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# Spatially explicit land-use and energy scenario of Tokyo using household level microdata

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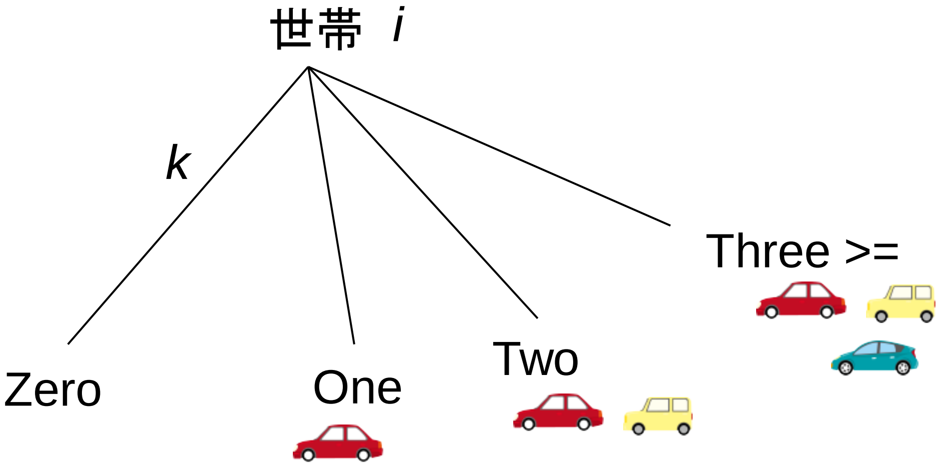
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# Data

- Household level Microdata of “National survey of family income and expenditure” of Ministry of Internal Affairs and Communications, Japan.
- This survey is conducted in the autumn of every five years since 1959, to investigate household’s monthly expenditure behavior.
- This is a quite extensive survey implemented against approximately 60,000 households.
- We had applied the microdata data to the ministry, and finally obtained it. Here, we use the data of 2004.

→ *Using this data, we try to provide useful information to support real urban policy.*

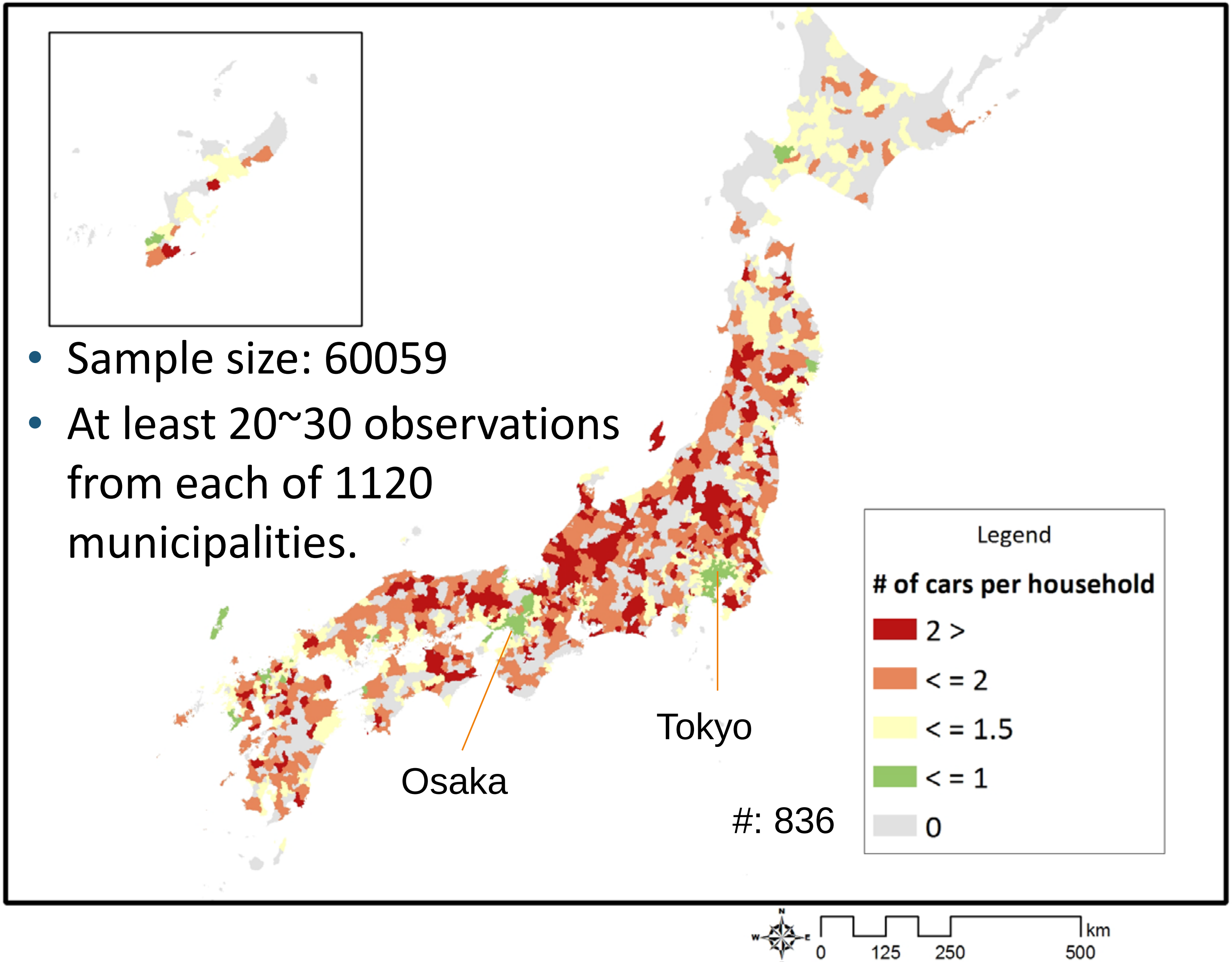
# Research agenda

1. **Identify key factors that affect vehicle ownership behavior.**
   - This is important because Nakamichi et al. (2013) suggested that once people own cars, they may keep using it even after their moving to fairly dense public transportation areas.
   - Especially, we focus on the question: Is parking price affect vehicle ownership behavior ?
     - The possibility of controlling parking prices to reduce vehicle ownership has recently been discussed in compact city related literatures (OECD, 2012; Guo, 2013), but based on our review, it is not empirically verified because of lack of data.

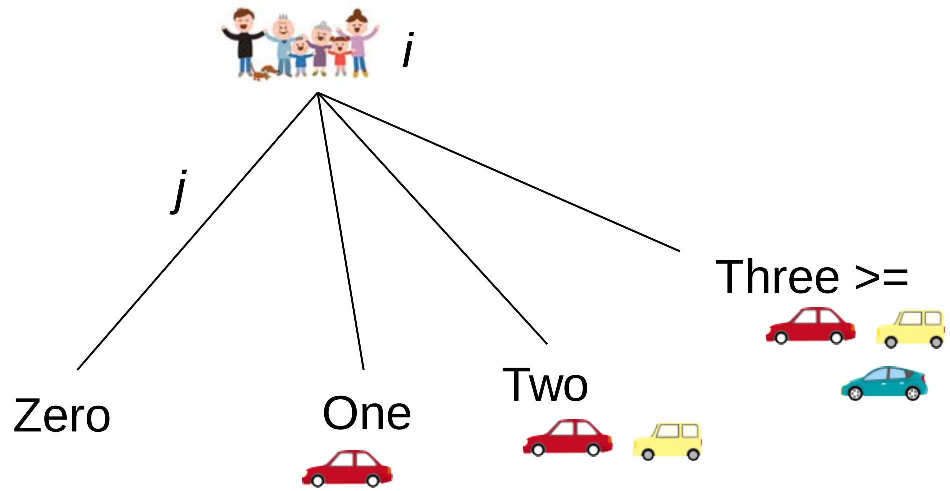
2. Create Japanese **municipality level electricity/gasoline intensity** data using spatial statistical model.
   - Existing studies: Prefecture level (We only show the prediction result)

3. Combining the data with our developed land-use model, and create future energy scenarios of Tokyo.
   - Ongoing (We show some progress)

- Sample size: 60059
- At least 20~30 observations from each of 1120 municipalities.



# Vehicle ownership behavior




- We assume that each household *i* choose the highest utility alternative *j*.
- The choice behavior is formulated as ordered logit model based on random utility theory.

$$\begin{cases} R_{ij} = 0 & \text{if } -\infty < U_{ij} < \mu_{i1}, \\ R_{ij} = 1 & \text{if } \mu_{i1} < U_{ij} < \mu_{i2}, \\ R_{ij} = 2 & \text{if } \mu_{i2} < U_{ij} < \mu_{i3}, \\ R_{ij} = 3 \text{ (and over)} & \text{if } \mu_{i3} < U_{ij} < \infty. \end{cases}$$

$U_{ij}$: Utility of alternative *j* for household *i*

# Specification of the utility function

- $U_{ij} = \beta_{i0}x_{i1} + \beta_{i1}x_{i1} + \ldots + \beta_{iK}x_{iK} + \varepsilon_{ij}$.

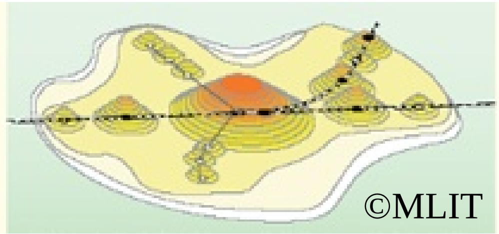
  *i.i.d.* gumbel

  - Variable (expected sign)

Household specific
    - Income (+)
    - Number of person in a household (+)
    - Family types (+-)

Urban compactness
    - Employment density (-)
    - Depopulation areas dummy (+)
    - Area (+)
    - Population density (-)
    - Bus stop density (-)
    - Train station density (-)
    - Mixed density index [MDI] (-)

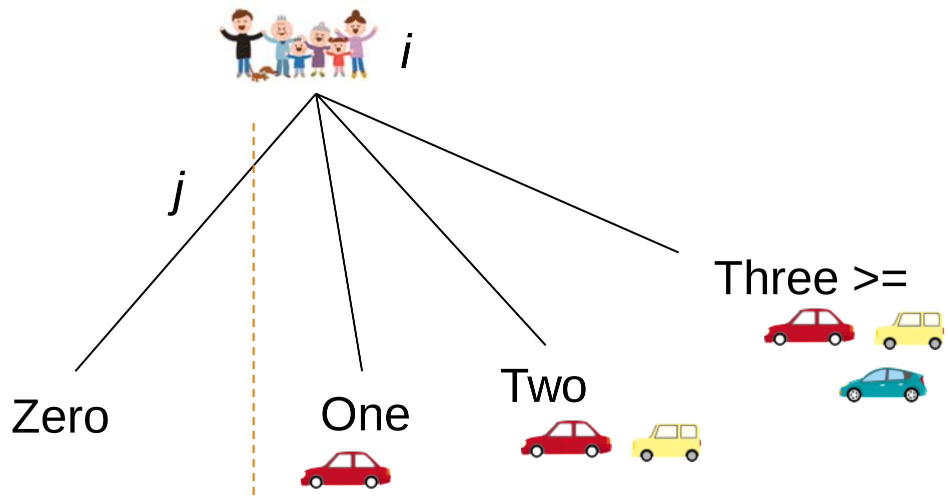
Urban policy
    - **Parking price expenditure per car (-)**




Compact urban form

| Household family type |
| --- |
| a. One-person households (65 years of age or over) |
| b. One-person households (under 65 years of age ) |
| c. Married couple only (either of them 65 years of age or over) |
| d. Married couple only (both under 65 years of age) |
| e. Married couple with child(ren) |
| f. Single parent and child(ren) |
| g. Other type |

# Parking price prediction for non-car users




Vehicle ownership

Parking prices (expenditure)

unknown

Project expected prices in each municipality

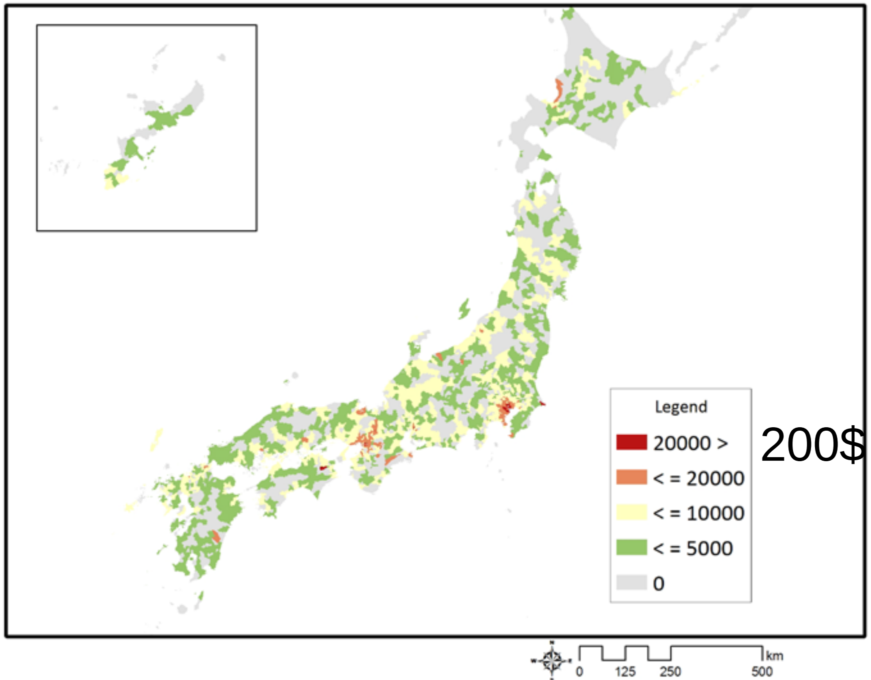
Typical examples:

0 [$/Month/car]: Parking to home

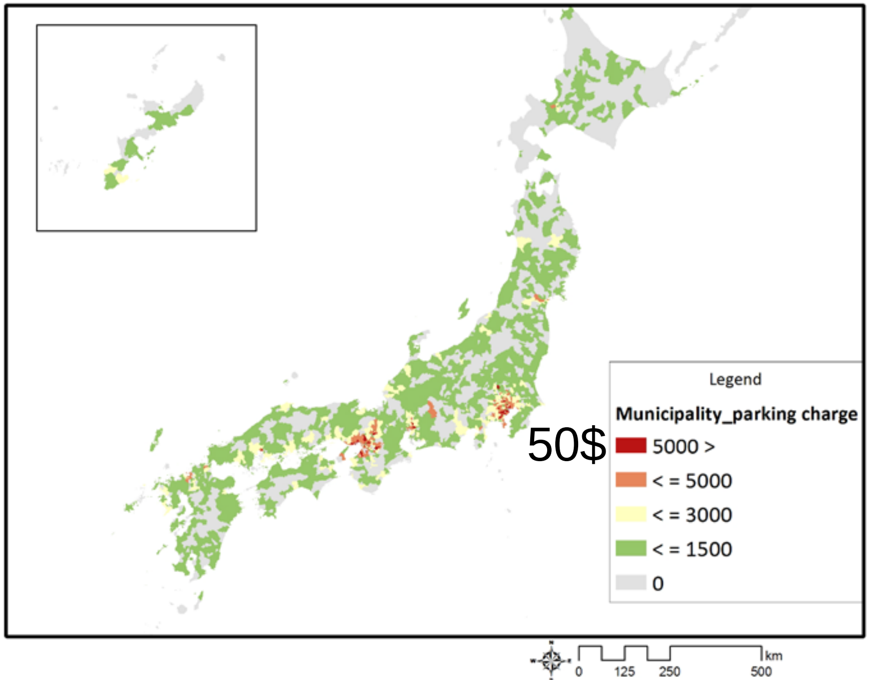
30: Suburbs

600: Center of Tokyo, etc…

# Average parking price




Exclude parking to home




Include parking to home

# Prediction of municipality average parking price

- Zero-inflated negative binomial model

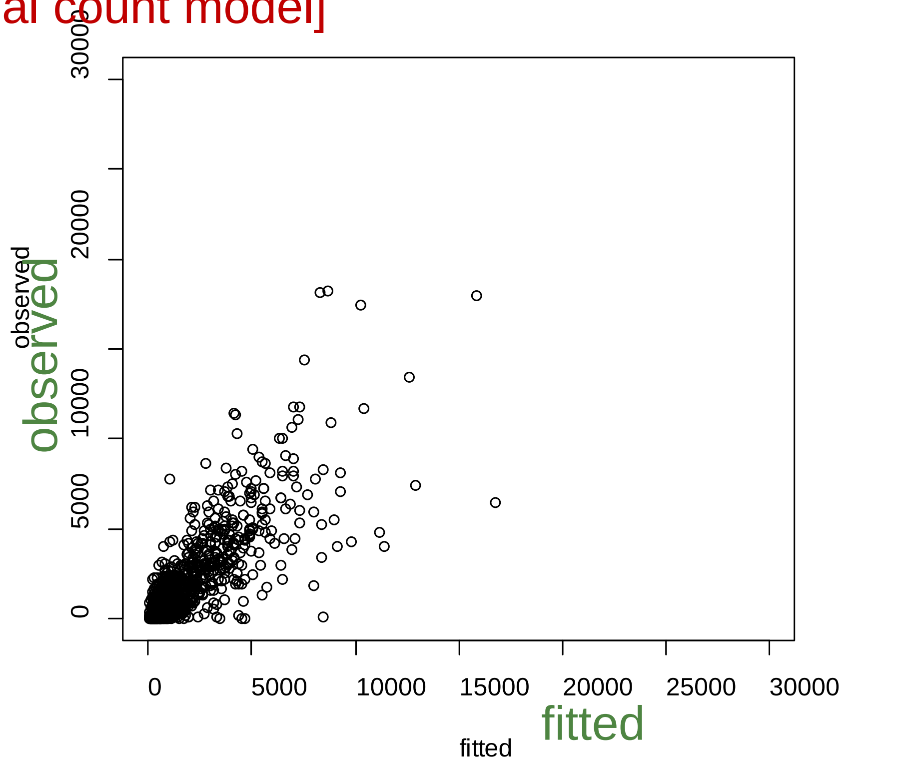
Parking to home or not [binary logit (zero-inflation) model]

$$\begin{cases} y_i = 0 & with\ \ probability\ \pi_i \\ y_i \sim NB(\lambda_i, v) & with\ \ probability\ (1-\pi_i) \end{cases} \qquad \mathrm{logit}(\pi_i) = \boldsymbol{z}_i'\boldsymbol{\gamma}$$

Parking prices [negative binomial count model]

| NB | Count model | | |
|---|---|---|---|
| | Coef. | Std. error | z |
| (Intercept) | 4.468 | 0.116 | 38.6 |
| log(PopDens.) | 0.2434 | 0.0680 | 3.58 |
| log(EmpDens.) | 0.1504 | 0.0669 | 2.25 |
| Condo | 1.386 | 0.151 | 9.18 |
| Log(theta) | 0.4440 | 0.0404 | 11.0 |
| | | | |
| **Logit** | **Zero-inflation model** | | |
| | Coef. | Std. error | z |
| (Intercept) | 1.488 | 0.424 | 3.51 |
| log(EmpDens.) | -0.7969 | 0.104 | -7.66 |
| Condo | -5.092 | 1.45 | -3.50 |
| Log-likelihood: | | -8676 | |

Condominium share



# City size category

- C1: Mega-city (Population over 1 million + Tokyo 23 wards)
- C2: Middle size city (Population 150 thousand～1 million)
- C3: Small city A (Population 50～150 thousand)
- C4: Small city B (Population 30～50 thousand)
- C5: Town and village

We use the given city size categories of this survey.
The model parameters are estimated for each of the category.

# Estimation result

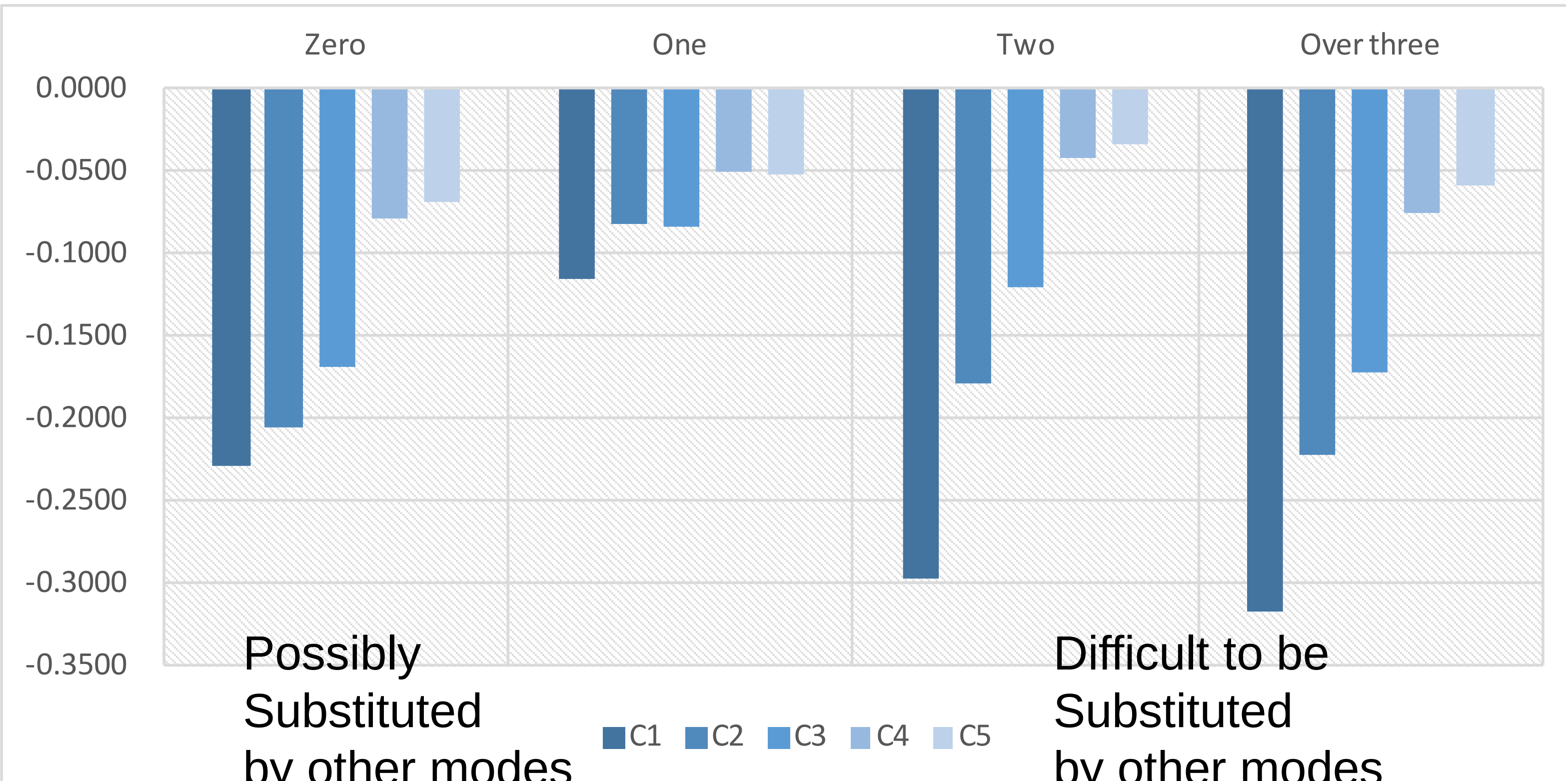
| | C1: 1 million > | | | C2: 1M~150T | | | C3: 150T~50T | | | C4: 50T~30T | | | C5: Town/villages | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Category 1 | | | Category 2 | | | Category 3 | | | Category 4 | | | Category 5 | | |
| | Coef. | z | | Coef. | z | | Coef. | z | | Coef. | z | | Coef. | z | |
| (Intercept) | | | | | | | | | | | | | | | |
| 0\|1 | -6.377 | -7.94 | *** | -3.315 | -8.04 | *** | -3.905 | -11.8 | *** | -1.263 | -3.24 | ** | -1.845 | -8.49 | *** |
| 1\|2 | -2.953 | -3.70 | ** | -0.09890 | -0.241 | | -0.8608 | -2.62 | ** | 1.494 | 3.86 | *** | 0.6848 | 3.22 | ** |
| 2\|3 | -0.4276 | -0.533 | | 2.257 | 5.48 | *** | 1.587 | 4.82 | *** | 4.119 | 10.5 | *** | 3.113 | 14.4 | *** |
| Parking/1000 | -0.06211 | -12.7 | *** | -0.09715 | -24.3 | *** | -0.1187 | -16.5 | *** | -0.1692 | -8.33 | *** | -0.1707 | -10.5 | *** |
| Income/1000 | 0.001287 | 12.9 | *** | 0.001426 | 14.3 | *** | 0.001954 | 19.5 | *** | 0.002568 | 25.7 | *** | 0.002433 | 24.3 | *** |
| EmpDens. | -0.1044 | -1.29 | | -0.06530 | -1.11 | | 0.5628 | 6.16 | *** | -0.2284 | -2.05 | * | 0.2722 | 3.51 | *** |
| Depop | -1.137 | -3.50 | *** | 0.2430 | 2.59 | ** | -0.1791 | -2.17 | * | -0.2434 | -3.13 | ** | -0.1449 | -2.41 | * |
| Area | -0.003973 | -5.68 | *** | -0.000008664 | -0.0866 | | -0.0003564 | -3.56 | . | -0.00007205 | -0.360 | | 0.00007567 | 0.757 | |
| PopDens | -0.6119 | -7.03 | *** | -0.1485 | -3.33 | *** | -0.7229 | -8.94 | *** | 0.2106 | 2.18 | ** | -0.2021 | -2.63 | ** |
| BusDens | -0.03042 | -1.69 | . | -0.009024 | -0.668 | | 0.002091 | 0.132 | | 0.2095 | 3.92 | *** | -0.01983 | -0.646 | |
| StaDens | -0.2250 | -3.00 | ** | 0.4297 | 2.42 | * | -0.7783 | -3.08 | ** | 0.01760 | 1.25 | | -0.9260 | -2.90 | ** |
| MDI | 0.000009421 | 0.230 | | -0.0004627 | -4.63 | *** | -0.0004343 | -4.34 | *** | -0.001132 | -2.83 | ** | -0.001000 | -5.00 | *** |
| HH_num | 0.3433 | 7.97 | *** | 0.3461 | 16.8 | *** | 0.3059 | 11.5 | *** | 0.4506 | 12.1 | *** | 0.3770 | 14.8 | *** |
| Type1 | -2.209 | -9.22 | *** | -3.469 | -27.4 | *** | -3.705 | -22.1 | *** | -3.045 | -14.5 | *** | -3.106 | -18.3 | *** |
| Type2 | -0.7684 | -4.20 | *** | -1.628 | -16.2 | *** | -1.822 | -13.5 | *** | -1.301 | -7.04 | *** | -1.780 | -12.0 | *** |
| Type3 | -0.5532 | -3.82 | *** | -1.398 | -18.8 | *** | -1.690 | -16.9 | *** | -1.188 | -9.09 | *** | -1.334 | -13.7 | *** |
| Type4 | 0.5846 | 4.00 | *** | -0.2251 | -3.11 | ** | -0.4868 | -5.13 | *** | -0.1351 | -1.08 | | -0.4146 | -4.46 | *** |
| Type5 | -0.3367 | -2.04 | * | -0.9895 | -11.8 | *** | -1.221 | -10.5 | *** | -0.9972 | -6.21 | *** | -1.159 | -9.20 | *** |
| Type6 | 0.3810 | 3.61 | *** | -0.3665 | -7.65 | *** | -0.5571 | -9.03 | *** | -0.2849 | -3.50 | *** | -0.4886 | -8.60 | *** |
| Hit ratio | 0.6419 | | | 0.5659 | | | 0.5529 | | | 0.5614 | | | 0.5511 | | |
| Initial log-likelihood | -5644.4 | | | -22503 | | | -12478 | | | -6166.3 | | | -10860 | | |
| Final log-likelihood | -4585.2 | | | -18289 | | | -10013 | | | -4904.6 | | | -8793.8 | | |
| PseudoR2(McFadden) | 0.1877 | | | 0.1873 | | | 0.1976 | | | 0.2046 | | | 0.1902 | | |

Signif. codes: 0.1%(***), 1%(**), 5%(*), 10%(.)

# Discussion

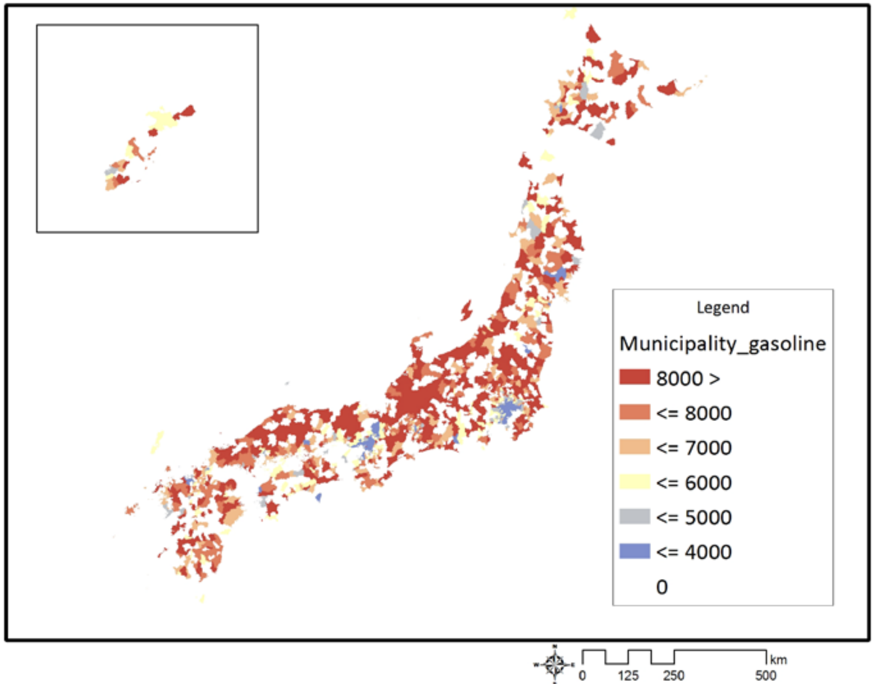
## Elasticity of parking price

| | Ordered logit model | | | |
|---|---|---|---|---|
| | Zero | One | Two | Over three |
| C1 | -0.2288 | -0.1144 | -0.2966 | -0.3167 |
| C2 | -0.2056 | -0.08263 | -0.1784 | -0.2225 |
| C3 | -0.1686 | -0.08350 | -0.1195 | -0.1714 |
| C4 | -0.07814 | -0.05080 | -0.04198 | -0.07444 |
| C5 | -0.06842 | -0.05139 | -0.03358 | -0.05920 |

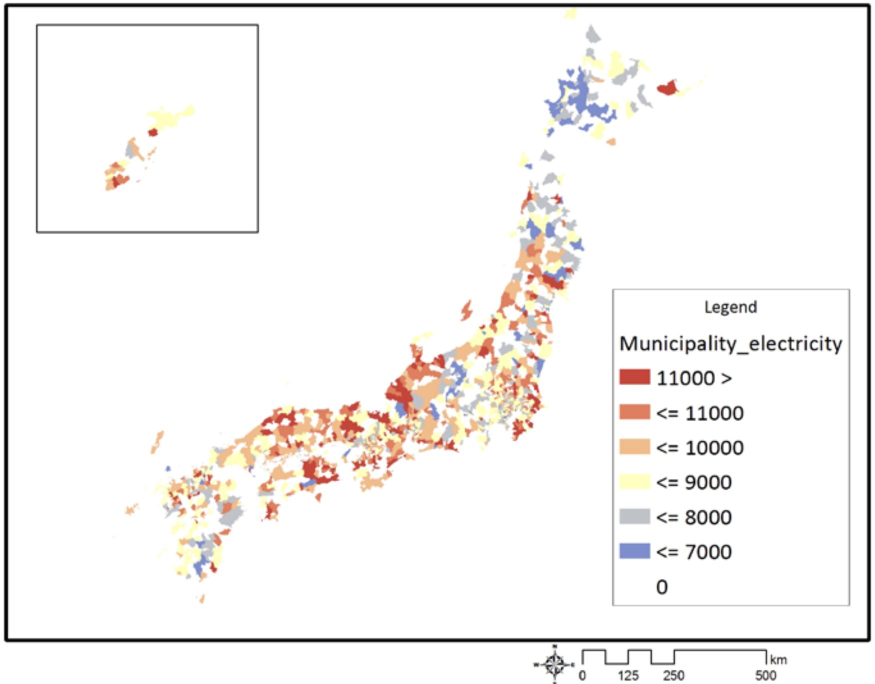



Elasticity value is rather small in absolute value.

# Energy intensity prediction using spatial statistical model




Average gasoline expenditure per household



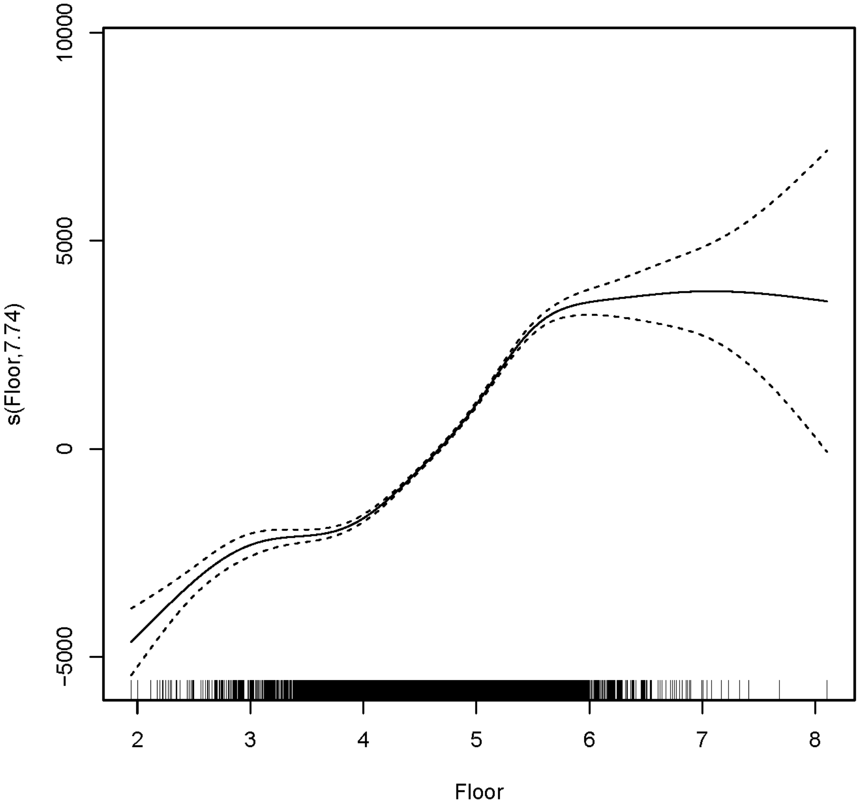

Average electricity expenditure per household

Constructing municipality level intensity (expenditure) data by statistical approach (**geoadditive model**).

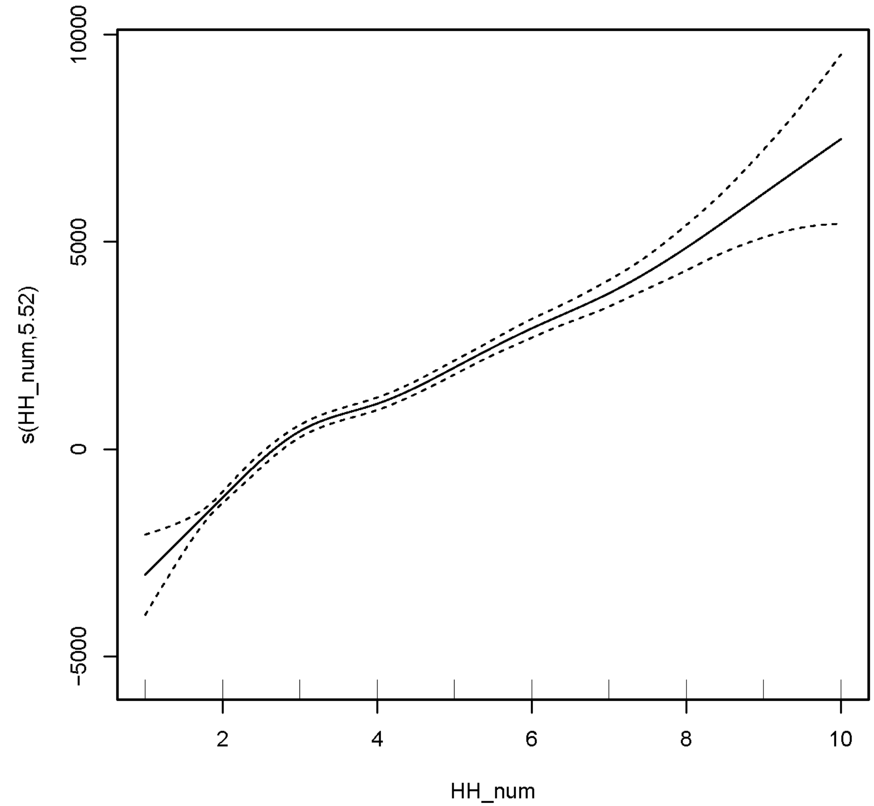
- We can consider sampling bias, and that future changes of intensity value by using projected value of explanatory variables.

# Some of the estimation results

- Nonlinear- effects by geoadditive model

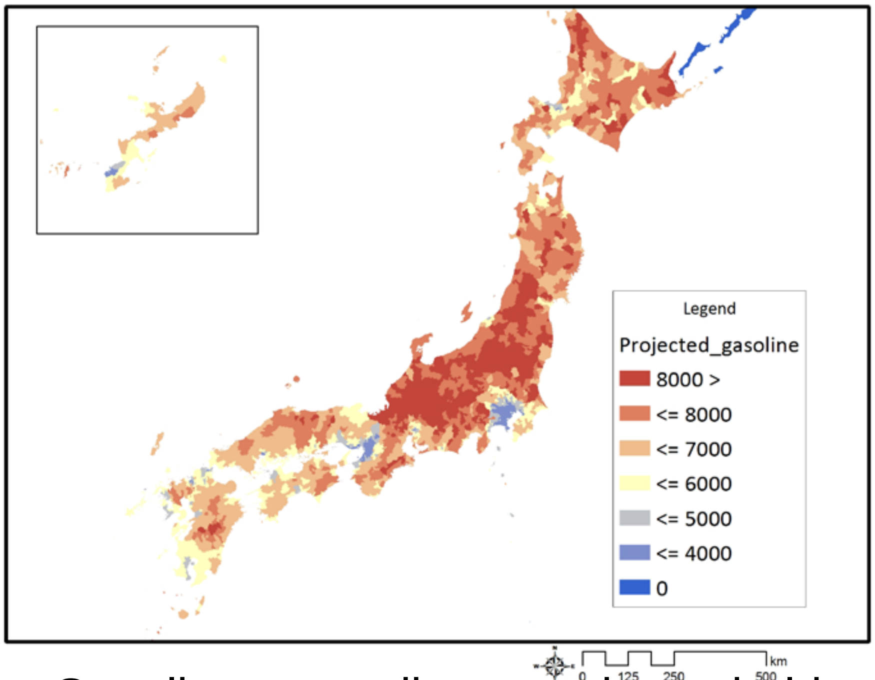



Effects of log of Floor area on electricity expenditure in a household

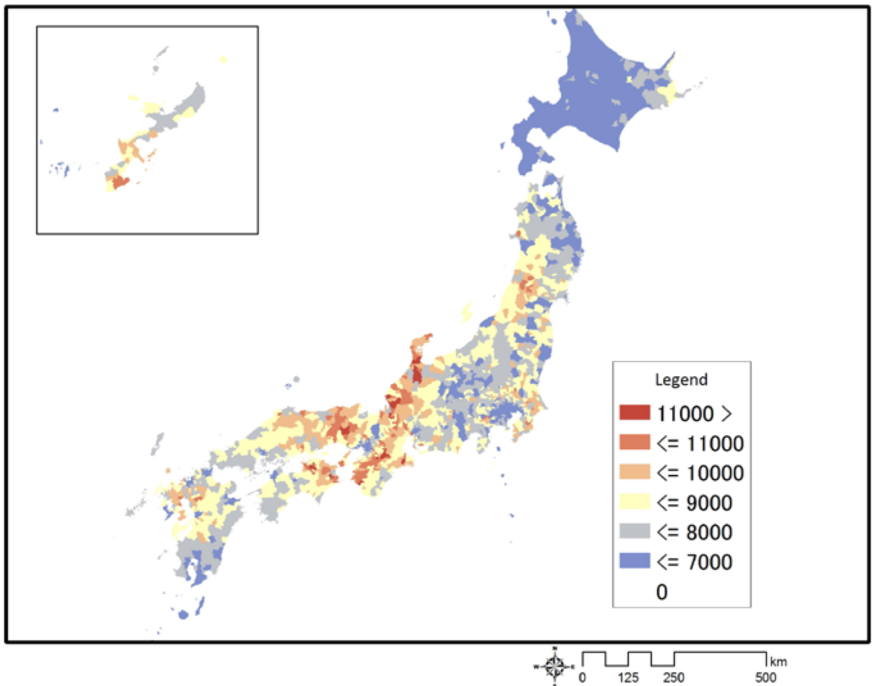



Effects # of person in a household on electricity expenditure in a household

# Energy intensity prediction using spatial statistical model




Gasoline expenditure per household



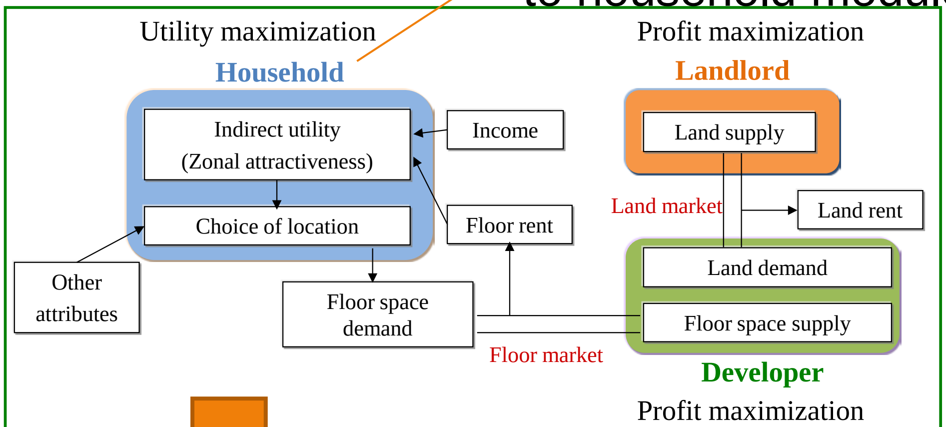

Electricity expenditure per household

- Significant differences among municipalities.
  - Does everyone need to move Tokyo or Osaka?
  - It is important to consider other various aspects for creating future scenarios.

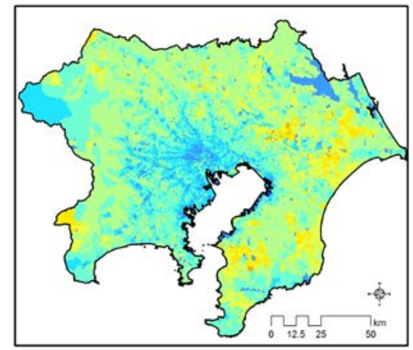
# Future works:
# Combining with land-use model of Yamagata et al. (2013)

Land use model

Combining the data to household module

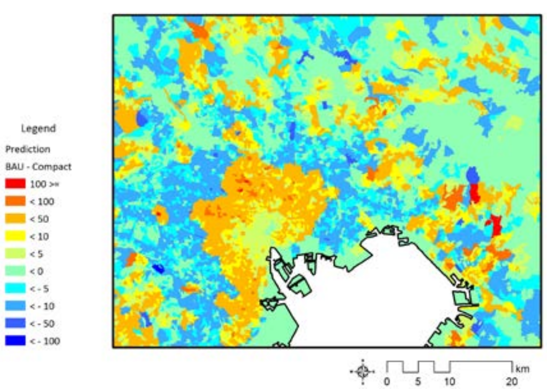



Current Micro-district level prediction of electricity intensity for 2005.

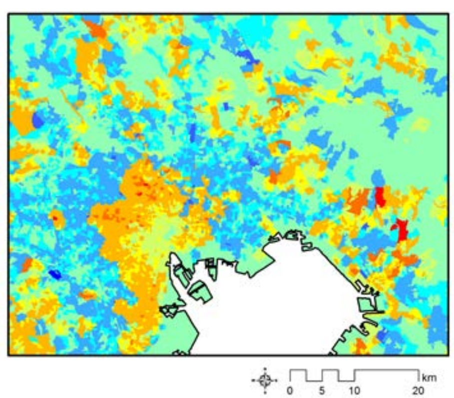



2050 urban form scenario

Population increase
Compact scenario




Population increase
Compact + adaptation scenario




Statistical models
$f$(car ownership) = $\boldsymbol{X\beta}$
$f$(energy consumptions) = $\boldsymbol{X\beta}$

Scenario assessment

Output: Floor space, population density, Ratio of condominiums, income, etc.