377	0.186	615	0.191 (0.172 – 0.210)	1.030 (0.926 – 1.134)	0.151
600	32,945	0.215	698	0.217 (0.197 – 0.237)	1.007 (0.912 – 1.102)	0.148
700	37,047	0.242	751	0.233 (0.212 – 0.254)	0.963 (0.877 – 1.049)	0.141
Total	152,879		3,218		6.807	1.000

Table 9. Estimated selection indices and Bonferroni confidence interval for lower collision risk zone (100-700m). Values in parenthesis mean the lower and upper confidence intervals.

Distance (m)	Available		Used		Selection index With Bonferroni CI	Standardized selection index
	Count	Proportion	Count	Proportion		
100	1,469	0.021	94	0.042 (0.030 – 0.054)	2.041 (1.474 – 2.608)	0.260
200	4,844	0.068	171	0.077 (0.061 – 0.093)	1.126 (0.893 – 1.359)	0.143
300	8,337	0.117	239	0.107 (0.089 – 0.125)	0.914 (0.757 – 1.071)	0.116
400	10,919	0.154	289	0.130 (0.110 – 0.150)	0.844 (0.714 – 0.974)	0.107
500	13,105	0.185	327	0.147 (0.126 – 0.168)	0.796 (0.682 – 0.910)	0.101
600	15,150	0.213	256	0.160 (0.138 – 0.182)	0.749 (0.647 – 0.851)	0.095
700	17,201	0.242	751	0.337 (0.309 – 0.365)	1.392 (1.246 – 1.508)	0.177
Total	17,025		2,227		7.863	1.000

Table 10. Estimated selection indices and Bonferroni confidence interval for higher collision risk zone (100-700m). Values in parenthesis mean the lower and upper confidence intervals.

Distance (m)	Available		Used		Selection index With Bonferroni CI	Standardized selection index
	Count	Proportion	Count	Proportion		
100	398	0.020	1	0.003 (-0.005 – 0.011)	0.133 (-0.262 – 0.528)	0.022
200	1,401	0.071	21	0.056 (0.023 – 0.089)	0.794 (0.325 – 1.262)	0.130
300	2,316	0.117	44	0.117 (0.071 – 0.163)	1.006 (0.610 – 1.402)	0.165
400	3,070	0.155	59	0.157 (0.120 – 0.207)	1.018 (0.686 – 1.350)	0.167
500	3,673	0.185	73	0.195 (0.138 – 0.252)	1.053 (0.743 – 1.363)	0.173
600	4,243	0.214	84	0.224 (0.164 – 0.284)	1.049 (0.767 – 1.331)	0.172
700	4,765	0.240	93	0.248 (0.186 – 0.310)	1.034 (0.774 – 1.294)	0.170
Total	19,866		375		6.087	1.000

Table 11. Estimated selection indices and Bonferroni confidence interval for above collision risk zone (100-700m). Values in parenthesis mean the lower and upper confidence intervals.

Distance (m)	Available		Used		Selection index With Bonferroni CI	Standardized selection index
	Count	Proportion	Count	Proportion		
100	181	0.023	1	0.006 (-0.011 – 0.023)	0.284 (-0.471 – 1.039)	0.045
200	554	0.070	10	0.065 (0.010 – 0.120)	0.927 (0.135 – 1.719)	0.148
300	923	0.116	16	0.103 (0.035 – 0.171)	0.891 (0.302 – 1.480)	0.142
400	1,231	0.155	25	0.161 (0.078 – 0.244)	1.043 (0.510 – 1.576)	0.166
500	1,466	0.184	31	0.200 (0.110 – 0.290)	1.086 (0.597 – 1.575)	0.173
600	1,714	0.215	35	0.226 (0.132 – 0.320)	1.049 (0.661 – 1.487)	0.167
700	1,894	0.238	37	0.239 (0.143 – 0.335)	1.004 (0.601 – 1.407)	0.160
Total	7,963		155		6.284	1.000

5. Discussion

5.1 Movement modes

It is crucial to determine which dataset exhibited a higher proportion. Among the movement modes (LL, LH, HL, HH), only LH behavior demonstrated a higher observed proportion than the simulated proportion (Figure 11), whereas the other behaviors showed higher simulated proportions than observed. The findings suggest that Black-tailed Gulls predominantly displayed LH behavior when encountering wind turbines. This behavioral preference is effectively captured by Jacobs' selectivity index, which exhibited a positive value exclusively for the LH behavior (Figure 12). The positive index value further supports and accurately reflects the observed phenomenon of Black-tailed Gulls favoring LH behavior over other flight behaviors in the presence of wind turbines. In the study on gannets (Peschko et al. 2021), it was observed that among various movement modes, gannets exhibited a higher frequency of HH behavior towards the wind farm, which was classified as "foraging" in this particular study. Both studies revealed that when confronted with the presence of a wind farm, birds displayed increased utilization of high angle movements. However, there was a discrepancy in the utilization of speed, with gannets displaying a preference for high speed/high angle movements, while Black-tailed Gulls exhibited a preference for low speed/high angle movements. This difference could potentially be attributed to species-specific variables, variations in data collection periods, and discrepancies in study areas. Nonetheless, the significance lies in the fact that both studies indicated that birds tend to adopt high angle movements when confronted with a wind farm.

In summary, the specific behaviors exhibited varying proportions, with LH behavior showing a higher observed proportion, while other behaviors displayed higher simulated proportions. Black-tailed Gulls lower their speed and change their direction within wind farm areas suggesting that gulls be able to identify obstacles and engage in tortuous flights.

However, it is important to note that the act of categorizing behavior does not necessarily indicate that they were adopting those behaviors specifically to avoid wind turbines. There were freshwater resources present alongside the wind turbines, and the Black-tailed Gulls would often pause to rest or forage in those areas. Given the availability of water resources, the utilization of low velocity, high angle flight by birds may align with their natural behavioral patterns. However, it is important to note that the simulated data used in this study represents a scenario where random spatial utilization occurs in the absence of wind turbines. Therefore, it is possible that the presence of wind turbines could influence their behavior differently. In order to accurately assess the behavioral change, the environment around the wind turbine must be uniform. There are offshore wind farms located near the study area but due to insufficient data, the study around offshore could not be conducted. A few more years of data collection should be required in order to conduct such a study around the offshore wind farm.

5.2 Horizontal spatial utilization

The chi-square test conducted at the maximum distance of 700m revealed a significant difference in proportion within the 700m buffer area. When the chi-square test for micro and meso-scale buffer were conducted, the p-values were distinct, with the range of 50m to 100m showing a p-value of less than 0.05, while the range of 100m to 700m had a p-value of 0.221. The spatial utilization differed between the observed and simulated data, suggesting that Black-tailed Gulls did not exhibit as frequent flight within the 50-100m buffer area around wind turbines as would be expected. However, there was no significant difference in the spatial utilization within the 100m-700m buffer area, potentially indicating that a spatial utilization threshold of 100m could exist to avoid collisions. The results indicate that when Black-tailed Gulls approach wind turbines from a distance (meso-scale), they do not exhibit specific avoidance movements. However, within close proximity where the risk of collision is higher (micro-scale), they tend to avoid flying in that area.

The significance of the 100m distance is noteworthy due to its close proximity to the rotor diameter, making it a critical threshold for assessing micro-avoidance behavior. Given its proximity, the 100m distance is highly relevant as it represents the point where such avoidance behaviors are more likely to occur. This implies that when gulls come within this range, the likelihood of a collision increases. However, the proportion of flights differs when gulls are inside or outside the 100m range, suggesting that the gulls have the ability to recognize collision-prone areas and actively avoid them by altering their flight paths. This behavior indicates that gulls are capable of perceiving visible threats and making adjustments to mitigate the risk of collision.

This finding aligns with previous investigations conducted by Cabrera-Cruz studies (Cabrera-Cruz & Villegas-Patraca, 2016; Therkildsen et al. 2021), which also observed horizontal movement patterns. However, it should be noted that the study by (Therkildsen et al. 2021) estimated horizontal avoidance based on bird distribution rather than actual trajectories. The rotor diameter varies due to the specification of a wind turbine, so it is important to note that the distance birds used also varies.

5.3 Vertical spatial utilization

The overall Jacobs' selectivity index consistently indicated a preference for the altitude below the collision risk zone (0-40m). The observed preference for lower altitudes was consistently observed across the entire buffer area (Figure 15). However, this preference was particularly concentrated within the 50m to 100m buffer area (Figure 16), clearly indicating that Black-tailed Gulls had a strong preference to fly at this altitude when the distance from a wind turbine was shorter. As the buffer extends beyond the 100m range, the value of the index was close to 0 (Figure 17), suggesting no preference or avoidance. This was observed throughout the height categories, indicating that the Black-tailed Gulls did not exhibit preference or avoidance as they moved further away from the wind turbines. The tendency of vertical spatial utilization, which involves a preference for lower altitudes consistent with a previous study (Schaub et al. 2020; Therkildsen et al. 2021) which also suggested that birds are likely to fly below the collision risk zone while avoiding collision risk zones. However, it differs from another study (Johnston et al. 2014), which reported opposite results. This discrepancy may be attributed to species-specific variations in behavior, as different species are known to exhibit distinct behaviors.

The data used in this analysis are coordinates, which are points that have spatial information such as longitude, latitude, speed, and altitude. When generating simulation data based on the observed data, it is ideal to use paths rather than individual coordinate points. This is because, during rotation, certain coordinates may fall outside the specific buffer area, while connected paths ensure that the entire trajectory is included. The analysis of horizontal movement successfully used such data. However, incorporating altitude information into the paths was not possible. As a result, the analysis of vertical movement had to be conducted using the available coordinates points. It is important to note that this limitation in combining altitude information with paths may affect the accuracy of vertical movement analysis, but the analysis was conducted to the best of its ability using the available data and methodologies.

The target species of this study was Black-tailed Gulls. Therefore, the findings and conclusions of this study pertain solely to this particular species. However, it was confirmed that other bird species were spotted in the study area, including Eurasian Spoonbill (*Platalea minor*), Chinese Egret (*Egretta eulophotes*), Eurasian Oystercather (*Haematopus ostralegus*), and Far Eastern Curlew (*Numenius madagascariensis*), which are classified as endangered, vulnerable, or near threatened according to the IUCN Red List (Kim et al. 2021). These birds may have distinct behavioral patterns due to species-specific matter, suggesting that behavioral change could be different from that of Black-tailed Gulls. Consequently, it is imperative to conduct similar research on these species to investigate potential species-specific behavioral changes.

Behavioral changes in response to wind turbines are currently being actively studied, although the majority of research has been conducted in Europe and North America, focusing primarily on raptors or migratory species. Some studies have explored methods to mitigate collisions with wind turbines, such as increasing blade visibility (May et al. 2020) and implementing AI cameras for curtailment triggers (McClure et al. 2021). Additionally, collision risk models, like the one developed by (Band, 2012) can calculate wind turbine specifications that minimize the risk of collisions. If behavioral change studies incorporate these collision-mitigating techniques, the observed behavioral changes could be even more distinct.

As wind turbine installations continue, whether it's on onshore or offshore, offshore wind turbines provide a more homogeneous surrounding environment, facilitating the identification of how wind turbines influence behavioral changes. The result of this study sheds light on how bird behavior changes in the presence of wind turbines, serving as a valuable predictor for potential future wind turbine construction projects. For future research associated with this topic, it is expected to evaluate the potential population-level effects resulting from these behavioral changes.

5.4 Overall discussion

This study aimed to investigate the changes in flight behavior of Black-tailed Gulls towards wind turbines, considering their frequent interaction with the wind farm area. Previous research has indicated that the clutch size of Black-tailed Gulls is influenced by the proximity of their foraging site to their breeding site, highlighting the impact of food availability on clutch size (Kwon et al. 2006). Furthermore, a higher clutch size directly correlates with a higher rate of successful breeding. It is expected that Black-tailed Gulls would frequently visit the wind farm area for foraging purposes because the wind farm is relatively close to the breeding islands, and the shallow sea level along with the mudflats near the wind farm provides ample food resources for them. Additionally, observations revealed that groups of Black-tailed Gulls would rest near the freshwater resources present within the wind farm area. The tracks and coordinates of Black-tailed Gulls were widely dispersed within the wind farm area during the breeding season, indicating their utilization of the wind farm area during this period. In contrast, during the non-breeding season, particularly winter (November to February), the distribution of Black-tailed Gulls was predominantly found in the sea rather than on the coastline or breeding islands. Therefore, it is likely that the interaction with the wind farm area primarily occurs during the breeding season, and this increased interaction potentially leads to behavioral changes in Black-tailed Gulls to avoid wind turbines.

6. Conclusions

The flight behavior of Black-tailed Gulls was examined in close proximity to a wind farm, revealing three distinct components of behavioral change. Each component exhibited unique behaviors, encompassing velocity/angle change, horizontal spatial utilization through flight path adjustments, and vertical spatial utilization via altitudinal changes. A comparative analysis was conducted using the proportions of observed and simulated data to investigate these components.

The results showed that Black-tailed Gulls predominantly employed slow and directional changing flights. Furthermore, they exhibited horizontal spatial utilization by not flying near wind turbines and demonstrated a tendency to lower their altitude, indicating a deliberate avoidance strategy to mitigate potential collisions. Notably, both horizontal and vertical spatial utilization became more pronounced as the distance between a wind turbine and Black-tailed Gulls decreased.

This study elucidates the flight behavioral changes of Black-tailed Gulls in the vicinity of a wind farm. Although Black-tailed Gulls are common species, it cannot be ignored the fact that such abundant species help maintain the ecosystem. The gulls exhibited a range of adaptive responses, including adjustments in velocity, angle, flight paths, and altitude, to navigate and mitigate collision risks.

These findings underscore the significance of comprehensively considering both horizontal and vertical spatial utilization patterns when assessing the impact of wind farms on the specific species under investigation. It is important to note that while the results of this study are specific to Black-tailed Gulls due to their unique traits, the methodology employed can be adapted to conduct conservation research on the impact of wind turbines on other avian species, especially collision-prone or endangered species. Furthermore, these research findings provide valuable insights for the development of mitigation strategies. For instance, the study identified the preferred altitude of Black-tailed Gulls, which can inform targeted collision mitigation efforts. Based on the findings of this study, mitigation strategies can be developed, including the possibility of increasing the height of wind turbines or reducing the diameter of blades. Although the applicability of the study's results may be limited to this particular species, they can serve as a basis for developing mitigation strategies that consider species-specific behaviors and preferences.

Lastly, for future research, the collection of data before and after wind farm construction should be conducted in any form. It is crucial to gather data in the specific locations where wind turbines are planned to be installed and subsequently conduct comparisons between the two datasets. By collecting data both prior to and after construction, a more comprehensive understanding of the effects on avian species and their behaviors can be obtained. Additionally, it is recommended to incorporate species-specific movement while accounting for environmental factors. Bird movement is influenced not only by artificial objects but also by environmental factors, therefore both aspects must be taken into consideration.

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Abstract in Korean

탄소 중립정책의 영향으로 다양한 종류의 친환경 에너지가 개발되고 있는 가운데, 풍력발전이 주목을 받고 있다. 하지만 풍력발전의 개발은 환경에 부정적인 영향을 끼치고 있으며, 특히 야생동물 서식지 파괴 및 조류 충돌 등으로 인해 생물다양성에 위협을 유발하고 있다. 특히, 조류는 풍력발전기 개발과 관련하여 논의되는 주요 야생동물이며 충돌 및 서식지 파괴 등 직접적인 영향을 가장 크게 받는 야생동물로 알려져 있다. 야생동물들은 위협을 회피하기 위해 행동을 변화할 가능성이 있으므로, 풍력발전기 건설로 인한 야생동물의 행동변화에 대한 연구가 필요하다. 본 연구는 전라남도 영광에 위치한 풍력발전기 주변에서 서식하는 괭이갈매기를 대상으로 거리에 따른 비행행동 변화와 풍력발전기 회피를 파악하는 것을 목적으로 하였다. 데이터 수집은 GPS 추적기를 괭이갈매기에게 부착하여 비행정보를 수집하는 것으로 진행되었다.

먼저 거리에 따른 비행행동 변화를 파악하기 위해 풍력발전기 주변으로 일정 간격의 버퍼를 생성하였다. 버퍼는 풍력발전기와 충돌 직전 일어나는 회피행동인 micro-avoidance 를 파악하기 위해 50-100m 간격으로, 풍력발전단지 내의 회피행동인 meso-avoidance 를 파악하기 위해 100-700m 간격으로 버퍼를 생성하였다. 버퍼 생성 후, 풍력발전기의 고도를 충돌 위험구간을 기준으로 4 가지 (below collision risk zone, lower collision risk zone, higher collision risk zone, above collision risk zone)로 나누었다.

풍력발전기에 대한 괭이갈매기의 비행행동의 변화는 회피를 목적으로 하며 기존 연구에서 밝혀진 각도변화, 수평적 공간이용인 비행 경로변화, 수직적 공간이용인 고도변화로 나눌 수 있다. 각도변화는 괭이갈매기의

비행속도와 각도의 낮음/높음을 사용하여 행동을 4 가지 modes(낮은 속도/낮은 각도, 낮은 속도/높은 각도, 높은 속도/낮은 각도, 높은 속도/높은 각도)로 구분 후 버퍼 내 포함되는 비율을 산출하였다. 경로변화는 괭이갈매기의 좌표를 선으로 이어 비행 경로를 생성한 후 버퍼 내 포함되는 경로의 비율을 산출하였고 마지막으로 고도변화는 좌표의 고도정보를 이용하여 버퍼 내 포함되는 비율을 산출하였다. 풍력발전기에 대한 조류의 움직임 연구는 발전단지 건설 전/후의 데이터를 수집하고 비교하는 것을 기본으로 한다. 하지만 단지 건설 전의 데이터 부족으로 인해 발전단지 건설 후 수집된 데이터를 무작위 각도로 여러 번 회전 후 시뮬레이션 데이터를 생성하여 풍력발전기가 없는 상황을 가정하였다. 이후, 시뮬레이션 및 실제 데이터 간의 비율 비교를 통해 풍력발전기로부터의 거리에 따른 비행행동의 변화의 차이를 분석하였다.

연구 결과, 시뮬레이션 데이터와 실제 데이터 간의 비행행동에 차이가 있었으며 실제 데이터는 낮은 속도를 이용한 비행행동에 집중되어 있었다. 이는 괭이갈매기의 실제 데이터가 시뮬레이션 데이터 보다 낮은 속도로 비행하는 비율이 높은 것을 의미한다. 또한, 낮은 속도의 비행 중 높은 각도로 비행하는 비율이 낮은 각도로 비행하는 비율보다 높았다. 비행의 수평적 공간이용을 실제 데이터와 시뮬레이션 데이터를 비교하여 분석하였을 때, 풍력발전기 주변 50-100m 거리에서 근접하여 비행하지 않는 모습을 보였고 100-700m 거리에서는 차이가 없었다. 마지막으로 비행의 수직적 공간이용을 실제 데이터와 시뮬레이션 데이터를 비교하여 분석하였을 때, 발전단지 내 비행 시 약 40m 아래의 고도를 선호하는 모습을 확인하였고 풍력발전기와 충돌위험이 있는 고도는 회피하는 것으로 확인되었다. 이는 풍력발전기의 존재가

괭이갈매기의 속도와 각도변화 등 비행 행동에 영향을 주며 수직적, 수평적 공간이용에도 영향을 준다는 것을 확인하였다.

이 연구는 풍력발전단지를 이용하는 조류의 행동변화를 연구함으로써 풍력발전기 제원의 높낮이 조절로 이 종의 충돌저감을 고려할 수 있고, 향후 설치될 풍력발전기에 대해 괭이갈매기의 행동을 사전에 예측하고, 후속연구를 통해 이러한 행동변화가 추후 개체군에 미치는 영향을 평가한다는 데 활용될 수 있다는 점에서 유의미하다. 하지만 괭이갈매기의 행동변화는 주변의 환경 (수원, 논 등)에 영향을 받을 가능성도 있어 풍력발전기로 인한 행동변화 연구를 위해서는 균일한 주변 환경을 가정하고 풍력발전기에 대한 영향을 평가하는 연구가 필요하다. 또한, 해당 지역에 출몰하는 다양한 종과 환경을 고려하는 모니터링과 연구가 필요할 것으로 보인다.

주요어 : 괭이갈매기, 수직적 공간이용, 수평적 공간이용, 풍력발전기, 행동 변화, 회피 행동

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