Regional Parks Travel Patterns

This app visualizes traffic patterns between transportation analysis zones (TAZs) and regional parks using Location-Based Services from individual cell phone devices. The app also visualizes metrics pertaining to trip purpose, traffic locality, and agency and region metrics. This app is not meant to replace annual counts and visitor studies, and the app's findings will not be used in any funding formulas at the Metropolitan Council.

Data Sources and Cleaning Methods

Regional Park Implementing Agency Zones (RPIAs)

The areas for each of the ten Regional Park Implementing Agencies (RPIA) were constructed from the 7-county metropolitan area and the city boundaries of Minneapolis, Saint Paul, and Bloomington. For county-level RPIAs, the RPIA is the county area, minus the areas of Minneapolis, Saint Paul, and Bloomington. City-level RPIAs only include the area within the city boundary. Shapefiles of 7-county metropolitan area and city boundaries are available on the Minnesota Geospatial Commons.

Transportation Analysis Zones (TAZs)

Transportation Analysis Zones (TAZs) are areas used by the Metropolitan Council and other government agencies for planning. Each TAZ contains about 3,000 people; there are 3,030 TAZs included in this app. Each TAZ was assigned an RPIA by the location of the TAZ's centroid in the given RPIA area. Shapefiles for all Transportation Analysis Zones (TAZs) are available on the Minnesota Geospatial Commons.

Regional Parks

Shapefiles for regional parks are available on the Minnesota Geospatial Commons.

Regional parks open to the public were included in the analysis. Above the Falls Regional Park data for 2016 were excluded because the Metropolitan Council did not begin collecting annual counts for this park until 2017. Cottage Grove Ravine Regional Park data for 2017 have been removed as the park was closed due to site renovation.

Mississippi Gorge, Coon Rapids Dam, and Hyland-Bush-Anderson Lakes Regional Parks are jointly operated by multiple RPIAs. In this app, each of these regional parks is assigned to just one of the agencies that manage them.

StreetLight InSight®

StreetLight InSight® (hereafter referred to as StreetLight) is a Big Data firm specializing in traffic analytics. StreetLight data in this app are sourced by StreetLight from other data vendors, such as Cuebiq, who collect Location-Based Services (LBS) on smartphones. LBS is gathered from smartphone apps such as couponing, dating, weather, tourism, productivity, and locating nearby services (such as a local business). The apps collect anonymous user locations when the user is moving while using the app in the foreground or running in the background. LBS offers spatial precision to 20 meters (approximately 65 feet). As of September 2017, the StreetLight sample includes about one quarter (23%) of the US and Canadian adult population.[1] StreetLight trips detected must have definite start and stop locations. The trip must be at least 300 meters, and the device must stop moving for 10-15 minutes at the end of a trip. This means that park visitors who never stop moving (such as when riding a bike, running, jogging, hiking, etc.) are not included in the sample. StreetLight cannot infer visitor activity within any regional park.

The StreetLight Traffic Index value represents the volume of traffic from the Origin area (a given TAZ) to the Destination area (a given regional park). The Traffic Index is normalized such that a census block with

1,000 residents and 200 devices (smartphones) will be scaled differently than a device from a census block with 1,000 residents and 500 devices.

The Traffic Index represents an "average day" during the specified filters. Temporal attributes are based on the time that a trip starts in the origin TAZ. App users can filter by year (2016-2018), season (Winter, Spring, Summer, Fall), day-type (weekend, weekday, or all days), and day part (all day, or selected hours). For instance, a user could select the StreetLight data from only Summer 2017 during weekdays from the hours of 8am to 10pm.

If the Traffic Index for a TAZ-regional park pair is below StreetLight's significance threshold, no results are provided. StreetLight does not release the significance level value. Winter 2016 includes only January and February 2016, as 2015 data are unavailable. Season dates and sample sizes (number of unique devices used in our analysis) are provided in Table 1 below.

Table 1. StreetLight Data Dates and Sample Sizes

Season	Date	Sample Size (approximate)
Winter 2016	January 1, 2016 - February 29, 2016	2,000
Spring 2016	March 1, 2016 - May 29, 2016	22,000
Summer 2016	May 30, 2016 - September 5, 2016	31,000
Fall 2016	September 6, 2016 - November 30, 2016	22,000
Winter 2017	December 1, 2016 - February 28, 2017	17,000
Spring 2017	March 1, 2017 - May 28, 2017	22,000
Summer 2017	May 29, 2017 - September 4, 2017	34,000
Fall 2017	September 5, 2017 - November 30, 2017	18,000
Winter 2018	December 1,2017 - February 28, 2018	12,000

Measures

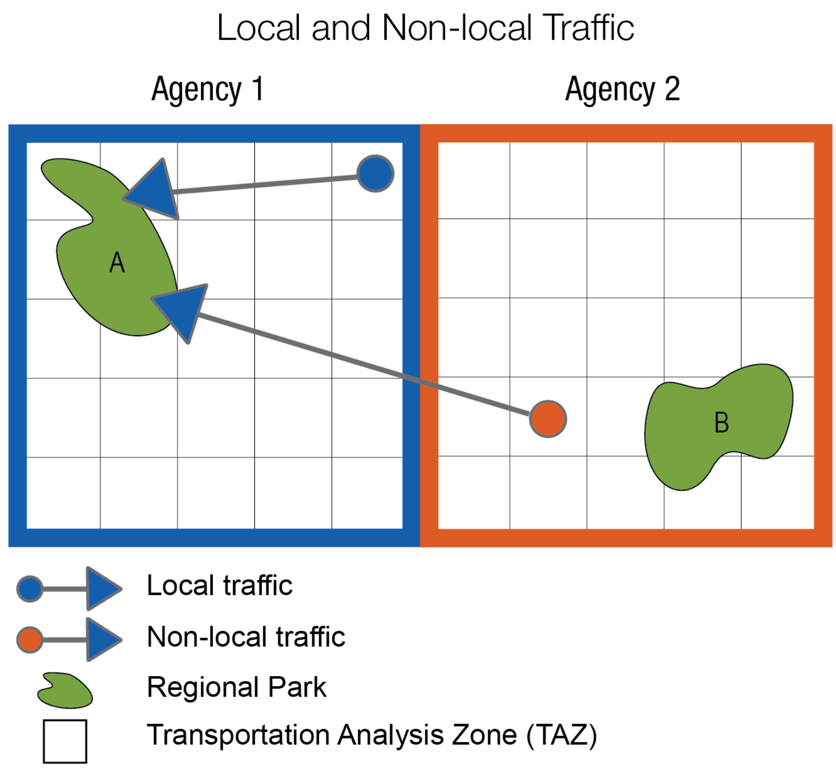
Local and non-local traffic

Local traffic is defined as traffic coming from a TAZ with the same agency designation as the destination park, whereas non-local traffic is traffic coming from a TAZ with a different agency designation than the destination park (see Figure 1). Agency-level local/non-local measures are taken by averaging the local/non-local values for all individual parks managed by that agency. The region-level local/non-local measures are taken by averaging the local/non-local values of individual parks. This measure is only calculated by year and season filters, as the sample size for day type and day part filters is highly variable across individual regional parks.

For Three Rivers Park District facilities located in Scott County, traffic is considered local if coming from a Scott County TAZ and nonlocal if coming from a Hennepin County TAZ.

For example, assume that there are two agencies, Agency 1 and Agency 2, with corresponding parks, Park A and Park B. There is traffic coming from a TAZ in Agency 2 to Park A (which is an Agency 1 park). This traffic would be non-local because it is coming from Agency 2 to an Agency 1 park. Any traffic coming from a TAZ in Agency 1 to Park A would be considered local. This hypothetical is further illustrated in Figure 1.

Figure 1: Local and non-local traffic example



Traffic by origin agency

Traffic origin by agency takes the sum of the selected regional park's Traffic Index values and finds the percentage of traffic coming from each agency area. This metric is calculated by year, season, day-type, and day-part filters.

Returning to our first example, say that Park A has four units of traffic going to it: three from TAZs in Agency 1, and one from TAZs in Agency 2. Three of the four units come from Agency 1, and one of the four units comes from Agency 2, so the breakdown of all traffic for Park A would be 75% Agency 1 and 25% Agency 2.

Inferred trip purpose

StreetLight can infer the home and work locations of groups of people by analyzing the devices' aggregated behavior in the last thirty days. StreetLight provides estimates of the share of trips in an analysis that are

- Home-Based Work (HBW): Travel between home and work in either direction.
- Home-Based Other (HBO): Travel to and from home, to anywhere other than work.
- Non-Home Based (NHB): All travel not to or from home.[2]

This app displays the average values for home-based work, home-based other, and non-home based for all TAZs with traffic to the selected regional park.

Demographics

StreetLight uses a device's inferred home to estimate the percentage of travelers with certain demographic characteristics in a given TAZ-regional park pair. For example, demographic data for a TAZ with traffic to a regional park would include the estimated percentage of travelers who self-identify as white, black, Indian, Asian, Pacific Islander, Hispanic, multiple races, or other.

Demographic data is not included in the app to maintain a cohesive interface and because further research must be conducted to better compare demographic information available in these analyses to the region.

Limitations

Demographic Factors Affecting Cell Phone Ownership and Usage

Due to the proprietary nature of StreetLight Data, exact details of which smartphone apps are used to collect LBS data are unknown. StreetLight states that apps include "couponing, dating, weather, tourism, productivity, locating nearby services (i.e., restaurant/bank/gas station), and many more apps." We are also unable to comment on the exact demographic characteristics of the sample, such as the distribution of age, income, and educational attainment. These demographic factors are associated with cell phone ownership and use. For example, a survey by the Pew Research Center found that 69% of US adult high school graduates own a smartphone, compared to 91% of college graduates [3]. People of age 65 and older, with a high school education and lower, and/or who live in rural areas have lower cell phone ownership rates. The digital divide is particularly stark for racial and ethnic groups with less education and whose primary language is not English [4].

People living with disabilities have also been shown to have different cell phone ownership rates. In 2017, the Pew Research Center about 58% of Americans with any disability own smartphones, compared to 80% in Americans with no disability [5]. However, a 2016 survey conducted by the Shepard Center and the Wireless Rehabilitation Engineering Research Center (RERC) found that smartphone ownership expanded in persons with disabilities as it has in the general population, while ownership gaps in regards to age and household income persist [6].

Representative sampling

StreetLight claims to have a representative sample in their analyses, as is evidenced in a case study of device penetration rate and income bias in Florida.[7] The device sample share measures how much of the population StreetLight is accounting for. For example, a census block that is assigned 15 StreetLight devices with 100 people living there, the device sample share for that block is 15%. For census tracts in Florida, the average device sample share is 10.1%. Also, the Florida case study noted slight differences in the average device share by census tracts with varying income. A graph of this data revealed that the lowest average device share, at about 8%, were tracts with average income ranging from $20,000 to $35,000, and the highest average device share, at nearly 12%, were tracts with average income ranging from $100,000 to $125,000. The StreetLight Traffic Index has no public validation studies, though other StreetLight metrics, such as Annualized Average Daily Traffic and passthrough zones, have undergone validation.[8,9]

Due to the proprietary nature of StreetLight data, our researchers are unable to validate StreetLight data used in this app.

Technical

This app was built using R Shiny with packages including leaflet, shinydashboard, htmlWidgets, plotly, shinyalert, rintrojs, shinycssloaders, and data.table. A full list of R packages is available after the Acknowledgements section.

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License

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Endnotes

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