Aircraft Wildlife Strikes

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Abstract

Wildlife strike is a common scenario and can be a significant threat to the aircraft safety. With the increase in air traffic, not only the wildlife strike will increase in future, but also more strikes will result in aircraft engine failure. Wildlife Strike is the collision between the animals and the aircraft, either in flight, take-off, or landing. This result due to the migration of species, weather conditions, the phase of flight, and region of the flight's route. The term "wildlife" covers a number of birds' species like bats, eagle, vultures, sparrow and ground animals like duck, cat, raccoon, fox etc. The smaller aircraft may face significant damage to the aircraft structure like ingestion of the birds in the engine air passage leading to fatal accidents. So, to have a closer look the following report visualizes the subset of data collected on Wildlife Strike in U.S.A by Federal Aviation Administration (FAA) from 2000-2011. FAA is a national authority which regulates all aspect of civil aviation. The visualization tool used is Microsoft Power BI (Business Intelligence). We found that airport location, the phase of the day, seasonal pattern, altitude, and phase of flight were among the main contributing factors. Our initial thought was that the climatic conditions like precipitation and presence of cloud will hinder the pilot's visibility leading to more incidents but, after visualizing we found that the clear sky leads to more incidents. Overall, each of the factor presented in the dataset is explored using visualization to understand their effects on the strikes rate, the population of wildlife species, damage caused to the aircraft, and the cost model over years.

Keywords: visualization, Microsoft Power BI, wildlife strikes, aircraft.

Objective

The objective of our analysis was two-fold:

1) To examine all the available factors contributing to the strikes.
2) To visualize the impact of wildlife strikes on wildlife species.

Dataset

The wildlife Strikes data has been taken from data.world site (https://data.world/shihzy/2000-2011-birds-strikes-planes). Data World is a process driven organization with well-defined datasets and software delivery methodologies. This dataset is the subset of the data present on Federal Aviation Administration National Wildlife Strike Database (NWSD) for the 11 years of the period from 2000 through 2011 (https://wildlife.faa.gov/).

Since the original data is highly complex and carries dozens of different fields, we narrowed the focus of the visualization to build a system that would help viewers to explore relationships between the main contributors; aircraft/operators, wildlife species, and years. Although the dataset starts in 1990, for this report we selected the data from 2000 to 2011. Our rationale for selecting the dataset from 2000 to 2011 is to capture the significant spike in the number of incidents starting in the early 2000s. We also believe that the increment in the incidents may have had a notable impact on the quality and quantity of the data.

The dataset consists of 26 attributes:

1. Record_ID: Individual aircraft record number.
2. Aircraft_Type: Airline
3. Airport_Name: Name of the airport.
4. Altitude_Bin: Height from the ground in bins.
5. Aircraft_Make&Model: Model of the aircraft.
6. Wildlife_NumberStruckActual: Number of wildlife struck
7. Effect_ImpactToFlight: Effect on flight after the strike-aborted, shut-down, precautionary landing, or other effects.
8. Flight_Date: Date of the incident.
9. Effect_IndicatedDamage: Indicates whether the aircraft was damaged
10. Aircraft_NumberOfEngines: Indicates the total number of engines-1, 2, 3, or 4.
11. Aircraft_AirlineOperator: Indicates the name of the airlines.
12. Origin_States: Name of the states.
13. PhaseOfFlight: Phase of flight during which strike occurred- approach, climb, landing roll, taxi, take-off, or parked.
14. Conditions_Precipitation: Type of precipitation-rain, fog, snow, or none.
15. Remains_Collected: Indicates if bird or wildlife remains were found and collected
16. Remains_SentToSmithsonian: Indicates if remains were sent to the Smithsonian, an Institution for identification.
17. Remarks: Remarks written by analysts in the text.

18. Wildlife_Size: Size of the species-small, medium, or large. If more than one species was struck, the larger bird is entered.
19. Conditions_Sky: Type of cloud cover, if any.
20. Wildlife_Species: Common name for bird or other wildlife.
21. PilotWarned_Wildlife: Pilot warned of birds/wildlife-yes or no.
22. Cost_Total$: Estimated costs for repairs or replacement in dollars (USD).
23. Feet_Above_Ground: Feet above ground level the aircraft was flying.
24. Number_People_Injured: Number of people injured or died.
25. Visibility: Phase of the day- day, night, dusk, and dawn.
26. Aircraft_Large: Indicated the size of aircraft.

Tools

We have chosen Microsoft Power BI Desktop as our visualization tool for the following reasons: -

1) According to Gartner's report, Microsoft Power BI and Tableau are two of the top leaders in BI and Analytics Platforms for ten consecutive years. Since we were already covering Tableau in the class, we thought it's a great opportunity to do our data visualization in Power BI and explore the tool simultaneously. This also in a way gave us a chance to compare both the tools and get familiar with their strengths and limitations.

2) Power BI Desktop is a feature-rich data mashup and reports authoring tool. It enables users to create compelling stories that perfectly visualize data and also create custom visuals that are uniquely tailored to suit user needs. Moreover, it also enables users to share insights that they have created.

Data Preparation

We performed multiple data preparation steps in this data visualization project. Below is the list of data preparation steps that we performed.

1) Firstly, we loaded the excel file in Power BI. To do that we clicked on get data and selected excel from the options as our data was stored in an excel file. Refer Figure 1.

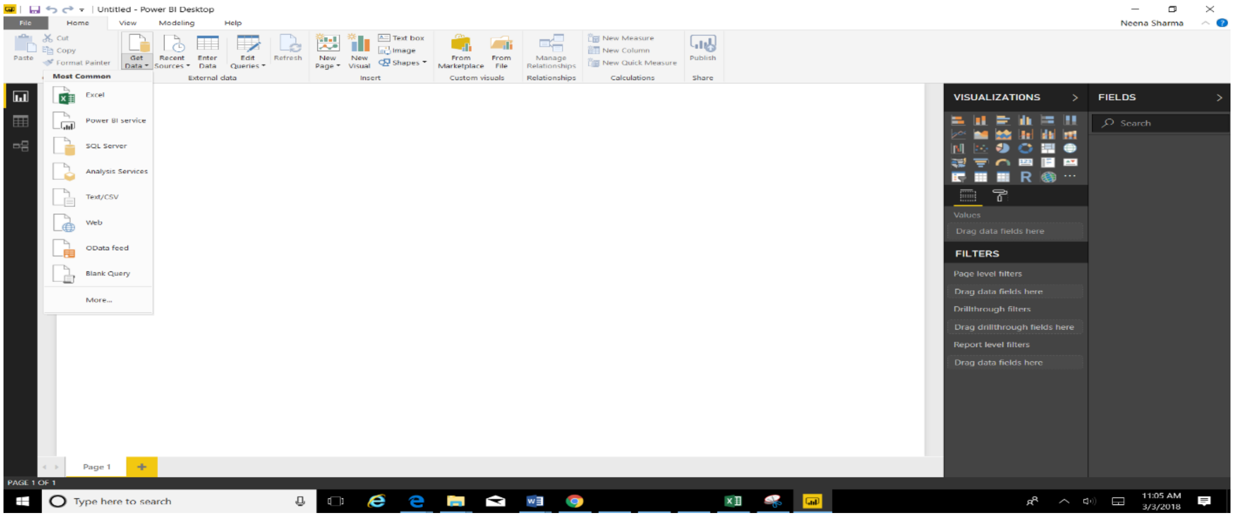


Figure 1

2) Go to Edit Queries and click Edit Queries. Refer Figure 2.

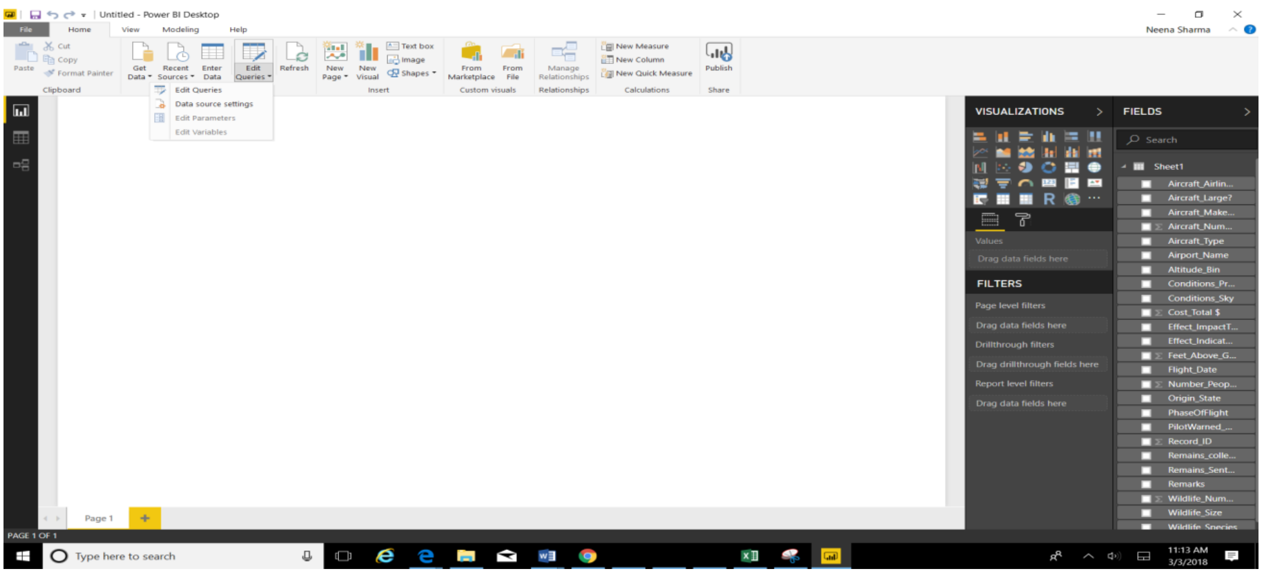


Figure 2

3) We removed Remarks column from the data as it had 4701 missing value. Also, since it was a text field, we thought it would not be of great significance. See Figure 3 & 4.

Before: -

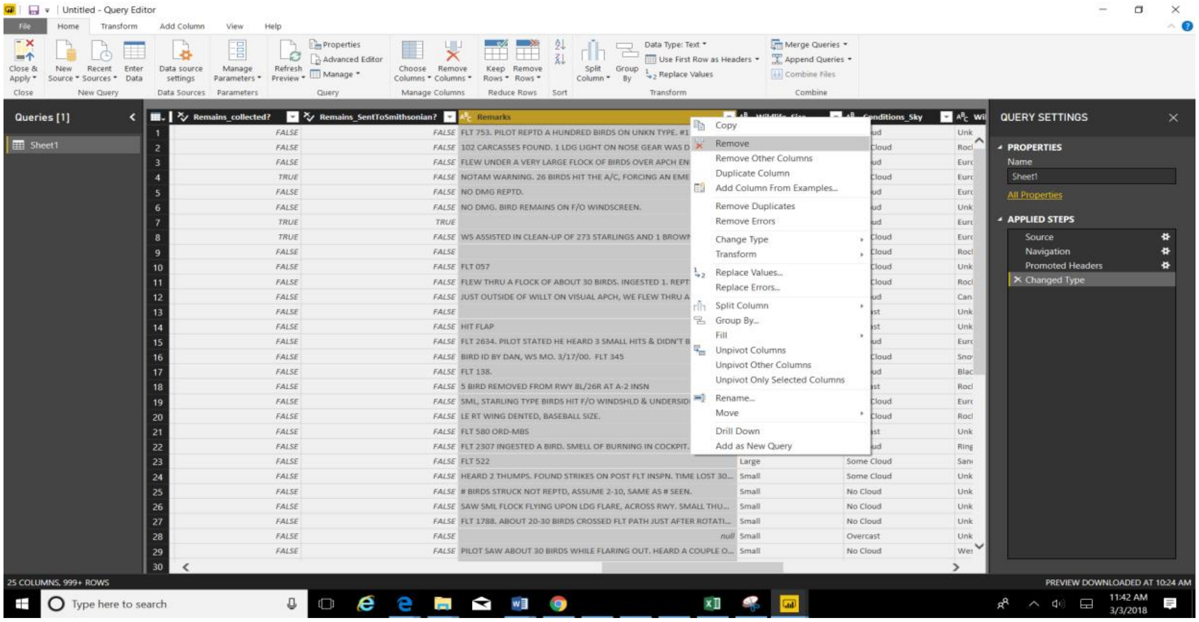


Figure 3

After: -

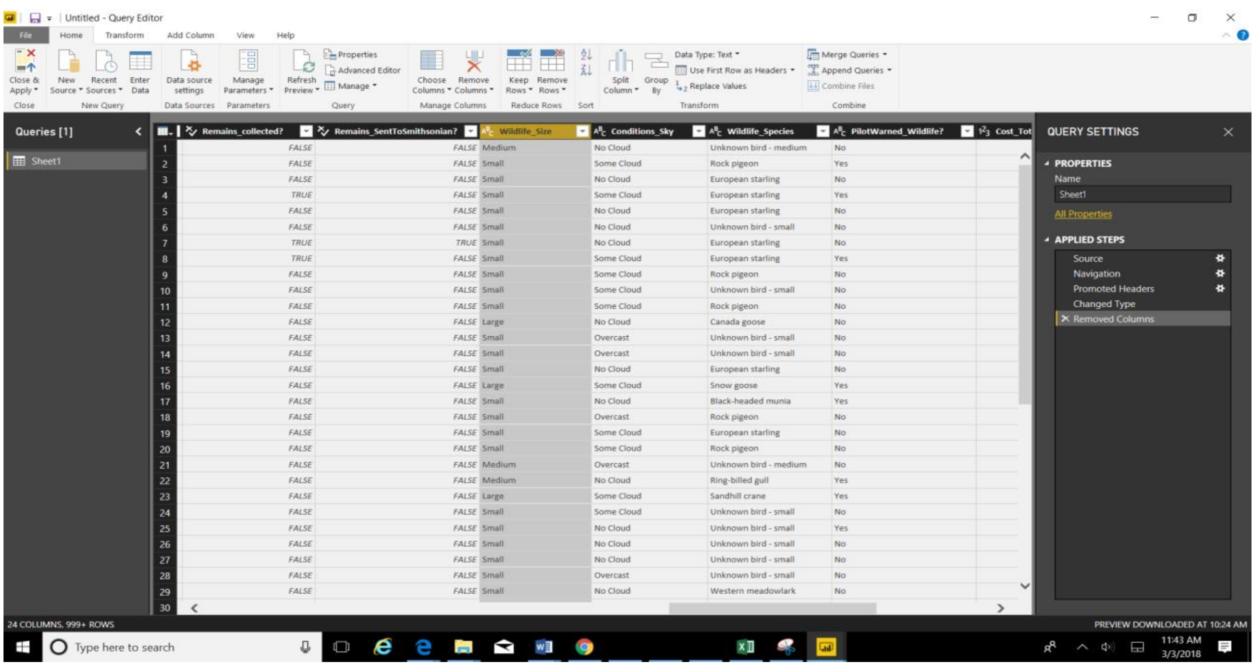


Figure 4

4) We removed rows from Aircraft Make & Model that had missing values. Since the number was insignificant (6 rows), we didn't remove the whole column. We used

"Remove empty" filter for this action in figure 5. To compare before and after result refer to figure 6 and 7.

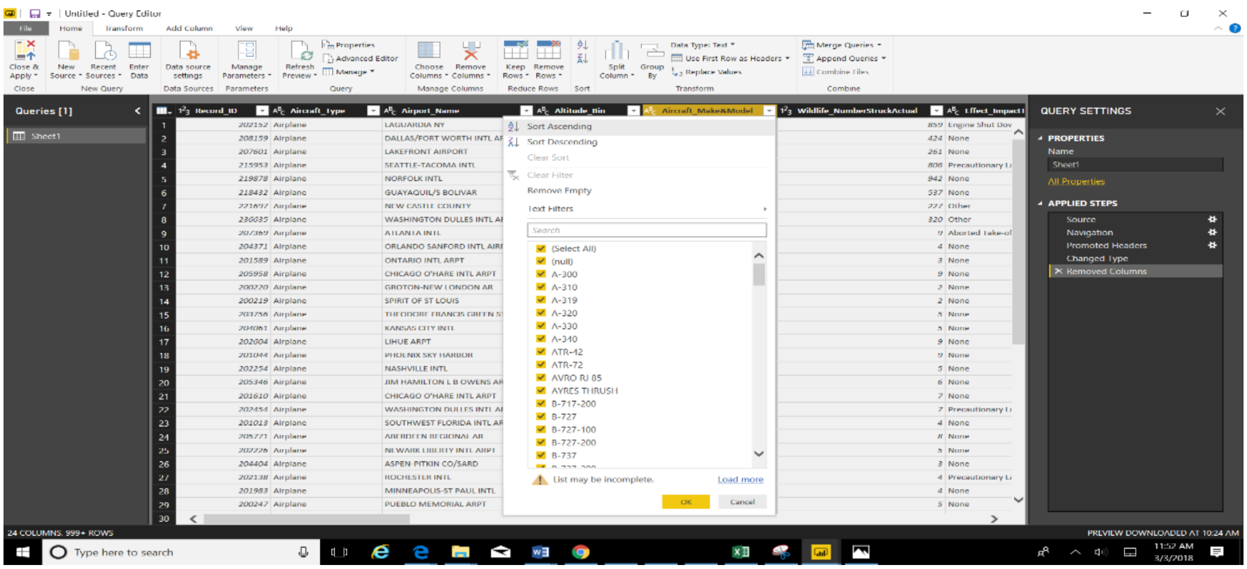


Figure 5

Before: -

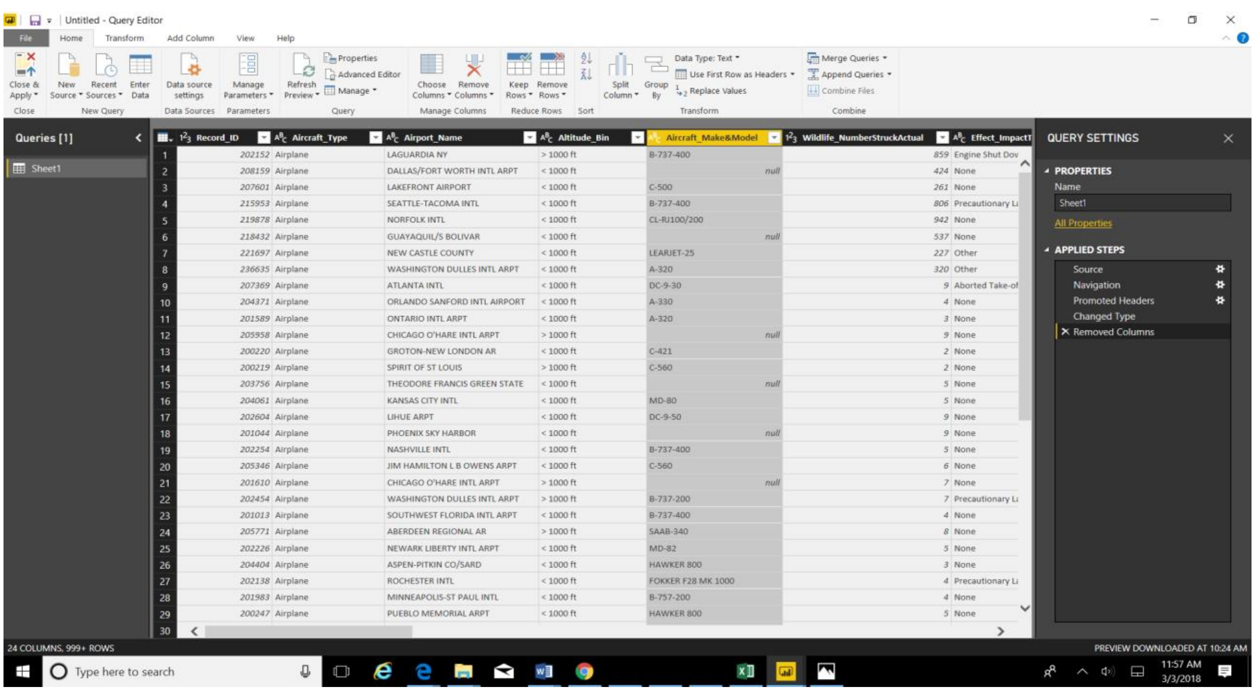


Figure 6

After:-

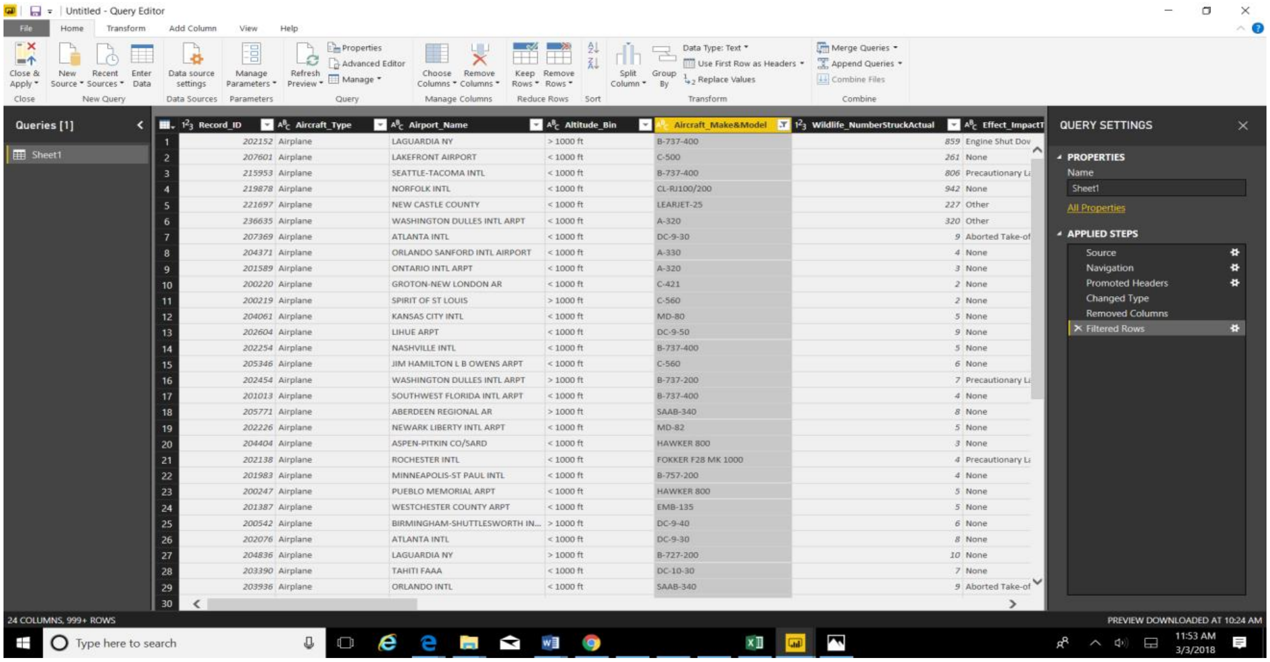
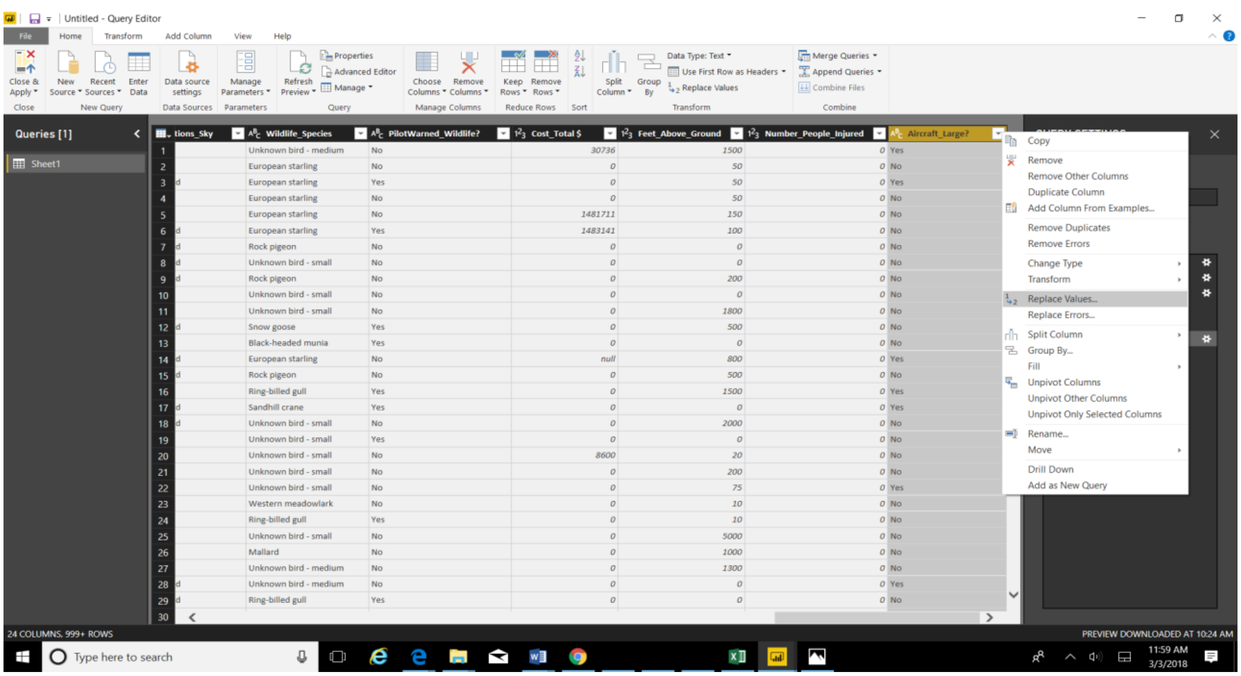


Figure 7

5) We also changed the values of Aircraft_Large? Columns from text to binomial. Refer to figure 8, 9 and 10.

Before: - *Figure 8*



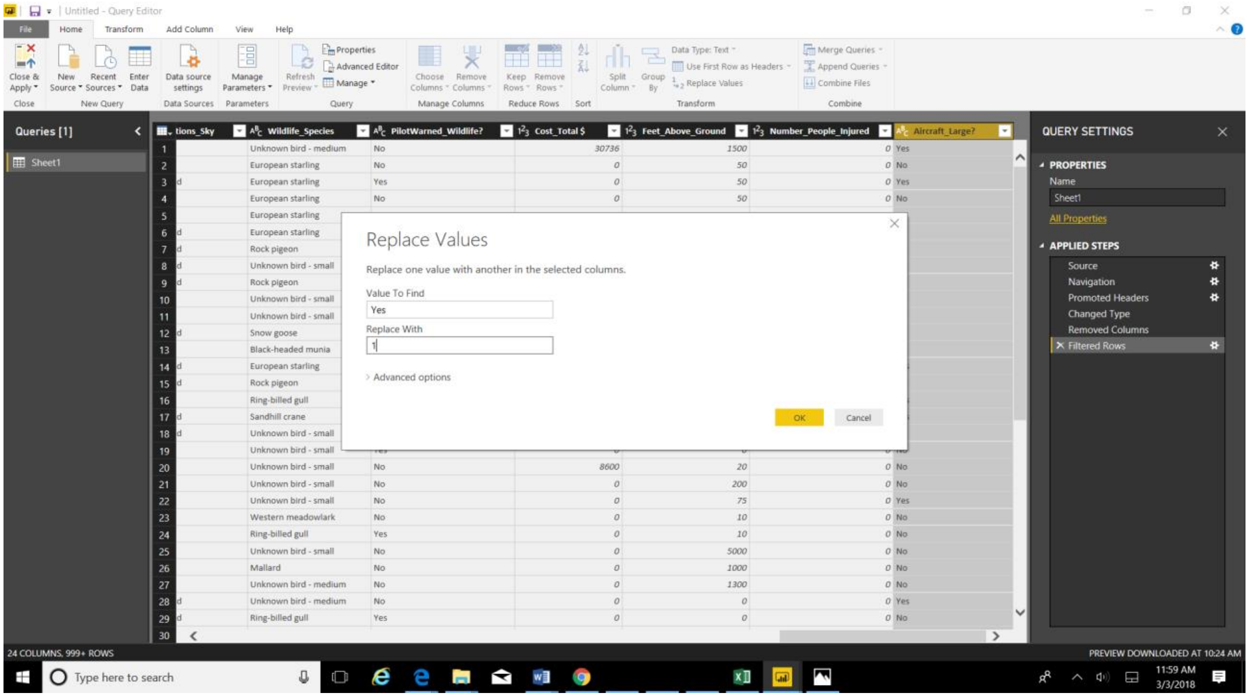


Figure 9

After: -

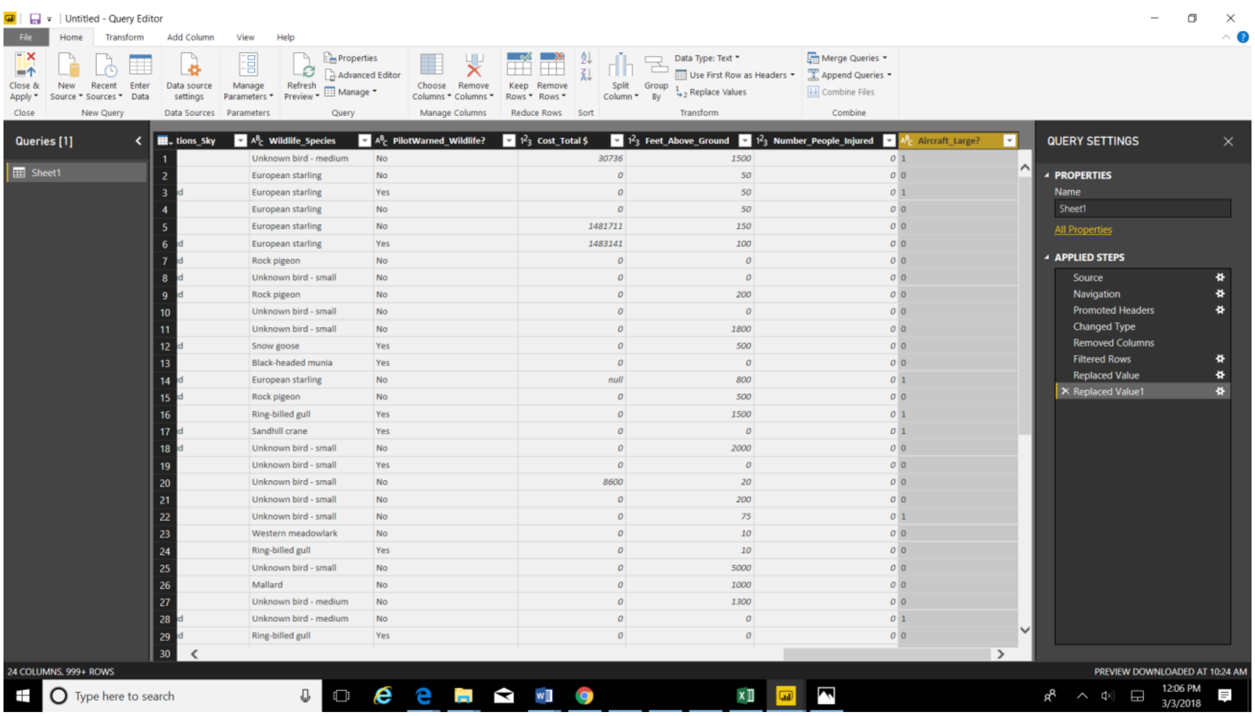


Figure 10

6) We also used transform function and converted Date/Time data type to Date only data type. Refer to Figure 11 and 12.

Before: -

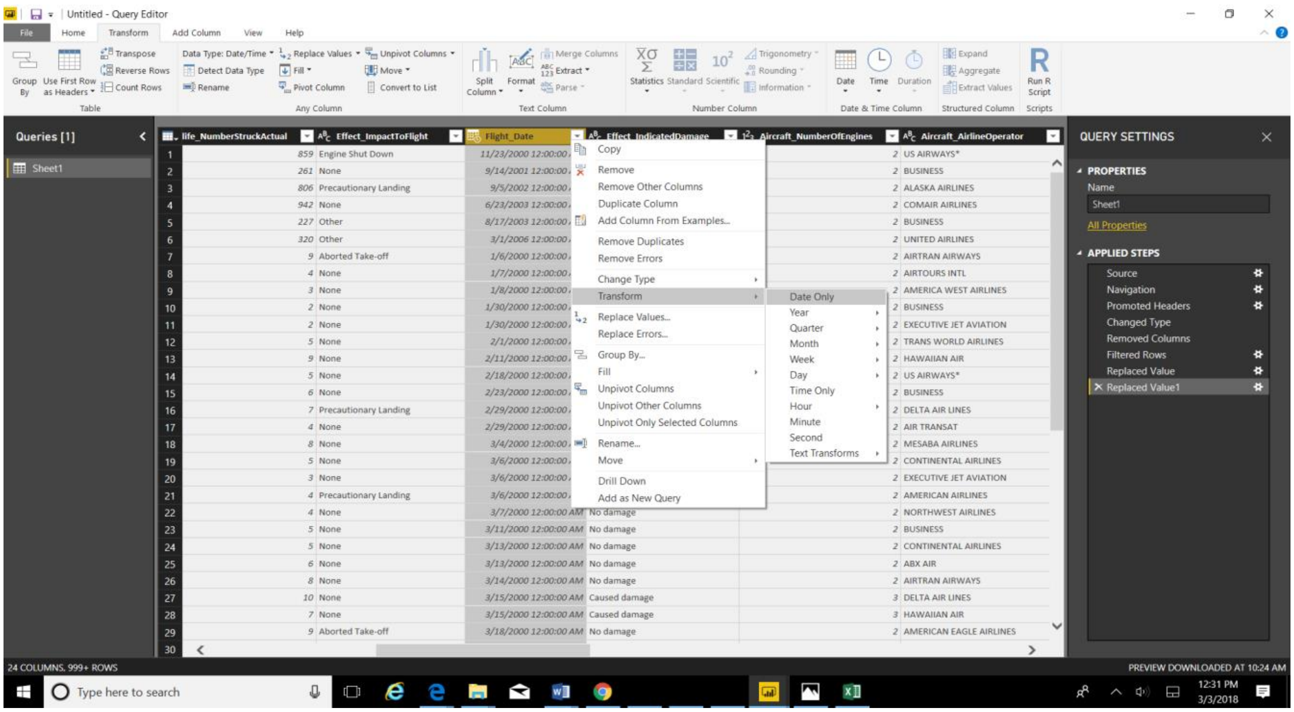


Figure 11

After: -

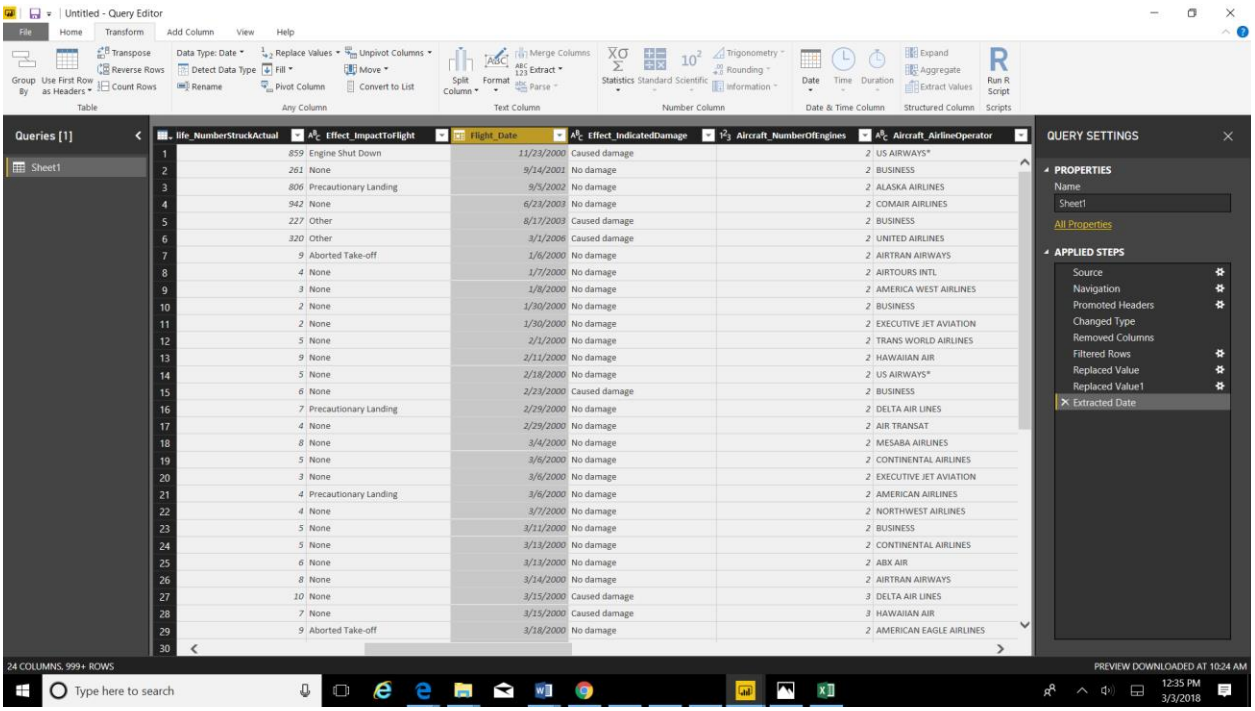


Figure 12

7) We also generated an attribute by adding a conditional column. We used "Wildlife_NumberStruckActual" column and created four different bins in the new column "Wildllife_NumberStruck_Bin" using if/else conditions. This is the first calculation that we performed. The objective of this calculation is to divide the number of wildlife struck into four different ranges:- 1, Between 2 to 10, Between 11 to 100 and More than 100. We have later used the newly constructed column in one of the visualizations. Refer to figure 13 and 14.

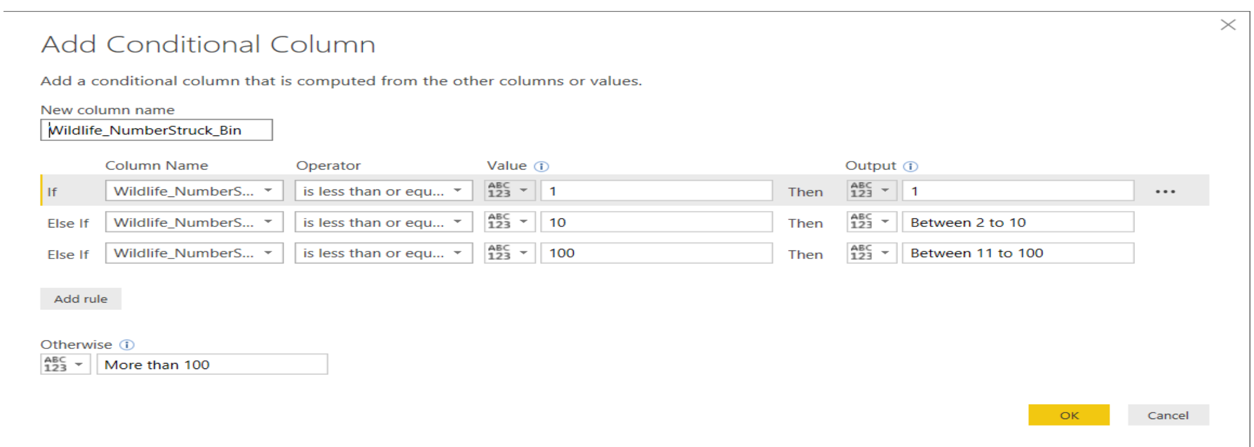


Figure 13

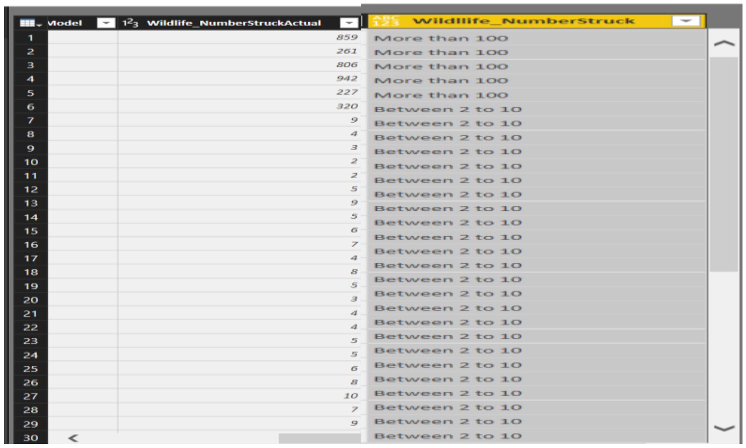


Figure 14

8) We grouped all the species of gulls into one, “Gulls” in a new column. Initially, during our analysis, we found that there is a huge number of gulls involved in strikes. So, we were curious to see the impact of strikes on the entire gulls’ population. This was the second calculation and we initially performed it in Tableau. Refer to figure 15 below.

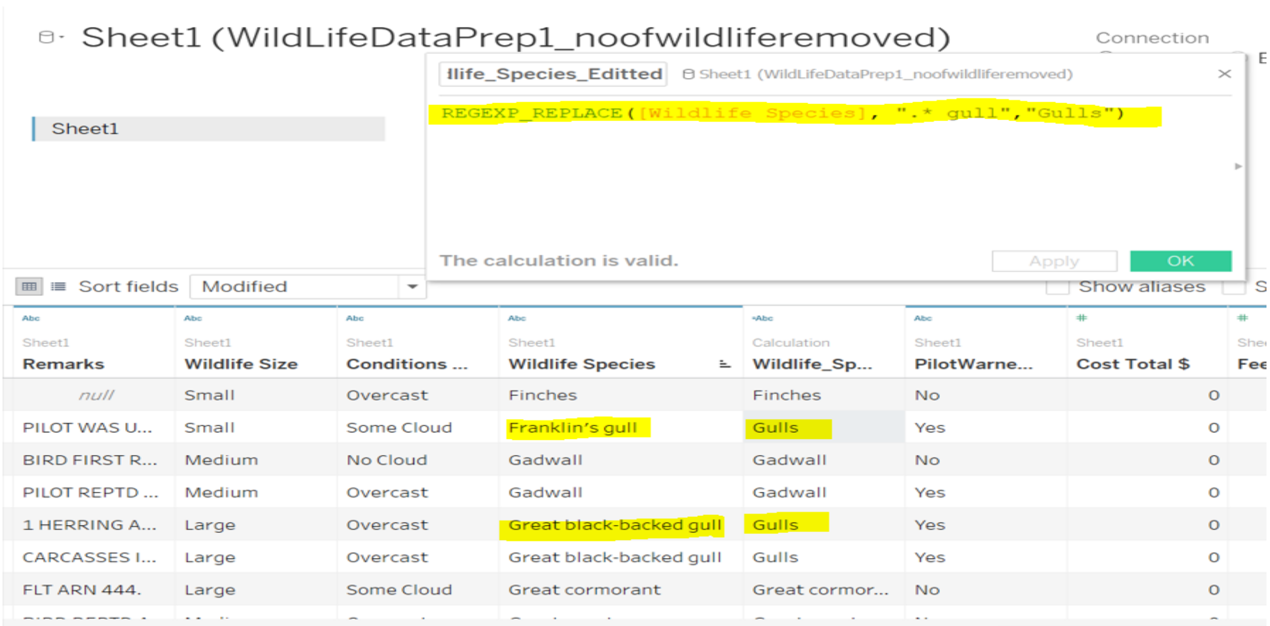


Figure 15

We initially performed the above calculation in Tableau since we couldn’t do it in Power BI. We wanted to replace all the species of gulls by "Gulls" without affecting the rest of the species in the new column. But we weren't sure what value to put in the "Otherwise" tab. At last, after multiple tries, we cracked the logic and were able to perform it in Power BI (Figure 16 & Figure 17). In the "otherwise" tab we put the name of the column(Wildlife_Species).

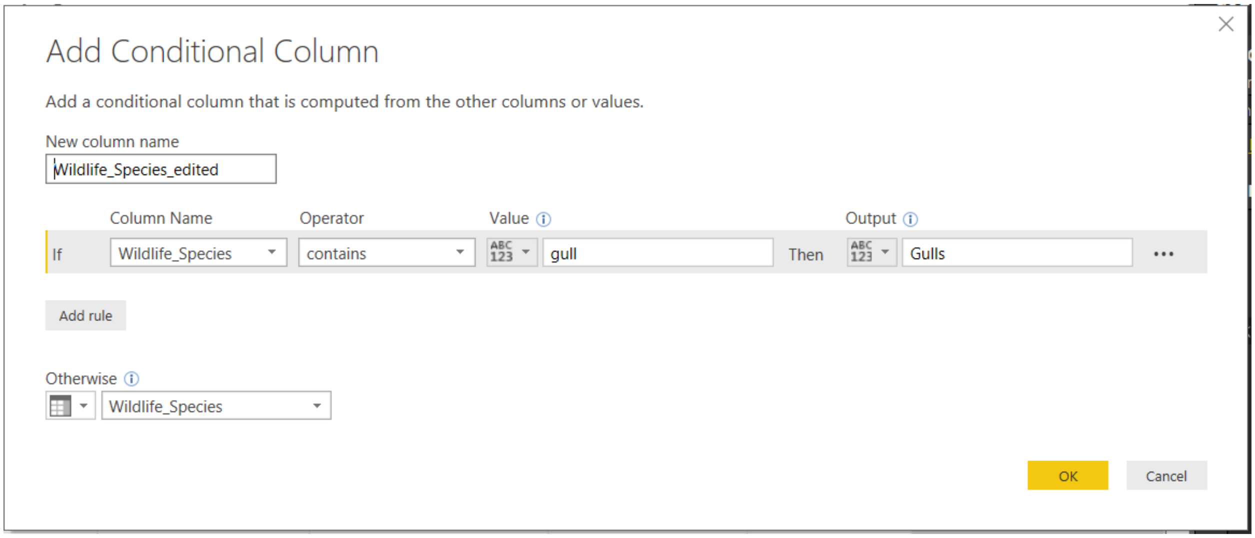


Figure 16

Wildlife_Species	Wildlife_Species_edited
European starling	European starling
Rock pigeon	Rock pigeon
Unknown bird - medium	Unknown bird - medium
Ring-billed gull	Gulls
Sandhill crane	Sandhill crane
Unknown bird - small	Unknown bird - small
Unknown bird - small	Unknown bird - small
Unknown bird - small	Unknown bird - small
Unknown bird - small	Unknown bird - small
Unknown bird - small	Unknown bird - small
Western meadowlark	Western meadowlark
Ring-billed gull	Gulls
Unknown bird - small	Unknown bird - small
Mallard	Mallard
Unknown bird - medium	Unknown bird - medium
Unknown bird - medium	Unknown bird - medium
Ring-billed gull	Gulls
Turkey vulture	Turkey vulture
Tundra swan	Tundra swan
Unknown bird - small	Unknown bird - small

Figure 17

Dashboard

We have created three dashboards in our entire reports. Each dashboard highlights a specific topic and lets the user have an interaction with the data.

Let’s discuss each dashboard one by one.

Dashboard 1: Geography Dashboard

We created three visualizations to analyze the number of strikes across U.S.A (Figure 18)

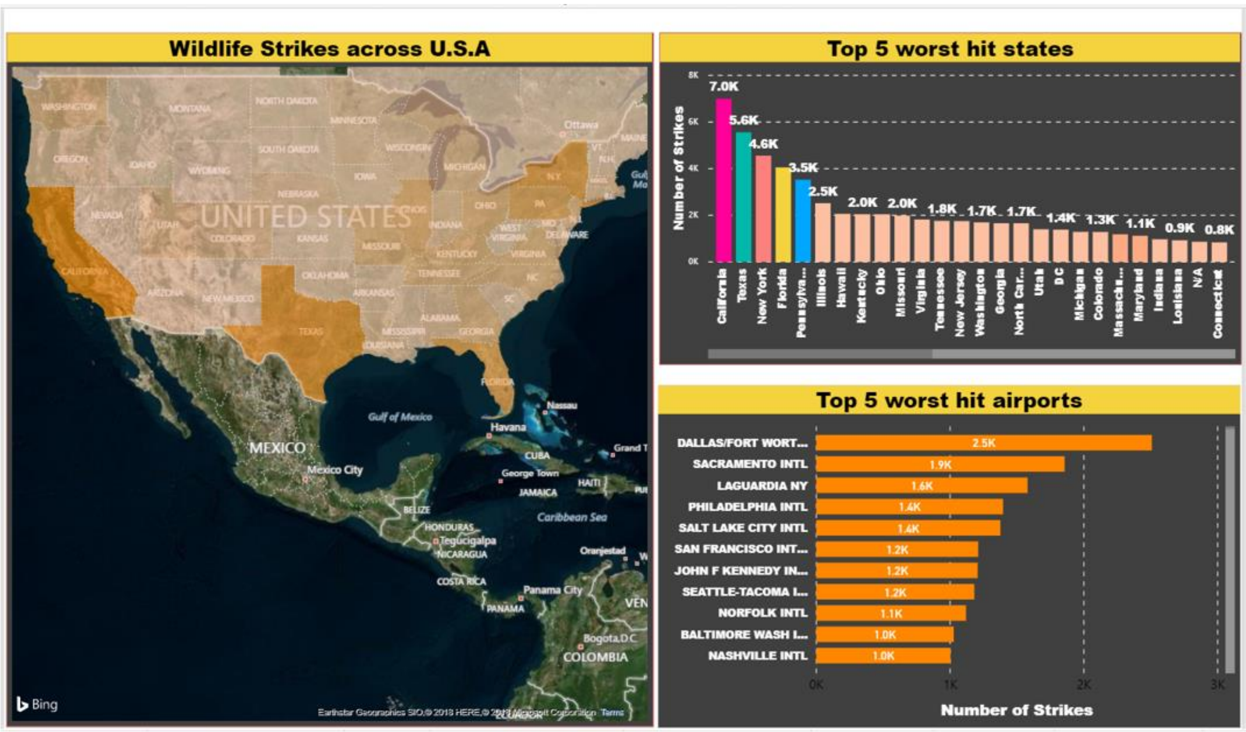


Figure 18

Visualization 1: - Wildlife Strikes across U.S.A

We want to analyze the wildlife strikes across the USA. We have chosen an aerial map to get a realistic view of each state in the US. We performed the following configurations on the visualization tab.

Configuration (refer to figure 19): - Location: Origin_State

Color Saturation: Wildlife_NumberStruck_Actual

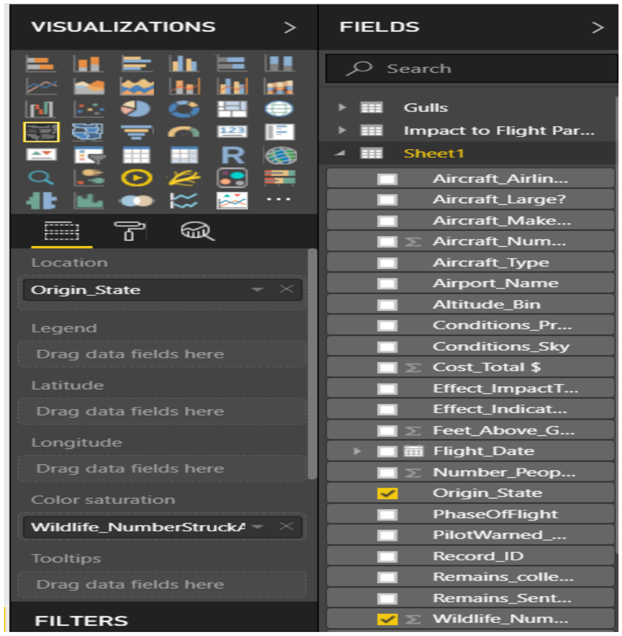


Figure 19

After plotting the geographical map, we can see that the darkening shade of orange is more towards the right side of the map. We can infer from this analysis that wildlife strikes have predominately affected the eastern side of the USA. Also, from the above graph, we can see that the regions around the coast are more susceptible to strikes. This may be due to a higher level of un-managed bird activity than the inland airports. Also, the presence of wetlands and crops and optimal temperature provides a suitable habitat for the wildlife.

Visualization 2: - Top 5 worst hit states

We wanted to analyze the top five US Airlines in terms of having encountered bird strikes. We chose a stacked column chart for this analysis. The reason for picking a column chart is to show the states in columns. Initially, we selected a pie chart but the view was a bit congested, so we decided to switch to a column chart.

Configuration (refer to figure 20): - Axis: Origin_State

Value: Wildlife_NumberStruck_Actual

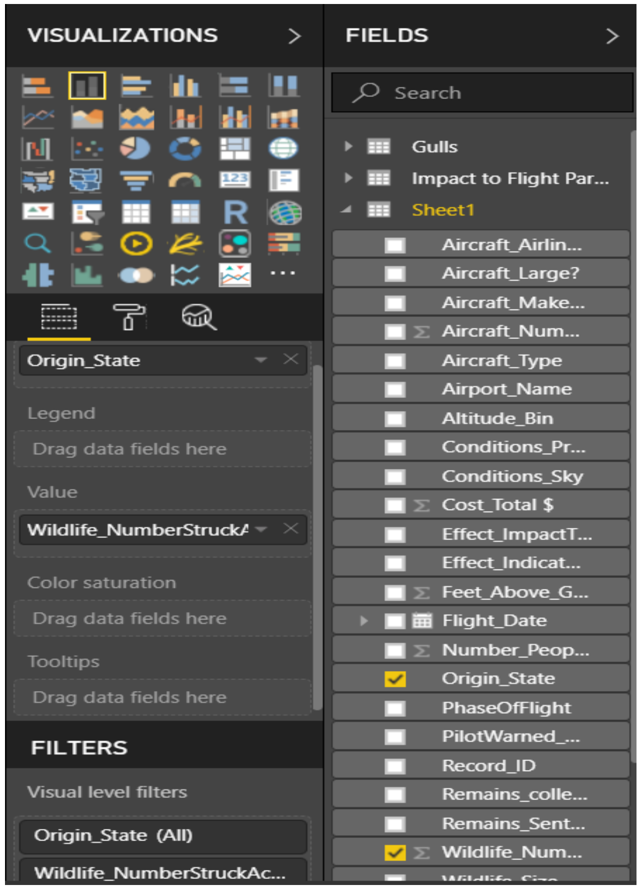


Figure 20

From the above graph, we can see that California, Texas, New York, Florida and Pennsylvania are the top five states that are predominately affected by the strikes. The number of wildlife strikes happened in these five states are:

California – 6998

Texas – 5559

New York – 4557

Florida – 3525

Pennsylvania - 2518

Visualization 3: - Top 5 worst hit airports

We also wanted to see the top five airports with most incidents of wildlife strikes. We used a stacked bar chart in order to create a symmetry within the dashboard.

Configuration (refer to figure 21): - Axis: Airport_Name

Value: Wildlife_NumberStruck_Actual

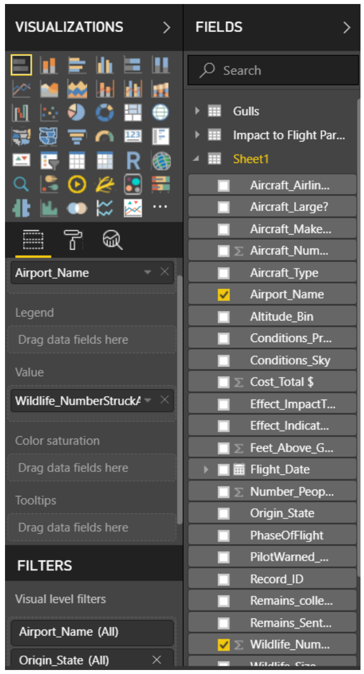


Figure 21

From the above graph we can see that even though California is the worst-hit state, Dallas/Fort Worth International airport [Texas] tops the list with a maximum number of wildlife strikes. The number of wildlife strikes happened in these five airports are:

Dallas/Fort Worth International Airport – 2508

Sacramento International Airport - 1856

LaGuardia International Airport - 1579

Philadelphia International Airport – 1396

Salt Lake City International Airport – 1376

Dashboard 2 – Seasonality and weather effect

We created five visualizations to analyze the seasonal patterns and weather effects on the number of strikes. Refer Figure 22

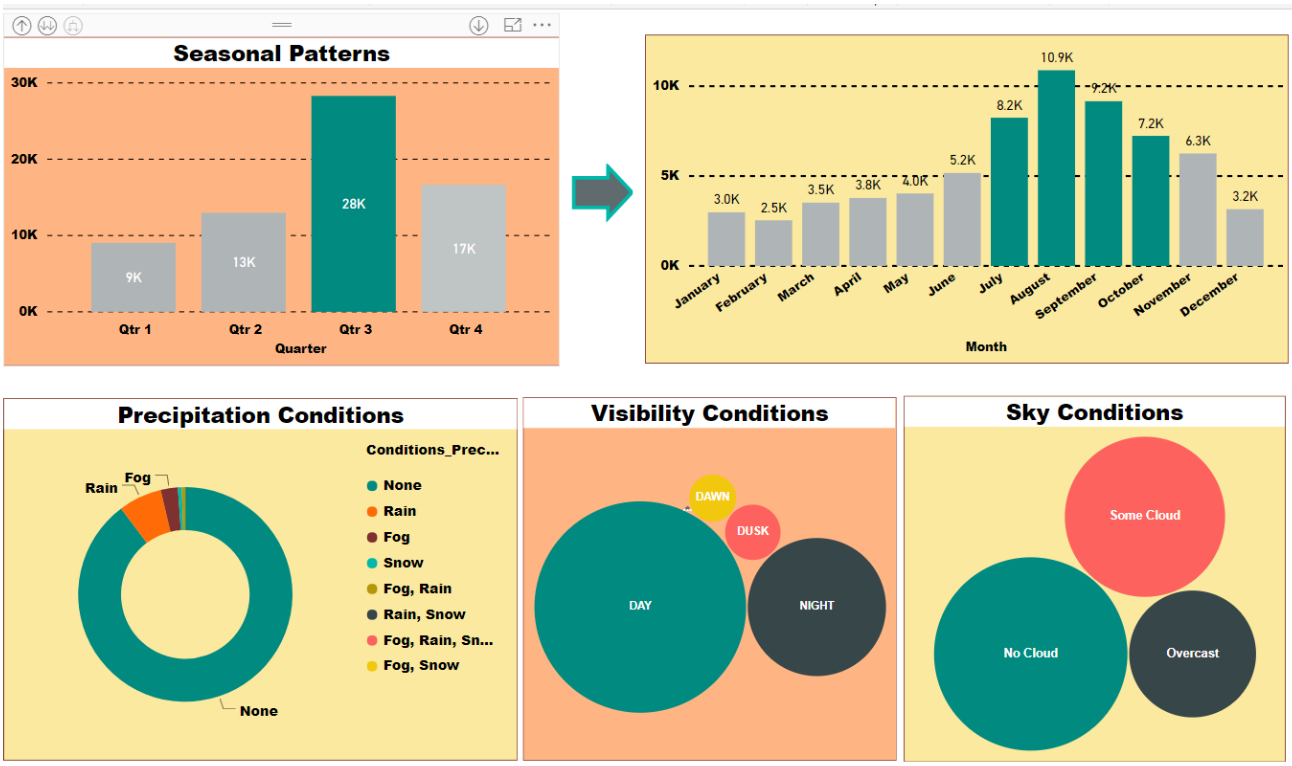


Figure 22

Visualization 1: - Seasonal patterns - For this visualization, we have chosen stacked column chart to show the comparison between the four quarters (winter, spring, summer, fall) of a year.

Configuration: - Figure 23

Axis: - Flight Date

Value: - Wildlife_NumberStruckActual

Our intention was to find out if there is any seasonal pattern for the strikes. The quarter is defined by the calendar: January - March (1st quarter), April – June (2nd quarter), July - September (3rd quarter) and October - December (4th quarter). The average number of birds' strike per quarter is Quarter 1 – 0.13, Quarter 2 –0.19, Quarter 3 –0.43 and quarter 4 – 0.25. (refer to figure). From the visualization, we can infer that the aggregate data indicates July through October (quarter 3rd) has a significantly higher frequency of bird strikes. This may be due to the migration of birds in search food or nesting locations to prepare for the approaching winter.

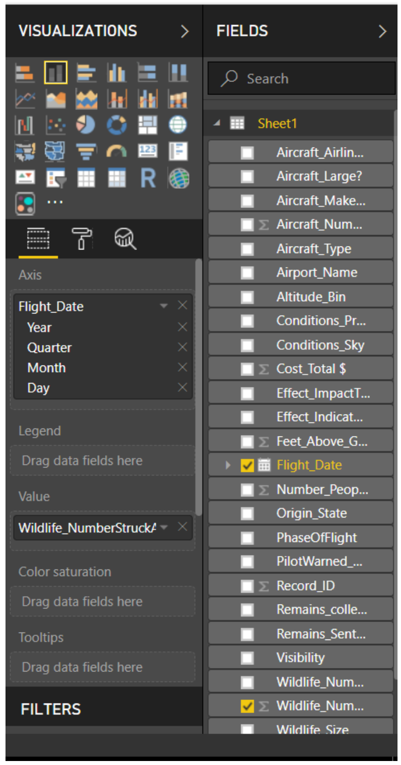


Figure 23

Visualization 2: - Precipitation Conditions - This visualization utilizes donut chart because of its advantages like minimum space consumption and the ability to draw viewers' attention towards reading the length of the arcs.

Configuration: - Figure 24

Legend: - Conditions_Precipaitation

Value: - Wildlife_NumberStruckActual

In this graph, we wanted to see if precipitation has any contribution to the strikes. The visualization totally invalidates our hypothesis- "The number of strikes increases with the decrease in the visibility for the pilot due to conditions like fog, snow, rain". We can clearly see that Snow, Fog, and Rain seem to have a considerable low impact on the number of strikes.

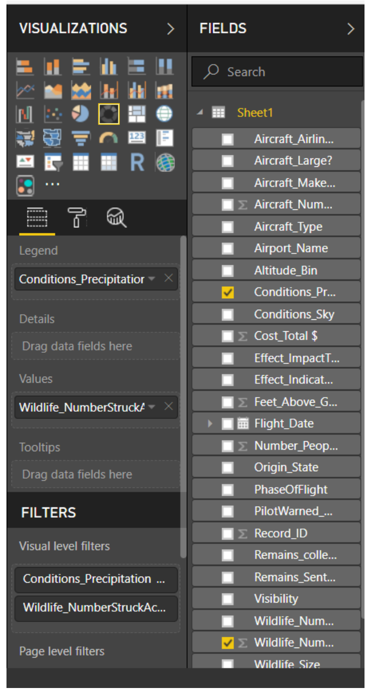


Figure 24

Visualization 3: - Visibility Conditions- This visualization is shown using bubble charts.

Configuration: - Figure 25

Bubble Name: - Visibility

Value: - Wildlife_NumberStruckActual

We chose bubble charts as we had a lot of variation in values for the four phases in a day (Dawn, Day, Dusk, Night). Here, we wanted to analyze the time of the day when most strikes take place. From the graph, we can say that the strikes seem to take place more during the "DAY" (65%). Since most birds fly mainly during the day, most bird strikes occur during daylight hours. Adding to this "NIGHT" also seems to record a lot of strikes with almost 28%. This can be attributed to the ability of many birds to have eyes that are much better adapted for seeing at night. In comparison to this, strikes during "DAWN" and "DUSK" shows a low number. From the statistics, we examined that birds do fly at night as night has a considerable number of strikes.

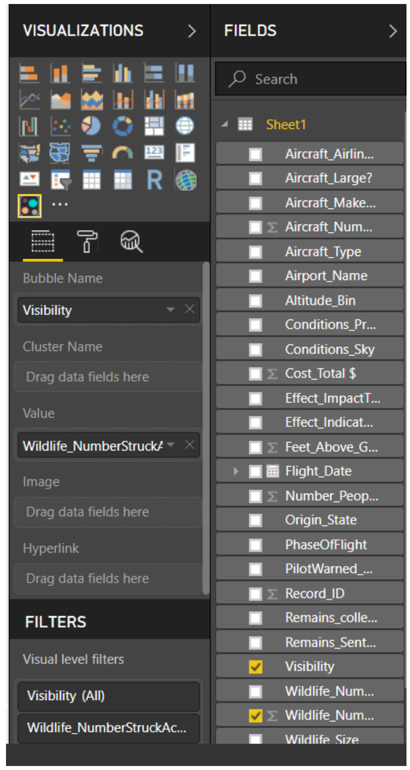


Figure 25

Visualization 4: - Sky Conditions - This visualization is also shown using bubble charts.

Configuration: - Figure 26

Bubble Name: - Sky_Conditions

Value: - Wildlife_NumberStruckActual

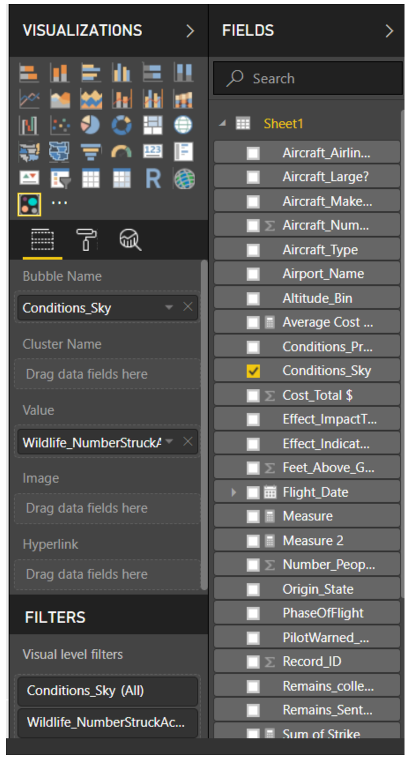


Figure 26

This chart shows how the sky condition contributes to the strike. As we can see clouds considerably have a low impact on the number of strikes. On the other hand, a clear sky seems to record a lot more strikes (47%). The reasons may be: -

1) A number of flights tend to fly in the clear sky.

2) In the cloudy sky, visual cues are reduced, therefore, the wildlife activities might be affected.

3) We can also see a significant number of strikes in "Some Cloud" condition (32%). This can be due to the migratory birds that fly non-stop for weeks or months irrespective of the sky conditions.

Dashboard 3 – Impact on Flights

We created four different visualizations to analyze the impact of flights due to wildlife strikes based on precautionary warning and altitude of flight. Refer to figure 27.

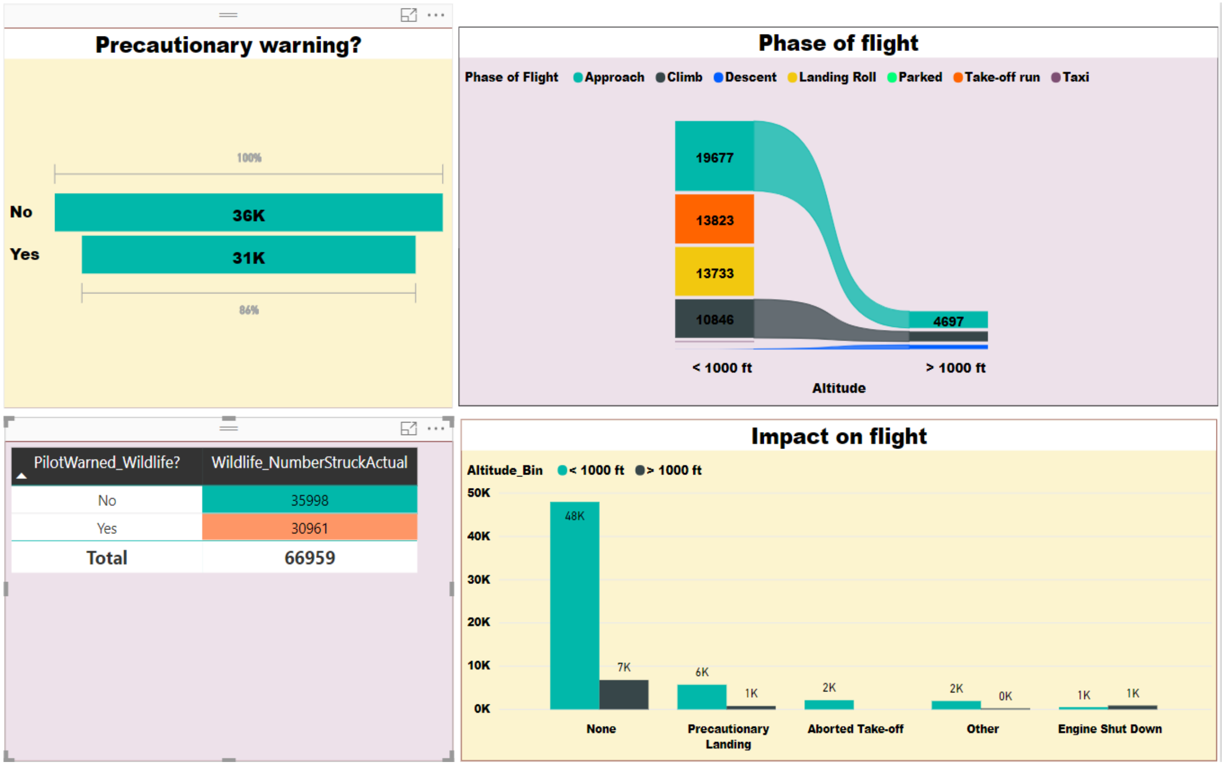


Figure 27

Visualization 1- Precautionary warning? - For the first visualization, we chose a Funnel Chart to explore a new charting style.

Configuration: - Figure 28

Group: - PilotWarned_Wildlife?

Value: - Wildlife_NumberStruckActual

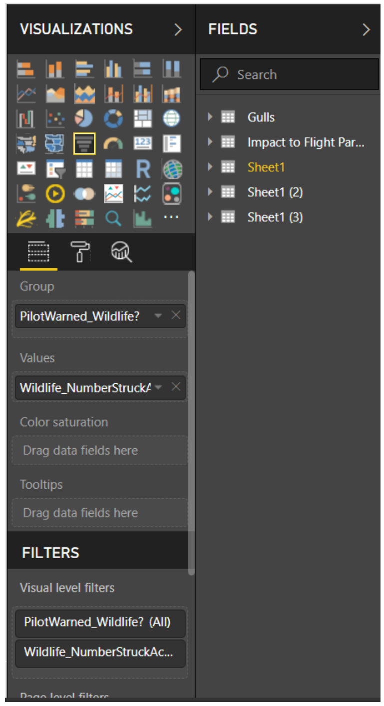


Figure 28

This chart was used to analyze if any precautionary warning was given before strike. And if it was given, then did it help in lowering the occurrence of the strikes. But, we realized that despite the prior warning, the strikes have occurred to a large extent (46%).

Visualization 2- Phase of flight-: The second visualization is shown using Ribbon charts (see figure). We used ribbon chart as it is great at showing rank change, with the highest value always displayed on top.

Configuration: - Figure 29

Axis: - Altitude_Bin

Legend: - Phase of Flight

Value: - Wildlife_NumberStruckActual

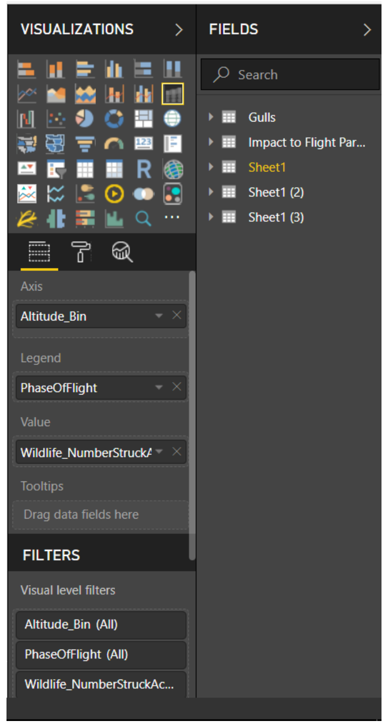


Figure 29

Our main aim was to find out which phase of flight has a greater number of wildlife strikes. In our analysis, we found that most of the total strikes occur during the "Approach" phase of the flight (we can see that in the below figure 30).

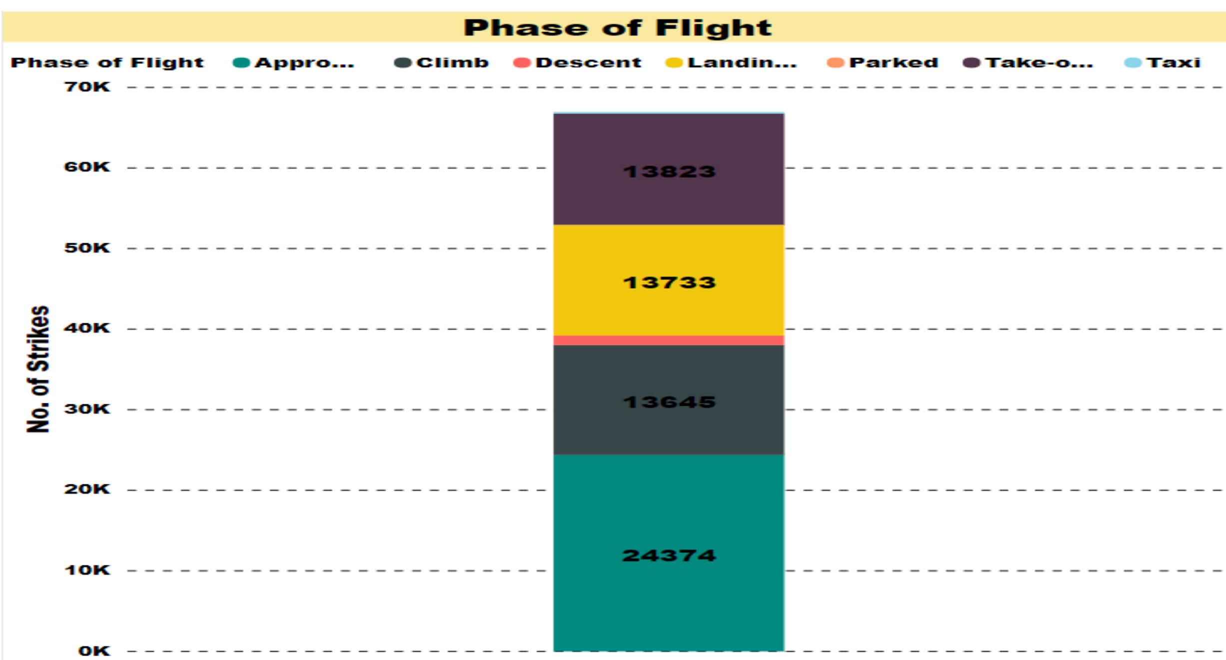


Figure 30

Also, when compared to the altitude of the flight, we have observed that wildlife strikes may occur during any phase of flight but are most likely during the take-off run, initial climb, approach and landing roll phases due to greater number of birds in flight and other wildlife like cat, alligators at lower levels (< 1000 feet). On the other hand, at higher levels (>1000 feet), the number of strikes is relatively low and the majority of those are also during the approach phase of flight.

Visualization 3- Impact on the flight: - Finally, the third visualization in the Dashboard shows the impact of strikes on the flight.

Configuration: - Figure 31

Axis: - Effect_ImpactToFlight

Legend: - Altitude_Bin

Value: - Wildlife_NumberStruckActual

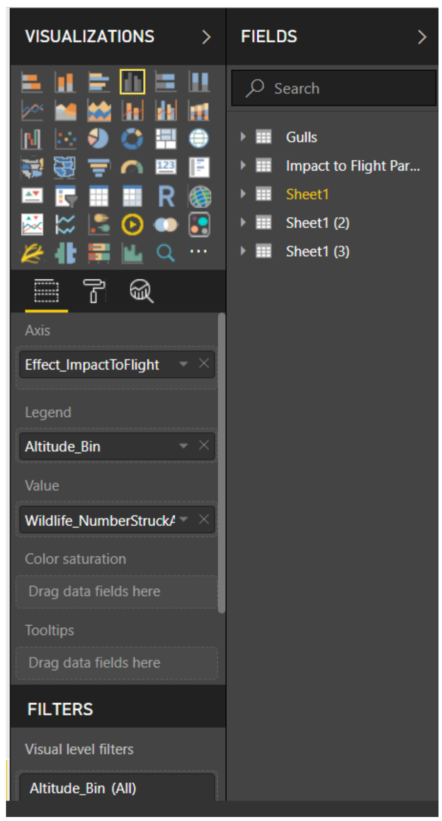


Figure 31

To our surprise, the majority of the flights (82%) have not displayed any sign of impact on the flight. Only 13% of the flights had either aborted take-off or performed a precautionary landing after a strike.

Analysis of the main contributing factors

1) State with highest amount of wildlife strikes: - When we analyzed the top five states involved in the strikes (California, Texas, Florida, New York, New York, Pennsylvania), we were not so surprised with the first four states due to their size and their coastal location, but Pennsylvania came as a surprise.

2) Role of weather: - We found that fog and rain were factors contributing to the strikes but when compared to "no precipitation", the strikes are significantly lower. Same goes for clouds. Sky with no cloud has considerably high amount of strikes.

3) Precautionary warning? - We realized that the number of strikes is lower if the pilot is given warning, but the decrease is not significant.

4) Time of day: - We have observed the highest amount of strikes during day and night. One can argue that this increase can be due to more number of flights available during the day and night as compared to dawn and dusk. But in order to answer this question, we would need to take a close look at data about all the flights that fly at the various times of the day.

5) The phase of flight and altitude: - Bird strikes may occur during any phase of flight, but are most likely during the Approach, followed by Take-off run and Landing roll phases. Also, the strikes are more at the lower altitude (< 1000 feet) than the higher altitude (>1000 feet). This indicates that most wildlife strikes happen around airports at a lower altitude.

Among all these contributing factors, we found that weather indeed is a factor, but the time of the day and altitude has been the top 2 factors that contribute to more number of strikes.

Query Parameter

1) We used query parameter in our queries in Power BI Desktop. To do that we defined the new parameter by using the "Manage Parameters" dialog in the Query Editor window and clicked on New Parameter (Figure 32).

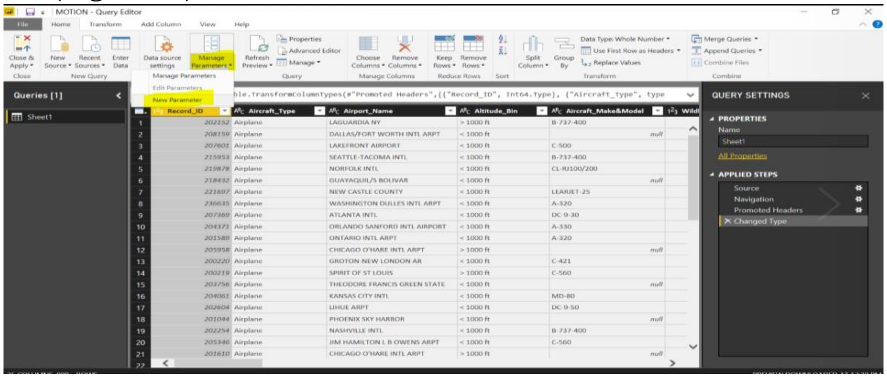


Figure 32

2) The below window would pop-up. We specified the values in the below sections. We have named the parameter as "Selection of States_Parameters" (Figure 33).

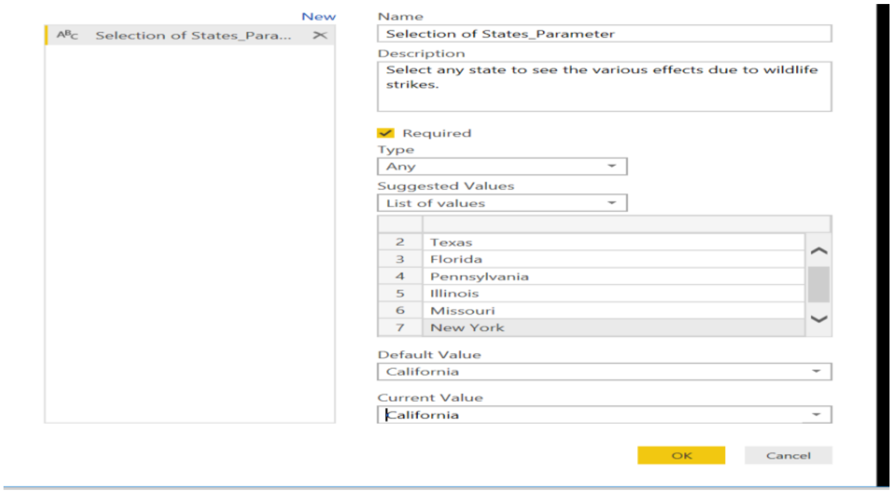


Figure 33

3) After defining one or more parameters and clicking OK in the “Manage Parameters” dialog, we got back to the Query Editor dialog and right-clicked on a parameter and selected “Enable Load”.
4) Now we referenced the parameter from the “Filter Rows” dialog. For that, we clicked on the attribute and selected “Text Filter” and “Equals” (Figure 34).

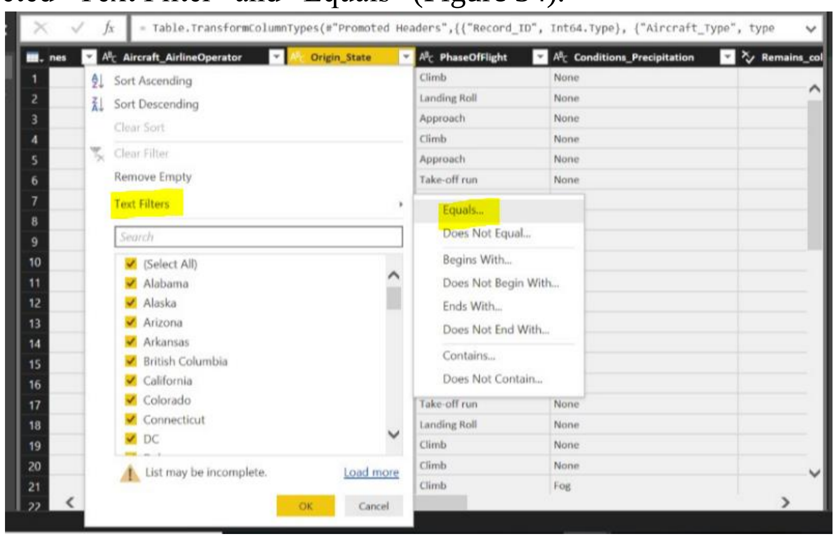


Figure 34

5) Now we selected the parameter option and entered the parameter that we created “Selection of States_Parameters” (Figure 35 & 36).

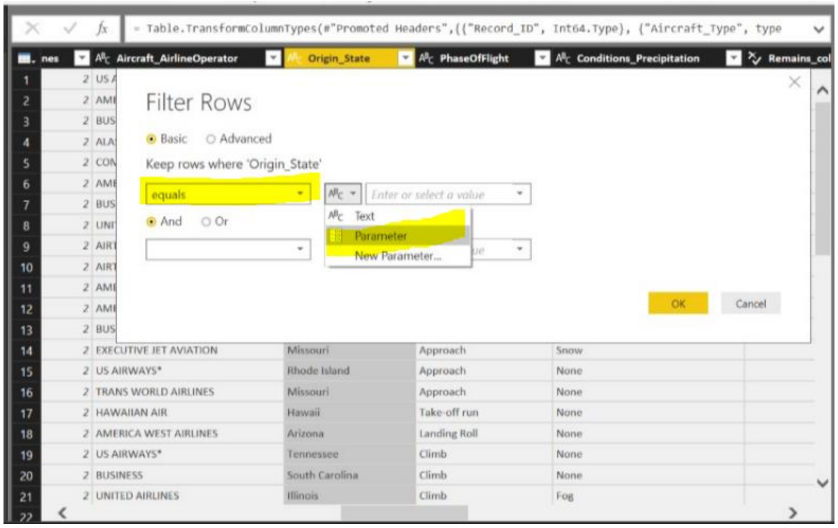


Figure 35

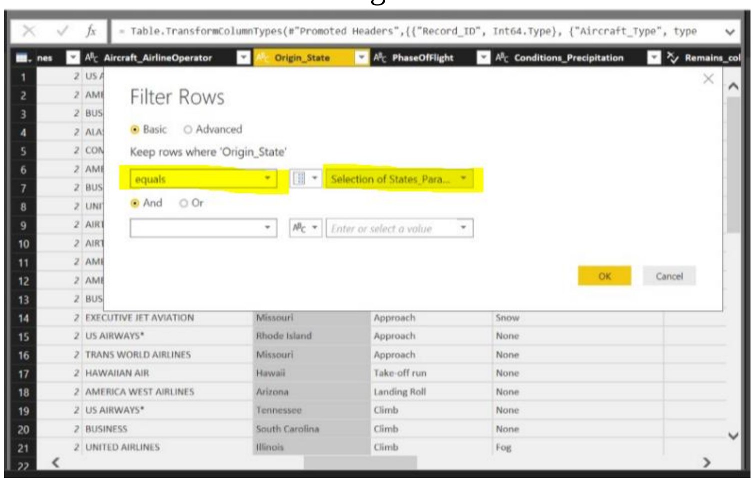


Figure 36

6) After Query Parameters have been referenced from another query we clicked “Close & Apply” in the Query Editor ribbon to get their data and parameters loaded into the data model.
7) Now we went to the report tab and created three visualizations: -
    - Geographic map representing the state
    - Stacked graph showing number of species strikes in the specific state
    - Table showing number of wildlife strikes per year.
8) Now we created a template which can be shared with new users. Before selecting the state, the new user should go to the edit query to click source’s setting icon under applied steps tab. Give the path where the original access file is stored on the new user’s laptop. Hit Ok and go to report tab and select edit parameter under edit queries. Now, after selecting a specific state from the drop-down box, the visualization would change accordingly (Figure 37).

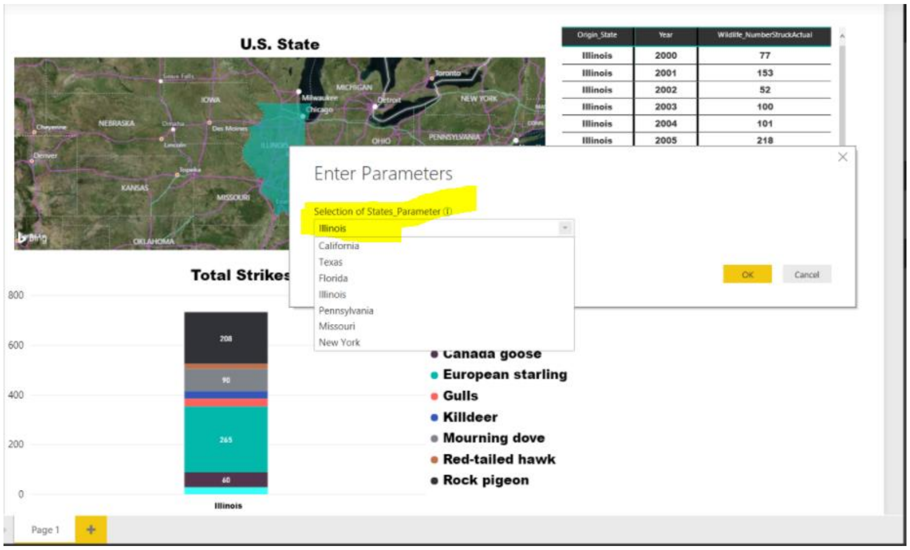


Figure 37

Motion (Cost Model)

In the united states, wildlife strikes have resulted in approximately $ 140 million in monetary losses from 2000 –2011. Below is the visualization (Figure 38) showing the total cost incurred per year.

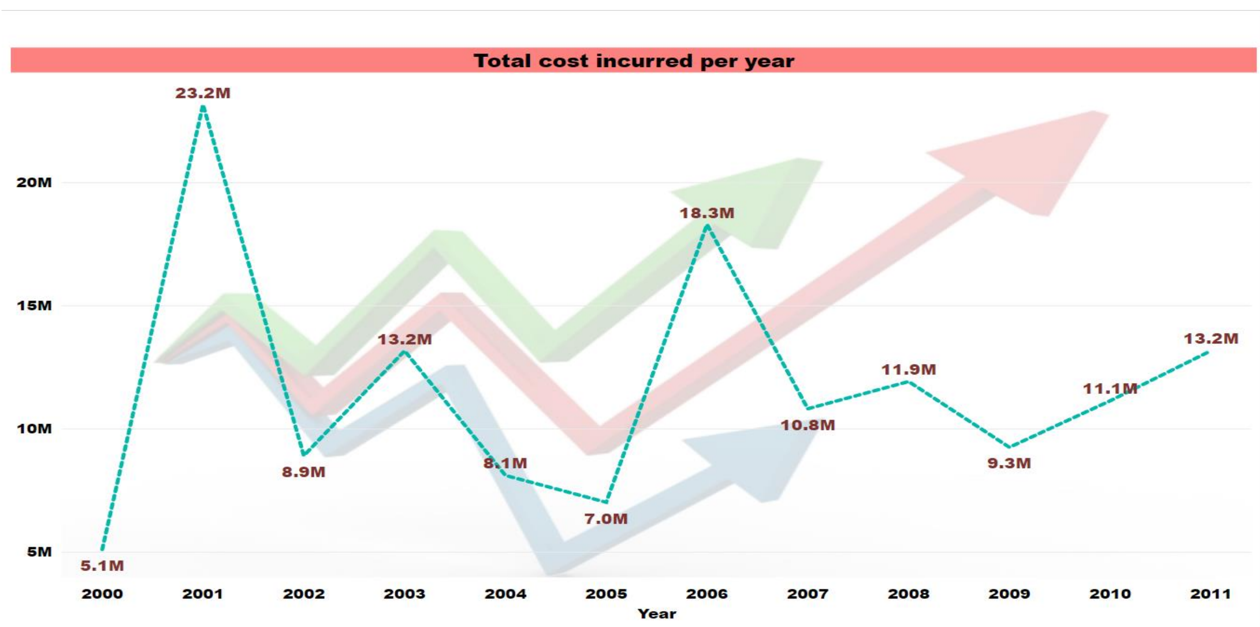


Figure 38

However, we have realized that although there is an increase in wildlife strike reporting, many wildlife strikes do not provide accurate cost estimate even though the "Effect_IndicatedDamage" column indicates damage. Since it's a voluntary reporting system, some of the airlines do not choose to report to FAA, therefore some of the monetary loss may go unreported. We have used motion chart to see how cost incurred on average for each strike changes over the years for the states with most strikes. Cost may include repair of damages caused by strikes, loss of revenue, hotel expenses due to flight cancellation, costs of fuel dumped etc.

Before creating motion chart, we created three measures by using the "new measure"(Figure 39) operator present on navigation tab on the shelf in power BI: -

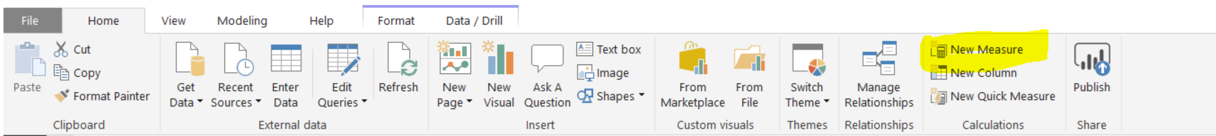


Figure 39

1) Total Cost = This is the summation of the cost incurred over years.

```
Total Cost= SUM(Sheet1[Cost_Total $])
```

2) Sum of Strike = This is the summation of the wildlife strikes over the year

```
Sum of Strike = SUM(Sheet1[Wildlife_NumberStruckActual])
```

3) Average cost per Strike – This is the cost incurred on average per strike

```
Average Cost per Strike= DIVIDE([Sum of Strike], [Total Cost])
```

The motion chart is created by dragging and dropping a scatter chart from the visualization tab (Figure 41).

Configuration: - Figure 40

Legend – Origin_State

X-axis – Sum of Strikes

Y-Axis – Total_Cost

Size – Average cost per strike

Play axis: - Flight Date (Sorted by Year)

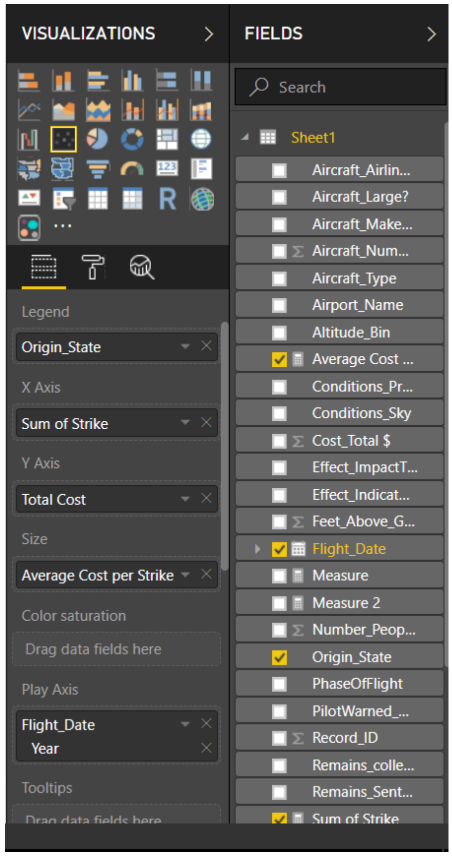


Figure 40

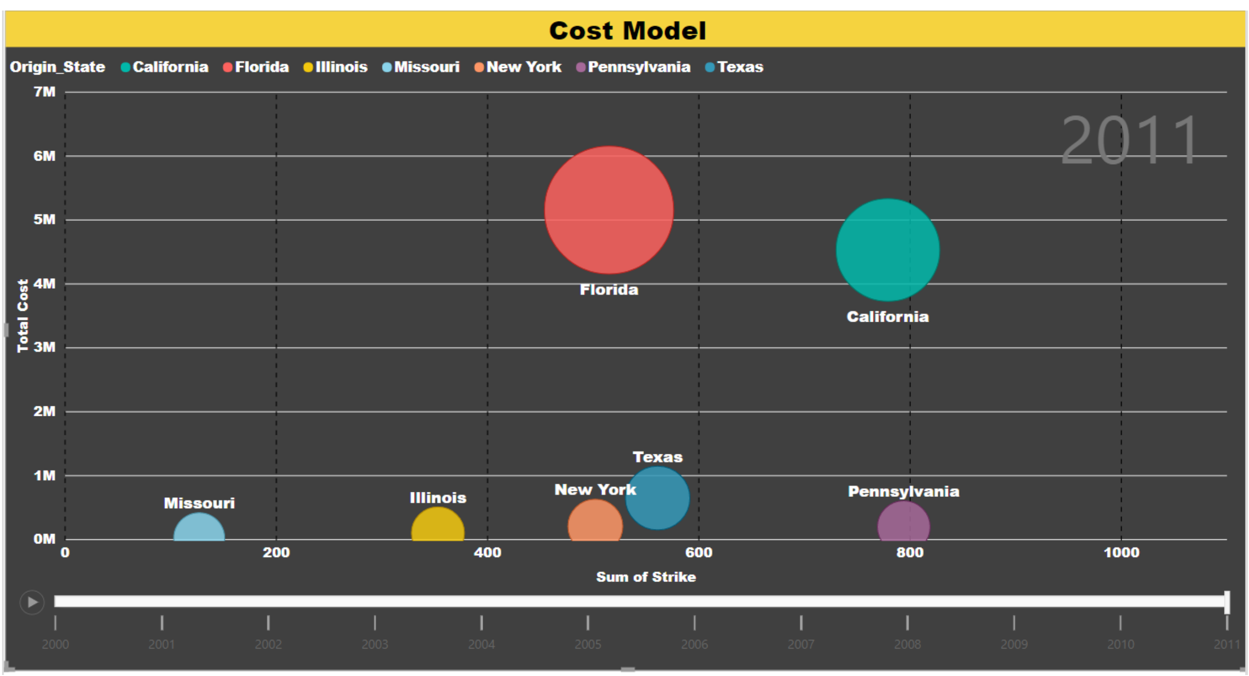


Figure 41

These are the trends that we have observed for each state: -

1**) California: -** The green color ball is California and as we can see from the below figure, California shows a very erratic distribution of average cost/strike (Figure 42).

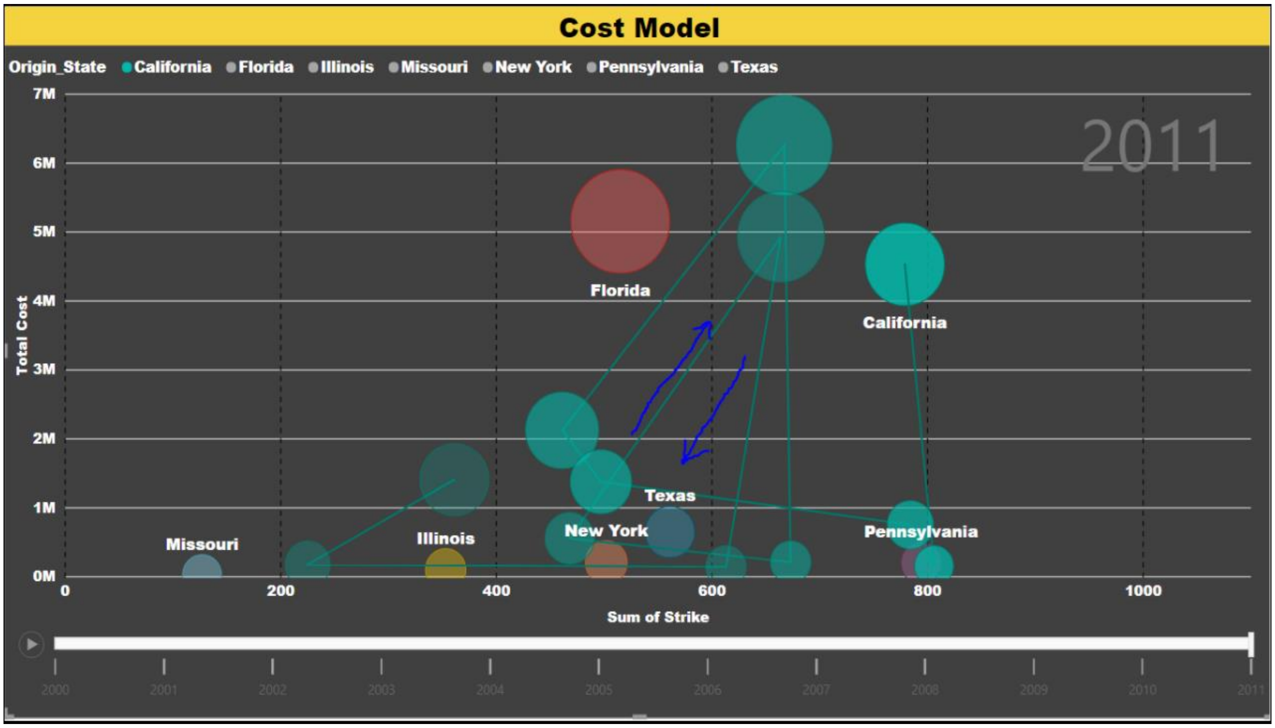


Figure 42

2) Pennsylvania: - We saw a drastic increase in the size of the bubble (Purple color) in 2007, indicating significant damage (Figure 43). When we tried to find the reason, we discovered that at Philadelphia International Airport, one of the flight collided into a flock of geese in September 2007 and the flight had to make an emergency landing. There was a substantial repair cost due to the shattering of the entire windshield.

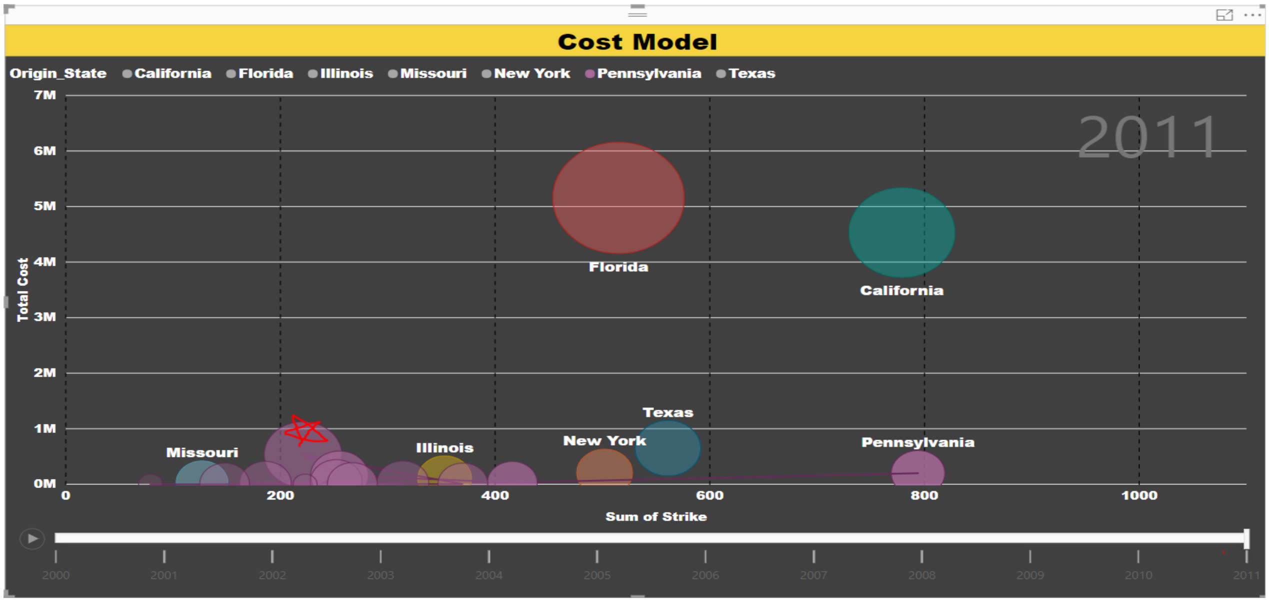


Figure 43

3) Florida: - We analyzed that Florida has shown a sudden increment in cost from 2010 to 2011(Figure 44). When we dig further, we found that in May 2010 and April 2011, flights out of Orlando International airport were hit by birds causing engine failure.

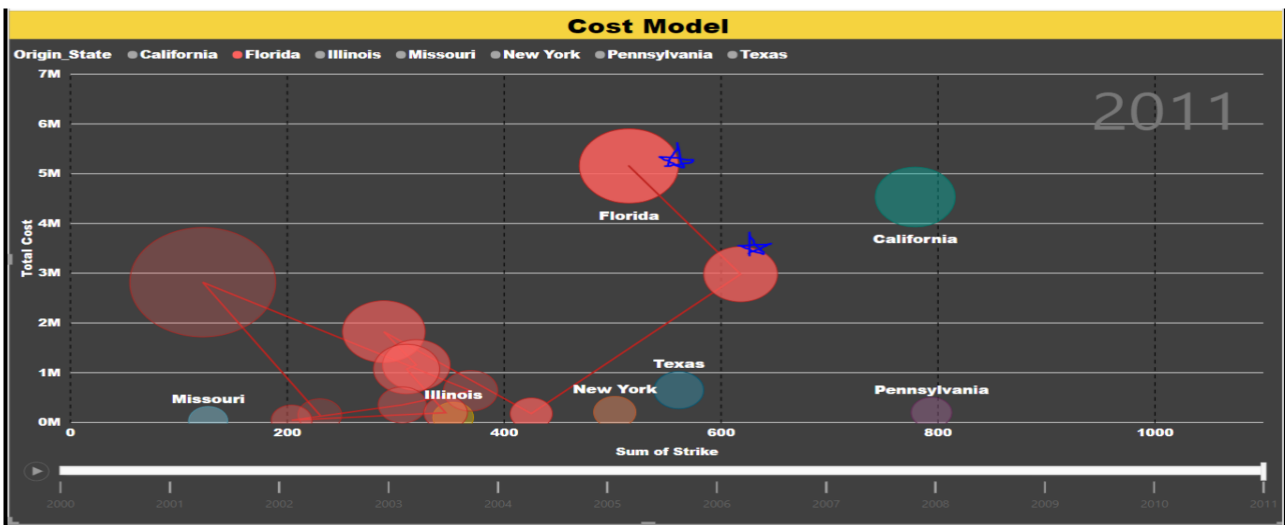


Figure 44

Overall the increment in a total strike from 2000 to 2011 is 4%(10.7%- 6.69%).

Use cases

1) Environmentalists: - The visualizations can be an excellent source to visualize the impact of wildlife strikes on animal populations. The dashboard #1 would allow the user to focus on a single geographic point, year by year, and analyze the number of wildlife strikes that have occurred there. The environmentalist can find a wildlife species of interest and they can look for all the strikes associated with that species. For example, in the below visualization (Figure 45), the user can select a strike range and look at the top 5 worst hit states to look for the species of birds that have been involved in the strike.

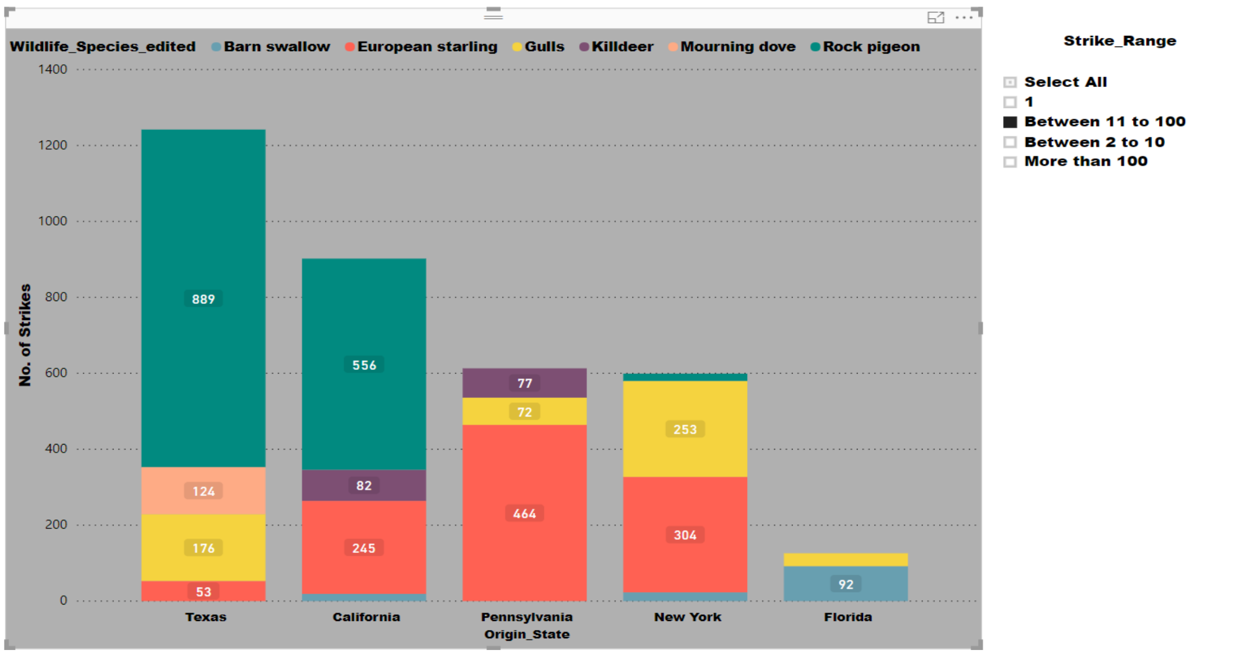


Figure 45

2) Airline industry: - This visualization can be used by airlines that are curious to know where their planes are more likely to be damaged. This information can also be a great insight to the insurance companies that want to find if they should charge more for airlines that have most of their planes flying in areas where there are most of wildlife strikes.

Conclusion

What did go well?

We got a good and clean dataset as Data World had slightly reformatted the original version which was highly complex with too many attributes. We referred to various YouTube tutorials and peer-reviewed articles to get familiar with Microsoft Power BI tool. This helped us understand the necessity of particular visualization. The basic functionality of Power BI was user-friendly. For Example, drag- & drop functionality, creating motion charts, importing new chart styles from the marketplace etc. We performed serval data preparation steps like the transformation of date format, creating measures and conditional columns with ease. Due to "applied steps" tab it was easy to track all the changes and deletion of any step was just a click away. We resonated well with each other. Since creating visualization is a creative process, working as a team benefited us. We both brought different ideas to the table. We had regular meetings were agenda was to review our previous work, ask the professor if any doubt and make a new plan for the next week. We were feeling happy when we finally figure out how to implement parameter feature and one of the calculation in Power BI. Overall working with Power BI was a great idea as now we are familiar with both the tools - Tableau and Power BI.

What did not go well?

We did our data mining project in text mining and we had the option to use the same clean data for our data visualization project. But, since the data had limited fields (3-4 attributes), we couldn't use that for our visualization project. So, we had to start from scratch and look for a new data set and perform data preparation before using the data for visualization. This whole process took a lot of time. Also, many times when we tried to save the file, Power BI Desktop stopped working. That mostly happened when we tried to create a geographic map or a motion chart. To resolve the issue, we had to restart the computer all over again. This happened multiple times in a day and created a big nuisance while working on the project. We also realized after working on the project for one week that the data we chose had limited measures. We felt this as a limiting factor when choosing visualizations like motion chart that require quantitative attributes. We tried to work around this limitation by generating new measures from the available attributes. When we tried to share the query parameter template that we created, the process seemed cumbersome. In order for it to work on the new user's laptop, one has to share the source data along with the template to the user. Moreover, unlike Tableau, power BI does not support interactive PPT and Story feature. So, we couldn't incorporate those two features in our visualization. Lastly, since wildlife strike data collection is via a voluntarily reporting system, not all incidents are reported in their entirety.

Next time

We believe that our visualizations are thoughtful, and the end results are insightful. From our analysis, we can say that along with weather, altitude and phase of a day are the three most important factors that influence the number of strikes. In future, we would like to integrate population of species of interest with current data and make some correlations to see if we can come up with some insights in wildlife preservation. If we find out that the population of a bird is decreasing, and that same bird is also involved in most of the strikes, we can infer that the bird's population is in danger and necessary steps have to be taken to preserve the species. Next time we would also want to explore the correlation between migration path of certain species of birds and altitude they fly on. It would be interesting to see if we can generate any pattern between migration traits and several strikes. Next time we would also like to receive the current (2018) data on wildlife strikes and compare our results with the current to see if there is any decrease in several strikes. And, if it as decreased, what are the contributing factors for that decrease.

Reference

Cleary, E. C., Dolbeer, R. A., & Wright, S. E. (2006). Wildlife strikes to civil aircraft in the United States 1990-2005.

https://www.youtube.com/watch?v=L0Y1KL7o3aQ

https://www.youtube.com/watch?v=XcUsniWenuM

https://www.youtube.com/watch?v=GgwXt4LVmsU

---The End---