MATSim User Meeting in Japan Nov.21, 2024

Evaluating Transport and Land Use Impacts of Automated Vehicles in a Japanese Regional Area using Microsimulation

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Background: Automated vehicle (AV) expected to be operated in near future.

Definition/hypothesis of AV: "…entire dynamic driving task without any expectation that a user will respond to a request (SAE, 2021)."

⬇

Main feature of AV: Human will cede controllability of vehicles to the robotics.

⬇

Implications (assumed) of AV, for example:

Good:

1. No driving burden;
2. Availability for those unable to drive;
3. …

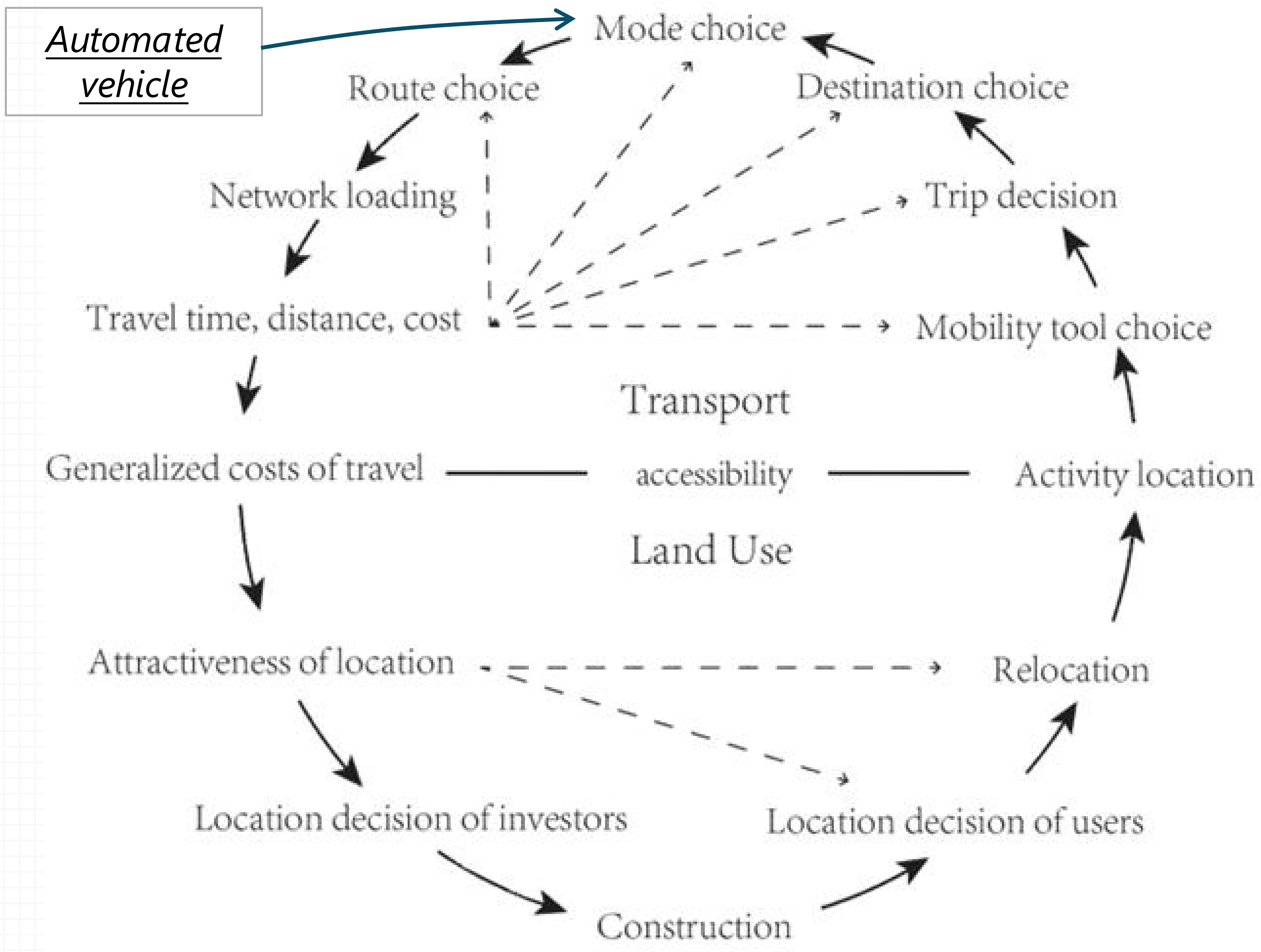
Not so good:

1. Induce more travel;
2. Trigger urban sprawl;
3. …

Image of Automated Vehicles made by H. Miller in 1957 (Anderson et al., 2014)

Anderson, J. M., Nidhi, K., Stanley, K. D., Sorensen, P., Samaras, C., & Oluwatola, O. A. (2014). Automated Vehicle Technology: A Guide for Policymakers. Rand Corporation.

Research rationale: how could residential location be impacted?



Feedback cycle between land use and transport systems (adapted from Bierlaire et al., 2015)

Bierlaire, M., De Palma, A., Hurtubia, R., & Waddell, P. (2015). Integrated transport and land use modeling for sustainable cities (No. BOOK). EPFL Press.

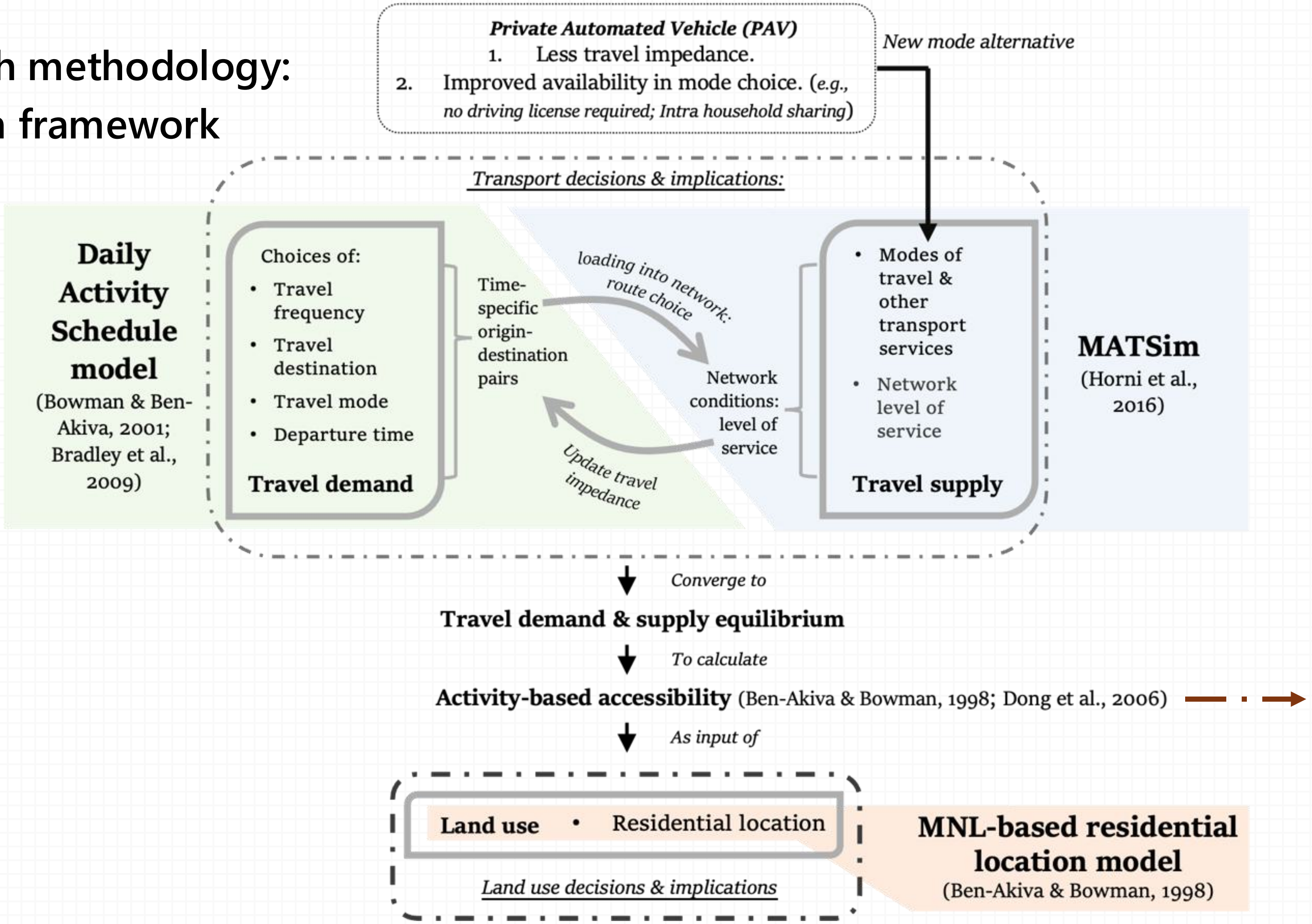
Research objective

- To quantify the impacts of privately owned automated vehicles (PAVs) on residential location in Gunma Prefecture Japan.
- To achieve this objective, a Land Use Travel Integrated (LUTI) model system considering various scenarios of PAV adoption and different policy interventions was adopted.

Research scope

- Only fully automated private vehicles (PAV) are considered
- Not predicted time for AV introduction/commercialization.
- Not considered Connected Vehicle Technology.
- Not considered ridesharing service is not assumed allowed.

Research methodology: research framework



Methodology Framework Adopted

A utility-based measure of accessibility (Geurs & van Wee, 2004) calculated expected utility from the top level of DAS model (Dong et al., 2006).

$$A_n = \frac{1}{\mu} \ln\left(\sum_{i \epsilon C_n} e^{\mu V_{in}}\right)$$

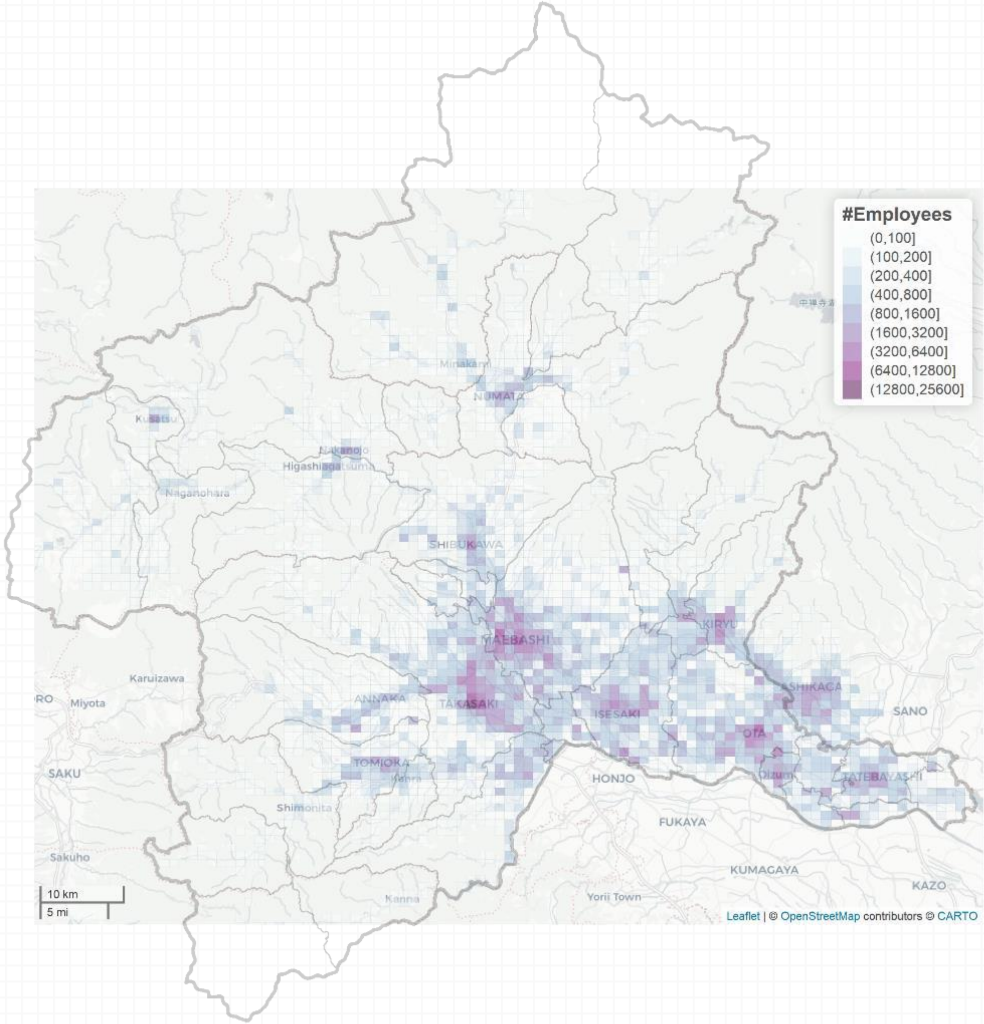
Where,

n: individual; C_n : choice set of travel schedule;

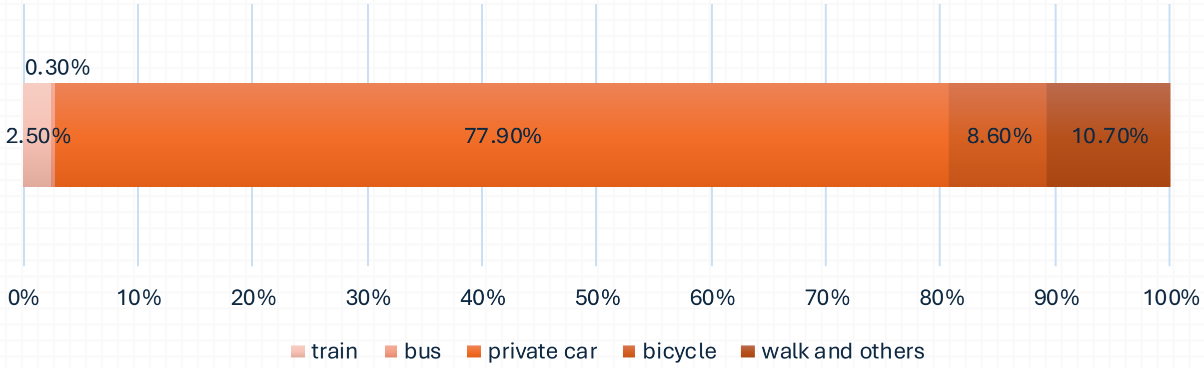
μ: scale parameter; V_{in}: systematic component of utility of alternative *i* for *n*.

Ben-Akiva, M. E., & Bowman, J. L. (1998b). Integration of an activity-based model system and a residential location model. Urban Studies, 35(7), 1131-1153.
Bowman, J. L., & Ben-Akiva, M. E. (2001). Activity-based disaggregate travel demand model system with activity schedules. Transportation Research A: Policy and Practice, 35, 1–28.
Bradley, M. A., Bowman, J. L., & Griesenbeck, B. (2010). SACSIM: An applied activity-based model system with fine-level spatial and temporal resolution. Journal of Choice Modelling, 3(1), 5-31.
Dong, X., Ben-Akiva, M. E., Bowman, J. L., & Walker, J. L. (2006). Moving from trip-based to activity-based measures of accessibility. Transportation Research Part A: Policy and Practice, 40(2), 163-180.
Geurs, K. T., & Van Wee, B. (2004). Accessibility evaluation of land-use and transport strategies: review and research directions. Journal of Transport Geography, 12(2), 127-140.
Horni, A, Nagel, K., & Axhausen, K. W. (2016). The Multi-Agent Transport Simulation MATSim. Ubiquity Press, London.

Study Region: Gunma Prefecture & Ashikaga City from Tochigi Prefecture (Gunma PT Area).



Spatial Distribution of Number of Employees by Mesh Cells in Study Region (Map source from Openstreetmap)



Modal share in Gunma Person Trip Area in 2015/2016 (Inahara et al., 2017)

Public transits are not considered in this modeling as an assumption

Inahara, H., Daimon, H., Hayashi, K., Sekimoto, M., Akimoto, M., Amamori, E. & Ito, M. (2017). Consideration on Future Urban Transport Policy in Regional Metropolitan Area - Picturing the Future of Japan Based on the Results of Gunma Person Trip Survey. The Institute of Behavioral Sciences (IBS) Annual Report. (In Japanese. 稲原宏、大門創、林健太郎、関本稀美、秋元伸裕、雨森恵理子、伊藤 京. (2017). 地方都市圏のこれからの都市交通政策を考える ～群馬県PT調査結果から読み解く日本の将来～. IBS研究活動報告).

Research Data:

Initial travel demand

2015 Gunma Person Trip Survey (PT data = 平成２７年度群馬県パーソントリップ調査.)

Effective #N: 16,425 households with 33,300 persons; (1.6% of the total population)

Land use data (Spatial resolution = 1km mesh)

Mesh level analysis of (地域メッシュ統計):

- Japanese National Census 2015 (国勢調査)
- Economy Census 2016 (経済センサス－活動調査)

Network data: bounding box covering Gunma

- Network data extracted from OpenStreetMap.
- No network pruning applied.

Level	Variables		Data Type	Descriptive summary				
				Mean	Median	Min.	Max.	Standard Error
Household *(Total #households = 16,425)*	Has household member whose age is	< 20	Binary	True: 16.0%; False: 84.0%				
		> 65	Binary	True: 33.5%; False: 66.5%				
	#Household member		Continuous	2.41	2	1	9	1.20
	Bike ownership		Continuous	0.55	0	0	10	0.86
	Car ownership		Continuous	1.80	2	0	12	0.88
	Home location		Coordinates	-				
	Work or School Location		Coordinates	-				
Individual *(Total #individuals = 33,300)*	Holds license or not		Binary	True: 84.4%; False: 15.6%				
	Car availability by individual		Categorical	Always available: 78.5%; Shared with other household members: 4.8%; Not available: 16.7%				
	Age		Continuous	49.00	50	7	100	19.95
	Gender		Binary	Female: 51.3%; Male: 48.7%				
	Job type		Categorical	Tertiary sector: 38.9%; Secondary sector: 17.4%; Primary sector: 1.8%; Student: 10.1%; Other: 0.6%; Homemaker: 12.8%; Unemployed (excluding students): 18.4%				
	Type of employment (among employees)		Categorical	Full time worker: 59.8%; Temporary worker: 2.1%; Part-time worker: 21.5%; Board members: 3.9%; Self-employed worker: 7.3%; Family worker: 3.2%; Others: 2.2%				
	#Trips in the day		Continuous	1.02	1	0	13	0.84

Notes: Temporary worker refers to paid employee who are hired through dispatched labor; Family worker refers to employee who are hired in a family business either paid or unpaid.

Summary to the Demographic Attributes in the Effective PT Data Sample.

Land use data: UFAA and DAA

Two concepts from Location Optimization Plan (立地適正化計画) are used to define “center area”.

- Urban Function Attraction Area (UFAA, 都市機能誘導区域).
- Dwelling Attraction Area (DAA, 居住誘導区域).

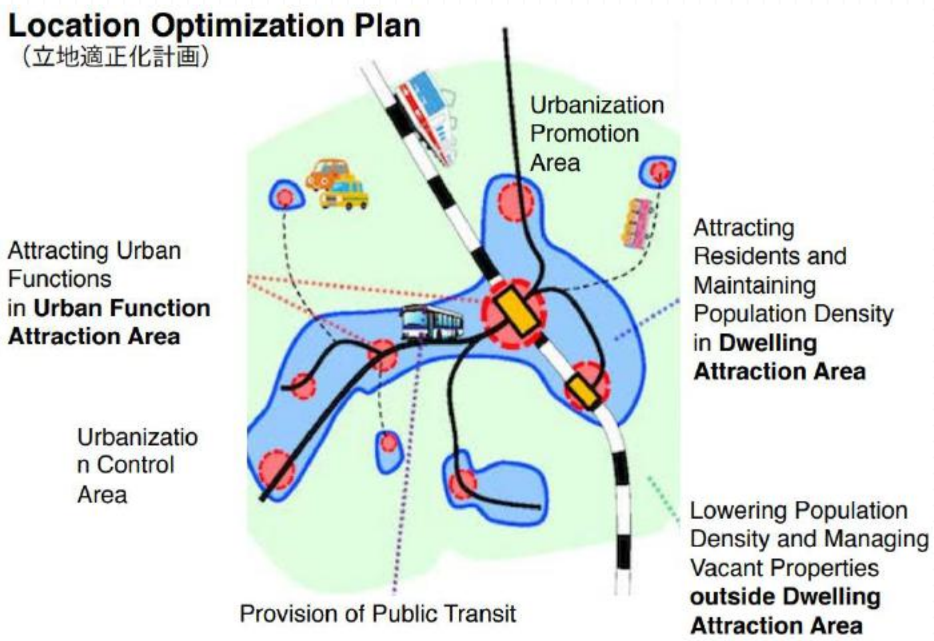
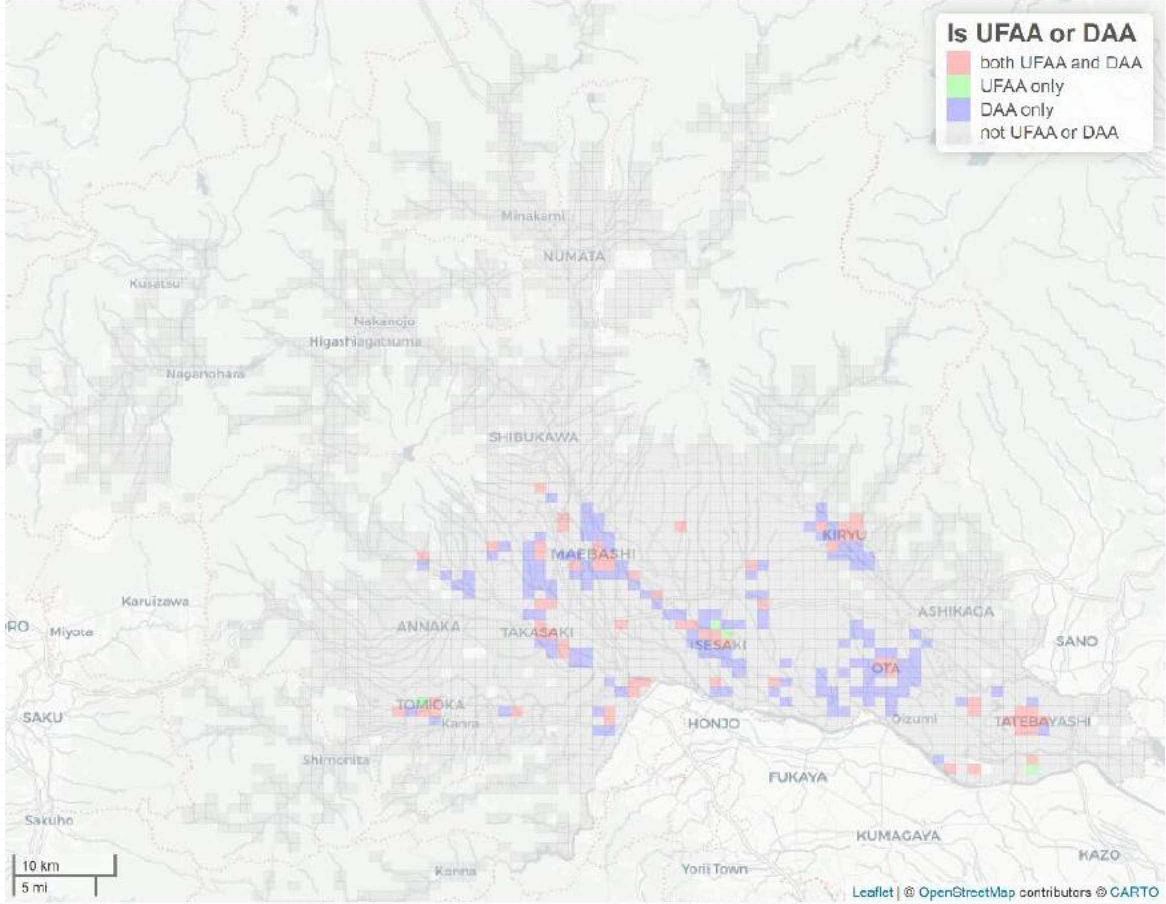


Illustration of Location Optimization Plan and Purposes of UFAA and DAA (Murayama et al., 2015)

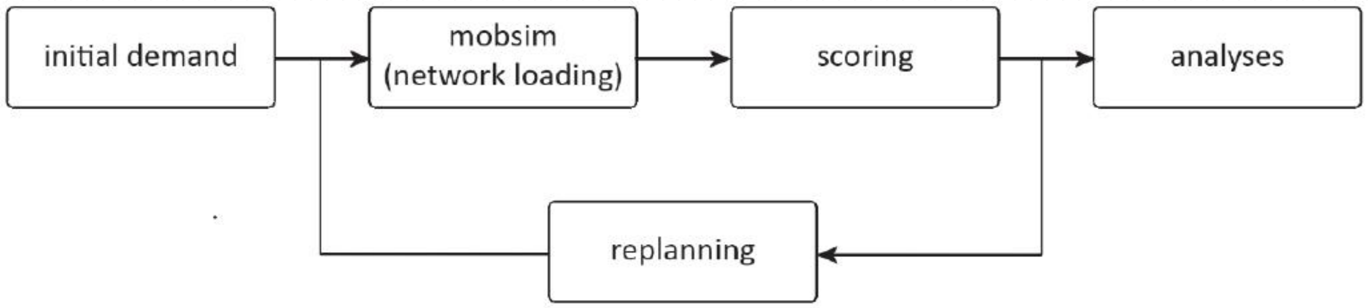


Distribution of DAA & UFAA in Gunma PT region

Source: Murayama et al., 2015. https://www.cger.nies.go.jp/gcp/pdf/tokyo-workshop-dec2015/murayama.pdf

MATSim as Travel Supply Model: settings

MATSim (Horni et al., 2016) employed as the travel supply model.



MATSim Iterative Loop (Horni et al., 2016).

MATSim settings:

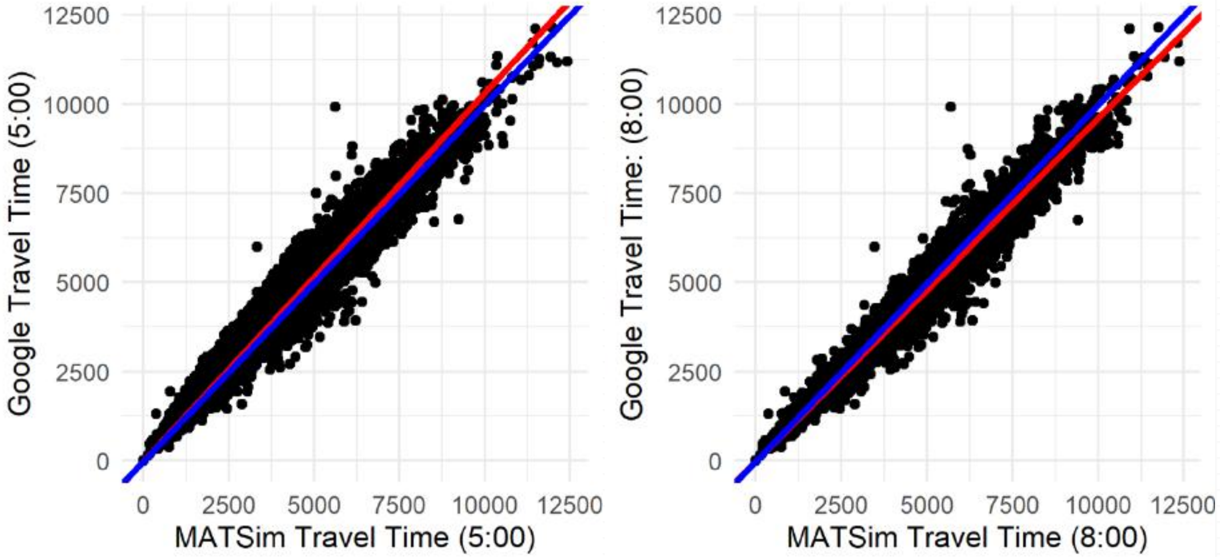
- #Iterations = 30.
- Share of replanning strategy:
  - MNL Selector (SelectExpBeta) 40%.
  - Reroute Mutator 60% (switched off in the final 10% of simulations).
- Road capacity was scaled down:
  - By 0.0166 to match the sample/population ratio (= 1.66%).
  - By 0.66 to reflect the delay effects from such as intersections.

Horni, A, Nagel, K., & Axhausen, K. W. (2016). The Multi-Agent Transport Simulation MATSim. Ubiquity Press, London.

MATSim as Travel Supply Model: validation (travel time)

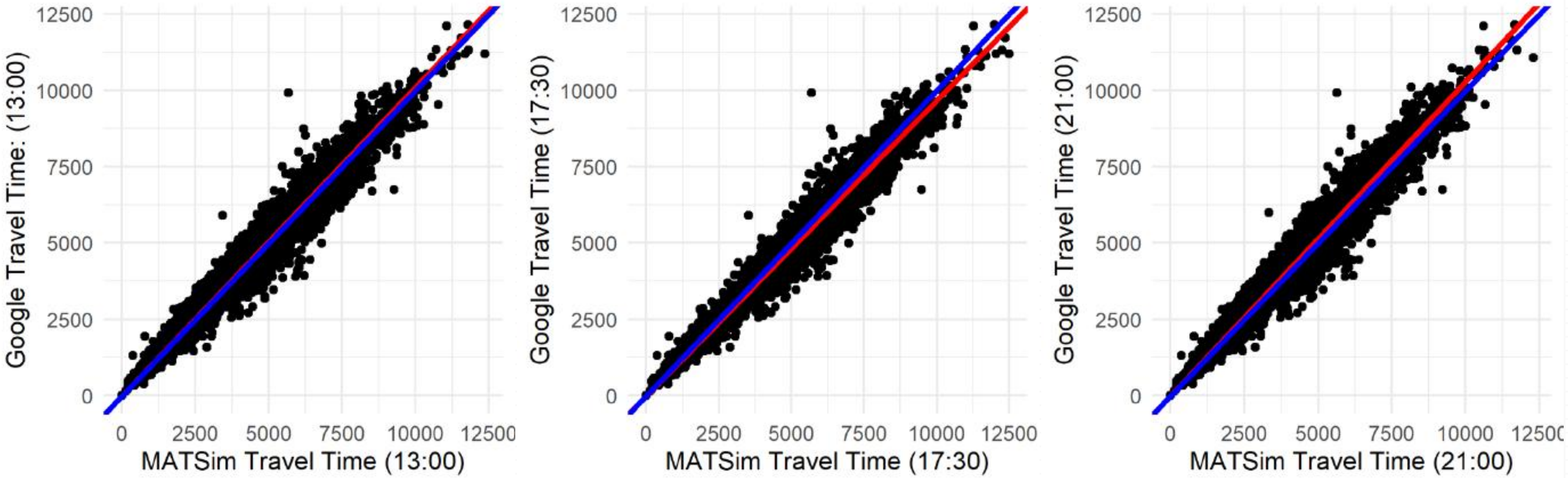
Comparison between MATSim and Google Distance Matrix API.

- 5,000 pairs of randomly sampled 1km mesh centroid pairs are set as the origin and destination.



Summary of MATSim Model Validation: Travel Time.

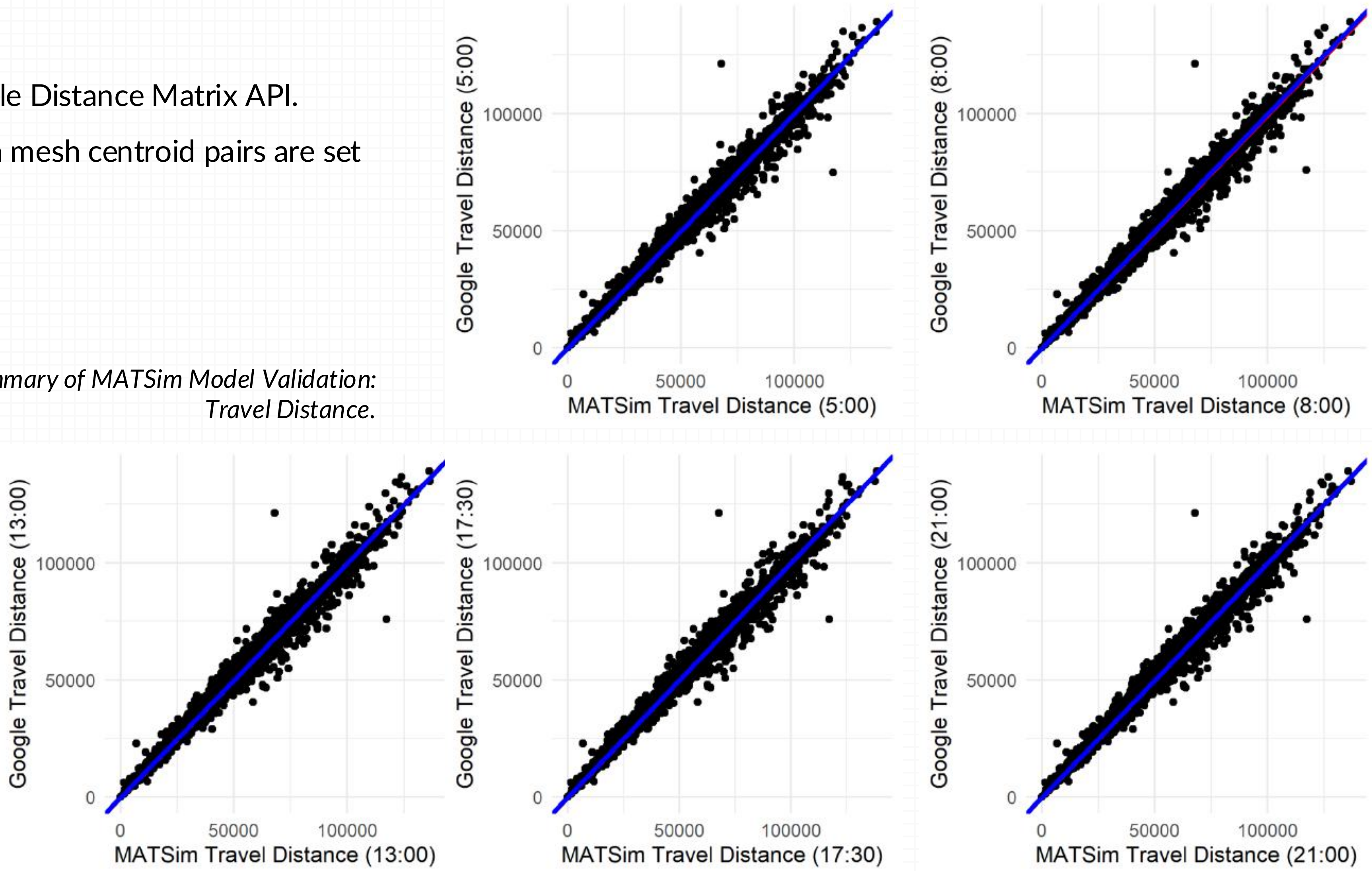
Time Points	Slope	R Square
5:00	1.0319	0.990
8:00	0.9622	0.993
13:00	1.0114	0.992
17:30	0.968	0.993
21:00	1.0297	0.991



MATSim as Travel Supply Model: validation (travel distance)

Comparison between MATSim and Google Distance Matrix API.

- 5,000 pairs of randomly sampled 1km mesh centroid pairs are set as the origin and destination.



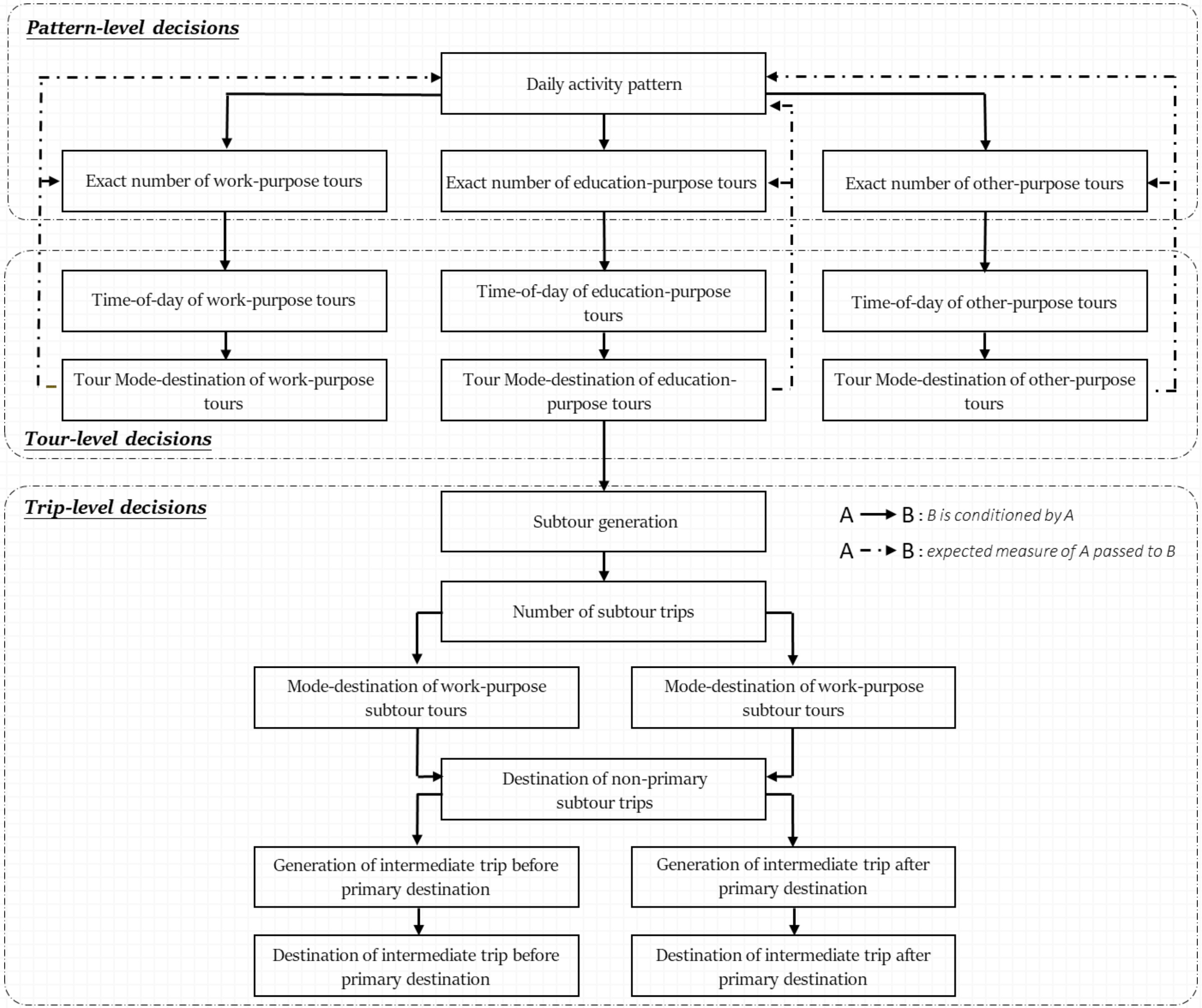
Summary of MATSim Model Validation: Travel Distance.

Time Points	Slope	R Square
5:00	1.000052	0.997
8:00	0.995	0.997
13:00	1.0014	0.997
17:30	1.0015	0.997
21:00	1.00042	0.997

DAS as Travel Demand Model: introduction

An activity-based travel demand model based on Daily Activity Schedule model (DAS model. Bowman & Ben-Akiva, 2001).

- Solid arrows: conditioned by the models pre-defined over them.
- Dashed arrows: dependent to the expected maximum utility from lower models.



Adopted DAS-type Travel Demand Model Structure

DAS as Travel Demand Model: estimation results (example of mode-destination model)

The DAS model was calibrated on 80% of Gunma PT survey data with Maximum Likelihood.

Variable	Variable#	Car Driver		Bicycle		Walk		Car Passenger	
		Coef.	T value	Coef.	T value	Coef.	T value	Coef.	T value
Alternative-specific constant	#4-1				*0.94*	2.35	*19.62*	-3.34	*-19.28*
Age∈ [6, 35]	#4-2			0.60	*6.32*		*-0.44*		*-0.34*
Male	#4-3	*Base alternative*		0.28	*3.28*	0.19	*1.92*	-0.94	*-5.50*
Is not primary tour	#4-4				*-0.37*	1.23	*7.03*	0.90	*2.87*
Has stop in the day	#4-5			-0.73	*-6.79*	-1.27	*-8.32*		*0.02*
Travel time (hour)	#4-6	-5.86	*-98.00*	-6.70	*-35.78*	-14.44	*-31.41*	-8.57	*-15.81*
#Employees of tertiary sector/size variable	#4-7	0.026	*45.72*	0.026	*45.72*	0.026	*45.72*	0.026	*45.72*
#Employees of primary and secondary sector/size variable	#4-8	0.027	*62.55*	0.027	*62.55*	0.027	*62.55*	0.027	*62.55*
Is the same city as origin's	#4-9	0.86	*35.66*	0.86	*35.66*	0.86	*35.66*	0.86	*35.66*
Size variable: #Offices	-	1.00	-	1.00	-	1.00	-	1.00	-
#Observations	13,206								
Initial likelihood	-82,169.88								
Final likelihood	-57,839.20								
Adjusted rho squared	0.296								

- **Destination sampling settings**:

Destination object:	1km mesh (3次メッシュ);
#Alternative sampled:	100 *(out of 2784)*
Sampling method:	Independent importance sampling with replacement; Sampling weight = $\exp(\frac{-2d}{mean(d)})$, *d for distance.*

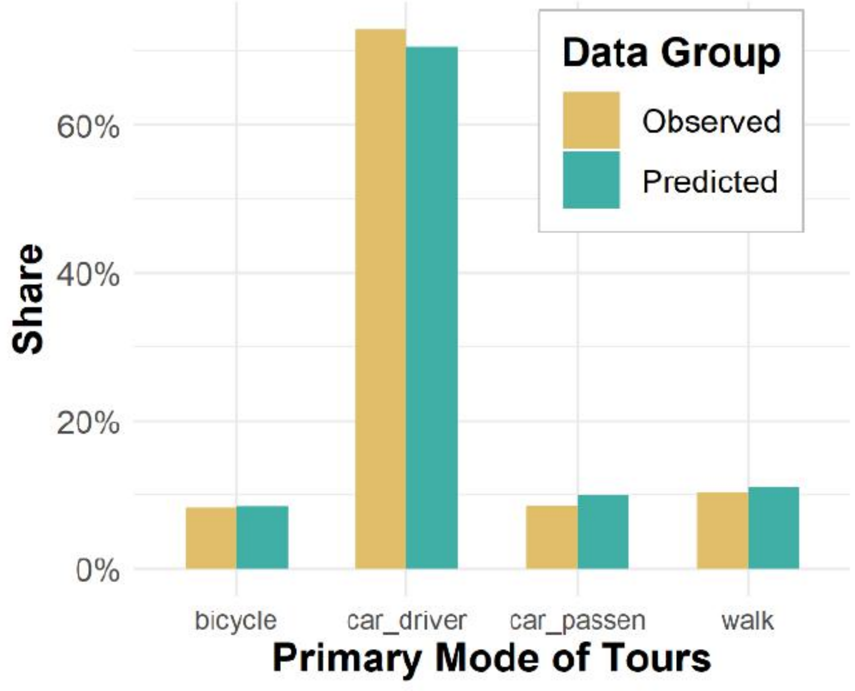
Estimation Results of Mode-destination Model for Work-purpose Tours.

DAS as Travel Demand Model: validation results (examples)

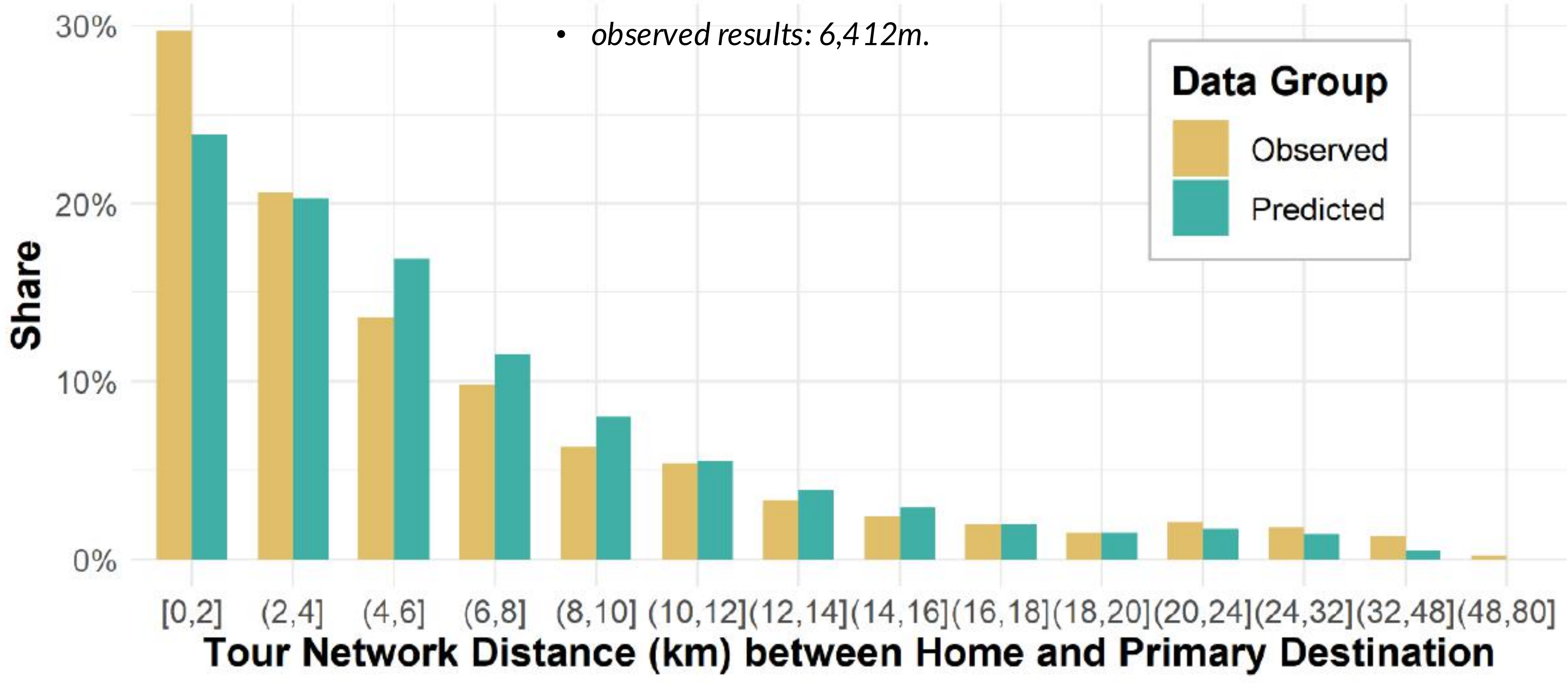
The DAS model was validated on 20% of Gunma PT survey data not used in the estimation.

Average value of distance between home and primary activity destination:

- *simulated results: 6,357m.*
- *observed results: 6,412m.*



Validation Results of Primary Travel Mode of Tours



Validation Results of Home-Primary Destination Travel Distance of Tours

Scenario Settings

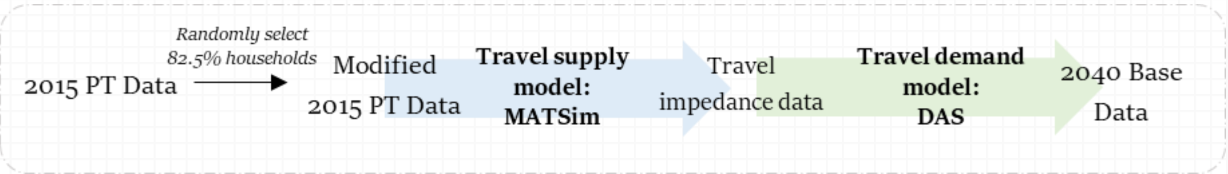
- Target year: 2040 (Litman, 2021).
- Population decreased to 82.45%. (NIPSSR, 2023 国立社会保障・人口問題研究所).
- Cohort proportions for age groups 0-9, 10-19, 20-29, 30-39, 40-49, 50-64, and above 65 years old through over- or down-sampling to align with NIPSSR (2023).

Scenario	Population change	PAV ownership	PAV or HV availability	Value of time for AVs of HVs (drivers) (Steck et al., 2018 and Kolarova et al., 2019)		Road Capacity for AVs of HVs
				Commuting-purpose tours and subtours	Other-purpose tours and subtours	
Base Scenario	82.45% to the current	100%	Requiring driving license & depending on vehicle ownership	-	-	-
Scenario 1		The same as of HV ownership patterns	Depending on vehicle ownership	75%	85%	1.0
Scenario 2				50%	70%	1.0
Scenario 3				75%	85%	1.2
Scenario 4				50%	70%	1.2

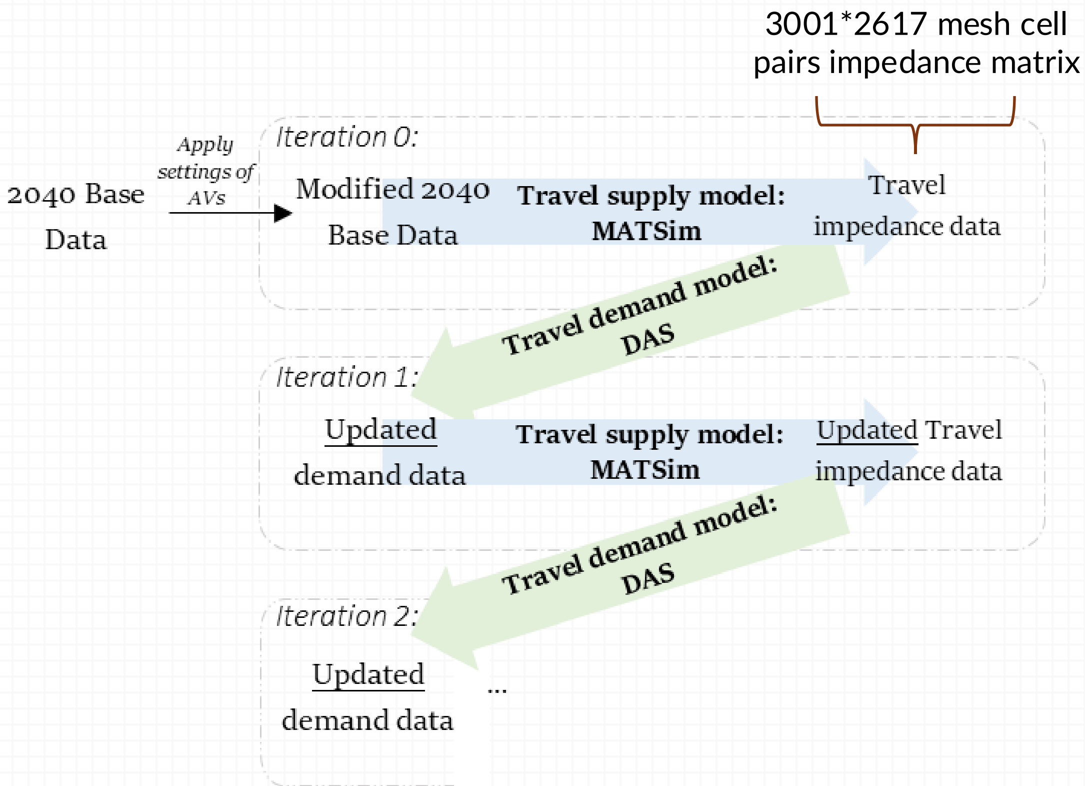
Summary of Scenario Settings

Litman, T. (2021). Automated Vehicle Implementation Predictions: Implications for Transport Planning. Victoria Transport Policy Institute.
Steck, F., Kolarova, V., Bahamonde-Birke, F., Trommer, S., & Lenz, B. (2018). How automated driving may affect the value of travel time savings for commuting. Transportation Research Record, 2672(46), 11-20.
Kolarova, V., Steck, F., & Bahamonde-Birke, F. J. (2019). Assessing the effect of automated driving on value of travel time savings: A comparison between current and future preferences. Transportation Research Part A: Policy and Practice, 129, 155-169.

Simulation Results: simulation flow



Simulation Running Flow for Generating 2040 Base data



Simulation Running Flow for Scenarios with Automated Vehicles

Simulation Results: on transport

Findings:

- PAV dominate all Scenarios with taking around 86-89% modal share of trips.
- Travel distances significant increase, as a result of:
  - 1) PAV trips of existing car drivers.
  - 2) new PAV trips as a result of modal shift and induced demand from who cannot drive.
  - 3) PAV zero-occupancy trips.

Measures		**Base Scenario**	**Scenario 1**	**Scenario 2**	**Scenario 3**	**Scenario 4**
		Value	Value (% change against base)	Value (% change against base)	Value (% change against base)	Value (% change against base)
#Persons who conducted at least one tour		22,333	22,289 (+0.2%)	22,360 (+0.1%)	22,317 (-0.1%)	22,426 (+0.4%)
#Tours		26,566	26,560 (-0.02%)	26,850 (+1.1%)	26,685 (+0.4%)	26,805 (+0.9%)
#Trips		64,642	67,792 (+4.9%)	68,408 (+5.8%)	68,152 (+5.4%)	68,266 (+5.6%)
Mode share (by trips)	PAV or Car (driver)	71.7%	86.4%	89.2%	87.0%	89.3%
	Bicycle	7.5%	4.1%	3.2%	3.8%	3.1%
	Walk	9.9%	4.9%	3.9%	4.7%	3.9%
	Car (passenger)	10.9%	4.6%	3.6%	4.4%	3.6%
Total distance traveled (100km)	by PAV or Car (driver)	3,401	4,679 (+37.5%)	5,541 (+62.9%)	4,815 (+41.6%)	5,676 (+66.9%)
	by Bicycle	136	74 (-45.6%)	61 (-55.1%)	74 (-45.6%)	58 (-57.3%)
	by Walk	79	43 (-45.6%)	33 (-58.2%)	40 (-49.4%)	34 (-57.0%)
	by Car (passenger)	372	161 (-56.7%)	124 (-66.7%)	159 (-57.3%)	129 (-65.3%)
Average trip distance (m)	by PAV or Car (driver)	7,339	7,987 (+8.8%)	9,076 (+23.7%)	8,121 (+10.7%)	9,307 (+26.8%)
	by Bicycle	2,792	2,681 (-4.0%)	2,756 (-1.3%)	2,813 (+0.8%)	2,746 (-1.6%)
	by Walk	1,240	1,304 (+5.2%)	1,230 (-0.8%)	1,250 (+0.8%)	1,235 (-0.4%)
	by Car (passenger)	5,287	5,134 (+2.9%)	5,028 (-4.9%)	5,246 (-0.8%)	5,288 (+0.02%)

Simulation Results Summary of Transport Evaluators

Simulation Results: on transport

Findings:

- Average speed in the central area reduced in all AV scenarios.
- Benefits from road capacity (Scenarios 3&4 v.s 1&2) improved the average speeds by around 3 to 4%.
- PAV zero-occupancy trips account mostly for the increase of #trips
- 10% of the PAV trips in each AV scenario performed by those who cannot drive.

Measures	Base Scenario	Scenario 1	Scenario 2	Scenario 3	Scenario 4
	Value	Value (% change against base)	Value (% change against base)	Value (% change against base)	Value (% change against base)
Average speed among DAA mesh cells in AM Peak time (km/h)	33.57	31.63 (-5.8%)	31.06 (-7.5%)	33.07 (-1.5%)	32.36 (-3.6%)
%PAV Trips by persons unable to drive of total trips	-	10.4%	10.8%	10.7%	10.5%
%Tour that PAV or Car (driver) availability reassigned through Intra-household sharing	1.1%	10.8%	10.4%	10.7%	10.3%
%PAV zero-occupancy trips of total trips	-	4.8%	4.8%	4.9%	4.8%
%Total distance traveled attributed to PAV zero-occupancy trips	-	5.4%	5.3%	5.6%	5.6%

(Continued) Simulation Results Summary of Transport Evaluators

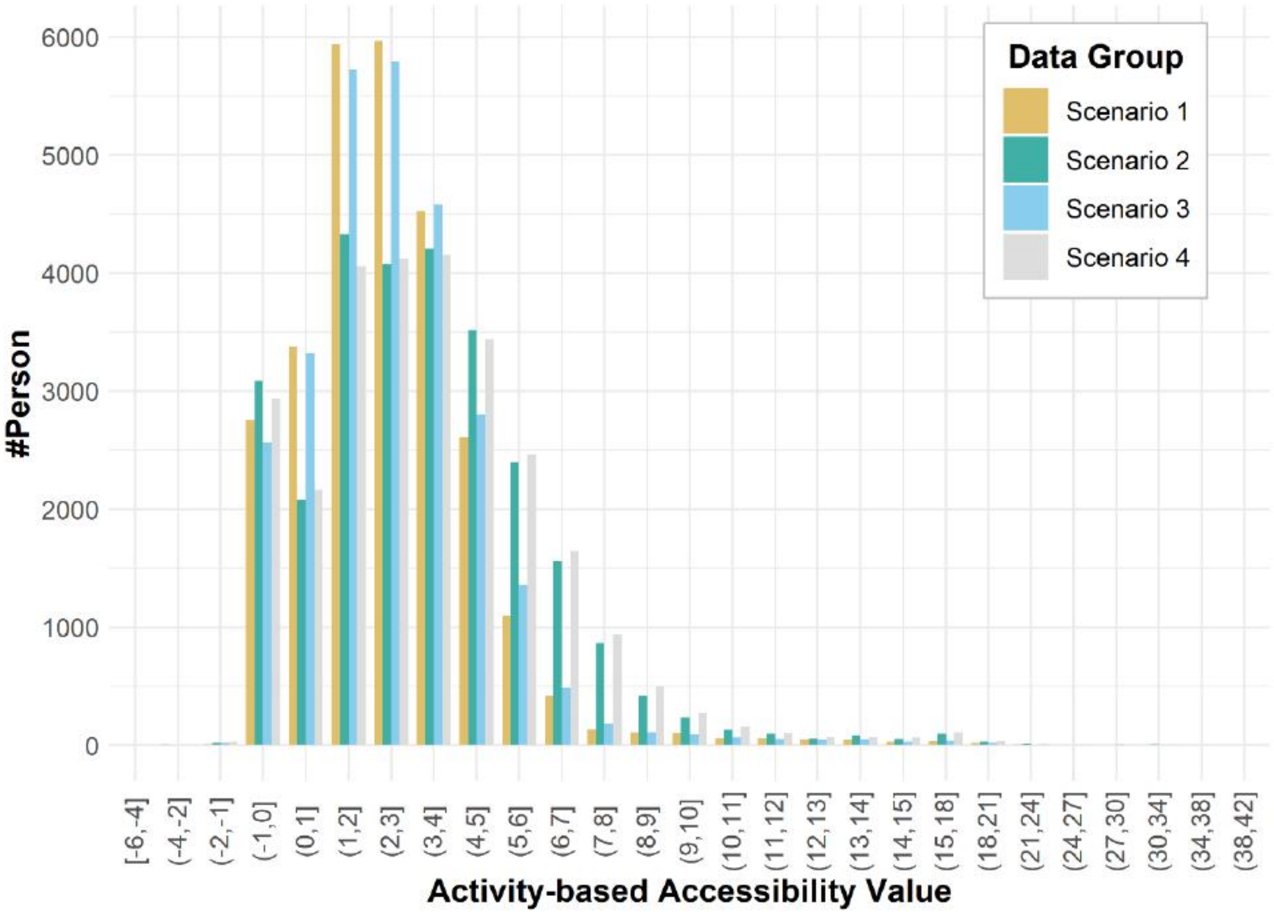
Simulation Results of Activity-based Accessibility (ABA)

Normalized ABA values against Base Scenario (min)	Descriptive summary				
	Mean (95% confidence level)	Median	Min.	Max.	Standard Deviation
Scenario 1	2.48 (± 0.025)	2.26	-5.54	35.65	2.15
Scenario 2	3.32 (± 0.033)	3.02	-2.46	40.24	2.79
Scenario 3	2.58 (± 0.026)	2.36	-4.24	36.05	2.18
Scenario 4	3.41 (± 0.034)	3.09	-2.91	40.81	2.85

Descriptive Summary to ABA (normalized to minutes)

Findings:

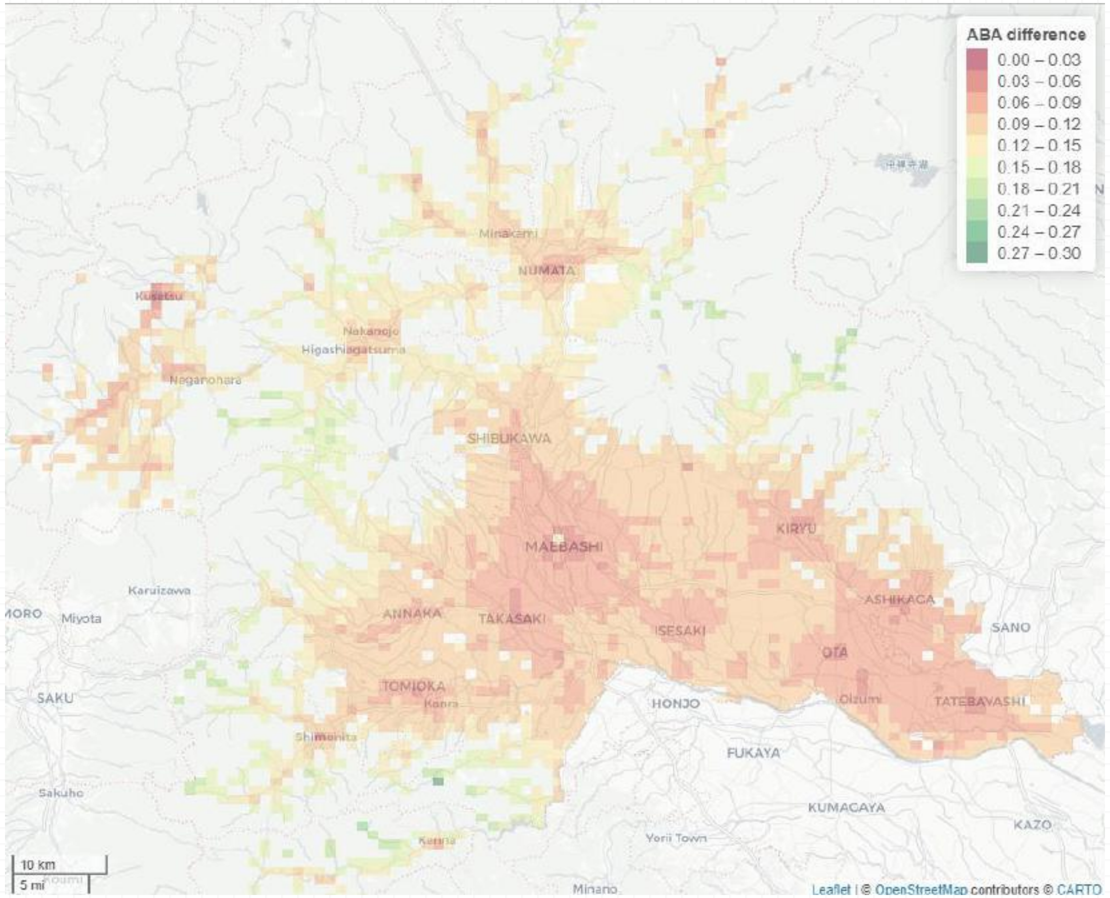
- ABA is on average and by median increased by a 2-3 minutes in all Scenarios
- Level of ABA are highly dependent on each individual's demographic characteristics and residence location (*see next page*).



Distribution of Activity-based Accessibility under Automated Vehicle Scenarios

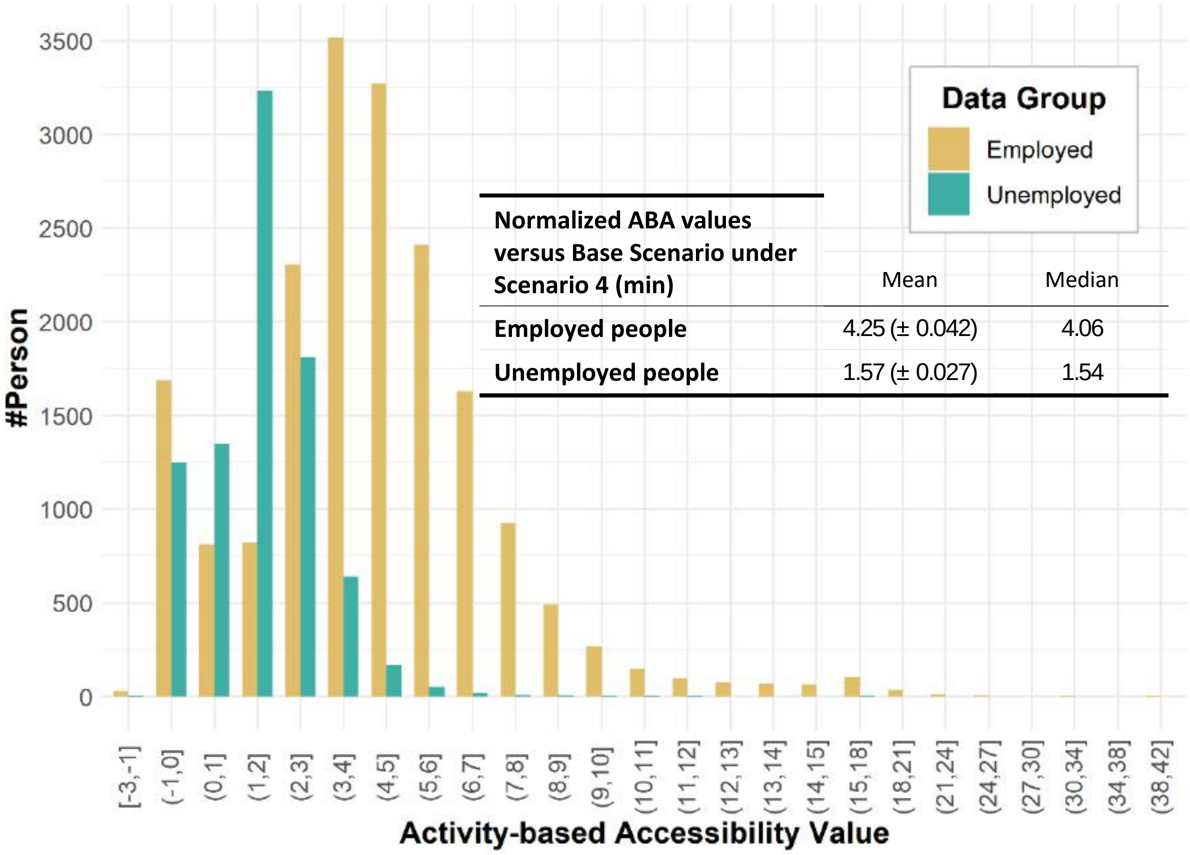
Simulation Results of Automated Vehicle Scenarios: Activity-based Accessibility analysis

By residence location:



Change Distribution of Activity-based Accessibility (not normalized) under Scenario 4 for a Representative Person

By employment status:



Normalized ABA values versus Base Scenario under Scenario 4 (min)	Mean	Median
Employed people	4.25 (± 0.042)	4.06
Unemployed people	1.57 (± 0.027)	1.54

Change Distribution of Activity-based Accessibility under Scenario 4 by Employment Status

Specification of Residential Location Model

Residential location model specification (Ben-Akiva and Bowman, 1998) as an integrated model connected to an activity-based model system.

- specified as an MNL model in household level.
- the observed component of the utility of residential location *l* for household *i* is of two parts:

$$V_{il} = \beta X_l + \alpha A_{i|l}$$

$$A^w{}_{i|l} = \frac{\sum_{w \in W_i} A_{w|l}}{W_i}$$

$$A^s{}_{i|l} = \frac{\sum_{s \in S_i} A_{s|l}}{S_i}$$

$$A^U{}_{i|l} = \frac{\sum_{u \in U_i} A_{u|l}}{U_i}$$

Where,

- X_l, the attributes of *l*,
- $A_{i|l}$, Activity-based Accessibility value.
  - three types of $A_{i|l}$ are included.

Where,

- $A^w{}_{i|l}$, $A^s{}_{i|l}$, $A^u{}_{i|l}$, the average Activity-based Accessibility for workers, students, and unemployed people in the household *i*, respectively.
- W_i, S_i, U_i, the number of workers, students, and unemployed people in the household *i*, respectively.

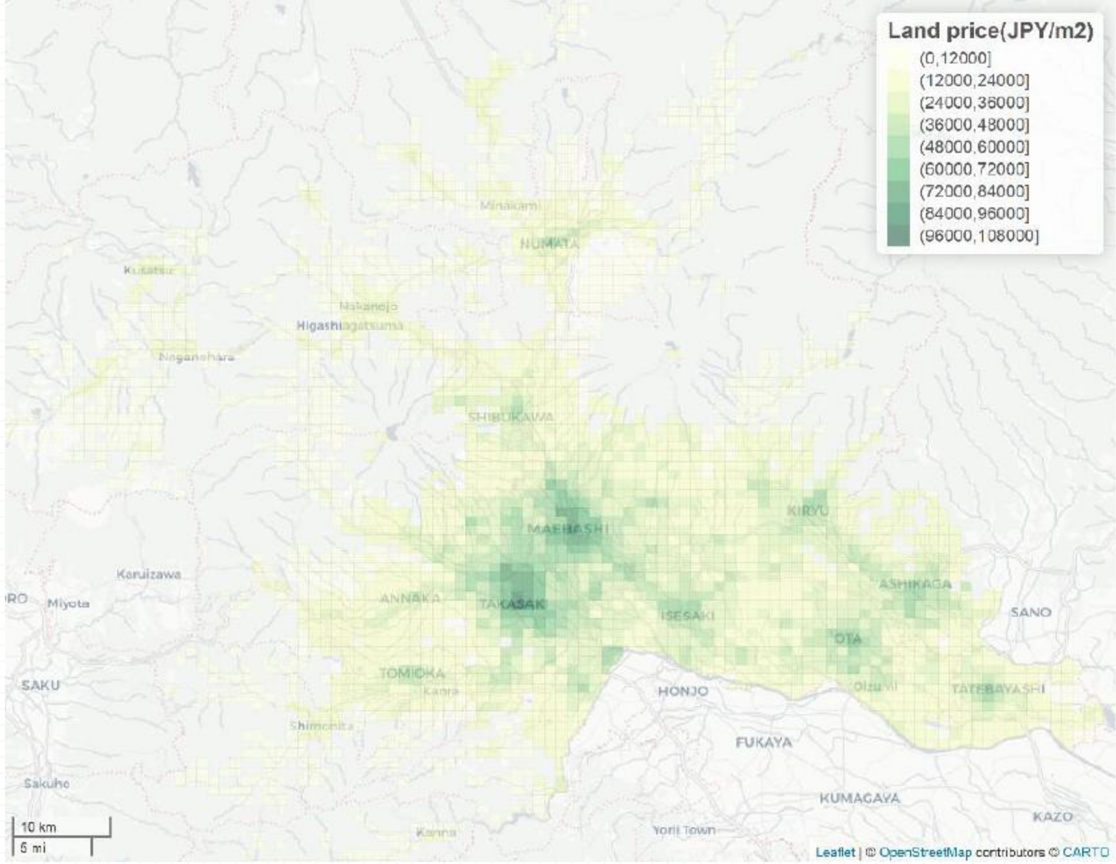
Land Price Hedonic Model:

Estimation results:

Data Source	Variable	Coefficient	T Value
Dependent variable: natural log of land price (JPY per m squared)			
-	Intercept	7.83	*27.52*
Housing and Land Census 2018 (Processed)	#Housing stock		*-0.64*
DAS model	Tour-based Logsum of work-purpose	0.15	*5.02*
	Tour-based Logsum of education-purpose	0.043	*6.91*
	Tour-based Logsum of other-purpose	0.13	*4.91*
Boundary Data in Economic Census Data 2016	Is Takasaki City	0.30	*6.37*
	Is Maebashi City	0.21	*4.37*
	Is Ota City		*-0.34*
	Is Isesaki City		*-0.89*
	Is Kiryu City	-0.11	*-1.81*
Land Use Mesh Data	Ratio of agricultural use area	-0.48	*-3.80*
	Ratio of forest area		*-0.46*
	Ratio of freshwater use area		*-0.15*
Land Use Subdivided Mesh Data of Urban Area	Ratio of industrial use area	-0.58	*-2.27*
#Count	557		
Adjusted R squared	0.728		
F statistic	115.4		

Estimation Results of Mesh Land Price Hedonic Model

Prediction Results of Land Price Model:



Predicted Land Price by Mesh Cell in Gunma PT Area

Estimation Results of Residential Location Model

- Same estimation data sample used in DAS model
- 13,140 households divided into five market segments
    - o by the age of the household head and number of household members.

Findings:

- Expected coefficient signs of household average ABA and land price.
    - o indicating the trade-off between the transportation and housing cost is captured.

Market segments	Segment #1		Segment #2		Segment #3		Segment #4		Segment #5	
Age of the head of household	[6,50]		[6,50]		[50,100]		[50,65)		[65,100]	
#Household members	3 or more		1 or 2		3 or more		1 or 2		1 or 2	
Variable	Coef.	T Val.	Coef.	T Val.	Coef.	T Val.	Coef.	T Val.	Coef.	T Val.
Household average ABA for workers	**0.63**	***57.86***	**0.62**	***57.91***	**0.40**	***45.24***	**0.43**	***45.93***	**0.33**	***34.65***
Household average ABA for students	**0.060**	***8.35***	**0.12**	***6.36***	**0.026**	***2.47***		***0.60***		***0.98***
Household average ABA for unemployed people	**0.17**	***10.45***	**0.28**	***11.43***	**0.24**	***19.18***	**0.37**	***23.56***	**0.61**	***49.91***
Land price (10,000 JPY per km²)	-1.24	*-21.81*	-0.74	*-13.89*	-0.84	*-17.05*	-0.82	*-15.57*	-0.73	*-16.73*
Ratio of buildings use area	-1.17	*-10.89*	-1.21	*-11.84*	-0.56	*-5.67*	-0.75	*-7.34*	-0.58	*-6.90*
Ratio of agricultural use area	-2.09	*-10.26*	-1.77	*-8.45*	-0.92	*-4.99*	-1.25	*-6.12*	-0.85	*-5.04*
Ratio of freshwater area		*-0.06*		*1.15*	0.31	*1.91*		*0.98*	0.41	*2.66*
Ratio of forest use area	0.74	*3.34*	0.70	*3.13*	1.18	*6.43*	1.16	*5.78*	1.41	*8.76*
Is Takasaki city	0.73	*5.86*		*0.038*	0.42	*3.91*	0.30	*2.51*	0.64	*6.57*
Is Maebashi city	0.24	*2.28*		*-0.42*	0.26	*2.93*	0.29	*2.98*	0.73	*9.14*
Is Ota city	-0.73	*-7.97*	-0.59	*-6.67*	-0.48	*-5.90*	-0.40	*-4.58*	0.13	*1.82*
Is Isesaki city	-0.69	*-7.39*	-0.61	*-6.60*	-0.54	*-6.26*	-0.52	*-5.61*		*-0.94*
Is Kiryu city	-0.37	*-3.15*	-0.32	*-2.67*	-0.24	*-2.54*	-0.35	*-3.21*		*-1.56*
#Employees of Primary and Secondary Sector	-0.10	*-13.31*	-0.054	*-9.30*	-0.065	*-8.86*	-0.067	*-8.70*	-0.023	*-4.55*
#Employees of Tertiary Sector	-0.033	*-9.08*	-0.038	*-11.87*	-0.047	*-11.42*	-0.022	*-6.97*	-0.048	*-47.82*
Size variable: Housing stock	1.00	-	1.00	-	1.00	-	1.00	-	1.00	-

Estimation Results of Residential Location Model

#Observations	**2,630**	**2,554**	**2,578**	**2,192**	**3,186**
Initial likelihood	-9,477.81	-9,128.47	-9,407.29	-7,953.38	-11,534.37
Final likelihood	-6,406.43	-6,142.27	-7,586.59	-6,335.93	-9,561.44
Adjusted rho squared	0.322	0.325	0.192	0.201	0.170

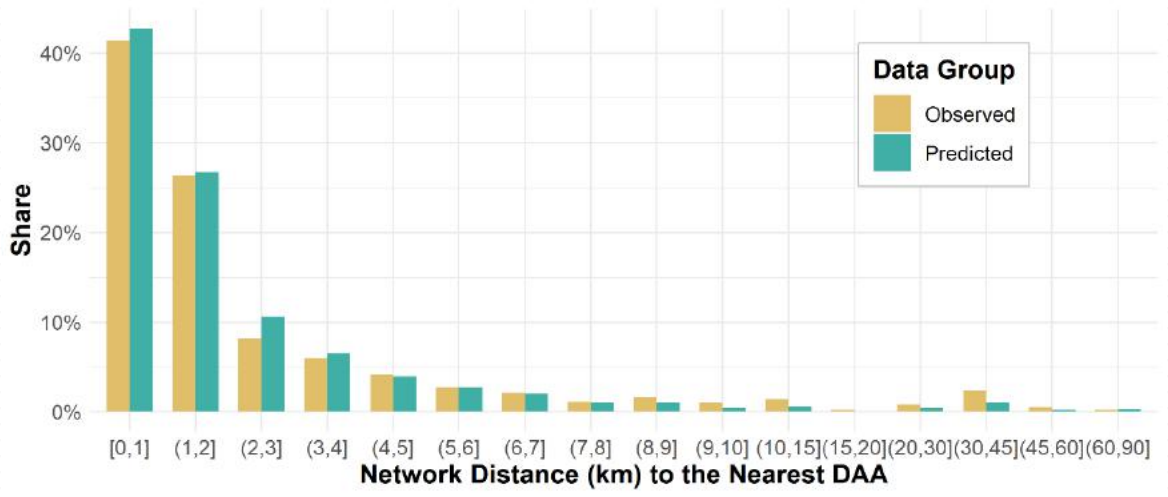
Validation of Residential Location Model

Network distance to the closest Dwelling Attraction Area (m)	Mean	Median	Standard Deviation
Observed	3,172	1,237	7,308
Simulated	2,265	1,222	5,425
Observed (data farther than 10,000m removed)	1,658	1,158	2,149
Simulated (data farther than 10,000m removed)	1,561	1,195	1,928

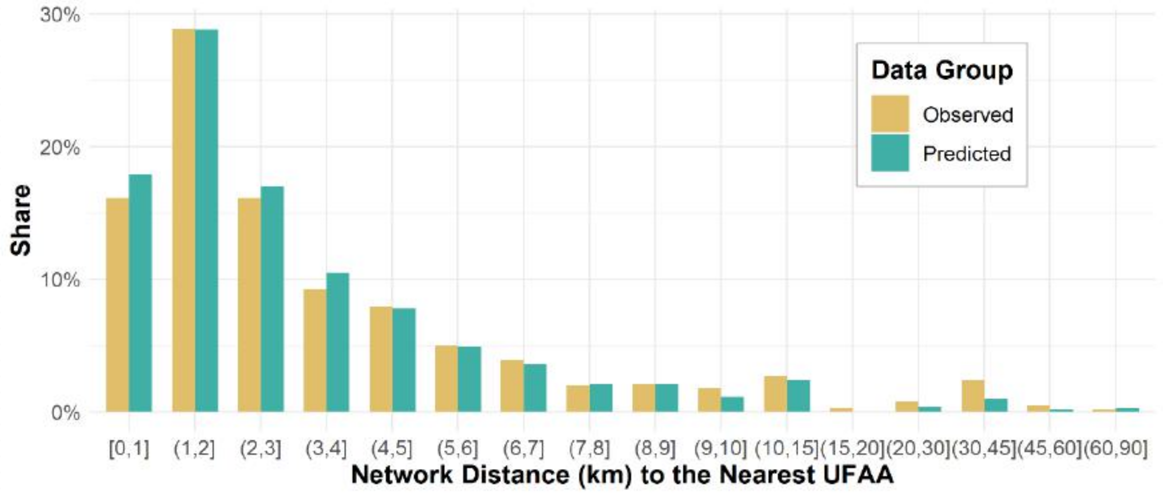
Validation Results of Network Distance to the Closest DAA (m).

Network distance to the closest Urban Function Attraction Area (m)	Mean	Median	Standard Deviation
Observed	4,297	2,298	7,245
Simulated	3,458	2,170	5,567
Observed (data farther than 10,000m removed)	2,712	2,067	2,299
Simulated (data farther than 10,000m removed)	2,626	2,059	2,220

Validation Results of Network Distance to the Closest UFAA (m).



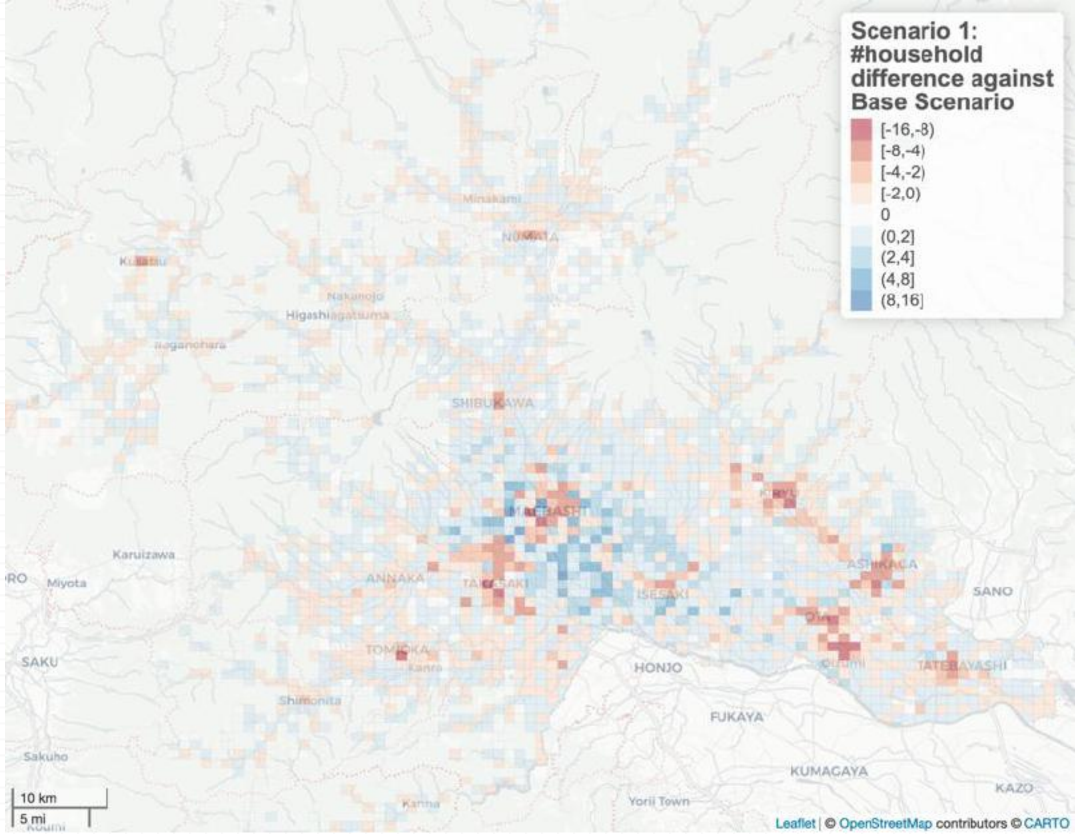
Validation Results of Distribution of Distance to the Nearest DAA



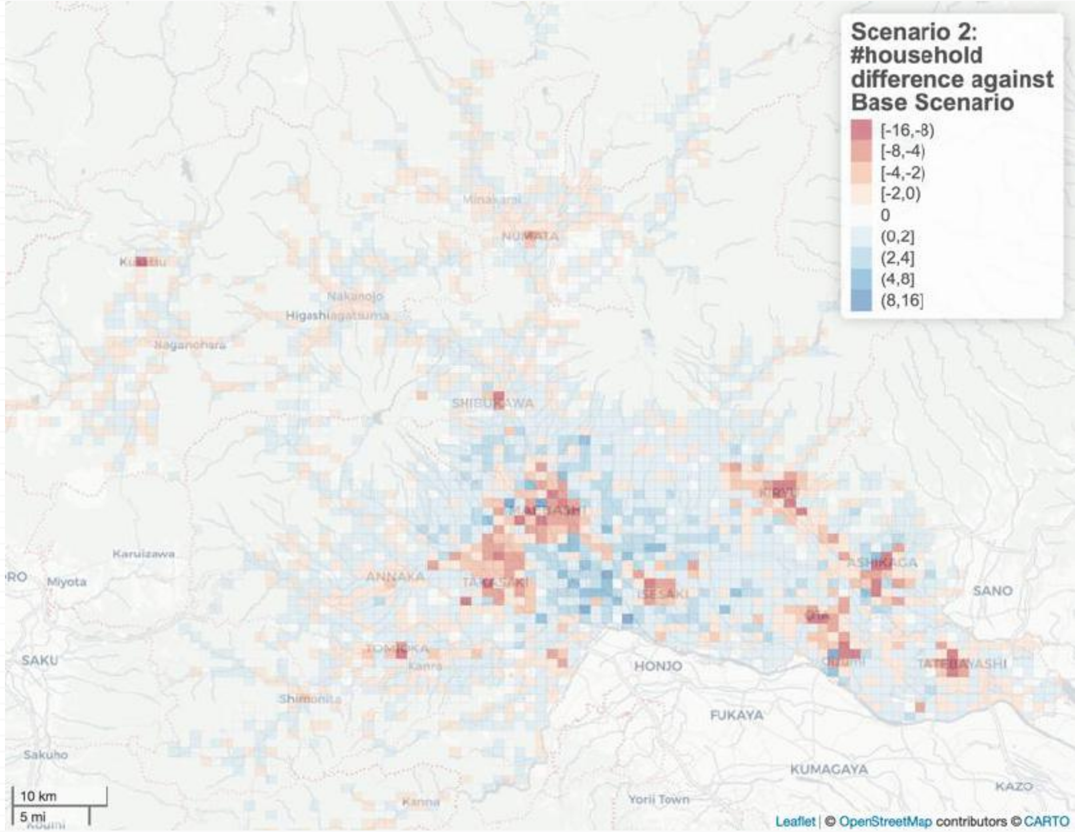
Validation Results of Distribution of Distance to the Nearest UFAA

Findings: good reliability in predicting the median value of the distance to both the nearest UFAA and DAA.

Simulation Results on Residence Distribution



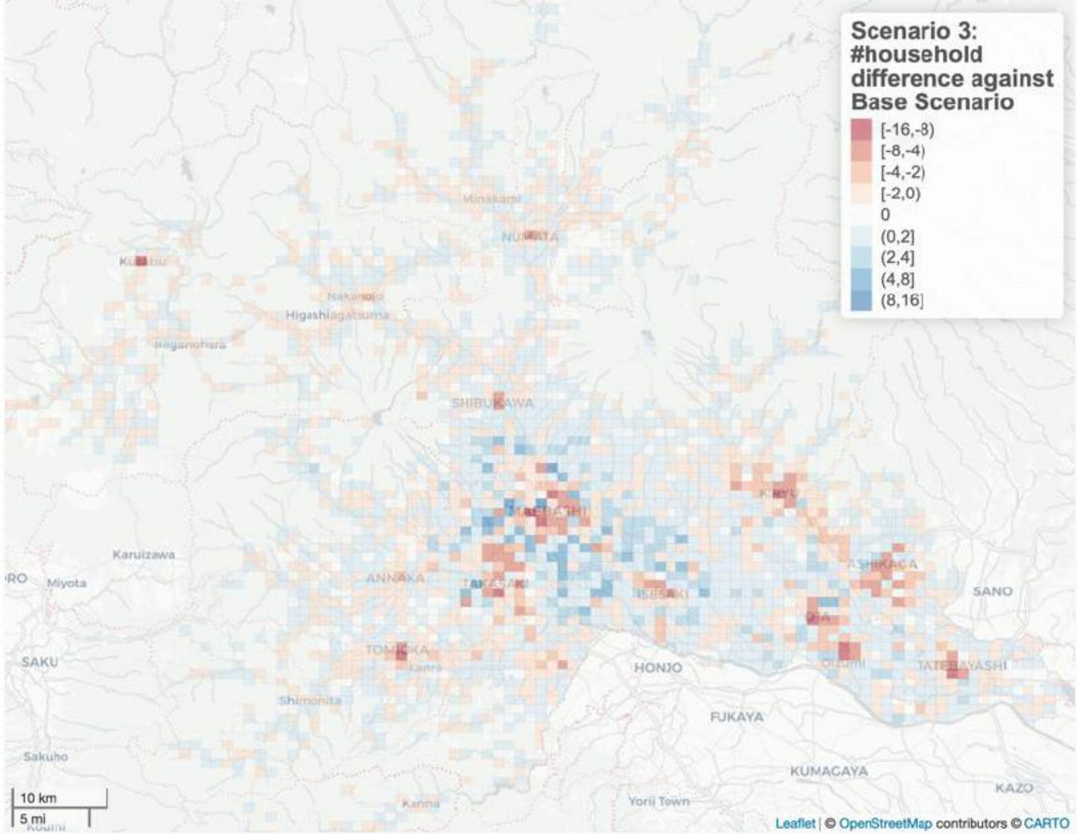
Residence Count Difference by Mesh Cell of ***Scenario 1*** *against Base Scenario.*



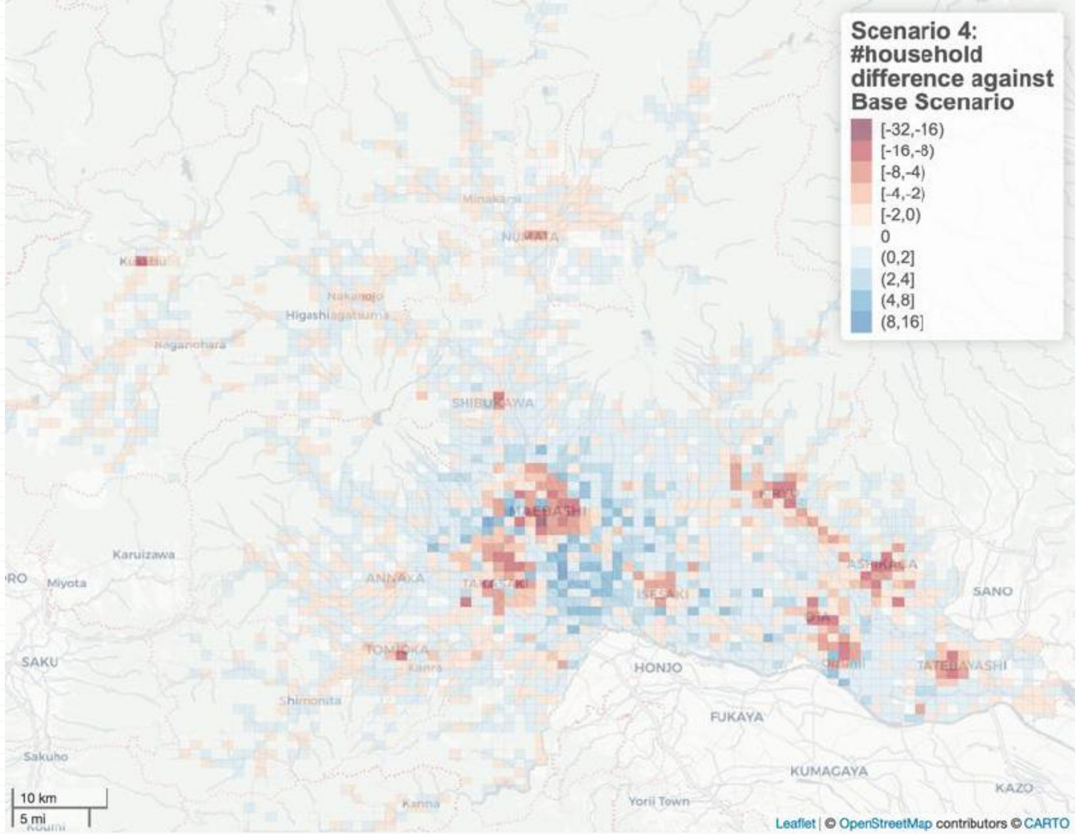
Residence Count Difference by Mesh Cell of ***Scenario 2*** *against Base Scenario.*

Findings: Moving trends from the center areas found in AV Scenarios against Base Scenario,

Simulation Results on Residence Distribution



Residence Count Difference by Mesh Cell of ***Scenario 3*** *against Base Scenario.*



Residence Count Difference by Mesh Cell of ***Scenario 4*** *against Base Scenario.*

Findings: Moving trends from the center areas found in AV Scenarios against Base Scenario,

Simulation Results: Land Use Evaluators

Findings:

- The median value to the residents' nearest DAA and UFAA escalate to up to 10.1% and 6.7%, respectively, under Scenario 4.
- As for the ratio of residents in DAA, all AV Scenarios decreases against Base Scenario, dropped at most to 34.2% from 31.0%.

Evaluation indicators	2015 PT Data	Base Scenario	Scenario 1	Scenario 2	Scenario 3	Scenario 4
	Value	Value (% change against PT)	Value (% change against Base)	Value (% change against Base)	Value (% change against Base)	Value (% change against Base)
Median value of network distance to the closest DAA (m)	1,243	1,396 (+12.3%)	1,470 (+5.3%)	1,539 (+10.2%)	1,485 (+6.4%)	1,537 (+10.1%)
Median value of network distance to the closest UFAA (m)	2,328	2,699 (+15.9%)	2,808 (+4.0%)	2,897 (+7.3%)	2,824 (+4.6%)	2,881 (+6.7%)
Ratio of household residing in DAA	40.2%	34.2%	32.0%	30.7%	32.0%	31.0%

Simulation Results Summary of Residential Location Model

Limitations and Future Works

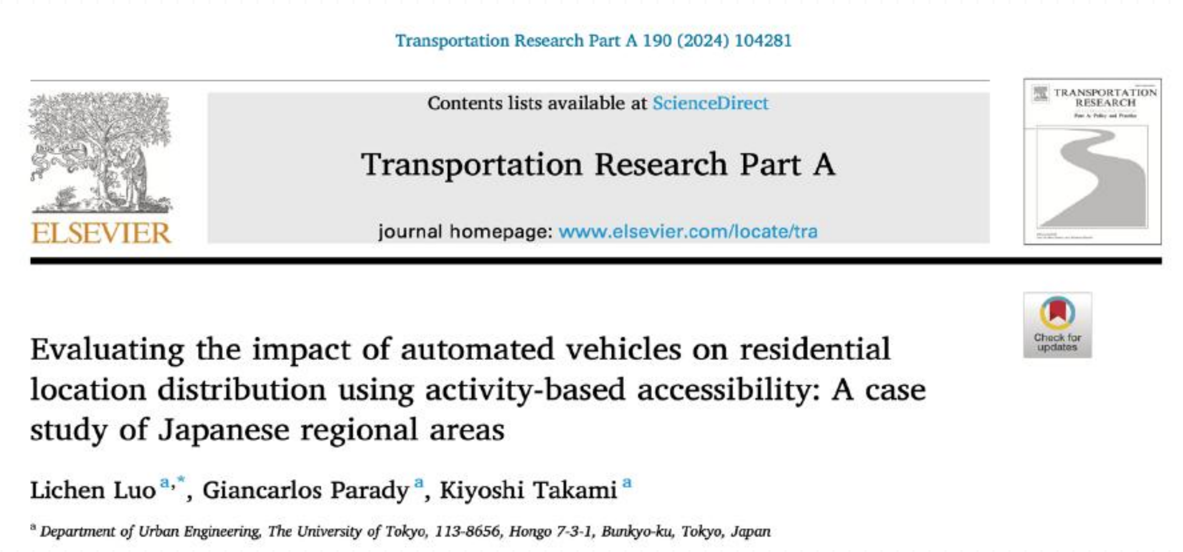
- Focused on certain aspects of AVs only from the data with no AV operated,
    - One of the very basic assumptions that travel impedance of AVs would decrease is being questioned by some scholars.
    - Stated Preference survey might be advised to conduct to better reflect the travel impedance reduction of AVs.
- Limitations in the current DAS model specification.
    - Individual specific time budget has not explicitly incorporated.
    - Logsum variable fail to reflect changes from time of day and other trip-based level choices.
- To incorporate more choice dimensions in the long term, including household transition choice, job location choice, development choice of housing or other facilities, etc. to obtain more reliable forecasts.
- To use tour-based travel demand data directly to avoid source of error during the tour and daily pattern identification processing.

MATSim User Meeting in Japan Nov.21, 2024

Thank you

LUO Lichen

Urban Transportation Research Unit
the University of Tokyo



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Evaluating the impact of automated vehicles on residential location distribution using activity-based accessibility: A case study of Japanese regional areas

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