Mobility Based Environmental Justice: Understanding Inequity in Transit-Oriented Development (TOD) Station Usage and Artificial Light at Night (ALAN) Exposure

モビリティベースの環境正義：公共交通指向型開発（TOD）ステーションの使用と夜間の人工照明（ALAN）曝露における不公平の理解

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Environmental justice (EJ) means that no one, regardless of race, nationality, income, age, or gender, should suffer a disproportionate share of the negative environmental consequences. Previous EJ studies have been residence-based, assuming that people's environmental exposures only occur in the residential environment. The current challenge for EJ research is how to measure the environmental resources and exposures that people are actually exposed to during their daily travel and activities. A possible solution is to use mobility data to conduct mobility-based EJ studies. This thesis outlines my efforts in mobility-based EJ research.

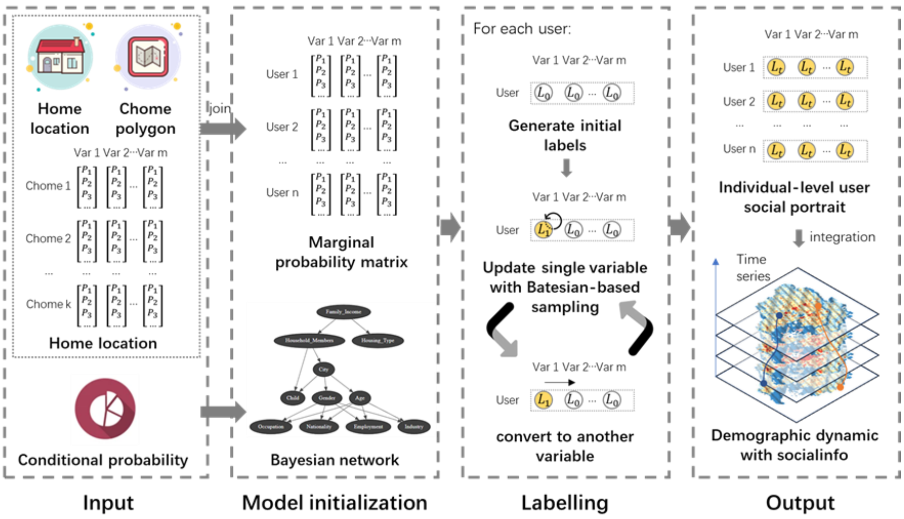

Figure 1. The framework of chapter 2

In chapter 2, I propose a method for user attribute inference on trajectory data using a small number of known labels and non-sensitive government statistics (Figure 1). By matching the user's home location with the demographic statistics of the block where it located in, we determine the marginal probability distribution matrix of each user's social labels. Using multivariate statistics published by the government, we build a Bayesian network for all social labels. After generating a set of initial labels for each user with sampling based on probability matrix, the Bayesian network is used to resample each social attribute and update the labels by rotating the axes. Finally, I obtained the exact inference of social information labels for individual users.

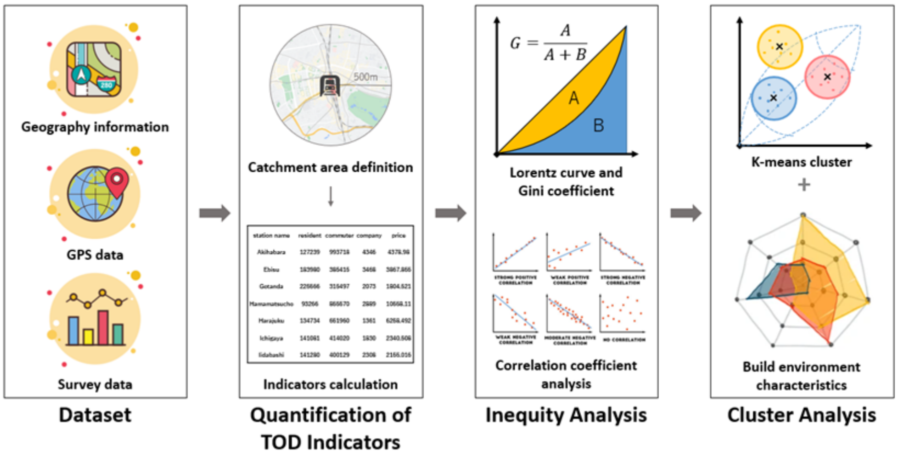

Figure 2. The framework of chapter 3

Table 1. The indicators of TOD

Dimension	Component	Indicator	Scope	Source
Node	Metro station operational capability	N_1 - passenger load	station	Homepage of JR station
		N_2 - number of transfer lines	station	Homepage of JR station
	Connectivity with multimodal transportation	N_3 - Length of footway and cycleway	500m	OSM
		N_4 - Walkability index	--	Real Estate Homepage
		N_5 - Intersection density	500m	OSM
		N_6 - Number of bus stops	500m	OSM
		N_7 - Number of bicycle parking lots	500m	OSM
Place	Employment density	P_1 - Number of commuters	1500m	e-Stat
	Residential density	P_2 - Number of residents	1500m	e-Stat
	POI density	P_3 - Number of hospitals	500m	MLIT
		P_4 - Number of welfare facilities	500m	MLIT
		P_5 - Number of parks	500m	MLIT
		P_6 - Number of entertainment facilities	500m	OSM
		P_7 - Number of restaurants	500m	OSM
		P_8 - Number of shopping malls	500m	OSM
	Price	P_9 - Average land price	1500m	MLIT
		P_{10} - Average housing price	--	Real Estate Homepage
	Diversity	P_{11} - Land use diversity	1500m	MLIT
User	average age	U_1 - Average age of TOD users	1500m	NTT DOCOMO

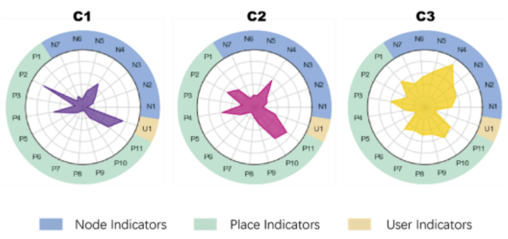

Figure 3. Indicator visualization results for each cluster

In chapter 3, I provide a framework for TOD age inequity research applicable to high-density and public-transport-oriented cities (Figure 2). This chapter uses big mobile phone positioning data to extract the demographic information of TOD (Transit-Oriented Development) station users and uses geographic information and survey data to quantify the TOD service level (Table 1). Then, I used the Gini coefficient, correlation coefficient analysis, and cluster analysis to explore the differences in TOD resource allocation across age groups on the JR Yamanote Line and part of the JR Chuo line in Tokyo. The results show that inequity indeed exists at the TOD service level in terms of user age, and there is a negative correlation between the average age of users and most indicators of TOD. In the clustering results, three unique TOD groups are formed: a) Residence-oriented aging TOD, b) Livable middle-age TOD, and c) Commuter-oriented young TOD (Figure 3). Based on the research results, I made three suggestions for building an age-friendly TOD: a) More diverse land use, b) Better connectivity between transit nodes and multimodal transportation, and c) Affordable housing cost.

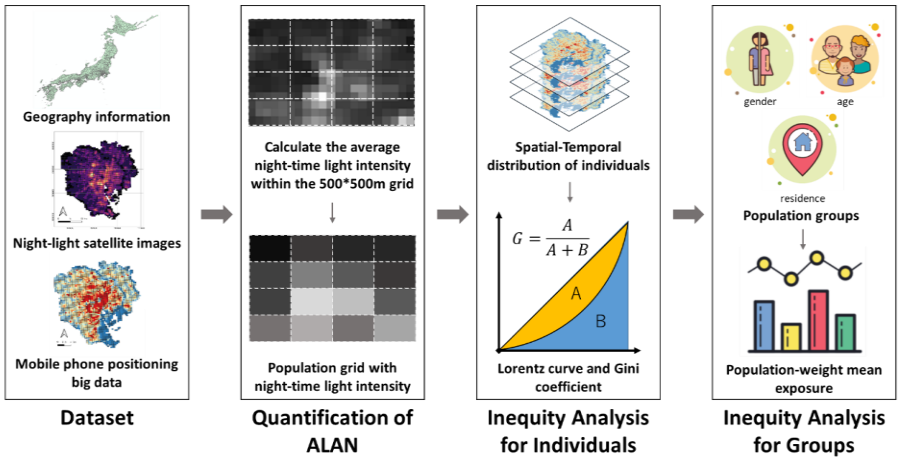

Figure 4. The framework of chapter 4

In chapter 4, based on mobile phone positioning big data and night-light satellite imagery, I conducted an empirical study on the inequity of ALAN exposure in Tokyo, Japan (Figure 4). I quantified the intensity of ALAN on the grid of mobile phone positioning data. Then I used the Gini coefficient and population-weighted mean exposure to evaluate the inequity of ALAN exposure among individuals and between different population groups. As a result, I found evidence of the inequity of ALAN exposure in Tokyo. For age inequity, younger people suffer higher exposure to light pollution at night, but children are an exception (Figure 5). For gender inequity, there is almost no inequity between men and women

(Figure 6). For residence inequity, the average ALAN exposure of non-residents can reach up to about twice that of residents (Figure 7). At time and space nodes where there are more travel behaviors, such as central Tokyo during 18:00-24:00, I have detected higher exposure and stronger inequity, indicating that ignoring personal mobility will cause underestimation (Figure 8).

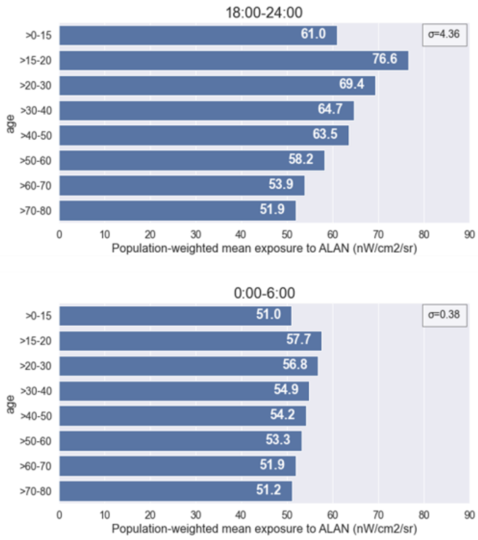

Figure 5. population-weighted mean exposure to ALAN for different age groups in two time periods

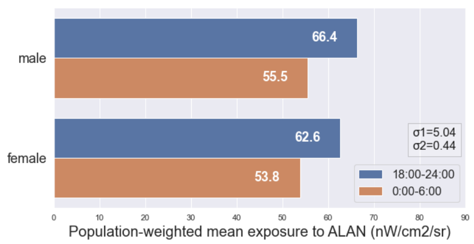

Figure 6. Population-weighted mean exposure to ALAN for different age groups in two time periods.

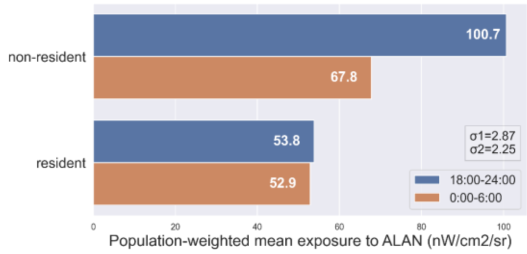

Figure 7. Population-weighted mean exposure to ALAN for different residence groups in two time periods

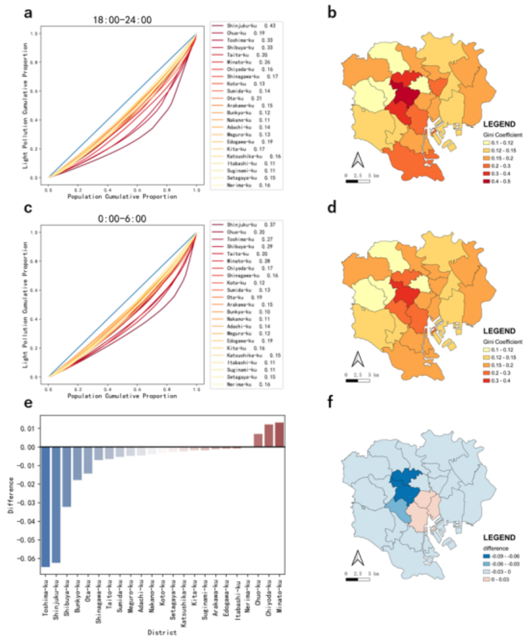

Figure 8. a. c. Lorentz curve and Gini coefficient of each district in two time periods. b. d. Spatial visualization of Gini coefficients for each district in two time periods. e. The difference in the Gini coefficient of each district between two time periods. f. Spatial visualization of Gini coefficients difference for each district between two time periods.