Modelling the effect of weather parameters on bird migration patterns

by

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Declaration

I hereby declare that

i) the thesis comprises of my original work towards the degree of Master of Technology in Information and Communication Technology at Dhirubhai Ambani Institute of Information and Communication Technology and has not been submitted elsewhere for a degree,

ii) due acknowledgment has been made in the text to all the reference material used.

Devanshi Chandegra

Certificate

This is to certify that the thesis work entitled Modelling the effect of weather parameters on bird migration patterns here has been carried out by Devanshi Chandegra for the degree of Master of Technology in Information and Communication Technology at *Dhirubhai Ambani Institute of Information and Communication Technology* under my supervision.

Prof. Minal Bhise
Thesis Co-Supervisor

Prof. Sanjay Srivastava
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Contents

Abstract

History views birds as mere messengers, but they are a critical part of our ecosystem. However, study shows that bird species are undergoing extinction over hundreds times faster than we thought [3]. Bird conservation addresses the dual threats of climate change and habitat loss on bird migration. The effect of climatic changes has a direct or indirect effect on bird migrations and it is a natural process. However, human-induced global warming has accelerated climatic fluctuations leading to abrupt changes in bird migration and also their extinction.

India suffers significant climate variations because of its geographic location, which has a significant impact on bird migration. This study is aimed on establishing the association between climate change and bird migration in India based on the research that has been done till now. We will have a better understanding of how climate conditions impact bird migration patterns in Kerala as a result of the study. And in order to do that, it seeks to analyse the relationship of the arrival and departure dates with the climate parameters such as temperature, wind speed, and precipitation. The study also intends to show which bird species behave similarly depending on the given climate factor of the region.

To conduct the described study I examined the relationship between bird migration factors, such as arrival and departure dates, and climatic parameters, such as temperature, wind speed, and precipitation for the each regions of Kerala state which are divided based on their similarity to the climate. It is done to prevent inaccuracies caused by the high variance in Kerala State's climate parameters. For this study Linear Regression is used for the citizen-science website eBird data and NASA POWER's climate data from 2011 to 2019. Other than this I also analysed which bird species are showing similar migration behaviour with change in given climatic parameter for given region of kerala.

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Chapter 1
Introduction

1.1 The Importance of Birds

Apart from adding sound, color, and aesthetic enjoyment to our lives, birds play a crucial role in our ecosystem. They are the favorite environmental indicator of ecologists. Many ecologists have suggested that birds could survive without humans but that humans would be extinct if birds did not exist. There is a strong interdependence between all the living organisms in our natural habitat, and one can learn so much about nature by learning about birds. They act as a pollinator, seed dispersers, destroyers of insect pests and other vermin, and as scavengers. They are strong indicators of many environmental changes. Their movements reflect seasonal changes, and a decline in their numbers tells us that we are damaging the environment. A good habitat for the birds implies that it is a good environment for humans as well. Hence, Ornithology, or the study of birds, is significant because it aids in understanding bird behavior, evolution, conservation, distribution, and migration, among other things.

1.2 Bird Migration

Migration is the seasonal movement of birds from one place to another. This migration can be short-term, medium-term, or long-term. Birds migrate with the seasons and weather changes, primarily for food and habitat. They migrate to places with warmer or better-suited weather, better food, or at times a safe place to give birth to their offspring. Their migration pattern is often the same for each year. For example, birds that belong to the northern hemisphere will tend to move northward in spring to take advantage of the increasing insect population and plenty of nesting options. Birds use different signals of the environment, such as a change in weather, the length of the day, or the availability of food for migration. They navigate with the aid of stars and sun patterns to find their way. Some birds use wind patterns and landmarks like mountains, lakes, and rivers to get the direction.

It has surprised many scientists how the birds travel thousands of miles across seas when they weight even less than an apple. Some studies have also explained how they prepare for this journey [36, 46]. Birds spend weeks gorging themselves on food to fatten themselves up, and increase the levels of cryptochromes (Cry4) protein in their body, as flying for long distances requires excessive energy [4]. It is crucial for bird survival that they eat enough before they leave. It is also essential for them to spend the right amount of energy while flying.

1.3 Threats to Migratory birds

Out of 10,000 known bird species across the globe, approximately 1800 birds are migratory. Many of these species face a global decline in numbers due to human-migratory bird interactions like hunting, habitat modifications, and deforestation. Increasing industrialization and technological advancements also endanger these species. Electromagnetic radiations from sources like mobile towers disorient the birds. The microwave radiations affect the egg and embryos of the birds as well. A well-known phenomenon called the "Tower kill" is when the birds collide with antenna towers due to night illuminations [4].

Another threat to the migratory birds is deforestation. Scientists have proved that many birds are in danger because bird homelands are disappearing. Scientists studied the migration or travel paths of almost 1500 species of birds. They mentioned that 91% of them passed through dangerous areas. The most significant danger for migratory birds is housing and commercial sites development. Building and paving now cover some natural areas where birds stop and feed as they move from one part of the world to another. Researchers say that many small birds die along their migration route as there is no place for them to get energy for the next part of their journey. Researchers say that all the countries need to work together and come up with safe stopover areas for birds that pass through their boundaries. According to scientist Peter Marra, even though some ecosystems are changing, more can be done to maintain urban areas safe for birds [22]. He has implied small changes like growing more native plants could make a big difference. In addition to this, significant dangers to bird life include light pollution, plastic pollution, biofuel plantations, inappropriate harvesting, and oil spills. When we factor all the threats mentioned into a world where the climate is changing rapidly, we have an extraordinary situation where we don't know exactly what will happen.

Another major issue is climate change. Birds can cope with natural climate changes that occur over time due to natural phenomena. However, we are experiencing rapid climate change owing to human-induced global warming. Scientists from the National Audubon society have analyzed the observations of thousands of bird watchers and information from leading climate scientists. They have concluded that birds are on the move in response to global warming. Nearly half the bird species in the United States and Canada are seriously threatened by climate change, and if nothing is done to decrease this threat, many of the bird species could disappear forever. Each species is finely tuned to a set of environmental conditions so that everything about its physiology, behavior, and genetics allows it to be successful in that environment. Still, when those environment fundamentals begin to shift, it can be a catastrophe for birds.

1.4 Motivation

Most animals' environments are altered by global climate change, and it is anticipated that this will cause changes in bird migration, breeding, body form, and other aspects. Organisms must adjust to climate change if they want to survive over the long run. The climate of India is characterised by a vast variety of weather conditions that shift quickly and over a huge geographic area. This constantly has an effect on bird migration, which is what motivated me to do this study. This study's findings will help us understand how environmental factors influence bird migration, which could eventually be useful in a variety of industries, including agriculture, aviation, and can also help in stating birds conservation strategies [31].

1.5 Objective

The objective of the thesis is defined as follows :

- Study to investigate a natural event using publicly available bird and climate data.

- Study of migratory behavior using different migratory parameters such as arrival and departure dates and extracting such parameters from the data using some analytical method.

- Study of relationship between above extracted migrating parameters and climate parameters such as precipitation, temperature and windspeed.
- Study to analyse which bird species show similar migration response to given climate parameter.

1.6 Thesis Outline

The entire thesis is organized as follows: Chapter 2 presents the literature survey. Chapter 3 presents the research methodology used for the study. Chapters 4 and 5 present the experimental setup of the research and its results, respectively. Finally, chapter 6 presents the conclusion.

CHAPTER 2

Related Work

This chapter presents a literature survey on bird migration and climate change.

2.1 Research fields and Datasets for bird studies

Many studies have been conducted on diversity patterns, distribution modeling, migration strategies, population estimation, range shifts, climate change effect, etc. [26, 41, 44, 17, 16, 20, 25, 42, 40, 33, 23].

The variety of birds is significantly higher than that of mammals, reptiles, and amphibians. An ecosystem's general health can be strongly inferred from the diversity of its bird populations. Ecologists also use the richness, abundance, and community composition of birds to understand the diversity of species [35]. One of several research areas that could only be effectively addressed with the development of huge databases is the understanding of patterns of biodiversity at spatial scales [26]. Species distribution modeling is related to spatiotemporal variation within and across scales. It is widely used in conjunction with extension in both space and time to estimate distributions across landscapes and gain ecological and evolutionary insights [17]. The migration of species is an important area of study and comprehending it is fascinating and vital. The discovery of significant stopping, breeding and wintering grounds is one of the objectives of migration study [7, 34]. Once discovered, these important sites can be saved and maintained. Births, deaths, disease incidence, and other statistics are studied concerning population strategy. According to the study, the effects of climate change on birds include an earlier spring migration, altered habitats, increased risk of disease transmission, earlier egg-laying times, decreased food availability, and a fall in population [27].

2.2 Big data in Ornithology

Varied and substantial data are available in this field to work with. Some of them are listed below [26].

- Structured data
  - Breeding Bird Survey (BBS) [9]
  - Audubon's Christmas Bird Count (CBC) [1]
- Semi-structured data
  - ebird [15]
- Unstructured data
  - weather surveillance radar [28]

These big data applications have several challenges: noise accumulation, misleading correlations, and inadvertent endogeneity due to high data volume and dimensionality. Big data resources continue to expand ornithology's empirical breadth and detail.

The long-running national and regional bird population monitoring programmes like the North American Breeding Bird Survey (BBS), the British and French Breeding Bird Survey, and Audubon's Christmas Bird Count are just a few examples of structured datasets with large volumes and low variety and velocity in ornithology [26]. The BBS is a great example; since 1966, it has collected data on breeding bird populations across much of North America using a systematic data gathering methodology. The roughly 2000 random roadside routes carried out yearly throughout North America's breeding season create a vast database of information on the distribution and abundance of breeding birds with immense potential application [9]. BBS has been used to investigate the species-energy theory, the distinction between core and migratory species in ecological communities, and the spatial scaling of biotic interactions [13, 11, 5]. It has also been used in the development of spatiotemporal niche models and in the examination of population responses to urbanisation and climate change at the continental scale [26, 38]. Christmas Bird Count (CBC) data from Audubon is structured. Due to Chapman's motivation and the excitement of 27 dedicated birders, the plan to gather this data was launched [1]. This data extends across North and South America, but the majority of counts have been conducted in the United States and Canada

[29]. Additionally, CBC data is used in other research, including ones on population dynamics, changes in breeding and wintering ranges, etc.[8, 12].

ebird is a crowd-sourced data launched in 2002 by the Cornell Lab of Ornithology at Cornell University and the National Audubon Society. It is a web-enabled community of bird watchers who collect, manage and store their observations in a globally accessible unified database [39]. It is a way in which anyone in the world will be able to keep their birding observations, photos, and their sound recordings and make them available to educators, scientists, and birders. It's straightforward to use and is very powerful. All that one needs to do is add the details about when and where they went for birding, how far they have traveled, and what they saw. It's powerful because around 700,000+ people all around the world are doing it and it's growing [15]. It is among the world's most significant science projects related to biodiversity, with more than 100 million bird sightings annually by eBirders around the world and an average participation growth rate of approximately 20% year over year. A collaborative enterprise with hundreds of partner organizations, thousands of regional experts, and hundreds of thousands of users [15]. ebird maintains lists of birds that one has observed and noted and shares them with the other birders worldwide. By sharing, it's now possible for anyone, anywhere, to find target birds and the best birding hotspots any time of the year. Before ebird, there was no way to comprehensively understand the population-level movements of many species. ebird data have been used in many studies related to Migration Patterns and Climate Effects on Migration [45, 24, 18], Population monitoring [32, 43], Geographic range shift [19], Species Distribution Modelling [37, 6] etc.

Data from weather surveillance radar (WSR) is a prime example of unstructured data that has been applied to ornithological research It has been known since the 1940 that radar can detect birds in flight and may thus be used to study a variety of characteristics of bird migration inside the atmosphere [26]. WSR systems in use today are made to measure and monitor meteorological occurrences, especially precipitation.

2.3 Bird migration and Climate change

There is a significant need to determine whether and how ecological and climatic parameters affect migratory movements [31]. It's impossible to generalize these effects to all birds because variation in the annual cycle is species-specific [10]. So, it is impossible to predict which species will survive, struggle, or become extinct. Different factors representing migration movements and climate are considered to study the relationship between migration and climate.

Migration changes can be interpreted in several ways. For example, arrival dates for specific species at migrating sites throughout several years, departure from those sites, stopover period, stopover locations [10], etc. Some research used the first observed date as the arrival date, believing that population-level migration advancements are ultimately determined by individuals who advance or postpone migration [45]. However, according to some research, this measure of arrival date is susceptible to outliers and fluctuations in sampling effort and population size, and hence is not always representative of the population's migration patterns [21]. So, they have used some other statistical methods to extract such parameters, like considering inflection point as an arrival after fitting a logistic curve to their analytical parameter [21]. Climate, like migration, also has numerous parameters. Temperature fluctuations and precipitation patterns, both daily and seasonal, are anticipated to produce significant adjustments in global climates, and these changes affect bird migration behavior [10]. Other than this, wind speed is also an essential factor affecting bird migration [14].

Weather conditions observed before arrival at, and expected after departure from, a stopover site may have a significant impact on the bird's decision to stop there, as well as the stopover period [31]. Variability in population arrival dates can reveal whether the population is arriving earlier or later than usual. A variety of models are used to model bird migration behavior concerning various climatic parameters. Regression analysis is used in the majority of the models [21, 32, 43, 45].

2.4 Importance of Study in India

Bird counting projects in India have focused on endangered wetlands and birds located in terrestrial areas of significant conservation value. India is a country with enormous diversity. India's known biological variety accounts for 8% of global biological diversity, accounting for only 2.4 percent of the total geographical area. India has been classified into ten biogeographic zones Transhimalayan, Himalayan, Indian desert, Semi-arid, Western ghats, Deccan peninsula, Gangetic plain, North-East India, Islands, and Coasts. With this much variety in biogeographical zones, it has a wide range of weather conditions across this vast geographic scale. According to the Hindu calendar, India has six seasons in a year like Spring, Summer, Monsoon, Autumn, Pre-winter, and Winter.

Apart from that, India is home to a diverse range of bird species. According to the research conducted in 2020, at least 1,317 bird species have been identified, compared to roughly 10,000 worldwide. Only 72 of India's 1,317 species are distinctive to the country [2].

Chapter 3
Research Methodology

3.1 Data Preprocessing

Bird observations in Kerala state were extracted from the ebird database between 2011 and 2019. The extracted data is primarily filtered by species name. All invalid species were deleted, such as those with "hybrid" or a "slash." The complete checklists are then extracted. Complete checklists are ebird lists that include all of the birds seen at the birding spot and were created with birdwatching as the primary purpose of observers. Because of group checklists, ebird checklists can be redundant. Duplicate checklists are eliminated as well. Then it is determined whether there were enough data for each species in each year. That is defined based on the number of days with the data in particular year. Years with at least 150 days of observation are taken into account. If data for a species is available in less than seven years, it is removed. Figure 3.1 shows the flow chart explaining this data-leaning process.

3.2 Extraction of Migratory Birds

We have devised two methods for identifying the migratory birds and extracting them from the data. Each of these methods is further explained in subsections with their algorithms.

Method 1 From ebird data we fetch month-wise observation count for all birds by using the function *get_observation_cnt_month(year)*. This function returns values -1, 0, and any positive integer value for each month in that particular year. -1 indicates that the bird was observed, but the count value is missing, 0 indicates the bird was absent, and the positive integer value represents the count observed in that month. We fetch these observation values for pairs of consecutive years, like 2016-2017, 2017-2018, etc., and row-wise concatenate them in the table using the function *concatenate(data1, data2)*. To handle the presence of missing values, i.e., -1, we perform interpolation of data. Function *interpolation(data)* takes values from previous and next month and updates the current value. To determine which bird is migratory from these values, we check three consecutive months' observation count. If we find even one such consecutive group with all the values less than the threshold value, we term the bird as migratory. The entire process is explained in the Algorithm 1.

Algorithm 1 Extract Migratory birds

Input : birds,year
Output : migartory_birds
$observation\_cnt \leftarrow concatenate(get\_observation\_cnt\_month(year), get\_observation\_cnt\_month(year+1))$
$migratory\_birds = list()$
$observation\_cnt \leftarrow inter\,polation(observation\_cnt)$
$threshold \leftarrow 50$
for bird **in** birds **do**
    $i = bird.index$
    if $consecutive(observation\_cnt[i], threshold)$ **then**
        $migratory\_birds \leftarrow add(bird)$
    end if
end for

Method 2 From bird data we fetch day-wise observation count for all birds by using the function *get_observation_cnt_days(year)*. This function returns values -1, 0, and any positive integer value for each day in that particular year, and the values indicate the same as mentioned in Method 1. To handle the presence of missing values, i.e., -1, we perform interpolation of data. Function *interpolation(data)* takes values from previous and next day and updates the current value. After interpolation, the average observation count for each window size is calculated for each bird, and then we calculated count variability for each bird using all of its window averages. After that, birds were sorted in descending order based on count variability, and all the birds with count variability greater than the threshold value 0.7 were selected. This Algorithm is performed for years, like 2017, 2018, and 2019. The entire process is explained in Algorithm 2.

Algorithm 2 Extract Migratory birds

Input : birds, year

Output : migartory_birds

$observation\_cnt \leftarrow get\_observation\_cnt\_days\ (year)$

$migratory\_birds = list()$

$observation\_cnt \leftarrow inter\ polation(observation\_cnt)$

$ws \leftarrow 7$

for bird **in** birds **do**

  $i = bird.index$

  while $i \leq 366 - ws$ **do**

    $Average\_list[i][j] = mean(observation\_cnt[i][j + ws])$

    $j = j + 1$

  end while

  $count\_variability[i] = 1 - \frac{min(Average\_list[i])}{max(Average\_list[i])}$

end for

$count\_variability = sort_{reverse}(count\_variability)[:100]$

for i **in** $count\_variability$ **do**

  $migratory\_birds \leftarrow add(birds[i.index])$

end for

3.3 Extraction of Migratory Parameters

Population-level arrival date is estimated for around 17 migratory species of Kerala for each year by fitting Gaussian CDF to cumulative observation count as a function of Julian day. As individuals of a species arrive in a region, the cumulative observation count rises from zero to the value representing the species' overall prevalence during the migrating season. I used the 2 sigma point of the guassian CDF fit to measure the mean arrival date (MAD) as shown in figure 3.2.

For the population level departure date same method is applied in reverse as shown in figure 3.3

3.4 Mapping of Climate and Migratory Parameters

NASA's Prediction Of Worldwide Energy Resources (https://power.larc.nasa.gov/) was used to obtain historical climate data at every 1/2 x 1/2 degree resolution for the entire kerala region. Then kerala region was also divided into 1/2 x 1/2 lat-long blocks, and then those blocks were clustered in two parts based on climate similarity. Using the method described above, migratory parameters were extracted for each year-cluster combination. The temperature and wind speed of every 1/2 x 1/2 degree point where bird data was present in the respective cluster is then averaged over a month before the arrival/departure range's midpoint and mapped to arrival/departure dates. In the same way, Cumulative data from May to October was used to map precipitation with arrival, and cumulative data from October to March was used to map precipitation with departure.

3.5 Relationship between Climate & Migratory Parameters

Many species that did not have enough data for reliable analysis were eliminated during the data-cleaning step (Figure 3.1). Using this more conservative dataset, linear regression is used to look at the relationships between mean, maximum, minimum wind speed, wind speed range, precipitation, maximum and minimum temperatures, and temperature range, with arrival and departure dates. Linear relationships were considered strong if p-value < 0.05. There was no consideration of a relationship between the parameters if p-value > 0.1. A weak relationship is defined as one with a p-value between 0.1 and 0.05. Here, p-value is statistical measure which describes the significance of result in relation to the null hypothesis.

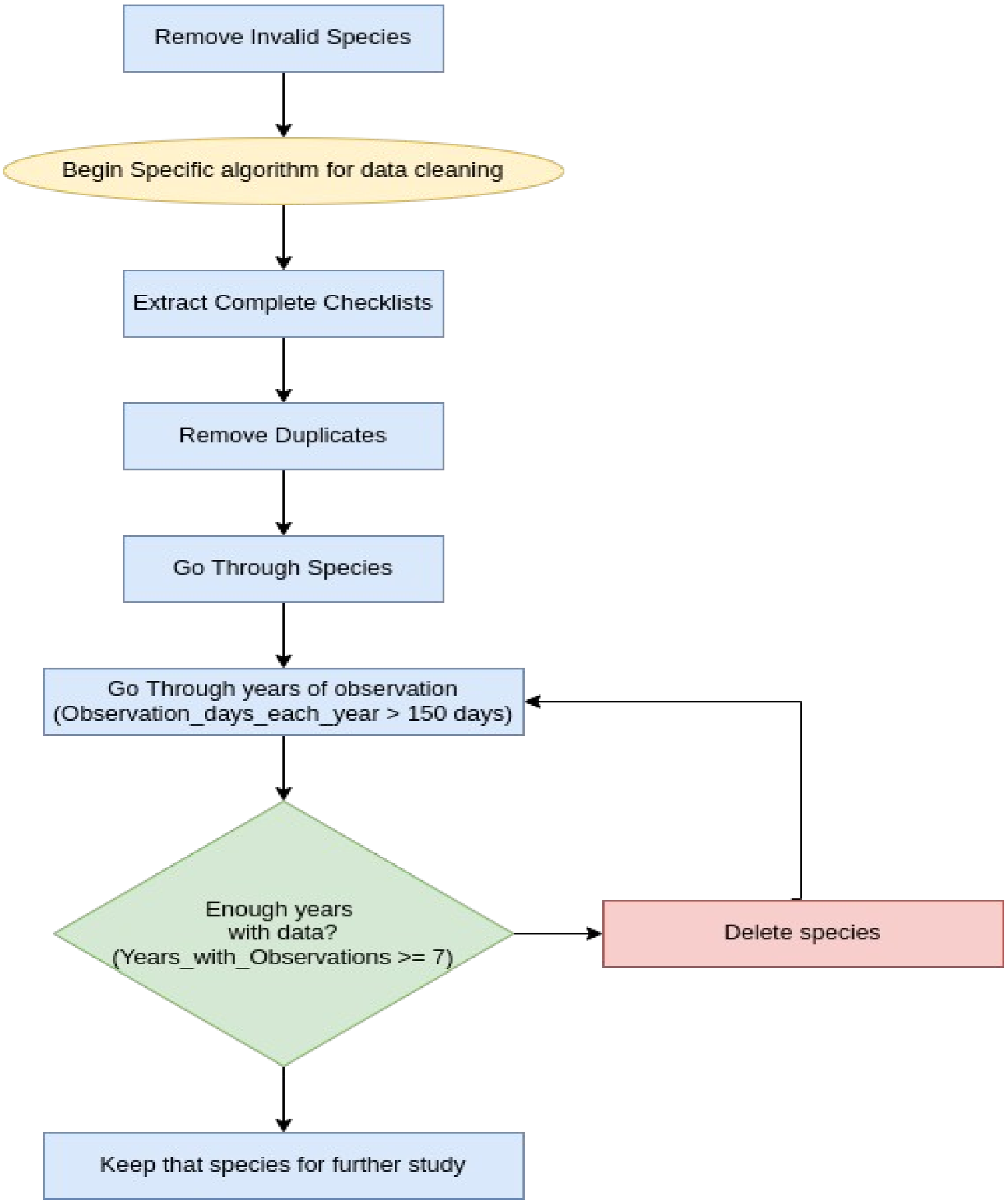


Figure 3.1: Flow chart of general data-cleaning algorithm.

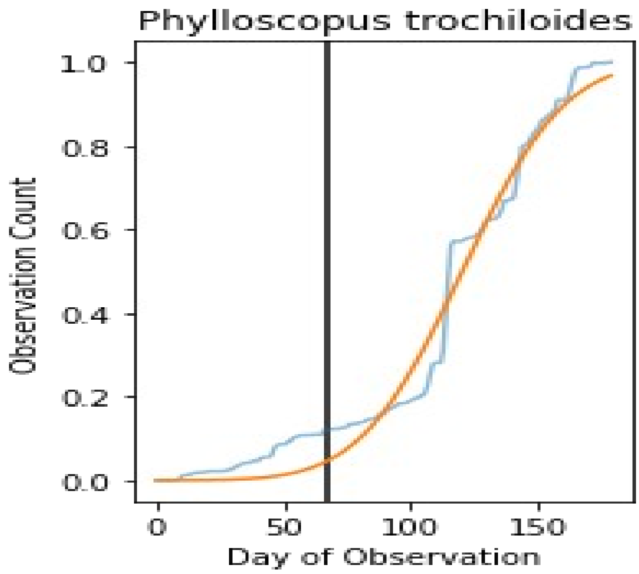


Figure 3.2: Estimating arrival date
Cumulative observation count of Phylloscopus Trochilidae(Greenish Warbler) from the last 90 days of 2018 and the first 90 days of 2019. The line in orange shows the best Gaussian CDF fitting to the data. The vertical black line represents a 2 sigma point used to estimate the mean arrival date.

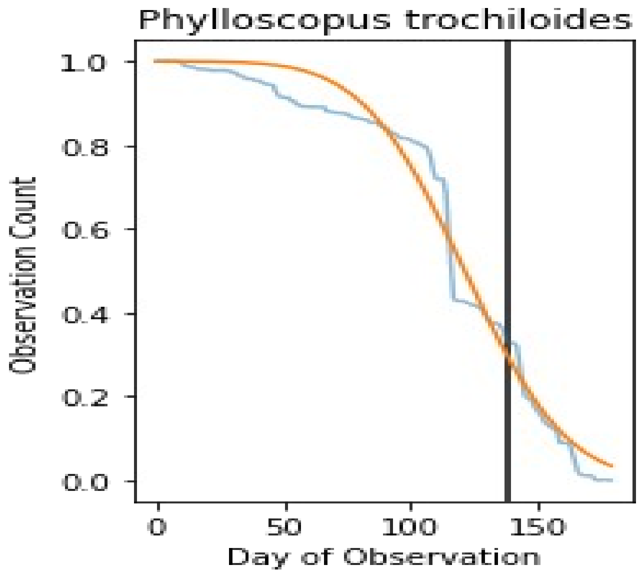


Figure 3.3: Estimating departure date
The cumulative observation count of Phylloscopus Trochilidae(Greenish Warbler) from the last 90 days of 2018 and the first 90 days of 2019 is considered reverse to see the other side of arrival. The line in orange shows the best gaussian CDF fitting to the data. The vertical black line represents 2 sigma point which is used to estimate the mean departure date.

CHAPTER 4
Experimental Setup

4.1 Bird Data: ebird-Citizen Science data by Cornell lab

For this study, ebird data is used, and the fundamental dataset for eBird was obtained from the eBird website [15]. It is an online database with a wide area of coverage. It provides open data access where data is collected using citizen-based observation [39]. ebird data is obtained and structured using the checklist idea, which represents sightings from a single birdwatching activity, for example, a 2-kilometer walk across a park or 10 minutes observation of bird feeders. Each checklist includes a list of species seen, counts of the number of individuals seen of each species, the location and time of the observations, and an estimate of the effort expended while gathering the information. The ebird dataset has forty-six columns, many of which are superfluous. Country, state, county, Locality, and Protocol, for example, each contain two columns, one for the name and the other for the code. Other columns are poorly relevant, such as the checklist's Important Bird Area (IBA), Bird Conservation Region (BSR) code, ATLAS block, trip notes, and checklist comments. We may significantly reduce the size of the ebird dataset by deleting these columns.

Some participants record birds occasionally. In contrast, others provide daily checklists of all the species they see, typically from multiple locations such as their residence, workplace, vacation site, or favorite birdwatching area. Such checklists are called complete checklists, which include all species reported, and allow researchers to determine which species were not detected rather than merely not reported. Furthermore, ebirders can submit an "X" instead of a count for a species to indicate it was there, but they don't track how many individuals were seen. Interpolation of these data is done during the modeling step. Group checklists, which numerous people share, are also possible with eBird. These checklists result in record duplication or near-duplicate within the dataset.

4.2 Climate Data: POWER data by NASA

NASA-POWER is used for the climate data. It provides single-point data access, regional data access, and global downloads. In addition, it also provides a different format for downloading [30]. The Prediction of Worldwide Energy Resources (POWER) project was started to improve the current renewable energy data set and create new data sets using new satellite systems. Three user populations are targeted by the POWER project: renewable energy, sustainable buildings, and agroclimatology [30]. The POWER Data Access viewer includes weather and solar-related parameters which can be used to study and design renewable energy systems.

Following climatic parameters from these datasets are used in this study:

- Minimum Temperature: It is the daily minimum temperature.
- Maximum Temperature: It is the daily maximum temperature.
- Temperature Range: It ranges between a minimum and maximum temperature.
- Precipitation: It is the daily average precipitation.
- Average Wind Speed: It is the daily average Wind Speed.
- Minimum Wind Speed: It is the daily minimum Wind Speed.
- Maximum Wind Speed: It is the daily maximum Wind Speed.
- Wind Speed Range: It ranges between a minimum and maximum Wind Speed.

All the above data are available at every 1/2 x 1/2 degree lat-long point.

4.3 Study Area and Period

The selected migrating birds for the Kerala region are being studied. Kerala was chosen for the study because it has the highest number of reported in compared to other states of India. There was very less data available before 2011, and 2020 had limited data due to COVID; data from 2011 to 2019 is utilized to analyze the relationship between climate and migration factors. Figure 4.1 shows the total bird observation counts in India from 2011 to 2019. The number of observations is rapidly increasing.

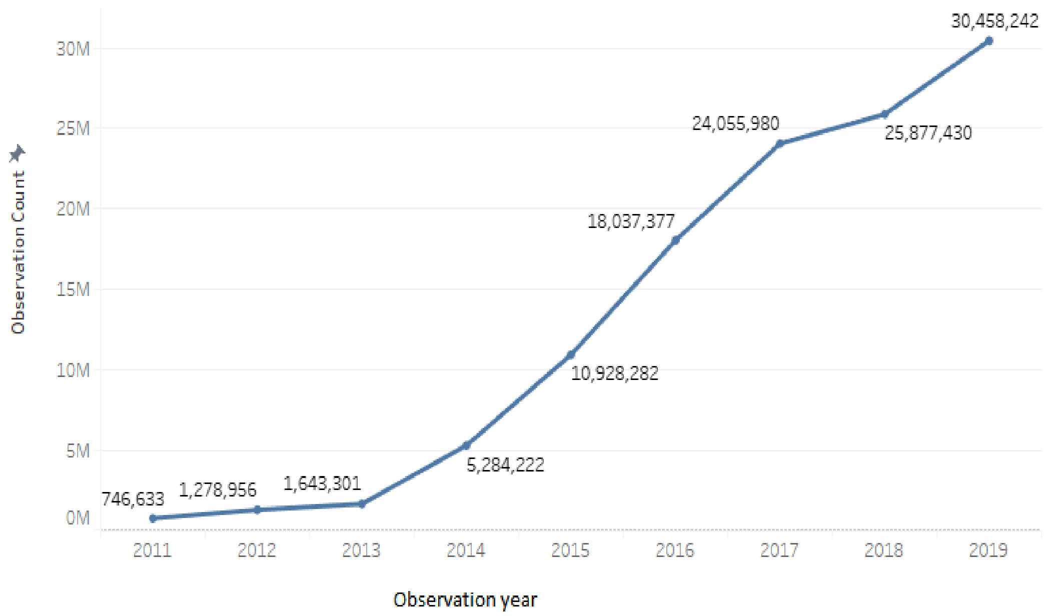


Figure 4.1: number of total bird observation counts of India over recent years.

CHAPTER 5
Results

5.1 Data Preprocessing

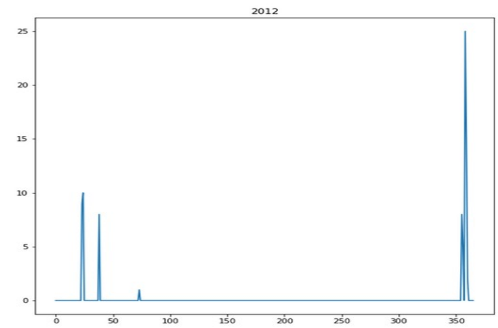
Initially, there were 705 species documented in Kerala's bird data. In the data preprocessing step, after extracting complete checklists and removing duplicates, the number of species was reduced to 690. After removing species reported in less than seven years, the number of species dropped from 690 to 329.

5.2 Extraction of Migratory Birds

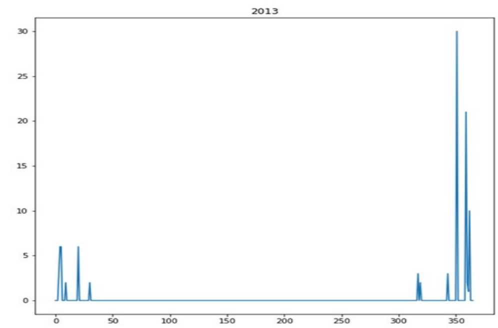
From the two methods used to extract migratory birds, method 1 yielded a list of 254 species of migratory birds, while the method 2 yielded a list of 194 species. In method 1 many species with very little observation reported were returned as migratory, even though they were residual birds. In method 2, residual birds with a very high observation report on at least one day compared to the other days were classified as migratory. Because the maximum value in those cases increased significantly while the minimum value remained unchanged, the count of variability value increased significantly. The final 17 species were selected from the common species of each method based on data availability checks each year and manual verification, which contributed to the removal of every residual bird. Table 5.1 shows the list of finalized species for further study. Figure 5.1 shows the day-wise observation count of species HRBS (Hirundo rustica) for the years 2012 to 2019. Species are usually observed at the beginning and end of each year, indicating the migratory behavior of species. Figure 5.2 represents similar behaviour of species OKIGO (Oriolus kundoo) and PTGW (Phylloscopus trochiloides) specified in table 5.1.

	SCIENTIFIC NAME	COMMON NAME	CODE
1	Hirundo rustica	Barn Swallow	HRBS
2	Tringa nebularia	Common Greenshank	TNCG
3	Anas acuta	Northern Pintail	AANP
4	Muscicapa dauurica	Asian Brown Flycatcher	MDABF
5	Dicrurus leucophaeus	Ashy Drongo	DLAD
6	Terpsiphone paradisi	Indian Paradise-Flycatcher	TPIPF
7	Motacilla cinerea	Gray Wagtail	MCGW
8	Oriolus kundoo	Indian Golden Oriole	OKIGO
9	Acrocephalus dumetorum	Blyth's Reed Warbler	ADBRW
10	Lanius cristatus	Brown Shrike	LCBS
11	Sturnia malabarica	Chestnut-tailed Starling	SMCTS
12	Actitis hypoleucos	Common Sandpiper	AHCS
13	Phylloscopus trochiloides	Greenish Warbler	PTGW
14	Tringa ochropus	Green Sandpiper	TOGS
15	Spatula querquedula	Garganey	SQG
16	Pastor roseus	Rosy Starling	PRRS
17	Phylloscopus nitidus	Green Warbler	PNGW

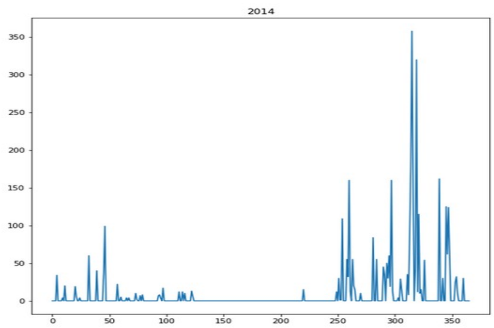
Table 5.1: The species analyzed in this study, along with species abbreviations



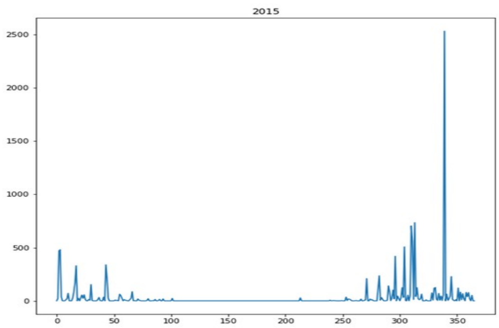
(a) Year 2012



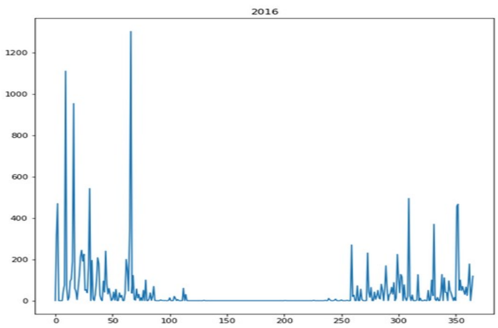
(b) Year 2013



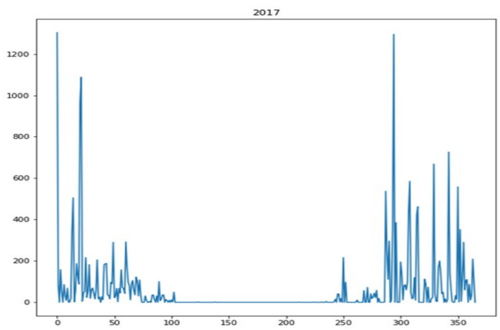
(c) Year 2014



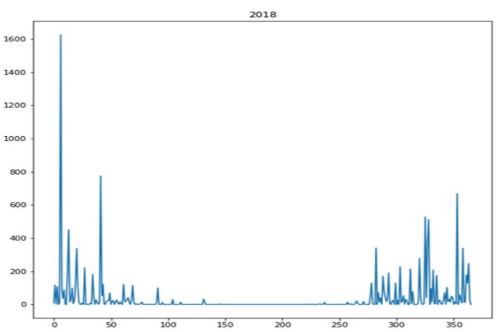
(d) Year 2015



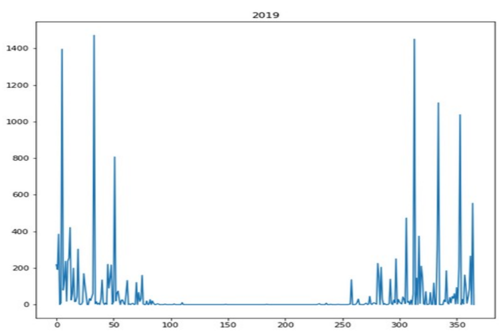
(e) Year 2016



(f) Year 2017

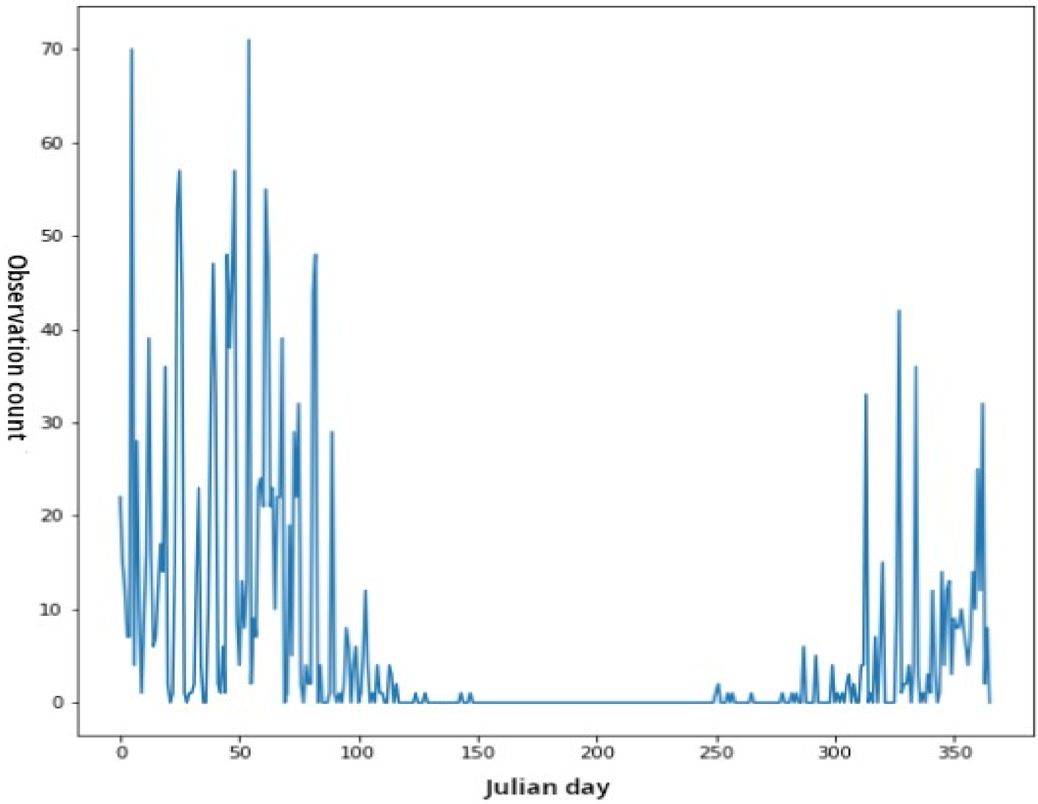


(g) Year 2018

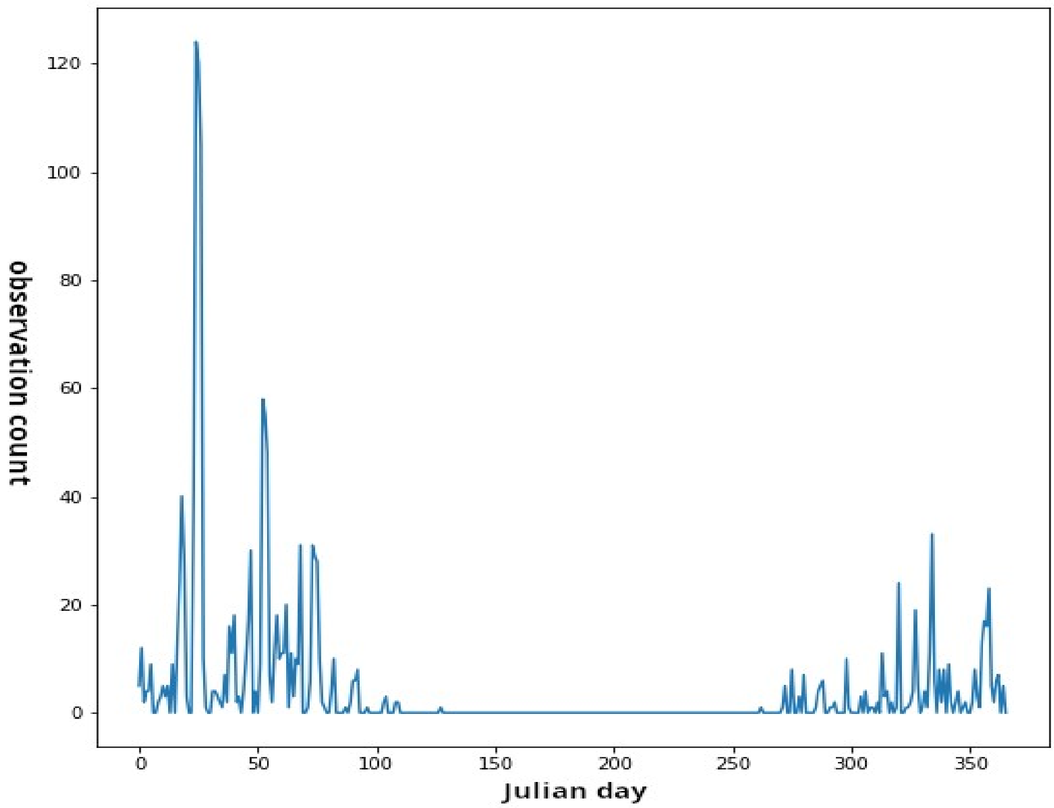


(h) Year 2019

Figure 5.1: Day-wise observation count of Hirundo rustica (Barn Swallow) for years 2012 to 2019.



(a) Oriolus kundoo



(b) Phylloscopus trochiloides

Figure 5.2: Day-wise observation count in 2019 of species Oriolus kundoo (Indian Golden Oriole) and Phylloscopus trochiloides (Greenish Warbler).

(a) Acrocephalus dumetorum

(b) Actitis hypoleucos

(c) Anas acuta

(d) Dicrurus leucophaeus

(e) Hirundo rustica

(f) Lanius cristatus

(g) Motacilla cinerea

(h) Muscicapa dauurica

(i) Oriolus kundoo

(j) Pastor roseus

(k) Phylloscopus nitidus

(l) Phylloscopus trochiloides

(m) Spatula querquedula

(n) Sturnia malabarica

(o) Terpsiphone paradisi

(p) Tringa nebularia

(q) Tringa ochropus

Figure 5.3: Study Species

5.3 Region Clustering

The Kerala region was separated into two clusters based on climate similarities to minimize large climate variances when mapping migratory factors. Figure 5.4 shows the clusters of Kerala. The area in dark blue represents the Coastal area while the other represents the Inland area.

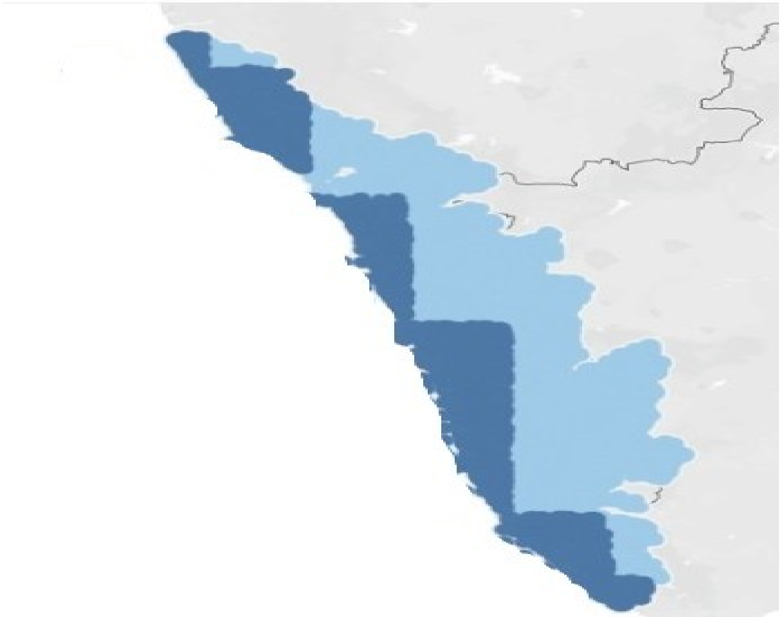


Figure 5.4: Kerala's cluster based on similarity of climatic conditions.

5.4 Linear Regression analysis

5.4.1 General Analysis

The responses of all birds to climate change are distinct, and those responses vary with location. In coastal places, precipitation has a greater impact on arrival than inland areas. The majority of the birds studied had a strong (p-value < 0.05) or weak relationship ($0.05 \leq$ p-value < 0.1) with climate data.

5.4.2 Arrival analysis in Inland area

Ten of the seventeen species in this cluster had a strong relationship in arrival timings with some of the climatic parameters. In contrast, the two species had no relationship with any climatic variables. Some of such strong relationships are shown in figure 5.13. Precipitation is one of the most important factors for Hirundo Rustica's arrival timings. The relationship between precipitation and the bird's arrival is depicted in figure 5.13(a). It indicates that as precipitation increases, arrival is delayed, whereas as precipitation decreases, arrival is advanced. Tringa ochropus showed a similar relationship with average wind speed as shown in figure 5.13(b).

The arrival of Phylloscopus nitidus, Actitis hypoleucos, Anas acuta, and Tringa ochropus in inland areas is strongly correlated to all temperature parameters, including minimum temperature, maximum temperature and temperature range as shown in Figure 5.5, 5.6 and 5.7. The arrival of Phylloscopus trochiloides, Oriolus kundoo, Dicrurus leucophaeus, Pastor roseus, and Muscicapa dauurica in the inland area has no correlation with temperature. while the arrival of Acrocephalus dumetorum, Sturnia malabarica, and Lanius cristatus in inland areas is weakly correlated with all temperature parameters. Hirundo rustica and Terpsiphone paradisi, on the other hand, exhibit a strong relationship with minimum temperature, a weak relationship with temperature range, and no relationship with maximum temperature. The arrival of Spatula querquedula is weakly correlated with minimum temperature, while the arrival of Tringa nebularia is strongly correlated with maximum temperature. Temperature range and minimum temperature have a weak correlation with Motacilla cinerea and Tringa nebularia's arrival.

The arrival of Hirundo rustica, Phylloscopus nitidus, Sturnia malabarica, Actitis hypoleucos, Anas acuta, and Terpsiphone paradisi has a significant impact on precipitaion as shown in 5.8, but the arrival of Acrocephalus dumetorum, Phylloscopus trochiloides, Oriolus kundoo, Dicrurus leucophaeus, Pastor roseus, Spatula querquedula, Tringa ebularia, Tringa ochropus, Lanius cristatus and Motacilla cinerea has No impact on it.

As shown in Figure 5.9, 5.10, 5.11, and 5.12 all windspeed parameters have a strong correlation with arrival of Phylloscopus nitidus, Actitis hypoleucos, Anas acuta, Tringa ochropus, and Lanius cristatus. While no Wind speed parameters have effect on arrival of Hirundo rustica, Phylloscopus trochiloides, Oriolus kundoo, Spatula querquedula, Muscicapa dauurica, and Motacilla cinerea. Maximum windspeed and windspeed range have a weak correlation with the arrival of Pastor roseus and Tringa nebularia. Table 5.2 shows the p-values retrieved using linear regression for the arrival in inland area.

Bird Name	T2M_ MIN	T2M_ MAX	T2M_ RANGE	PREC TOT	WS10M_ MIN	WS10M_ MAX	WS10M_ RANGE	WS10M
Hirundo rustica	0.040993	2.976856	0.071110	0.005291	2.383420	3.084777	4.988514	4.638564
Acrocephalus dumetorum	0.089713	0.055859	0.051509	0.290808	0.087708	1.765738	0.034889	0.087652
Phylloscopus nitidus	0.012564	0.036813	0.047994	0.015954	0.012241	0.002514	0.032885	0.031225
Phylloscopus trochiloides	3.397388	0.928908	1.402384	0.951643	1.431452	3.369702	1.937976	1.232051
Oriolus kundoo	4.783107	3.804666	2.789280	0.294437	2.729102	1.667221	3.974486	1.531685
Sturnia malabarica	0.058768	0.052505	0.087297	0.006469	0.066987	0.071954	0.067580	0.037896
Actitis hypoleucos	0.028070	0.040584	0.017102	0.011156	0.045472	0.039686	0.011123	0.016395
Dicrurus leucophaeus	2.029827	3.703727	1.735543	3.794766	0.055044	0.093391	0.069927	0.087582
Pastor roseus	2.887352	4.029522	4.792275	2.535072	2.687202	0.084004	0.072638	4.900103
Spatula querquedula	0.063581	4.755042	2.148207	1.661705	2.639549	3.309453	0.183487	3.538477
Anas acuta	0.032878	0.020445	0.021675	0.005772	0.008660	0.002246	0.016331	0.001096
Tringa nebularia	0.095551	0.042977	0.097060	3.618939	2.988561	0.057000	0.057987	3.968847
Terpsiphone paradisi	0.004245	0.806462	0.077549	0.025882	1.429207	0.055284	3.210458	1.508448
Tringa ochropus	0.000610	0.006800	0.033119	3.554105	0.035079	0.048147	0.029336	0.017932
Lanius cristatus	0.095159	0.074020	0.082310	2.662352	0.048136	0.045914	0.031557	0.007375
Muscicapa dauurica	1.428180	0.935587	0.782394	0.051824	4.771340	1.997404	0.578666	4.146014
Motacilla cinerea	0.062155	2.155743	0.081591	0.514637	1.354196	4.265457	1.712894	4.861606

Table 5.2: p-values retrieved using linear regression for each species for arrival in inland area

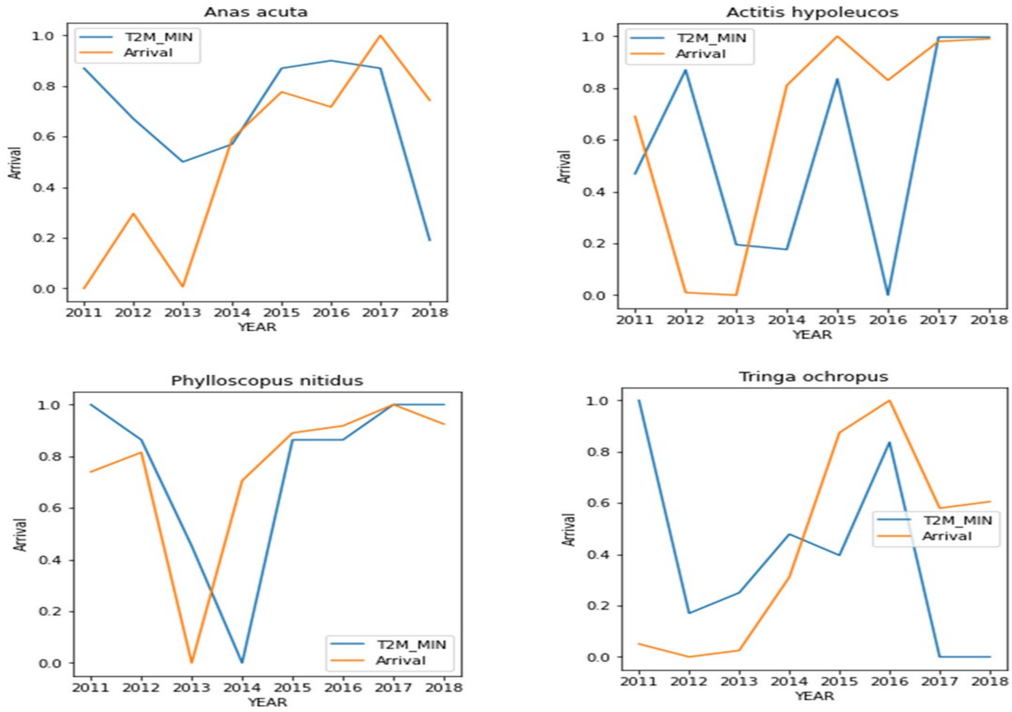


Figure 5.5: Yearwise variation of arrival time in response to minimum temperature for Anas acuta, Phylloscopus nitidus, Actitis hypoleucos and Tringa ochropus in Inland area.

5.4.3 Arrival analysis in Coastal area

Except for four out of seventeen, each species had a strong or weak relationship with some climate characteristics. The temperature range, maximum temperature, and all windspeed parameters showed a strong relationship with the arrival of Phylloscopus trochiloides in coastal areas. The relationship with temperature range is shown in the figure 5.14(a). It indicates that this species arrived earlier in coastal areas when the temperature range increased. The arrival relationship of Tringa nebularia with precipitation is depicted in figure 5.14(b). Acrocephalus dumetorum (p-value = 0.0673288) and Terpsiphone paradisi (p-value = 0.078625) showed weak relationship with precipitation and no relationship with other parameters. They both advanced arrival as increase in precipitation. Anas acuta showed a strong relationship (p-value = 0.01257) with minimum temperature and a weak relationship with other climatic parameters. Decrease in minimum temperature advanced the arrival of anas acuta in coastal areas.

The arrival of Lanius cristatus and Motacilla cinerea shows weak correlation with minimum temperature and temperature range. The arrival of Hirundo rustica,

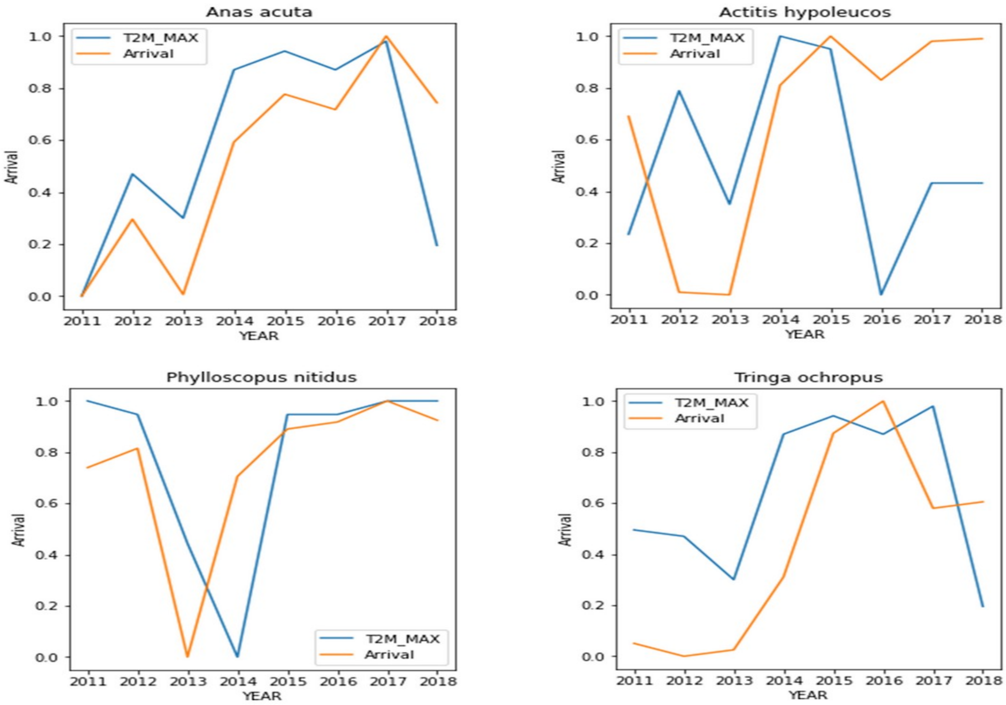


Figure 5.6: Yearwise variation of arrival time in response to maximum temperature for Anas acuta, Phylloscopus nitidus, Actitis hypoleucos and Tringa ochropus in Inland area.

Acrocephalus dumetorum, Phylloscopus nitidus, Oriolus kundoo, Actitis hypoleucos, and Terpsiphone paradisi in coastal areas is unaffected by temperature, whereas the arrival of Sturnia malabarica, Dicrurus leucophaeus, Pastor roseus, Tringa ochropus, and Muscicapa dauurica have weak correlation with all temperature parameters like minimum temperature, maximum temperature and temperature range.

Spatula querquedula and Tringa nebularia is strongly affected by precipitation in coastal area while Acrocephalus dumetorum, Phylloscopus trochiloides, Sturnia malabarica, Anas acuta, Terpsiphone paradisi, Tringa ochropus, Lanius cristatus, Muscicapa dauurica and Motacilla cinerea are weakly affected by precipitation.

Phylloscopus trochiloides is strongly affected by all windspeed parameters like minimum windspeed, maximum windspeed, average windspeed and windspeed range. Sturnia malabarica, Dicrurus leucophaeus, Pastor roseus, Anas acuta, Tringa ochropus, Lanius cristatus, Muscicapa dauurica and Motacilla cinerea are weakly affected by all windspeed parameters while Hirundo rustica, Acrocephalus dumetorum, Phylloscopus nitidus, Oriolus kundoo, Actitis hypoleucos and Terpsiphone

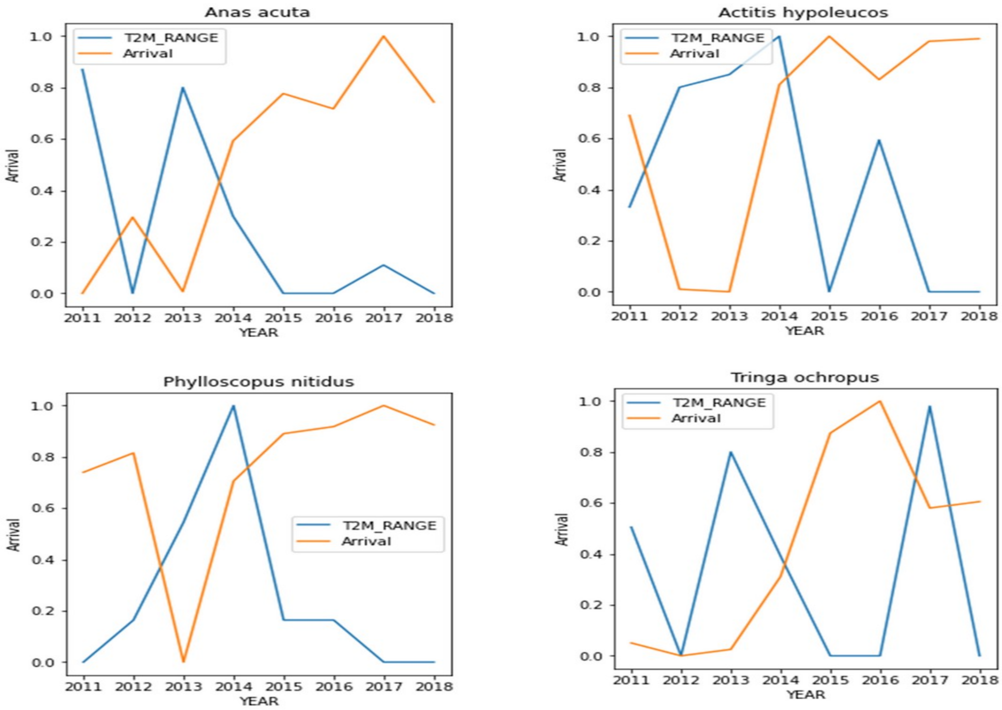


Figure 5.7: Yearwise variation of arrival time in response to temperature range for Anas acuta, Phylloscopus nitidus, Actitis hypoleucos and Tringa ochropus in Inland area.

paradisi shows no relation with any of the windspeed parameter. Table 5.3 shows the p-values retrieved using linear regression for the arrival in coastal area.

5.4.4 Departure analysis in Inland area

We discovered that two of the seventeen species evaluated using eBird sightings during the 2011 to 2019 period had a strong relationship in their departure timing due to climate change. Hirundo rustica, on the other side, exhibits this variation in departure in response to fluctuations in precipitation. As depicted in the figure 5.15, early departure was associated with a decrease in precipitation, while later departure was associated with increased precipitation for Hirundo rustica. Four of the remaining species had no relationship with any of the climate parameters, while the others had a weak relationship with several climate parameters.

The departure of Hirundo rustica and Phylloscopus trochiloides has weak correlation with temperature range and minimum temperature. while these both factor has strong impact on departure of Tringa nebularia. Sturnia malabarica, Tringa ochropus and Muscicapa dauurica has weak relationship with all three parame-

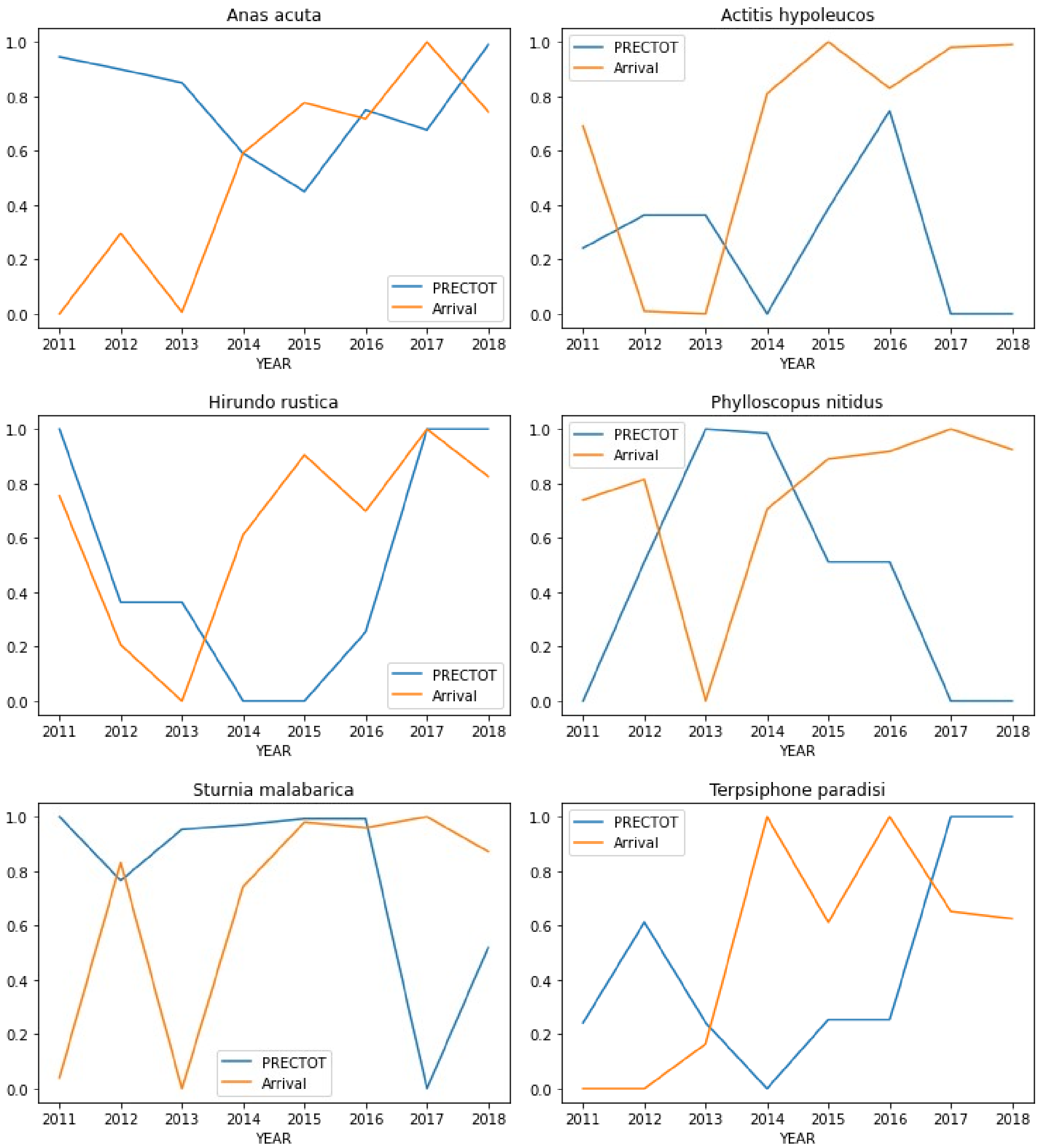


Figure 5.8: Yearwise variation of arrival time in response to precipitation for Anas acuta, Actitis hypoleucos, Hirundo rustica, Phylloscopus nitidus, Sturnia malabarica, and Terpsiphone paradisi in Inland area.

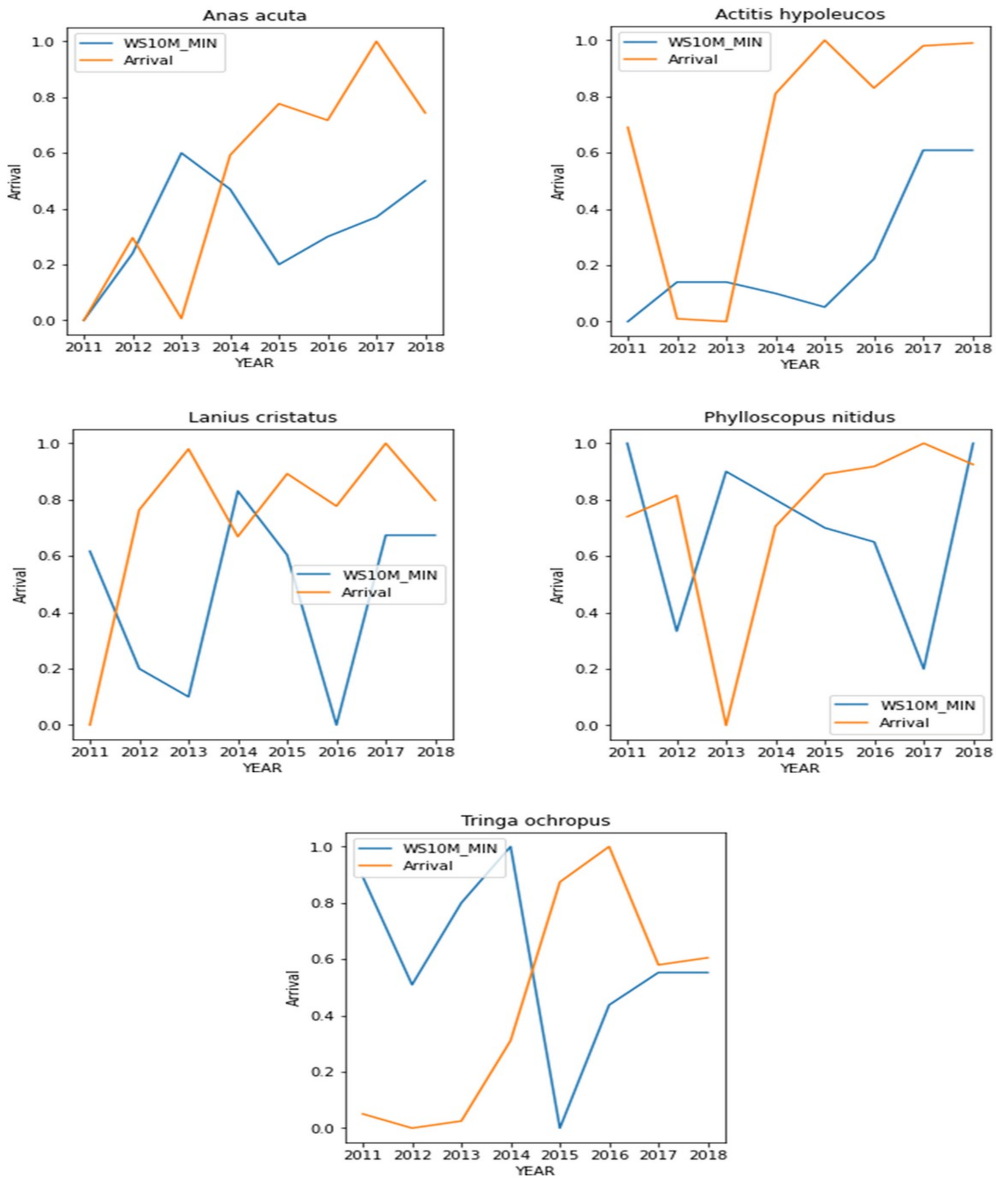


Figure 5.9: Yearwise variation of arrival time in response to minimum Windspeed for Anas acuta, Actitis hypoleucos, Lanius cristatus, Phylloscopus nitidus, and Tringa ochropus in Inland area.

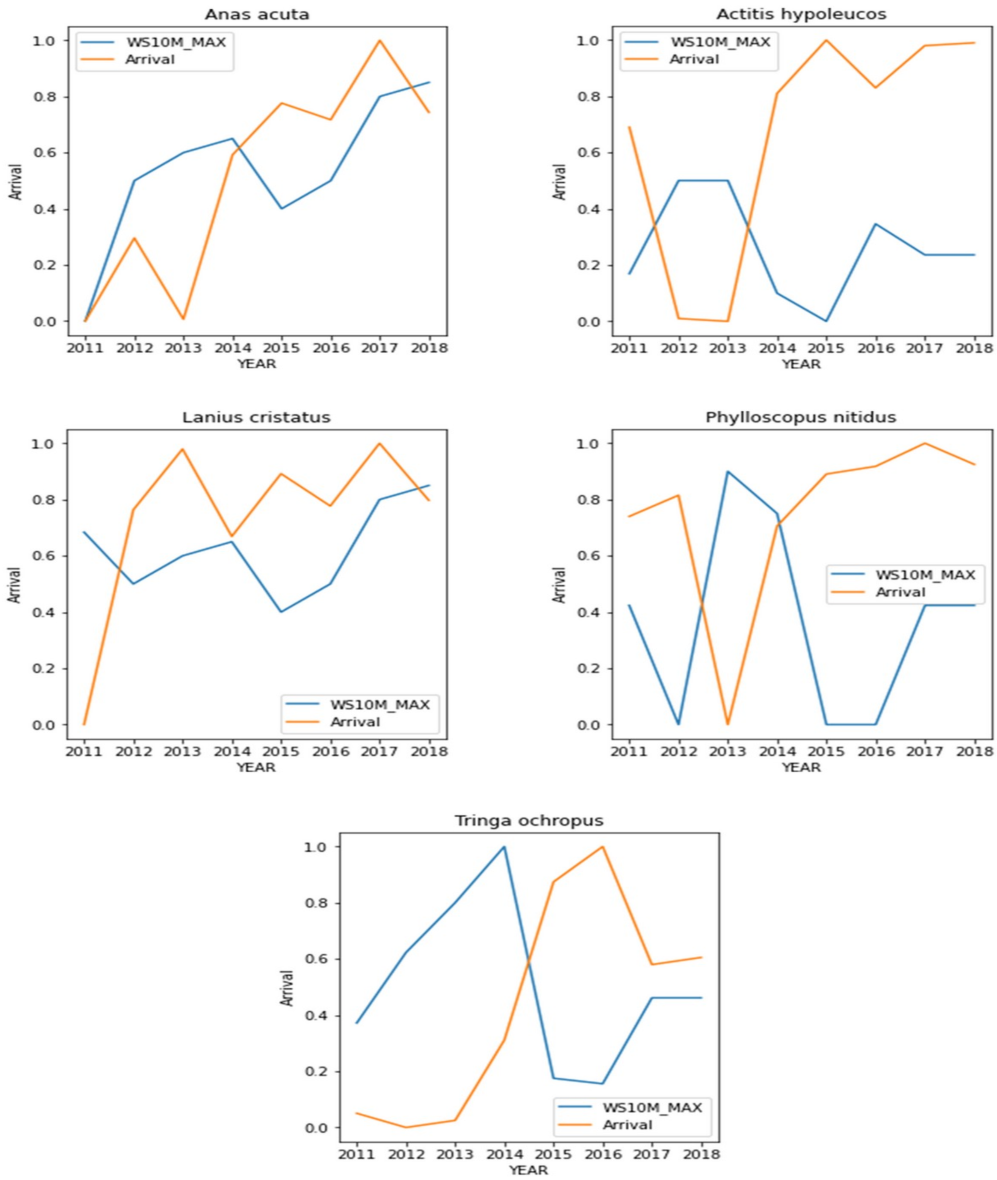


Figure 5.10: Yearwise variation of arrival time in response to maximum Windspeed for Anas acuta, Actitis hypoleucos, Lanius cristatus, Phylloscopus nitidus, and Tringa ochropus in Inland area.

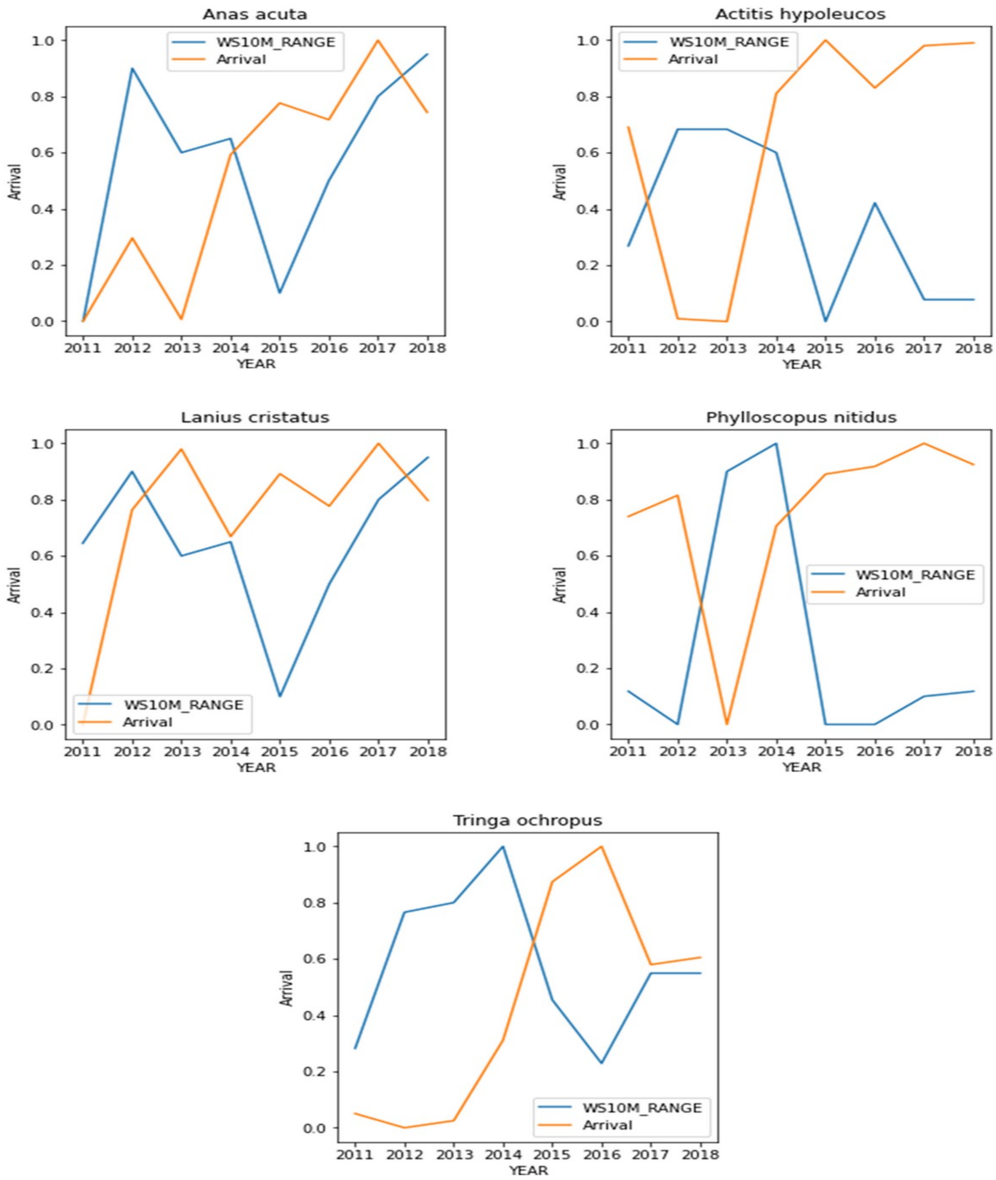


Figure 5.11: Yearwise variation of arrival time in response to Windspeed range for Anas acuta, Actitis hypoleucos, Lanius cristatus, Phylloscopus nitidus, and Tringa ochropus in Inland area.

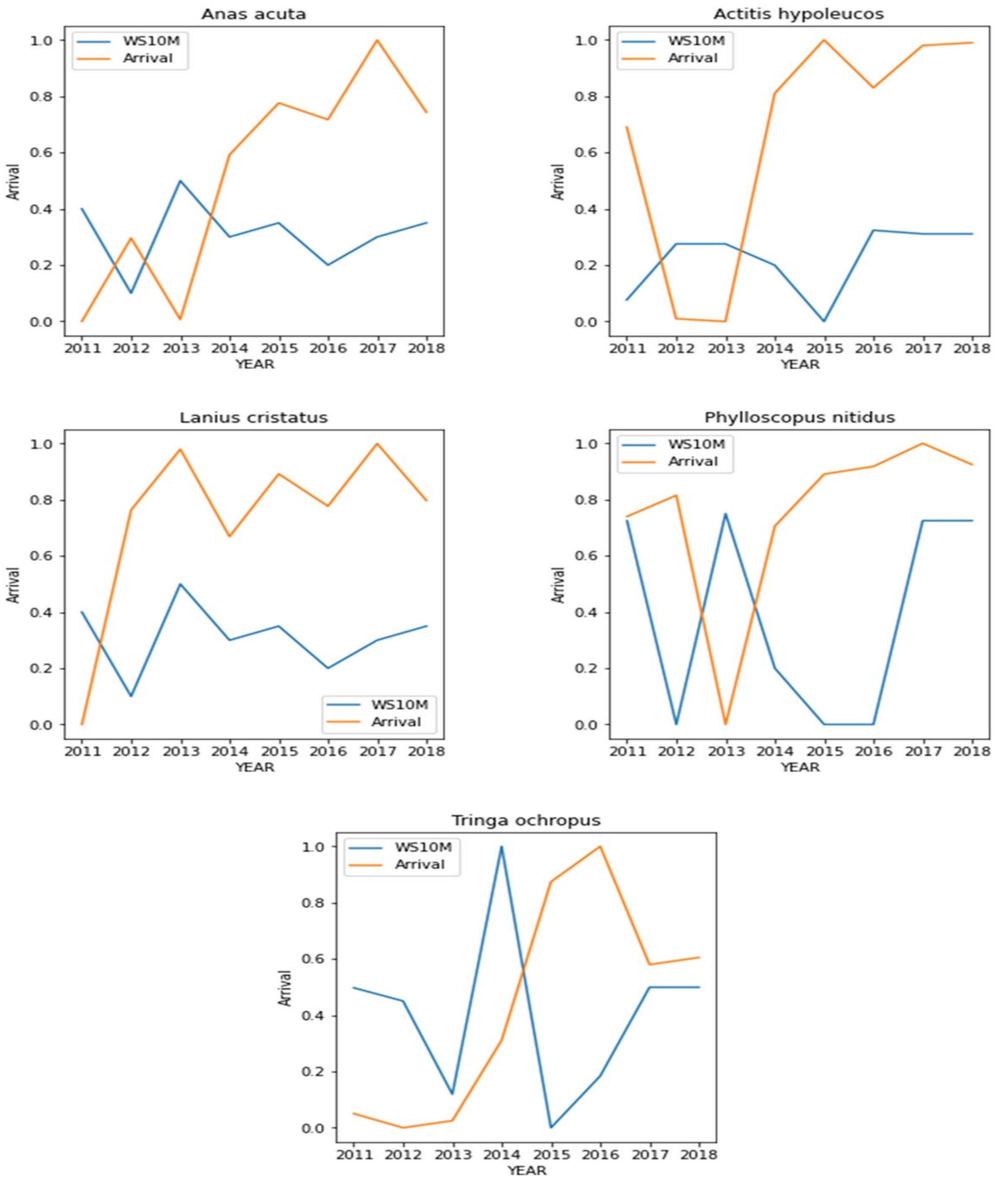
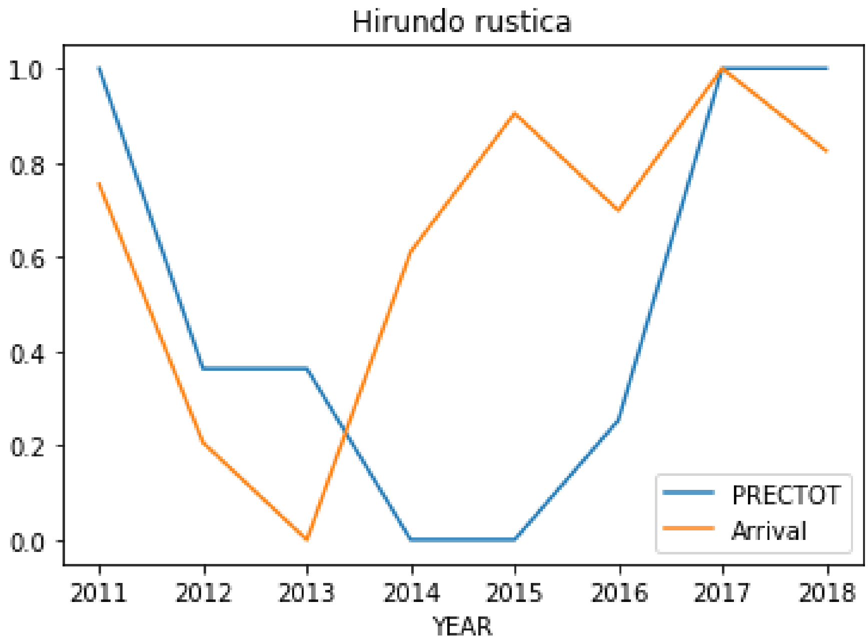
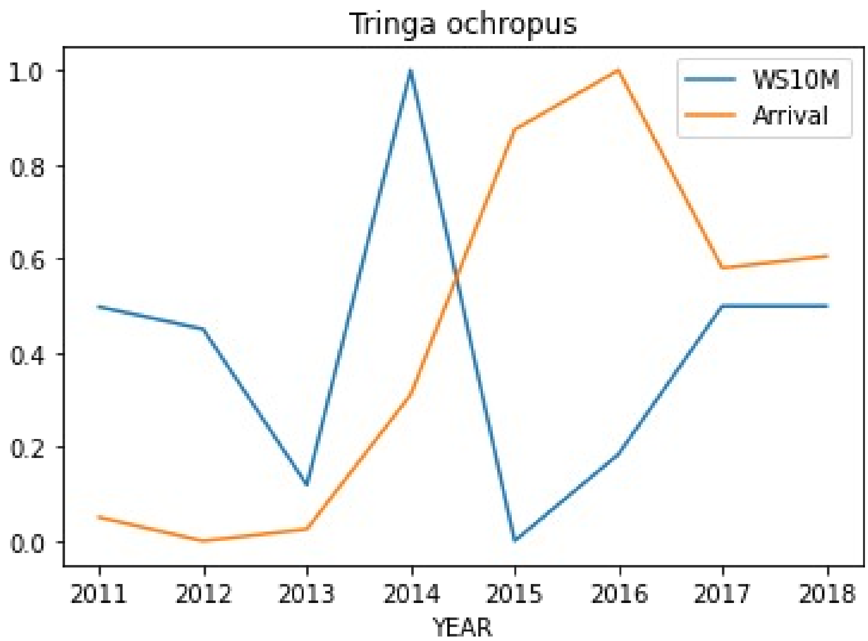


Figure 5.12: Yearwise variation of arrival time in response to Windspeed average for Anas acuta, Actitis hypoleucos, Lanius cristatus, Phylloscopus nitidus, and Tringa ochropus in Inland area.



(a) Hirundo rustica shows strong relationship (p-value = 0.005291) with precipitation

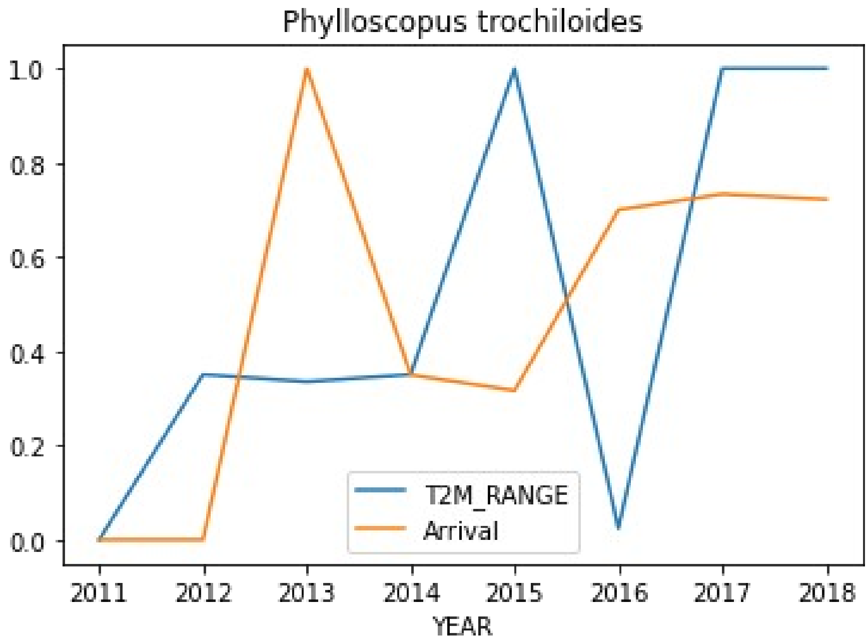


(b) Tringa ochropus shows strong relationship (p-value = 0.017932) with average windspeed

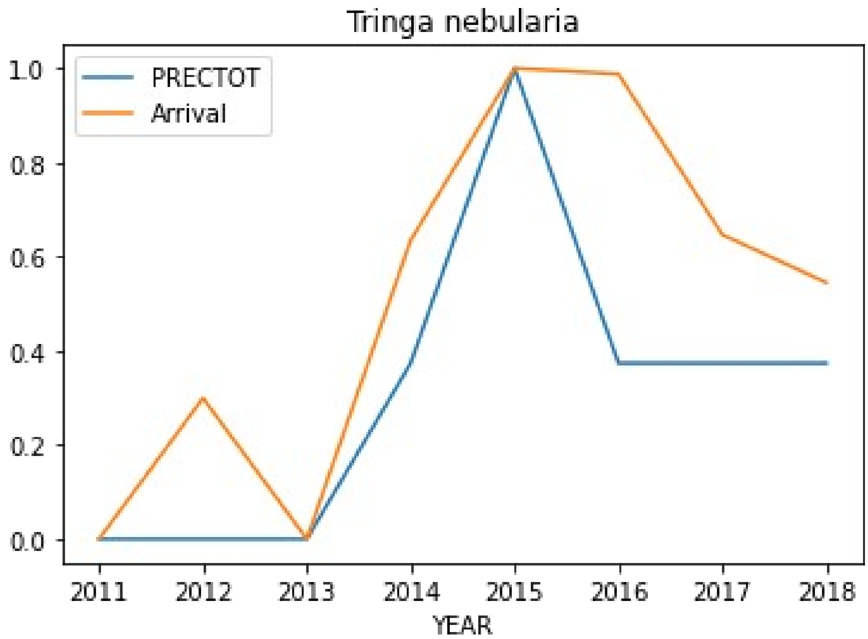
Figure 5.13: Yearwise variation of arrival time for Hirundo rustica and Tringa ochropus in Inland area

Bird Name	T2M_ MIN	T2M_ MAX	T2M_ RANGE	PREC TOT	WS10M_ MIN	WS10M_ MAX	WS10M_ RANGE	WS10M
Hirundo rustica	4.025026	4.234229	4.546684	4.882854	1.655706	0.361105	1.607155	0.519764
Acrocephalus dumetorum	2.247614	2.472564	1.576607	0.067328	2.169719	0.766713	1.090724	4.452014
Phylloscopus nitidus	1.482277	4.704820	1.967214	2.851389	4.097269	3.352660	3.600913	0.828425
Phylloscopus trochiloides	2.319896	0.038611	0.036110	0.082479	0.015399	0.022416	0.039316	0.009154
Oriolus kundoo	1.501314	2.532033	3.239665	4.579585	0.753767	4.295800	2.182270	0.276898
Sturnia malabarica	0.059153	0.065519	0.072076	0.071327	0.098480	0.072006	0.089032	0.073623
Actitis hypoleucos	4.007700	1.049176	4.078021	0.896514	2.138634	4.931096	2.369668	0.809792
Dicrurus leucophaeus	0.096599	0.072073	0.077502	4.783276	0.064951	0.062602	0.064929	0.098267
Pastor roseus	0.089518	0.061099	0.068765	3.948852	0.066272	0.078086	0.088506	0.064453
Spatula querquedula	0.058073	0.013411	2.180964	0.045839	0.007959	0.061419	0.090849	0.023634
Anas acuta	0.012575	0.089983	0.082015	0.095509	0.068577	0.089288	0.094172	0.065429
Tringa nebularia	0.087001	0.044330	0.021662	0.003827	0.011980	0.052445	0.004835	0.084299
Terpsiphone paradisi	2.969688	1.319666	3.214952	0.078625	1.557445	1.085393	2.462731	2.246114
Tringa ochropus	0.064177	0.054476	0.079714	0.053827	0.082314	0.059880	0.059365	0.083607
Lanius cristatus	0.053627	3.097463	0.084851	0.097605	0.089557	0.073104	0.086026	0.092726
Muscicapa dauurica	0.099145	0.062606	0.096725	0.074167	0.053800	0.056793	0.063953	0.093181
Motacilla cinerea	0.064136	4.524592	0.073017	0.075408	0.060535	0.086710	0.078129	0.074600

Table 5.3: p-values retrieved using linear regression for each species for arrival in coastal area



(a) Phylloscopus trochiloides shows strong relationship (p-value = 0.036110) with Temperature range



(b) Tringa nebularia shows strong relationship (p-value = 0.003827) with precipitation

Figure 5.14: Yearwise variation of arrival time for Phylloscopus trichiloides and Tringa nebularia in Coastal area

ters of temperature while Acrocephalus dumetorum, Actitis hypoleucos, Pastor roseus, Spatula querquedula, Anas acuta, Terpsiphone paradisi, Lanius cristatus and Motacilla cinerea has no correlation with temperature.

The departure of Hirundo rustica shows strong correlation with precipitation while Sturnia malabarica, Pastor roseus, Tringa nebularia, Terpsiphone paradisi, Tringa ochropus and Muscicapa dauurica has weak correlation.

Other than maximum windspeed, three windspeed parameters have a weak relationship with Sturnia malabarica and Acrocephalus dumetorum departure, while all four parameters have a weak relationship with Oriolus kundoo, Tringa nebularia, and Muscicapa dauurica departure. The departure of Phylloscopus nitidus, Actitis hypoleucos, Dicrurus leucophaeus, Pastor roseus, Spatula querquedula, Anas acuta and Motacilla cinerea has no relation with windspeed. Table 5.4 shows the p-values retrieved using linear regression for the departure in inland area.

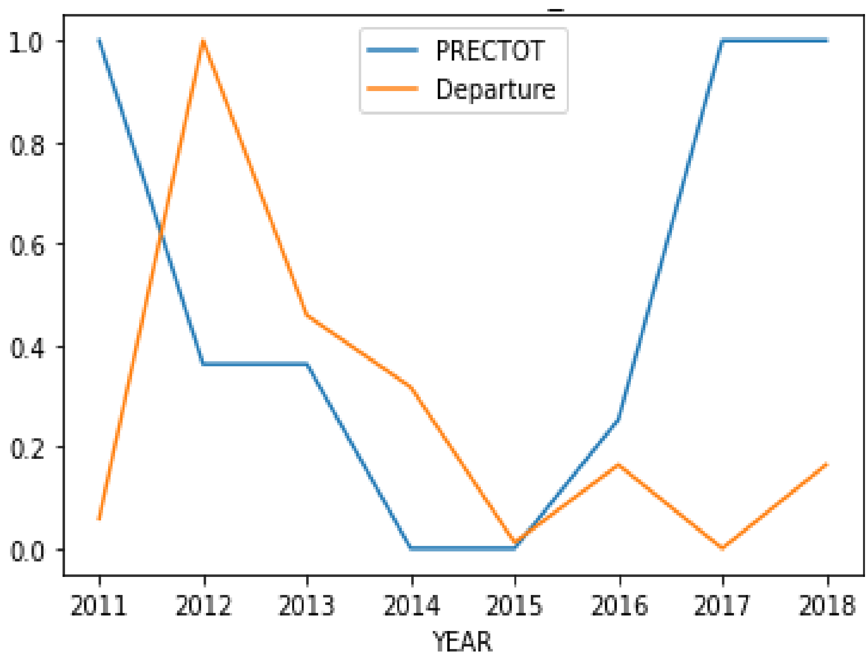


Figure 5.15: Yearwise variation of departure time in relation with precipitation for Hirundo rustica (Barn swallow) in Inland area

5.4.5 Departure analysis in coastal area

Out of seventeen species analyzed in the coastal area, the departure of eleven species had a relationship with temperature, nine species had wind speed, and

Bird Name	T2M_ MIN	T2M_ MAX	T2M_ RANGE	PREC TOT	WS10M_ MIN	WS10M_ MAX	WS10M_ RANGE	WS10M
Hirundo rustica	0.055164	4.079965	0.063013	0.005231	0.354139	0.062844	0.056724	0.072029
Acrocephalus dumetorum	2.607279	3.264453	2.549524	3.832042	0.056710	4.557005	0.082650	0.066452
Phylloscopus nitidus	3.925378	0.082908	0.097751	0.977078	2.977507	4.580566	4.960179	2.775798
Phylloscopus trochiloides	0.058027	3.457205	0.073451	1.285095	0.091982	4.470728	0.072234	2.848833
Oriolus kundoo	3.263301	0.051690	0.616947	2.428919	0.075988	0.093300	0.056791	0.062555
Sturnia malabarica	0.068061	0.093787	0.071728	0.090579	0.067779	3.572270	0.069195	0.097407
Actitis hypoleucos	1.222446	0.215389	0.420118	1.504852	2.388896	1.683181	4.787072	4.304778
Dicrurus leucophaeus	0.082781	0.628776	0.443543	1.101620	3.600938	1.006691	1.635355	1.420522
Pastor roseus	2.826918	0.680563	2.428872	0.064966	1.896066	2.601246	4.978162	4.627600
Spatula querquedula	1.879300	0.622270	2.009634	3.839912	2.866740	1.872254	1.437046	3.943874
Anas acuta	4.005281	1.891375	4.227945	0.909717	2.345701	4.652049	2.004048	0.820321
Tringa nebularia	0.088274	0.021957	0.035290	0.094437	0.076713	0.066537	0.062973	0.095614
Terpsiphone paradisi	2.517056	1.709807	4.739675	0.097738	2.095062	0.064908	0.095389	3.385261
Tringa ochropus	0.098319	0.086273	0.081824	0.097090	0.061986	0.083964	0.078966	4.039443
Lanius cristatus	0.588154	1.946711	0.693183	1.213327	2.102231	0.094453	1.348186	0.077852
Muscicapa dauurica	0.065042	0.051512	0.081922	0.059933	0.062239	0.060849	0.078616	0.090043
Motacilla cinerea	2.784416	1.614045	4.367040	0.242575	1.849817	3.091745	1.471229	4.904468

Table 5.4: p-values retrieved using linear regression for each species for departure in inland area

seven species had precipitation. The maximum temperature was a significant climatic parameter in this area, with ten species associated with maximum temperature as one of the impacting climate parameters out of eleven species that exhibited a relationship with temperature. Spatula querquedula's departure is most affected by maximum temperature, and the relationship between both is shown in 5.16. An increase in the maximum temperature of the coastal area delays this bird's departure.

Phylloscopus trochiloides, Lanius cristatus and Motacilla cinerea has weak relationship with maximum temperature while no relation with other temperature parameters. The departure of turnia malabarica, Actitis hypoleucos, Tringa ochropus and Muscicapa dauurica has weak correlation with all three parameters of temperature. Departure of Hirundo rustica, Acrocephalus dumetorum, Phylloscopus nitidus, Oriolus kundoo, Dicrurus leucophaeus and Pastor roseus has no correlation with temperature.

The departure of Tringa nebularia shows strong correlation with precipitation while Phylloscopus trochiloides, Sturnia malabarica, Actitis hypoleucos, Anas acuta, Tringa ochropus and Muscicapa dauurica has weak correlation.

Sturnia malabarica, Actitis hypoleucos, Spatula querquedula, Terpsiphone paradisi, Tringa ochropus and Muscicapa dauurica departure in coastal area is weakly affected by all climate parameters. Table 5.5 shows the p-values retrieved using linear regression for the departure in coastal area.

Bird Name	T2M_ MIN	T2M_ MAX	T2M_ RANGE	PREC TOT	WS10M_ MIN	WS10M_ MAX	WS10M_ RANGE	WS10M
Hirundo rustica	0.486047	2.480178	0.385189	3.627315	1.079264	2.639499	0.780998	2.596232
Acrocephalus dumetorum	0.772141	2.560711	0.461962	2.559358	3.144001	4.006982	3.481240	2.327702
Phylloscopus nitidus	3.700109	1.231025	3.929626	3.613893	4.597152	1.439497	1.196749	3.269425
Phylloscopus trochiloides	0.274914	0.071124	0.500086	0.057460	0.074929	0.096729	0.071723	0.606831
Oriolus kundoo	4.794733	2.824344	3.825986	4.321965	2.214819	1.747457	2.821542	0.643744
Sturnia malabarica	0.056568	0.073967	0.073159	0.073988	0.079145	0.087665	0.077849	0.063912
Actitis hypoleucos	0.089761	0.064579	0.089606	0.066068	0.087970	0.075758	0.091826	0.053824
Dicrurus leucophaeus	1.849617	4.036033	3.409073	0.175522	4.899054	1.218569	2.477668	2.814359
Pastor roseus	4.963653	3.718804	4.080973	0.480094	4.894171	0.149336	2.282197	3.514340
Spatula querquedula	0.091530	0.038310	1.235556	0.610750	0.054438	0.088737	0.051691	0.051692
Anas acuta	0.041889	0.096498	0.003021	0.053041	0.032455	0.025816	0.001460	0.000785
Tringa nebularia	0.057963	0.047603	0.029130	0.009145	0.013107	0.068291	0.083077	0.013892
Terpsiphone paradisi	0.087901	1.523517	0.069602	2.751392	0.078671	0.093949	0.067716	0.055161
Tringa ochropus	0.077505	0.088150	0.077324	0.092096	0.051686	0.061251	0.056013	0.058868
Lanius cristatus	4.134936	0.090508	3.426868	2.660262	4.036705	0.672488	1.588911	3.687897
Muscicapa dauurica	0.061164	0.063686	0.075923	0.089068	0.068384	0.096813	0.087098	0.083931
Motacilla cinerea	3.478133	0.052457	4.829390	4.402805	1.239667	0.923279	1.415129	3.228693

Table 5.5: p-values retrieved using linear regression for each species for departure in coastal area

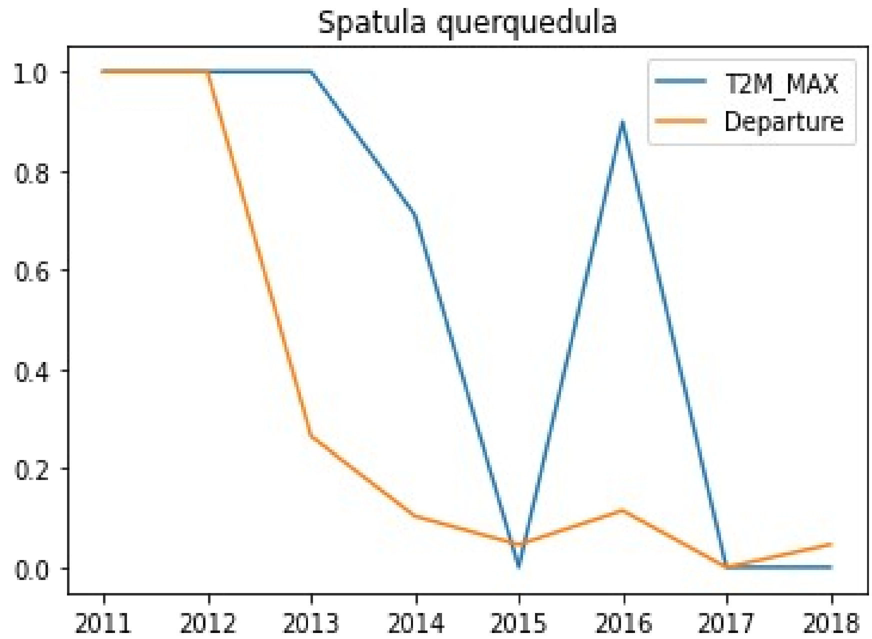


Figure 5.16: Yearwise variation of departure time in relation with maximum temperature for Spatula querquedula in Coastal area

Chapter 6
Conclusions and Future Work

According to research, these birds' migration times are influenced by the climate of their habitats. This study demonstrates how easily accessible data from citizen science initiatives can be utilised to analyse bird activity across wide geographic areas. The ebird dataset was used to derive bird migratory parameters for various species, and it was discovered that these parameters responded in a predictable manner to changes in temperature, precipitation, and windspeed. Arrival and departure dates were taken into account in this migration parameter analysis, and it was shown that these dates vary with the climate. Depending on the climate, certain species will either advance or delay their arrival or departure. Different types of species are affected differently by each climate parameter. The response of species to these changes is also affected by their location. It has been demonstrated that precipitation is more substantial in coastal areas in the event of an arrival. While Temperature plays a vital role in inland areas. According to the migratory bird extraction method, nearly all birds exhibit identical behaviour each year.

Since Kerala gave the most observations during the study period, which spanned from 2011 to 2019, Kerala is the subject of this experiment. Also, Kerala is clustered into a region in order to reduce the amount of climatic variation when mapping climate data with migratory parameters. However, given the considerable data availability in all sub-regions for each year of the study period, identical research can also be carried out in another specific area i.e., all the methods employed in this study are applicable to other areas. Therefore, one may research a similar topic for other areas in the future to take action to conserve birds.

The grouping of similar species indicates that they have similar responses to the climate, and this information can be used to determine prior conservation strategies for some birds if one of them is extinct or on the verge of going extinct.

We aim to determine the correlation between smaller sub-region migratory parameters and climate data in the future. This may help study the migration route of birds and strengthen our analysis results. Currently, the available data to conduct this correlation is limited and will not yield accurate relations. Furthermore, with the acquirement of ample data, we can conduct extensive statistical analysis. Other significant elements affecting birds, such as food availability, urbanisation, greenery, cloud cover, etc., can also be taken into account in addition to climate parameters like temperature, wind speed, and precipitation.

References

[1] Audubon's christmas bird count. *National Audubon Society*, 1900.

[2] M. Aggarwal. Indian government proposes a 10-year plan to protect birds. 2020.

[3] S. F. U. Arne Mooers, Professor. Bird species today are dying out a hundred times faster than we thought.

[4] A. R. Ashirita V Dewan, Abhiroop Chowdhury. Threats to migratory birds. 2021.

[5] J. Belmaker, P. Zarnetske, M.-N. Tuanmu, S. Zonneveld, S. Record, A. Strecker, and L. Beaudrot. Empirical evidence for the scale dependence of biotic interactions. *Global Ecology and Biogeography*, 24(7):750–761, 2015.

[6] R. Biddle, I. Solis-Ponce, M. Jones, S. Marsden, M. Pilgrim, and C. Devenish. The value of local community knowledge in species distribution modelling for a threatened neotropical parrot. *Biodiversity and Conservation*, 30(6):1803–1823, 2021.

[7] A. Bounas, M. Solanou, M. Panuccio, S. Barišić, T. Bino, K. Erciyas-Yavuz, P. Iankov, C. Ieronymidou, and C. Barboutis. Mining citizen science data to explore stopover sites and spatiotemporal variation in migration patterns of the red-footed falcon. *Current zoology*, 66(5):467–475, 2020.

[8] G. S. Butcher, D. K. Niven, and J. R. Sauer. Using christmas bird count data to assess population dynamics and trends of waterbirds. *American Birds*, 59(105th Christmas Bird):23–25, 2005.

[9] D. Bystrak. The north american breeding bird survey. 1981.

[10] C. Carey. The impacts of climate change on the annual cycles of birds. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 364(1534):3321–3330, 2009.

[11] J. R. Coyle, A. H. Hurlbert, and E. P. White. Opposing mechanisms drive richness patterns of core and transient bird species. *The American Naturalist*, 181(4):E83–E90, 2013.

[12] S. R. Curley, L. L. Manne, and R. R. Veit. Differential winter and breeding range shifts: Implications for avian migration distances. *Diversity and Distributions*, 26(4):415–425, 2020.

[13] L. L. Dobson, F. A. La Sorte, L. L. Manne, and B. A. Hawkins. The diversity and abundance of north american bird assemblages fail to track changing productivity. *Ecology*, 96(4):1105–1114, 2015.

[14] A. Drake, C. A. Rock, S. P. Quinlan, M. Martin, and D. J. Green. Wind speed during migration influences the survival, timing of breeding, and productivity of a neotropical migrant, setophaga petechia. *PloS one*, 9(5):e97152, 2014.

[15] Ebird. ebird: An online database of bird distribution and abundance. *eBird, Cornell Lab of Ornithology*, 2002.

[16] J. Elith and C. H. Graham. Do they? how do they? why do they differ? on finding reasons for differing performances of species distribution models. *Ecography*, 32(1):66–77, 2009.

[17] J. Elith and J. R. Leathwick. Species distribution models: ecological explanation and prediction across space and time. *Annual Review of Ecology, Evolution and Systematics*, 40(1):677–697, 2009.

[18] M. Elmohamed, D. Kozen, and D. R. Sheldon. Collective inference on markov models for modeling bird migration. *Advances in Neural Information Processing Systems*, 20, 2007.

[19] K. S. Girish and U. Srinivasan. Preliminary evidence for upward elevational range shifts by eastern himalayan birds. *bioRxiv*, 2020.

[20] K. G. Horton, B. M. Van Doren, P. M. Stepanian, A. Farnsworth, and J. F. Kelly. Seasonal differences in landbird migration strategies. *The Auk: Ornithological Advances*, 133(4):761–769, 2016.

[21] A. H. Hurlbert and Z. Liang. Spatiotemporal variation in avian migration phenology: citizen science reveals effects of climate change. *PloS one*, 7(2):e31662, 2012.

[22] A. khan. 91% of migratory birds face peril on their journeys.

[23] E. Knudsen, A. Lindén, C. Both, N. Jonzén, F. Pulido, N. Saino, W. J. Sutherland, L. A. Bach, T. Coppack, T. Ergon, et al.Challenging claims in the study of migratory birds and climate change. *Biological Reviews*, 86(4):928–946, 2011.

[24] F. A. La Sorte and D. Fink. Migration distance, ecological barriers and en-route variation in the migratory behaviour of terrestrial bird populations. *Global Ecology and Biogeography*, 26(2):216–227, 2017.

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

[26] F. A. La Sorte, C. A. Lepczyk, J. L. Burnett, A. H. Hurlbert, M. W. Tingley, and B. Zuckerberg. Opportunities and challenges for big data ornithology. *The Condor: Ornithological Applications*, 120(2):414–426, 2018.

[27] X. Li, Y. Liu, and Y. Zhu. The effects of climate change on birds and approaches to response. In *IOP Conference Series: Earth and Environmental Science*, volume 1011, page 012054. IOP Publishing, 2022.

[28] J. S. Marshall and E. H. Ballantvne. Weather surveillance radar. *Journal of Applied Meteorology and Climatology*, 14(7):1317–1338, 1975.

[29] T. D. Meehan, N. L. Michel, and H. Rue. Spatial modeling of audubon christmas bird counts reveals fine-scale patterns and drivers of relative abundance trends. *Ecosphere*, 10(4):e02707, 2019.

[30] NASA. Nasa prediction of worldwide energy resources.

[31] S. Natali, L. Fusani, E. Bartocci, and M. Hirtl. Bird Migration and Climate Variables. In *EGU General Assembly Conference Abstracts*, EGU General Assembly Conference Abstracts, page 14671, Apr. 2018.

[32] M. H. Neate-Clegg, J. J. Horns, F. R. Adler, M. Ç. K. Aytekin, and Ç. H. Şekercioğlu. Monitoring the world's bird populations with community science data. *Biological Conservation*, 248:108653, 2020.

[33] M. H. Neate-Clegg, S. E. Jones, J. A. Tobias, W. D. Newmark, and Ç. H. Şekercioğlu. Ecological correlates of elevational range shifts in tropical birds. *Frontiers in Ecology and Evolution*, 9:621749, 2021.

[34] D. A. Potvin, K. Välimäki, and A. Lehikoinen. Differences in shifts of wintering and breeding ranges lead to changing migration distances in european birds. *Journal of Avian Biology*, 47(5):619–628, 2016.

[35] E. Shochat, S. Lerman, and E. Fernández-Juricic. Birds in urban ecosystems: population dynamics, community structure, biodiversity, and conservation. *Urban ecosystem ecology*, 55:75–86, 2010.

[36] M. M. Skrip, U. Bauchinger, W. Goymann, L. Fusani, M. Cardinale, R. R. Alan, and S. R. McWilliams. Migrating songbirds on stopover prepare for, and recover from, oxidative challenges posed by long-distance flight. *Ecology and Evolution*, 5(15):3198–3209, 2015.

[37] V. A. Steen, C. S. Elphick, and M. W. Tingley. An evaluation of stringent filtering to improve species distribution models from citizen science data. *Diversity and Distributions*, 25(12):1857–1869, 2019.

[38] P. A. Stephens, L. R. Mason, R. E. Green, R. D. Gregory, J. R. Sauer, J. Alison, A. Aunins, L. Brotons, S. H. Butchart, T. Campedelli, et al. Consistent response of bird populations to climate change on two continents. *Science*, 352(6281):84–87, 2016.

[39] B. L. Sullivan, C. L. Wood, M. J. Iliff, R. E. Bonney, D. Fink, and S. Kelling. ebird: A citizen-based bird observation network in the biological sciences. *Biological conservation*, 142(10):2282–2292, 2009.

[40] S. L. Taylor and K. S. Pollard. Evaluation of two methods to estimate and monitor bird populations. *PLoS One*, 3(8):e3047, 2008.

[41] N. G. Tilghman. Characteristics of urban woodlands affecting breeding bird diversity and abundance. *Landscape and Urban planning*, 14:481–495, 1987.

[42] A. Urfi, M. Sen, A. Kalam, and T. Meganathan. Counting birds in india: Methodologies and trends. *Current Science*, pages 1997–2003, 2005.

[43] J. Walker and P. Taylor. Evaluating the efficacy of ebird data for modeling historical population trajectories of north american birds and for monitoring populations of boreal and arctic breeding species. *Avian Conservation and Ecology*, 15(2), 2020.

[44] M. F. Willson and T. A. Comet. Bird communities of northern forests: patterns of diversity and abundance. *The Condor*, 98(2):337–349, 1996.

[45] J. Zaifman, D. Shan, A. Ay, and A. G. Jimenez. Shifts in bird migration timing in north american long-distance and short-distance migrants are associated with climate change. *International Journal of Zoology*, 2017, 2017.

[46] L. Zwarts, B. J. Ens, M. Kersten, and T. Piersma. Moult, mass and flight range of waders ready to take off for long-distance migrations. *Ardea*, 55(1–2):339–364, 1990.