From Lake to Lakeplace: A Case Study of Lake-Related Human Activities in the Twin Cities

Meicheng Xiong and **Di Zhu**

ABSTRACT: Urban freshwater ecosystems in a city, composed of rivers, ponds, lakes and other water bodies are important for residents in terms of both their socioeconomic and ecological values. However, research on the interactions between human activities and intra-city lakes remains limited, especially at finer spatiotemporal resolutions and based on individual-level human activity information. To fill this gap, we offer a data-driven analytical framework that senses the interactions between lakes and their associated human activities to profile the socioeconomic characteristics of intra-city lakes. We use the term "lakeplace" to depict the place containing a lake and the human activities within this place. For each lake, the spatial extent of its lakeplace refers to the first-order contiguous census blocks, as they reflect the neighboring scale of lake socioeconomics. Utilizing large-scale individual mobile positioning data in the Twin Cities Metropolitan Area (TCMA), Minnesota, we analyze human activities related to 18964 lakes during July 2021. The results indicate the daily most popular lakeplaces vary from local centers, recreation parks, and large lakes alongside the increase of on-lake activity intensity. Furthermore, by comparing human activities on lakes and lakeplaces, the most popular lakes are found and classified to depict whether the attractiveness of a lake is mostly brought by the lake itself, or the socioeconomic environment around it. Our work exemplifies the social sensing of human-environment interactions via geospatial big data, shedding light on human-oriented sustainable urban planning and urban water resource management.

KEYWORDS: *lakeplace, social sensing, human activities, urban freshwater ecosystem, spatiotemporal analysis*

Background

Urban freshwater ecosystems composed of rivers, ponds, lakes, and other water bodies inside cities serve as ideal attractions for human activities including recreation, exercise, education, working, etc. (Chapman, 2020). In this context, the interaction between human and urban water bodies, especially urban lakes, has received wide attention over the past years. However, most studies focused on to what extent human activities impact the physical attributes of lakes, such as water quality, while the socioeconomic values of lakes are often neglected (Dodds, 2013; Matthews, 2016; Xia, 2020). To bridge the gap, social sensing has emerged as an effective tool to capture high-resolution spatial-temporal characteristics of human behavior based on individual-based geospatial big data, which is a complement of natural features extracted by remote sensing based on satellite images (Liu, 2015).

For decades, places have been regarded as locations with certain meanings (Fig 1) (Cress, 2009). In other words, a location becomes a place when human-environment interaction is attached to it. The type of place varies by its social and physical context. As such, a general place becomes a "*lakeplace*" as there are interactions between human and lakes, where

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socioeconomic profiles can be depicted by social sensing and physical features can be uncovered by remote sensing.

In this study, we develop a data-driven analytical framework to profile lake socioeconomics by capturing fine-scale spatial-temporal features reflected by human activities on and near the lakes. We propose the term "*lakeplace*" to depict a place where people interact with lakes. For a lake, the extent of its lakeplace refers to the geospatial area covering and surrounding it. A case study incorporating geospatial big data was conducted in the Twin Cities metropolitan area, Minnesota, where all lakeplaces were identified and each lakeplace was profiled by the spatial-temporal features of human activities and the demographic characteristics of visitors. Our research offers insightful policy implications for human-oriented development as well as urban water resource management.

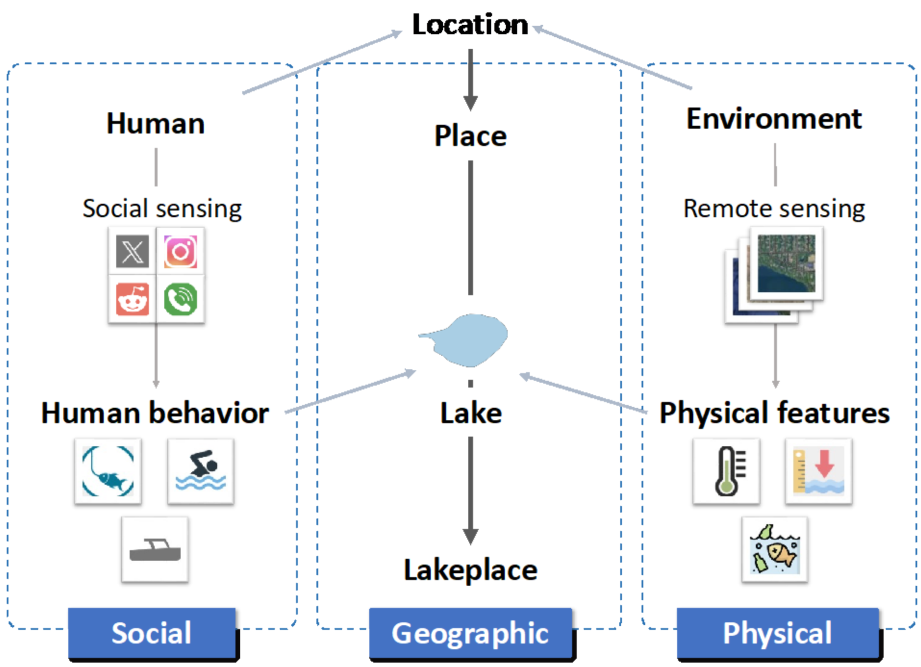

Figure 1: Location, place and lakeplace.

From lake to lakeplace

Human-environment information collection

The first step is to project human activities on corresponding locations, serving as the basis of this study. It contains two subsections: lakeplace identification and human activity extraction. To identify lakeplaces in bulk, all first-order contiguous units (e.g., census units) of a lake are merged to generate a lakeplace by processing spatial selection and aggregation. In this way, each lake is encompassed by its lakeplace. Human activity extraction is executed at the same time, which extracts and projects visitations on lakeplaces referring to their coordinates provided by geospatial big data. Each visitation record should at least contain key information about the individual including individual ID, timestamp, and coordinates. After getting the human activity information and the geometry of lakeplaces, visitation records are mapped onto the lakeplace layer.

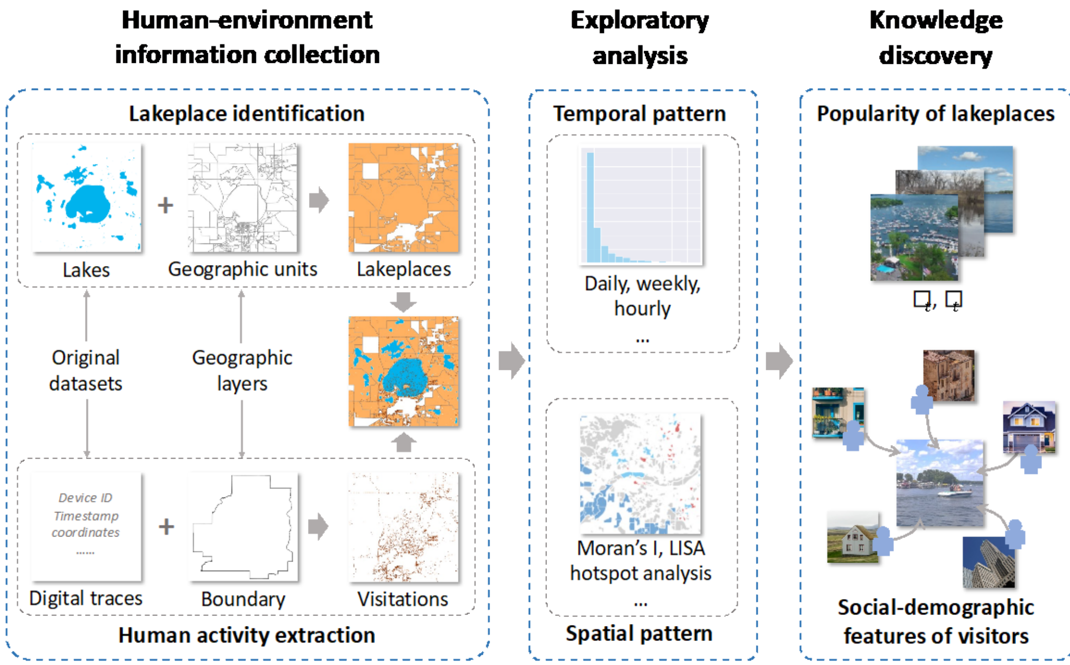

Figure 2: Framework of lakeplace sensing.

Exploratory analysis

This section serves to reveal the general spatial and temporal patterns of human-lake interactions. Temporal pattern mainly depicts temporal statistics of visitations on lakes and lakeplaces at different temporal scales, such as the number of individuals and the number of visitations in each month, each week, and each day. Spatial pattern analysis aims to show the spatial distribution and clusters of human activities by applying exploratory spatial data analysis (ESDA) such as Moran's I, LISA, and hotspot analysis.

Knowledge discovery

The third section is based on all analyses in the first two sections, centering around human activities inside lakeplaces and the relationship between lakes and lakeplaces. To answer the question: **"Which are the most popular lakeplaces?"**, Human activity intensity of lakeplaces at different temporal scales are calculated and ranked to reveal the popularity of each lakeplace. Bearing that the total amount of visitations commonly increases by the area of lakeplace, we employ α_t to represent adjusted human activity intensity at a certain temporal scale t for each lakeplace:

$$\alpha_t = \frac{Rank(vp_t)}{Rank(ap)}$$

Where vp_t donates the average number of visitations on the lakeplace at temporal scale t such as several days or several hours, and ap refers to the area of this lakeplace. For any lake, $Rank(vp_t)$ and $Rank(ap)$ indicate the ranking of its average lakeplace visitations and the ranking of lakeplace area among all lakeplaces, respectively. For instance, the lower the value of $Rank(vp_t)$, the higher the human activity intensity.

Comparing the number of visitations to lakes to corresponding lakeplaces helps to answer another important question: **"Is a lakeplace popular due to lakes or non-lake areas?"**. For instance, a lakeplace containing attractive lakes for on-lake recreation like fishing and boating may belong to the former type, while a lakeplace with only a small artificial lake inside an airport area is a typical example of the latter type, as people visit the airport for travel purposes, not to interact with the lake. Here we propose another index namely lake contribution c_t to quantify the proportion of on-lake visitations among all visitations inside the corresponding lakeplace at temporal scale t, which is shown as:

$$c_t = \frac{vl_t}{vp_t}$$

Where vl_t and vp_t indicate the number of on-lake visitations and of visitations inside the corresponding lakeplace at temporal scale t, respectively. The higher the value of c_t, the more human activities brought by on-lake visitations as well as more intense interaction between human and the lake itself.

Case study

Data and study area

Twin Cities Metropolitan Area (TCMA), one of the largest metropolitan areas in the US, is chosen as our study area (Fig 3). Covering the urban areas of Minneapolis–Saint Paul with over 3 million inhabitants, the TCMA contains seven counties and accounts for more than half of Minnesota's total residents. The populated area is dotted with a variety of lakes, offering a large urban freshwater ecosystem serving urban residents.

To conduct our case study, an individual mobile phone positioning dataset collected by PlaceIQ is employed. The dataset records a user's spatiotemporal information when the mobile device is used (Weill, 2020). It accounts for around 5% of the population in the US. Each record of the dataset includes a unique device ID, time, coordinate (longitude-latitude format), and stay duration of the user. We chose July 2021 as the study period (a whole month) to ensure the sample size is adequate. During the selected period, over 720,000 users and about 21,000,000 records are observed, accounting for around 20% population in the TCMA.

We employ the fine-scale census block layer and waterbody layer of TCMA to generate lakeplaces. The block-level zoning layer of TCMA is provided by the National Historical Geographic Information System (NHGIS), and the waterbody layer is obtained from

OpenStreetMap (OSM). In this study, we consider lakes containing typical lakes and ponds, but not riverbanks, reservoirs, or swamps.

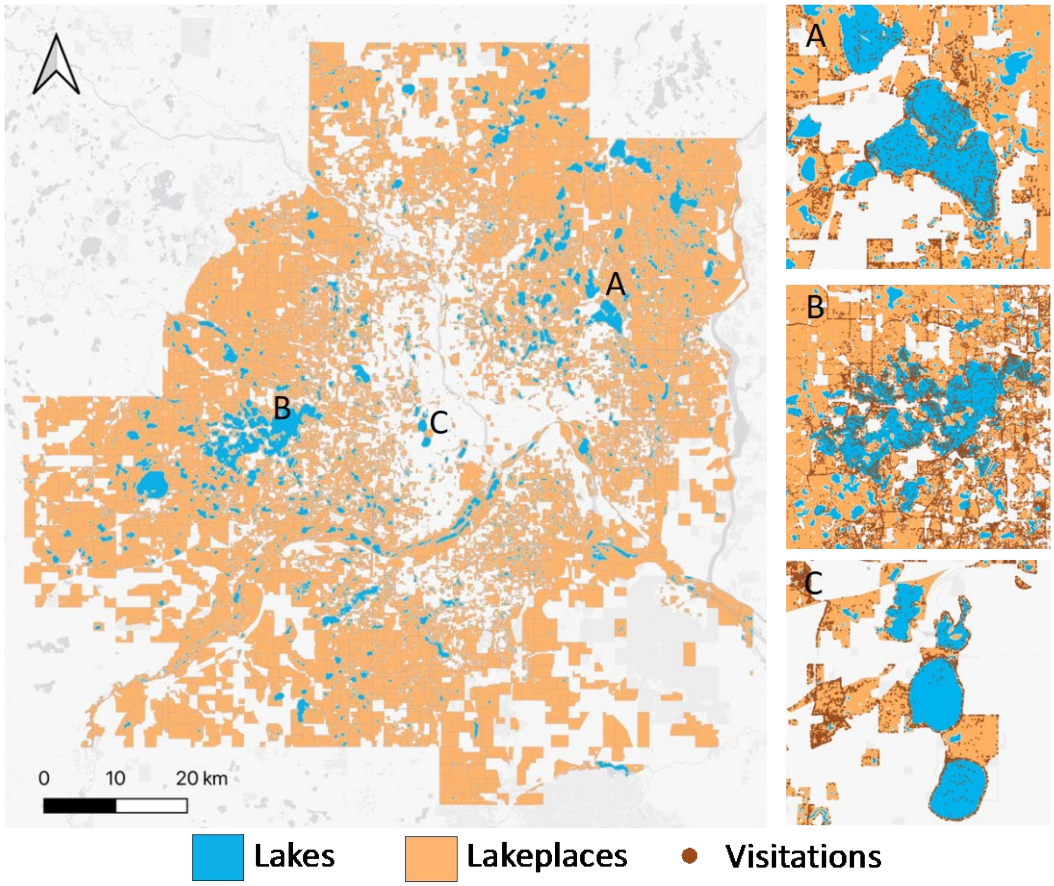

Figure 3: Lakes, lakeplaces and human visitations in the study area. Subfigures A, B and C are examples of lake and lakeplace groups surrounding Lake Minnetonka, White Bear Lake, and Lake Harriet, respectively.

Evidence from lake sensing: human in lakeplaces

18,964 pairs of lakes and lakeplaces are obtained, and visitation records in a month are utilized to support knowledge discovery. We first investigate daily lakeplace popularity by employing adjusted daily human activity intensity α_d inside the lakeplaces and rank the results. It's worth noting that lakeplaces of nearby lakes may share the same spatial extent, so we only use one lakeplace out of them. To understand the driving force behind lakeplace popularity, we employ c_d to represent the proportion of average daily on-lake activities. We hereby divide lakeplaces into three types: low on-lake intensity ($c_d < 0.01$), medium on-lake intensity ($0.01 \leq c_d < 0.1$), and high on-lake intensity ($c_d \geq 0.1$). For each type, we find out the top 30 lakeplaces by c_d and map them. We also explore the land use of these popular lakeplaces by zooming in on several examples for each type.

Our results show that the built environment and function of the most popular lakeplaces in each type present similarity (Fig 4). As observed, the most popular lakeplaces with low on-lake intensity tend to be local centers near highways, where local services like the gas stations, stores, and restaurants are located in. Most of lakeplaces falling in this type merely cover small ponds, which are seldom visited by people. One interesting example is Minneapolis–Saint Paul International Airport (MSP), a large transportation hub for a mass of visitors. When on-lake intensity reaches the medium level, the most popular lakeplaces are prone to be recreation centers including lake parks and amusement parks. Equipped with recreation facilities and ornaments, the lakes covered in these lakeplaces are larger and more attractive for local residents to take activities nearby or on the lakes such as sightseeing, fishing, boating, exercising and so forth. Compared with these two types, the most popular lakeplaces with high on-lake intensity are not so crucial for residents' daily life, but have a broader influence. Though sharing the similar on-lake recreation types to those of medium on-lake intensity, lakes in such lakeplaces are much larger, more well-known, and attractive ones. Thus, these lakeplaces are generally attractions recorded by the online map, which attract only not local visitors. Lake Waconia, White Bear Lake and Crystal Lake all belong to this type.

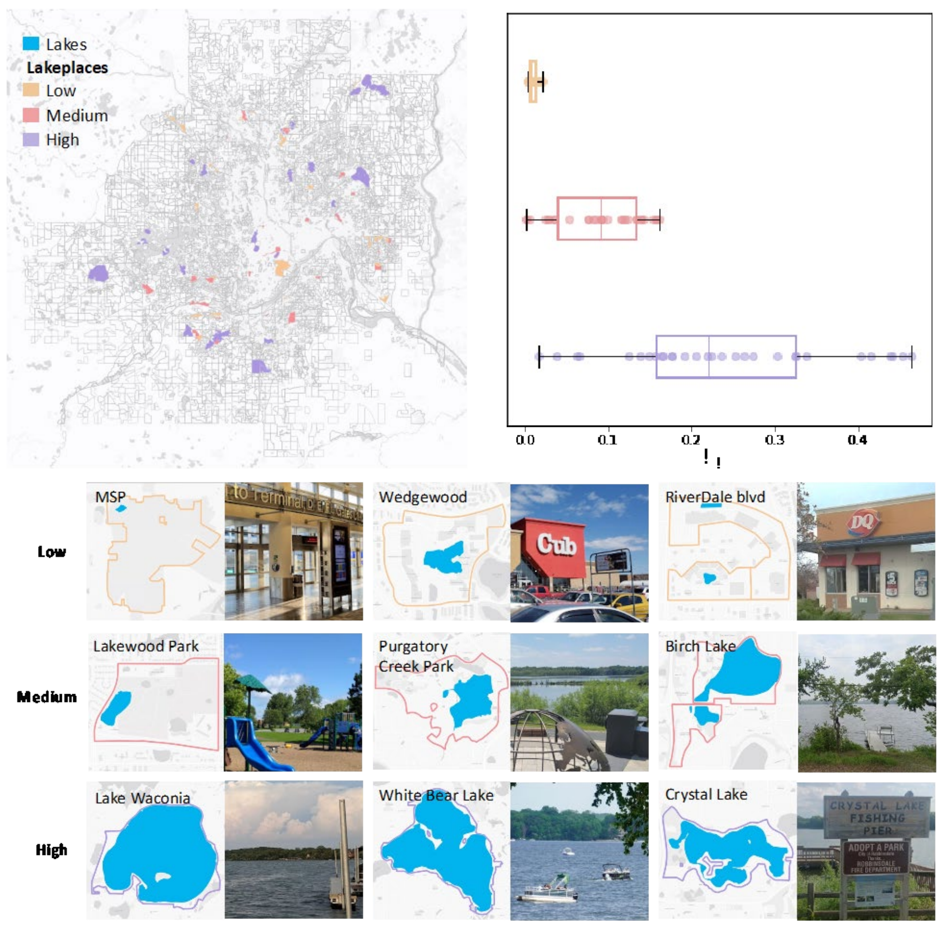

Figure 4: Distribution of top 30 popular lakeplaces and typical examples: High, medium and low on-lake daily activity intensity.

Conclusions

Exploring urban lakes from the perspective of human-environment interaction is crucial for understanding how human activities are embedded in urban freshwater ecosystems.

This study approaches lake-related human activities from a new perspective of lakeplace and utilizes social sensing approaches. As for the case study, we chose Twin Cities Metropolitan Area (TCMA) as our study area and adopted large-scale spatiotemporal data to accomplish lakeplace identification, conduct exploratory analysis, and find out the most popular lakeplaces. The results indicate the daily most popular lakeplaces vary from local centers, recreation parks, and large lakes alongside the increase of on-lake activity intensity. To fulfill knowledge discovery, further analysis will include investigating lakeplace popularity at other temporal scales such as weekdays vs. weekends and daytime vs. nighttime, then profiling lakeplaces referring to socioeconomic features of visitors.

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