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List of Acronyms

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1 Introduction

Through the U.S. Department of Energy's Energy Transitions Initiative Partnership Project (ETTIP), researchers from the National Renewable Energy Laboratory and Lawrence Berkeley National Laboratory worked with Hawaii Natural Energy Institute and Kauai County to assess the suitability of emerging transportation technologies and quantify potential electric vehicle charging demands on the island of Kauai. Understanding how residents and visitors move around on the island is important for measuring the infrastructure demand and understanding the tradeoffs of different mobility options on Kauai. One possible source of such data is a local travel demand model. However, the most recent round of travel demand modeling for the area was conducted more than a decade ago, and updating the model to make it appropriate for current use would require a significant amount of resources and time. In comparison, app-based cellphone data is very affordable and can be updated very frequently. The high granularity that cellphone data offers also allows observation of seasonal and even weekly travel patterns. The objective of this task is to analyze trip patterns of the residents and visitors using app-based cellphone data and compare the travel patterns of different seasons of the year. The results generated here can be used to assess the suitability of emerging mobility. The travel hotspots and hot corridors generated from the two-tiered clustering approach can be applied to inform the feasibility analyses and deployment locations of new mobility options. One major caveat of this approach is that it underrepresents locations with no or weak cellphone signals. For example, popular destinations such as Waimea Canyon State Park and Waimea Canyon Lookout have much higher levels of activity than what is captured by these cellphone datasets.

This report documents the steps we took to generate the trip characteristics from raw GPS locations provided by Near.com and records the travel pattern comparisons using hotspots and hot corridors. We start with descriptions and summary statistics of the raw datasets (Section [2\)](#page-8-0), then proceed with descriptions of the methods and results of trip chaining (Section [3\)](#page-10-0), trip origin clustering (Section [4\)](#page-12-0), and trip distribution (Section [5\)](#page-36-0).

2 Data Description

The primary data source of this analysis is a collection of location reports (in coordinates) of a sample of smartphone devices on the island of Kauai provided by Near.com. The unique anonymous device IDs allow the locations to be linked to form GPS traces, which allows us to filter and chain the locations into meaningful movements. The GPS locations captured by Near datasets are collected through the mobile phone locations. The access is enabled by the smartphone users when certain applications are opened. The users typically have the option to choose whether their locations can be accessed by the application, and if so, whether it can always be accessed or can only be shared while the app is active. The location reports often do not follow a constant and definite temporal pattern, as they often depend on the usage of cellphone applications. To differentiate it from the cellphone GPS data collected through cellphone towers with relatively regular and higher frequency, we refer to this type of location data as "app-based" cellphone data.

Datasets for six different seasons are processed and analyzed in this report: summer 2019, winter holidays 2021, around Valentine's Day 2022, around spring break 2022, off-season 2022 (late April to early May), and summer 2022, as shown in some data collection changes that influenced the frequency of GPS points because these datasets were collected during different time periods. During the collection of the latter five datasets, there were no COVID-19 quarantine restrictions on the island, but there were still restrictions on mask-wearing and large group gatherings. As the locations of the devices are often not reported constantly, most devices are only captured sporadically throughout a day. We refer to devices that have at least one GPS record for each 30 minute interval between 6 a.m. and 11 p.m. as frequent reporters. For each dataset, we list out the number of frequent reporter devices. Some data collection changes may influence the frequency of GPS points, because these datasets were collected at different time periods. Therefore, the analyses are carried out for different seasons independently.

Table 1. Data Collection Duration, Device Counts, GPS Counts, Home Locations, and Number of Frequent Reporters

3 Trip Filtering and Chaining

3.1 Method

To generate trips from the GPS points, we developed an algorithm in Python to chain the trip segments and filter out duplicated GPS locations. The first step of the algorithm is to analyze the raw data to identify whether a device actually moved between two consecutive GPS locations, or if the small shifts in reported locations were due to the inaccuracy of GPS. The next step in the filtering process is to calculate the speed of movement for each origin and destination based on Euclidean distance and the time stamps. When the speed of a trip segment is larger than 75 miles per hour, it is not considered as a trip segment on the ground and is removed from the dataset. This was done because the maximum speed limit on the island is 50 miles per hour and there were GPS points recorded during air travel, such as helicopter rides. After these treatments, the next step is to chain the trip segments to generate the trips. There are two conditions in determining whether two consecutive trip segments should be merged to be part of the same trip: (1) the distance between the end point of the first trip segment and the starting point of the second trip segment is less than or equal to 0.25 miles, and (2) the time lapse between the end time of the first trip segment and start time of the second trip segment is less than or equal to 30 minutes. As a final treatment, we removed any records that had a trip distance less than 0.25 miles, which is generally used as the minimum distance that is considered a trip. This algorithm was applied to the six datasets, respectively.

3.2 Trip Summary

[Table 2](#page-10-3) shows the summary statistics of the daily trip distance and trip frequency for all six datasets for visitors and residents, respectively. The average daily total trip distance is between 21 and 28 miles for visitors and between 18 and 25 miles for residents, with slight variation across different seasons. In general, the distances traveled by residents and visitors are very similar, contrary to our previous assumption about visitors driving more than residents.

Season	Statistic	Visitor		Resident	
		Daily Trip Distance	Daily Trip Frequency	Daily Trip Distance	Daily Trip Frequency
July 2019	Count	8,892.0	8,892.0	21,111.0	21,111.0
	Mean	22.3	3.3	18.7	3.4
	STD ^a	28.1	4.8	25.9	4.6
	10%	1.3	1.0	1.2	1.0
	50%	12.6	2.0	10.4	2.0
	90%	55.0	7.0	46.7	8.0
Summer 2022	Count	9,128.0	9,128.0	42,359.0	42,359.0
	Mean	24.2	4.4	25.5	5.8
	STD	27.3	5.9	32.8	9.4
	10%	1.4	1.0	1.5	1.0

Table 2. Trip Summaries for Visitors and Residents

^a Standard deviation

4 Clustering

4.1 Method

To find hotspots for travel locations, we used the density-based spatial clustering of applications with noise (DBSCAN) clustering algorithm. DBSCAN is an efficient algorithm to detect outliers and handle noise when it comes to density-based clustering. The two central components of the algorithm are minimum samples (*min_samples*) and epsilon value (*eps*). The *min_samples* value is the number of points to be considered a cluster. The *eps* value, which can also be thought of as radius, is the maximum distance between two samples for one to be considered in the neighborhood of the other. DBSCAN categorizes a point as a core point if there is at least the value of *min_samples* in its neighborhood within the radius of *eps*. A point is categorized as a border point if its neighborhood contains less than the value of *min_samples* and it is within *eps* distance from another point.

Although *min_samples* and *eps* values are generally at the discretion of the user based on the needs and the dataset at hand, one suggested method to determine *eps* is to find the distribution of nearest neighbor distances and select the eps value based on the highest slope of the elbow (Rahmah and Sitanggang 2016). Based on [Figure 1](#page-12-2) and Figure 2, we selected the *eps* value for visitor clustering as 0.00013 degrees (~45 feet) and 0.001 degrees (~340 feet) for resident clustering.

Figure 1. Visitor nearest neighbor distance distribution

Figure 2. Resident nearest neighbor distance distribution

There is no rule in determining the *min_samples* value for DBSCAN, and, as previously mentioned, it is left to the intuition, needs, and dataset the user wants to examine. In this case, experimenting on the July 2019 data showed a clear pattern of clusters on the island, which we confirmed with the partners in Kauai to make sure that they were reasonable within the local context. This experimentation used 8 as the *min_samples* value for visitors and 32 for residents for July 2019 dataset. These numbers gave us 400 sub-clusters [\(Table 3\)](#page-14-0) for visitors and 216 for residents. Using this finding, to determine whether there were seasonal differences, we selected the other *min_samples* values, keeping the number of clusters close to each other, and selected the other *min_samples* values accordingly. This can be seen in the "Sub-Cluster" columns of [Table 3](#page-14-0) and Table 4 to note that the number of clusters are close to each other.

Table 3. Clustering Parameters for Visitors

Table 4. Clustering Parameters for Residents

To determine the larger clusters, we kept the *min_samples* value at 1 to make sure that the model produced clusters that were at the minimum at a walking distance $(0.25 \text{ miles} = 402 \text{ meters})$ and all sub-clusters were a part of a large cluster. This essentially removed the *min_samples* parameter from the equation. This gave us clues to better understand the seasonality and see regional patterns, compared to what sub-clusters presented, which provided a more local (smaller-scale) understanding.

To produce larger clusters that were farther apart to inform the feasibility analyses of mobility programs such as car-sharing and autonomous vehicle shuttles, we decided to apply the clustering algorithm on the smaller clusters generated. We call this process upper-level clustering. With this second round of clustering, the *min_samples* value was selected as 1. This meant that after eliminating the noise and outliers from the dataset with the first clustering, we forced the algorithm to make sure that every remaining point was assigned to a cluster and there were no outlying points. The *eps* value for this round of DBSCAN application was selected as 0.25 miles, which can be considered a comfortable walking distance. Both first and second rounds of clustering were done for both visitors and residents for different seasons of Near data,

as well as daytime and nighttime hours. Daytime hours for visitors were 8 a.m. to 10:59 p.m., and nighttime hours were 11 p.m. to 7:59 a.m. For residents, daytime hours were selected as 8 a.m. to 6:59 p.m., and nighttime hours were 7 p.m. to 7:59 a.m. As an example, for all hours of the day, the lower-level clustering (small clusters) with the radius selected as 45 feet results in 370 clusters for the summer 2019 visitor dataset and 213 clusters for the resident dataset, which were informative for analyzing the feasibility of micromobility options, such as bike-share and scooter-share programs. The upper-level clustering (large clusters) with the radius selected as 0.25 miles results in 91 large clusters for visitors and 60 large clusters for residents, which are more suitable to inform planning decisions for auto-based mobility options, such as autonomous vehicle shuttles and transit routes.

4.2 Hotspots

4.2.1 Visitor Clusters (Second Round of Clustering) for Different Seasons

Results of the second round of clustering (large clusters) based on Near data [\(Figure 3](#page-16-0)[–Figure 8\)](#page-18-1) show that, although the sizes of the clusters change based on the season and location, the overall pattern of the trip start location clusters largely stay the same. In Lihue, besides the Lihue Airport, large clusters form around Nawiliwili Bay, signifying the lodging and resort locations that visitors frequent. Additional large clusters appear in and around the commercial areas in Lihue, such as the shopping area where Highway 50 meets Nawiliwili Road, commercial area across Kauai Community College, and along other commercial land uses throughout Rice Street. The large clusters that form in Kapa'a signify the hotels and other commercial areas for visitor trips. Some large clusters appear along the portion of Highway 50 that is within Waimea. These are again mainly commercial and lodging spots. The overall pattern of large clusters largely stays the same throughout seasons in Hanalei and Princeville, showing the lodging, shopping, and other commercial areas. Lastly, clusters appear along HI-550 where points of interest such as Hohonu Awawa Lookout, Niihau Lookout, and Kekaha Lookout are located.

Figure 3. Spring break, visitor, large clusters

Figure 4. Off-season, visitor, large clusters

Figure 5. July 2019, visitor, large clusters

Figure 6. Summer travel (2022), visitor, large clusters

Figure 7. Valentine's Day, visitor, large clusters

Figure 8. Winter holidays, visitor, large clusters

4.2.2 Resident Clusters (Second Round of Clustering) for Different Seasons

Similar to the visitor clusters, the formation of large clusters shows a similar pattern throughout the seasons based on Near data [\(Figure 9–](#page-19-1)[Figure 14\)](#page-22-1). These resident clusters form throughout Kekaha, Waimea, Pakala Village, Kaumakani, Hanapepe, Eleele, Kalaheo, Lawai, Koloa, Poipu, Lihue, Kapa'a, Anahola, Kilauea, Princeville, and Hanalei. In addition, significant resident clusters formed in the southwest of the island around Barking Sands Airport and Barking Sands Beach.

Figure 9. July 2019, resident, large clusters

Figure 10. Spring break, resident, large clusters

Figure 11. Off-season, resident, large clusters

Figure 12. Summer travel (2022), resident, large clusters

Figure 13. Valentine's Day, resident, large clusters In this figure, each dot is a device, and the devices in one cluster share the same color.

Figure 14. Winter holidays, resident, large clusters In this figure, each dot is a device, and the devices in one cluster share the same color.

4.2.3 A Closer Look Into Several Points of Interest for Visitors

We also wanted to take a closer look at how the small clusters form in certain areas of interest throughout the seasons.

Lihue Civic Center

Around Lihue Civic Center, small visitor clusters appear at fast food stores, restaurants and cafes, gas stations, convenience stores, and department stores [\(Figure 15–](#page-23-0)[Figure 20\)](#page-25-1).

Figure 15. July 2019, visitor, Lihue Civic Center, small clusters In this figure, each dot is a device, and the devices in one cluster share the same color.

Figure 16. Off-season, visitor, Lihue Civic Center, small clusters In this figure, each dot is a device, and the devices in one cluster share the same color.

Figure 17. Spring break, visitor, Lihue Civic Center, small clusters In this figure, each dot is a device, and the devices in one cluster share the same color.

Figure 18. Summer travel (2022), visitor, Lihue Civic Center, small clusters In this figure, each dot is a device, and the devices in one cluster share the same color.

Figure 19. Valentine's Day, visitor, Lihue Civic Center, small clusters In this figure, each dot is a device, and the devices in one cluster share the same color.

Figure 20. Winter holidays, visitor, Lihue Civic Center, small clusters In this figure, each dot is a device, and the devices in one cluster share the same color.

Coconut Marketplace

Around Coconut Marketplace, small visitor clusters appear at clothing and gift shops, restaurants and cafes, hotels, and beach facilities [\(Figure 21](#page-26-0)[–Figure](#page-29-0) 26).

Figure 21. July 2019, Coconut Marketplace, visitor, small clusters In this figure, each dot is a device, and the devices in one cluster share the same color.

Figure 22. Off-season, Coconut Marketplace, visitor, small clusters In this figure, each dot is a device, and the devices in one cluster share the same color.

Figure 23. Spring break, Coconut Marketplace, visitor, small clusters In this figure, each dot is a device, and the devices in one cluster share the same color.

Figure 24. Summer travel (2022), Coconut Marketplace, visitor, small clusters In this figure, each dot is a device, and the devices in one cluster share the same color.

Figure 25. Valentine's Day, Coconut Marketplace, visitor, small clusters In this figure, each dot is a device, and the devices in one cluster share the same color.

Figure 26. Winter holidays, Coconut Marketplace, visitor, small clusters

Hanalei

In Hanalei, small visitor clusters form at Waioli Beach Park and Hanalei Pavilion Beach Park, as well as restaurants and shops along Kuhio Highway [\(Figure 27–](#page-29-1)[Figure](#page-32-0) 32).

Figure 27. July 2019, Hanalei, visitor, small clusters In this figure, each dot is a device, and the devices in one cluster share the same color.

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Figure 28. Off-season, Hanalei, visitor, small clusters

Figure 29. Spring break, Hanalei, visitor, small clusters In this figure, each dot is a device, and the devices in one cluster share the same color.

Figure 30. Summer travel (2022), Hanalei, visitor, small clusters In this figure, each dot is a device, and the devices in one cluster share the same color.

Figure 31. Valentine's Day, Hanalei, visitor, small clusters

Figure 32. Winter holidays, Hanalei, visitor, small clusters

Old Koloa Town

In Old Koloa Town, small visitor clusters appear at restaurants and cafes, gas stations, markets, convenience stores, and department stores [\(Figure 33](#page-32-1)[–Figure](#page-35-0) 38).

Figure 33. July 2019, Old Koloa Town, visitor, small clusters In this figure, each dot is a device, and the devices in one cluster share the same color.

Figure 34. Off-season, Old Koloa Town, visitor, small clusters

Figure 35. Spring break, Old Koloa Town, visitor, small clusters In this figure, each dot is a device, and the devices in one cluster share the same color.

Figure 36. Summer travel (2022), Old Koloa Town, visitor, small clusters In this figure, each dot is a device, and the devices in one cluster share the same color.

Figure 37. Valentine's Day, Old Koloa Town, visitor, small clusters In this figure, each dot is a device, and the devices in one cluster share the same color.

Figure 38. Winter holidays, Old Koloa Town, visitor, small clusters In this figure, each dot is a device, and the devices in one cluster share the same color.

5 Trip Distribution

5.1 Method

We explored trip distribution by counting the number of trips between the transportation analysis zone (TAZ) groups and identified the hot travel corridors. The total population (73,454) was obtained from American Community Survey 2021 1-year estimates, and the monthly daily census of visitors corresponding to each season of Near data was obtained from the Hawaii Tourism Authority (2022). The penetration rate for residents was calculated by dividing the Near data daily resident census by the total population of Kauai. The penetration rate for visitors for each season was calculated by dividing the Near data daily average visitor census by the daily visitor census obtained for each month from the Hawaii Tourism Authority.

Table 5. Resident Daily Census and Penetration Rates

Table 6*.* **Visitor Daily Census and Penetration Rates**

5.2 Hot Corridors

The hot corridors were mapped for different seasons for both visitors and residents. Because the sample sizes across seasons are different [\(Table 1\)](#page-9-0), the absolute values of the number of trips for the origin-destination (OD) pairs are not comparable across seasons. Therefore, the percentiles of the trip counts are used to generate the brackets. These respective percentile values for visitors were 85%, 95%, 98%, 99%, and 100%. The respective percentiles for the resident dataset were 88%, 97%, 98%, 99%, and 100%.

5.2.1 Visitor Hot Corridors

[Figure 39–](#page-37-2)[Figure 44](#page-42-1) show that the highest number of visitor trips occur between TAZs covering the central Poipu area, regardless of season. The second-busiest corridors appear between Poipu and Lihue, including the Lihue Airport, as well as between Lihue and Princeville and Hanalei. The third tranche of hot corridors for visitors appears within and between Koloa, Poipu, Kapa'a, Hanalei, and Princeville. Additionally, some visitor hot routes form between the TAZs covering Waimea and the TAZ that includes points of interest such as Hohonu Awawa Lookout, Niihau Lookout, and Kekaha Lookout.

Figure 39. July 2019, visitor, hot corridors

Figure 40. Spring break, visitor, hot corridors

Figure 41. Off-season, visitor, hot corridors

Figure 42. Summer travel (2022), visitor, hot corridors

Figure 43. Valentine's Day, visitor, hot corridors

Figure 44. Winter holidays, visitor, hot corridors

5.2.2 Closer Look at TAZ Groups (Towns) for Visitors

[Figure 45–](#page-43-0)[Figure](#page-46-2) 52 show the trip distribution of visitors while zooming in to a few towns on Kauai. The figures show that visitor travel within big towns is more concentrated in TAZs that contain attractions such as beaches and commercial areas. Lodging locations also appear to be the center of travel for visitors within the selected towns. These patterns could be helpful in determining the locations of micromobility such as bike and scooter share locations for shortrange visitor travel within these towns.

Figure 45. Kekaha and Waimea summer 2022 visitor trips

Figure 46. Kaumakani and Hanapepe summer 2022 visitor trips

Figure 47. Kalaheo, Koloa, and Poipu summer 2022 visitor trips

Figure 48. Lihue summer 2022 visitor trips

Figure 49. Kapa'a summer 2022 visitor trips

Figure 50. Anahola summer 2022 visitor trips

Figure 51. Hanalei, Princeville, and Kilauea summer 2022 visitor trips

Figure 52. Wainiha summer 2022 visitor trips

5.2.3 Closer Look at TAZ Groups (Towns) for Residents

[Figure 53–](#page-47-0)[Figure](#page-51-1) 60 show the trip distributions of residents while zooming in to a few towns on Kauai. Compared to visitor travel, where certain TAZs appear to be central, resident travel

within these towns highlights several central TAZs. These TAZs are where residential, work, and commercial locations (such as big box stores) are located. These patterns could be helpful in determining the micromobility locations and infrastructure planning for short- and mid-range commute and shopping trips.

Figure 53. Kekaha and Waimea summer 2022 resident trips

Figure 54. Kaumakani and Hanapepe summer 2022 resident trips

Figure 55. Kalaheo, Koloa, and Poipu summer 2022 resident trips

Figure 56. Lihue summer 2022 resident trips

Figure 57. Kapa'a summer 2022 resident trips

Figure 58. Anahola summer 2022 resident trips

Figure 59. Hanalei, Princeville, and Kilauea summer 2022 resident trips

Figure 60. Wainiha summer 2022 resident trips

5.2.4 Resident Hot Corridors

[Figure 61–](#page-52-0)[Figure 66](#page-57-0) show that the highest number of resident trips occur between TAZ groups covering the shopping areas in the Lihue area, regardless of season. Lihue seems to be the center of resident travel based on the hot corridors. Additionally, high amounts of resident travel occur within and between TAZ groups covering Kekaha, Hanapepe, Kalaheo, Poipu, Kapa'a, Kilauea, Princeville, and Hanalei.

Figure 61. July 2019 resident hot corridors

Figure 62. Spring break resident hot corridors

Figure 63. Off-season resident hot corridors

Figure 64. Summer travel (2022) resident hot corridors

Figure 65. Valentine's Day resident hot corridors

Figure 66. Winter holidays resident hot corridors

6 Conclusion

Understanding the travel patterns of residents and visitors on Kauai Island is important for measuring the infrastructure demand and understanding the trade-offs of different mobility options. App-based cellphone data is very valuable as a complementary data source due to its low costs, high granularity, and accessibility. This report documents the steps taken to process raw GPS traces reported by smartphone devices to generate trip samples for residents and visitors, respectively. By clustering the trip origins and destinations, we produced maps of traveling hotspots and hot corridors that are informative for the planning and deployment locations of new mobility options. Due to the limitations of the app-based cellphone data, particularly the underrepresentation of locations with weak cellphone signals, we recommend that the county staff combine these results with other data sources (such as parking data) and local knowledge to support decision-making related to mobility system planning and design.

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