A STUDY ON TRANSPORT GAP INDICATOR FOR TRANSPORT PLANNING IN RURAL TOURISM AREAS UNDER PERSPECTIVE OF MOBILITY AS A SERVICE

- A case in Hokuto City, Yamanashi Prefecture, Japan -

MaaS 導入を見据えた地域観光地交通計画のための交通需給ギャップ指標の研究-山梨県北杜市を事例に

By

PHAM DUY HOANG

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Doctor of Philosophy

Supervised by

Professor. Tetsuo SHIMIZU

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The Graduate School of Urban Environmental Sciences

Department of Tourism Science

Tokyo, Japan

Declaration of Committee

Name:	**Pham Duy Hoang**
Degree:	**Doctor of Philosophy**
Title:	**A study on transport gap indicator for transport planning in rural tourism areas under perspective of Mobility as a Service – A case in Hokuto City, Yamanashi Prefecture, Japan** **MaaS** 導入を見据えた地域観光地交通計画のための交通需給ギャップ指標の研究**-**山梨県北杜市を事例に

Committee:

Chair:

Professor, Dr. Tetsuo SHIMIZU
Supervisor/ Chief Examiner

Professor, Dr. Hiroyuki ONEYAMA
Committee Member/ Examiner

Associate Professor, Dr. WU Lingling
Committee Member/ Examiner

Wu Lingling

Professor, Dr. Susumu KAWAHARA
Committee Member/ Examiner

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Abstract

Motivation and objectives of the study

The transport gap might result from gaps in transport supply to meet the accessibility needs and transport demands of a community. Moreover, the transport gap is also viewed as synonymous with low accessibility, such as unavailable services, long access distance to services, long waiting time, low service frequency, and high travel cost, which in turn influence user's perceptions of ease of access, convenience, comfort, and availability of service to reach a specific destination or social activity. It appears that for vulnerable individuals, such as non-car ownership, elderly, and disabled, transport gaps become more critical. It is not surprising that transport gap analysis and improvement are of interest to local governments, planners, and transport service providers.

The transport gap is not fully understood in the existing literature. Most previous studies focused on measuring transport gaps and suggested public transport improvement as one way to reduce transport gaps in urban areas. The transport gap was rarely explored in rural areas, especially rural tourism areas, where there are tourism activities. Low population density, low and dispersed demands in rural areas might lead to difficulty to provide traditional public transport services. Lack of understanding about transport gap leads to many important questions from the planning perspective to be answered, such as how transport gaps vary over areas, time, and transport modes; and to what extent transport gaps need to be addressed. Addressing the transport gaps is a challenge and becomes the primary priority for many rural areas.

The introduction of Mobility as a Service (MaaS) appears to be a new opportunity for car-dependent reduction and public transport enhancement in both urban and rural areas. MaaS integrating the existing public transport (i.e., buses and trains) with on-demand services (e.g., ridesharing, ride-sourcing, taxi, on-demand bus, and social services), has provided more alternative options and improved accessibility gaps in areas where public transport is poor or nonexistent (Jiang et al. 2018; S. T. Jin et al. 2019; Murphy 2016; Wang 2018; Zhang and Zhang 2018). The role of MaaS in satisfying user' needs and matching individual mobility to different transport options were widely acknowledged in the literature, but its role in addressing the transport gap for an area was rarely explored. Particularly, among potential transport services integrated into MaaS, what transport service is required to fulfill transport gaps and how are its potential impacts on transport gap reduction are important question to be answered.

In rural tourism areas, facilitating locals and tourists is one of the efficient ways to promote the local economic situation, enhance the attractiveness, and reduce or suspend the de-population. Improving transport gaps becomes the primary priority for many rural tourism areas. To fill the gaps in previous studies, this study aims to explore spatial-temporal transport gaps and the role of MaaS to suggest policies for improving transport gaps in rural tourism areas, especially where tourism facilities and residential areas are separated.

Case study

In this study, Hokuto City, Yamanashi prefecture, Japan was selected as a case study for some reasons. First, Hokuto was known as a rural and mountain area. It is similar to many rural areas with general characteristics, such as low population density, high rate of transit-

dependent population, and poor public transport. Second, Hokuto was also known as a popular tourism area for sightseeing, cultural activities, camping, golf, and hot springs in Japan. Most popular tourism and remote residential areas were separated from main towns, so it is difficult to expand public transport for both local and non-local residents/visitors in areas with such low population density and scattered tourism facilities. As a result, studying to address transport gaps in this area contributes to both academic and practical aspects.

Research methodology

The transport gap model based on the standardized score of transport supply and demands was used to identify spatial-temporal transport gaps. The analytical framework is shown in Figure 0-1. There were two core models (i.e., supply and demand model) related to each other in the transport gap model.

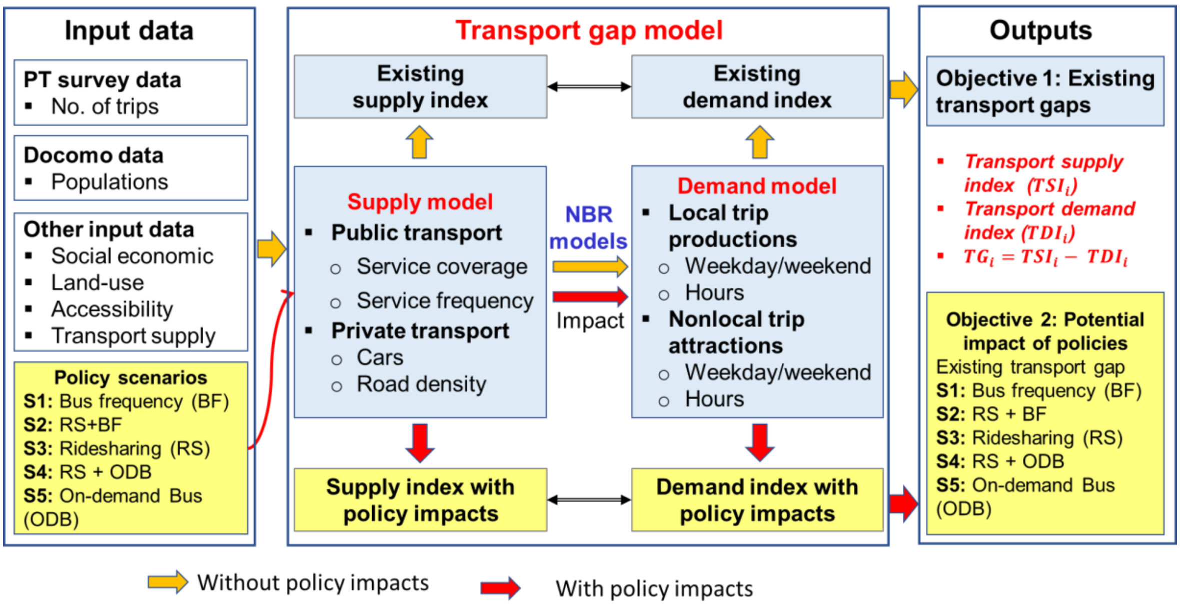

Figure 0-1 Conceptual framework within transport gap model

To identify the existing transport gaps, the transport supply index was measured from indicators representing the supply of public transport and private transport. Service coverage and frequency were used to quantify the public transport supply while available cars and road density were utilized for determining the private transport supply. The relevant supply data were collected from publicly available data sources.

On the other hand, the transport demands were measured by the number of trips generated and attracted by local and nonlocal residents/visitors from and to each zone. To quantify local and nonlocal demands, several different data sources were used in this study. The data included the aggregated person trip survey data on a typical weekday in three metropolitan regions (Kanto, Kinki, and Chubu) provided by MLIT in 2010 and mobile spatial statistics data provided by Docomo Insight Marketing Inc in five months in 2020. First, the negative binomial regression (NBR) models were developed based on the person trip survey data to explore factors related to the local and non-local demands. Second, the developed models were applied to predict the trip productions of local residents and trip attractions of nonlocal residents per zone in Hokuto. In the next step, the maximum entropy models were developed to decompose the predicted demands on a weekday into a weekend, a weekend/holiday, and different hours based on the mobile spatial statistics data. The adjusted results were then used for analyzing the spatial and temporal distribution of transport demands and transport gaps in Hokuto.

Once transport demands and supplies per zone were determined, the standardized scores of transport supply and demand were determined and relatively compared to point out areas where transport supplies are lower than transport demands. Furthermore, the important performance analysis model was used to identify areas, where are strongly suggested to enhance transport services.

Five different policy scenarios aiming at transport gap reductions were developed based on the existing public transport, ridesharing, and on-demand bus service. The impacts of policy scenarios on both transport supplies and demands were also considered and estimated. Particularly, the policy scenarios changed the public transport supply indicators, such as service coverage, service frequency, access time to the nearest train station, and accessibility. The transport demands changed corresponding to changes in transport supply. In each scenario, the transport supply and demand indices were redetermined to point out transport gaps with policies. Finally, the comparisons between transport gaps with and without policy scenarios were made to point out the influence of policy scenarios.

Findings

The findings further confirmed traditional understanding about what factors influenced the number of trip productions and attractions per zone. Transport supply indicators and accessibility were the most significantly related to trip productions and attractions by different trip purposes and transport modes. The findings also showed that the transport gaps were scattered in both local residential and tourism areas. Furthermore, the study provided new insight into temporal transport gaps, which became more critical on the weekend and during peak hours.

The potential impact of policy scenarios on transport gap reductions were different. Nonlocal residents were more sensitive to policy scenarios than residents. Local and nonlocal demands significantly changed by the introduction of ridesharing and less changed by bus frequency improvement. Particularly, local and nonlocal demands increased 1.37% and 2.46% when the current bus frequency was double in scenario 1, which increased to 3.06% and 13.96% in scenario 5, respectively. Scenario 4 had the most impacts when ridesharing and on-demand bus were introduced. The local and nonlocal demands increased to 8.79% and 25.57%, followed by 8.6% and 25.22% in scenario 3, and 8.53% and 25.10% in scenario 2, respectively.

The transport gaps were most significantly improved under most policy scenarios. There were a significant reduction of transport gaps and a shift to medium and large supply in both residential and tourism zones under policy scenarios. In scenario 1 and scenario 5, low and medium transport gaps significantly decreased while large gaps remained in tourism zones. The analytical results showed the crucial role of ridesharing in transport gap reductions. The introduction of ridesharing in scenario 2, scenario 3, and scenario 4 significantly contributed to reducing transport gaps in both residential and tourism zones. Most zones with transport gaps shifted to large supply with ridesharing.

The percentage of ridesharing and on-demand bus balancing gaps between transport supply and demands in rural areas was an important finding. Particularly, most transport gaps can be removed by either 10% of ridesharing, 5% of ridesharing and 5% of bus frequency increase, 5% of ridesharing and 5% of on-demand bus, or 40% of on-demand bus. The results suggest that improving ridesharing is the most effective intervention for reducing existing transport gaps for residential and tourism areas. The findings could also help local governments, planners, and transport operators generate important strategies for transport planning, such as optimizing the transport supply, service integration, and multimodal transport for transport gap reductions in an area.

Contributions

There were two major academic contributions in this study. Firstly, this study contributed to literature with a comprehensive understanding of transport gaps in the context of scattered rural tourism areas, where residential areas, tourism areas, public facilities are widely separated. Secondly, the study generated a macroscopic model with very limited data to evaluate the role of different transport services in transport gap reduction.

For practical contribution, the developed model can support decision makers and transport planners identify priority areas and evaluate potential transport services for transport gap reduction. Although this approach was evaluated in rural tourism areas, it can be easily applied to other areas when planning strategies for transport gap reduction are considered.

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List of Abbreviations

MaaS	:	Mobility as a Service
TSP	:	Transport service provider
MPO	:	MaaS platform operator
PuT	:	Public transport
SAV	:	Shared autonomous vehicles
AV	:	Autonomous vehicle
RS	:	Ride-share service
ODB	:	On-demand Bus
MLIT	:	Ministry of Land, Infrastructure, Transport and Tourism
e-Star	:	Portal site of Official Statistics of Japan

1. Introduction

1.1. Background of the study

Rural areas often characterized by low population density and scattered public facilities suffer from scarce and inadequate access to public transport services and opportunities (Daniels and Mulley 2012; Farrington and Farrington 2005). A number of studies have demonstrated that the lack of transport supply might have negative impacts on rural residents who cannot or do not want to drive or do not have access to cars to reach destinations or social activities (Farrington and Farrington 2005; Verma and Taegen 2019), and consequently leads to social exclusion (Currie and Stanley 2008; Hine and Fiona Mitchell 2004; Mattioli 2014). In rural tourism areas, where there are tourism resources and tourism activities, the lack of transport supply impacts not only economic activities but also the attractiveness of these areas (Hurma, H., Turksoy, N., Inan 2016; Neumeier and Pollermann 2014). Moreover, promoting local economic development is an essential activity to reduce or suspend the de-population in advanced countries. Research has demonstrated that in rural areas, where there are tourism resources, facilitating locals and tourists is one of the efficient ways to enhance the issues. As a result, it is so important to understand to what extent transport supply is lacking and to point out appropriate and efficient transport services to guarantee adequate levels of accessibility for both residents and visitors in rural tourism areas.

In Japan, local governments promote tourism activities in rural areas as a potential way to cope with depopulation and to develop rural areas. Hokuto City was known as a rural tourism area, locates in the north of Yamanashi prefecture. It covers a very large area of 602.5km^2 with 76.4% of its land is covered by forest and 78 persons/km^2. Furthermore, Hokuto was also known as one of the popular cities for migration and second house, a remarkably rural tourism destination with natural and cultural resources as well as scenic mountain ranges for sightseeing and seasonal tourism activities. Residential areas in Hokuto were scattered in three main topographical areas due to geo-demographical conditions, namely Yatsugatake, Kayagatake, and Kai-Komagatake area. Geographical characteristics generated popular tourism areas and remote residential areas, which were separated from the city center. Therefore, it is difficult to provide public transport services for both local and non-local residents in these areas in Hokuto.

a) Spatial distribution of tourism facilities

b) Residential and tourism zones

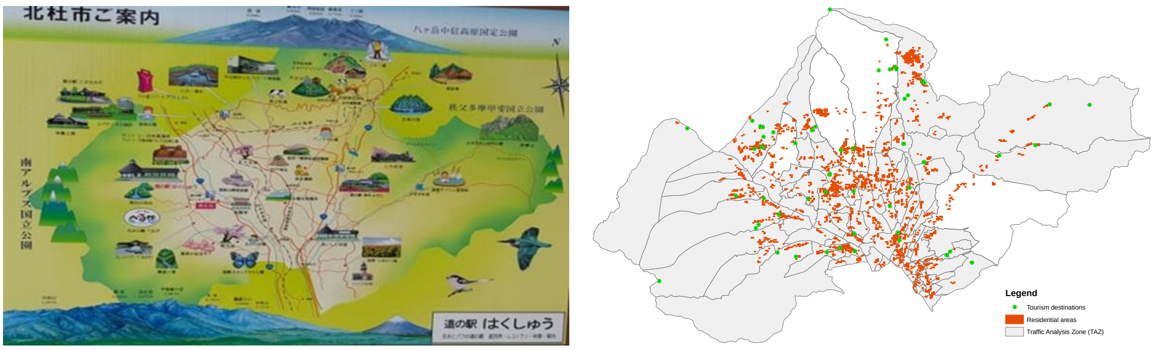


Figure 1-1 Spatial distribution of residential buildings and tourism facilities in Hokuto

Figure 1-1 shows the scattered distribution of tourism and residential facilities in Hokuto. There were 97 zones identified as administrative divisions in Hokuto. In particular, there were 15 tourism zones (including both residential areas and tourism areas) and 24 residential zones (only residential areas) in Yatsugatake area. There were 41 zones (including four tourism zones and 37 residential zones) and 17 zones (including seven tourism zones and 10 residential zones) in Kayagatake and Kai-Komagatake area, respectively. Figure 1-2 shows the spatial distribution of tourism and residential areas in three main geo-demographical areas in Hokuto.

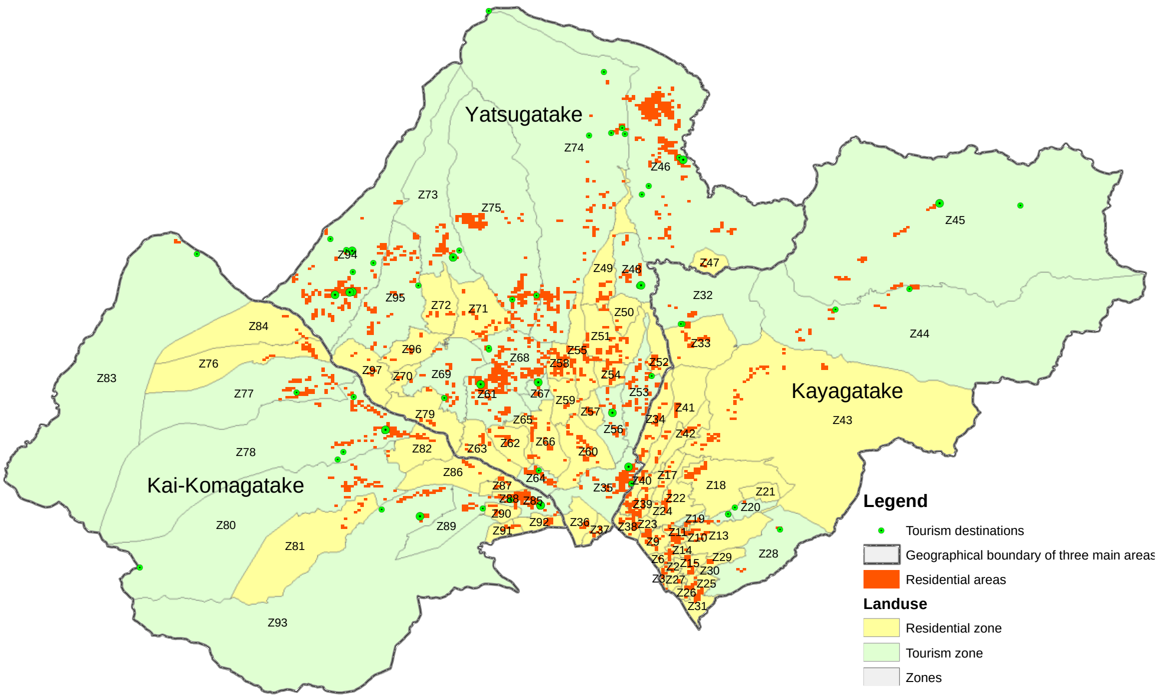


Figure 1-2 Tourism and residential zones in three geographical areas in Hokuto

There were 46,888 persons of which 51% of population was under 15 years and over 65 years old. According to Yamanashi tourism statistics, from 2015 to 2019, the number of visitors to Hokuto accounted for 10.6% to 12.5% of total visitors to Yamanashi prefecture. Overnight victors accounted for 21% to 25% of visitors to Hokuto. The number of visitors to Hokuto varied across seasons, was the highest in summers and lowest in winters. Moreover, the number of visitors and nonlocal residents visiting Hokuto on weekends was higher than on weekdays.

The supply of public transport within Hokuto was poor. There were 14 community bus routes with low frequency (refer to Figure 1-3). The number of taxies is very low, approximately 30 cars operated by 2 taxi operators in Hokuto. There were on average 57.8% of tourism facilities, 84.4% of local public facilities, and 69.6% of residential areas covered by transit service catchment, respectively. Moreover, there were 10 bus routes operating on weekends and holidays with service frequency significantly reduced. As a result, Hokuto might face transport gaps since a large rate of transit-dependent populations, higher number of visitors on the weekends, and poor public transport supply.

The transport gap was not fully understood in the existing literature. Most previous studies focused on measuring transport gaps in urban areas. The transport gap was rarely explored in rural areas, which are commonly characterized by low population density and poor public transport provision. Lack of understanding about transport gaps leads to many important questions from the planning perspective waiting for answers, such as how transport gaps vary over areas, time, and transport modes; and to what extent transport gaps need to be addressed.

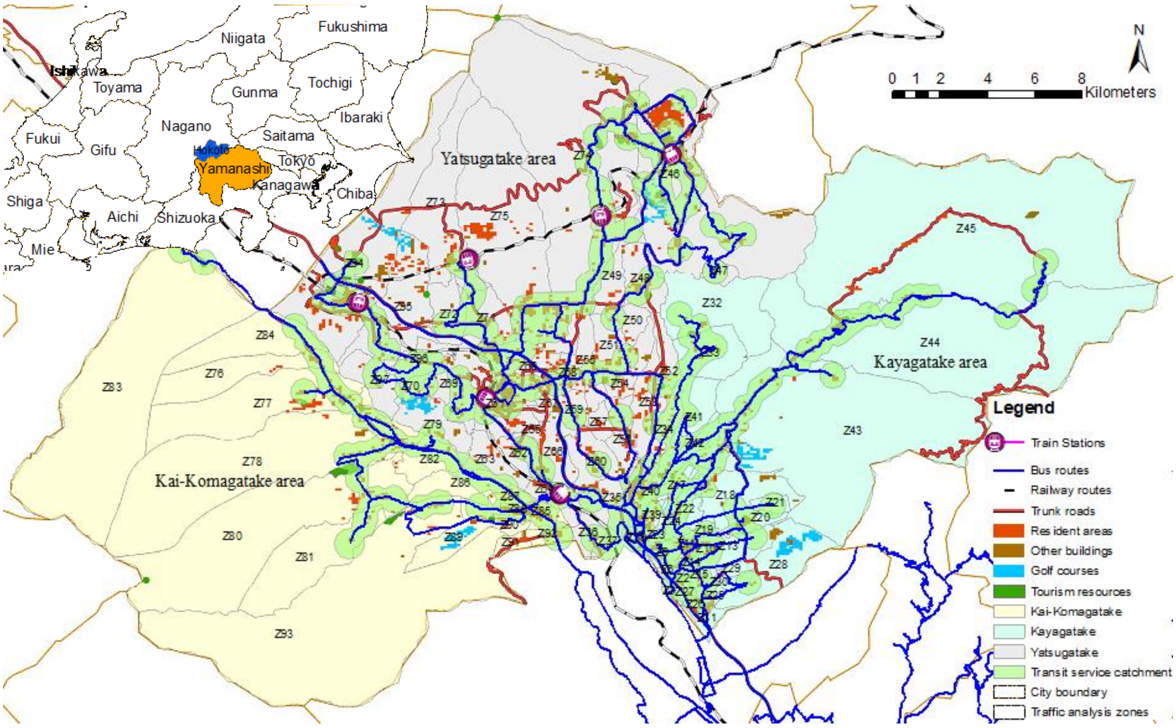


Figure 1-3 The public transport network and its service coverage in Hokuto

The transport gap reduction based on public transport improvement is a challenging problem for many rural areas. Recently, MaaS which integrates the existing transport services with new on-demand services (e.g., ridesharing, ride-sourcing, and on-demand bus), has created more alternative services and improved accessibility gaps in public transport service (Jiang et al. 2018; S. T. Jin et al. 2019; Murphy 2016; Wang 2018; Zhang and Zhang 2018). The introduction of MaaS appears to be a new opportunity for car-dependent reduction, public transport enhancement, and transport gap reduction in rural areas. The role of MaaS in satisfying user's needs and matching individual mobility to different transport options were widely acknowledged in literature, but its role in addressing the transport gap for an area is rarely explored. Many important questions from the planning perspective are thus waiting for answers, such as: what transport services are required to fulfill transport gaps; and how are their potential impacts on transport gap reduction.

In rural tourism areas, facilitating locals and tourists is one of the efficient ways to promote the local economic situation, enhance the attractiveness, and reduce or suspend the de-population. This study aims to identify transport gaps and use the identified transport gap as an indicator for evaluating the potential impacts of transport services and suggesting policies for improving transport gaps in rural tourism areas.

1.2. Motivations and objectives of the study

1.2.1. Research motivations

It is a challenging problem to provide the ease, convenience, and comfort of travelers to access a specific destination or social activity by traditional public transport services in rural areas. This is because enlarging spatial and temporal coverage of public transport is difficult in terms of operational efficiency and matching supply and demand in remote and scattered tourism areas. In this context, it requires more efficient and flexible transport services to meet the traveler's needs, especially travelers who cannot or do not want to drive or do not have access to cars to reach destinations or social activities.

Under MasS context, it provides on-demand services, more flexibility, convenience, and comfort of mobility as well as public transport enhancement in an area. However, there are gaps in understanding about the role of potential transport services integrated into MaaS in addressing transport gaps in an area. Moreover, the transport gap was not fully understood in the existing literature. The lack of understanding about transport gaps and the potential impacts of different services on transport gap reduction leads to many important questions from the planning perspective. This study aims to answer some important questions as follows.

- How do transport gaps vary over rural tourism areas, time, and transport modes?
- To what extent do transport gaps need to be addressed?
- What transport services are required to fulfill transport gaps?
- How does the transport gap vary across potential alternative services?

Findings from the research could be useful for policymakers and planners to resolve transport gap problems generally and particularly in rural tourism areas.

1.2.2. Research questions

The study aims to answer following specific and important research questions as follow:

Question 1: To what extent are transport gaps in rural tourism areas?

Most previous studies focused on measuring transport gaps in urban areas. The transport gap was rarely explored in rural tourism areas. The study addresses this research question by answering the following sub-questions:

- Where appear transport gaps in rural tourism areas?
- What transport gaps are different between a weekday and a weekend as well as during hours?
- To what extent do transport gaps need to be addressed?
- Which areas are priority to address transport gaps?

Question 2: What are potential impacts of transport services on transport gaps?

The literature recognized that MaaS had impacted on transport supply, accessibility, and user's mobility. As a result, the implementation of these services inevitably impacts the transport gaps of an area or region, but little is known about their impacts. Under MaaS concept, several on-demand services integrated into MaaS, such as on-demand bus or demand responsive transport, ridesharing, car-sharing, carpooling, and taxi are commonly concerned to enhance accessibility to rural areas. Particularly, among potential transport services integrated into MaaS, what transport service is required to fulfill transport gaps and how are its potential impacts on transport gap reduction are important questions waiting for answers. This study focuses on quantifying the impacts of potential on-demand services to inform policies and priority services for transport gap reduction. Specifically, this research question can be addressed by the following sub-questions:

- What transport services are required for improving transport gaps?

- How does the transport gap impact vary across potential alternative services?
- What are the services and policies recommended for improving the transport gaps?

1.2.3. Research objectives

This study aims to identify transport gaps and use the identified transport gap as an indicator for evaluating the potential impacts of transport services and suggesting policies for improving transport gaps in rural tourism areas. Particularly, there are two objectives as follows.

- **Objective 1:** Understand spatial-temporal transport gaps in rural tourism areas
- **Objective 2:** Explore the potential impacts of transport services on transport gaps

1.3. Scope of the study

In this study, Hokuto City, Yamanashi prefecture, Japan was selected as a case study for some reasons. First, Hokuto was known as a rural area with low population density, high rate of transit-dependent population, and poor public transport. Second, Hokuto was also known as a popular tourism area in Japan. However, most popular tourism and remote residential areas were separated from main towns, so it is important to improve the mobility and accessibility for both local residents and visitors.

The potential services used to develop policy scenarios were based on the existing public transport and ridesharing and/or on-demand bus, which were widely acknowledged in the literature. Transport demand models were built for a typical weekday so quantifying impacts of policy scenarios on transport demands at different hours and on weekends was limited. Analyses on user behaviors and preferences for different policy scenarios were also limited. Transport supply models mainly focused on spatial-temporal aspects of transport services. Travel costs or fares were not considered in quantifying the transport supply index. The value of private transport was assumed to be the same between the policy scenarios.

1.4. Structure of the study

The study was organized into eight chapters as follows.

Chapter 1 focused on the introduction of the study. The background, motivations, research questions, and objectives of the study were presented.

Chapter 2 illustrated a comprehensive literature review of related studies. First, the literature was conducted to provide a general understanding of transport gaps, MaaS concept, and the role of MaaS in transport gap reduction as well as to point out what have been studied and what have not been studied. Second, transport gap models and indicators were reviewed to construct the methodology for the current study.

Chapter 3 provided an overview of the analytical framework. First, this chapter presented the important linkages of the main research questions and objectives. Second, an overview of the methodology of whole study was presented. Transport supply, demand, and transport gap model and related indicators were also described in this chapter.

Chapter 4 focused on data preparation. All statistical data related to the demand model and supply model were described in this chapter.

Chapters 5 and 6 corresponded to the two primary research questions. The analytical results and major findings were presented in each chapter.

Chapter 7 integrated the results from all analytical pieces, summarized major findings and discussed planning and policy implications. The study ended with Chapter 8 that briefly summarized the whole dissertation and pointed to the next steps.

2. Literature review

This part aims to provide a comprehensive literature review of related studies. The part is based on a review of previously published studies and includes the following aspects. Firstly, different terms reflecting the concept of transport gap are reviewed from the literature. Moreover, quantitative measures and relevant indicators used for quantifying transport gap are reviewed from equity and mobility perspective. The research gaps are summarized from the reviews. Secondly, MaaS concept, its impacts on transport supply, accessibility, users' demands, and its potentials for transport gap reduction are reviewed. Finally, a summary is conducted to point out what have been studied and what have not been studied.

2.1. The transport gaps

2.1.1. The transport gap definitions

There were different terminologies used interchangeably to describe transport gap and different contributing factors. The following terms outlined some of the definitions used to reflect transport gap.

Transport poverty was defined as "*The process by which people are prevented from participating in the economic, political and social life of the community because of reduced accessibility to opportunities, services and social networks, due in whole or part to insufficient mobility in a society and environment built around the assumption of high mobility*" (Kenyon, Lyons, and Rafferty 2002). Poor accessibility and lack of transport services were the key aspects of transport poverty. Moreover, some studies clarified three aspects to represent transport poverty, including (1) the lack of transport options (i.e., private car and/or public transport); (2) poor accessibility resulting in the inability to reach daily activities or destinations by the existing transport options and/or within a reasonable amount of time; and (3) high transport costs (Allen and Farber 2020; Kong et al. 2021; Lucas et al. 2016; Martens and Bastiaanssen 2014).

Transport disadvantage was another term, that is commonly used to present the transport gap. Murray and Davis (2001) and Hurni (2004) described transport disadvantage as little or no access to public transport by comparing the distribution of public transport supply to the location of transit-dependent populations (Hine and Fiona Mitchell 2004; Murray and Davis 2001). Currie et al. (2009) have used the term 'transport disadvantage' to reflect the ability of access to the dispersed land-use (e.g., healthcare, working, shopping, and recreational locations) and inadequate transport services (e.g., no car access, lack of adequate public transport, and affordability) for disadvantaged people (Currie et al. 2009). Others offered a broader definition that includes the wider aspects of the transport system, such as temporal-spatial of transport services and travel costs and individual perceptions (Church, Frost, and Sullivan 2000; Lucas and Markovich 2016; Wixey, S., Jones, P., Lucas, K., & Aldridge 2005). Particularly, these studies referred to factors related primarily to public transport access as follows:

(1) Spatial - where travelers cannot access to desired locations or activities.

(2) Temporal - when people cannot access to desired locations at a certain time, for example, late evening or on weekends when bus services have reduced or stopped.

(3) Personal - including vulnerable individuals or personal safety concerns.

(4) Financial - high transport costs compared to travelers' incomes and ability to pay for transport services.

(5) Environmental - where people suffer from the negative impacts of transport, such as noise and air pollution or vehicle collisions.

(6) Infrastructural - where transport infrastructure occurs physical barriers such as a freeway dividing a community.

In addition, Jiao and Dillivan have used the term "transit desert" in 2013, which reflects the gap between public transport supply and demands. The gap was the result of the inequitable distribution of resources and services, which in turn fails to meet the accessibility needs of communities (Jiao and Dillivan 2013). Furthermore, the term "supply-demand gap" and "public transport gap" were also used to reflect the difference between public transport supply and demands (Bejleri et al. 2018; Chen et al. 2018; Cui et al. 2016; Farber, Ritter, and Fu 2016; H. Jin, Jin, and Zhu 2019; Kaeoruean et al. 2020; Kahrobaei 2015; Liu et al. 2020; Morency, Negron-Poblete, and Lefebvre-Ropars 2021; Peungnumsai et al. 2020; Wu, Pei, and Gao 2015a; ZHOU and ZHU 2007) and gaps in the supply of taxis and/or rideshared service (Inturri et al. 2021; Kashyap 2019; Ling, Lai, and Feng 2019; Yang et al. 2019). Most studies referred to physical gaps in transport system, particularly, capacity, services available (i.e., temporal-spatial service coverage of public transport, number of vehicles available, travel speed, travel time, and accessibility) and accessibility while several studies reflected transport gap from individuals' perception on transport system (Awaworyi Churchill and Smyth 2019; Currie and Delbosc 2010).

No matter the definition, the literature generally showed the three dimensions of transport gaps, including the lack of transport supply, poor accessibility, and individual dimension. The individual component considered travel demands, transport disadvantages (i.e., physical mobility, non-car ownership, aging people), and psychological aspects (i.e., safety, physical access to transport services). In this study, transport gap is conceptualized through the interactions between three main dimensions and is shown as Figure 2-1.

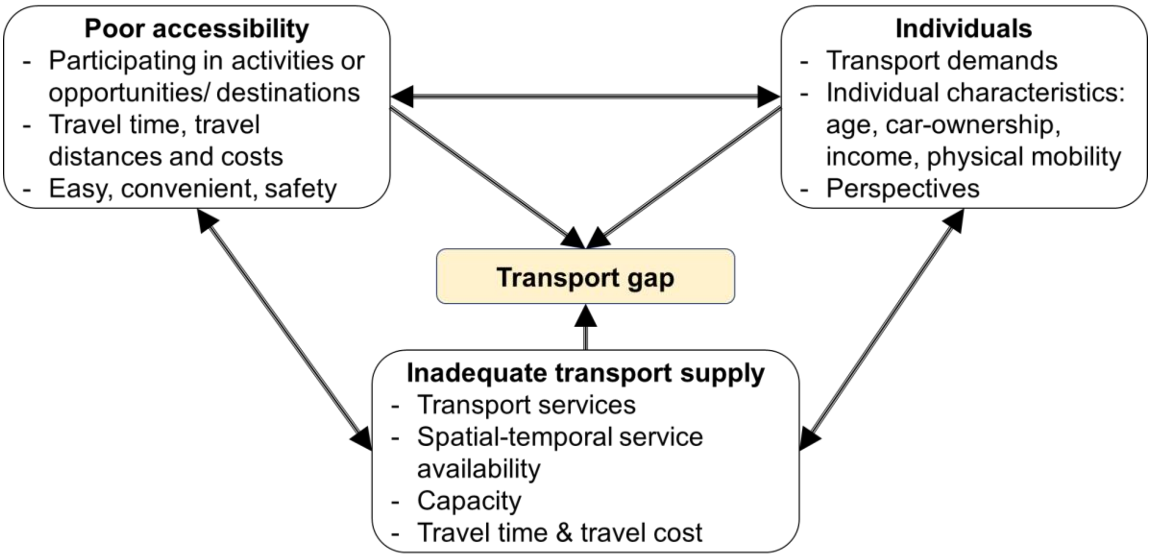


Figure 2-1 Interactions and indicators influencing transport gap

The lack of transport supply or lack of accessibility is a major barrier to individuals participating in activities (e.g., job, business, education, health, and recreation). A number of studies have demonstrated that the lack of transport supply might have negative impacts on individuals, who cannot or do not want to drive or do not have access to cars to reach destinations or social activities (Farrington and Farrington 2005; Verma and Taegen 2019), and consequently leads to social exclusion (Currie and Stanley 2008; Hine and Fiona Mitchell 2004; Mattioli 2014). Therefore, transport gap needs to be considered in the interactions between access to opportunities and access to transport supply-both personal mobility and accessibility. While accessibility referred to the "ease of reaching destinations", mobility reflected the "ease of moving" to all travelers. As a result, transport gap measurement should consider the interactions between three main dimensions and different influencing factors on each dimension.

2.1.2. Transport gap measures

Kamruzzaman et al (2016) and Pyrialakou et al (2016) have reviewed different measures to identify transport disadvantage and capture the relationships among disadvantage, social exclusion, and well-being from the equity perspective (Kamruzzaman et al. 2016; Pyrialakou, Gkritza, and Fricker 2016). Such measures can be categorized as deprivation-based measures, accessibility-based measures, and mobility-based measures, which aim to evaluate transportation systems and/or areas. This study focused on reviewing measures accounting for indicators related to transport supply and transport demands and approaches to identify transport gaps from both equity and mobility perspective. Table 2-2 represents the quantitative measures used for transport gap measurement in the literature.

Different indicators referring to transport supply and demands were used to analyze transport gap. For example, some studies utilized the number of transit-dependent populations as a representative for transit demands to figure out the extent to which transport gap improvement is critical to those groups (e.g., Bejleri et al., 2018; Cai et al., 2020; Carleton & Porter, 2018; Currie, 2004, 2010; Fransen et al., 2015; Jiao, 2017; Jiao & Cai, 2020; Jiao & Dillivan, 2013). Different to these scholars, some others utilized a part of actual travel demand such as smart car data (Lee, Nam, and Jun 2018), user's location data (Cai et al. 2020), or user's demand (Wu, Pei, and Gao 2015b). On the one hand, the transport supply included public transport, private transport, and other transport services (e.g., taxi and on-demand services). The public transport supply was measured by some indicators, such as service coverage, service frequency, and the number of transit routes (Al Mamun & Lownes, 2011; Cao et al., 2018; Chen et al., 2018; Currie, 2010; Jiao, 2017; Jiao & Cai, 2020; Jiao & Dillivan, 2013; Kaeoruean et al., 2020; Lee et al., 2018). In some cases, when an aggregated indicator of transport supply is considered, transport supply can be obtained by multiple transport services (Bejleri et al., 2018; Wu et al., 2015).

In a general approach, the values of transport supply and demand were determined and relatively compared to indicate areas or individuals/groups facing transport gap. A gap occurred when the supply value was smaller than the demand value. Since supply and demand values were often represented in different units, so a simple value subtraction cannot be used to directly calculate the gap between them. As a result, most studies based on a normalized value using a method such as min–max (e.g., Currie 2010; Toms and Song 2016) or z-score (e.g., Jiao and Dillivan 2013; Jiao 2017) or M-score (Kaeoruean et al. 2020) to project the value of transport demands and supply onto the same scale for comparison. There were some studies used the statistical analysis or regression model to clarify the difference between transport demands and supply (Farber et al. 2016; H. Jin et al. 2019; Ling et al. 2019; Oleyaei-Motlagh and Vela 2019).

Moreover, the gap between demand and supply varies not only across areas of transit service, but also over all time scales, including weekdays, weekends, and times of day.

Some studies measured dynamic transport gaps by considering the variations in transport demands at different times of the day or public transport supply based on timetable (Fransen et al. 2015; Kaeoruean et al. 2020; Lee et al. 2018; Ling et al. 2019).

The identified transport gap can be explained from both equity and mobility perspective. From the equity perspective, the results indicated the imbalanced distribution of transport supply among areas or individuals and/or population groups, which lead to un-meeting transport demands. From the mobility perspective, the results directly indicated the gaps in transport supply to meet transport demands.

In general, the previous studies provided a comprehensive understanding about measures to quantify the spatial-temporal transport gaps. However, these studies mostly focused on analyzing transport gaps in the urban context. Few studies have considered rural areas (Parolin and Rostami 2016; Pyrialakou et al. 2016). For example, Parolin and Rostami (2016) identified transport gaps for administrative subdivisions in the rural areas of New South Wales, Australia. The study measured transport supply based on the route length and service frequency of regional public transport (e.g., coaches, regional buses), community buses, and taxis. Parolin and Rostami (2016) took the number of transit-dependent populations as a representative of transport demand.

Table 2-1 The measures and indicators used for transport gap measurement

Studies	Areas	Transport demands and measures	Transport supply and measures	Transport gap measures	Perspective
(Ling et al. 2019)	Beijing, China	▪ Demands measured by the number of rider's requirements ▪ Mobility patterns explored from Global Positioning System (GPS) data of e-hailing services	▪ E-hailing service ▪ Supply measured by the number of drivers successfully responded to rider's requirements	▪ Gaps between demands and supply at peak hours on weekdays ▪ Non-linear support vector machine and back propagation neural network	Mobility
(Currie 2004, 2010; Currie and Senbergs 2007)	Metropolitan Melbourne, Australia	▪ Transport needs index measured by transport disadvantaged groups ▪ Demographic data (i.e., aging, low income, unemployment, and non-car ownership) from census data	▪ Public transport supply index measured by service coverage and frequency per week ▪ Public transport network data	▪ Need gaps index ▪ Relative comparison between normalized supply and needs index	Equity
(Sun and Thakuriah 2021)	England	▪ Job accessibility focused on households with low income and no-car ownership ▪ Demographic data (household income and car availability)	▪ Public transport availability index measured by service coverage, frequency on five weekdays, and populations within transit service coverage ▪ General Transit Feed Specification (GTFS) data (stops/stations, routes, and time services)	▪ Transport poverty index ▪ Relative comparison between level of job accessibility and public transport availability	Equity
(Jomehpour Chahar Aman and Smith-Colin 2020)	City of Dallas, Texas	▪ Transit demand index measured by the number of dependent populations ▪ Demographic data from United States Census Bureau	▪ Transit supply index accounting for service coverage, service frequency, and number of jobs accessible within time threshold ▪ GTFS data	▪ Transit desert index ▪ Relative comparison between normalized transit demand and supply index	Equity

Studies	Areas	Transport demands and measures	Transport supply and measures	Transport gap measures	Perspective
(Kaeoruean et al. 2020)	Calgary, Canada	▪ Transit demand measured by the number of realized and predicted transit riders per area (trip rate model) ▪ Data census and transit survey data	▪ Public transport supply index ▪ Supply indicators: bus/ train stops, service coverage, and hourly service frequency ▪ GTFS data	▪ Demand–supply gaps at different times of day ▪ Relatively comparing the normalized index (M-score) of transit demand and supply	Equity

(Brussel et al. 2019)	City of Bogotá in Colombia	▪ Actual working trips
		▪ Activity pattern data
			▪ Potential accessibility indicator measured by cumulative potential accessibility (Gravity-based measure)
			  ▪ Working-purpose trips
			  ▪ Within 60 mins of travel
			▪ Public transport systems (routes, schedules, etc.), transit trips, and travel times
				▪ Transport poverty
				▪ Relative comparison between actual and potential accessibility indicator
					Equity

(Kashyap 2019)	-	▪ Number of trip requirements by hourly accounting for ▪ Waiting time ▪ Uber data	▪ Service availability accounting for available drivers and waiting time	▪ Gap between supply and demand by comparing available drivers and trip requirements	Mobility
(Jiao and Dillivan 2013)	Four major U.S. cities	▪ Transit demand index measured by transport disadvantaged groups ▪ Demographic and car ownership data from census data	▪ Public transport supply index considering bus/ train stops, service coverage, number of routes, service frequency per week, and length of bike routes and sidewalks ▪ GTFS data	▪ Transit desert index ▪ Relative comparison between normalized supply and demand index	Equity

Studies	Areas	Transport demands and measures	Transport supply and measures	Transport gap measures	Perspective
(Chen et al. 2018)	Edmonton, Canada	▪ Transport demand index focused on senior population (over 65 years old) ▪ Census data	▪ Public transport supply index ▪ Partial least squares path modeling considering service coverage, frequency, service density, and number of stops reachable within 60 minutes ▪ Public transport systems (stops, routes, schedules, etc.) and travel times	▪ Public transport gap index ▪ Relative comparison between normalized supply and need index ▪ Lorenz curves and Gini coefficient	Equity
(Toms and Song 2016)	Jefferson County, Kentucky	▪ Transport needs index measured by transport disadvantaged groups ▪ Census data	▪ Public transport supply index ▪ Supply indicators: bus/ train stops, service coverage, and service frequency per week ▪ Public transport network data	▪ Need gaps index ▪ Relative comparison between normalized supply and need index	Equity
(Lee et al. 2018)	Seoul, Korea	▪ Demand index measured by actual public riders between O-D pairs ▪ Smart card data	▪ Supply index measured by travel time by public transport between O-D pairs ▪ Public transport network and timetable	▪ Public transport gap index by different time periods ▪ Relative comparison between normalized supply (travel time) and need index (riders)	Mobility
(Wu et al. 2015a)	Eight cities in China	▪ Demand index measured by the total number of trips for an area determined by households and activities ▪ Statistical and survey data	▪ Supply index measured by maximum amount of passenger carrying by rail, bus, taxi, and car ▪ Statistical and survey data	▪ Supply-Demand Ratio	Mobility

Studies	Areas	Transport demands and measures	Transport supply and measures	Transport gap measures	Perspective
(Al Mamun and Lownes 2011)	City of Meriden, Connecticut	▪ Transport needs index measured by transport disadvantaged groups ▪ Census data	▪ Public transport supply index measured transit accessibility ▪ Models: Time-of-day-based transit accessibility, transit capacity and quality of service manual measures, and local index of transit availability ▪ Public transport network data	▪ Public transport gap index ▪ Relative comparison between normalized supply and need index	Equity
(Jiao 2017)	Five major Texas cities	▪ Transport needs index measured by transport disadvantaged groups ▪ Census data (disadvantaged population and vehicle available)	▪ Transit supply index accounting for transit stops, frequency, transit routes, length of sidewalks and bikes, low speed limit roads, and intersection density	▪ Transit desert index ▪ Relative comparison between normalized supply and need index	Equity
(Cao et al. 2018)	Guangzhou, China	▪ Demand index ▪ Socioeconomic (disadvantage population) and land-use data (No. of public facilities within walking and bicycle distance)	▪ Transit supply index ▪ Geospatial Data Cloud and Baidu map and Amap (stops/ stations, routes, and frequency)	▪ Public transit gap index ▪ Relative comparison between normalized supply and need index ▪ Lorenz curves and Gini coefficient	Equity
(Cai et al. 2020)	Wuhan Metropolitan Area, China	▪ Demand index measured by transit-dependent commuters among the commuting flows between communities ▪ Baidu users' location data (origin-destination data) and official demographic census	▪ Transit supply index accounting for transit stops, frequency, transit routes, length of sidewalks and bikes, low speed limit roads, intersection density, and total transit capacity	▪ Transit gap index ▪ Relative comparison between normalized supply and demand index	Equity

Studies	Areas	Transport demands and measures	Transport supply and measures	Transport gap measures	Perspective
(Parolin and Rostami 2016)	Rural Areas of New South Wales (NSW), Australia	▪ Transport needs index measured by transport disadvantaged groups ▪ Census data (disadvantage population and vehicle available)	▪ Supply index measured by length of routes (rail, bus, regional bus, non-commercial school bus, and community services) and frequency ▪ NSW Bureau of Transport Statistics	▪ Transport disadvantage index ▪ Relative comparison between normalized supply and transport needs index	Equity
(Fransen et al. 2015)	Flanders, Belgium	▪ Public transport needs index based on disadvantage populations ▪ Socio-demographic data	▪ Public transit supply measured by potential accessibility within different time thresholds ▪ Cumulative potential opportunity (Gravity-based) ▪ Public transport systems (routes, schedules, etc.), transit trips, and travel times	▪ Public transport gap index at different times of day ▪ Relative comparison between normalized supply and demand index	Equity
(Bejleri et al. 2018)	Alachua County, Florida	▪ Demand index measured by disadvantage populations ▪ Demographic data and National Household Travel Survey	▪ Transportation supply measured by public transport, taxi, and on-demand bus accounting for ▪ Number of populations covered by public transport, on-demand, and taxi services	▪ Transportation service gap index ▪ Relative comparison between normalized supply and demand index	Equity
(Pittman and Day 2015)	Canberra, Australia	▪ Demand index measured by disadvantage populations and potential accessibility	▪ Public transport supply index ▪ Supply indicators: bus/ train stops, service coverage, and service frequency per week	▪ Transport disadvantaged index ▪ Relative comparison between normalized public	Equity

Studies	Areas	Transport demands and measures	Transport supply and measures	Transport gap measures	Perspective
		▪ Level of accessibility: Cumulative potential job opportunity (Gravity model) ▪ Demographic data	▪ Public transport network data	transport supply and demand index	
(Oleyaei-Motlagh and Vela 2019)	New York City	▪ The realized demands of taxi service measured by the number of satisfied demand (pickups) ▪ GPS sensor from taxi and weather data	▪ Supply measured as the number of taxis operate at the city in sum	▪ Mismatch between demand and supply measured by statistical tests (nonparametric test of Mann-Whitney)	Mobility
(Farber et al. 2016)	Wasatch Front, Utah	▪ Travel patterns: the spatial-temporal travel patterns for different social groups (the origin and destination, and travel time) ▪ Utah household travel survey and UTA Onboard Survey	▪ Transit supply index measured by travel time and travel speed ▪ Utah Transit Authority (UTA) GTFS data: travel time for a weekday and weekend	▪ Transit gap by individual, household, and trip-type characteristics ▪ ANOVA and multivariate ordinary least squares (OLS) regression	Equity
(Cui et al. 2016)	Harbin, China	▪ Taxi passenger travel patterns at time periods of a day ▪ Measures: total number of the trips average travel speed and route directions ▪ GPS taxi data	▪ Transport network performance measured by travel time and travel speeds	▪ Areas with mismatch between supply and demands ▪ Comparison between demand and supply indicators	Mobility
(H. Jin et al. 2019)	Beijing, China	▪ Number of regular transit riders ▪ Location Maximum Likelihood Estimation ▪ Smart card data and data census	▪ Location of train stations	▪ Relative comparison between the spatial distribution of regular transit riders and bus/ train stations ▪ Cell Space Collector	Mobility

Studies	Areas	Transport demands and measures	Transport supply and measures	Transport gap measures	Perspective
(Peungnumsai et al. 2020)	Bangkok Metropolitan Region	▪ Demand index measured by total trip generations ▪ Trip generation model (Trip rate) ▪ Data census and travel demand survey	▪ Supply index measured by total number of the capacity of public transportation services (Rail, bus, van, taxi, boat, train) ▪ Open Street Map and Bangkok Mass Transit Authority	▪ Public transport supply–demand gap index measured by relatively comparing normalized supply and demand index on a weekday ▪ Lorenz curves and the Gini coefficient	Equity
(Pyrialakou et al. 2016)	Urban and rural areas in India	▪ Transport need index measured by disadvantaged groups ▪ Socioeconomic and demographic data	▪ Public transport supply index measured by levels of accessibility within the travel time and/or distance ▪ Potential opportunity measures (Gravity model)	▪ Need gap index on a weekday ▪ Relative comparing between transport demand index and level of accessibility	Equity
(Morency et al. 2021)	Montréal, Canada	▪ Demand measured by passenger-kilometers traveled by each transport mode ▪ Travel survey data (Origin-destination trip survey)	▪ Supply measured by total space estimated for each transport mode (pedestrian, cyclist, public riders, cars)	▪ Needs-gap index for each transport mode at morning peak hours ▪ Relative comparison between observed space and total space supply for each mode	Mobility

2.1.3. Indicators associated with transport supplies

Table 2-2 showed that transport supply index was measured by a wide range of indicators, e.g., direct or indirect. Rood's (1998) directly measured the level of transit supply for census tracts from route coverage, service frequency, and transit capacity. Most reviewed studies have determined the transit supply based on the number of transit stops, service frequency, and spatial service coverage (Cao et al. 2018; Carleton and Porter 2018; Currie 2010; Toms and Song 2016). In empirical research, some studies have combined a number of indicators into one aggregated indicator. This approach has been recognized in studies of Jiao (2017), Jiao & Cai (2020), and Jiao & Dillivan (2013) in some American and Chinese cities. These studies combined the indicators of the density of bus stops, service frequency, number of transit routes, the total length of sidewalks, bike routes, low-speed limit roads, and transit capacity.

In some cases, indirect indicators were used to represent the value of transport supply, for example, average travel time and/or travel speeds (Farber et al. 2016; Lee et al. 2018), number of services available (Ling et al. 2019; Oleyaei-Motlagh and Vela 2019), capacity (space) of transport system (Morency et al. 2021), the number of jobs and facilities which are accessed within a time threshold (Fransen et al. 2015; Jomehpour Chahar Aman and Smith-Colin 2020; Pyrialakou et al. 2016). Most studies focused on a particular service (i.e., public transport or taxi) to present transport supply index.

There were few studies including transit and other transport services to quantify the level of transport supply. For instance, the study by Wu et al. (2015) has considered public transport, taxi, and private transport to generate a comprehensive transport supply index. However, this study did not consider spatial-temporal transit service coverage. Another study measured transport supply by combining public transport, taxi, and on-demand, but this study did not consider temporal service coverage (Bejleri et al. 2018; Peungnumsai et al. 2020). In addition, Parolin and Rostami (2016) measured transport supply index from the length of service routes and service frequency per week for transit services, regional buses, school buses, and subsidized taxi services; however, the spatial service coverage of these services did not consider (Parolin and Rostami 2016). Although multiple services were considered in the abovementioned studies, the impacts of the integration of services on transport supply index and demand index as well as transport gap did not consider.

2.1.4. Indicators associated with transport demands

The transport demand index can be measured from either the number of transit dependent populations as potential demands or the observed trips. The transit dependent populations included young people, elderly, non-car ownership, low-income, disable, and unemployed. For instance, the transport demands can be derived from the number of transit-dependent populations, disadvantaged groups and those maybe rely on public transport to reach designed activities (Bejleri et al. 2018; Cai et al. 2020; Carleton and Porter 2018; Currie 2004, 2010; Fransen et al. 2015; Jiao 2017; Jiao and Cai 2020; Jiao and Dillivan 2013). In these studies, populations are based on demographic data from data census. The populations were generally aggregated into census tracts, traffic analysis zones, and sub-administrative divisions in a city.

Furthermore, transport demands were explored from actual transport demands. In particular, several studies used smart car data (H. Jin et al. 2019; Lee et al. 2018), GPS data (Cui et al. 2016; Ling et al. 2019; Oleyaei-Motlagh and Vela 2019), user's location data

(Cai et al. 2020), and travel survey data (Brussel et al. 2019; Cai et al. 2020; Lee et al. 2018; Wu et al. 2015b) to estimate the realized transport demands. In addition, the number of trips generated from an area, which is identified according to the traditional four-step model, was considered to measure transport demand index (Cai et al. 2020; Morency et al. 2021; Peungnumsai et al. 2020). Other indirect indicators were also used to measure transport demand index, such as cumulative potential accessibility (Pittman and Day 2015), travel time and speeds (Cui et al. 2016), and passenger-kilometers traveled (Morency et al. 2021).

The study by Farber et al (2016) has considered the relationship between individual characteristics and transport supply to explain the transport gap (Farber et al. 2016). Although transport demands were determined, all previous studies did not consider the demands of nonlocal residents. Identifying the total number of trips generated and attracted to each zone is an important step in transportation planning activities. The trip productions and attractions are commonly measured for the residents and non-local residents, who are either outside of local area or visitors. There are some factors associated with trip productions and attractions. These factors can be roughly categorized into three groups, including socioeconomic characteristics, built environment/land use variables, and accessibility. Table 2-2 summarizes factors significantly associated with trip generations and attractions.

Table 2-2 Explanatory factors associated with trip generations and attractions

Factors	Description	References
Populations	Number of populations at zone	(Chen et al. 2021; Sofia, Hamsa, and Al-Zubaidy 2011; Juan and Luis, 2011)
Geographical	Urban and rural area	(Jayasinghe et al. 2017)
Road density	Total road length per 1km2 (Km/Km2)	(Chen et al. 2021)
Land-use type	Residential, commercial and business, industrial, and mixed land	(Chen et al. 2021; Jayasinghe et al., 2017)
Residential density	Ratio of residential building area and total area of a zone (%)	(Jayasinghe et al., 201)
Public facilities	Number of public offices, schools, hospitals, post offices, social welfare facilities within a zone	(Chen et al. 2021; Yang et al. 2020; Christian 2021; Sun et al., 2014)
Recreational facilities	Number of tourism facilities, culture facilities, museum, and recreational facilities within a zone	(Sun et al. 2014; Yang et al. 2020; Christian 2021)
Service coverage	Areas of residential building covered by public transport services (%)	(Wang et al. 2016)
Bus frequency	The mean of bus arrivals to a zone measured from transit timetable	(Chen et al. 2021)
Train frequency	The number of train arrivals to a zone during hour on a weekday as timetable	(Chen et al. 2021)

Access distance	Distance from a central point of zone to the nearest train station (km)	(Chen et al. 2021)
Distance	Average travel distance between a zone to inner urban center (km)	(Chen et al. 2021; Kim et al. 2013)
Accessibility	Utility-based measure accounting for all existing transport services	(Chen et al. 2021; Cordera et al. 2017)

It is widely acknowledged that socioeconomic characteristics are strongly associated with trip generations and attractions in each area. The most used socioeconomic explanatory includes vehicle ownership, household size, number of workers, number of populations and/or population density. The built environment and land use factors commonly reflected population density, buildings and public facilities, geographical aspects (e.g., urban, rural), and land-use characteristics (e.g., commercial, industrial, residential, and mixed land-use). The built environment factors, including the number of facilities, spatial-temporal service coverage of public transport, travel distance, and access distance have significant impacts on total trip generations and trip generations for different purposes (Chen et al. 2021; Sun et al. 2014; Yang et al. 2020; Zhang et al. 2019).

2.1.5. Summary

In the literature different terminologies have been referred to transport gap, namely transport poverty, transport disadvantage, transport gap, supply-demand gap, and transport desert. Although different definitions were used, transport gap generally referred to a lack of transport supply, poor accessibility, and individual aspects. A lack of transport supply referred to no car access, unavailable services, lack of spatial-temporal coverage of public transport, lack of capacity, and affordability. Poor accessibility referred to the inability to reach daily activities (e.g., healthcare, working, shopping, and recreational locations) by existing transport options and within a reasonable amount of travel time or distance. Individuals referred to transport demands and accessible needs, transport disadvantages (i.e., physical mobility, non-car ownership), and psychological aspects (i.e., safety, physical access to transport).

The transport gap is described in the interactions between three main dimensions. The lack of transport supply or a lack of accessible opportunities were major barriers to individuals participating in activities (e.g., job, business, education, health, and recreation), especially, populations who cannot or do not want to drive or do not have access to cars. Therefore, transport gap measurement should consider the interactions between three main dimensions and different influencing factors on each dimension. From both equity and mobility perspective, transport gap was generally measured by relatively comparing transport supply and demand index, which are estimated and normalized. Indicators considered in transport gap measurement are summarized in Table 2-3.

Table 2-3 The indicators associated with transport gap measurement

Transport services	Transport supply							Transport demands					Areas	
	Infras tructure	No. of drivers (vehiles)	Spatial coverage	Fre-quency	Capacity	Access ibility	Travel time	Disadvantage populations	Realized demands	Predicted demands	Travel time	Access ibility	Urban	Rural
Public transport	O	∇	O	O	O	O	O	O	O	O	O	O	O	O
Taxis/on-demands	O	O	O	∇	O	∇	∇	∇	O	O	∇	∇	O	∇
Multiple services	O	O	O	O	O	∇	∇	O	∇	∇	∇	∇	O	∇
Service integration	∇	∇	∇	∇	∇	∇	∇	∇	∇	∇	∇	∇	∇	∇

O: Consideration; ∇: Not consideration

There were some limitations in the existing literature as follows.

- Most previous studies focused on analyzing transport gaps in the urban context while few studies considered rural areas.
- Transport gap measurement focused mainly on public transport. Although multiple services were considered, the impacts of the integration of multiple services on transport supply index and demand index as well as transport gap did not consider.
- In terms of indicators associated with transport supply measurement, infrastructure (i.e., road network, bus/train stations, and bike/walking length), the number of vehicles (drivers) available, the spatial-temporal service coverage of public transport, and capacity were the main indicators. Accessibility was just considered for public transport while other services and the integration of different services were not considered. Other important indicators, such as transport costs and travel time were also not considered.
- The previous studies focused on local demands while the demands of nonlocal residents and tourism/ recreational demands did not consider yet.

2.2. Mobility as a Service and its potential impacts

2.2.1. Mobility as a Service concept

Mobility as a Service (MaaS) is considered as an innovation mobility concept. The first definition of MaaS was defined as "*a mobility distribution model that deliver users' transport needs through a single interface of a service provider*" (Hietanen 2014). The different definitions and descriptions of MaaS were comprehensively reviewed by several studies (Arias-Molinares and García-Palomares 2019; Jittrapirom et al. 2017; Sochor et al. 2018).

However, no matter the definition, MaaS concept aimed to integrate on-demand services, such as taxi, carsharing, bike-sharing, ridesharing, ride-hailing, and demand-responsive services with public transport services (PuT) to offer user-oriented mobility options, providing travel information, payment, and ticketing on and through a single platform. Consequently, MaaS allowed users to focus on integral mobility solutions instead of modes of transport (Finger, Bert, and Kupfer 2015), which also leaded to a shift from ownership-based to access-based transportation (Jittrapirom et al. 2017). Two intrinsic characteristics of MaaS make it different from both conventional public and private mobility options: it is demand based and it does not require the traveler to own the vehicle. Figure 2-2 illustrates an example of MaaS platform with different integrated services.

Sochor et al provided four levels of integration behind the MaaS concept (Sochor et al. 2018). The first level denoted information integration that supports users in finding travel information. The second level integrated booking and payment for single trips while the third level focused on the provision of multimodal services and packages. All three first levels improve access to transport services and support users in identifying and choosing between alternative services. The last level represented policies and societal goals integrated into MaaS service. A MaaS ecosystem was built on the interactions between users, transport service providers (TSPs), a MaaS platform operator (MPO), public authorities, and other related partners (Jittrapirom et al. 2017). The users provided trip requests, including a pick-up point, drop-off point, departure and/or arrival time interval, and mobility preferences. The TSPs included (1) PuT providers (i.e., buses and trains) operated by fixed routes, predefined service frequency, and fares; (2) on-demand service providers operated by a fleet of vehicles, flexible operational plans, and fare policies. The MPO played a role in connecting the TSPs and users by integrating different TSPs to design mobility options according to user preferences and personalization of mobility services that optimally adjust to user needs.

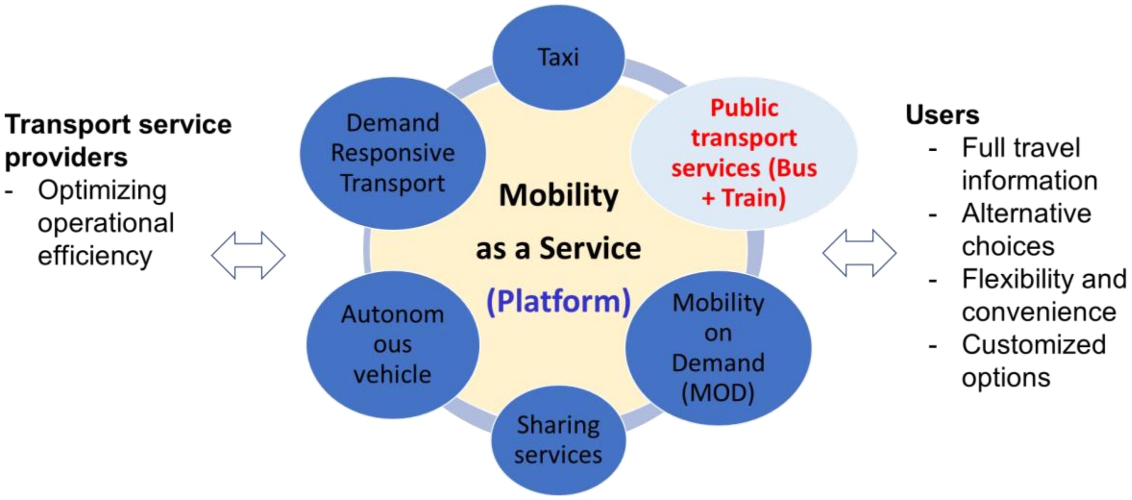


Figure 2-2 Transport services related to MaaS

A MaaS framework was inherently market-oriented, encompassing interactions between demand and supply, competition among TSPs, and shared economy. User demands can be adequately addressed by a user-oriented approach, considering user preferences (Giesecke, Surakka, and Hakonen 2016; Jittrapirom et al. 2017). On the other hand, the TSPs can maintain profitability while keeping supply and demand balanced by operational strategies, such as dynamic pricing or balancing empty vehicles (MItchell 2008). It was highlighted that understanding MaaS market is important to define the role of policies and government involvement towards fair competition and societal objectives, such as network efficiency and accessibility (Wong, Hensher, and Mulley 2018).

2.2.2. Impacts on accessibility

Accessibility, a core concept of urban and transportation planning, has been widely studied theoretically and empirically. The definitions of accessibility take assorted forms with consideration from different perspectives, including "the potential of opportunities for interaction" (Hansen 1959); "the extent to which land-use and transport systems enable (groups of) individuals to reach activities or destinations by means of a (combination of) transport mode(s)" (Geurs and van Wee 2004); and "the ease of reaching goods, services, activities and destinations" (Litman 2008). Geurs & Wee (2004) identified four interrelated components of accessibility: land-use, transportation, temporal, and individual component. Among the four components of accessibility, the emergence and expansion of MaaS will directly influence the transportation component and individual's behaviors in the short term, but in the long term, MaaS may also influence the temporal and land use components of accessibility (Rantasila 2015).

In MaaS context, accessibility is considered as the ease of utilizing the integrated transport services to reach desired activities and destinations. The improvement of accessibility is mainly caused by changes in transport supply structure (e.g., the frequency, travel time and travel distance designated in advanced for each transport mode in the service packages offered by the MPO to users); the flexibility of available transport alternatives; operational plans (e.g. flexible pricing scheme and the integration of flexible shared mobility services with fixed PuT to maximize travel choices and cost efficiency); user information (i.e. real-time travel information, pricing and time options, recommended routes/modes); and ticketing and payment integration (i.e. the ease of transferring between different transport modes), which in turn influence travel demands such as the likelihood of using MaaS service.

Accessibility generally included both physical and psychological indicators. The former reflected travel time, distances and costs to reach spatial-temporal activity patterns by a particular transport mode (Geurs and van Wee 2004; Litman 2008; Páez, Scott, and Morency 2012; Saif, Zefreh, and Torok 2018). In multimodal transport, indicators were added to the number of transfers, transfer time, waiting time, access/egress time to desired stations or locations (Kumar, Bosch, and Brussel 2011). The latter reflected user's perception on safety, security, comfort, available information, and their perception on physical indicators through utilizing transport services (Geurs and van Wee 2004; Lättman, Friman, and Olsson 2016). Both physical and psychological indicators were crucial to be considered as the goal in transport planning. Accessibility was an important indicator that reflects the interests of different stakeholders in MaaS (Tong et al. 2019; Wen et al. 2018a). The TSPs generally provided physical infrastructure, facilities, and services described as physical indicators based on user demand. In contrast, users' perceptions of safety, security, comfort, available information, and their perception of initial physical indicators were formed through utilizing transport infrastructure, facilities, and services. Users decided whether to utilize transport services at a later time based on their psychological evaluation of physical accessibility indicators. For example, Went el al (2018) presented supply-demand interactions through accessibility indicators, indicated that changes in supply parameters regarding vehicle fleet sizing, vehicle capacity, fare policy and hailing policy (on-demand or in-advance request) of shared autonomous vehicles (SAVs) impact not only waiting time and travel costs for users but also influencing service rate and mode share of both SAVs and PuT operator (Wen et al. 2018a).

2.2.3. Impacts on user demands

Based on travel survey results, several studies pointed out that car users and frequent car users were less adoption in MaaS while non-car users and frequent public transport users were the most likelihood to adopt MaaS (Alonso-González et al. 2020a; Fioreze, de Gruijter, and Geurs 2019a; Ho et al. 2018a; Ho, Mulley, and Hensher 2020a; Robinson 2018; Storme et al. 2020) and multimodal users were high intention to use MaaS (Fioreze et al. 2019a), (Alonso-González et al. 2020a). Furthermore, the most potential users in MaaS came from young people while elderly people were less likely to take up MaaS offerings (Alonso-González et al. 2020a; Casadó et al. 2020; Durand and Harms 2019; Ho et al. 2020a; Jittrapirom et al. 2017). The MaaS services also targeted to visitors as potential users. However, very little information was available for visitor behaviors under MaaS context.

Several studies exploring the results of MaaS pilots (e.g., Ubigo and Whim) indicated that simplicity, ease of access, comfort, flexibility, travel time, and travel costs were primary indicators leading to changes in users' behaviors (Fioreze, de Gruijter, and Geurs 2019b; Harms, Durand, and Hoogendoorn-Lanser 2018; Sochor, Karlsson, and Strömberg 2016). Furthermore, users' attitudes toward willingness to share and multimodal mobility were important indicators of the likelihood of using MaaS (Alonso-González et al. 2020b; Caiati, Rasouli, and Timmermans 2020; Fioreze et al. 2019b; Monzon, Lopez-Carreiro, and Lopez 2019; Schikofsky, Dannewald, and Kowald 2020; Ye, Zheng, and Yi 2020; Zijlstra et al. 2020). Moreover, the pricing schemes and amount of travel distances and/or hours predefined for each transport service influence users' preferences for MaaS packages (Caiati et al. 2020; Feneri, Rasouli, and Timmermans 2020).

Previous studies developed logit models to explore the willingness to pay (WTP) for different MaaS packages, showing that travel cost, travel time, and waiting time are important indicators affecting the WTP (Guidon et al. 2020; Ho et al. 2018b; Ho, Mulley, and Hensher 2020b; Liljamo et al. 2020; Ratilainen 2017). A user's preference for transport services in MaaS packages was another important indicator of WTP. Particularly, PuT services had significantly higher WTP than current market values, while bike sharing, car sharing, and taxi were significantly lower (Guidon et al. 2020; Ratilainen 2017). Feneri et al (2020) studied the impacts of MaaS on mode choice behaviors and indicated that monthly fees and discounts impacted the tendency to use a specific mode included in the MaaS packages (Feneri et al. 2020). Travel time, access time, waiting time, number of transfers, and fare schemes were key indicators that impact users' mode choices (Cangialosi, Di Febbraro, and Sacco 2016; Jamal et al. n.d.; H. K. R. de F. Pinto et al. 2018). In addition, schedule delays and transfer penalties (Nam et al. 2018), available bikes or parking (Ma et al. 2019a; Nam et al. 2018), and road pricing schemes (Salazar et al. 2018) were important indicators that impact users' behaviors.

Moreover, Narayan et al (2020) developed an agent-based model (ABM) considering total travel time (walking time, waiting time, and in-vehicle travel time), fare, travel distance, and number of transfers to model multimodal route choices; however, the model could not consider the influence of user preferences on mobility options (Narayan et al. 2020a). In their study, the user demands were adjusted by changes in travel time, waiting time, fare policies, and operational plans through iterations implemented in the ABM. Furthermore, Liu et al (2019) considered the impact of waiting time on the choices of bike-sharing and ride-sharing to public transport stations (L. Liu et al. 2019a). Wen et al (2018) and Printo et al (2020) improved the simulation models and considered the assumptions of user preferences for estimating travel demand in a multimodal context, but these analyses focused on the operation of autonomous vehicles (AVs) (Pinto et al. 2020; Wen et al. 2018b).

In summary, user demands toward MaaS were impacted by both psychological and physical accessibility indicators. The former was mainly related to simplicity, ease of access, comfort, flexibility, perceived travel time, travel costs, and users' willingness to share. In addition, user preferences for different transport services integrated into service packages also affected the likelihood of using MaaS. The latter primarily focused on travel time, access time, waiting time, number of transfers, and fare schemes.

2.2.4. Impacts on transport service providers

In general, the TSPs considered the vehicle fleet size, transfer locations, fares, and operational costs of shared mobility services and the service frequency and fares of PuT services in their operational processes (refer to Table 2-4). Wen et al (2018) identified the vehicle fleet, vehicle capacity, operational policy, and fare policy for AVs based on user demands (Wen et al. 2018b). Similarly, Narayan et al (2020) modeled the interactions between demands and supplies to determine fleet size, fare, and the level of service (waiting time and travel time) for the operation of ride-sharing services (Narayan et al. 2020a). Moreover, several studies considered the transfer locations (L. Liu et al. 2019a; Posada, Andersson, and Häll 2017; Salazar et al. 2018), and unavailable bike and parking spots (Hebenstreit and Fellendorf 2018) to model the operational plans of the TSPs.

Table 2-4 Supply indicators accounted for in modeling

Supply-side indicators	References
Physical indicators	
Fares, fleet sizes, capacities, and indicators related to operational plans	(L. Liu et al. 2019a; Narayan et al. 2020a; Shen, Zhang, and Zhao 2018a; Wen et al. 2018b)
Fleet sizes, capacities, PuT frequency, and transferring locations	(Chen and Nie 2017; Luo et al. 2018; Ma 2017; Pinto et al. 2020; Posada et al. 2017; Salazar et al. 2018; Vakayil, Gruel, and Samaranayake 2017)
Available bikes and parking spots	(Hebenstreit and Fellendorf 2018; Luo et al. 2018; Nam et al. 2018)
Psychological indicators (Drivers)	
Detour constraints and waiting time	(Aissat and Varone 2015; Levin et al. 2019a; Luo et al. 2018; Masoud et al. 2017; Pinto et al. 2020; Salazar et al. 2018; Shen et al. 2018a)
Detour constraints, waiting time, and perceived profits	(Djavadian and Chow 2017a; Fahnenschreiber et al. 2016)

Price was an important indicator of TSPs. Wischik (2019) determined the price of ride-sharing based on user demands and PuT fare (Wischik 2019). In addition, the study by Went et al (2018) applied the fare, including base fare, per-unit-time fare, per-unit-distance fare, discount for sharing and transferring for modeling the operation of AVs (Wen et al. 2018b), while other studies considered fare as cost per unit distance or time (X. Li et al. 2018a; Masoud et al. 2017; Nam et al. 2018; Narayan et al. 2020a; Pinto et al. 2020; Posada et al. 2017; Shen et al. 2018a). Furthermore, additional road pricing was considered by Salazar et al (2018) in modeling the assignment of user requests to mobility options (Salazar et al. 2018). The operational costs of the TSPs were modeled by the total travel time (Cangialosi et al. 2016; Narayan et al. 2020a; Pinto et al. 2020), and travel distance (Pinto et al. 2020; Posada et al. 2017) as well as generalized costs (time, distance, maintenance, energy costs, and fare) (Chen and Nie 2017; L. Liu et al. 2019a; Salazar et al. 2018; Shen et al. 2018a; Wen et al. 2018b).

On the contrary, some studies considered the perspective of service providers, particularly drivers' perspectives toward detour constraints (maximum distance and/or time) and maximum waiting time (Aissat and Varone 2015; Levin et al. 2019a; Luo et al. 2018; Masoud et al. 2017; Pinto et al. 2020; Salazar et al. 2018; Shen et al. 2018a) as well as expectations for perceived benefits (Djavadian and Chow 2017a; Fahnenschreiber et al. 2016) to describe the availability of shared mobility services.

2.2.5. Impacts on MaaS platform operator

A primary operational task of the MPO was to match users' requests to available service providers, which are either on-demand service, PuT services, or an integration of both services through vehicle dispatching, idle vehicle relocation, and route planning process. The modeling objectives of the MPO are described in Table 2-5.

Table 2-5 Modeling objectives of platform operation

Objectives of modeling	References
Minimize travel time for both users and drivers	(Aissat and Varone 2015; Hebenstreit and Fellendorf 2018; Jamal et al. n.d.; Levin et al. 2019a; Luo et al. 2018; Narayan et al. 2020a; Varone and Aissat 2015; Wright, Nelson, and Cottrill 2020)
Minimize users' travel time and maximize drivers' matching rate	(Cangialosi et al. 2016; Ma 2017; Nam et al. 2018; Stiglic et al. 2018a)
Minimize users' travel time and providers' operational costs	(Chen and Nie 2017; Fahnenschreiber et al. 2016; Liang, Correia, and van Arem 2016; L. Liu et al. 2019a; Ma et al. 2019a; Masoud et al. 2017; Pinto et al. 2020; Posada et al. 2017)
Maximize social welfare for both users and drivers	(Djavadian and Chow 2017a; Salazar et al. 2018)

The dispatching processes considered the users' travel time and drivers' detour time and waiting time to provide a journey by minimizing the total travel time for both users and drivers (Aissat and Varone 2015; Hebenstreit and Fellendorf 2018; Jamal et al. n.d.; Levin et al. 2019a; Luo et al. 2018; Narayan et al. 2020a; Varone and Aissat 2015; Wright et al. 2020), and maximizing the matched users (Cangialosi et al. 2016; Ma 2017; Nam et al. 2018; Stiglic et al. 2018a). Furthermore, several studies proposed dispatching models to minimize the operational costs of shared mobility services (Ma et al. 2019a; Masoud et al. 2017; Pinto et al. 2020).

Moreover, Posada et al (2017) have developed a mixed integer linear program, which aimed at minimizing the operational cost of the demand responsive service and the usage cost of PuT services (Posada et al. 2017). Chen et al (2017) used a mixed-integer optimization problem to minimize the total travel distance (PuT and e-hailing vehicles) and the total e-hailing fleet size (Chen and Nie 2017). Furthermore, Salazar et al (2019) proposed a linear optimization model considering travel time, waiting time, capacity, and operational costs of AVs to maximize social welfare in terms of users' travel time together with the operational costs of available service providers (Salazar et al. 2018). Djavadian and Chow (2017) proposed a non-myopic dynamic dial-a-ride model considering dynamic operational policies, such as dispatching, fare pricing, operational costs, to establish a generalized cost function for users and a consumer surplus function for on-demand service providers. In their study, maximum social welfare was obtained when the average consumer surplus of users was equal to the average profit of the providers (Djavadian and Chow 2017a).

However, the MPO optimized operational parameters of the TSPs in terms of total travel time, waiting time, vehicle fleet size, pricing schemes, waiting time, and number of transfer locations corresponding to demands (Chen and Nie 2017; Chen, Wang, and Meng 2020; Djavadian and Chow 2017a; Fahnenschreiber et al. 2016; Levin et al. 2019a; Liang et al. 2016; Ma et al. 2019a; Pinto et al. 2020; Wright et al. 2020). In contrast, Ma et al (2019) showed that a higher frequency of PuT can impact the performance of ride-sharing platforms, such as reducing users' waiting time while increasing the share of ride-sharing trips for ride-sharing platforms (Ma et al. 2019a).

2.2.6. Role of MaaS in transport gap improvement

The transport gaps might occur in rural areas, especially in remote and mountain ones, not only because of the spatial and social distribution of facilities, capacities, and resources but also because of poor public transport compared to urban areas offering services and development opportunities.

The low density and scattered residential areas of small towns and villages, typical of these rural areas, make it difficult to operate traditional public transport services, which can hardly be efficient with such low and dispersed demands (Daniels and Mulley 2012; Farrington and Farrington 2005; Li and Quadrifoglio 2010). As a result, rural areas are highly car-dependent. The vulnerable population groups, who are due to age, economic, or cultural barriers, do not have access to cars, were most influenced by transport gap (Shergold and Parkhurst 2010; Shergold, Parkhurst, and Musselwhite 2012; Verma and Taegen 2019). Moreover, rural areas very often suffer from lower spatial accessibility levels than urban ones, not only because of poor public transport supply but also because of physical distance challenges in rural areas.

Improving the transport gap in rural areas was a challenging problem and required policymakers and planners to act on several fronts by enhancing mobility, accessibility, and transport services. In order to reduce transport gap, the previous studies focused on three main countermeasures, including (1) Improving the level of current public transport supply, (2) Enhancing alternative services, and (3) Infrastructure improvement. In particular, improving the level of current public transport supply mainly focused on enhancing provision of public transport services, such as service coverage, service frequency, and adjusting the level of transport supply in over-serviced areas (Cai et al. 2020; Carleton and Porter 2018; Chen et al. 2018; Currie 2010; Fayyaz, Liu, and Porter 2017; Fransen et al. 2015; Jiao 2017; Al Mamun and Lownes 2011).

There were several studies suggested to improve non-motorized network construction (i.e., sidewalks and bike lanes) and/or construct bus and rail transit network (Jiao and Cai 2020; Kaeoruean et al. 2020; Wu et al. 2015b). Other recommendations on enhancing alternative services, such as on-demand services (Uber, Lyft), on-demand bus, and shared mobility were also discussed (Bejleri et al. 2018; Cao et al. 2018; Jomehpour Chahar Aman and Smith-Colin 2020).

MaaS might be considered as a potential option for rural context (Barreto, Amaral, and Baltazar 2018; Eckhardt et al. 2018), improving accessibility and social inclusion (Durand and Harms 2018). In this scene, Figure 2-3 shows the potentials of MaaS for transport gap reduction.

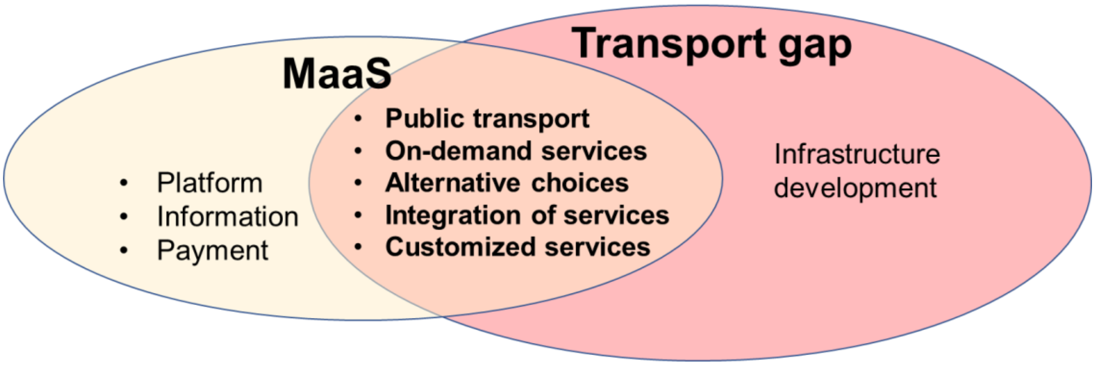


Figure 2-3 Potential of MaaS for transport gap reduction

The transport supply, accessibility, and individual mobility can be enhanced under MaaS context. The development of various on-demand mobility services (i.e., car-sharing, bike-sharing, ride-sharing, ride-hailing, and demand-responsive service) provided more alternative transport services, seamless mobility for users, and facilitated sharing journeys between local and nonlocal residents as well as visitors.

Furthermore, the on-demand mobility services had expanded the service coverage of fixed public transport services (Jiang et al. 2018; S. T. Jin et al. 2019; Murphy 2016; Wang 2018; Zhang and Zhang 2018). Elderly populations and travelers without cars are provided more alternative choices, service integration, and customized services to reach desired activities and locations.

Table 2-6 shows the examples of MaaS implications/pilots in rural areas in developed countries. In these studies, ride-sharing, ride-sourcing, or on-demand bus was proposed to enhance individual mobility, accessibility, and equity transport in places with poor/ nonexistent public transport.

Table 2-6 Implication of MaaS concept on rural areas in the world

Country	Rural areas	References
Finland	Ylöjärvi; Sastamala; Ylläs	(Andrea Lorenzini, Ambrosino, and Brendan Srl 2019; Anttila 2018; Eckhardt, Lauhkonen, and Aapaoja 2020)
US	Wisconsin; Allen; Allegan; Grand Traverse Country; Benzie; Needles	(Ruocco, Pani, and Misso 2019)
Switzerland	Willisau	(Andrea Lorenzini et al. 2019)
Slovenia	nine communities in Slovenia	(Julia Dick et al. 2020)
Denmark	Vejle	
Sweden	Trelleborg	(Andrea Lorenzini et al. 2019)
Italy	Elba	(Julia Dick et al. 2020)
Islands	Orkney	
Germany	Wismar; Neuenwalde; Geestland	(Andrea Lorenzini et al. 2019; Julia Dick et al. 2020)
UK	Wales, UK	
Australia	Carinthia, Austria	
Ireland	Carlow, Kilkenny and Wicklow, Ireland	

2.3. Summary

The literature showed that transport gap was caused by the lack of transport supply, a lack of accessible opportunities, which return restrict individuals participating in activities (e.g., job, business, education, health, and recreation), especially, populations who cannot or do not want to drive or do not have access to cars. There are however some limitations in the existing literature as follows:

The first research gap is a fundamental question relating to transport gap in rural tourism areas. The existing literature focused mainly on urban areas but rarely investigated in rural tourism areas, which are commonly characterized by low population density and scattered tourism attractions. As a result, many questions from the planning perspective, such as where appear transport gaps, the variation of transport gaps, and measures to address transport gaps in rural tourism areas need to be answered.

Secondly, the existing studies are not able to depict a comprehensive picture about transport demands. Modeling the transport demands mainly analyzed for local residents, whereas the analysis considering nonlocal demands and visitors is commonly overlooked. Considering local and nonlocal demands could describe more realistic transport demands and transport gaps.

Another research gap is relevant to transport supply modeling. The previous studies mainly focused on public transport. Although there were few studies that examine multiple transport services to analyze transport supply and transport gap, modeling the integration of different transport services was not considered.

Finally, the potential impact of MaaS on the transport gap reduction is not explored in the existing literature. MaaS had been found to impact transport supply, accessibility, and user's mobility as follows:

- The impact of MaaS on the performance of transport systems. MaaS may change the vehicle fleet size, transfer locations, fares, and operational costs of shared mobility services, the service frequency and fares of PuT services, and travel time, which are provided by transport service providers.
- MaaS will likely shift people's travel behaviors and preferences by psychological and physical accessibility indicators. The former was mainly related to simplicity, ease of access, comfort, flexibility, perceived travel time, travel costs, and users' willingness to share. The latter primarily focused on travel time, access time, waiting time, number of transfers, and fare schemes.
- MaaS may impact accessibility in some ways, such as (1) MaaS can serve transport demands that are not met by the existing public transport. (2) MaaS may change transport supply by influencing travel time/cost between locations and activities; (3) MaaS offers transport services with simplicity, ease of access, comfort, and flexibility, which impact also impact individual mobility and accessibility.

Under MaaS concept, several on-demand services integrated into MaaS, such as on-demand bus or demand responsive transport, ride-sharing, car-sharing, carpooling, and taxi are commonly concerned to enhance accessibility to rural areas. However, among potential transport services integrated into MaaS, what transport service is required to fulfill transport gaps and how are its potential impacts on transport gap reduction are important questions to be researched to inform future policy.

3. Research framework and research methodology

3.1. Conceptual framework

The conceptual framework of study is derived from existing literature and the research objectives. With a focus on transport gaps, the study aims to deeply answer two main research questions and objectives, including the “spatial-temporal transport gaps” and the “potential impacts of transport services on transport gap” in rural tourism areas. The two research questions/objectives are combined by important linkages that will be carefully considered in Figure 3-1.

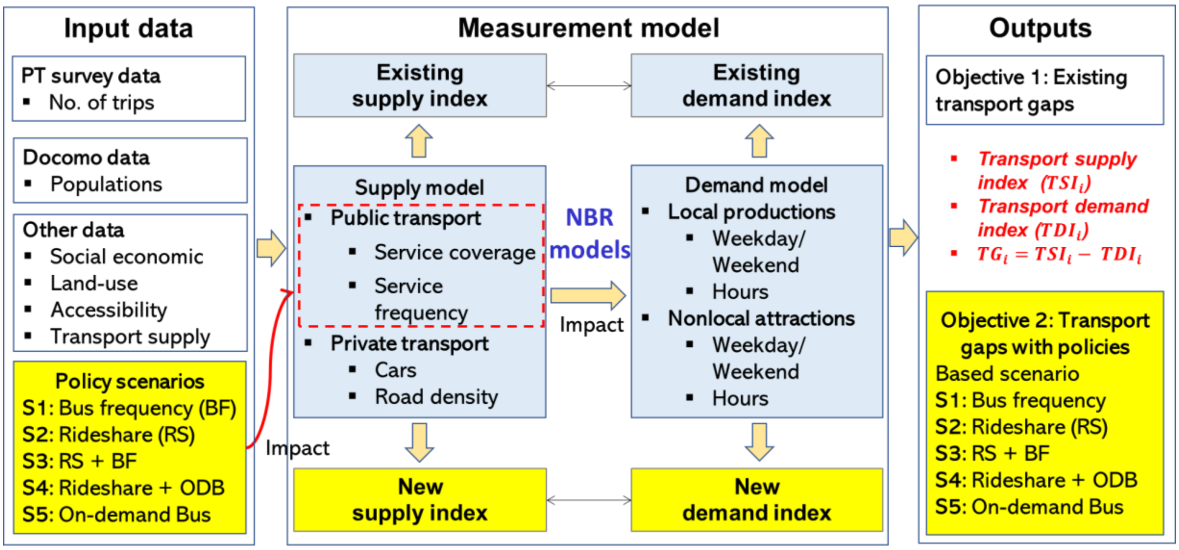


Figure 3-1 The analytical framework for transport gaps and policy assessment

The transport gap model is developed based on the standardized score of transport supply and demand. There are two core models (i.e., supply and demand model) related to each other in the transport gap model. In transport supply model, the transport supply index is measured from indicators representing the supply of public transport and private transport. Service coverage and frequency are used to quantify the public transport supply while available cars and road density are utilized for determining the private transport supply. The supply data are collected from publicly available data sources.

In transport demand model, the transport demands are measured by the number of trips generated and attracted by local and nonlocal residents/visitors from and to each zone. To quantify local and nonlocal demands, several different data sources are used in this study. The data include the aggregated person trip survey data on a typical weekday in three metropolitan regions (Kanto, Kinki, and Chubu) provided by MLIT in 2010 and mobile spatial statistics data provided by Docomo Insight Marketing Inc in five months in 2020. Based on the person trip survey data, the regression models are developed to explore relevant factors and applied to predict local and nonlocal demands per zone. Once transport demands and supplies per zone are determined, the standardized scores of transport supply and demand are determined and relatively compared to point out areas where transport supplies are lower than transport demands.

Five different scenarios for transport supply enhancement are developed based on existing public transport, ride-sharing, and on-demand bus service. The impacts of policy scenarios on both transport supplies and demands are also considered. Particularly, the policy scenarios will change the public transport supply indicators, such as service coverage, service frequency, access time to the nearest train station, and accessibility. The transport demands will change corresponding to changes in transport supplies. In each scenario, the new transport supply and demand indices will be redetermined to point out transport gaps with policies. Finally, the comparisons between transport gaps with and without policy scenarios are made to point out the influence of policy scenarios.

3.2. Research methodology

The research methodology was conducted based on two objectives and components of transport gap model as shown in Figure 3-2.

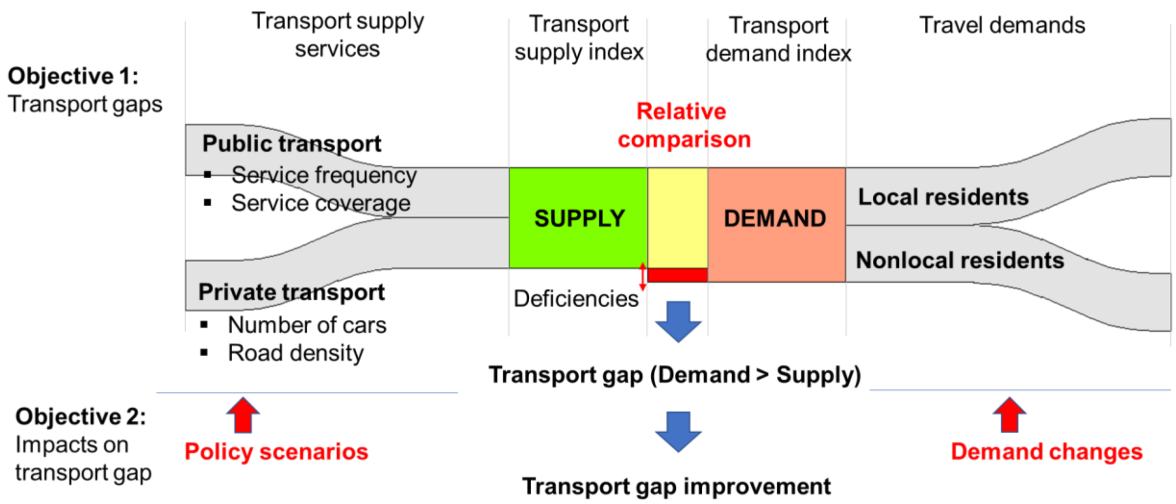


Figure 3-2 Method used for defining transport gaps

To identify the transport gaps, the study carried analyses for both transport supplies and demands in each zone without and with policy scenarios. It is so important to analyze transport gaps from the “macroscopic approach” because the objectives of study are to point out the deficiency between transport supply and demand in an area and to propose policies for accessibility and transport gap improvement for these areas.

3.2.1. Transport supplies

The method proposed by Jiao and Dillivan (2013) was adopted to quantify the value of private transport supply. Two different indicators, namely the number of available cars and road density, were used to measure the supply level of private transport as formula (1).

$$\mathrm{PrT}_i = (C_i + RD_i)/2 \tag{1}$$

Where

PrT_i : reflects the value of private transport supply for zone *i*.

$\mathrm{C_i}$ and $\mathrm{RD_i}$: are the standardized score of available cars and road density for zone *i*.

For public transport, the value of supply was calculated based on different indicators, including service frequency, the proportion of public facilities and residential areas covered by transit services coverage.

- The frequency of transit services was measured by the number of arrival vehicles per day according to the timetable (vehicle arrivals/day).
- The proportion of public facilities covered by transit service coverage is measured by the ratio of the number of public facilities within transit service coverage and the total of public facilities located in a zone.
- The proportion of residential area covered by transit service coverage is measured by the ratio of the area of residences within transit service coverage and the total residential area of a zone.

The transit service coverage was defined as the vicinity of a stop or station of a transit route (Andersen and Landex 2008), within which most users are comfortably walking to or from a transit stop. The transit service coverage was commonly reached by a walk distance of 400 m and 800 m from/to bus stops and train stations, respectively (Currie 2010). The concept of transit service coverage was used to represent the spatial supply of public transport. To identify the level of spatial supply, a geo-processing procedure was implemented by the GIS tool to capture the number of public facilities, residential buildings, and other buildings within transit service coverage.

Most previous studies commonly determined service frequency as the number of vehicles arrivals per week. In this study, the service frequency is defined by the summation of vehicle arrivals at transit stops in a zone on a weekday and a weekend (Peungnumsai et al. 2020). In case zones were not assigned transit stops but being covered fully by the transit service coverage, the number of vehicle arrivals to zones without transit stops was determined by the number of bus/train arrivals to the nearest stops that covered these zones.

Based on the method of Currie (2010), the value of public transport for each zone was calculated as formula (2).

$$\mathrm{PuT}_i^t = \sum_{i=0}^{n} \mathrm{SF}_i^t * (\mathrm{PF}_i + \mathrm{RA}_i)/2 \qquad (2)$$

Where

PuT_i^t : reflects the value of public transport supply for zone *i* on day *t*.

SF_i^t: refer to the z-score of service frequency on day *t*,

$\mathrm{PF_i}$, $\mathrm{RA_i}$: reflects the proportion of public facilities and residential area covered by public transport in zone *i*.

n : is the number of bus stop in zone *i*.

Once supply values of private and public transport were calculated, these values were then standardized to reflect value of each indicator and how values are far from their mean. The standardized score (called a z-score) was used because of some advantages: first, z-scores are calculated based on the distribution of the reference data (mean and standard deviation), and thus reflect the reference distribution; second, as unit of indicators is removed, z-scores are comparable among indicators. The z-score of each supply indicator was determined as formula (3).

$$S_{i,j} = \frac{s_{i,j} - \overline{S_{i,j}}}{sd_i} \qquad (3)$$

Where:

D_i: The standardized score of supply indicator *i* in zone *j*

$s_{i,j}$: Value of supply indicator *i* in zone *j*

$\overline{D}$: The mean of supply indicator *i*

sd_i: The standard deviation of the supply indicator *i*

In the next step, indicators were weighted equally and overall transport supply index for each zone was estimated as following formula (4).

$$\mathrm{TSI}_i^t = \mathrm{PrT}_i + \mathrm{PuT}_i^t \quad (4)$$

Where:

TSI_i^t : reflects transport supply index for zone *i* on day *t* (weekday or weekend).

PrT_i : reflects the value of private transport supply for zone *i*.

PuT_i^t : reflects the value of public transport supply for zone *i* on day *t*.

3.2.2. Transport demands

Transport demands have been identified using a three-step process. The first step attempted to understand the influencing factors of transport demands. The second step identified the transport demands. The final step determined the overall demand index.

In this study, the transport demands were measured by the number of trips generated and attracted by local and nonlocal residents/visitors from and to each zone. To quantify local and nonlocal demands, several different data sources were used in this study. The data included the 2010 aggregated person trip survey data on a typical weekday provided by MLIT, and mobile spatial statistics data provided by Docomo Insight Marketing Inc in five months in 2020. First, the regression models were developed based on the person trip survey data to explore factors related to the number of trips generated and attracted by local and non-local residents, respectively. Second, the estimated models were applied to predict the transport demand of residents and nonlocal residents in Hokuto. In the next step, the maximum entropy models were developed to decompose the predicted demands on a typical weekday into a weekend, a weekend/holiday, and different hours based on the mobile spatial statistics data. Finally, the adjusted results were used for analyzing the spatial and temporal distribution of transport demands and transport gaps in Hokuto.

Once the local and nonlocal demands were estimated, these values were then standardized to reflect value of each indicator and how values are far from their mean.

$$D_{i,j} = \frac{d_{i,j} - \overline{D_J}}{sd_j} \quad (5)$$

Where:

D_i: The standardized score of demands (local and nonlocal) in zone *i*

d_i: Local or nonlocal demands per zone *i*

D_j: The mean of the local and nonlocal demands

sd: The standard deviation of the local or nonlocal demands *j:* Local demands or nonlocal demands in a zone

The value of local and nonlocal demands was weighted equally. The overall transport demands index for each zone was determined as following formula (6).

$$\mathrm{TDI}_i^t = \mathrm{LDI}_i^t + \mathrm{NLDI}_i^t \tag{6}$$

Where:

- TDI_i^t reflects overall value of transport demands for zone i on day t.
- LDI_i^t and NLDI_i^t are z-scores of local and non-local demands for zone i on day t

3.2.3. Transport gaps

The transport gap was determined for each zone by subtracting the z-score of transport demands from transport supplies as formula (7). The transport gap was either negative value or positive value. A negative transport gap value indicates that transport supply is lower than transport demand while a positive value shows that transport supply is higher than transport demand.

$$\mathrm{TG}_i^t = \mathrm{TSI}_i^t - \mathrm{TDI}_i^t \tag{7}$$

Where TSI_i^t, and TDI_i^t describe overall value of transport supply and transport demand for zone *i* on day *t*. TG_i^t reflects transport gap for zone i on day *t*.

Transport gaps were classified into five levels by the natural breaks method and jointed with GIS tool to visually represent the areas with transport gap. The five level were classified as “large gap”, “medium gap”, “low gap”, “medium supply”, and “large supply”. The “larger gap” means that bigger gaps in transport supply and lower quality of transport services, which leads to difficulty of accessing transport services and desired activities or destinations. In contrast, a “larger supply” was a larger transport supply and better quality of transport services.

4. Data preparation

This part describes the data required for developing the transport supply and demand model, which provides input for analyzing transport gaps. The data represent zonal-based characteristics, including the number of trips produced and attracted by zone, its social, geographical, and land-use characteristics, and transport supply indicators in each zone.

4.1. Data related to transport demands

4.1.1. Personal trip survey data

The personal trip survey was a publicly available source provided by MLIT in 2010. The data presented the number of trip productions and attractions by different modes (i.e., train, bus, taxi, car, bike, and walk) and trip purposes (i.e., working, schooling, business, home, and recreation) for each zone within three major metropolitan regions (Kanto, Kinki, and Chubu) on a weekday and represented by origin-destination trip tables.

There is a total of 1532 zones, which are the boundary of districts/towns and cities within three major regions. There were 500, 600 and 432 zones in Chubu, Kanto and Kinki region, respectively. In this study, the number of trips was divided into trips generated and attracted by local residents and attracted by nonlocal residents/visitors. The data were very useful for developing transport demand models based on zonal characteristics.

Table 4-1 describes the statistics of trips per zone from personal trip data. Although there was a clear difference between the three regions, it is not fair to compare the three regions because the size of zones was different. In this study, the data of three regions were combined to explain the variation in trip making behavior between zones.

Table 4-1 Descriptive statistics of trips from personal trip data

Indicators	**Chubu region**	**Kanto region**	**Kinki region**	**Overall**
	(N=500)	**(N=600)**	**(N=432)**	**(N=1532)**
No. of trip productions (000 trips per zone)				
Mean (SD)	42.4 (25)	132 (93.7)	105 (119)	94.9 (95.2)
Median [Min, Max]	40 [0.32, 132]	116 [2.23, 646]	45.1 [0.68, 631]	60.5 [0.32, 646]
No. of trip attractions (000 trips per zone)				
Mean (SD)	42.4 (25)	132 (93.9)	105 (119)	94.9 (95.3)
Median [Min, Max]	40 [0.32, 132]	115 [2.18, 649]	45 [0.67, 631]	60.3 [0.32, 649]
No. of nonlocal trips (000 trips per zone)				
Mean (SD)	15.1 (10.7)	62.6 (59.5)	41.3 (55.6)	41.1 (51.9)
Median [Min, Max]	13.5 [0, 90.2]	49.2 [1.42, 519]	16.7 [0.92, 500]	22.7 [0, 519]
No. of local trips (000 trips per zone)				
Mean (SD)	25.8 (18.3)	69 (48.4)	62.9 (71.7)	53.2 (53.3)
Median [Min, Max]	22 [0.04, 101]	59.1 [0.75, 309]	31.2 [0.29, 357]	34.8 [0.04, 357]
No. of trip productions by recreational purpose (000 trips per zone)				
Mean (SD)	11.4 (0.706)	38.3 (26.8)	29.4 (33.6)	27 (27.3)
Median [Min, Max]	11 [0, 34.1]	34.1 [0.66, 157]	12.6 [0.07, 152]	16.9 [0, 157]

Note: N is number of observations; SD is standard deviation

Table 4-2 Descriptive statistics of trips from personal trip data (Continued)

Indicators	Chubu region (N=500)	Kanto region (N=600)	Kinki region (N=432)	Overall (N=1532)
No. of trip attractions by recreational purpose (000 trips per zone)				
Mean (SD)	10.8 (8.070)	37.9 (30.3)	29.3 (34.9)	26.6 (29.3)
Median [Min, Max]	9.32 [0, 63]	31.3 [0.34, 192]	12.6 [0.07, 179]	15.6 [0, 192]
No. of trip productions by commuting purpose (000 trips per zone)				
Mean (SD)	30.9 (18.2)	94.9 (68.1)	75.1 (85.8)	68.4 (68.9)
Median [Min, Max]	29.2 [0.32, 97.8]	84.5 [1.49, 497]	32.9 [0.49, 526]	43.9 [0.32, 526]
No. of trip attractions by commuting purpose (000 trips per zone)				
Mean (SD)	31.6 (18)	95.4 (66.5)	75.2 (85.1)	68.9 (67.9)
Median [Min, Max]	30.3 [0.23, 91]	84.4 [1.71, 496]	32.1 [0.42, 533]	44.2 [0.23, 533]
Trip productions by train (000 trips per zone)				
Mean (SD)	4.31 (5.71)	40 (53.4)	19 (35.6)	22.4 (41.4)
Median [Min, Max]	2.81 [0, 60]	25.4 [0, 477]	3.44 [0, 401]	6.28 [0, 477]
Trip attractions by train (000 trips per zone)				
Mean (SD)	4.3 (5.7)	40 (54.2)	19 (35.8)	22.4 (41.9)
Median [Min, Max]	2.8 [0, 58.8]	24.9 [0, 481]	3.39 [0, 408]	6.27 [0, 481]
Trip productions by bus (000 trips per zone)				
Mean (SD)	0.493 (0.707)	3.46 (3.75)	2.64 (4.30)	2.26 (3.53)
Median [Min, Max]	0.242 [0, 7.94]	2.21 [0, 25.8]	0.832 [0, 26.8]	0.757 [0, 26.8]
Trip attractions by bus (000 trips per zone)				
Mean (SD)	0.493 (0.684)	3.46 (3.73)	2.64 (4.28)	2.26 (3.52)
Median [Min, Max]	0.255 [0, 7.34]	2.20 [0, 25.3]	0.808 [0, 28.7]	0.761 [0, 28.7]
Trip productions by car (000 trips per zone)				
Mean (SD)	26 (17)	37.3 (29)	37 (35.9)	33.6 (28.5)
Median [Min, Max]	23.1 [0.24, 95.8]	28.7 [0.53, 154]	24.6 [0.18, 197]	25.8 [0.18, 197]
Trip attractions by car (000 trips per zone)				
Mean (SD)	26.1 (17)	37.3 (29.1)	37 (35.9)	33.6 (28.6)
Median [Min, Max]	23 [0.24, 95.9]	28.5 [0.56, 154]	24.5 [0.18, 196]	25.9 [0.18, 196]
Trip productions by taxi (trips per zone)				
Mean (SD)	417.7 (525.8)	Not available (NA)	199.1 (224.2)	308 (375)
Median [Min, Max]	262.5 [0, 4250]	NA	137 [0, 1378]	199.7 [0, 4250]
Trip attractions by taxi (trips per zone)				
Mean (SD)	417.7 (592.2)	NA	199.1 (223.1)	308 (407.6)
Median [Min, Max]	244 [0, 4390]	NA	135 [0, 1297]	189.5 [0, 4390]
Trip productions by bike (000 trips per zone)				
Mean (SD)	3.52 (3.17)	NA	18.45 (28.05)	9.61 (19.5)
Median [Min, Max]	2.91 [0, 14.4]	NA	3.95 [0, 164.8]	3.14 [0, 164.8]
Trip attractions by bike (000 trips per zone)				
Mean (SD)	3.52 (3.17)	NA	18.4 (28.04)	9.61 (19.5)
Median [Min, Max]	2.92 [0, 14.6]	NA	3.97 [0, 164.9]	3.14 [0, 164.9]

Note: N is number of observations; SD is standard deviation

The statistic results of trip productions and attractions within a region were the same or slightly different. This is because the total number of trip productions and attractions was slightly different in a zone and the total number of trip productions was similar to that of attractions in a day. The local trips were larger than nonlocal trips. The number of commuting trips was more than two times recreational trips. The number of trips by car was the largest, followed by trains, bike, and buses, respectively. Figure 4-1 and Figure 4-2 show spatial distributions of trip productions and attractions in Chubu, Kinki, and Kanto region, respectively. In general, zones located in the core urban areas tended to be higher trip productions/attractions than zones far from the city center.

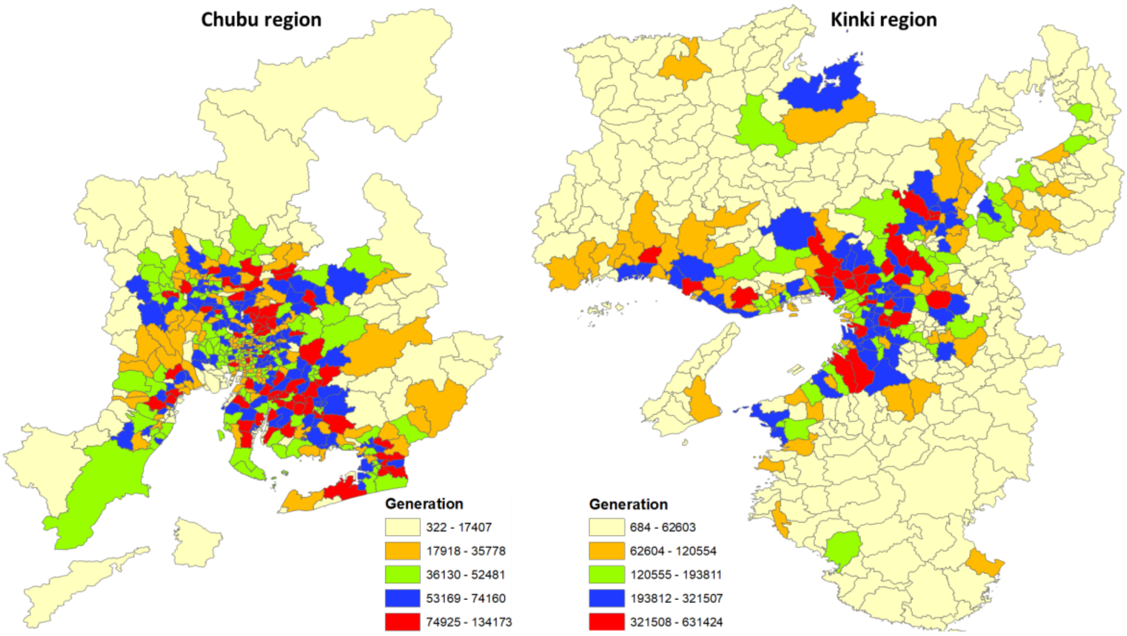


Figure 4-1 Trip productions/attractions by zones in Chubu and Kinki region

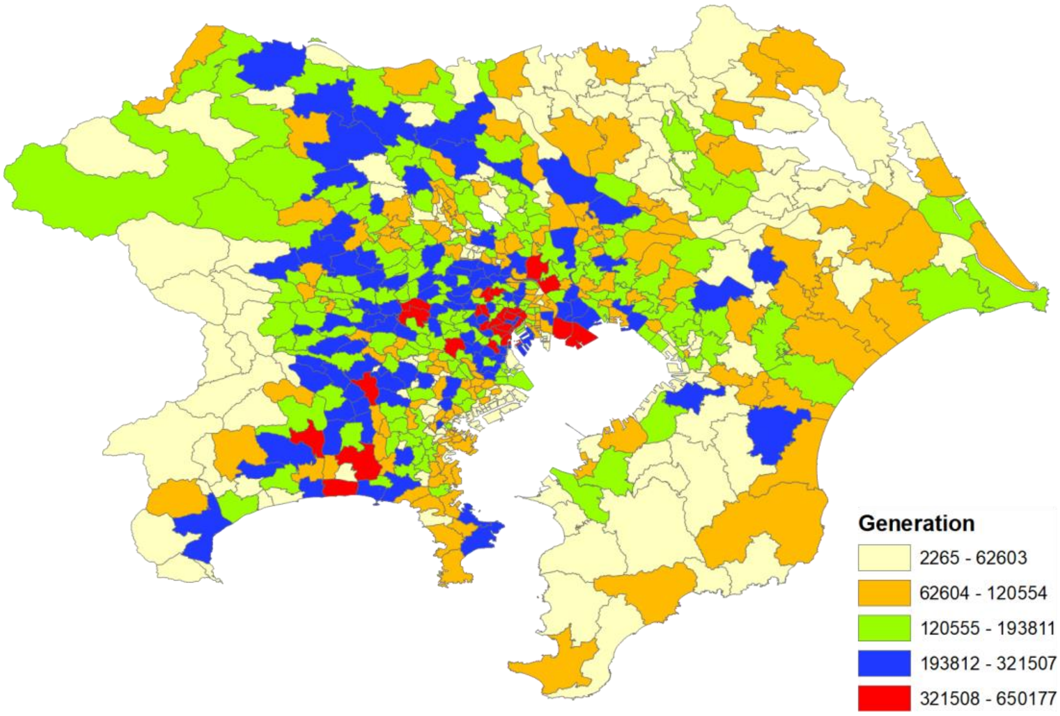


Figure 4-2 Trip productions/attractions by zones in Kanto region

The influencing indicators of trip making in this study, including geographical and land-use characteristics, built environments, and accessibility, were summarized from the literature (for example, Jayasinghe et al., 2017; Yang et al., 2020; Chen et al., 2021; Christian 2021) and shown in table 4-2. The zones are classified by geographical characteristics (i.e., urban and rural) and land-use characteristics (i.e., residential, industrial, commercial and business, and mixed land). The number of populations in a zone was collected from e-Stat. The points of interest (POI), including public facilities (i.e., city offices, schools, welfare facilities, and hospitals), accommodations/hotels, tourism facilities (i.e., tourism destinations and local tourism resources), and land-use types within a zone were collected from MLIT. Building density was determined from the GIS tool based on land-use types.

Table 4-3 Descriptive statistics of indicators characterized by zone

Indicators	**Chubu region**	**Kanto region**	**Kinki region**	**Overall**
	(N=500)	**(N=600)**	**(N=432)**	**(N=1532)**
Geographical characteristics (dummy)				
Rural	55 (11.0%)	51 (8.5%)	160 (37.0%)	266 (17.4%)
Urban	445 (89.0%)	549 (91.5%)	272 (63.0%)	1266 (82.6%)
Land use characteristics (dummy)				
Commercial	23 (4.6%)	36 (6.0%)	22 (5.1%)	81 (5.3%)
Mixed land	1 (0.2%)	6 (1.0%)	5 (1.2%)	12 (0.8%)
Industrial	13 (2.6%)	4 (0.7%)	1 (0.2%)	18 (1.2%)
Residential	251 (50.2%)	342 (57.0%)	240 (55.6%)	833 (54.4%)
Residential and industrial	212 (42.4%)	212 (35.3%)	164 (38.0%)	588 (38.4%)
Population (000 persons per zone)				
Mean (SD)	20.8 (13.4)	62.4 (41.7)	50.1 (60.6)	45.4 (45.7)
Median [Min, Max]	20.7 [0, 140]	54.5 [0, 264]	20.5 [0.44, 286]	28.6 [0, 286]
Public facilities (No. of facilities per zone)				
Mean (SD)	25.5 (15.0)	75.9 (43.9)	71.3 (59.0)	58.2 (48.2)
Median [Min, Max]	23.0 [0, 81.0]	68.0 [2.00, 268]	47.5 [6.00, 270]	41.0 [0, 270]
Hotels (No. of hotels per zone)				
Mean (SD)	3.56 (8.14)	5.23 (10.1)	6.02 (11.1)	4.91 (9.83)
Median [Min, Max]	1.00 [0, 65.0]	2.00 [0, 142]	2.00 [0, 109]	2.00 [0, 142]
Recreational facilities (No. of tourism facilities per zone)				
Mean (SD)	12.7 (10.7)	24.5 (18.4)	26.3 (19.2)	21.2 (17.6)
Median [Min, Max]	10.0 [0, 74.0]	20.0 [0, 143]	21.0 [0, 146]	18.0 [0, 146]
Building density (percent)				
Mean (SD)	0.482 (0.274)	0.608 (0.284)	0.264 (0.257)	0.470 (0.307)
Median [Min, Max]	0.51 [0.01, 1.00]	0.67 [0.01, 0.99]	0.15 [0.01, 0.91]	0.47 [0.01, 1.00]

Note: N is number of observations; SD is standard deviation

4.1.2. Mobile spatial statistics data

Mobile spatial statistics data provided by Docomo InsightMarketing INC., was recorded from 1st January 2020 to 31st May 2020 throughout Japan. The data recorded the number of populations, who currently located in activity locations (e.g., workplaces or tourism destinations) and aggregated into meshes (cells with an area of 500x500m^2) to protect individual confidentiality or privacy.

Moreover, the number of observed populations within a mesh was disaggregated by the ages, genders, and origins of populations (i.e., prefectures and residences/cities) by hours of a day and days of a week. Due to privacy protection, data could be removed when the total number of observed populations was less than ten. As a result, the summation of disaggregated data can be different from aggregated data.

Figure 4-3 describes the format of mobile spatial statistics data. For example, there are 39 persons, who are in the city (47382), are observed at mesh (362257353) at 00 am on 1st January 2020. A mesh might include both local and non-local residents. The local residents were considered as populations arriving from Hokuto while non-local residents were defined as populations arriving from other cities. In this study, hourly observed population data in each mesh on a typical weekday and weekend were randomly selected from the weekdays and weekends/holidays in five months, respectively.

Observation date & time

Mesh code

Origin of population (City code)

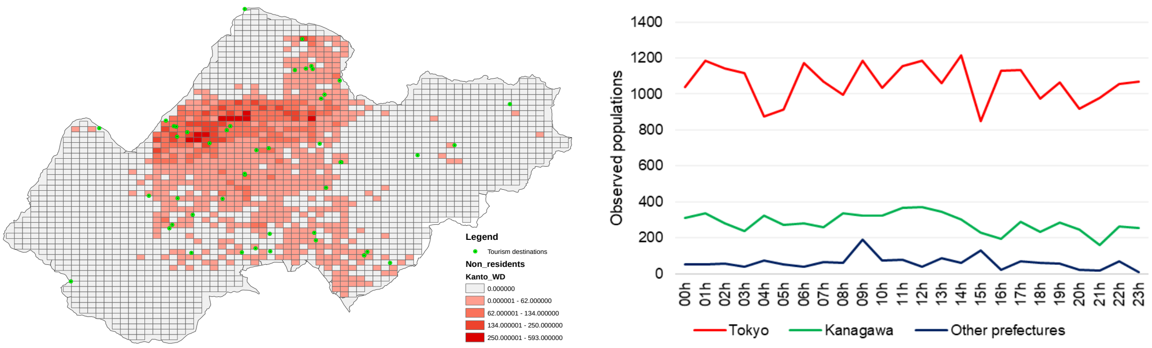
No. of populations observed at mesh (i) at observation time (t)

date	time	area	residence	age	gender	population
20200101	0	362257344	47382	-1	-1	39
20200101	0	362257353	47382	-1	-1	14
20200101	0	362257362	47382	-1	-1	14
20200101	0	362257442	47382	-1	-1	14
20200101	0	362257451	47382	-1	-1	47
20200101	0	362257452	47201	-1	-1	26
20200101	0	362257452	47207	-1	-1	21
20200101	0	362257452	47382	-1	-1	178
20200101	0	362257453	47382	-1	-1	10

Example – Data description
39 people, who are the residence (city: 47382), are observed at Mesh (36225744) at 00h on 1st Jan 2020.

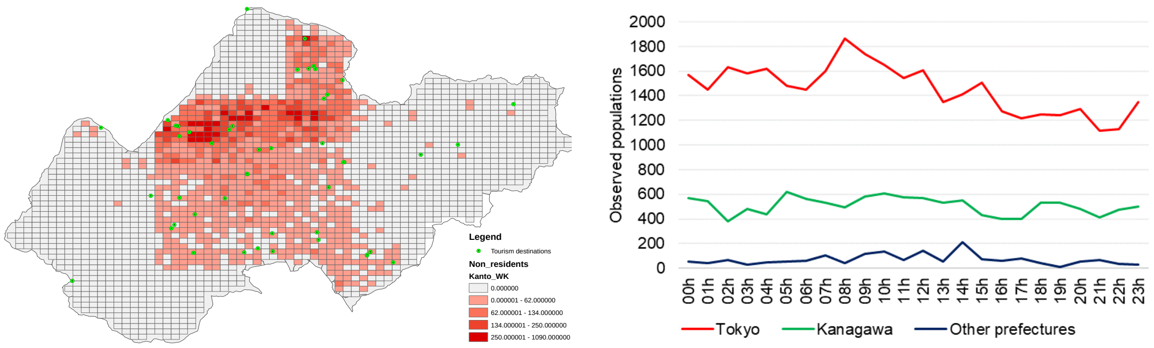
Figure 4-3 The format of mobile spatial statistics data

There were 2152 meshes identified from the mobile spatial statistics data and within Hokuto's boundary. Figure 4-4 and Figure 4-5 show the spatial-temporal distribution of nonlocal residents, who are from Tokyo, Kanagawa, and other prefectures to Hokuto observed in meshes on a weekday and weekend, respectively.



a) Spatial distribution of nonlocal residents b) Temporal variation of nonlocal residents

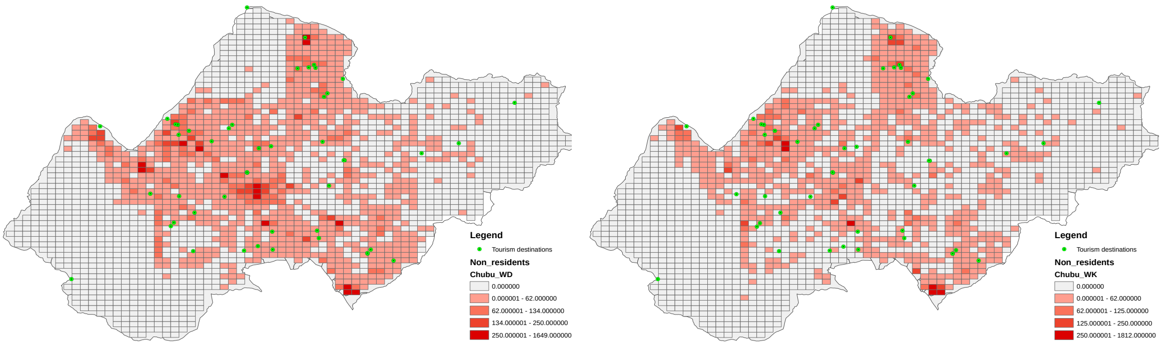
Figure 4-4 Residents from Tokyo, Nakagawa, and others to Hokuto on a weekday



a) Spatial distribution of nonlocal residents b) Temporal variation of nonlocal residents

Figure 4-5 Residents from Tokyo, Nakagawa, and others to Hokuto on a weekend

As can be seen that the observed population from Tokyo was the largest on both weekday and weekend. In Hokuto, Yatsugatake area was the most attractive area for non-local residents, especially tourism areas observed a larger number of nonlocal residents/visitors on the weekend.



a) Weekday b) Weekend

Figure 4-6 The spatial distribution of residents from neighboring cities in Hokuto

Figure 4-6 shows the spatial distribution of residents from neighboring prefectures (Nagano and Yamanashi) observed at Hokuto on a weekday and weekend, respectively. The spatial distribution of neighboring populations observed on the weekday was larger than on the weekend. In comparison with spatial distribution of neighboring cities and other cities to Hokuto. It was clearly seen that the spatial distribution of populations from neighboring prefectures was larger than other prefectures (i.e., Tokyo, Nakagawa, and others).

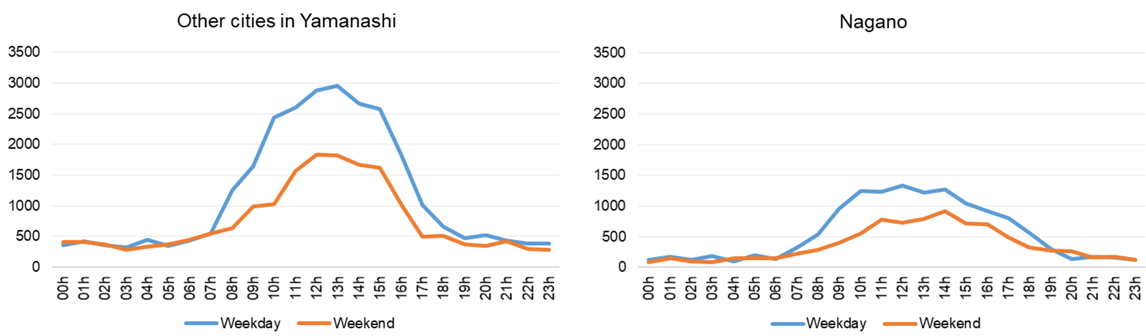


Figure 4-7 The temporal distribution of populations from neighboring cities

Figure 4-7 shows the temporal observation of population from neighboring prefectures. The nonlocal populations observed in the daytime (7 am to 6 pm) were higher than in the nighttime. In addition, the observed population on the weekday was larger than that on the weekend, which was opposite to Tokyo, Nakagawa, and other prefectures.

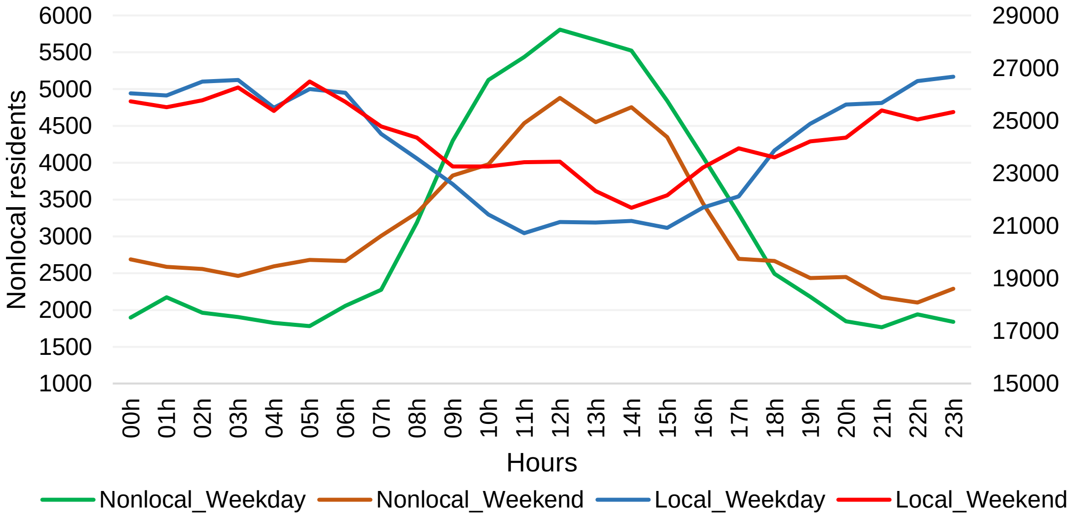


Figure 4-8 Hourly total local and nonlocal populations observed in Hokuto

Figure 4-8 illustrates the total number of local and nonlocal populations observed by hours in Hokuto on a weekday and weekend. The number of observed local populations tended to be lower in the daytime and higher in the nighttime. Changes in observed populations mean that there were the inflows and outflows of populations from and to each mesh. A mesh with large population changes means that transport demands might be high in that mesh. A higher observation of nonlocal populations in the daytime means that a larger number of nonlocal residents/visitors attracted to Hokuto in the daytime.

Although mobile spatial statistics data provided useful information on the spatial-temporal distribution of local and nonlocal residents, the information on trip productions and attractions per mesh was not directly obtained.

4.2. Data related to transport supplies

The transport supply data were collected from GIS database provided by MLIT. The data include public transport networks, the locations of stops/stations, and a list of bus/train routes passing the stops/stations as well as road networks.

The number of bus arrival at each bus stop was gathered from MLIT while the number of train arrivals at each train station was collected from Google maps. The data collected at each bus/train station were then aggregated into zones. The transit service coverage from stops/stations was analyzed by using the ArcGIS tool.

Table 4-4 Statistics of transport supply indicators in three metropolitan areas

Indicators	Chubu region (N=500)	Kanto region (N=600)	Kinki region (N=432)	Overall (N=1532)
Bus frequency (Average number of bus arrivals per zone on a weekday)				
Mean (SD)	464 (742)	1470 (1340)	930 (1240)	989 (1220)
Median [Min, Max]	262 [0, 7480]	1120 [0, 8570]	356 [0, 6070]	506 [0, 8570]
Train frequency (No. of train arrivals per zone per hour on a weekday)				
Mean (SD)	11.7 (14.2)	25.9 (28.4)	29.4 (35.1)	22.3 (28.0)
Median [Min, Max]	6.00 [0, 99]	18.0 [0, 207]	18.0 [0, 198]	12.0 [0, 207]
Service coverage (Percent)				
Mean (SD)	0.812 (0.202)	0.92 (0.144)	0.852 (0.167)	0.865 (0.177)
Median [Min, Max]	0.87 [0.05, 1.00]	0.99 [0.16, 1.00]	0.91 [0, 1.00]	0.94 [0, 1.00]
No. of bus stops per zone				
Mean (SD)	27 (27.2)	78.8 (53.5)	70.7 (51.6)	59.6 (51.3)
Median [Min, Max]	20 [0, 218]	66 [0, 276]	59 [0, 273]	46 [0, 276]
No. of train stations per zone				
Mean (SD)	1.67 (1.82)	9.27 (13.8)	10.8 (18.1)	7.22 (13.5)
Median [Min, Max]	1 [0, 12]	4 [0, 99]	4 [0, 120]	3 [0, 120]

Note: N is number of observations, SD is standard deviation

In Hokuto, there were 06 train stations and 312 bus stops. The service frequency of the community bus/train lines was gathered from the website of service providers and separated into weekdays and weekends/holidays. There were on average 21.6 weekday bus arrivals and around 12 weekend bus arrivals per zone, respectively. On weekends, the reduction of service frequency was the most significant in Kai-Komagatake area with around 55%, followed by Yatsugatake and Kayagatake area with approximately 49% and 37%, respectively.

The number of cars might be collected from some databases, such as statistical data and available images from Google Street View. However, the statistical data on the number of cars was only available for the whole of Hokuto and was not available at zonal level. To capture the distribution of private cars per zone, the study collected the number of cars from Google Street View by counting private vehicles at parking areas and households within zones.

There were 47,572 and 44,250 automobiles based on statistical data and Google Street View, respectively. Although the data collected from Google Street View was slightly different from the statistical data, it can be used to represent the number of car ownership in each zone. In addition, the number of cars identified from the images was static in comparison with transport demand data. This means that changes in the number of cars by hours and days in zones are not captured. The collected data were aggregated for each zone. On average, there were around 600 cars, 340 cars, and 125 cars per zone in Yatsugatake, Kai-Komagatake, and Kayagatake area, respectively.

Table 4-5 The overview of transport supply indicators in Hokuto

Indicators	Kai-Komagatake (N=17)	Kayagatake (N=41)	Yatsugatake (N=39)	Hokuto (N= 97)
Number of bus stops/trains per zone				
Mean (SD)	3.41 (3.64)	2.49 (3.49)	4.05 (5.27)	3.28 (4.33)
Median [Min, Max]	3.00 [0, 16.0]	1.00 [0, 17.0]	2.00 [0, 22.0]	2.00 [0, 22.0]
Service frequency (Average number of buses/trains arrival per zone on a weekday)				
Mean (SD)	22.4 (14.0)	22.0 (19.7)	20.9 (31.6)	21.6 (24.3)
Median [Min, Max]	18.0 [0, 51.0]	15.0 [0, 86.0]	10.0 [0, 156]	15.0 [0, 156]
Service frequency (Average number of buses/trains arrival per zone on a weekend)				
Mean (SD)	10.0 (8.43)	13.8 (13.0)	10.7 (21.7)	11.9 (16.5)
Median [Min, Max]	9.00 [0, 29.0]	11.0 [0, 59.0]	4.00 [0, 118]	8.00 [0, 118]
Facilities covered by public services (percent)				
Mean (SD)	0.854 (0.255)	0.913 (0.218)	0.768 (0.295)	0.844 (0.264)
Median [Min, Max]	1.00 [0, 1.00]	1.00 [0, 1.00]	0.867 [0, 1.00]	1.00 [0, 1.00]
Residential areas covered by public services (percent)				
Mean (SD)	0.752 (0.295)	0.817 (0.321)	0.543 (0.274)	0.696 (0.322)
Median [Min, Max]	0.866 [0, 1.00]	0.991 [0, 1.00]	0.563 [0.013, 1.00]	0.809 [0, 1.00]
Number of cars (**cars per zone)**				
Mean (SD)	339 (453)	126 (134)	598 (831)	353 (601)
Median [Min, Max]	168 [40.0, 1950]	60.0 [4.00, 574]	300 [21.0, 4270]	156 [4.00, 4270]
Road density (km/km2)				
Mean (SD)	3.19 (2.49)	4.86 (1.90)	4.62 (1.50)	4.47 (1.95)
Median [Min, Max]	2.85 [0.31, 8.34]	5.67 [0.71, 7.47]	4.61 [1.68, 8.90]	4.58 [0.30, 8.90]

Note: N is number of observations; SD is standard deviation

4.3. Accessibility measurement

Accessibility can be measured for a specific transport mode, such as private transport or private transport, walking, cycling and multimodal transport. There were several accessibility measures, such as cumulative opportunities model, gravity type model, logsum/utility model, and time-space model (Bhat et al. 2000; Geurs and van Wee 2004). Ben-Akiva and Lerman firstly presented the logsum model to measure accessibility (Ben-Akiva and Lerman 1979). The model effectively represented all transport services available to individuals into a comprehensive accessibility indicator and could be aggregated by individual characteristics. There were empirical studies on logsum measure based on the multinomial logit form of choice model (Bills and Walker 2017; KT and JR 2012; LaMondia, Blackmar, and Bhat 2011; Niemeier 1997; Sweet 1997). Similarly, this study measured accessibility for all available transport services (i.e., car, train, bus, taxi, bike, and walk) in a zone based on the logsum model.

To quantify accessibility and its impact on trip making, relevant data, including travel time (access time, waiting time, and on-vehicle travel time), travel costs, and travel distances between the central point of original zones and central point of destination zones within three regions were collected from Google maps and shown in Table 4.5. Although different options of different transport modes were available, the option with the lowest cost, the shortest travel time, and the shortest travel distance was selected.

Table 4-6 The descriptive statistics of indicators related to travel options

Indicators	**Chubu (N=307)**	**Kanto (N=599)**	**Kinki (N=429)**	**Overall (N=1335)**
Access time to train station (Minutes)				
Mean (SD)	15.1 (8.40)	15.3 (8.26)	21.0 (6.70)	17.1 (8.28)
Median [Min, Max]	15.0 [2, 36]	13.0 [2, 58]	20.0 [7, 57]	17.0 [2, 58]
Missing observation	17 (5.5%)	35 (5.8%)	21 (4.9%)	73 (5.5%)
Waiting time at train station (Minutes)				
Mean (SD)	18.6 (12.9)	16.3 (14.8)	28.6 (15.8)	19.2 (15.2)
Median [Min, Max]	15 [3, 90]	12 [3, 120]	30.0 [15, 120]	15.0 [3, 120]
Missing observation	64 (20.8%)	131 (21.9%)	267 (62.2%)	462 (34.6%)
Access time to bus stops (Minutes)				
Mean (SD)	16.1 (8.74)	19.5 (8.36)	24.2 (8.85)	20.6 (9.41)
Median [Min, Max]	15 [1, 55]	19.0 [5, 45]	23.0 [5, 57]	20 [1, 57]
Missing observation	53 (17.3%)	433 (72.3%)	59 (13.8%)	545 (40.8%)
Waiting time at bus stops (Minutes)				
Mean (SD)	40.7 (144)	23.0 (10.1)	33.6 (13.9)	34.7 (95.8)
Median [Min, Max]	25 [2, 1520]	20 [0, 40]	30 [15, 90]	30 [0, 1520]
Missing observation	198 (64.5%)	551 (92.0%)	337 (78.6%)	1086 (81.3%)
Travel distance by Car (Kilometer)				
Mean (SD)	28.6 (23.4)	43.5 (25.7)	124 (409)	66 (236)
Median [Min, Max]	21.5 [1.1, 122]	39.6 [1.9, 128]	92.7 [4.4, 8500]	47 [1.1, 8500]
Travel distance by bike (Kilometer)				
Mean (SD)	20.2 (19.6)	38.6 (25.6)	94.7 (51.9)	54.0 (46.8)
Median [Min, Max]	14 [1.2, 118]	33.6 [1.9, 139]	82.4 [4.3, 249]	38.9 [1.2, 249]
Missing observation	61 (19.9%)	37 (6.2%)	11 (2.6%)	109 (8.2%)
Travel distance by walk (Kilometer)				
Mean (SD)	23.7 (20.1)	36.7 (23.2)	94.7 (51.9)	52.0 (45.3)
Median [Min, Max]	17.2 [1.1, 101]	32.3 [1.5, 109]	82.4 [4.3, 249]	38.3 [1.1, 249]
Missing observation	0 (0%)	0 (0%)	11 (2.6%)	11 (0.8%)

Note: SD is standard deviation; N is number of observations

The logsum model measured accessibility by taking a summary of the maximum utility of all travel alternatives available to an individual in a choice model (Ben-Akiva and Lerman 1979), as shown in following formula.

$$Accessibility = E\left[Max_{i \in C_t} U_i\right] = ln \sum_{i \in C_t} e^{U_i} \tag{8}$$

Where U_i is the utility for alternative *i* belonging to the choice set C_t. The utility for a multinomial logit model is given by

$U_{car} = \alpha * Distance_{car} + ASC_{car}$

$U_{bike} = \alpha * Distance_{bike} + ASC_{bike}$

$U_{walk} = \alpha * Distance_{walk}$

$U_{taxi} = \alpha * Distance_{taxi} + \beta * Waiting\ time_{taxi} + ASC_{taxi}$

$U_{train} = \mu * Access\ time_{train} + \beta * Waiting\ time_{train} + \alpha * Distance_{train} + ASC_{train}$

$U_{train} = \mu * Access\ time_{bus} + \beta * Waiting\ time_{bus} + \alpha * Distance_{bus} + ASC_{bus}$

The estimated parameters based on multinomial logit model for mode choice are shown in Table 4-6. The logsum measures of accessibility corresponding to the identified model were calculated for each zone.

Table 4-7 Estimated parameters of utility

Variables	Coefficients	Estimates	t-stat
Travel distance	α	-0.0000547	-2.373665
Waiting time	β	-0.0006293	-29.502510
Access time	µ	-0.0007747	-90.816990
Alternative specific constant of train	ASC_{train}	-0.0000004	-0.000008
Alternative specific constant of bus	ASC_{bus}	-0.0000006	-0.000012
Alternative specific constant of car	ASC_{car}	0.0000030	0.000062
Alternative specific constant of bike	ASC_{bike}	-0.0000006	-0.000012
Alternative specific constant of taxi	ASC_{taxi}	-0.0000007	-0.000015

4.4. Summary

The study used different sources related to transport demands and supplies to develop demand and supply model, which were an important background to quantify transport gap in each zone. The personal trip survey data provided the number of trip productions and attractions by different purposes and modes per zone. Data related to the characteristics of a zone including populations, land-use, number of facilities, and transport supply were publicly available. The accessibility indicator was also measured and considered as a factor influencing local and nonlocal demands. The data were used to explore their relationships with the number of trips per zone and to build zone-based trip generation models. Moreover, the mobile spatial statistics data were used for adjusting the forecasted transport demands based on the personal trip data and analyzing the existing spatial-temporal distribution of transport gaps in Hokuto.

The supply model considered the spatial-temporal supply of public transport and private transport. Data related to bus, train, private car, relevant transport infrastructure network, and facilities (stations, bus stops) were used for the supply model.

5. Transport gaps in rural tourism areas

The transport gap is not fully understood in the existing literature. Most previous studies focused on measuring transport gaps in urban areas. Only a few studies have considered rural areas. For example, Parolin and Rostami (2016) identified transport gaps for administrative subdivisions in the rural areas of New South Wales, Australia. The transport gap is rarely explored in rural tourism areas, which are commonly characterized by low population density and scattered tourism attractions. Furthermore, previous studies mainly considered public transport as a primary mode of transportation in analyzing transport supply. Therefore, it would be important to consider all available transport modes to make a comprehensive and more realistic analysis of transport supply. On the other hand, the transport demands are mainly analyzed from disadvantaged groups, whereas the analysis based on actual demands is commonly overlooked. Considering different demands, such as local and nonlocal demands for commuting and recreational purposes, could be a more realistic description of current transport demands and transport gaps.

Although the transport gap for peak and off-peak hours is analyzed (Fransen et al. 2015; Kaeoruean et al. 2020), integrating differences between weekdays and weekends corresponding to changes in the supply of transport modes (i.e., public transport) would provide a better description of the level of transport gap. A consideration of all these issues would generate policy proposals, that can better tackle the current transport gaps.

This part attempts to address these research gaps by addressing the following two sub-questions:

- To what extent are transport demands and supplies in rural tourism areas?
- Where appear transport gaps in rural tourism areas?
- What transport gaps are different between a weekday and a weekend?
- Based on the analyses of existing transport gaps, what are the policy and practical implications for improving the transport gaps?

5.1. Transport demands

The aim of this part is to (1) understand indicators associated with variations in trip generations and attractions by zone; and (2) to predict the number of trips generated by local residents and attracted by nonlocal residents in each zone on a weekday and weekend in Hokuto, which are primary input data for analyzing transport gaps.

5.1.1. Methodology

The analytical framework for estimating transport demands by zone is shown in Figure 5-1. The analytical process includes three following steps.

Firstly, the variations of the number of trips generated and attracted by residents and nonlocal residents by zone were analyzed based on zone characterized data, including populations, geographical and land-use characteristics, transport supply indicators, and accessibility factors, and the person trip survey data combined from three main metropolitan regions. Regression models were developed to reveal the impacts of exploratory factors on the variations.

Secondly, by exploring the results of regression models estimated on a typical weekday, local trip productions, local trip attractions, and nonlocal trip attractions by zone were predicted according to zone-based characteristics (i.e., populations, geographical and land-use characteristics, transport supply indicators, and accessibility) in Hokuto.

Finally, by exploring mobile spatial statistics data provided by Docomo in 2020, the maximum entropy model was developed to decompose the estimated local and nonlocal demands into hourly trips on a weekday and a weekend.

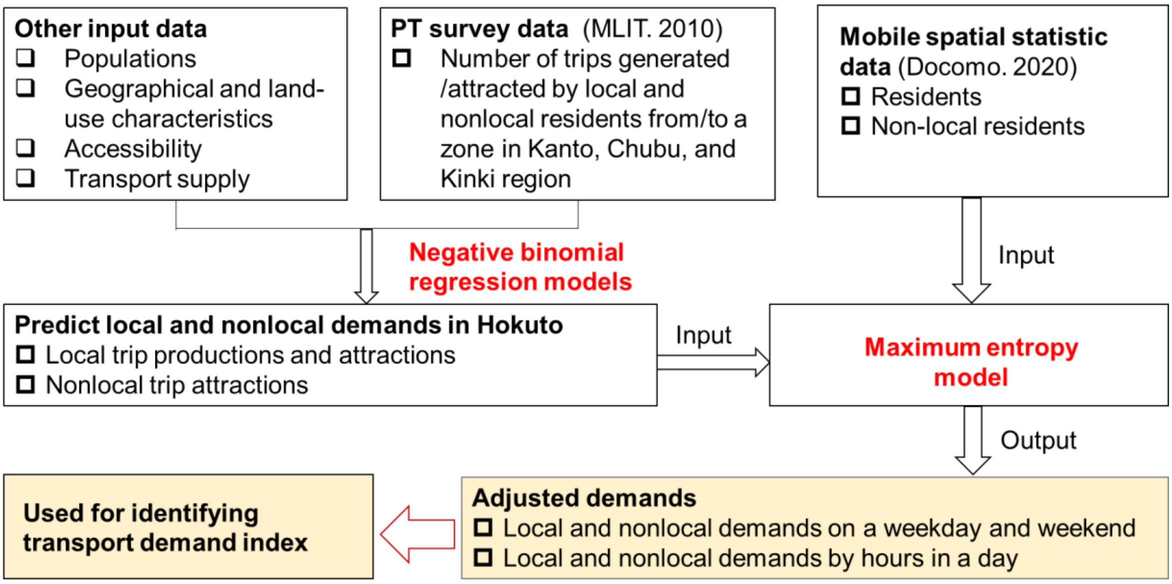


Figure 5-1 Analytical framework for transport demands

5.1.2. Transport demand models

5.1.2.1. Models and implementations

Zone-based trip models were used by many studies. An attempt was made to find the relationship between the number of trips produced and attracted by zone and zone-based characteristics. Given a set of 1532 destination zones and 1532 origin zones, separate models were produced for trip productions and attractions for different trip purposes. In trip models, dependent variables were the number of trips while explanatory variables include populations and land-use characteristics, built environments, transport supply indicators, and accessibility, which are summarized from literature (refer to Table 4-2, section 4.1).

The potential impacts of the socio-economical and land-use characteristics and built environments on the number of trips are examined. Unlike previous studies, this study focused on exploring the role of transport supply and accessibility indicators in local and nonlocal demands in each zone. This study also provided a comprehensive discussion on how indicators affect the transport demands of local and nonlocal residents.

In literature, two types of regression models were commonly used to estimate the influence of the independent indicators on trip generations, namely (1) linear regression and (2) nonlinear count models. Although the linear regression model can widely be applied to trip generations, the linear regression model commonly faces some problems, such as inefficient, inconsistent, biased estimates, and negative estimates (Long and Freese 2006).

To overcome problems of linear regression models, some studies focused on using non-linear models for trip generations (for example, Khattak and Rodriguez 2005; Shay et al. 2006; Shay and Khattak 2007; Zhang et al. 2019). In literature, two popular non-linear count models were widely used for estimating trip generation, namely: Poisson regression model and negative binomial regression (NBR) model. The Poisson model assumes that the sample variance was equal to its expected value. However, the variance of the dependent variables in this study was much greater than their expected values, which leaded to over-dispersion. Therefore, the NBR model was more appropriate to estimate those over-dispersed variables and to overcome the problems of linear regression model.

In NBR model, the relationship between a discrete numeric dependent variable and independent variables was expressed as following formula (9) (Washington, Karlaftis, and Mannering 2003).

$$\ln(\lambda_i) = \beta_i * X_i + \varepsilon_i \tag{9}$$

where

λ_i: denotes the mean of dependent variable i

X_i: represents the value of independent variable *i*

β_i: represents the estimated coefficient of independent variable i

ε_i: is a gamma-distributed error term

In order to build the NBR models, the following steps are implemented:

Step 1: **Check correlation between indicators**

Correlation coefficient (r) was used to evaluate the correlation between explanatory indicators and a dependent variable (number of trips per zone). The coefficient indicates the strength and direction of the correlation. A p-value for each coefficient associated with each explanatory variable was computed in a statistical test to determine whether the explanatory variable is an effective predictor. The null hypothesis for this statistical test was that a coefficient is not significantly different from zero. A coefficient with a p-value of 0.05 indicates the corresponding explanatory variable is statistically significant at the 95 percent confidence level.

Step 2: Estimate regression models by 70% of dataset

The study randomly selected 70% of dataset as the training dataset to develop the regression models. The estimated models will be checked with 30% of the remained dataset. The parameters (β_i and ε_i) of NBR models were obtained by using the "glmmTMB" package in R (Brooks et al. 2017).

Step 3: Check goodness of fit by 30% of dataset

In this study, two criteria, including R2 (R-squared value) and Mean Absolute Percent Error (MAPE) were used to check the goodness of the estimated models. The models with higher R2 and lower MAPE value present better goodness of fit or in other words, the estimated models are a better fit to data and reliability for further predictions.

R-squared value (R^2): The R-squared value was a statistical measure, that pointed out the percentage of the variance in a dependent variable explained by the independent variables in a regression model. Possible R-squared values range from 0 to 1. A higher R-squared indicates a better regression model.

$$R^2 = 1 - \left[\sum_1^n (y_i - \hat{y}_i)^2 \Big/ \sum_1^n (y_i - \bar{y}_i)^2 \right]$$

Mean Absolute Percent Error (MAPE): was a statistical measure of the accuracy of a forecasting model. Possible values range from 0 to 1. The estimated model indicating MAPE value is under 10% is ‘‘very good’’ model; between 10% and 20% is ‘‘good’ model’; between 20% and 50% is ‘‘acceptable’’ model; and above 50% is classified as ‘‘wrong and false’’ model (Lewis 1982). The value of MAPE can be quickly obtained by package “MLmetrics” in R or were determined by the following formula.

$$\mathrm{MAPE} = 100 * \left| \frac{1}{n} \sum_{1}^{n} \frac{(y_i - \hat{y}_i)^2}{y_i} \right|$$

Where:

y_i, $\hat{y}_i$ and $\bar{y}_i$ are observed value (number of trips), predicted value (number of trips), and mean value ((number of trips) in zone *i* respectively.

n is the number of zones.

5.1.2.2. Local and nonlocal trip production and attraction model

Local trip productions represent the number of trips generated by local residents from a zone. Local and nonlocal trip attractions describe the number of trips attracted by local and nonlocal residents to a zone, respectively. The correlations between explanatory variables and dependent variables were tested. The modelling process will exclude some variables due to insignificance. The final NBR models developed using the 2010 PT survey data are shown in Table 5-1.

Table 5-1 Estimation results of local and nonlocal trip generation models

Explanatory indicators	Local demand (Hokuto)				Nonlocal demand	
	Trip production		Trip attraction		Trip attraction	
	Estimate	Sig.	Estimate	Sig.	Estimate	Sig.
Intercept	3.3412	***	5.5626	***	-0.9116	*
Urban	0.1859	***	0.1164	*	0.2726	***
Commercial and business	0.6023	***	n.i	Insig.	0.8469	***
Residential and industrial	0.1090	***	0.1342	***	0.0981	***
Industrial	0.9444	***	1.2889	**	1.0974	***
Mixed	1.1047	***	n.i	Insig.	1.4353	***
Population (log)	0.5057	***	0.4941	***	0.3746	***
Residence density	0.3844	***	0.2499	***	0.5019	***
No. of public facilities	0.0043	***	0.0050	***	0.0056	***
No of tourism facilities	0.0029	***	0.0022	**	0.0028	***
Train frequency	0.0024	***	0.0010	*	0.0033	***
Bus frequency (log)	0.0493	***	0.0241	*	0.0872	***
Service coverage	n.i	Insig.	n.i	Insig.	0.4216	***
Accessibility (log)	0.1436	***	-0.1623	**	0.6615	***
AIC	34427.8		34203.6		32571.8	
Log likelihood	-17198.9		-17086.8		-16269.9	
R-squared	0.8068		0.8087		0.6792	
MAPE	0.322		0.642		0.411	
Number of observations	1532		1532		1532	

Note: "+" positive relationship; "-" negative relationship; "Insig" = "Insignificant", means the variable is not statistically significant in the model result; and "n.i." = "Not Included", indicates that the variable is not included due to statistical insignificance; Level of significance: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1; AIC: Akaike Information Criterion.

The estimated results of the local trip production and nonlocal trip attraction model showed that all indicators were positively related to the number of trips per zone. The land use characteristics and accessibility were significantly associated with the number of trips per zone. Trip making in an urban zone was more than in a rural zone. Zones with the characteristics of mixed land, commercial and business land, high building density, and large number of tourism facilities tended to be more likely to attract nonlocal residents. In contrast, zones with high residential and industrial land attracted more local residents.

Findings show that bus/train frequency, service coverage, and accessibility tended to affect nonlocal trip attraction more than local production and attraction. This means that most nonlocal residents were attracted to zones, where transport supply (bus and train frequency as well as service coverage) and accessibility were better provided. Accessibility was the most important factor, that impacted nonlocal trip attractions. The coefficient of accessibility was 0.14 and 0.66 for local and nonlocal trip attractions, respectively. In contrast, accessibility was negative associated with local trip attractions. This shows that travelers tended to make longer travel distances when accessibility was improved.

The signs of all the variables included in models were consistent with the theory of transport planning and all variables (social-geographical and land use characteristics, transport supply, and accessibility) were significantly associated with the number of trips generated and attracted from/to each zone. For example, increasing one bus arrival per day potentially increases 1.05 local and 1.09 nonlocal trip attractions per day per zone.

Overall, the models had the goodness of fit. The significance levels of the explanatory variables were also the same in the three models. The local trip production and attraction model had R-squares of 0.8, which reduced to 0.68 in the nonlocal trip attraction model, indicating that about 80% and 68% of the information contained in the data was explained by models, respectively. The MAPE values of estimated models ranges from 0.2 to 0.5. Both criteria evaluating the goodness of the models indicated that the models developed using personal trip data were suitable to predict local and nonlocal trips per zone.

5.1.2.3. Local and nonlocal trip production and attraction model by different trip purposes

Six NBR models developed for trip production and attraction by different trip purposes using the 2010 PT survey data are shown in Table 5-2 and Table 5-3.

Table 5-2 Estimation results of trip generation models for commuting purpose

Explanatory variables	Local demand (Hokuto)				Nonlocal demand	
	Commuting production		Commuting attraction		Commuting attraction	
	Estimates	Sig.	Estimates	Sig.	Estimates	Sig.
Intercept	5.0242	***	5.7680	***	-1.4766	***
Urban	0.1675	***	0.1342	**	0.3036	***
Commercial & Business	n.i	Insig.	n.i	Insig.	0.8242	***
Residential & industrial	0.1626	***	0.1548	***	0.1113	***
Industrial	1.1454	***	1.3399	***	1.2561	***
Mixed land	0.5300	**	n.i	Insig.	1.4816	***

Table 5-3 Estimation results of trip generation models for commuting purpose (Continued)

Explanatory variables	Local demand (Hokuto)				Nonlocal demand	
	Commuting production		Commuting attraction		Commuting attraction	
	Estimates	Sig.	Estimates	Sig.	Estimates	Sig.
Population (log)	0.5953	***	0.5097	***	0.3914	***
Building density	0.2209	***	0.1663	**	0.4995	***
No. of public facilities	0.0039	***	0.0050	***	0.0058	***
No. of tourism facilities	0.0030	***	0.0018	*	0.0019	*
Train frequency	0.0012	**	n.i	Insig.	0.0028	***
Bus frequency (log)	n.i	Insig.	n.i	Insig.	0.0805	***
Service coverage	n.i	Insig.	n.i	Insig.	0.4064	***
Accessibility	-0.2685	***	-0.2296	***	0.6914	***
R-squared		0.8470		0.8090		0.6475
MAPE		0.3710		0.6399		0.4113
AIC		31928.8		32920.9		31899.1
Log Likelihood		-15950.4		-16447.5		-15933.5
Number of observations		1532		1532		1532

Note: "+" positive relationship; "-" negative relationship; "Insig" = "Insignificant", means the variable is not statistically significant in the model result; and "n.i." = "Not Included", indicates that the variable is not included due to statistical insignificance; Level of significance: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1; AIC: Akaike Information Criterion.

Table 5-4 Estimation results of trip generation models for recreational purpose

Explanatory variables	Local demand (Hokuto)				Nonlocal demand	
	Recreational production		Recreational attraction		Recreational attraction	
	Estimates	Sig.	Estimates	Sig.	Estimates	Sig.
Intercept	1.5814	***	3.0625	***	-1.2110	*
Urban	0.1779	***	0.1182	*	0.1611	**
Commercial & Business	0.3420	***	0.2541	**	0.9304	***
Residential & industrial	0.0772	***	0.0956	**	n.i	Insig.
Industrial	0.5986	*	1.2229	**	n.i	Insig.
Mixed land	0.7662	***	n.i	Insig.	1.2931	***
Population (log)	0.6325	***	0.4723	***	0.3119	***
Building density	0.2858	***	0.4002	***	0.4956	***
No. of public facilities	0.0038	***	0.0056	***	0.0050	***
No. of tourism facilities	0.0031	***	0.0026	**	0.0062	***
Train frequency	0.0022	***	0.0022	***	0.0050	***
Bus frequency (log)	0.0502	***	0.0482	***	0.1139	***
Service coverage	n.i	Insig.	n.i	Insig.	0.4935	***
Accessibility	n.i	Insig.	n.i	Insig.	0.5421	***
R-squared		0.8376		0.7601		0.5483
MAPE		0.4077		0.6952		0.5067
AIC		29718.5		31091.3		28211.5

Log Likelihood	-14845.2	-15531.6	-14845.2
Number of observations	1532	1532	1532

Note: "+" positive relationship; "-" negative relationship; "Insig" = "Insignificant", means the variable is not statistically significant in the model result; and "n.i." = "Not Included", indicates that the variable is not included due to statistical insignificance; Level of significance: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1; AIC: Akaike Information Criterion.

Most variables were positively related to local and nonlocal transport demands. Land-use characteristics and accessibility were the most significant factors, that impact all trip purposes. Bus/train frequency and service coverage were insignificantly related to local commuting and recreational demands. This could be explained that either existing public transport services were provided well for local residents or local commuting and recreational demands were made by other means of transportation.

Comparison among models showed that, all factors tended to affect nonlocal demands more than local demands in both commuting and recreational demands. Moreover, the impacts on recreational demands were higher than commuting demands.

All the explanatory variables included in the models had significant levels. All models had the goodness of fit with good R-squared and acceptable MAPE value, which means that models developed by personal trip data were suitable to predict trips by different purposes per zone.

5.1.2.4. Estimation results of local and nonlocal transport demands in Hokuto

Based on the NBR models estimated for local and nonlocal trip productions and attractions, the total number of local trip productions, local trip attractions, and nonlocal trip attractions on a weekday in Hokuto was 67,583 trips, 67,173 trips, and 9,277 trips, respectively. The number of trips per person was 1.51 on a weekday.

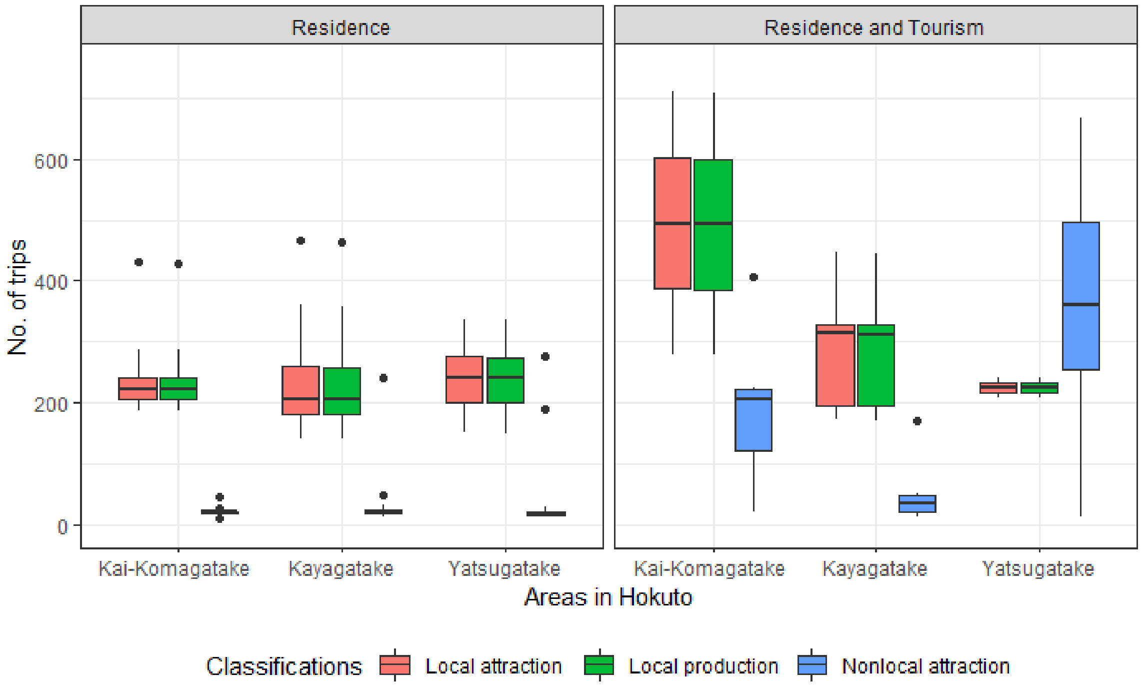


Figure 5-2 Distribution of estimated local and nonlocal transport demands in Hokuto

The variation of local and nonlocal trips per zone in three main areas separated in residential and tourism zones in Hokuto is shown in Figure 5-2. In residential zones, local demands were significantly larger than nonlocal demands and mainly focused on Yatsugatake area. Overall, there was 75 percent of the estimated trips per zone, which was less than approximately 300 trips/day/zone. On the other hand, in zones having both residential and tourism facilities, local demands focused on Kai-komagatake area while nonlocal demands were the highest in Yatsugatake area.

The spatial distribution of local trip productions, local trip attractions, and nonlocal trip attractions is shown in Figure 5-3. The number of trips was higher in zones with large populations and tourism facilities. Zones far from the city center were commonly fewer trip productions and attractions.

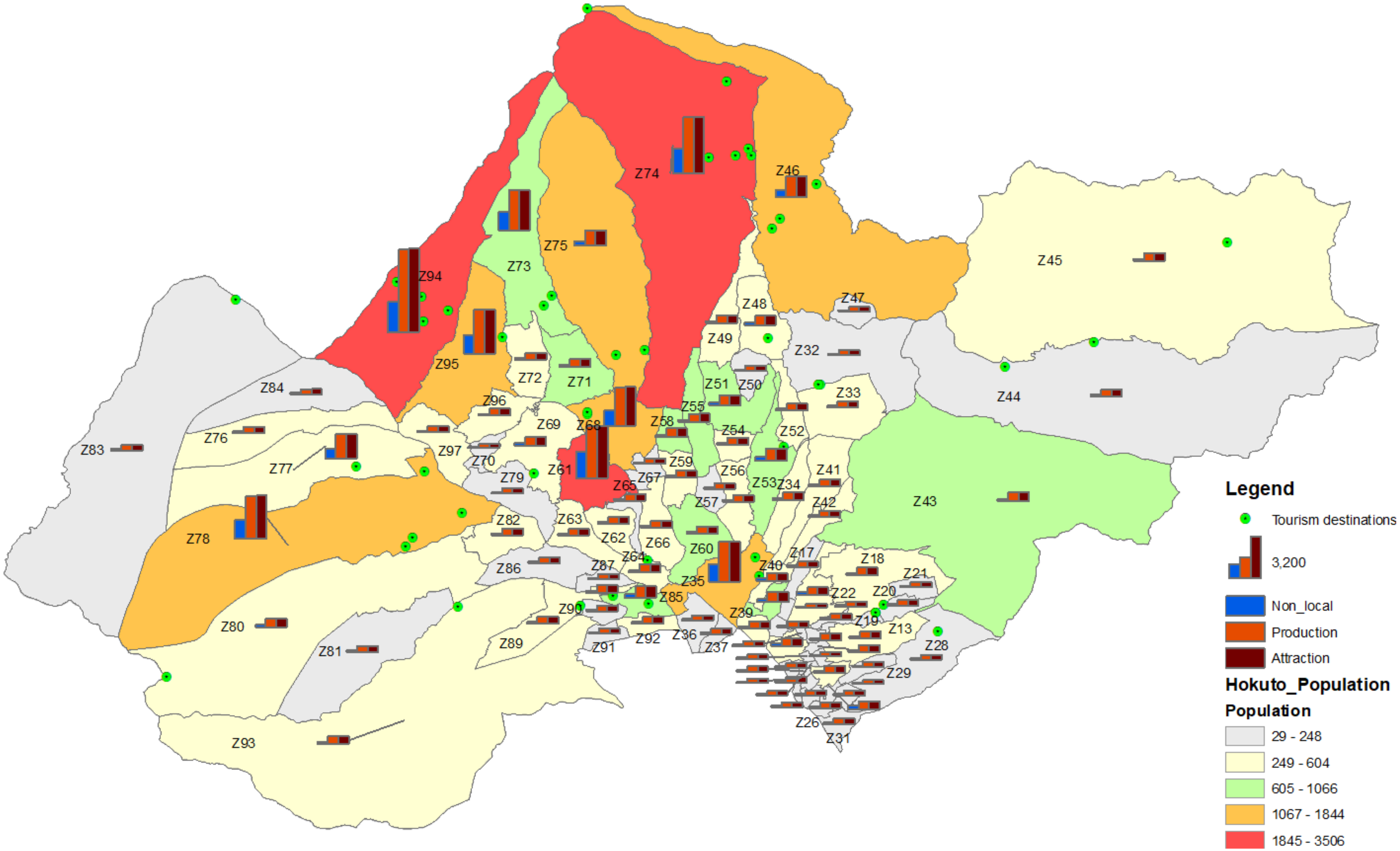


Figure 5-3 Spatial distribution of local and nonlocal transport demands

5.1.3. Adjustment of transport demands

5.1.3.1. Methodology

The most important question is how the observed populations in mobile spatial statistics data can be related to local and nonlocal transport demands. It is assumed that change in populations observed in each area is due to trip productions (outflows) and trip attractions (inflows). Based on this assumption, the predicted transport demands were integrated with mobile spatial statistics data to decompose travel demands on a weekday into different days (i.e., weekday and weekend) and hours of the day.

In this study, the maximum entropy principle was proposed for adjustment processes. Similar to previous studies (Ge and Fukuda 2016; Wilson 1970; Van Zuylen and Willumsen 1980), the study seeks the probability that the pattern of trip flows is proportional to the number of ways that trips can be arranged to obtain this pattern. Using combinatorial theory, the total number of ways is the multiplication of all possible combinations.

$$W_a = \binom{a_m}{A_m^1} \mathrm{x} \binom{a_m - A_m^1}{A_m^2} \mathrm{x} \dots \mathrm{x} \binom{a_m - A_m^1 - A_m^2 - A_m^{T-1}}{A_m^T} = \frac{a_m!}{\prod_{t=1}^{T} A_m^t} \tag{10}$$

The most probable pattern can be obtained by maximizing W_a. Taking the logarithm and approximating it using Stirling's formula, the objective function (10) becomes

$$\mathbf{Max}(W_a) = -\sum_i^T A_m \text{ or } \mathbf{Min}(W_a) = \sum_i^T A_m \tag{11}$$

As a result, the most probable pattern of trip productions incorporating the previously estimated trip productions takes the form of $\sum_{i,t}^{24} g_i^t$ *log($\sum_{i,t}^{24}(g_i^t / G_i) - 1)$. Similarly, the most probable pattern of trip attractions takes the form of $\sum_{i,t}^{24} A_i^t$ *log($\sum_{i,t}^{24}(A_i^t / a_i) - 1)$. Thus, an objective function with respect to both trip productions and attractions for each zone *i* is established as follows.

$$\mathrm{Min}(g_i^t, a_i^t) = \sum_{i,t}^{24} g_i^t * \log(\sum_{i,t}^{24}(g_i^t / G_i) - 1) + \sum_{i,t}^{24} a_i^t * \log(\sum_{i,t}^{24}(a_i^t / G_i) - 1) \tag{12}$$

Subject to

Population changes : $a_i^t - g_i^t = P_i^t - P_i^{t-1}$

Daily trip generation: $G_i = \sum_{i,t}^{24} g_i^t$

Daily trip attraction : $A_i = \sum_{i,t}^{24} a_i^t$

Hourly trip G/A : $a_i^t, g_i^t \geq 0$

Where:

a_i^t: Number of trip attractions at time t in zone *i*

g_i^t: Number of trip productions at time t in zone *i*

P_i^t, P_i^{t-1}: Number of populations observed at time t and t-1 in zone *i*

G_i , G_i : Number of trip productions and attractions in zone *i* predicted by regression models

The objective function (12) aims at minimizing the gaps between the adjusted values and predicted values. Each zone *i* corresponds to an independent problem in objective function. The objective function can be solved by the sequential quadratic programming (SQP) in R. Because the objective function is convex, the convergence of the SQP algorithm will be used to evaluate the goodness of model fit.

5.1.3.2. Results of adjustments

The total number of local trip productions/attractions and nonlocal trip attractions on a weekday in Hokuto, which were adjusted by the maximum entropy model, was 71,095 trips and 17,387 trips, respectively. The number of adjusted trips was higher than that of trips estimated by personal trip survey data on a weekday. There was a significant increase in the number of nonlocal trip attractions. For transport demands on a weekend, there were 70,927 local trips and 16,441 nonlocal trips, which were lower than weekday. The number of trips per person was 1.60 and 1.59 on a weekday and weekend, respectively.

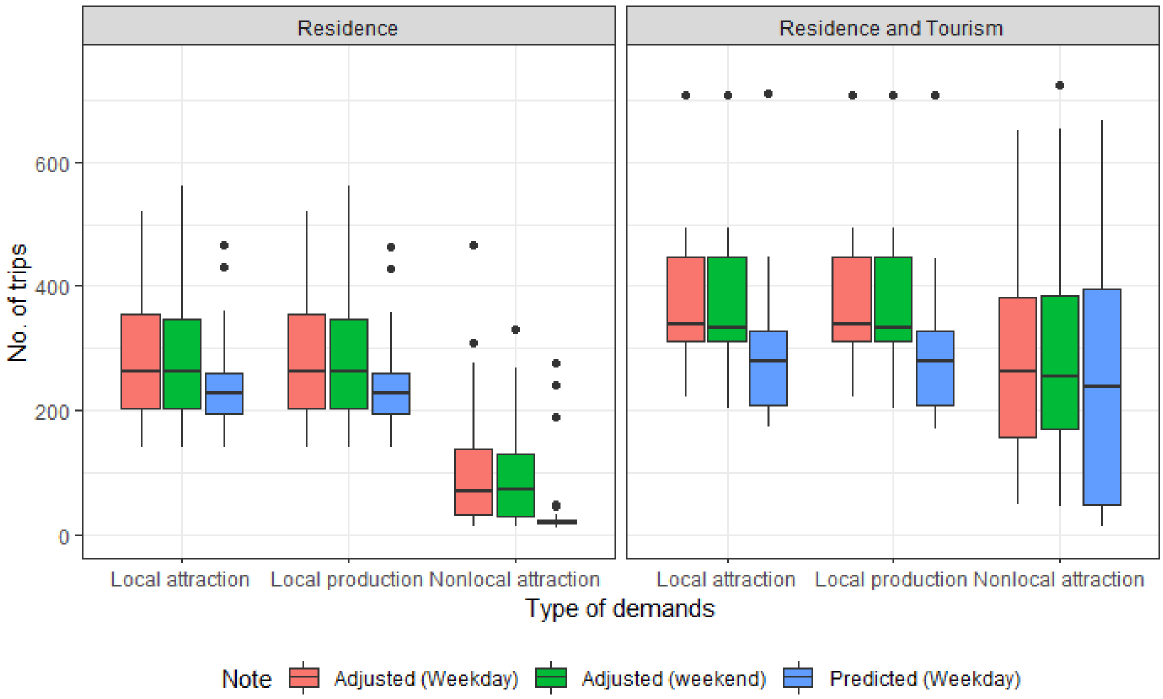


Figure 5-4 Variability in local and nonlocal demands per zone on weekday

The variation of estimated local and nonlocal trips by zone in Hokuto is shown in Figure 5-4. In residential zones, on overall, 75 percent of the adjusted trips by local residents was less than 400 trips while the adjusted trips by nonlocal residents were overall less than 200 trips per zone on both weekday and weekend. Transport demands were higher in tourism zones. The nonlocal demands on a weekend were slightly higher than on a weekday.

Figure 5-5 and Figure 5-6 illustrate the hourly variation in local and nonlocal demands on a weekday and a weekend. In general, local trip productions and nonlocal trip attractions tended to be higher in the morning peak hours (6 am to 9 am). In contrast, local trip attractions and nonlocal trip generations tended to be higher in the evening peak hours (4 pm to 7 pm).

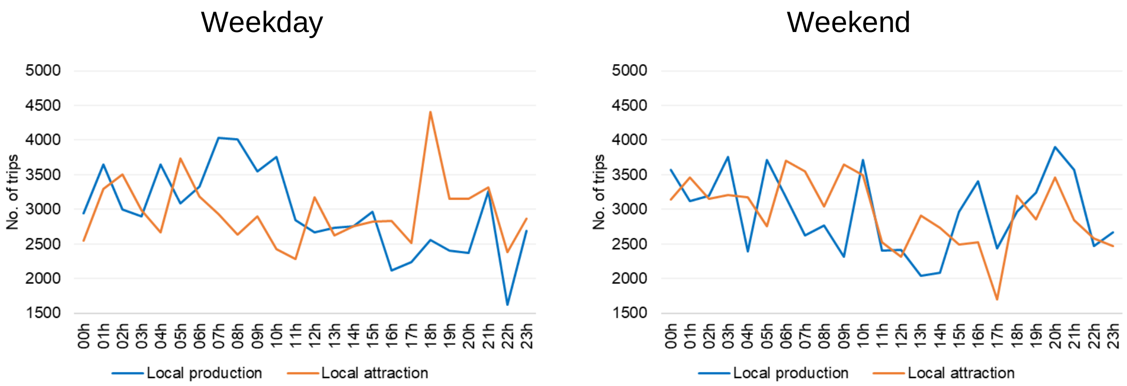


Figure 5-5 Hourly variations in local trip productions and attractions

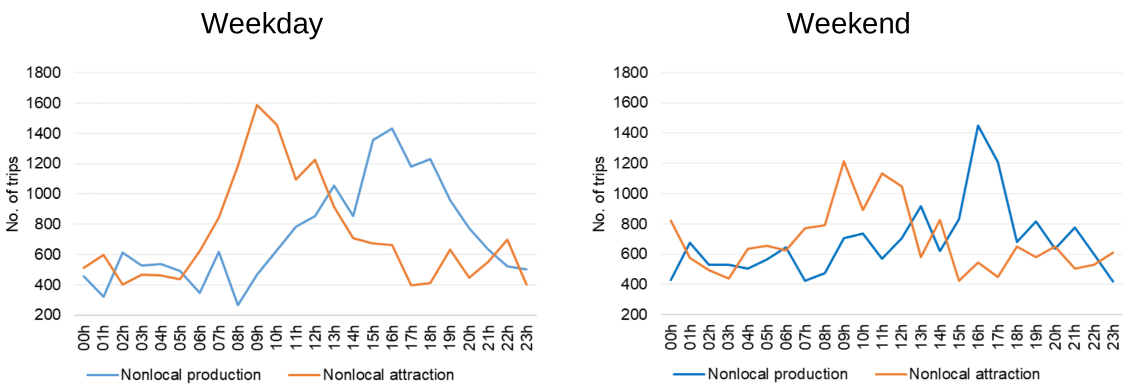


Figure 5-6 Hourly variations in nonlocal trip productions and attractions

5.2. Transport supplies

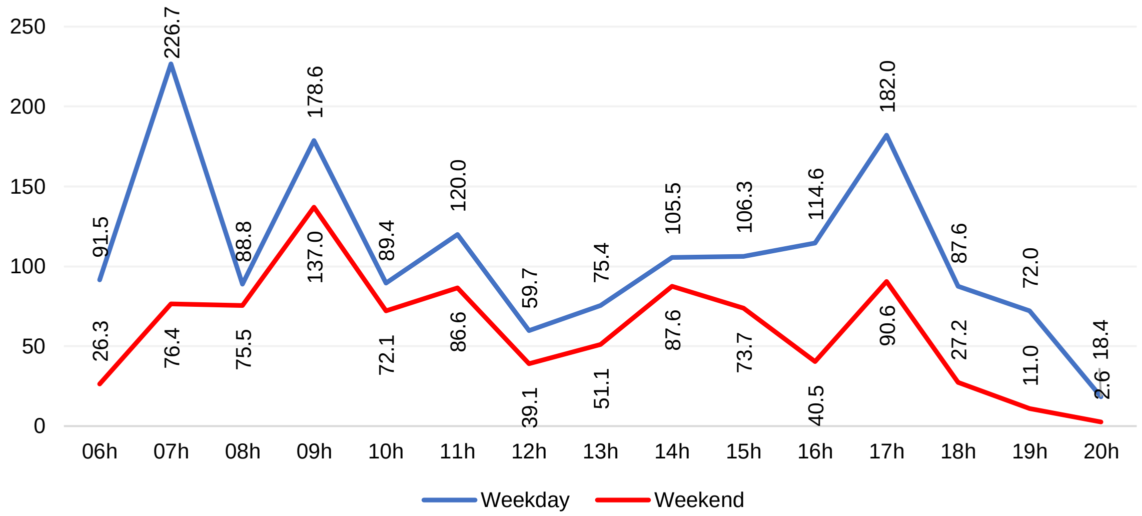


Figure 5-7 Variation in the values of public transport on a weekday and weekend

As illustrated more in-depth in the methodology chapter (Section 3.3), the transport supply was measured from indicators representing the supply of public transport and private transport. Service coverage and frequency were used to quantify the public transport supply while available cars and road density were utilized for determining the private transport supply.

The values of public transport calculated by hours on a weekday and a weekend are shown in Figure 5-7. Overall, the supply value of public transport was the largest in the morning peak hours and was larger on the weekday compared to the weekend.

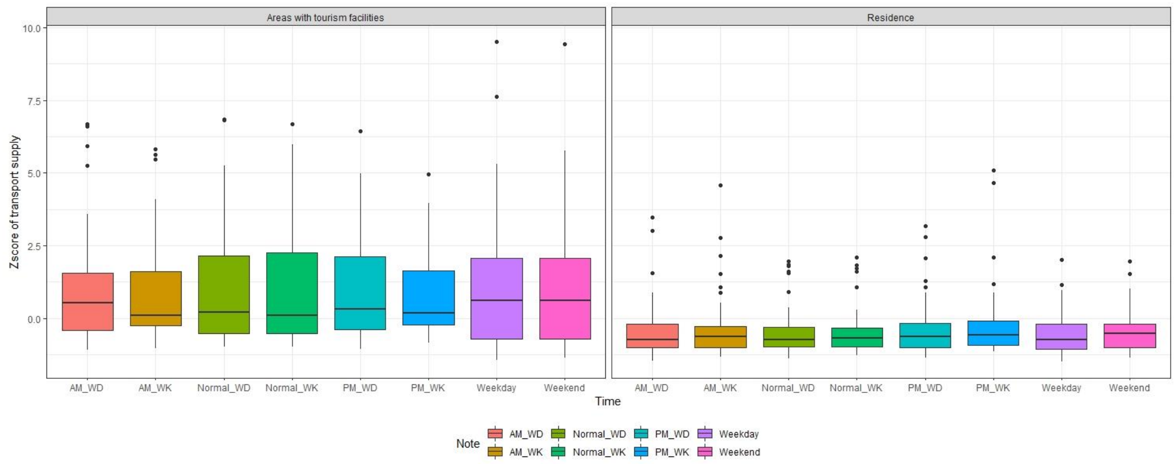


Figure 5-8 The variation of transport supply index in hours on a weekday

Figure 5-8 shows the variation of transport supply index in morning peak hours (06h-09h), evening peak hours (17h-20h), and normal hours (10h-16h) on a weekday and a weekend. The variation in the transport supply index was significant in tourism zones.

5.3. Transport gap estimation

5.3.1. Spatial-temporal transport gaps

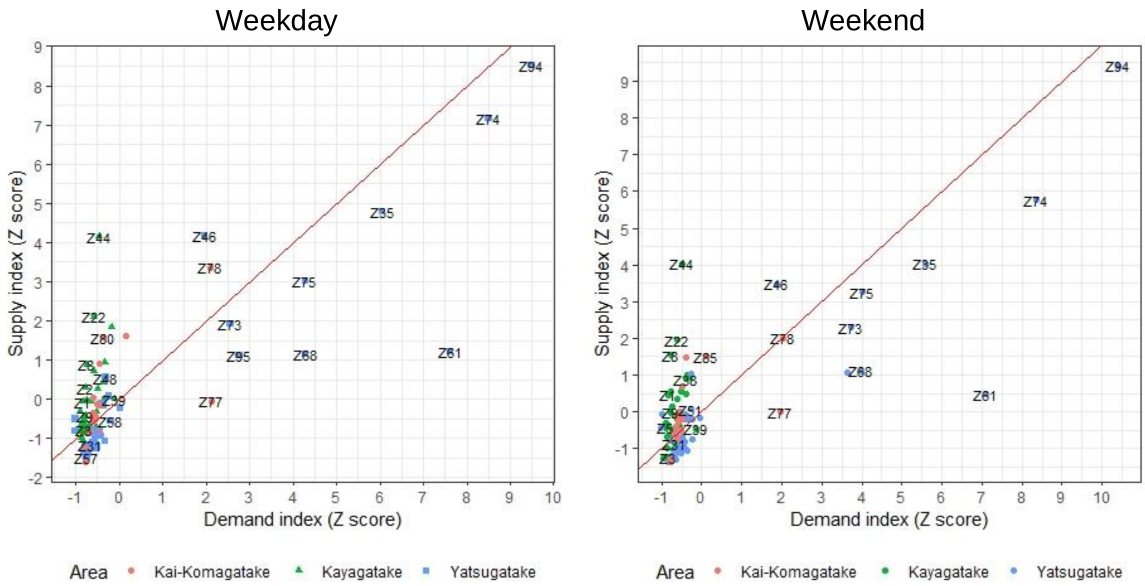


Figure 5-9 Existing transport demand and supply index on the weekday and weekend

There was an apparent correlation between the z-scores of transport supply and demands on the weekday ($r = 0.796$; p-value < 2.2e-16) and on the weekend ($r = 0.783$; p-value < 2.2e-16), indicating that the transport demands commonly concentrated in zones with high level of transport supplies.

Figure 5-9 shows the existing transport demand and supply index in each zone on a weekday and a weekend, respectively. Most transport demand index ranges from [-1.5, 0.5] while the values of transport supply index are in the range [-1.5, 2] on both weekday and weekend. There are several zones where the value of transport demand index is larger than that of transport supply index. The figure also shows that the number of zones with transport gaps (defined as points under the red diagonal line) in Yatsugatake area was more than in Kayagatake and Kai-Komagatake area.

The transport gap was identified by the transport supply index subtracting the transport demand index. The transport gap was either negative value or positive value. A negative transport gap value indicates that transport supply is lower than transport demand while a positive value shows that transport supply is higher than transport demand. The larger negative transport gap means that bigger gaps in transport supply and low quality of transport services, which leads to difficulty of accessing transport services and desired activities or destinations. In contrast, a larger positive transport gap was a larger transport supply and better quality of transport services from the travelers' perspective. Figure 5-10 shows the existing transport gaps on the weekday and weekend. Most transport gaps are ranged from "low gap" to "medium gap".

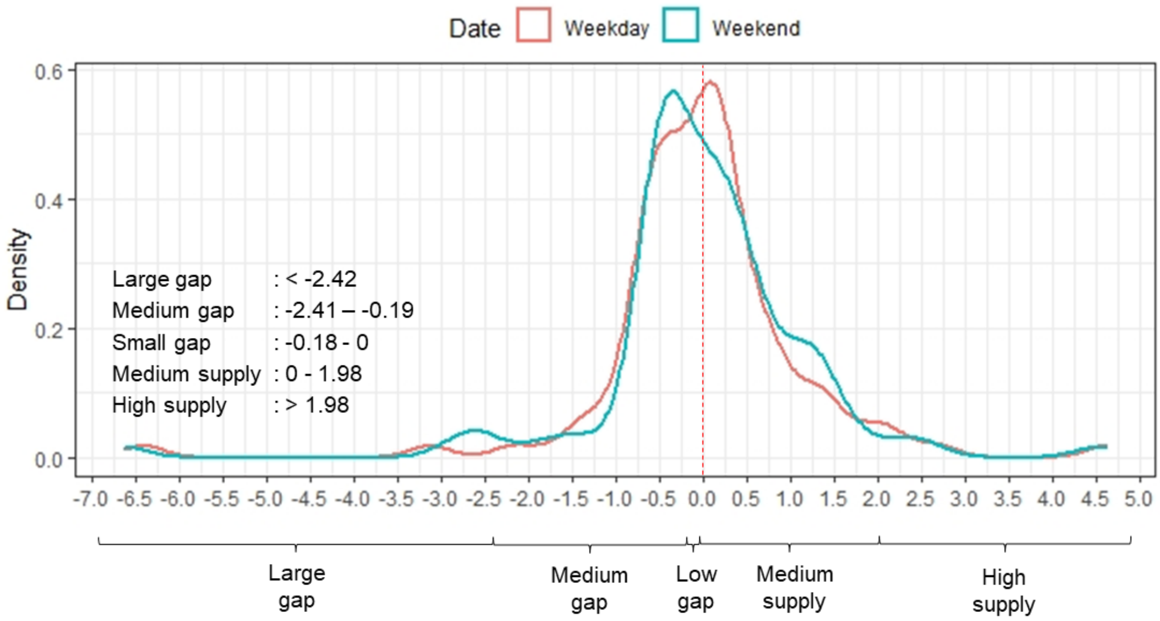


Figure 5-10 Existing transport gaps on the weekday and weekend

Figure 5-11 and Figure 5-12 represent the spatial distributions of transport gaps on a weekday and a weekend, respectively. In general, there was a slight difference in transport gaps between the weekday and weekend. Zones with transport gaps mainly focused on zones, where attracted large local and non-local residents and located more tourism facilities. Most zones far from the city center were low transport gaps. The transport gaps were scattered in Yatsugatake area while transport gaps only occur in tourism zones in Kayagatake and Kai-Komagatake area.

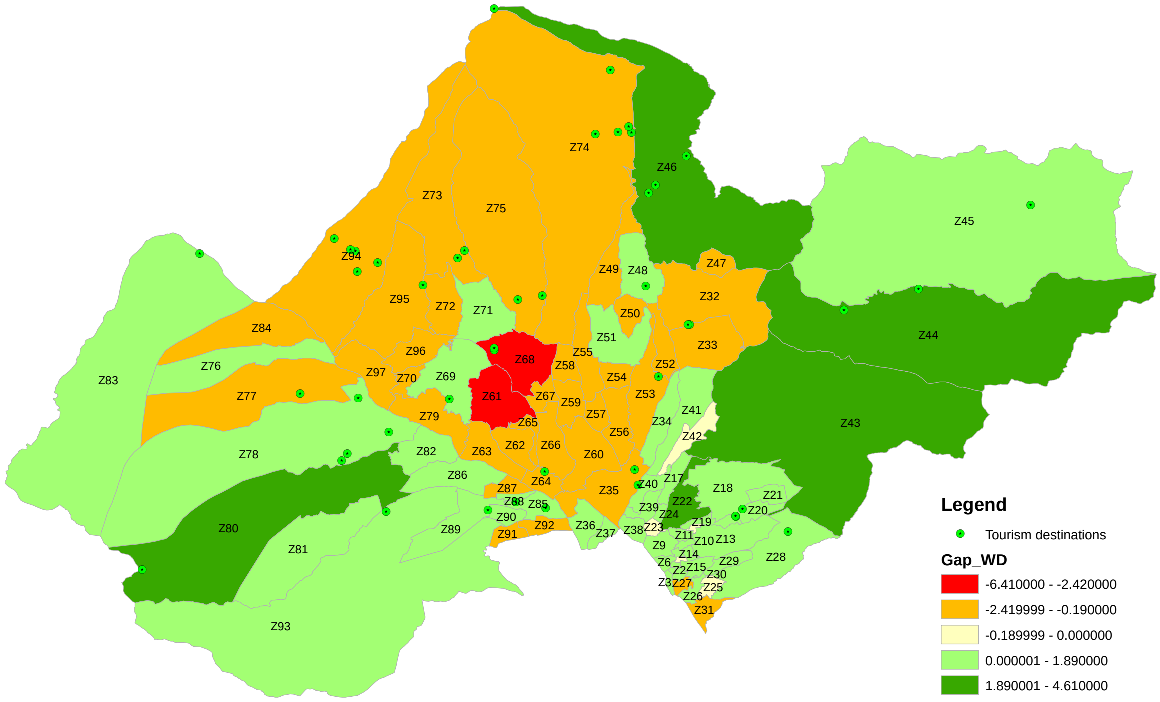


Figure 5-11 The spatial distributions of transport gaps on a weekday

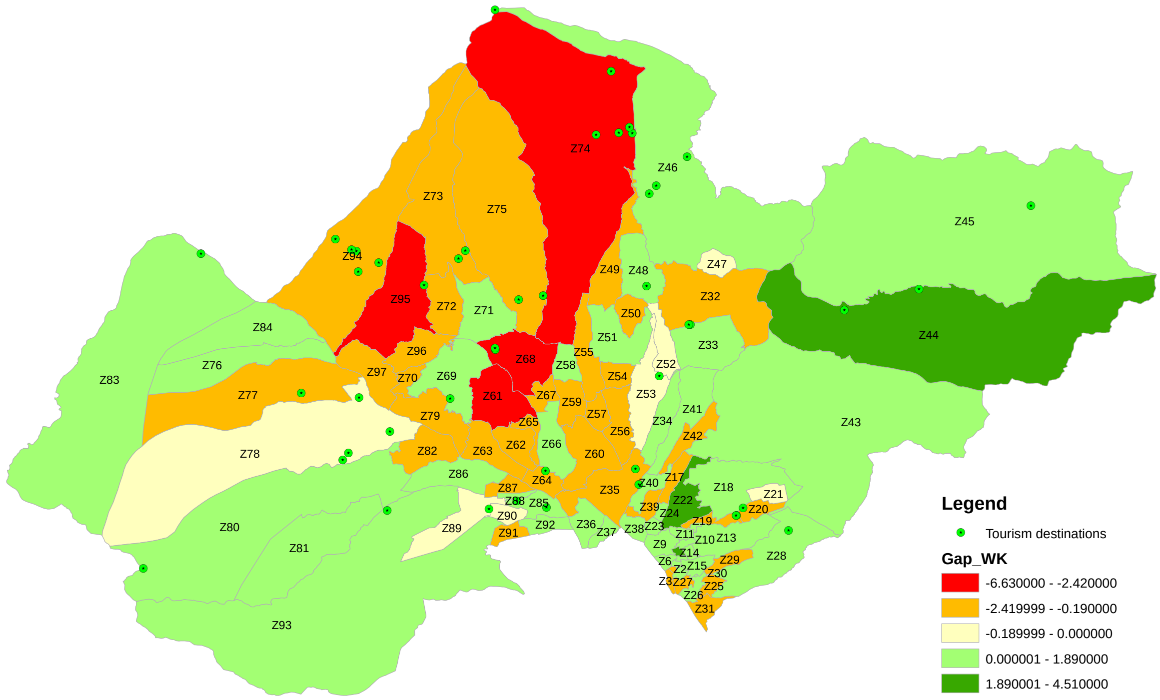


Figure 5-12 The spatial distributions of transport gaps on a weekday

In comparison with transport gaps between the weekday and weekend, the difference occurred in major tourism zones, such as Oizumicho Nishiide (Z74), Oizumicho Yato (Z75), Hakushucho Shirasu (Z78), Kobuchisawa (Z94), and Kamisasao (Z95). The transport gaps became more critical on the weekend. This could be explained by an increase in transport demands of non-local residents and a significant reduction in bus service frequency on weekends.

Figure 5-13 and Figure 5-14 describe the variation of transport gaps across morning peak hours, evening peak hours, and normal hours on a weekday and a weekend, respectively. In general, transport gaps became more critical during peak hours and on the weekend, especially in tourism areas. When comparing the hours, there was a similarity in transport gaps between morning and evening peak hours. Transport gaps on normal hours were relatively similar to a whole day.

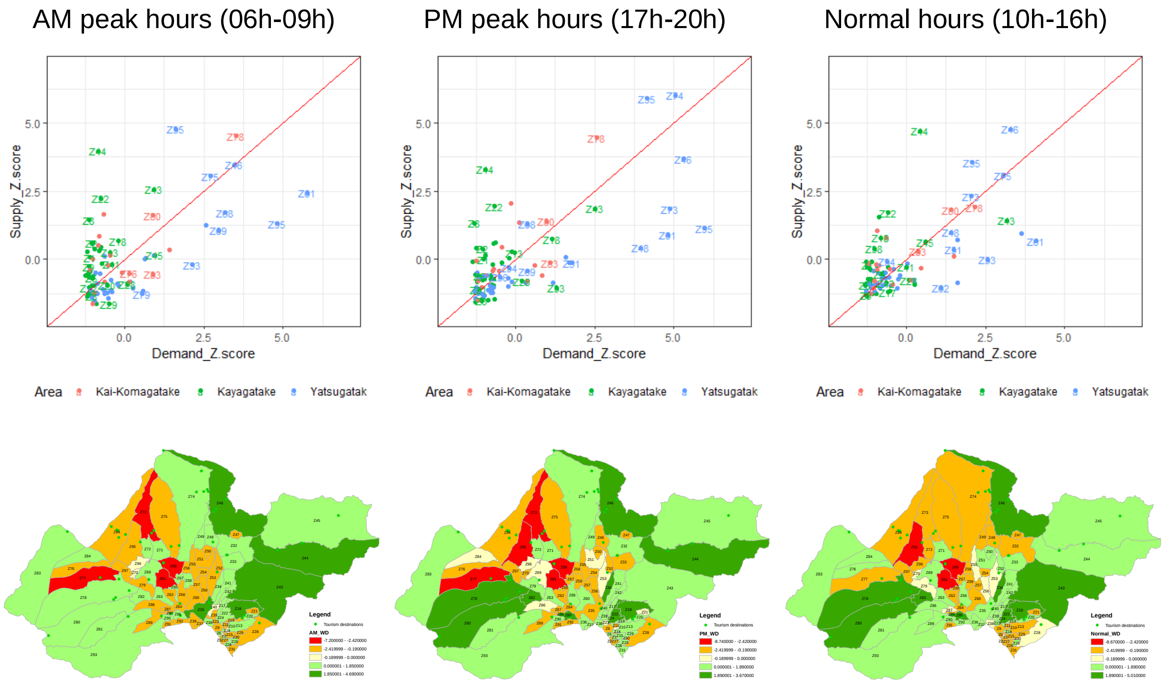


Figure 5-13 Transport gaps by hours on a weekday

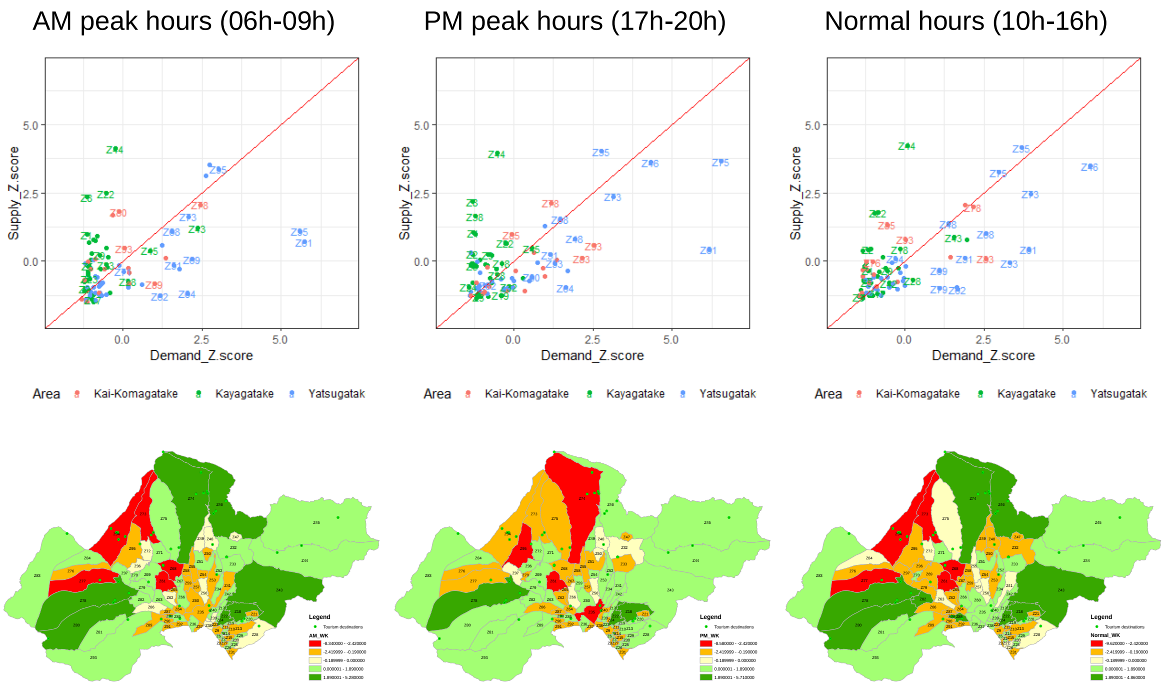
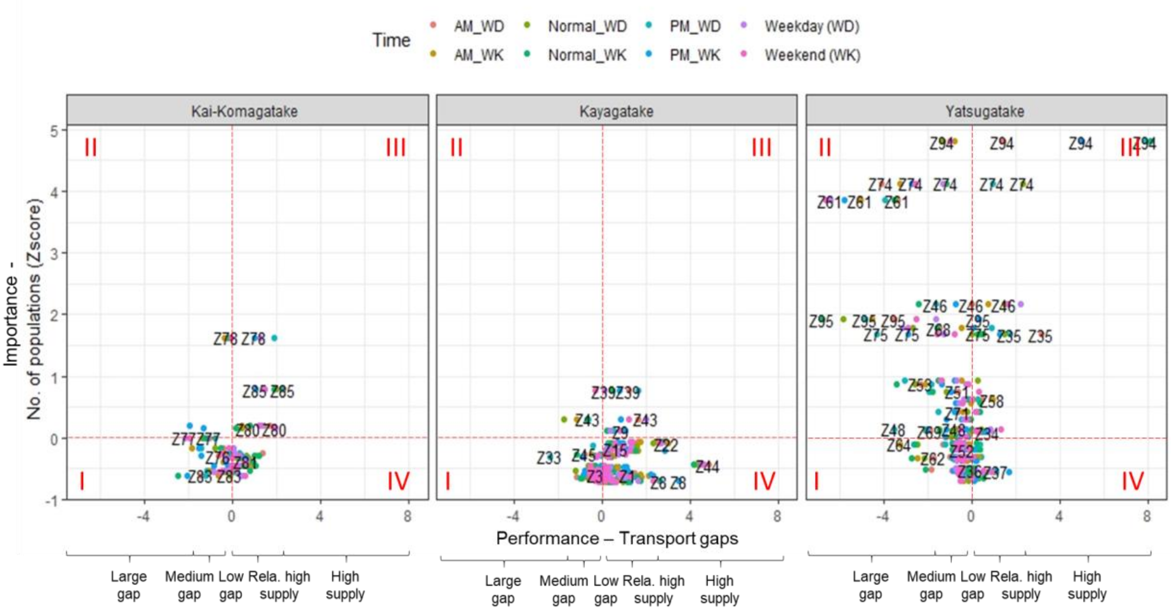


Figure 5-14 Transport gap by hours on a weekend

5.3.2. Importance performance analysis for transport gaps

The previous section already pointed out the variations in spatial-temporal transport gaps in zones within three main areas in Hokuto. This section aims to answer an important question of which areas should be prioritized to address transport gaps. The transport gaps demonstrated the performance of transport supply and described the ease of travelers to reach a specific destination or social activity. This means that larger positive transport gaps were better quality of transport services from the travelers' perspective and vice versa. Providing better transport services and accessibility to travelers was an important task of decision-makers and planners.

With the purpose of identifying priority zones for transport gaps improvement and suggesting suitable managerial actions for transit agencies and policy-makers, the importance performance analysis (IPA) is used (Martilla and James 1977). In this study, the transport gap was used to represent the performance while the number of populations at a zone was used as a simple representation of importance for improving transport gaps. This is because zones with greater demands require a larger transport supply than zones with lower demands.



Note: I = Not importance; II = Improvement Priority; III = Keep up the good work; IV = High supply

Figure 5-15 Importance performance analysis for transport gaps

Figure 5-15 describes the analysis of performance and importance for transport gaps improvement. The grand mean of importance and performance (standardized scores) was used to divide the zones into following four quadrants.

- Quadrant I (Low priority): involves zones with low populations and transport gaps. There is a low preference for improving transport supply in these zones.

- Quadrant II (Improvement Priority) involves zones with negative transport gaps and large populations. This means that zones are high demands and low transport supply. Priority needs to pay attention to improve transport gaps in these zones.

• Quadrant III (Keep up the good work): covers zones with positive transport gaps and large populations. The transport supply is high performance and meets large demands. Priority is recommended to be maintained or expanded in these zones.

• Quadrant IV (Possible overkill): includes zones where the transport supply is largely provided but transport demands are low. Priority is recommended to re-optimize or reallocate transport supply in these zones to other zones (especially those in quadrant II).

The analytical results in Figure 5-15 shows that transport gaps in quadrant I ranged from low to medium gaps while medium and large gaps were classified in quadrant II. Furthermore, there are some zones, which are classified into both quadrant II and quadrant III due to the variation of transport gaps by hours in a day and between days. Zones in quadrant II mainly focused on Yatsugatake area so the priority is recommended to address transport gaps in Yatsugatake area.

5.4. Summary and discussion

5.4.1. Factors associated with transport demands

The Figure 5-16 shows nine zone-based models, which have been built to explore factors related to local and nonlocal demands by different purposes. The factors associated with local and nonlocal demands were identified from the results of NBR model estimates. The factors included in the models were zone- characterized variables, indicating that transport demands vary by the changes in the characteristics of a zone and trip-making decisions are not only influenced by these factors.

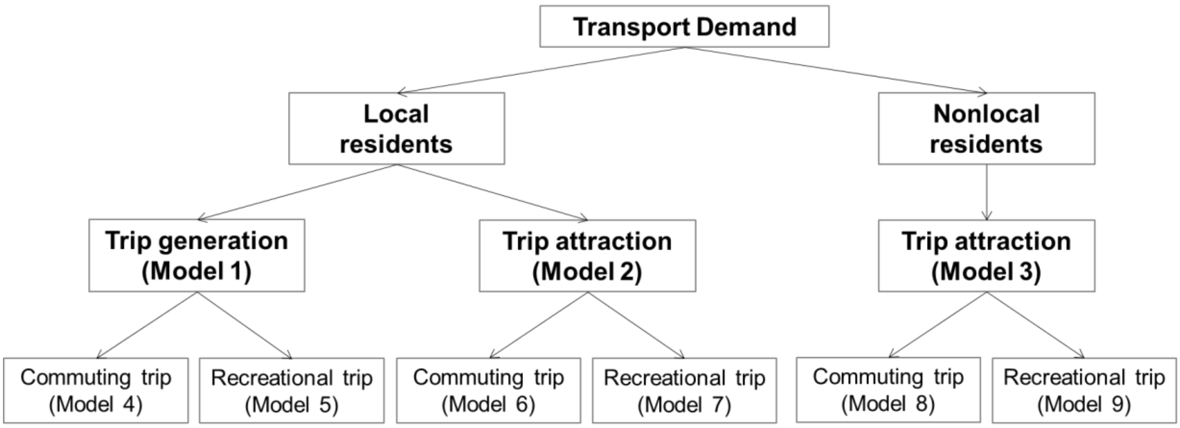


Figure 5-16 Local and nonlocal demand models by different purposes

The key findings from nine models were summarized as follows

- Overall, socio-demographic, land-use characteristics, transport supply, and accessibility indicators were found to be associated with local and nonlocal demands. The findings further confirmed traditional understanding about transport demands (for example, Chen et al. 2021; Cordera et al. 2017; Sofia et al. 2011; Sun et al. 2014; Yang et al. 2020).
- Transport supply indicators and accessibility tended to affect nonlocal demands more than local demands in both commuting and recreational demands. Moreover, recreational demands were more sensitive to transport supply

indicators and accessibility than commuting demands. This means that enhancing transport supply and accessibility could potentially help an area to attract more nonlocal demands, especially recreational demands and tourism promotion. Accessibility was the most significantly related to trip productions and attractions. When comparing the trips, accessibility was negative associated with local trip attractions. This reveals that travelers tend to make longer travel distance when accessibility is improved.

- Train frequency was significantly associated with local and nonlocal demands. This reveals the crucial role of train services in meeting mobility needs.
- Service coverage was not significantly associated with local demands but significantly related to nonlocal demands.

5.4.2. Factors associated with transport supplies

Transport supply includes public transport and private transport. The former is measured by service coverage and frequency. The variations in the service frequency of buses and trains are considered in quantifying the public transport index. The latter is measured by available cars and road density. All indicators included in the transport model were set as zone-specific indicators, indicating that changes in transport supply in a zone will change the supply value in that zone as well as the value of overall transport supply index.

There are some limitations in quantifying transport supply index. An important limitation of the supply analysis is the lack of consideration of travel costs or fares. Another limitation comes from the transport supply model in which all indicators are weighted equally.

5.4.3. Spatial-temporal transport gaps

The transport gap was identified by the transport supply index subtracting the transport demand index. The transport gap was either negative value or positive value. A positive transport gap means that transport supply can ensure the ease and convenience of mobility and accessibility for travelers while a negative transport gap is considered as a low level of accessibility as well as low transport supply.

The study identified transport supplies and demands according to different hours and days to identify spatial-temporal transport gaps in Hokuto, Japan. The findings show that transport supply in some residential and tourism zones was insufficient compared to the demand. The transport gaps were scattered in Hokuto, mainly focused on Yatsugatake areas, only occurred in tourism zones in Kayagatake and Kai-Komagatake area.

The transport gaps in tourism zones show that local and non-local residents without car ownership are likely to have difficulty in reaching tourism destinations by the existing public transport. Findings also reveal that transport gaps became more critical on the weekend and during peak hours, suggesting that enhancing transport supplies and accessibility is required to meet transport demands. Much attention must be paid to transport supply in tourism zones, especially on the weekend.

The previous studies on transport gaps in urban areas pointed out that transport gaps are often located at suburban or residential areas, scattered suburban areas (Jiao 2017; Jiao and Dillivan 2013; Toms and Song 2016) and historic old towns (Jiao and Cai 2020), where there are large populations and high-intensity industrial area. Another study in rural areas of New South Wales in Australia showed that transport gaps occurred in coastal and inland areas, where public transport was very poor (Parolin and Rostami 2016). The spatial distribution of transport gaps found in this study is similar to previous studies. The transport gaps are scattered in both residential and tourism areas, where there are large populations and tourism facilities. In contrast, the study pointed out a difference in transport gaps in zones far from the city center, where the transport gaps rarely appear.

IPA was used to identify zones, where transport gaps improvement needs to be prioritized. The performance was assumed to be transport gaps while the importance was assumed to be the number of populations in a zone. The zones with low populations and low transport supply were classified into quadrant I, suggesting a low preference for improving transport gaps. These zones were located at Kayagatake and Kai-Komagatake area. The zones with high population and low transport supply were classified into quadrant II, suggesting that policies need to prioritize transport gaps reductions in these zones. These zones mainly focus on Yatsugatake area, and a few were located at Kayagatake and Kai-Komagatake area. The zones were classified into quadrant III and quadrant IV showed that the transport supply levels were relatively high and met transport demands, suggesting that policies need to maintain the level of transit services and to promote travel behavior changes from private uses to transit uses for sustainable targets. IPA results suggested that transport operators, policy makers, and planners need to pay greater attention to improve transport gaps in Yatsugatake areas.

In order to reduce transport service providers' efforts in the expansion of spatial transit coverage, optimizing the existing transit networks was considered as a potential policy (Chen et al. 2018; Fransen et al. 2015). Moreover, MaaS can be considered as a mobility option for enhancing the integration of public transport and individualized services (Lyons, Hammond, and Mackay 2019) and improving accessibility and social inclusion (Durand and Harms 2018). Under the MaaS context, the development of various shared mobility services (e.g., carsharing, bike-sharing, ridesharing, ride-hailing, and demand-responsive service) provides more alternative transport services and seamless mobility for users. MaaS also facilitates sharing journeys among local residents and between local residents and visitors. Furthermore, shared mobility services are considered as feeder services for traditional transport services (Jiang et al. 2018; S. T. Jin et al. 2019; Murphy 2016; Wang 2018; Zhang and Zhang 2018). In this scene, MaaS is a very potential option for fulfilling spatial-temporal transport gaps. Although MaaS might be considered as a potential option for rural areas (Barreto et al. 2018; Eckhardt et al. 2018), in the future, local government needs to pay attention to evaluate the roles of MaaS in improving transport gaps then establish policies and regulations for the implementation of MaaS.

6. Potential impact of transport services on transport gaps

The previous section pointed out that transport gaps were scattered in both residential and tourism zones, where tourism facilities are separated from residential areas. The most important question to transport planners is how to reduce transport gaps in rural tourism areas, especially in scattered areas. Although solutions for transport gaps were widely discussed in the literature, empirical studies evaluating policy impacts on transport gaps reduction are rarely found in the literature. Most previous studies investigated transport gaps in urban areas or the edges of metropolitan areas and focused on the suggestions of public transport improvement. It is a different story in rural areas where the enhancement of public transport is difficult with low populations, scattered tourism areas, and difficulties matching transit supply and demand. As a result, it requires more effective transport modes instead of public transport improvement.

Recently, the introduction of MaaS appears to be a new opportunity for car dependent reduction and public transport improvement. In the MaaS context, on-demand services integrate with the existing transport services into one platform. On the one hand, greater travel information, flexibility, ease of accessing alternatives to private cars, trip reservations, and payment for trips are provided for both local and nonlocal residents. On the other hand, on-demand services also enlarge the geographical service coverage of public transport while lowering the cost of operations through improving fleet efficiency.

The potential on-demand services, such as bus on demand, demand-responsive transport, ridesharing, taxi, and shared taxicab, were widely acknowledged from both the academic literature and the practical projects related to rural accessibility improvement (Vitale Brovarone and Cotella 2020). Ridesharing is similar to a regular taxi, but drivers are regular car owners and share available seats in their cars with riders, who are going to the same place or origin/destination. On-demand bus is a form of public transport but providing flexible routes and timetable journeys of vehicles according to transport demands, such as pick-up and drop-off locations. Enhancing on-demand services in rural areas provides travelers with flexible and affordable travel options, allowing the vulnerable to conveniently access vital services. The growth of on-demand services appears to be a new opportunity for reducing transport gaps. However, what transport services are required to fulfill transport gaps and how are their potential impacts on transport gap reduction are rarely understood. Therefore, this part of the study is aimed at:

- Firstly, forecasting the potential impacts of different scenarios on both transport demand and supply
- Secondly, forecasting the potential impacts of different on-demand transport services on transport gap reductions by applying transport gap model developed in the previous part in rural tourism areas
- Finally, discussing possible policies on transport gap reduction based on potential impacts.

6.1. Methodology

An analytical framework for evaluating policy effects is shown in Figure 6-1. Five policy scenarios were proposed to improve spatial-temporal transport gaps. In each scenario, policies influence transport supply indicators, including service frequency, service coverage, and service availability which in turn affect the overall transport supply index. When transport supply was improved in each scenario, it impacted local and nonlocal demands in each zone. The transport gap was then re-estimated corresponding to changes in transport supply and demands and compared to the existing transport gap to capture the potential impacts of scenarios.

Quantifying the potential impacts of policy scenarios followed the three major steps:

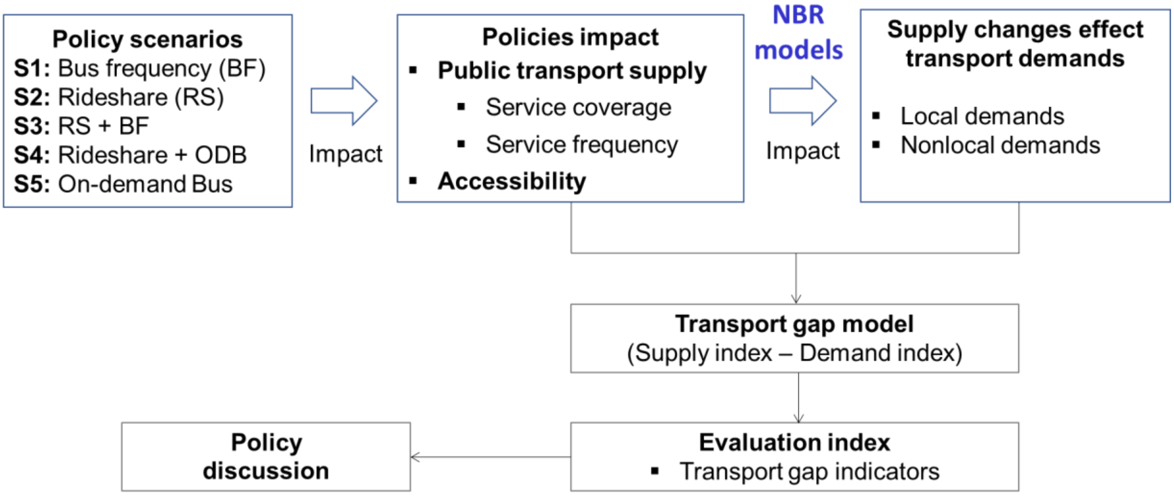


Figure 6-1 Analysis framework of policy impacts

<u>Step 1</u>: Identify transport supply index under policy impacts

The value of private transport in different scenarios was assumed similar to the existing value because the number of private cars and road density has long-term impacts on transport supply. Scenarios aim at public transport, ridesharing, and on-demand bus service. It is assumed that ridesharing and on-demand bus service behave similarly to public transport because these services take the characteristics of both taxi and transit modes. As a result, scenarios mainly improve the supply of public transport services.

Scenarios enhance service frequency, service coverage, service availability, and accessibility, which in turn affect the overall transport supply index. The improved public transport index and overall transport supply index were identified as following formulas:

$$PuT_{i,j} = \sum_{i=0}^{n} \mathrm{SF}_{i,j} * \mathrm{SC}_{i,j} \tag{13}$$

$$New\_PuT_{i,j} = \frac{PuT_{i,j} - \bar{S}}{SD_i} \tag{14}$$

$$New\_SI_i = \sum New\_PuT_{i,j} + PrT_i \tag{15}$$

Where:

$New\_SI_{i,j}$: Transport supply index in zone *i* under scenario *j*

$New\_PuT_{i,j}$: The standardized score of public transport in zone *i* under scenario *j*

$PuT_{i,j}$: The value of public transport in zone *i* under scenario *j*

$\mathrm{SC}_{i,j}$: The service coverage of public transport in zone *i* under scenario *j*

$\mathrm{SF}_{i,j}$: The service frequency of public transport in zone *i* under scenario *j*

PrT_i: The standardized scores of private transports in zone *i*

$\bar{S}$: The mean of the existing public transport

SD_i: The standard deviation of the existing public transport in zone *i*

Step 2: Identify transport demand index under policy impacts

When transport supply in each scenario was improved, it could lead to changes in local and nonlocal demands from/to each zone. Based on the estimated regression models, local and nonlocal demands with policy scenarios were identified corresponding to changes in transport supply indicators and accessibility.

Once the transport demands with policy scenarios were estimated, the overall transport demand index was identified as following formulas:

$$New\_D_{i,j} = \frac{d_{i,j} - \bar{D}}{sd} \tag{16}$$

$$New\_DI_{i,j} = \sum New\_D_{i,j} \tag{17}$$

Where:

$New\_DI_{i,j}$: Transport demand index in zone *i* under scenario *j*

$New\_D_{i,j}$: The standardized scores of local and nonlocal demands in zone *i* under scenario *j*

d_i: Local and nonlocal demands per zone *i* under scenario *j*

$\bar{D}$: The mean of the existing local and nonlocal demands

sd: The standard deviation of the existing local and nonlocal demands in zone *i*

Step 3: Quantify the transport gaps and potential impacts under scenarios

Once transport supply and demand index were determined for each scenario, transport gap was re-estimated and compared to existing gaps to point out the potential impacts.

$$New\_TG_{i,j} = New\_SI_i - New\_DI_i \tag{18}$$

$$Impact_{i,j} = \frac{New\_TG_{i,j} - TG_i}{TG_i} \tag{19}$$

Where:

$New\_TG_{i,j}$: Transport gap for zone *i* under scenario *j*

TG_i: The existing transport gap in zone *i* under base scenario

$Impact_{i,j}$: The impact of scenario *j* on transport gap in zone *i*

6.2. Developing the scenarios

6.2.1. Study Area

As analyzed in previous part of this study, transport gaps were mainly found in residential zones and tourism zones in Yatsugatake area while a few occurred in tourism zones in

Kayagatake and Kai-Komagatake area. In addition, the results of IPA pointed out that attention must be paid to transport gaps reduction in these zones. Zones with transport gaps in Kayagatake and Kai-Komagatake area seem to be straightforward to address by increasing the current public transport services. As a result, policies will focus on Yatsugatake area because zones with transport gaps were scattered and were not fully covered by the existing bus routes. It may require more effective policies and solutions to address transport gaps in Yatsugatake area.

There were 39 zones based on administrative divisions in Yatsugatake area in Hokuto and six community bus routes operating within this area. Detail on bus services is shown in Table 6-1. Although transport gaps varied by hours of the day and days of the week, the demand data and developed demand models were limited on a weekday. Therefore, this part only focused on assessing the policy scenarios on the changes of transport gaps on a weekday.

Table 6-1 Operational status of bus routes in Yatsugatake area

Bus routes	Frequency		No. of zones served	Fleet size
	Weekday	Weekend		
Koizumi line	5 – 6 trips	4 trips	05 zones	4-6 vehicles
Kiyosato line	4 – 5 trips	3 – 4 trips	16 zones	4 vehicles
Oizumi line	4 – 6 trips	3 – 4 trips	07 zones	3-4 vehicles
Kobuchisawa patrol line	5 trips	Not operation	08 zones	3 vehicles
Southern patrol line	8 trips	5 trips	10 zones	5 vehicles
Northern Circuit	7 trips	6 trips	05 zones	6 vehicles

Source: Collected from website of bus operators, November 2020

Source: Public transport planning report in Hokuto, 2018

Figure 6-2 Existing bus routes in Yatsugatake area in Hokuto

6.2.2. Transport service assumptions

There are generally limited options available to people getting around in rural areas. Popular transport modes include private cars, fixed bus routes, taxis, bicycles, and walking. In the context of wider travel zones and low demand in rural areas, private cars and buses continue to be the important transport modes as can be seen in Figure 6-3.

To address the spatial-temporal transport gaps, the improvement of transport supply is necessary. Public transport is important in supporting travelers and visitors, who are unable to drive or afford the upkeep of personal vehicles as well as do not want to drive. The introduction of MaaS provides a great opportunity for meeting transport demands and improving public transport supply. On the one hand, on-demand services integrated into MaaS, such as on-demand bus/demand-responsive transport, ridesharing, taxi, and shared taxicab provide greater flexibility and ease to access transport services and desired destinations. On the other hand, on-demand services also enlarge the geographical service coverage of public transport (Jiang et al. 2018; S. T. Jin et al. 2019; Murphy 2016; Wang 2018; Zhang and Zhang 2018) while lowering the cost of operations through improving fleet efficiency (Becker et al. 2019; Djavadian and Chow 2017b; Kamau et al. 2017; X. Li et al. 2018b; L. Liu et al. 2019b; Y. Liu et al. 2019; Shen, Zhang, and Zhao 2018b).

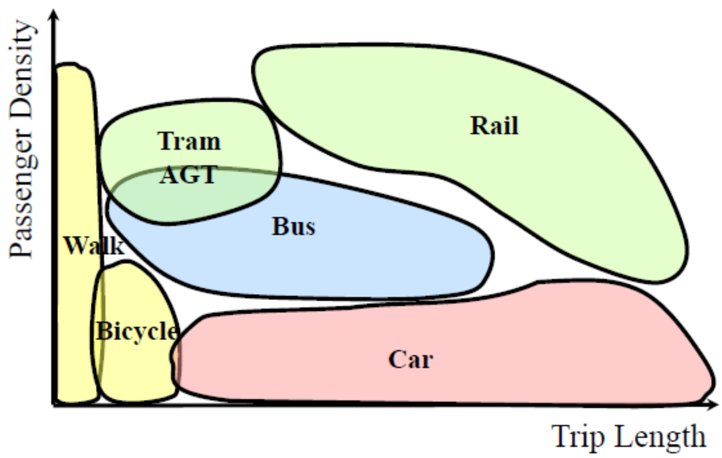


Figure 6-3 Transportation selection based on passenger density and trip length

In this study, public transport (bus), ridesharing, and on-demand bus were considered as means to reduce transport gaps and develop scenarios. Ridesharing is offered by private drivers, who are willing to share their journeys with other riders when drivers and riders have the same direction. On-demand bus is offered by local bus operators, who are shifted from fixed bus to flexible routes when a trip requirement is set. The number of zones served by ridesharing is larger than on-demand bus because on-demand bus only expands service coverage to zones along their route alignment.

6.2.3. Scenario development

There are many potential scenarios based on the combination of existing public transport, ridesharing, and on-demand bus. This study focused on five most potential scenarios after removing similar scenarios.

Figure 6-4 and Table 6-2 show the five developed scenarios. Every five percent of service improvement was considered in each scenario. Scenario 1 increased the frequency of six existing bus routes. Scenario 2 introduced ridesharing based on private cars available. Scenario 3 enhanced bus frequency and introduced ridesharing. Scenario 4 introduced both ridesharing and on-demand bus. Scenario 5 introduced on-demand bus, which is shifted from the current fleet of bus routes.

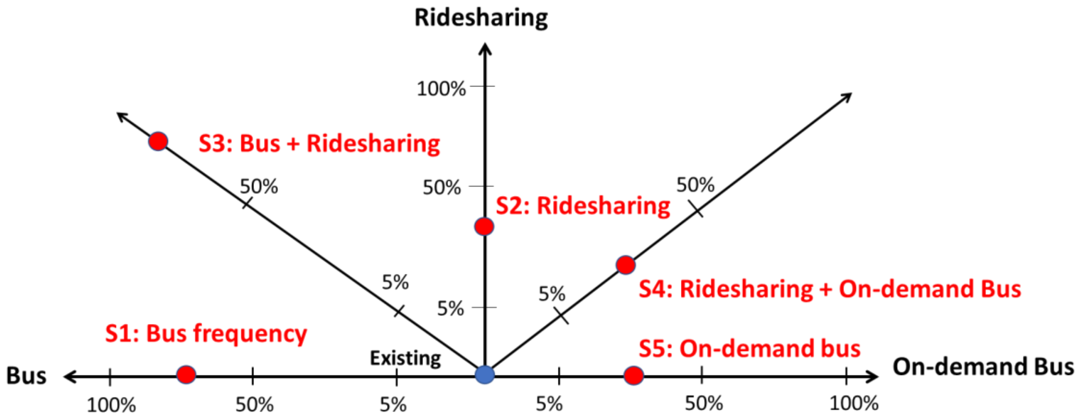


Figure 6-4 Scenarios of transport supply improvement by different services

In terms of operation, ridesharing and on-demand bus included the characteristics of both taxi and transit transport. Ridesharing and on-demand bus directly impacted the service coverage of public transport and service availability, which was assumed to be asymmetric with the number of bus arrivals per zone per day. Furthermore, the number of ridesharing and on-demand bus service available also impacted waiting time (Levin et al. 2019b; Ma and Klein 2020; Narayan et al. 2017, 2020b; H. K. R. F. Pinto et al. 2018; Sieber et al. 2020; Stiglic et al. 2018b). This is similar to the reality that more available on-demand services and more users are provided with shorter waiting times of service on average. Accordingly, zones with greater transport demands and services available had shorter waiting times than zones with lower demands and services.

Table 6-2 Scenarios for transport gap improvement by different services

Scenarios	Policy	Descriptions	Impacted indicators
Scenario 1	Bus frequency (BF)	• Improve current BF • Policy: Every 5% increase in the frequency of bus routes	• Bus arrivals/zone/day
Scenario 2	Ridesharing (RS)	• Provide RS service • Policy: Every 5% increase in the number of car drivers participating in RS service	• Service coverage • Bus arrivals/zone/day • Waiting time • Accessibility
Scenario 3	Ridesharing + Bus frequency (RS + BF)	• Provide RS and increase bus frequency • Policy: Every 5% increase in RS and bus frequency	• Service coverage • Bus arrivals/zone/day • Waiting time • Accessibility
Scenario 4	Ridesharing + On-demand bus (RS + ODB)	• Provide both RS and ODB • Policy: Every 5% increase in RS and on-demand bus	• Service coverage • Bus arrivals/zone/day • Waiting time • Accessibility
Scenario 5	On-demand bus (ODB)	• Provide ODB • Policy: Every 5% increase in on-demand bus	• Service coverage • Bus arrivals/zone/day • Waiting time • Accessibility

The combination of population size and available private cars at each zone was used as a simple way to assign waiting time as described in Table 6.3. Zones were divided into low population, middle population, high population, low cars, middle cars, and high cars categories. Within each category, zones were randomly assigned waiting times between given thresholds. In this study, waiting time for ridesharing was referenced from Pinto et al., (2018), Sieber et al., (2020), and Ma & Klein (2020), while waiting time for on-demand bus was based on Liu et al., (2019), Narayan et al., (2020), Li et al., (2018) (Inturri et al. 2019; X. Li et al. 2018b; Y. Liu et al. 2019; Ma et al. 2019b; Ma and Klein 2020; H. K. R. F. Pinto et al. 2018). Moreover, the introduction of on-demand services also impacted accessibility aggregated at the zonal level. The coefficients for on-demand services were assumed to be the same as taxis due to the lack of understanding about future on-demand services and uncertainty in system design.

Table 6-3 Assumptions on waiting time of on-demand services

Category	Low cars/zone (< 87 cars/zone)	Middle cars/zone (88 – 277 cars/zone)	High cars/zone (> 278 cars/zone)
Low population/zone (< 154 persons)	8-10 minutes	6-8 minutes	5-7 minutes
Middle population/zone (155 – 413 persons)	6-8 minutes	4-6 minutes	3-5 minutes
High population/zone (> 414 persons)	5-7 minutes	3-5 minutes	1-3 minutes

6.3. Potential impact of policy scenarios on transport gaps

6.3.1. Transport supply under scenarios

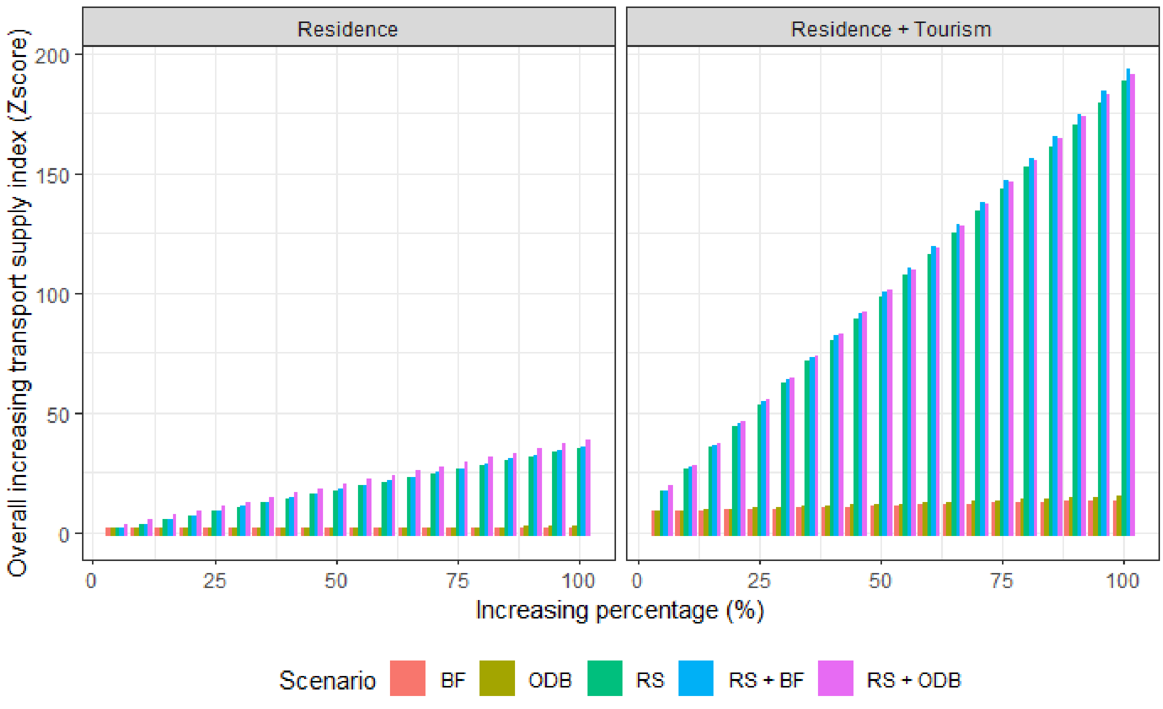


Figure 6-5 Distribution of transport supply index under policy scenarios

The transport supply index in each zone in each scenario was determined. The ranges of transport supply index under different scenarios are shown in Figure 6-5. The transport supply indices improved in tourism zones was significantly higher than in residential zones.

In the comparison of the scenarios, the transport supply index was significantly increased by the introduction of ridesharing (scenario 2) and was less improved by bus frequency (scenario 1). There was a slight difference between scenario 1 and scenario 5 and between scenario 3 and scenario 4. The difference became clear when the number of on-demand bus fleets was large enough, approximately current bus fleet.

6.3.2. Transport demands under scenarios

As can be seen in Figure 6-6, nonlocal residents were more sensitive to policies than residents. Local and nonlocal demands significantly increased when transport supply increase was less than 50%, but slowly increasing when the percentage of transport supply increase was over 50%. This could be explained that travelers can make longer travel distances or be attracted by other areas when transport supply and accessibility were significantly improved.

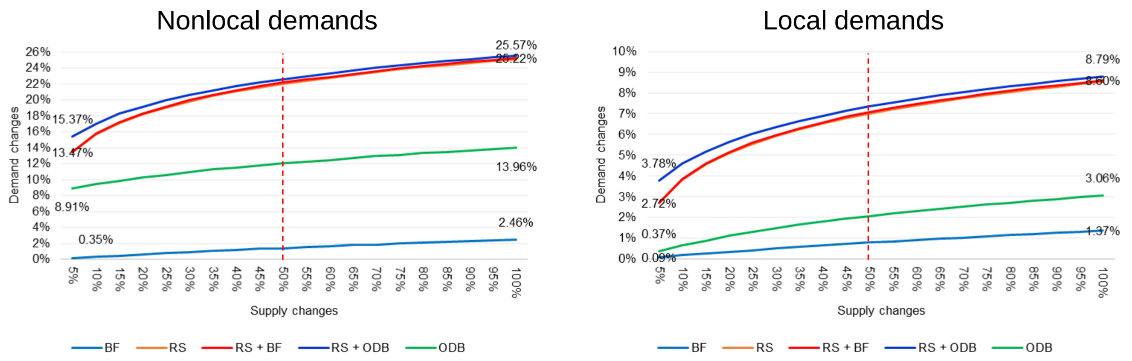


Figure 6-6 Impacts of policy scenarios on transport demands

Transport demands significantly changed by the introduction of ridesharing and less changed by bus frequency increase. Local and nonlocal demands increased 1.37% and 2.46% when the current bus frequency was double in scenario 1, which increased to 8.53% and 25.10% in scenario 2 by introducing ridesharing, respectively. Scenario 4 had the most impact on transport demands. The local and nonlocal demands increased to 8.79% and 25.57% when ridesharing and on-demand bus were introduced, respectively.

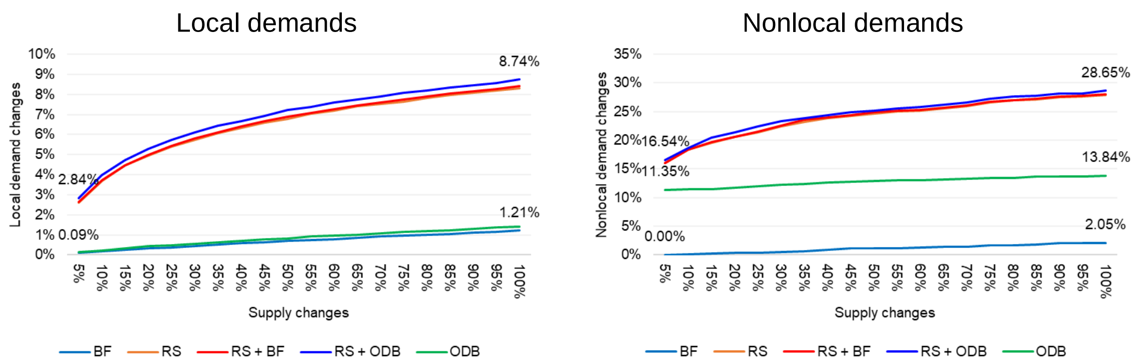


Figure 6-7 Impacts of policy scenarios on transport demands in residential areas

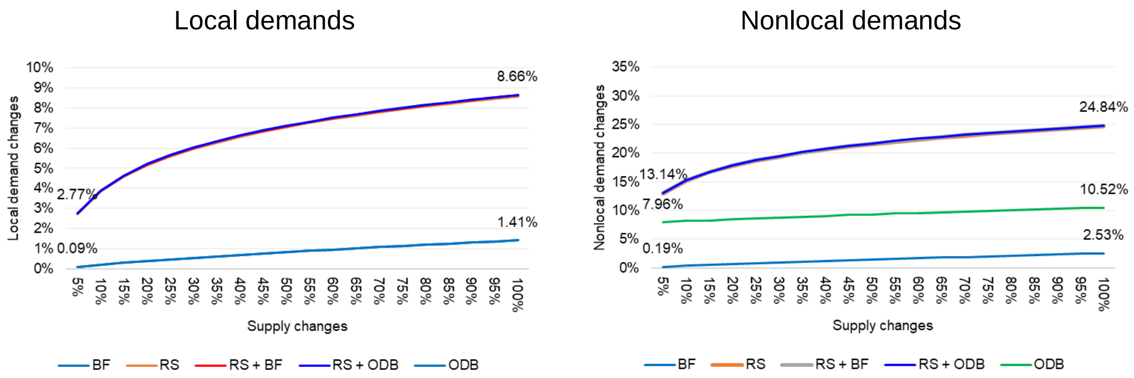


Figure 6-8 Impacts of policy scenarios on transport demands in tourism areas

Figure 6-7 and Figure 6-8 show the potential impacts of five scenarios on the changes of local and nonlocal demands in residential and tourism zones, respectively. In general, the change of transport demands in residential zones was slightly higher than in tourism zones. Nonlocal demands increased from 2.05% in scenario 1 to 13.8% in scenario 5 in residential zones.

In contrast, nonlocal demands increased from 2.53% in scenario 1 to 10.52% in scenario 5 in tourism areas. Scenario 4 had the most significant impact on transport demands. Local demands could increase by 8.66% and 8.74% in tourism zones and residential zones while nonlocal demand could be higher, with 24.84% and 28.65% of increase in tourism zones and residential zones, respectively.

6.3.3. Transport gap impacts

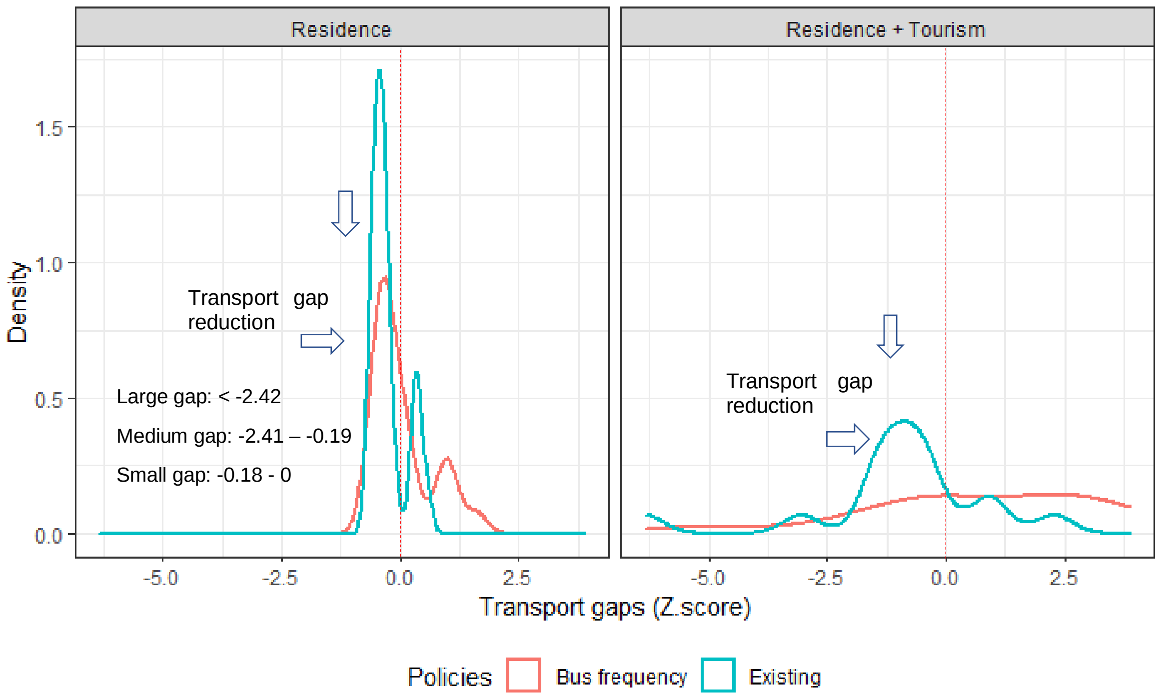


Figure 6-9 Conceptual impacts of policies on transport gaps

The objective of this analysis is to understand the potential impact of different policy scenarios on transport gaps. It is necessary to know how many transport gaps can be removed or improved by each scenario. There are two directions in which policy scenarios can impact transport gaps as can be seen in Figure 6-9. On the one hand, the transport gap moving from top to downside represents a decrease in the number of zones with transport gaps under policy impacts. On the other hand, the transport gap significantly shifting to the right side means that the transport gaps can be removed by policy impacts.

In scenario 1, transport gaps were in the range of [-6.29, 3.89] corresponding to the percentage of bus frequency increase. Figure 6-10a and Figure 6-10b illustrate changes in transport gaps in tourism and residential zones. There were 04 tourism zones and 04 residential zones in which transport gaps were removed by bus frequency increase. Transport gaps in tourism zones tended to be improved more than in residential zones.

As can be seen from Figure 6-10c, the percentage of zones with low and medium transport gaps significantly reduced while large gaps remained in tourism zones when the current bus frequency increased two times (100%). Figure 6-10d shows the distribution of transport gaps with 100% of bus frequency increase. There was a significant reduction of medium transport gaps and a shift to medium and large supply in both residential and tourism zones.

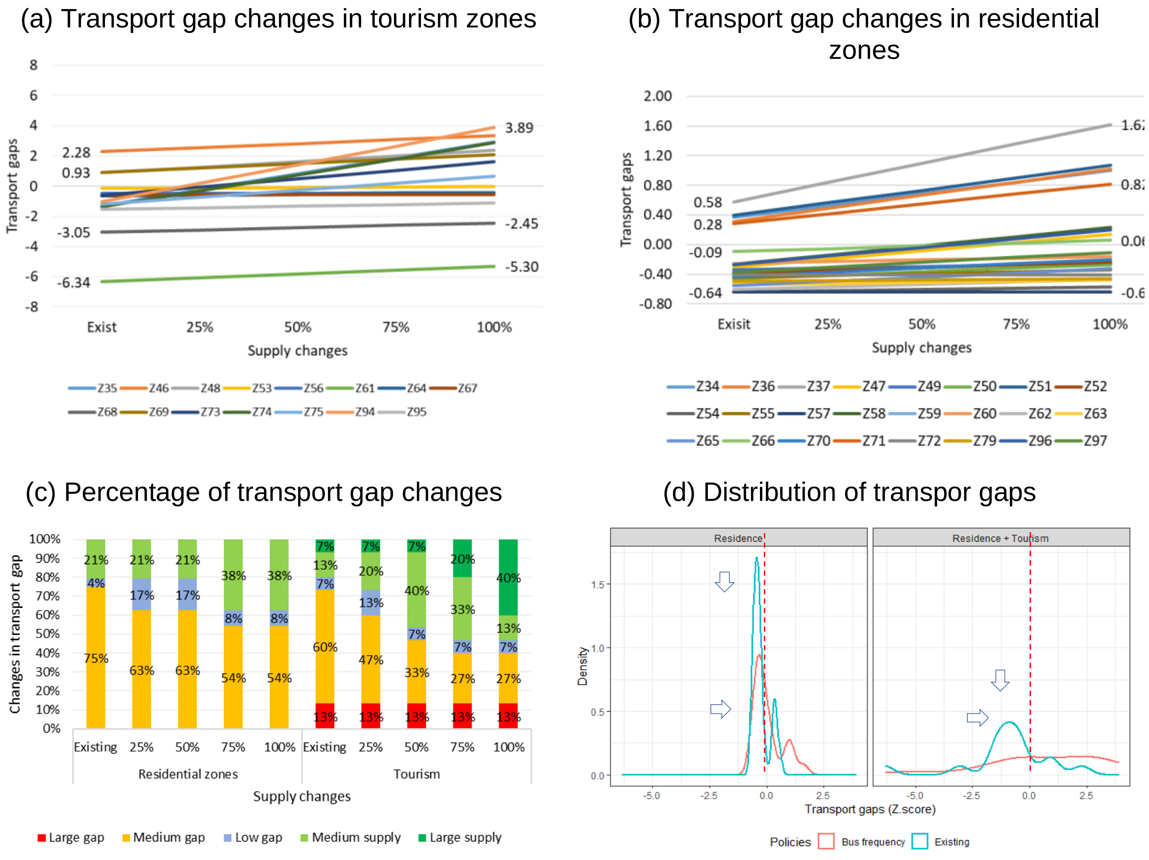


Figure 6-10 Changes in transport gaps under scenario 1

In scenario 2, transport gaps were in the range of [-3.13, 178.37] corresponding to the percentage of ridesharing. The finding revealed that most transport gaps can be removed with 10% of ridesharing as can be seen from Figure 6-11c and Figure 6-11d. Medium and low transport gaps were significantly shifted to medium and large supply in both residential and tourism zones.

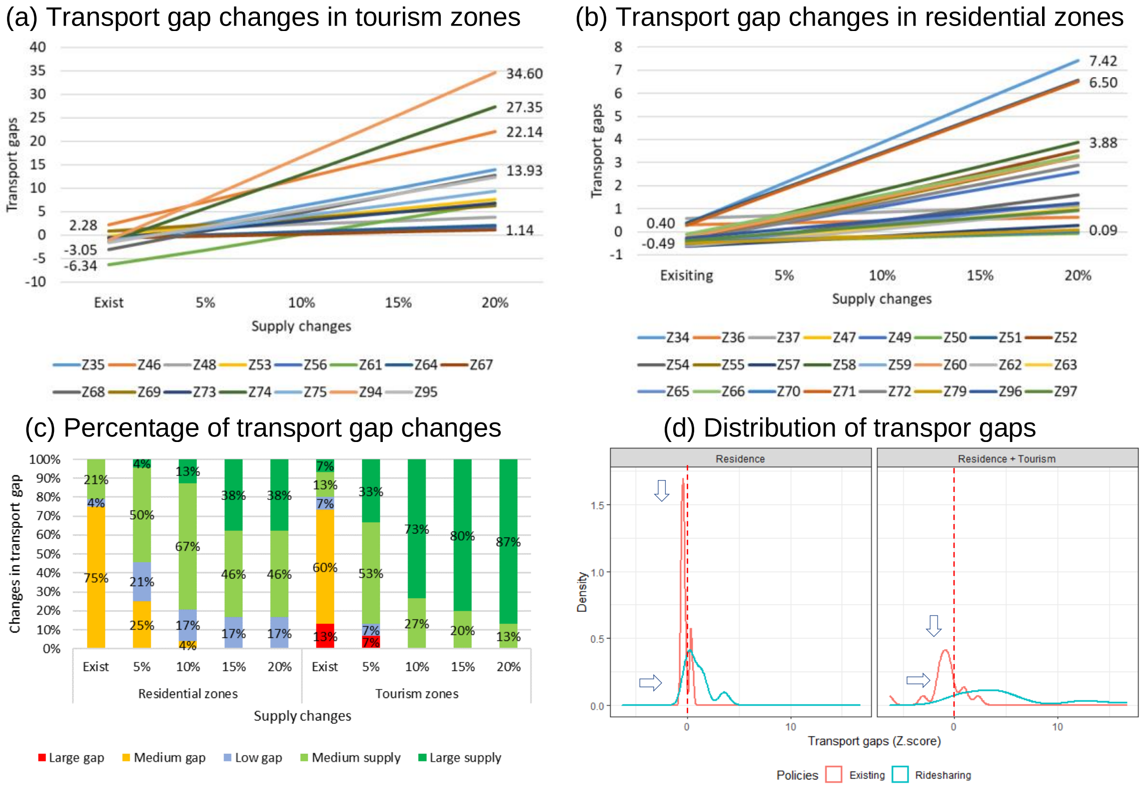


Figure 6-11 Changes in transport gaps under scenario 2

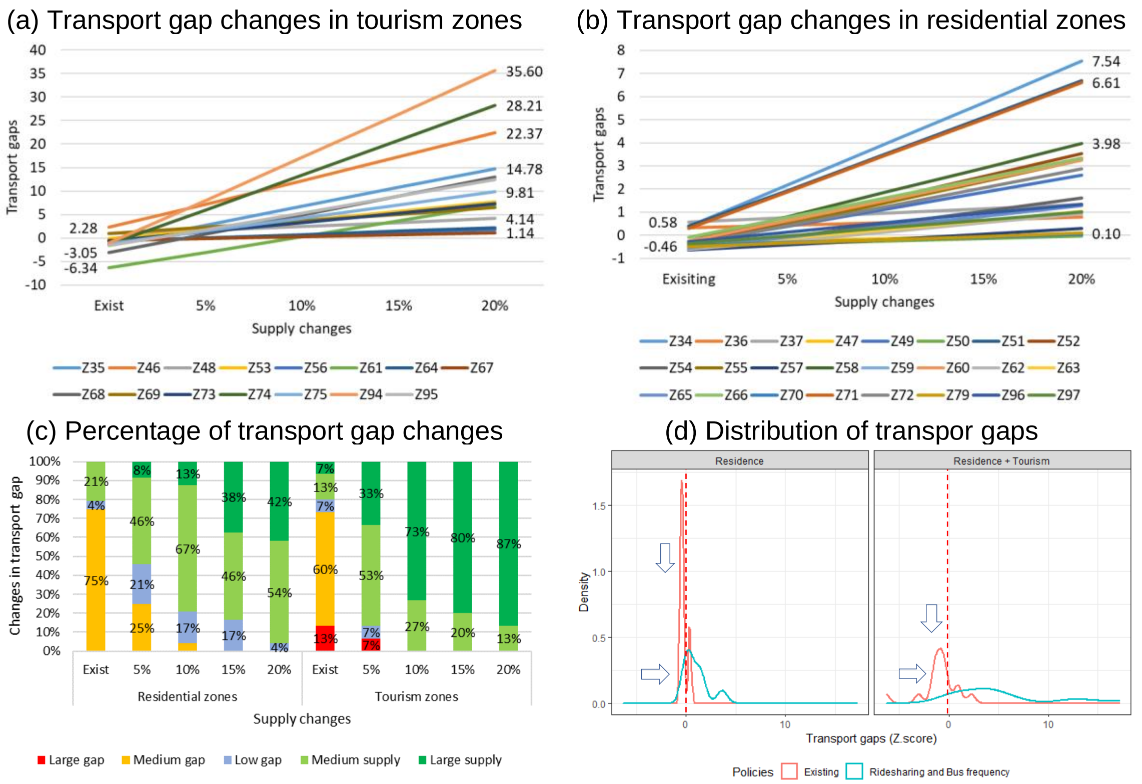


Figure 6-12 Changes in transport gaps under scenario 3

In scenario 3, transport gaps were in the range of [-3.07, 183.36] corresponding to the percentage of carsharing and bus frequency increase. Most transport gaps could be removed with 5% of ridesharing and 5% of bus frequency increase as can be seen from Figure 6-12c and Figure 6-12d. Medium and low transport gaps were significantly shifted to medium and large supply in both residential and tourism zones.

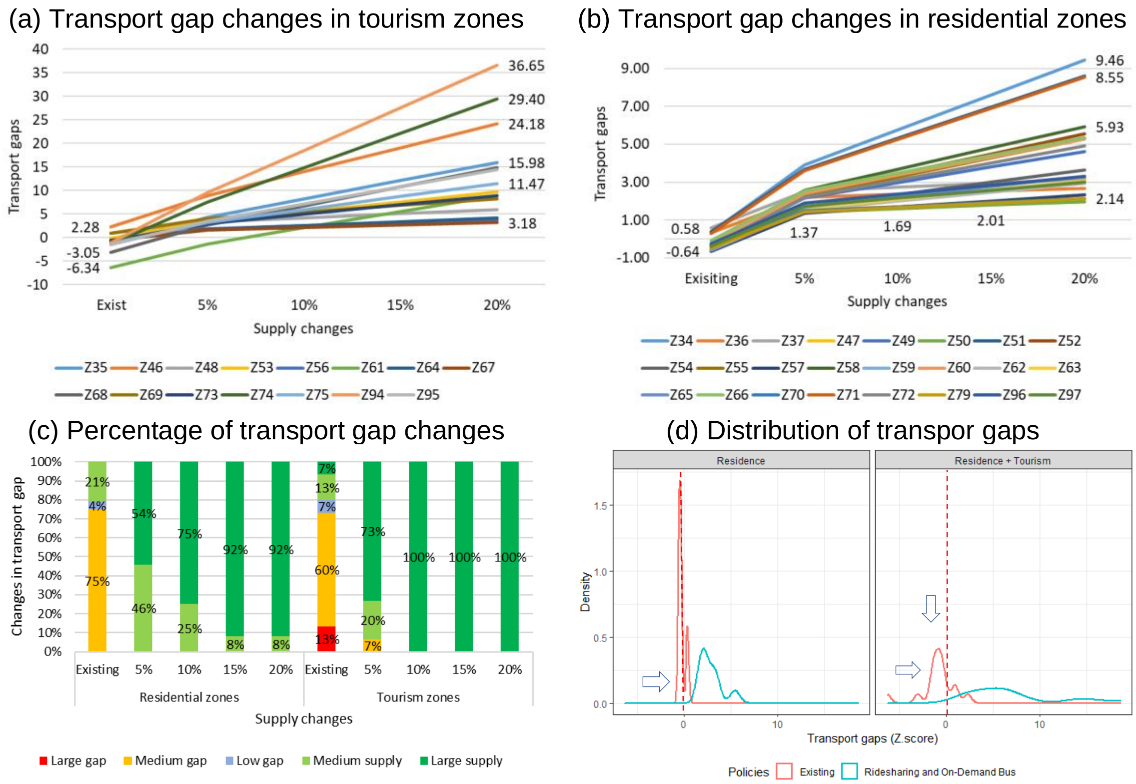


Figure 6-13 Changes in transport gaps under scenario 4

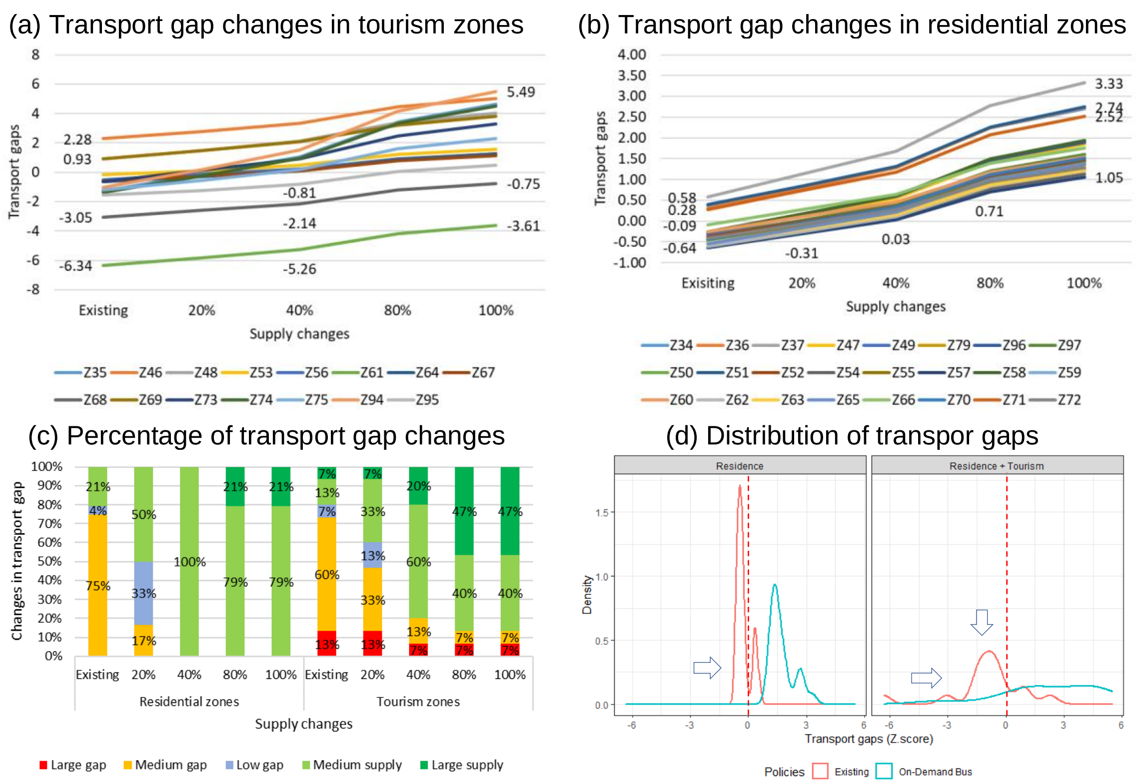


Figure 6-14 Changes in transport gaps under scenario 5

Similarly, transport gaps were in the range of [-1.31, 181.78] in scenario 4. All transport gaps can be removed by introducing 5% of ridesharing and 5% of on-demand bus as can be seen from Figure 6-13c and Figure 6-13d. Medium and low transport gaps were significantly shifted to large supply in both residential and tourism zones.

The transport gaps were in the range of [-6.22, 5.9] in scenario 5. There were 10 tourism zones and 19 residential zones in which transport gaps were removed by introducing on-demand bus. The finding showed that all medium and low gaps in residential zones could be removed with the introduction of 40% of on-demand bus. However, large and medium gaps remained in tourism zones when 100% of current bus fleet providing on-demand services.

In the comparison of the scenarios, the number of zones with removed transport gaps was the least in scenario 1 and more in scenario 5. The introduction of ridesharing significantly contributed to reducing transport gaps in both residential and tourism zones in scenario 2, scenario 3, and scenario 4. Furthermore, most zones had transport gaps shifted to large supply with ridesharing. The percentage of ridesharing or on-demand bus to balance transport demand and supply was an important finding, which can suggest strategies for transport planning, such as optimizing the transport supply and/or setting the maximum number of on-demand transport services for a zone.

6.3.4. Summary and discussion

The introduction of MaaS and integrated on-demand services provided a wide range of mobility options for local and nonlocal residents. There were several on-demand services, namely ridesharing, on-demand bus, taxi, and ride-sourcing which potentially support public passenger transport in rural areas. The important role of these services in meeting individual needs is widely acknowledged. However, their impacts on transport gap reduction for an area is rarely understood. Understanding their influence supports policymakers in identifying feasible services and planning strategies to fulfill transport gaps in rural areas.

This part of the study aimed to quantify the impacts of different on-demand services on transport gaps in Yatsugatake area in Hokuto city. There were five scenarios developed based on the current bus, ridesharing, and on-demand bus. The analytical results showed that scenarios had potential impacts on transport demands and transport supply as well as transport gap reductions in residential and tourism zones. The key findings were summarized as follows

(1) Nonlocal residents were more sensitive to influent scenarios than residents. There was a significant increase in local and nonlocal demands when the percentage of transport supply increase was up to 50% in all scenarios. How transport demands slowly increased when transport supply increased over 50%. This reveals that travelers might be attracted by other areas when transport supply and accessibility were significantly improved.

(2) Local and nonlocal demands significantly changed by the introduction of ridesharing and less changed by bus frequency increase. This is because the current bus frequency was low. The policy scenario on bus frequency increase might not be sensitive to attract more transport demands.

- Local and nonlocal demands potentially increased 1.37% and 2.46% when the current bus frequency was double in scenario 1, which increased to 3.06% and 13.96% in scenario 5, respectively.

- Introducing on-demand services probably led to significant changes in transport demands. Scenario 4 had the most impacts when ridesharing and on-demand bus were introduced. The local and nonlocal demands increased to 8.79% and 25.57%, followed by 8.6% and 25.22% in scenario 3, and 8.53% and 25.10% in scenario 2, respectively.
- An important limitation of the demand analysis in this part was the lack of consideration of user behaviors and preferences. The potential impacts of scenarios on transport demands were estimated based on the NBR models, which were developed by zonal characteristics, transport supply indicators, and accessibility. Therefore, the impact of the scenarios on a traveler's choice of destination and decision to make a trip was not considered in the estimate. This reveals an important need of collecting new information and data to further understanding about influence of the proposed services on individual choice.

(3) The potential impacts on transport gap reductions were summarized as follows

- There were a significant reduction of transport gaps and a shift to medium and large supply in both residential and tourism zones under policy scenarios.
- The number of zones removed transport gaps in scenario 5 was more than in scenario 1. In both scenarios, low and medium transport gaps significantly decreased while large gaps remained.
- The introduction of ridesharing in scenario 2, scenario 3, and scenario 4 significantly contributed to reducing transport gaps in both residential and tourism zones. Most zones with transport gaps shifted to large supply with ridesharing.
- The percentage of ridesharing or on-demand bus to balance transport demand and supply was an important finding. Particularly, most transport gaps can be removed with 10% of ridesharing, 5% of ridesharing and 5% of bus frequency increase, and 5% of ridesharing and 5% of on-demand bus. In scenario 5, transport gaps in residential areas can be removed by 40% of on-demand bus. The analytical results suggest important strategies for transport planning, such as optimizing the transport supply, service integration, and multimodal transport for transport gap reductions. This suggests an important field for future research.

Furthermore, changes in transport supply under policy scenarios were assumed by changes in service coverage, service frequency (i.e., number of vehicle arrival per day), and waiting time. It was limited in reflecting the real operation of on-demand services. Modelling and optimizing the dynamic operational plans of on-demand services in scenarios was neglected in this study. In particular, the operational plans can be optimized throughout matching, dispatching, routing, and relocation of empty vehicles, which not only significantly reduce waiting time for travelers but also minimize necessary vehicle fleet size for transport providers. This could impact the number of vehicles available, waiting time, and service coverage in each zone, which in turn impact the value of transport supply and transport gaps. This suggests an important need for developing microscopic models for quantifying the impacts of on-demand services on transport gaps reduction in each zone.

Nevertheless, this work was the first attempt that quantifies the benefits of different services on transport gap reduction in rural tourism zones and the developed methodology can be easily transferred to analyzing other regions. In term of application, this work can support transport planners, decision makers, and travel agencies in evaluating and selecting suitable transport services to fulfill transport gaps in one area.

7. Key findings and discussion

The study aims at analyzing transport demands and supply, quantifying the spatial-temporal transport gaps, and forecasting the potential impact of different services on transport gaps in rural tourism areas. The study utilized various public data sources in Japan for further understanding of transport gaps. Furthermore, the study considered ridesharing and on-demand bus as potential services for fitting into public transport gaps. The study provided new knowledge of transport gaps in rural tourism areas and pointed out the variations in the impact of different services on local and nonlocal demands, transport supply, and transport gaps reduction in residential and tourism zones.

This part shows the results of several key questions surrounding transport gaps, including to what extent are transport gaps in rural tourism areas; what transport services are required to fulfill transport gaps; and how are their potential impacts on transport gap reduction. The most important findings and their implications are summarized and discussed as follows.

7.1. Spatial-temporal transport gaps in rural tourism areas

The first research question attempts to provide a comprehensive understanding about transport gaps in rural tourism areas. Several models and different data in Japan were used to answer this question. First, the transport demand models were developed based on the person trip survey data and mobile spatial statistics data to explore factors related to the local and non-local demands in each zone and to predict demands on a weekend, a weekend/holiday, and different hours in the corresponding day. Second, the supply models considered the spatial-temporal supply of public transport and private transport. Finally, the transport gap model based on the standardized score of transport supply and demand was used to identify spatial-temporal transport gaps. There were several important findings from the analytical results of the first research question.

7.1.1. Factors related to transport demands

The factors associated with local and nonlocal demands came from the NBR models. Overall, socio-demographic, land-use characteristics, transport supply, and accessibility indicators were found to be associated with both local and nonlocal demands. The findings further confirmed traditional understanding about the factors influenced the number of trip productions and attractions per zone (for example, Chen et al. 2021; Cordera et al. 2017; Sofia et al. 2011; Sun et al. 2014; Yang et al. 2020). Table 7.1 summarizes the relationship between the factors and number of trips in each zone generated and attracted by local and nonlocal residents according to trip purposes.

Transport supply indicators and accessibility were the most significantly related to trip productions and attractions by different trip purposes. Nonlocal demands tended to be more sensitive to these indicators than local demands. Particularly, transport supply indicators and accessibility tended to affect nonlocal demands more than local demands in both commuting and recreational demands. The impacts on recreational demands were higher than commuting demands. Interestingly, accessibility was negatively associated with local trip attractions. This reveals that travelers tend to make longer travel distances when accessibility was improved. This suggests that enhancing transport supply and accessibility could potentially help a tourism area attract more recreational demands as well as tourism promotion.

Although the indicators identified in this analysis was likely factors traditionally considered to be relevant to transport demands, it does not mean that trip-making decisions were only influenced by those factors. The introduction of on-demand services played a critical role in providing mobility to disadvantaged people, supporting traditional transport services, serving areas with insufficient public transport (Wang 2018), and providing ease of access to desired destinations. In some circumstances, it would impact the number of trip productions and attractions from/to a zone. In this study, the analysis was limited by what variables were available from the personal trip survey data and zone-based characteristics. Therefore, transport demand analyses under the impact of multimodal transport and on-demand services are the direction of future study.

Table 7-1 Summary of factors influencing the transport demands by trip purposes

Explanatory variables	Local demand (Hokuto)												Nonlocal demand					
	Trip production		Trip attraction		Commuting production		Commuting attraction		Recreational production		Recreational attraction		Trip attraction		Commuting attraction		Recreational attraction	
	Sign	Sig.	Sign	Sig.	Sign	Sig.	Sign	Sig.	Sign	Sig.	Sign	Sig.	Sign	Sig.	Sign	Sig.	Sign	Sig.
Urban	+	***	+	*	+	***	+	**	+	***	+	*	+	***	+	***	+	**
Commercial & Business	+	***	n.i	Insig.	+	***	n.i	Insig.	+	***	+	**	+	***	+	***	+	***
Residential & industrial	+	***	+	***	+	***	+	***	+	***	+	**	+	***	+	***	n.i	Insig.
Industrial	+	***	+	**	+	***	+	***	+	*	+	**	+	***	+	***	n.i	Insig.
Mixed land	+	***	n.i	Insig.	+	***	n.i		+	***	n.i	Insig.	+	***	+	***	+	***
Population (log)	+	***	+	***	+	***	+	***	+	***	+	***	+	***	+	***	+	***
Residence	+	***	+	***	+	***	+	**	+	***	+	***	+	***	+	***	+	***
No. of public facilities	+	***	+	***	+	***	+	***	+	***	+	***	+	***	+	***	+	***
No. of tourism facilities	+	***	+	**	+	***	+	*	+	***	+	**	+	***	+	*	+	***
Train frequency	+	***	+	*	+	***	n.i	Insig.	+	***	+	***	+	***	+	***	+	***
Bus frequency (log)	+	***	+	*	+	***	n.i	Insig.	+	***	+	***	+	***	+	***	+	***
Service coverage	n.i	Insig.	n.i	Insig.	n.i	Insig.	n.i	Insig.	+	**	n.i	Insig.	+	***	+	***	+	***
Accessibility	+	***	-	**	+	***	-	***	+	***	n.i	Insig.	+	***	+	***	+	***

Note: “+” indicates positive relationship; “- “indicates negative relationship; “Insig” = “Insignificant”, means the variable is not statistically significant in the model result; and “n.i.” = “Not Included”, indicates that the variable is not included in the final model due to model specification consideration.

7.1.2. Spatial-temporal transport gaps in rural tourism areas

The study identified transport supplies and demands on a weekday and weekend to identify zones with spatial-temporal transport gaps in Hokuto, Japan. The findings showed that transport supply in some residential and tourism zones was smaller than transport demand. The transport gaps were found to be scattered in Hokuto. The finding confirmed traditional understanding about the spatial distribution of transport gaps (Jiao 2017; Jiao and Cai 2020; Jiao and Dillivan 2013; Parolin and Rostami 2016; Toms and Song 2016). Furthermore, the study also provided new insight into temporal transport gaps. The finding reveals that transport gaps became more critical on the weekend and during peak hours, suggesting that policies on enhancement transport supplies are needed to meet demands in these time periods.

The finding from IPA suggested a low preference for improving transport gaps in zones with low populations and low transport supply. Transport operators, policy makers, and planners need to pay greater attention to improve transport gaps in zones with high population and low transport supply. Policies are suggested to maintain the level of transit services and to promote travel behavior changes from private uses to transit uses in zones where transport supply levels were relatively high and meet transport demands. Although this approach was evaluated in rural tourism areas, it could be applied in urban areas when planning strategies for transport gap reduction are considered.

There were some limitations to this study. The most outstanding limitation in this study was to relatively compare the standardized score of transport demands and supply. Although estimates represented the real values of transport demands and supply in a zone, transport gaps might not accurately reflect the gaps in transport supply in a zone. Furthermore, the identified transport gaps do not include all the quality measures associated with the supply of transport services as well as user's perspectives and perceptions. Further studies are suggested to the consideration of transport gaps from the user's perspective. The analytical results can support policymakers and planners in identifying the specific levels of transport gaps that improvement needs to be prioritized. In addition, the identified transport gaps do not consider where travelers intend to travel. This is also a major limitation of the methodology, i.e., it only evaluated the transport supply and demands of a zone. Future studies could consider transport gaps between zones and evaluate the impacts of potential policies such as integrating on-demand services and public transport to improve the level of accessibility and transport gaps between zones. Considering all limitations could provide a comprehensive view of transport gap analysis and significantly support policy implications.

Although this methodology remained several limitations, it was useful for identifying relative transport gaps and supporting decision-makers and transport planners to identify priority areas toward narrowing transport service improvements.

7.2. The potential impact of on-demand services

Addressing the transport gaps is a challenge and primary priority for many areas. The second research question aims at measures to reduce transport gaps in rural tourism areas. Several studies suggested that policies can be implemented by optimizing existing public transport networks (Chen et al. 2018; Fransen et al. 2015). However, in rural areas, it is difficult to enhance traditional public transport services with such low and dispersed demands. The emergence of innovative mobility services, such as ridesharing, car-sharing, ride-sourcing, e-hailing, and on-demand public transport provides opportunities for enhancing transport supply in rural areas where traditional public transport services are poor or nonexistent. In this study, five policy scenarios based on the existing bus, ridesharing, and on-demand bus services were suggested for transport gap reduction.

Yatsugatake area was considered for scenario analysis. In each scenario, the potential change in transport demands and supply was identified. The transport gap was then re-estimated and compared to the existing transport gap to capture the potential impact of the proposed scenario. The analytical results showed that policy scenarios had potential impacts on transport demands and supply as well as transport gaps in both residential and tourism zones.

Nonlocal residents were more sensitive to policy scenarios than local residents. This is because the improvement of transport supply in tourism areas was significantly higher than in residential zones. Local and nonlocal demands significantly changed by the introduction of ridesharing and less changed by bus frequency improvement. This reveals that the policy scenario on bus frequency increase might not be much sensitive to attract more transport demands when the current bus frequency was low.

The introduction of ridesharing and/or on-demand bus changed service coverage, service availability, and accessibility of public transport. It significantly impacted local and nonlocal demands in each zone. Particularly, local and nonlocal demands increased 1.37% and 2.46% when the current bus frequency was double in scenario 1, which increased to 3.06% and 13.96% in scenario 5, respectively. Scenario 4 had the most impacts when ridesharing and on-demand bus were introduced. The local and nonlocal demands increased to 8.79% and 25.57%, followed by 8.6% and 25.22% in scenario 3, and 8.53% and 25.10% in scenario 2, respectively. An important limitation of the demand analysis in this part was the lack of consideration of user behaviors and preferences. The potential impacts of scenarios on transport demands were estimated based on the NBR models, which were developed by zonal characteristics, transport supply indicators, and accessibility. Therefore, the impact of the scenarios on a traveler's choice of destination and decision to make a trip was not considered in the estimate. This reveals an important need for collecting new information and data to further understand the influence of the proposed services on individual choice.

The transport gaps were most significantly improved under most policy scenarios. There was a significant reduction of transport gaps and a shift to medium and large supply in both residential and tourism zones under policy scenarios. In scenario 1 and scenario 5, low and medium transport gaps significantly decreased while large gaps remained in tourism zones. This suggests that scenario 1 and scenario 5 are less effective in removing large transport gaps. The analytical results showed the crucial role of ridesharing in transport gap reductions. The introduction of ridesharing in scenario 2, scenario 3, and scenario 4 significantly contributed to reducing transport gaps in both residential and tourism zones. Most zones with transport gaps shifted to large supply with ridesharing.

The percentage of ridesharing and on-demand bus balancing gaps between transport supply and demands in rural areas was an important finding. Particularly, most transport gaps can be removed by either 10% of ridesharing, 5% of ridesharing and 5% of bus frequency increase, 5% of ridesharing and 5% of on-demand bus, or 40% of on-demand bus. The finding could help local governments, planners, and transport operators generate important strategies for transport planning, such as optimizing the transport supply, service integration, and multimodal transport for transport gap reductions in an area. In this study, it was limited in reflecting the real operation of on-demand services. The operational plans not only impacted user behaviors and preferences but also transport supply, which in turn impact transport gaps. Further studies are suggested to develop microscopic models to reflect the operational plans of ridesharing and/or on-demand bus and to integrate user behaviors and preferences into evaluating transport gaps.

7.3. Discussion on transport gap indicators from MaaS perspective

In the scenario analyses, assumptions focused on physical indicators (i.e., waiting time and the number of vehicles available). Other importantly physical indicators, such as travel cost and travel time were not considered. Moreover, the psychological indicators, such as convenience, comfort, and ease of travelers to reach a specific destination or social activity impacted by the physical indicators, also influence user's behaviors and preferences. Both physical and psychological indicators changed in MaaS context because MaaS was built on the interactions between users, transport service providers (TSPs), a MaaS platform operator (MPO), public authorities, and other related partners (Jittrapirom et al. 2017).

This part of the study proposes a conceptual model that captures the operational characteristics of MaaS, physical and psychological indicators as well as user behaviors and preferences. The conceptual model could help local government and planners understand the interactions between transport demands and supply from a microscopic perspective so it could be useful for analyzing transport gaps.

Figure 7-1 conceptualizes the interactions among the three stakeholders through physical and psychological indicators. Users' perceptions of safety, security, comfort, available information, and their perception of initial physical indicators are formed through utilizing transport infrastructure, facilities, and services. Users decide whether to utilize transport services at a later time based on their psychological evaluation of physical accessibility indicators. In MaaS, the MPO conducts operational plans (e.g., dispatching and relocating strategy with integrated PuT) to serve user requests.

Furthermore, the MPO makes agreements with TSPs who provide initial physical indicators to create service packages, pay-as-usage options, operational plans and information, fare, and ticket integrations to offer to users. New physical indicators reflecting travel time, waiting time, fares, transfer locations, service integration, flexibility, etc., will present services provided by the MOP. Similarly, users also evaluate new accessibility indicators to decide whether to use the MaaS service. In this scenario, the provision of MPO may rely on a range of available TSPs and their operational plans. However, users also give requests and preferences for new physical indicators. The MPO might adjust the design of service packages, mobility options, and operational plans to meet users' needs, which in turn require the existing TSPs to adjust their operational plans and/or provisions of supply. In this case, TSPs adjust their operational plans and service provisions as per the requirement of the MPO, which may impact the operation of existing TSPs and generate an optimal transport system.

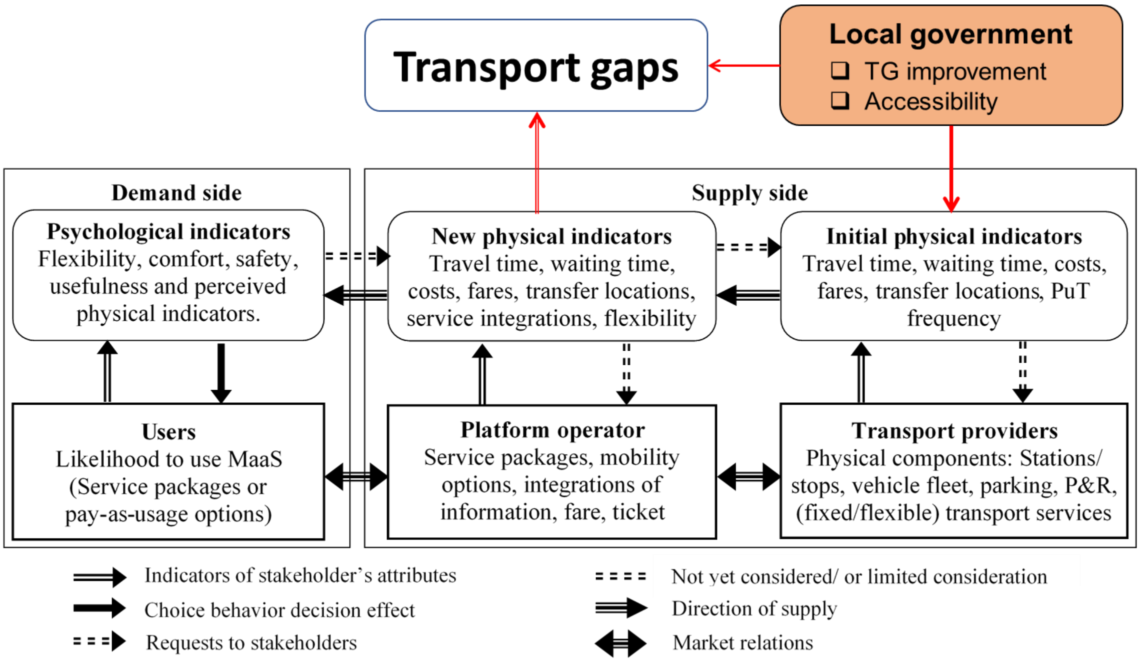


Figure 7-1 Conceptual microscopic modeling for further study on transport gaps

To capture the interactions between users and TSPs, Wen et al (2018) proposed an agent based model (ABM) in the context of integrated autonomous vehicles (AVs) and PuT systems (Wen et al. 2018b). In their study, the TSPs considered operational and fare policy, vehicle fleet, vehicle capacity reflecting in waiting time, travel time, detour factor (defined as the ratio of actual in-vehicle travel time with ridesharing to the shortest travel time without ridesharing), and travel cost. The demand-supply interactions were modeled by the waiting time and detour factor. In particular, the users' travel mode choices were affected by the waiting time and detour factor, which are changed by iterative simulation in the ABM, which in turn influenced the supply parameters of AV services. Furthermore, the dynamic demand-supply interactions in a multimodal context were impacted by various fleet sizes, number of transfers, fares, travel time, and waiting time (Chen and Nie 2017; Narayan et al. 2020a; H. K. R. de F. Pinto et al. 2018; Shen et al. 2018a). Moreover, the study by Pinto et al (Pinto et al. 2020) using an ABM and Becker et al (Becker et al. 2020) using MATSim to simulate the demand-supply interactions showed that travel time, travel cost, and PuT frequency are primary indicators. However, these studies are limited to the operation of an AV fleet and lack dynamic pricing for AVs as well. In addition, Li et al (2018) proposed an activity-based dynamic user equilibrium model to model the demand-supply interactions of free-floating shared cars and showed that the demands of shared cars depend on the availability and rental-parking price of free-floating shared cars at a location at a certain time interval (Q. Li et al. 2018). Furthermore, Wischik (2019) considered the demand-supply interactions based on the price of ridesharing and PuT fare (Wischik 2019). The study by Pentelidis et al (2019) presented cost allocations and pricing of services between a public MPO and existing TSPs based on modeling the interactions among user route choice decisions and provider operational decisions (Pantelidis, Chow, and Rasulkhani 2020).

The abovementioned models mainly considered physical accessibility indicators, including travel time, travel cost, and fare, to describe the interactions between user demand and TSPs. Another limitation of existing models is the lack of consideration of dynamic pricing (e.g., surge pricing) scheme, which is a key operational parameter of on-demand services. Egan and Jakob represented the interactions among users and on-demand service providers through maximum price, waiting time, and desired pick-up time intervals (Egan and Jakob 2016). Users make decisions on either accepting or rejecting journeys offered by providers according to their preferences for maximum price, maximum waiting time, and departure time intervals, while service providers aim to jointly optimize the scheduling, routing, and pricing to maximize profits; however, this study is unrelated to multimodal integration and the MaaS context.

Furthermore, the MPO captured user needs and preferences for travel modes and service features to develop MaaS plans (Arnaoutaki et al. n.d.) although there were few models considering the assumptions of user preferences for different available mobility services to estimate user demand in a multimodal context (Pinto et al. 2020; Wen et al. 2018b). There is a limitation in the integration of psychological indicators into modeling the interactions in existing studies, especially considering that users' willingness to share is a major limitation in modeling ridesharing and/or on-demand services. Moreover, existing models focused on modeling and matching a single request to available mobility options. There is a lack of studies accounting for the interactions between users who choose monthly service packages and other service providers.

Moreover, the reviewed models simulating the platform operation of on-demand services can establish and assign trip requests to other TSPs, such as PuT services and bike-sharing services, although the TSPs are independently operated and not yet integrated into a single MPO. As a result, the existing models focused on the objectives of minimizing travel cost and/or travel time or maximizing the benefits of on-demand service (Cangialosi et al. 2016; Chen and Nie 2017; Fahnenschreiber et al. 2016; Jamal et al. n.d.; Levin et al. 2019a; Liang et al. 2016; Luo et al. 2018; Ma 2017; Ma et al. 2019a; Masoud et al. 2017; Nam et al. 2018; Narayan et al. 2020a; Pinto et al. 2020; Posada et al. 2017; Salazar et al. 2018; Stiglic et al. 2018a; Varone and Aissat 2015; Wright et al. 2020). Therefore, a gap found in the literature is identified as a lack of studies accounting for the efficiency of both on-demand services and PuT services.

In addition, Djavadian and Chow (2017) proposed an ABM to simulate a two-sided market where the operational policy is a function of user demand, and user costs are a function of the operational policy and network. Users are impacted by travel time (waiting time and in-vehicle time), schedule delay, and fare price. Drivers may decide whether to participate in service provision based on their expected profit threshold and the probability of getting a passenger. The platform is represented by operational policies and infrastructure network and is modeled in terms of maximizing the total welfare of both users and operators. The study showed that fare price and drivers' profit threshold significantly affected fleet size, which in turn impacts the performance of on-demand services, taxi demand, and total consumer surplus of users (Djavadian and Chow 2017a). Similarly, several studies also considered drivers' perspectives toward detour constraints (maximum distance and/or time) and maximum waiting time (Aissat and Varone 2015; Levin et al. 2019a; Luo et al. 2018; Masoud et al. 2017; Pinto et al. 2020; Salazar et al. 2018; Shen et al. 2018a). However, these studies overlooked the decisions of other TSPs, such as bike-sharing providers and shared car providers, on providing available vehicles, which became another gap in the existing models. Further studies need to address the limitations found in this study and generate a conceptual framework for modeling the interactions among users, TSPs, and MPO in further work.

7.4. Discussion on implication of transport gap indicator

Before considering policy implications based on transport gap indicator, the most important and interesting findings from analytical results were summarized as follows.

Spatial transport gaps: The spatial distribution of transport gaps requires the policy makers and planners identify the areas which transport gap reduction needs to be prioritized. The analytical results showed that.

- Low preference for zones with low populations and transport gaps.
- Highly prioritizing zones with high population and transport gaps.
- Optimizing transport supply in zones with low populations and transport gaps.
- Maintaining transport supply in zones with high population and transport gaps.

Potential impacts of different services: The analytical results of policy scenarios showed that.

- Bus frequency improvement or on-demand bus contributed to addressing low and medium transport gaps.
- Introduction of ridesharing significantly contributed to removing transport gaps
- A certain percentage of ridesharing and on-demand services was highlighted to balance transport supply and demands.

Based on the findings, several applications of transport gap indicator were considered for transport planning as follows.

(1) Policy recommendations for areas with transport gaps

- Areas with large population and transport gaps: it is prioritized to enhance transport services to meet transport demands in these areas.
- Areas with large population and without transport gaps: it is recommended to maintain the existing transport services in these areas.
- Areas with low population and transport gaps: it is recommended that improvement of transport gap in these zones is not necessary.

- Areas with low population and without transport gaps: it is recommended to optimize or rearrange the transport services in these areas to areas with transport gaps.

(2) Transport services suggested for transport gap reduction

Based on the potential impacts of different transport services on transport gaps, the policies and applications are considered in Table 7-2. The low and medium transport gaps can be addressed by bus service improvement and on-demand bus. The service improvement requires more financial supports/subsidies and operational costs from local government and transport service providers. Furthermore, ridesharing is considered a feasible service to reduce transport gaps in areas without public transport. Although the introduction of ridesharing can reduce the great efforts of local government and transport service providers in geographical service expansion, operational costs, and subsidies, it also requires efforts in economic deregulation.

Table 7-2 Application of transport gap indicator in select feasible services

Transport gaps	Bus frequency improvement	On-demand bus	Ridesharing and/or multimodal
Low transport gap	O	O	O
Medium transport gap	O	O	O
Large transport gap	X	X	O

Note: O: consideration; X: Not consideration

(3) Establishing supply management strategy

Transport gaps also can be seen as technical and strategic tool for transport planning. Based on a certain percentage of ridesharing and on-demand services to remove transport gap in one area, a maximum number of ridesharing will ensure available service and a certain level of transport gap in one area.

In conclusion, introducing transport gap indicator for transport planning is practical and useful. This work can support transport planners, decision makers and travel agencies evaluate and select suitable transport services to fulfill transport gaps in an area.

8. Conclusions

8.1. Research summary

It was widely acknowledged from the literature that the transport gap was viewed as synonymous with low accessibility and low service frequency, which in turn influenced the ease of access, convenience, comfort, and availability of service to reach a specific destination or social activity. In this study, the transport gap described the lack of transport services from the physical perspective and was representative of the convenience, comfort, and ease of travelers to reach a specific destination or social activity by using a specific transport mode or different modes from the psychological perspective. It appears that for vulnerable individuals, such as non-car ownership, elderly, and disabled, transport gaps became more critical.

Addressing the transport gaps is a challenging problem for many rural areas. In practice, it is difficult to provide sufficiently traditional public transport services, which can hardly be efficient with such a low and dispersed demand in rural areas. The emergence of innovative mobility services, such as ridesharing, car-sharing, ride-sourcing, e-hailing, and on-demand public transport provided travelers with a wide range of mobility options for fulfilling their daily mobility needs, especially travelers in rural areas where traditional public transport services are poor or nonexistent. As potential services integrated into Mobility as a Service (MaaS), on-demand services provide point-to-point mobility options, easily fitting into public transport gaps, and enhancing accessibility for transit-dependent travelers. The growth of MaaS is a new opportunity for reducing transport gaps in rural tourism areas. However, its role in addressing the transport gap for an area was rarely explored. Moreover, the study on transport gap in rural tourism areas was rarely found in the existing literature. As a result, this study investigated several key questions surrounding transport gaps, including (1) to what extent are the transport gaps in rural tourism areas; (2) what transport services are required to fulfill transport gaps; and how are their potential impacts on transport gap reduction.

The study used different sources related to transport demands and supply to develop demand models and supply models, which are important backgrounds to quantify transport gaps in each zone. The different regression models were implemented to analyze demand data, including personal trip survey data, mobile spatial statistics data, demographic, land-use data, and built environment data, etc. The supply models considered the spatial-temporal supply of public transport and private transport. The transport gap model based on the standardized score of transport supply and demand was used to identify spatial-temporal transport gaps. This study attempted to incorporate on-demand services into the existing transport supply to further understanding on-demand services and variations in their potential impacts on transport gap reduction in an area.

The findings further confirmed traditional understanding about factors influencing the number of trip productions and attractions per zone. Transport supply indicators and accessibility were the most significantly related to trip productions and attractions by different trip purposes. Findings showed the spatial distribution of transport gaps, which are scattered in both local residential and tourism areas. Furthermore, the study also provided new insight into temporal transport gaps, which became more critical on the weekend and during peak hours. The findings also showed the role of different services in transport gap reductions in rural tourism areas. The role of ridesharing was highlighted from its potential impact on transport demands, supplies, and transport gap reductions.

Based on analytical analyses, some implications for transport planners and decision makers were suggested as:

(1) Priority areas for transport gap improvement: high population and large gaps.

(2) Suitable transport services and options: bus improvement, on-demand services and multimodal transport corresponding to level of transport gaps.

(3) Establishing supply management strategy: guidance tool for transport gaps and maximum number of ridesharing services to balance the supply and demands.

8.2. Contribution of the study

8.2.1. Academic contribution

There were two major academic contributions in this study. Firstly, this study contributed to literature with a comprehensive understanding of transport gaps in the context of scattered rural tourism areas, where residential areas, tourism areas, public facilities are widely separated. Secondly, the study generated a macroscopic model with very limited data to evaluate the role of different transport services in transport gap reduction.

8.2.2. Practical contribution

Findings in the study highlighted areas, which are the most in need of transport gap improvement. Furthermore, the developed model can support decision makers and transport planners in identifying transport services for transport gap reduction. Although this approach was evaluated in rural tourism areas, it can be easily applied to other areas when planning strategies for transport gap reduction are considered.

8.3. Further studies

Although the study provided some important findings on transport gaps, it is suggested some further studies to extend and improve the current study as follows

- The most important limitation in this study was to relatively compare the standardized score of transport demands and supply. Although estimates represented the real values of transport demands and supply in a zone, relative transport gaps might not accurately reflect the gaps in transport supply in a zone. Furthermore, user’s perspectives and perceptions on transport gaps were not considered in this study. Further studies are suggested to measure transport gaps from the user’s perspective. The analytical results can support policymakers and planners in identifying the specific levels of transport gaps that improvement needs to be prioritized to meet user’s satisfaction.
- An important limitation of the demand analysis was the lack of consideration of user’s behaviors and preferences. The potential impact of ridesharing and service combinations on a traveler's choice of destination and decision to make a trip needs to be considered in further study.

- In the policy scenario analyses, assumptions on accessibility indicators were made in the physical indicators (i.e., waiting time and the number of vehicles available). Other important indicators, including travel cost/fares, travel time, and psychological indicators, user's preferences and behaviors are not considered. In terms of operation, these indicators could be changed, especially in MaaS context. Developing microscopic models to model the real operation of on-demand services, to capture both physical and psychological indicators as well as user's behaviors and preferences is suggested for further study. The conceptual model in the further study will provide a more comprehensive understanding about potential impact on transport gaps reduction per zone.

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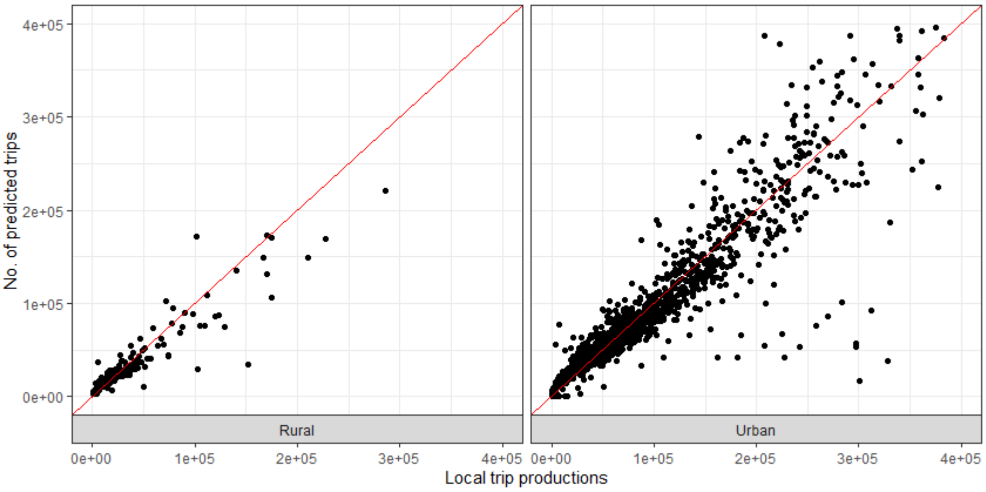
10. Appendix

Model 1 – Local trip production model

```
Formula:
Pro ~ Note + factor(Character) + Popu + Residence + Facilities +
Recreation + Train.frequency + Bus + log(Accessibility)
Dispersion:          ~Popu
     AIC      BIC   logLik deviance df.resid
 34427.8  34507.8 -17198.9  34397.8     1517

Conditional model:
                    Estimate Std. Error z value Pr(>|z|)
(Intercept)        3.3411869  0.2763313   12.09  < 2e-16 ***
NoteUrban          0.1859181  0.0292702    6.35 2.13e-10 ***
factor(Character)2 0.6023338  0.0434079   13.88  < 2e-16 ***
factor(Character)3 0.1089891  0.0162456    6.71 1.96e-11 ***
factor(Character)4 0.9444159  0.2193084    4.31 1.66e-05 ***
factor(Character)5 1.1046622  0.1654580    6.68 2.45e-11 ***
Popu               0.5056534  0.0136977   36.92  < 2e-16 ***
Residence          0.3844183  0.0425856    9.03  < 2e-16 ***
Facilities         0.0043494  0.0002580   16.86  < 2e-16 ***
Recreation         0.0029226  0.0005123    5.70 1.17e-08 ***
Train.frequency    0.0024486  0.0003096    7.91 2.60e-15 ***
Bus                0.0493317  0.0069057    7.14 9.09e-13 ***
log(Accessibility) 0.1435510  0.0415606    3.45 0.000552 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Dispersion model:
            Estimate Std. Error z value Pr(>|z|)
(Intercept) -4.03764    0.27654  -14.60   <2e-16 ***
Popu         0.62311    0.02731   22.82   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```



Notification

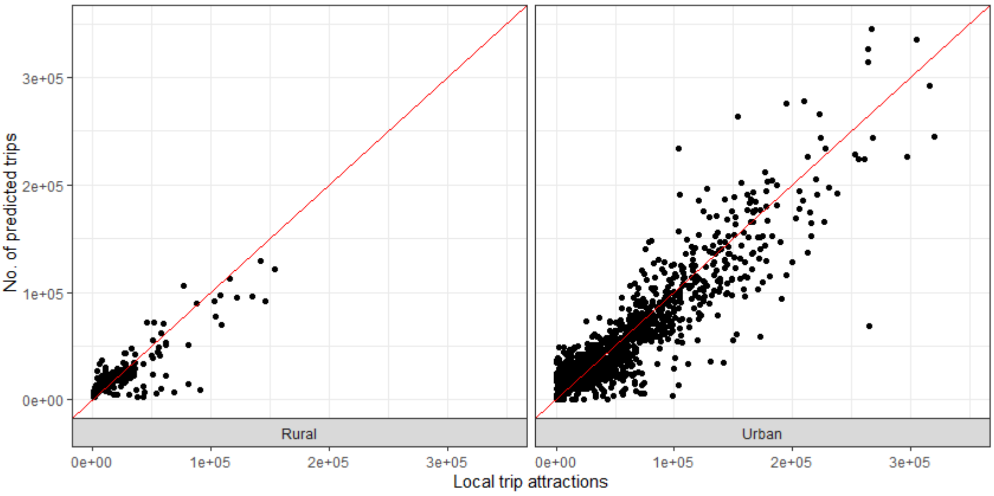
Note	:	Urban or rural	Service	:	Service coverage
factor(Character)	:	Different type of land-use	Pro	:	Local trip production
Popu	:	Population			
Residence	:	Residential density			
Facilities	:	Number of public facilities			
Recreation	:	Number of tourism facilities			
Train. frequency	:	Train frequency			
Bus	:	Bus frequency			

Model 2 – Local trip attraction model

```
Formula:
dm ~ Note + factor(Character) + Popu + Residence + Facilities +
    Recreation + Train.frequency + Bus + log(Accessibility)
Dispersion:          ~Popu
     AIC      BIC   logLik deviance df.resid
 34203.6  34283.7 -17086.8  34173.6     1517

Conditional model:
                     Estimate Std. Error z value Pr(>|z|)
(Intercept)         5.5626284  0.4289843  12.967  < 2e-16 ***
NoteUrban           0.1163681  0.0466300   2.496  0.01258 *
factor(Character)2  0.0663010  0.0670456   0.989  0.32271
factor(Character)3  0.1341564  0.0244156   5.495 3.91e-08 ***
factor(Character)4  1.2889290  0.3947794   3.265  0.00109 **
factor(Character)5  0.1908156  0.2835162   0.673  0.50093
Popu                0.4940594  0.0231127  21.376  < 2e-16 ***
Residence           0.2498695  0.0637371   3.920 8.84e-05 ***
Facilities          0.0050414  0.0003978  12.672  < 2e-16 ***
Recreation          0.0021509  0.0007415   2.901  0.00372 **
Train.frequency     0.0010213  0.0004498   2.270  0.02318 *
Bus                 0.0240620  0.0108121   2.225  0.02605 *
log(Accessibility) -0.1623131  0.0623228  -2.604  0.00920 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Dispersion model:
            Estimate Std. Error z value Pr(>|z|)
(Intercept) -6.55836    0.32930  -19.92   <2e-16 ***
Popu         0.77912    0.03279   23.76   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```



Notification

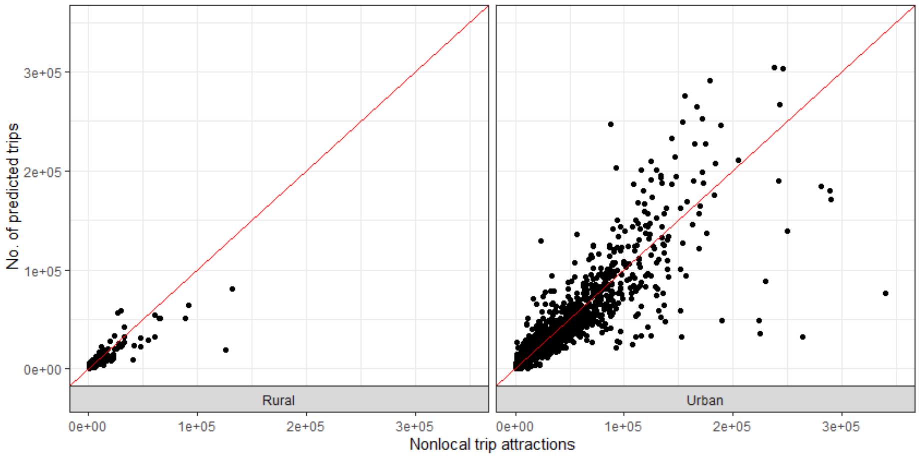
Note	:	Urban/rural
factor(Character)	:	Different type of land-use
Popu	:	Population
Residence	:	Resident density
Facilities	:	Number of public facilities
Recreation	:	Number of tourism facilities
Train. frequency	:	Train frequency
Bus	:	Bus frequency
Service	:	Service coverage
dm	:	Local trip attraction

Model 3 – Nonlocal trip attraction model

```
Formula:
ndm ~ Note + factor(Character) + Popu + Residence + Facilities +
    Recreation + Train.frequency + Bus + Service + log(Accessibility)
Dispersion:             ~Popu
     AIC       BIC    logLik deviance df.resid
 32571.8   32657.1 -16269.9  32539.8     1516

Conditional model:
                     Estimate Std. Error z value Pr(>|z|)
(Intercept)        -0.9115556  0.4255182  -2.142 0.032175 *
NoteUrban           0.2725825  0.0423555   6.436 1.23e-10 ***
factor(Character)2  0.8468622  0.0653554  12.958  < 2e-16 ***
factor(Character)3  0.0980880  0.0259307   3.783 0.000155 ***
factor(Character)4  1.0974251  0.2768916   3.963 7.39e-05 ***
factor(Character)5  1.4352545  0.2175436   6.598 4.18e-11 ***
Popu                0.3746250  0.0194390  19.272  < 2e-16 ***
Residence           0.5018838  0.0686688   7.309 2.70e-13 ***
Facilities          0.0055891  0.0004039  13.838  < 2e-16 ***
Recreation          0.0027718  0.0008258   3.356 0.000790 ***
Train.frequency     0.0032776  0.0004994   6.563 5.27e-11 ***
Bus                 0.0872267  0.0106122   8.219  < 2e-16 ***
Service             0.4215770  0.0972737   4.334 1.46e-05 ***
log(Accessibility)  0.6615001  0.0647508  10.216  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Dispersion model:
            Estimate Std. Error z value Pr(>|z|)
(Intercept) -3.13113    0.28213  -11.10   <2e-16 ***
Popu         0.45651    0.02786   16.39   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```



Notification

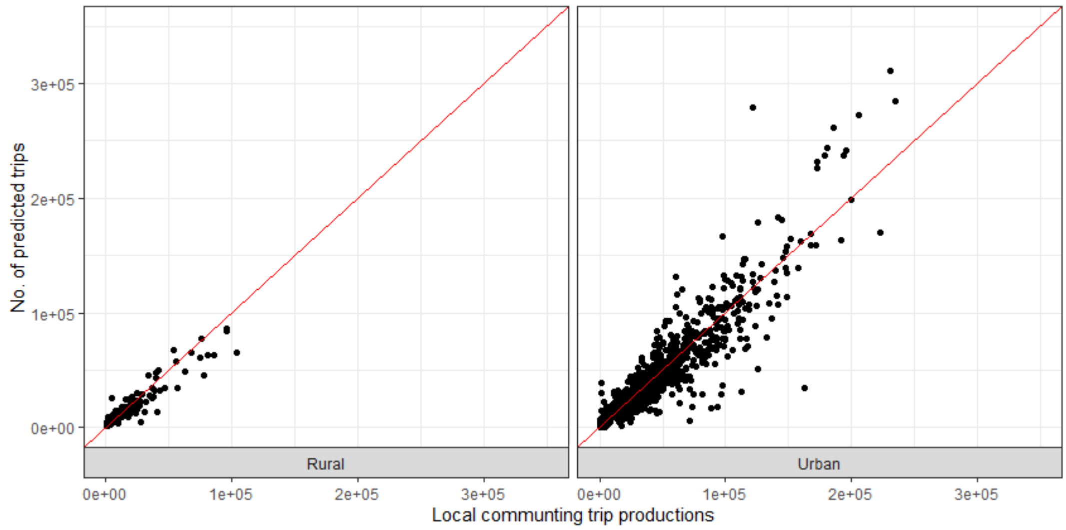
Note	:	Urban/rural
factor(Character)	:	Different type of land-use
Popu	:	Population
Residence	:	Resident density
Facilities	:	Number of public facilities
Recreation	:	Number of tourism facilities
Train. frequency	:	Train frequency
Bus	:	Bus frequency
Service	:	Service coverage
ndm	:	Local trip attraction

Model 4 – Local commuting trip production model

```
Formula:
G..Local.Com ~ Note + factor(Character) + Popu + Residence + Facilities
+ Recreation + Train.frequency + log(Accessibility)
Dispersion:                   ~Popu
     AIC      BIC    logLik deviance df.resid
 31928.8  32003.5 -15950.4  31900.8     1518

Conditional model:
                     Estimate Std. Error z value Pr(>|z|)
(Intercept)         5.0241937  0.3271828   15.36  < 2e-16 ***
NoteUrban           0.1674609  0.0346154    4.84 1.31e-06 ***
factor(Character)2  0.0722386  0.0499263    1.45  0.14792
factor(Character)3  0.1625994  0.0194386    8.36  < 2e-16 ***
factor(Character)4  1.1454454  0.2464269    4.65 3.35e-06 ***
factor(Character)5  0.5300366  0.1854198    2.86  0.00426 **
Popu                0.5953262  0.0151975   39.17  < 2e-16 ***
Residence           0.2208734  0.0503095    4.39 1.13e-05 ***
Facilities          0.0039371  0.0003015   13.06  < 2e-16 ***
Recreation          0.0029922  0.0006229    4.80 1.56e-06 ***
Train.frequency     0.0011564  0.0003731    3.10  0.00194 **
log(Accessibility) -0.2684826  0.0498433   -5.39 7.18e-08 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Dispersion model:
            Estimate Std. Error z value Pr(>|z|)
(Intercept) -3.78966    0.26976  -14.05   <2e-16 ***
Popu         0.56698    0.02661   21.30   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```



Notification

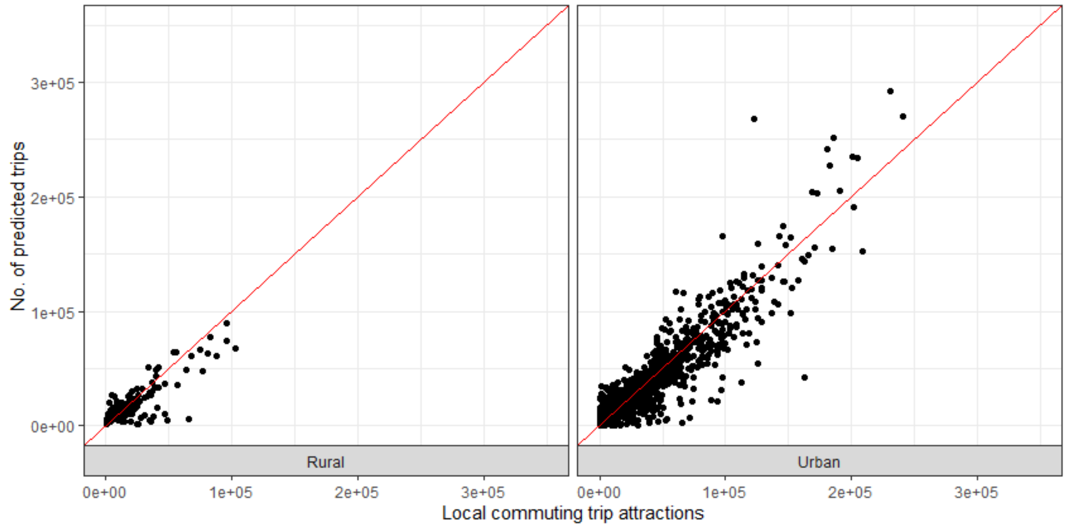
Note	:	Urban/rural
factor(Character)	:	Different type of land-use
Popu	:	Population
Residence	:	Resident density
Facilities	:	Number of public facilities
Recreation	:	Number of tourism facilities
Train. frequency	:	Train frequency
Bus	:	Bus frequency
Service	:	Service coverage
G..Local.Com	:	Local commuting trip production

Model 5 – Local commuting trip attraction model

```
Formula:
Local.Com ~ Note + factor(Character) + Popu + Residence + Facilities +
Recreation + log(Accessibility)
Dispersion:                  ~Popu
     AIC      BIC    logLik deviance df.resid
 32920.9  32990.3 -16447.5  32894.9     1519

Conditional model:
                     Estimate Std. Error z value Pr(>|z|)
(Intercept)         5.7679778  0.4092342  14.095  < 2e-16 ***
NoteUrban           0.1341910  0.0449270   2.987 0.002818 **
factor(Character)2 -0.0651000  0.0633987  -1.027 0.304499
factor(Character)3  0.1548176  0.0235933   6.562 5.31e-11 ***
factor(Character)4  1.3398794  0.3859030   3.472 0.000516 ***
factor(Character)5  0.1664105  0.2753410   0.604 0.545591
Popu                0.5096814  0.0214886  23.719  < 2e-16 ***
Residence           0.1662992  0.0612432   2.715 0.006620 **
Facilities          0.0050470  0.0003465  14.567  < 2e-16 ***
Recreation          0.0018027  0.0007124   2.531 0.011390 *
log(Accessibility) -0.2295546  0.0596975  -3.845 0.000120 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Dispersion model:
            Estimate Std. Error z value Pr(>|z|)
(Intercept) -6.59683    0.32755  -20.14   <2e-16 ***
Popu         0.78878    0.03261   24.19   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```



Notification

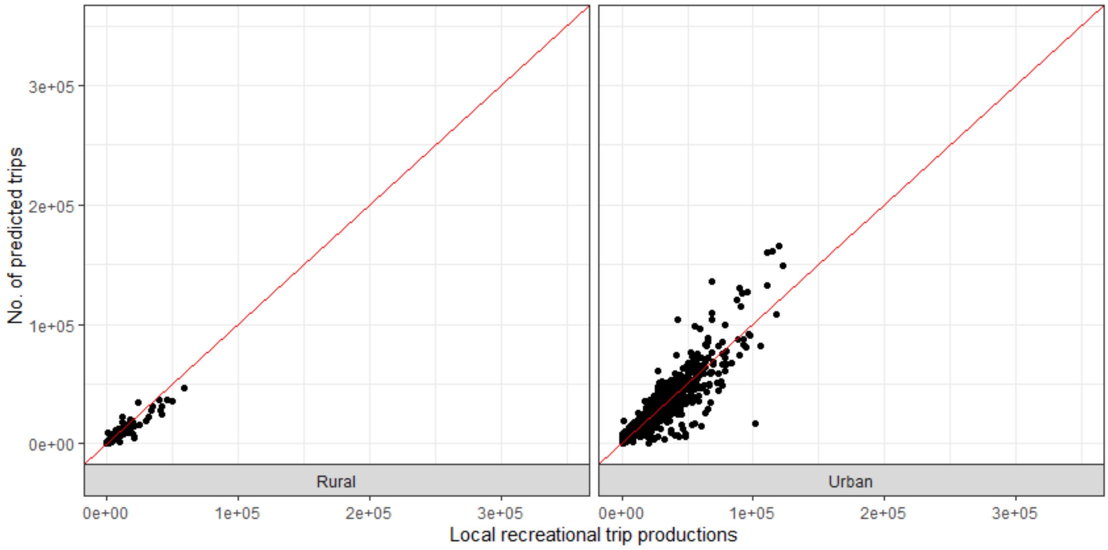
Note	:	Urban/rural
factor(Character)	:	Different type of land-use
Popu	:	Population
Residence	:	Resident density
Facilities	:	Number of public facilities
Recreation	:	Number of tourism facilities
Train. frequency	:	Train frequency
Bus	:	Bus frequency
Service	:	Service coverage
Local.Com	:	Local commuting trip attraction

Model 6 – Local recreational trip production model

```
Formula:
G.Local.Rec ~ Note + factor(Character) + Popu + Residence + Facilities +
    Recreation + Train.frequency + Bus
Dispersion:                    ~Popu
     AIC      BIC   logLik deviance df.resid
 29718.5  29793.1 -14845.2  29690.5     1518

Conditional model:
                    Estimate Std. Error z value Pr(>|z|)
(Intercept)        1.5814207  0.1489763   10.62  < 2e-16 ***
NoteUrban          0.1779107  0.0365272    4.87 1.11e-06 ***
Popu               0.6324794  0.0170500   37.10  < 2e-16 ***
factor(Character)2 0.3420207  0.0538222    6.35 2.09e-10 ***
factor(Character)3 0.0771834  0.0198297    3.89 9.93e-05 ***
factor(Character)4 0.5985829  0.2965336    2.02 0.043529 *
factor(Character)5 0.7661896  0.2193962    3.49 0.000479 ***
Residence          0.2858355  0.0417903    6.84 7.93e-12 ***
Facilities         0.0038391  0.0002999   12.80  < 2e-16 ***
Recreation         0.0030813  0.0006087    5.06 4.16e-07 ***
Train.frequency    0.0021850  0.0003720    5.87 4.27e-09 ***
Bus                0.0501612  0.0085452    5.87 4.35e-09 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Dispersion model:
            Estimate Std. Error z value Pr(>|z|)
(Intercept) -5.37028    0.28871  -18.60   <2e-16 ***
Popu         0.70871    0.02847   24.89   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```



Notification

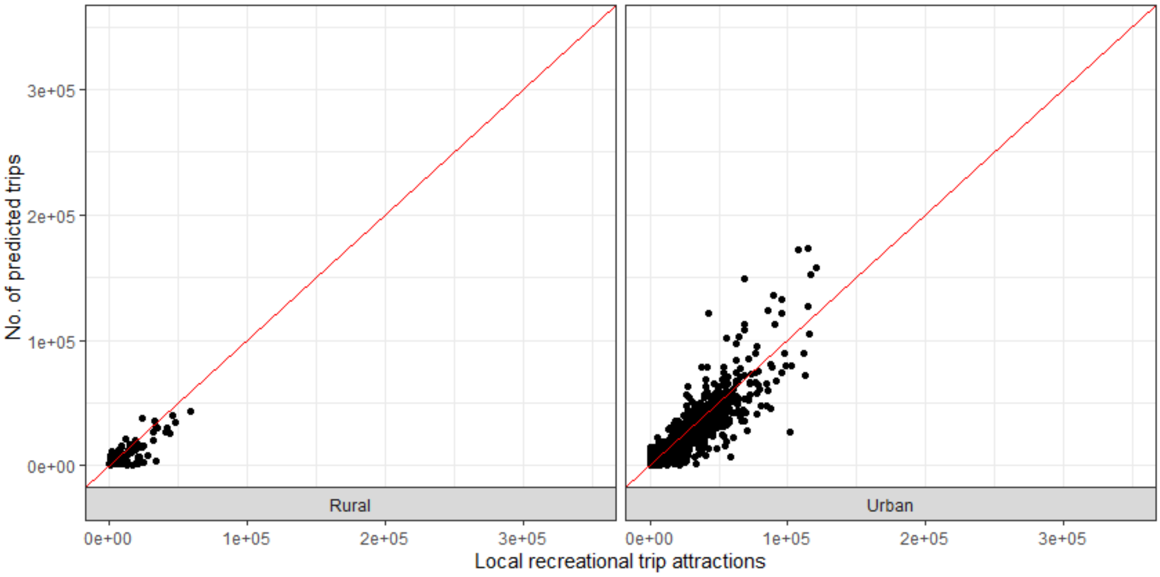
Note	:	Urban/rural
factor(Character)	:	Different type of land-use
Popu	:	Population
Residence	:	Resident density
Facilities	:	Number of public facilities
Recreation	:	Number of tourism facilities
Train. frequency	:	Train frequency
Bus	:	Bus frequency
G.Local.Rec	:	Local recreational trip production

Model 7 – Local recreational trip attraction model

```
Local.Rec ~ Note + factor(Character) + Popu + Residence + Facilities +
    Recreation + Train.frequency + Bus
Dispersion:                 ~Popu
     AIC      BIC   logLik deviance df.resid
 31091.3  31166.0 -15531.6  31063.3     1518

Conditional model:
                    Estimate Std. Error z value Pr(>|z|)
(Intercept)        3.0624710  0.2356443  12.996  < 2e-16 ***
NoteUrban          0.1181883  0.0560457   2.109 0.034963 *
factor(Character)2 0.2540552  0.0821087   3.094 0.001974 **
factor(Character)3 0.0955535  0.0299972   3.185 0.001445 **
factor(Character)4 1.2229018  0.4600714   2.658 0.007859 **
factor(Character)5 0.2661845  0.3352297   0.794 0.427174
Popu               0.4723226  0.0274108  17.231  < 2e-16 ***
Residence          0.4002231  0.0635009   6.303 2.93e-10 ***
Facilities         0.0055811  0.0004750  11.750  < 2e-16 ***
Recreation         0.0025662  0.0009135   2.809 0.004967 **
Train.frequency    0.0022077  0.0005620   3.929 8.55e-05 ***
Bus                0.0482203  0.0131336   3.672 0.000241 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Dispersion model:
            Estimate Std. Error z value Pr(>|z|)
(Intercept) -6.44009    0.33094  -19.46   <2e-16 ***
Popu         0.72995    0.03297   22.14   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```



Notification

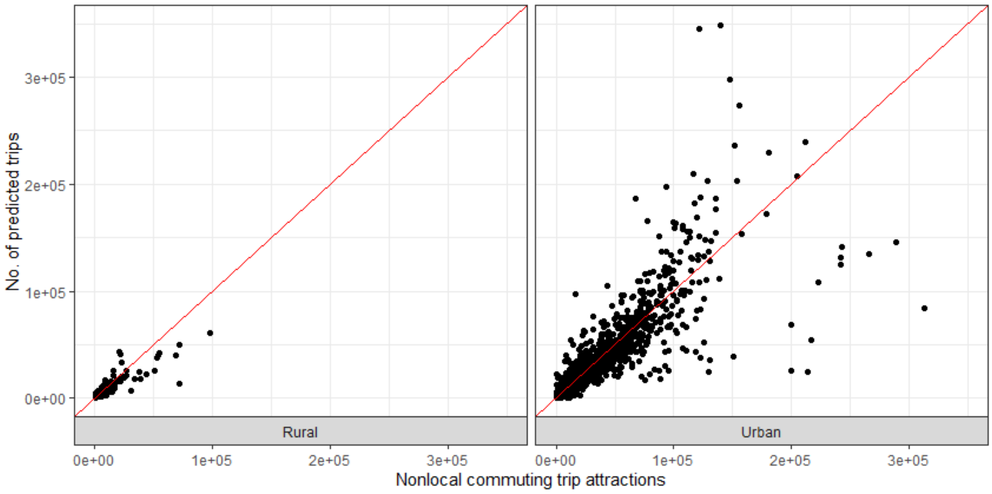
Note	:	Urban/rural
factor(Character)	:	Different type of land-use
Popu	:	Population
Residence	:	Resident density
Facilities	:	Number of public facilities
Recreation	:	Number of tourism facilities
Train. frequency	:	Train frequency
Bus	:	Bus frequency
Local.Rec	:	Local recreational trip attraction

Model 8 – Nonlocal commuting trip attraction model

```
Non.Com ~ Note + factor(Character) + Popu + Residence + Facilities +
    Recreation + Train.frequency + Bus + Service + log(Accessibility)
Dispersion:                 ~Popu
     AIC      BIC    logLik deviance df.resid
 31899.1  31984.4 -15933.5  31867.1     1516

Conditional model:
                     Estimate Std. Error z value Pr(>|z|)    
(Intercept)        -1.4765627  0.4268662  -3.459 0.000542 ***
NoteUrban           0.3035756  0.0427594   7.100 1.25e-12 ***
factor(Character)2  0.8242219  0.0658872  12.510  < 2e-16 ***
factor(Character)3  0.1112753  0.0260913   4.265 2.00e-05 ***
factor(Character)4  1.2560760  0.2839654   4.423 9.72e-06 ***
factor(Character)5  1.4815561  0.2219809   6.674 2.48e-11 ***
Popu                0.3914495  0.0195512  20.022  < 2e-16 ***
Residence           0.4995070  0.0692063   7.218 5.29e-13 ***
Facilities          0.0057525  0.0004050  14.204  < 2e-16 ***
Recreation          0.0019201  0.0008243   2.330 0.019832 *  
Train.frequency     0.0028326  0.0005002   5.663 1.49e-08 ***
Bus                 0.0805020  0.0106782   7.539 4.74e-14 ***
Service             0.4063912  0.0984104   4.130 3.63e-05 ***
log(Accessibility)  0.6914125  0.0649628  10.643  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Dispersion model:
            Estimate Std. Error z value Pr(>|z|)    
(Intercept) -3.30161    0.27569  -11.98   <2e-16 ***
Popu         0.47149    0.02722   17.32   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```



Notification

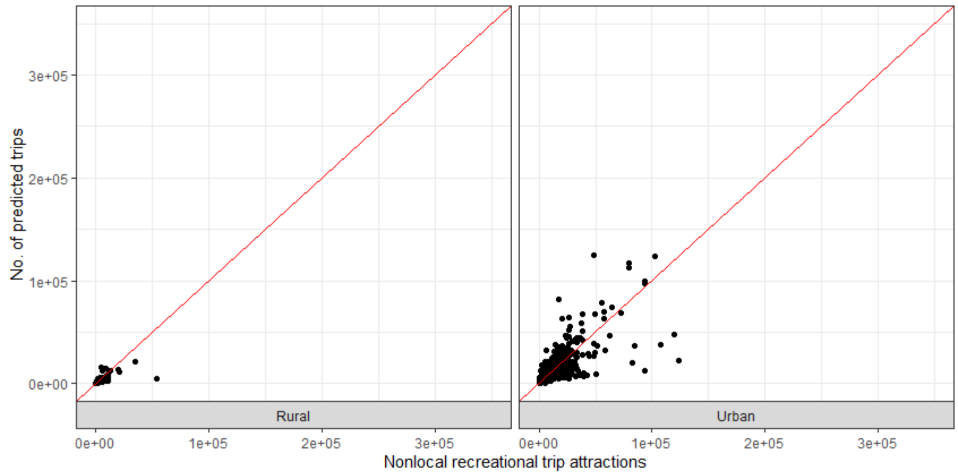
Note	:	Urban/rural
factor(Character)	:	Different type of land-use
Popu	:	Population
Residence	:	Resident density
Facilities	:	Number of public facilities
Recreation	:	Number of tourism facilities
Train. frequency	:	Train frequency
Bus	:	Bus frequency
Service	:	Service coverage
Non.Com	:	Nonlocal commuting trip attraction

Model 9 – Nonlocal recreational trip attraction model

```
Non.Rec ~ Note + factor(Character) + Popu + Residence + Facilities +
Recreation + Train.frequency + Bus + Service + log(Accessibility)
Dispersion:                 ~Popu
     AIC      BIC   logLik deviance df.resid
 28211.5  28296.9 -14089.8  28179.5     1516

Conditional model:
                     Estimate Std. Error z value Pr(>|z|)
(Intercept)        -1.2109721  0.5746818  -2.107  0.03510 *
NoteUrban           0.1610676  0.0555355   2.900  0.00373 **
factor(Character)2  0.9303669  0.0860449  10.813  < 2e-16 ***
factor(Character)3  0.0475250  0.0345171   1.377  0.16856
factor(Character)4  0.1506847  0.3386257   0.445  0.65633
factor(Character)5  1.2931081  0.2722202   4.750 2.03e-06 ***
Popu                0.3119179  0.0253862  12.287  < 2e-16 ***
Residence           0.4955614  0.0907599   5.460 4.76e-08 ***
Facilities          0.0049926  0.0005404   9.240  < 2e-16 ***
Recreation          0.0061906  0.0011350   5.454 4.91e-08 ***
Train.frequency     0.0050006  0.0006762   7.396 1.41e-13 ***
Bus                 0.1139162  0.0141714   8.038 9.10e-16 ***
Service             0.4935393  0.1265357   3.900 9.60e-05 ***
log(Accessibility)  0.5420933  0.0871150   6.223 4.89e-10 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Dispersion model:
            Estimate Std. Error z value Pr(>|z|)
(Intercept) -2.99561    0.27833  -10.76   <2e-16 ***
Popu         0.38936    0.02742   14.20   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```



Notification

Note	:	Urban/rural
factor(Character)	:	Different type of land-use
Popu	:	Population
Residence	:	Resident density
Facilities	:	Number of public facilities
Recreation	:	Number of tourism facilities
Train. frequency	:	Train frequency
Bus	:	Bus frequency
Service	:	Service coverage
Non.Rec	:	Nonlocal recreational trip attraction