Estimating Vacant Houses Using Deep Learning with Satellite Embedding Dataset

—A Case Study of Kashiwa City, Japan

衛星画像情報を用いた深層学習による空き家数の推定に関する研究
—柏市を事例として

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1.1 Research Background
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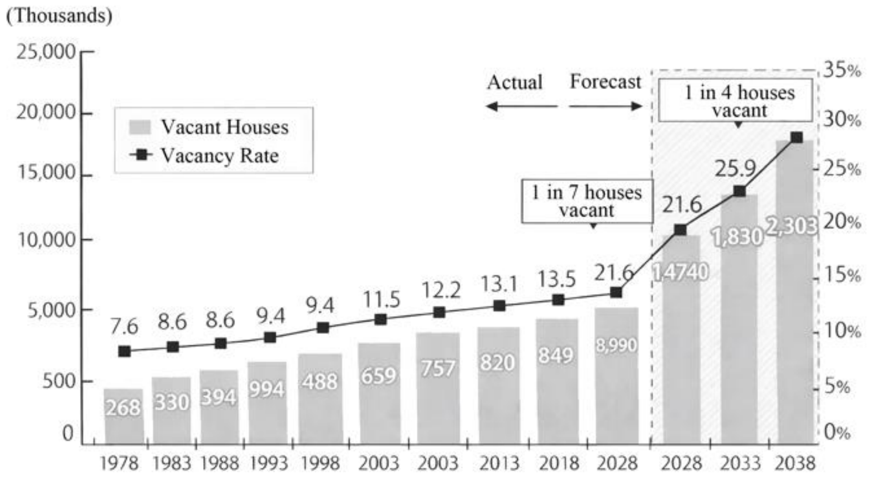
1.1 Research Background

Current situation

- **A major social problem in Japan**
- **Detection and monitoring required**
- 8.46 million vacant houses
- 13.6% vacancy rate



Trends in Vacant Houses in Japan

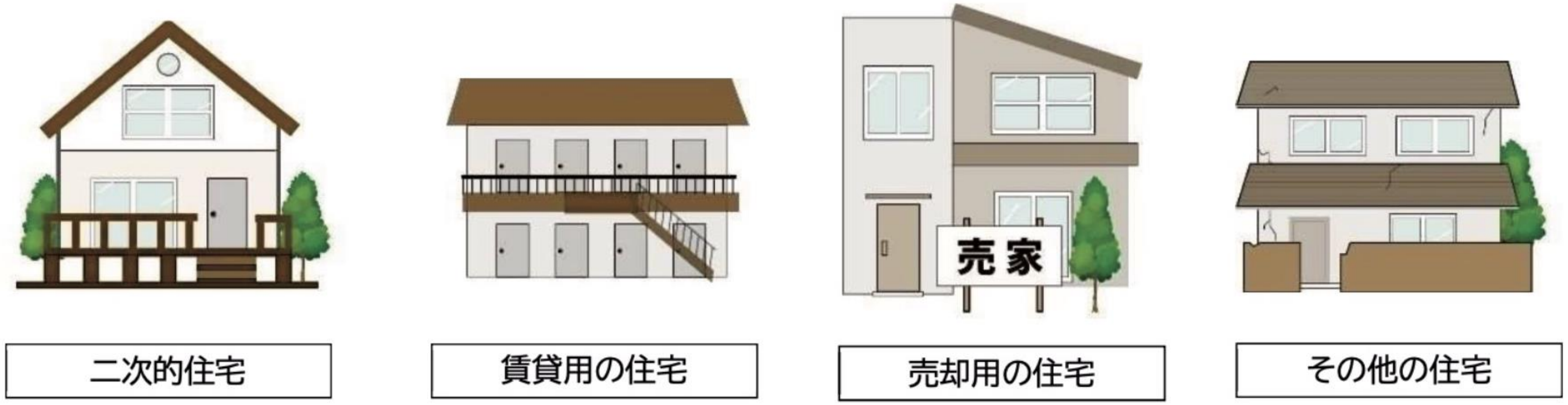
Need

- **A method support field surveys**
- **Providing vacant house information**

Source: Internet resources

1.2 Research Subject

- The subject of this research focuses on **vacant houses** from **145 cities** in **Japan** between **2020** and **2025** in block level. Vacant houses are classified into four official categories defined by the Vacant House Condition Survey.



Secondary dwelling
For-rent dwelling
For-sale dwelling
Other dwelling

Source: Housing and Land Survey

1.3 Research Objective

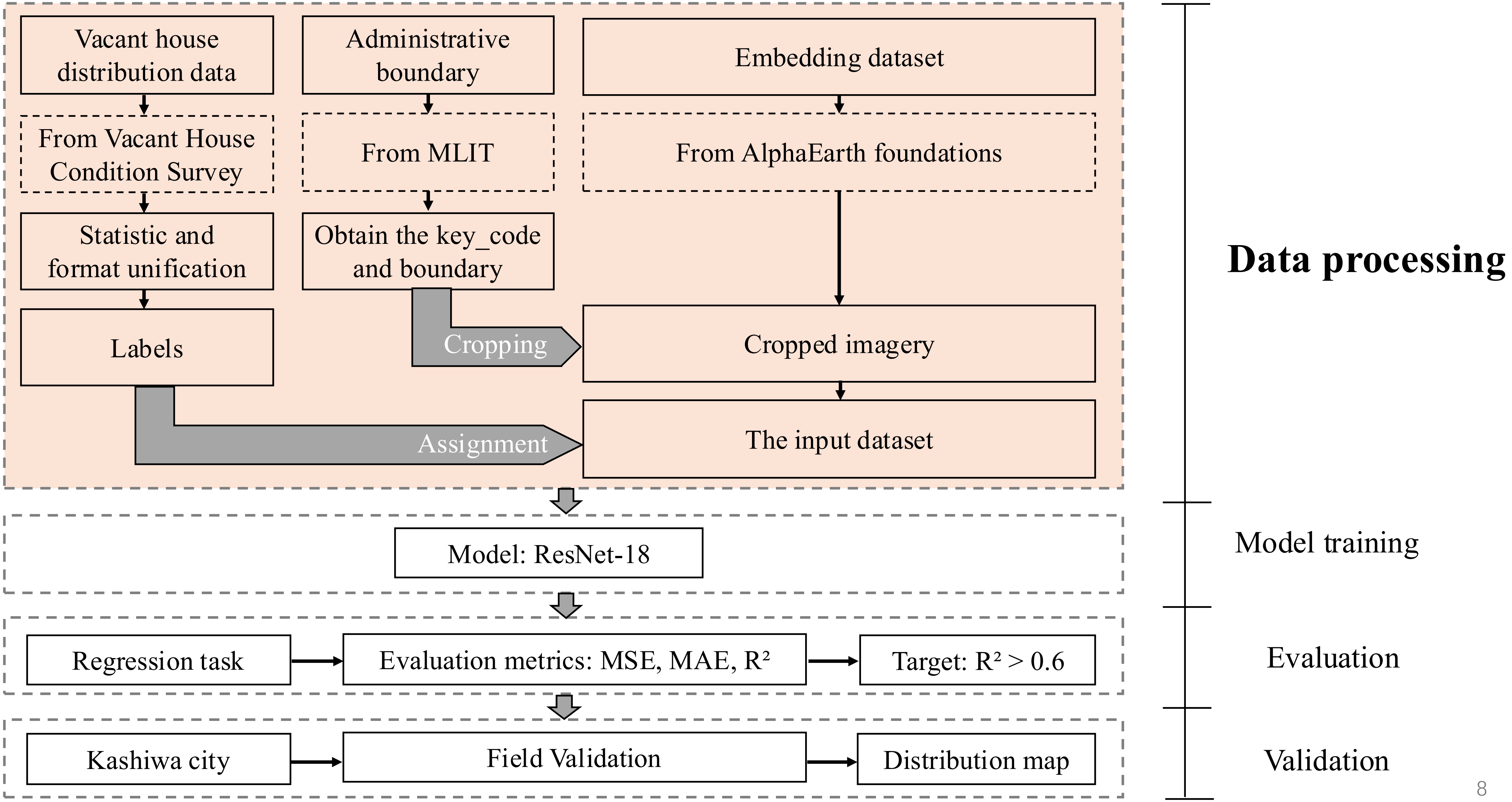
- Develop a a framework that link **vacant house survey data** with **administrative blocks.**
- Apply **embeddings** as inputs to a deep learning-based vacant house estimation and validate the method in **Kashiwa City**.
- Evaluate the feasibility of vacant house estimation using only **open and free data** in Japan.

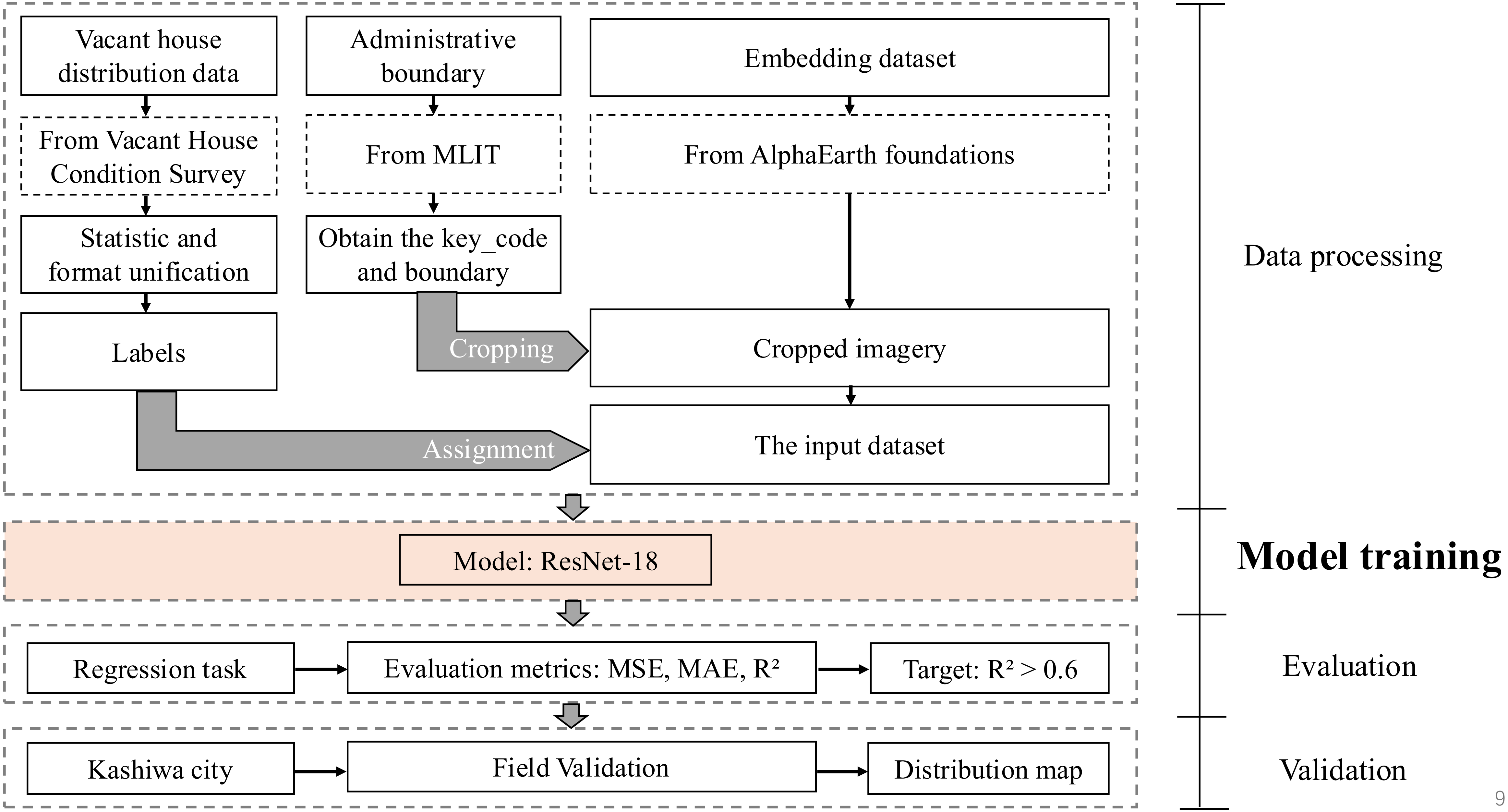
Source: Internet resources

1.4 Research Methodology

- First, datasets are integrated to generate labels and cropped satellite imagery.
- Second, the input data and labels are used to train the model based on ResNet.
- Then, model performance is evaluated using MSE, MAE, and R^2, where $R^2 > 0.6$ is a satisfactory level for block-level vacant house estimation.
- Finally, the trained model is applied to Kashiwa City to generate spatial distributions and is supplemented by field surveys for model interpretation.

The next page presents the Research Methodology Flowchart


Vacant house distribution data
From Vacant House Condition Survey
Statistic and format unification
Labels
Administrative boundary
From MLIT
Obtain the key_code and boundary
Cropping
Embedding dataset
From AlphaEarth foundations
Cropped imagery
Assignment
The input dataset
Model: ResNet-18
Regression task
Evaluation metrics: MSE, MAE, R²
Target: R² > 0.6
Kashiwa city
Field Validation
Distribution map
Data processing
Model training
Evaluation
Validation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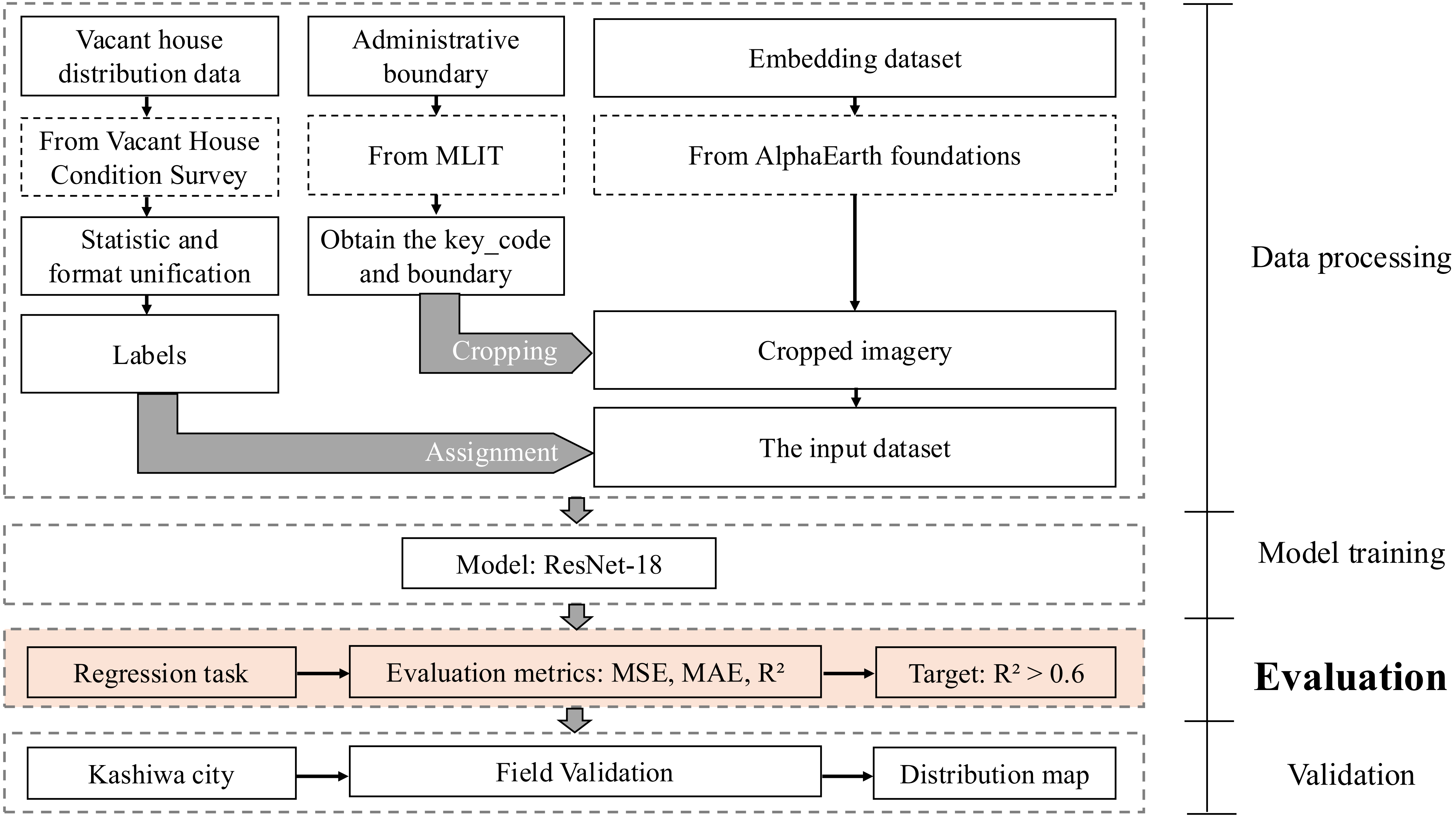
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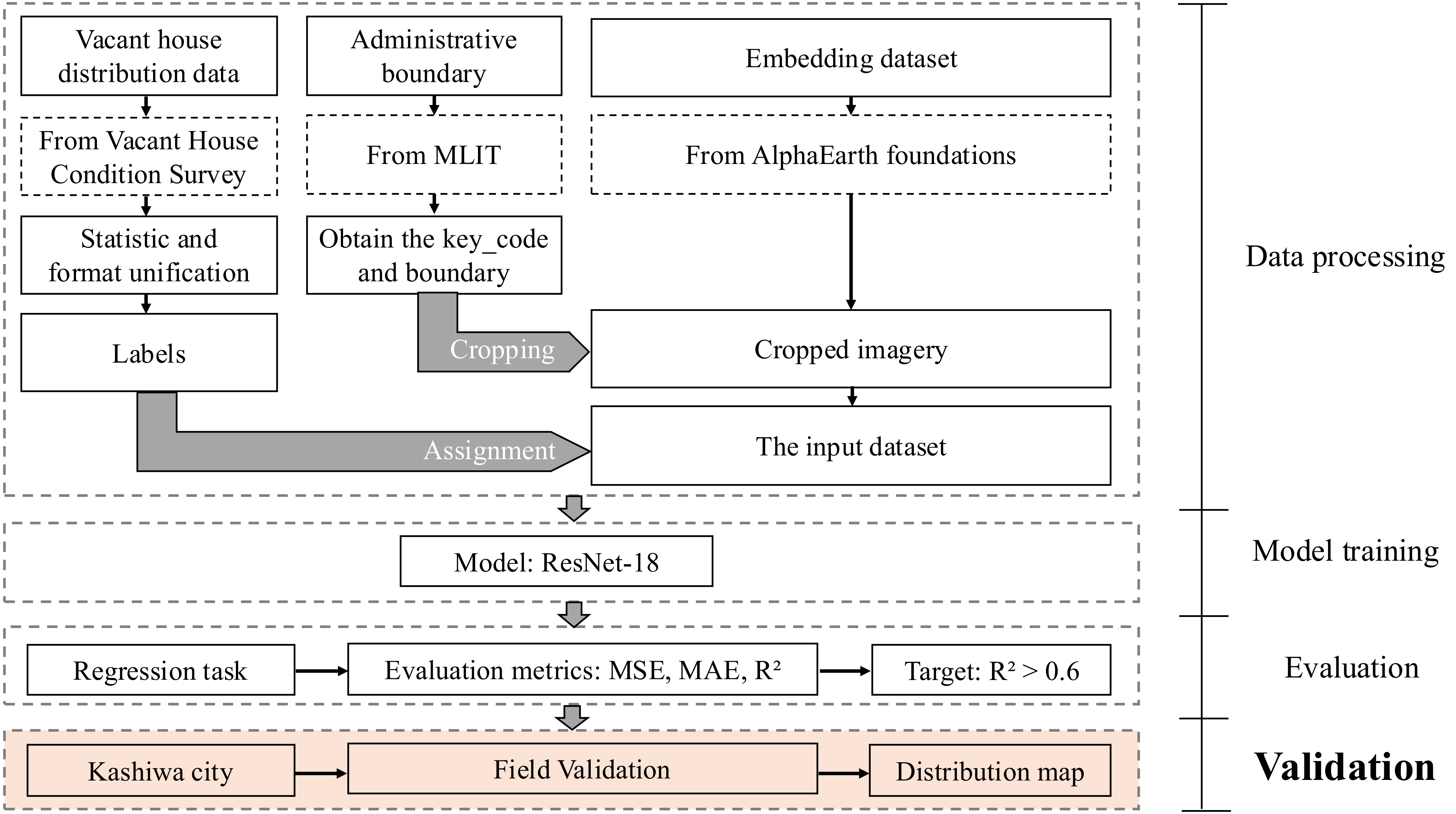
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2. Background on Vacant Housing Detection

2.1 Mechanism-Based Perspectives on Vacant House studies

2.2 Technology-Based Perspectives on Vacant House studies

2.1 Mechanism-Based Perspectives on Vacant House studies

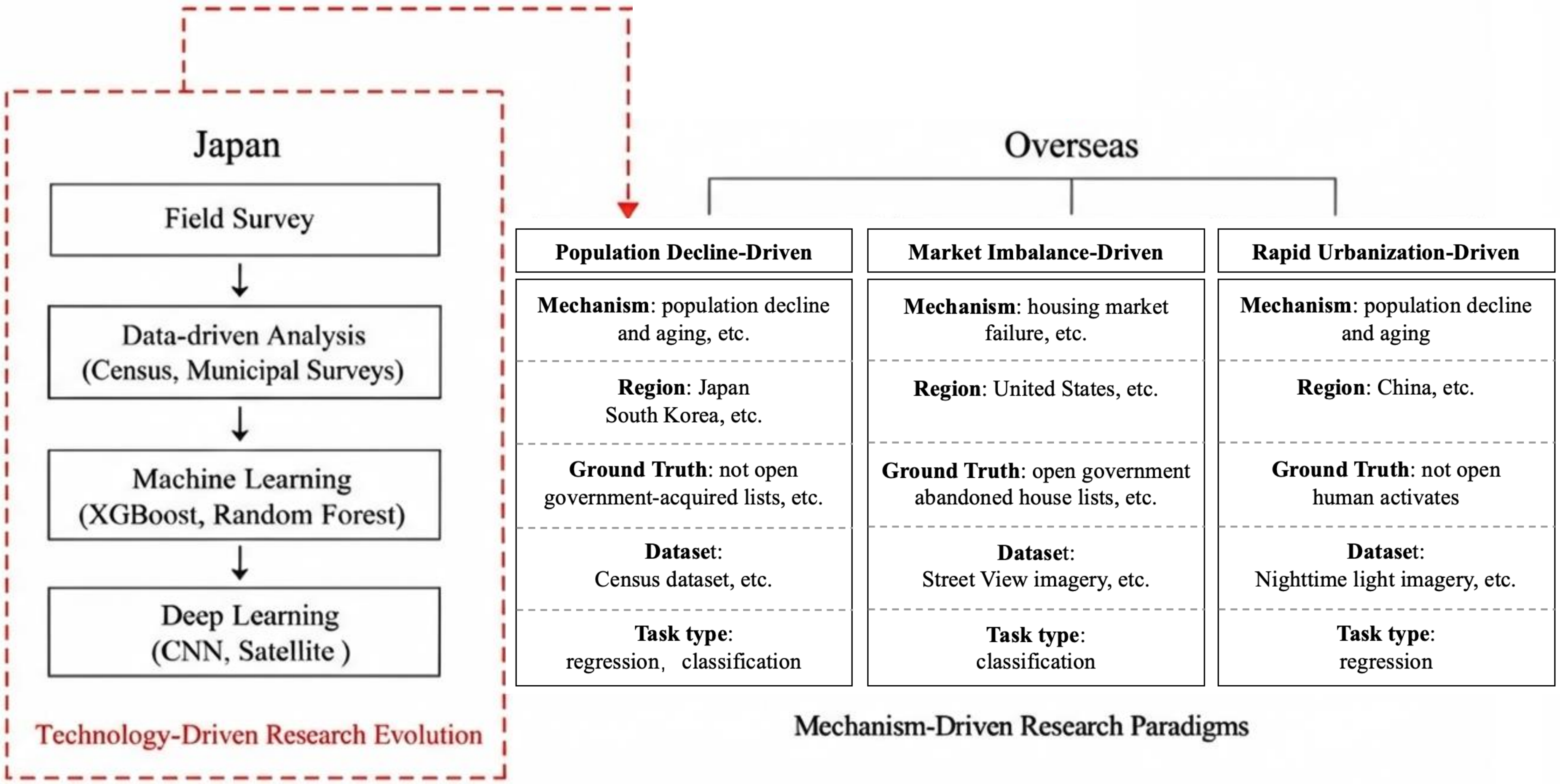
Population Decline-Driven	Market Imbalance-Driven	Rapid Urbanization-Driven
Mechanism: population decline and aging, etc.	**Mechanism**: housing market failure, etc.	**Mechanism**: rapid urbanization
Region: Japan South Korea, etc.	**Region**: United States, etc.	**Region**: China, etc.
Ground Truth: not open government-acquired lists, etc.	**Ground Truth**: open government abandoned house lists, etc.	**Ground Truth**: not open human activates
Dataset: Census dataset, etc.	**Dataset**: Street View imagery, etc.	**Dataset**: Nighttime light, etc.
Task type: Regression, classification	**Task type**: classification	**Task type**: regression

2.1 Mechanism-Based Perspectives on Vacant House studies

Population Decline-Driven
Mechanism: population decline and aging, etc.
Region: **Japan** South Korea, etc.
Ground Truth: not open government-acquired lists, etc.
Dataset: Census dataset, etc.
Task type: Regression, classification

- **Under this condition, ground truth data are not open due to privacy concerns.**
- **Studies rely on closed census datasets**
- **It is important to develop an estimation method suitable for Japan.**

Using Japan as a typical example to discuss the technological development of vacant house studies



2.2.1 Field Survey

Characteristics

- Vacant houses are identified through field surveys
- Provide detailed information

Limitations

- Require **time, money, and manpower**
- Unsuitable for large-scale monitoring

Source: Internet resources

2.2.2 Data-Driven Analysis

Characteristics

- Faster than field surveys
- Utility usage data
- water supply, electricity supply, etc.

Limitations

- **Non-public data**
- Limited scalability
- Limited spatial resolution

Source: Internet resources

2.2.3 Machine Learning-Based Method

Characteristics
- **Combines more datasets**
- **Usually gives better results**

Limitations
- **Obtaining ground truth of vacant houses is difficult due to privacy concerns**

2.2.4 Deep Learning-Based Method

Characteristics
- Widely used for vacant house study
- Automatic feature learning

Limitations
- Black-box nature
- Hard to interpret

2.2.3 Machine Learning-Based Method

Characteristics

- Combines more datasets
- Usually gives better results

Limitations

- Obtaining ground truth of vacant houses is difficult due to privacy concerns

2.2.4 Deep Learning-Based Method

Characteristics

- **Widely used for vacant house study**
- **Automatic feature learning**

Limitations

- **Black-box nature**
- **Hard to interpret**

Limitations of Current Studies

- Reliance on **non-public** or proprietary data
- Ground truth collection requires **local cooperations**
- **Difficult to scale and apply to other regions**

What approach I want to create

- Use public and freely available datasets only
- Provide a fully reproducible estimation framework
- **All the datasets and the code will be made public**

3. Data Used in This Study

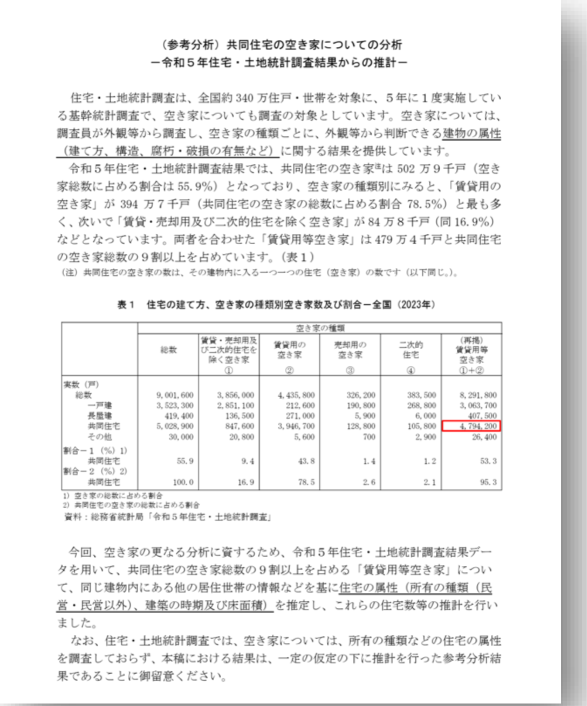
3.1 Vacant House Distribution Data

3.2 Japanese Administrative Divisions

3.3 AlphaEarth Foundations embedding dataset

3.1 Vacant House Distribution Data

Housing and Land Survey



（参考分析）共同住宅の空き家についての分析
－令和５年住宅・土地統計調査結果からの推計－

住宅・土地統計調査は、全国約 340 万住戸・世帯を対象に、５年に１度実施している基幹統計調査で、空き家についても調査の対象としています。空き家については、調査員が外観等から調査し、空き家の種類ごとに、外観等から判断できる建物の属性（建て方、構造、腐朽・破損の有無など）に関する結果を提供しています。

令和５年住宅・土地統計調査結果では、共同住宅の空き家注は 502 万９千戸（空き家総数に占める割合は 55.9%）となっており、空き家の種類別にみると、「賃貸用の空き家」が 394 万７千戸（共同住宅の空き家の総数に占める割合 78.5%）と最も多く、次いで「賃貸・売却用及び二次的住宅を除く空き家」が 84 万８千戸（同 16.9%）などとなっています。両者を合わせた「賃貸用等空き家」は 479 万４千戸と共同住宅の空き家総数の９割以上を占めています。（表１）

（注）共同住宅の空き家の数は、その建物内に入る一つ一つの住宅（空き家）の数です（以下同じ。）。

表１　住宅の建て方、空き家の種類別空き家数及び割合－全国（2023年）

	空き家の種類					
	総数	賃貸・売却用及び二次的住宅を除く空き家 ①	賃貸用の空き家 ②	売却用の空き家 ③	二次的住宅 ④	（再掲）賃貸用等空き家 ①+②
実数（戸）						
総数	9,001,600	3,856,000	4,435,800	326,200	383,500	8,291,800
一戸建	3,523,300	2,851,100	212,600	190,800	268,800	3,063,700
長屋建	419,400	136,500	271,000	5,900	6,000	407,500
共同住宅	5,028,900	847,600	3,946,700	128,800	105,800	4,794,200
その他	30,000	20,800	5,600	700	2,900	26,400
割合－１（%）1)						
共同住宅	55.9	9.4	43.8	1.4	1.2	53.3
割合－２（%）2)						
共同住宅	100.0	16.9	78.5	2.6	2.1	95.3

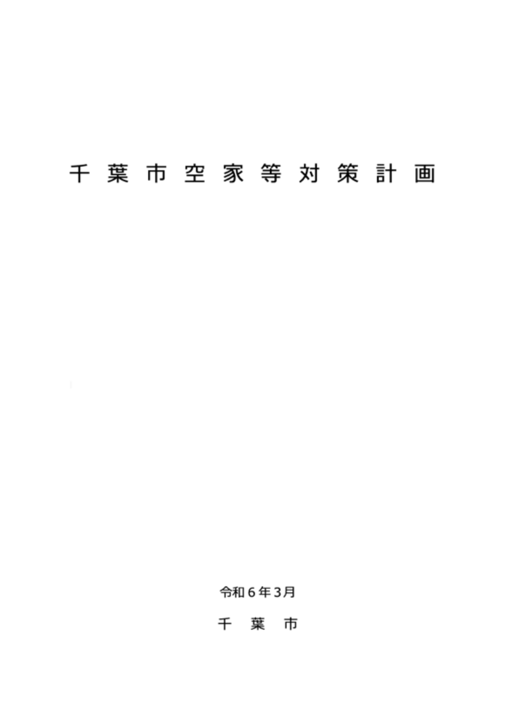
1）空き家の総数に占める割合
2）共同住宅の空き家の総数に占める割合
資料：総務省統計局「令和５年住宅・土地統計調査」

今回、空き家の更なる分析に資するため、令和５年住宅・土地統計調査結果データを用いて、共同住宅の空き家総数の９割以上を占める「賃貸用等空き家」について、同じ建物内にある他の居住世帯の情報などを基に住宅の属性（所有の種類（民営・民営以外）、建築の時期及び床面積）を推定し、これらの住宅数等の推計を行いました。

なお、住宅・土地統計調査では、空き家については、所有の種類などの住宅の属性を調査しておらず、本稿における結果は、一定の仮定の下に推計を行った参考分析結果であることに御留意ください。

- Published by the nationwide government
- Provides estimated information

Vacant House Condition Survey



千 葉 市 空 家 等 対 策 計 画

令和６年３月

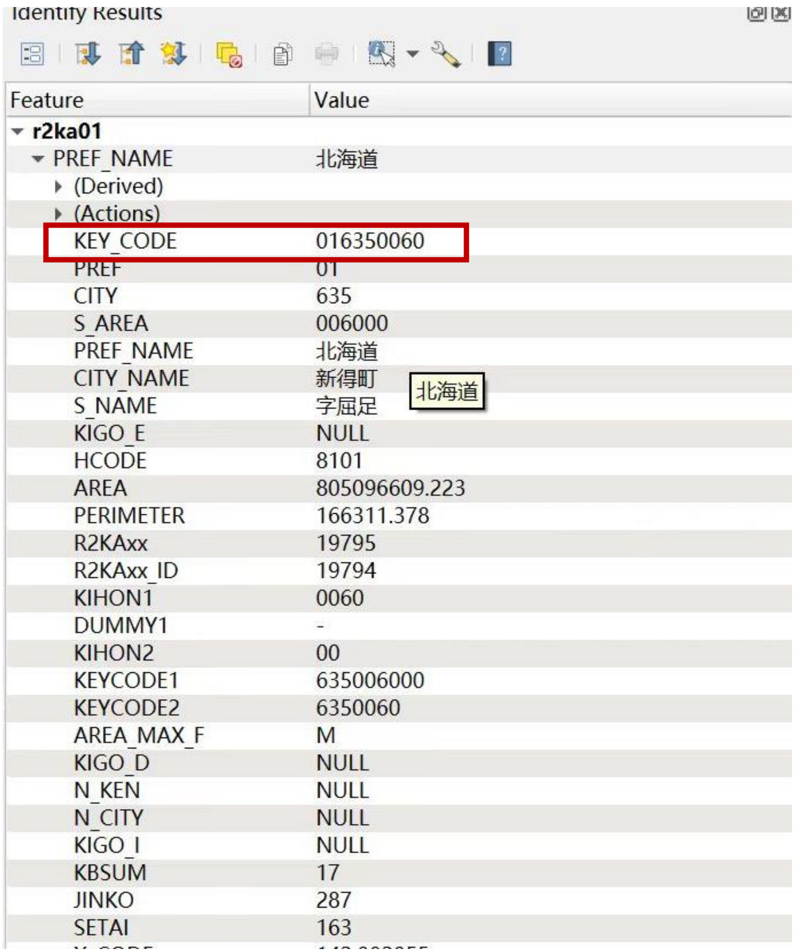
千　葉　市

- **Published by local government**
- **Based on field surveys**
- **More detailed information**

Used this one as the ground truth

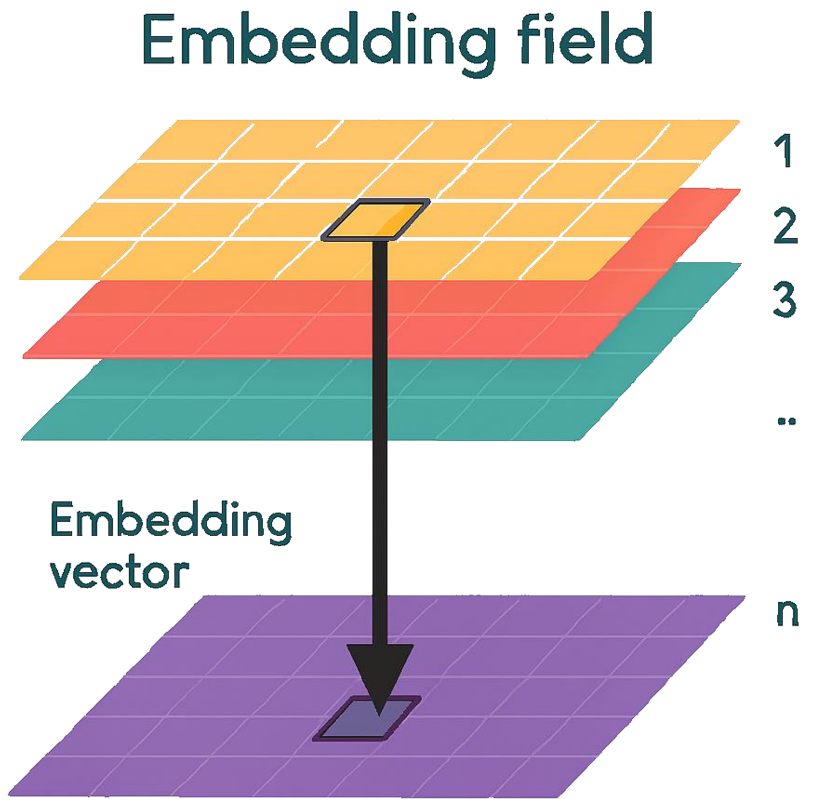
3.2 Japanese Administrative Boundary

- Provided by the Ministry of Land, Infrastructure, Transport, and Tourism (**MLIT**)
- Get the **KEY_CODE for each city block**
- It is an important bridge connecting embeddings with vacant house information



3.3 AlphaEarth Foundations embedding dataset （AEF）

- **Developed by Google DeepMind, Sep 2025**
- **Multi-modal**: optical, radar, LiDAR, climate, text
- **10 m resolution**, 64-dim embeddings, annual
- **Designed for mapping and detection research**
- **Applications: land use,** disaster monitoring, etc.

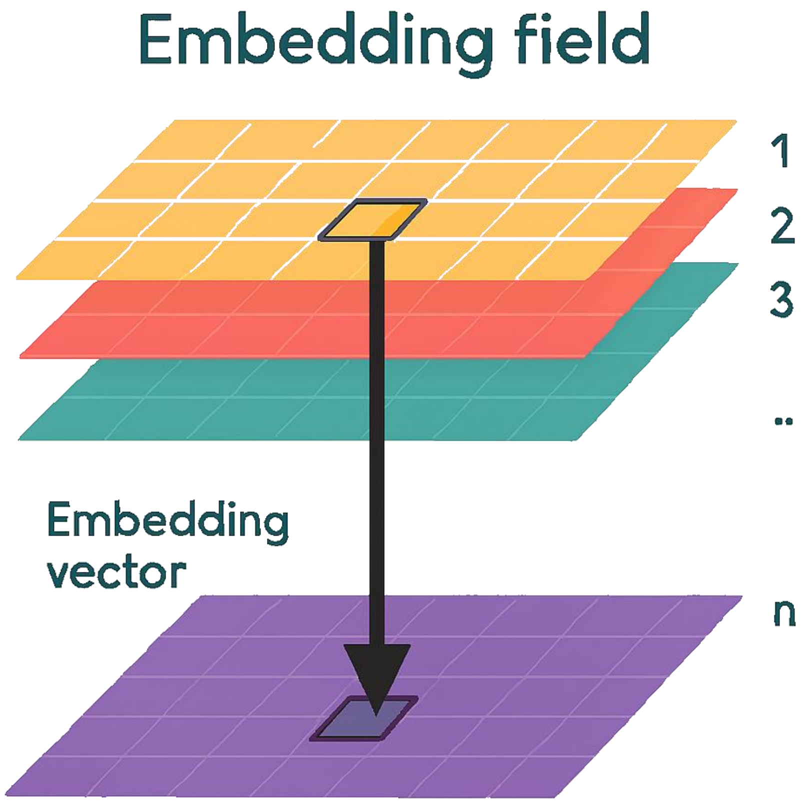


Source: Internet resources

3.3 AlphaEarth Foundations embedding dataset （AEF）

- Embedding means turning complex data into a small set of numbers that only **keep the essential information**, which makes them more **suitable for model training**.

- This is one of the early studies that applies embeddings to vacant house estimation.



Source: Internet resources

Training Data Sources for AlphaEarth Foundations Model

- Embedding is one of its products
- Not only visual appearance
- But also land use
- Environmental context
- Human activity patterns, etc.

Type	**Dataset**
Optical	Sentinel-2
Optical, Thermal	Landsat-8, Landsat-9
C-band SAR	Sentinel-1A, Sentinel-1B
L-band SAR	ALOS PALSAR ScanSAR
Elevation	Copernicus DEM
LiDAR	GEDI
Climate	ERA5-Land
Gravity fields	GRACE
Land cover	National Land Cover Database
Text	Wikipedia
Text	GBIF

4. Estimating Vacant Houses by Using Deep Learning

4.1 Label Construction

4.2 Model Input Construction

4.3 Model Training and Evaluation

4.1 Label Construction

Labels

	町名	建物棟数	空家等		特定空家等（空家等の内数）		特定空家等/空家等
			棟　数	割　合	棟　数	割　合	割　合
東央部	川原町	434棟	19棟	4.4%	3棟	0.7%	15.7%
	深堀町	1,515棟	72棟	4.8%	13棟	0.9%	18.0%
	駒場町	531棟	14棟	2.6%	0棟	0.0%	0.0%
	広野町	142棟	1棟	0.7%	0棟	0.0%	0.0%
	湯浜町	616棟	29棟	4.7%	7棟	1.1%	24.1%
	湯川町1丁目	589棟	35棟	5.9%	10棟	1.7%	28.5%
	花園町	793棟	21棟	2.6%	5棟	0.6%	23.8%
	湯川町2丁目の一部	618棟	43棟	7.0%	4棟	0.6%	9.3%
	湯川町3丁目の一部	195棟	9棟	4.6%	2棟	1.0%	22.2%
	日吉町3丁目の一部	25棟	2棟	8.0%	0棟	0.0%	0.0%
	根崎町の一部	26棟	2棟	7.7%	1棟	3.8%	50.0%
	地区計	5,484棟	247棟	4.5%	45棟	0.8%	18.2%

```
PROBLEMS 2    OUTPUT    DEBUG CONSOLE    TERMINAL    PORTS

196      字松川      472010721
197    松川一丁目    47201072201
198    松川二丁目    47201072202
199    松川三丁目    47201072203
200    三原一丁目    47201073001
201    三原二丁目    47201073002
202    三原三丁目    47201073003
203      字寄宮      472010741
204    寄宮一丁目    47201074201
205    寄宮二丁目    47201074202
206    寄宮三丁目    47201074203
207       None     472010750
208   住吉町一丁目   47201076001
209   住吉町二丁目   47201076002
210   住吉町三丁目   47201076003
211      字当間      472010770
212      字鏡水      472010780
213    松島一丁目    47201079001
214    松島二丁目    47201079002
215  おもろまち一丁目   47201080001
216  おもろまち二丁目   47201080002
217  おもろまち三丁目   47201080003
218  おもろまち四丁目   47201080004
yino@yinoAir ~ %
```

- To ensure consistency, directly extracted KEY_CODE from administrative boundary shapefiles.

4.1 Label Construction

- The survey data are provided at **three different levels of detail**.
- It is necessary to develop a method to transform them **into the same level.**
- Sheet 1: records **the number of vacant houses**
- Sheet 2: defines **the mapping between survey records and KEY_CODEs**.

City-level

prefecture	city	Vacant house
福井県	あわら市	619

District-level

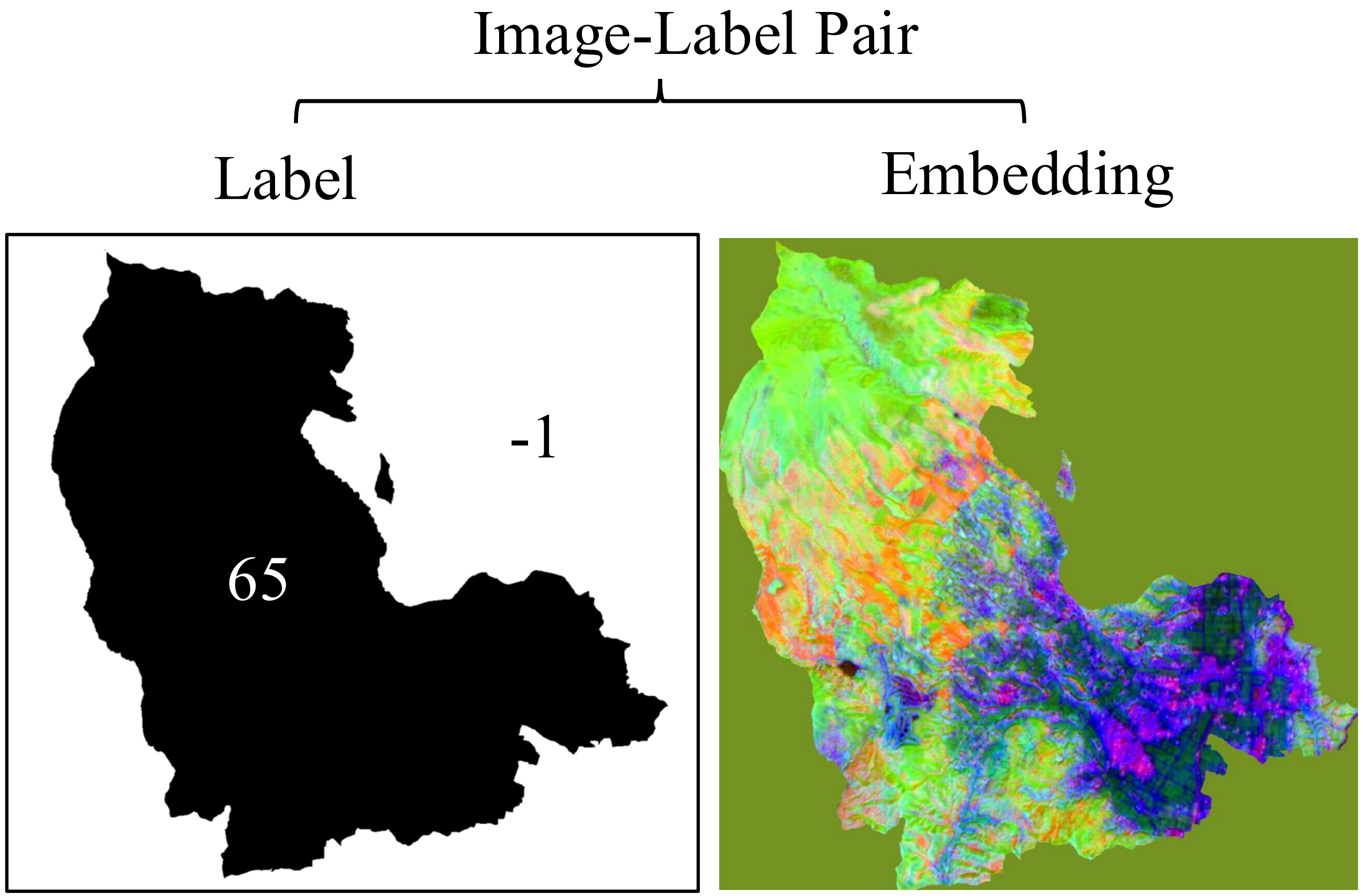
地区名	調査日	件数
韮崎地区	９月１１日	１１７件
穂坂地区	７月１２日	５１件
藤井地区	８月１０日	４２件

Chome-level

町名	建物棟数	空家等	
		棟　数	割　合
川原町	434棟	19棟	4.4%
深堀町	1,515棟	72棟	4.8%
駒場町	531棟	14棟	2.6%

4.2 Model Input Construction

- Each training sample is an image–label pair at the block level.
- For consistency, the **same suffix** is used:
- label_07322 , image_07322
- Imagery: **vacant house counts**
- Other areas: **-1**



Why a log(1 + x) transformation is necessary

Reducing label imbalance

- Vacant house counts are highly uneven, with many zeros and a few very large values. The log(1 + x) transformation reduces the influence of extreme values.

Preserving zero values

- Many blocks contain zero vacant houses, which are meaningful observations. Using log(1 + x) keeps zero values valid:

$$x = 0 \rightarrow \log(1) = 0$$

Vacant House Count

0

1

10

100

↓

Transformed Value

log(1) = 0.0000

log(2) = 0.6931

log(11) = 2.3979

log(101) = 4.6151

4.3 Model Training and Evaluation

Supervised Learning

- A supervised model learns only what the labels define.
- Each training sample is constructed as an image–label pair:

$$(x_i, y_i)$$

x_i: block-level satellite embedding representing the spatial pattern of the area
y_i: observed number of vacant houses within the block

4.3 Model Training and Evaluation

The model learns a regression function:

$$\hat{y}_i = f(x_i)$$

- Maps block-level patterns to a single number.
- This number represents the value of vacant houses.

Training reduced the difference between estimation and label:

$$\min \sum_i (\hat{y}_i - y_i)^2$$

4.3 Model Training and Evaluation

- This study focuses more on framework design rather than model accuracy
- chose ResNet-18 as a lightweight and stable baseline.

Regression Metrics

- MSE： Mean squared error, ≥0. Lower is better.
- MAE： Mean absolute error, ≥0. Lower is better.
- where y_i denotes the observed vacant house count for block i,
- $\hat{y}_i$ is the corresponding model prediction,
- and N is the number of validation samples.

$$\mathrm{MSE} = \frac{1}{N}\sum_{i=1}^{N}(\hat{y}_i - y_i)^2$$

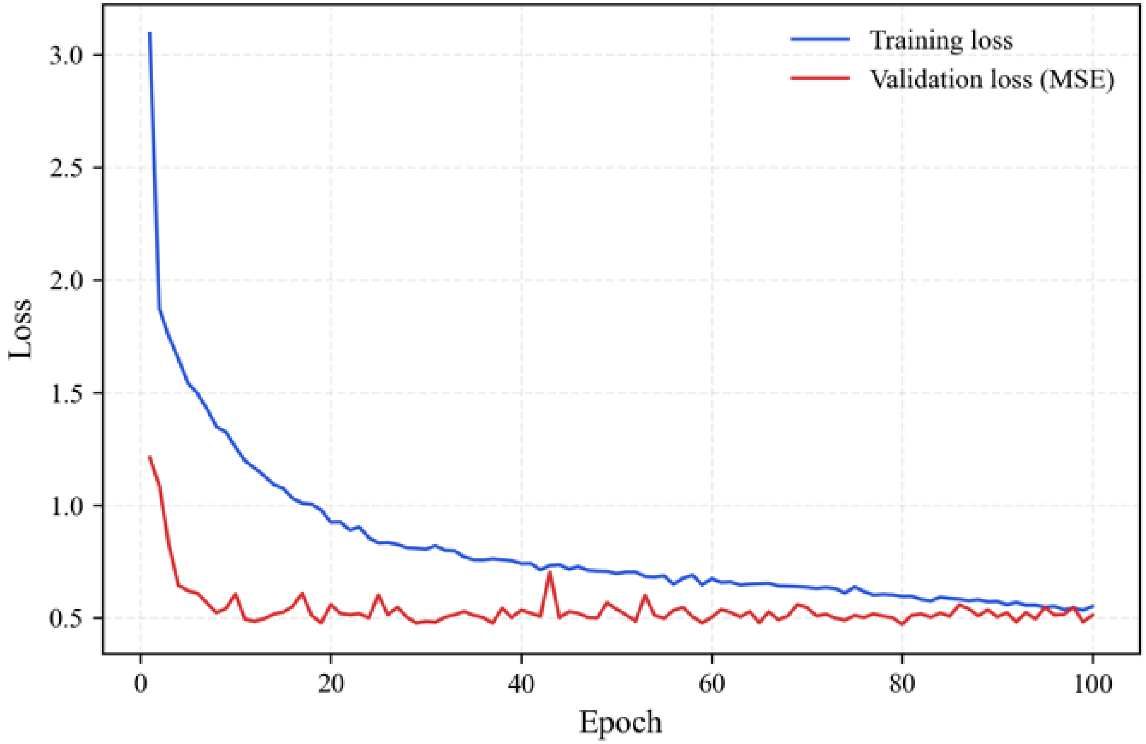
$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N}|\hat{y}_i - y_i|$$

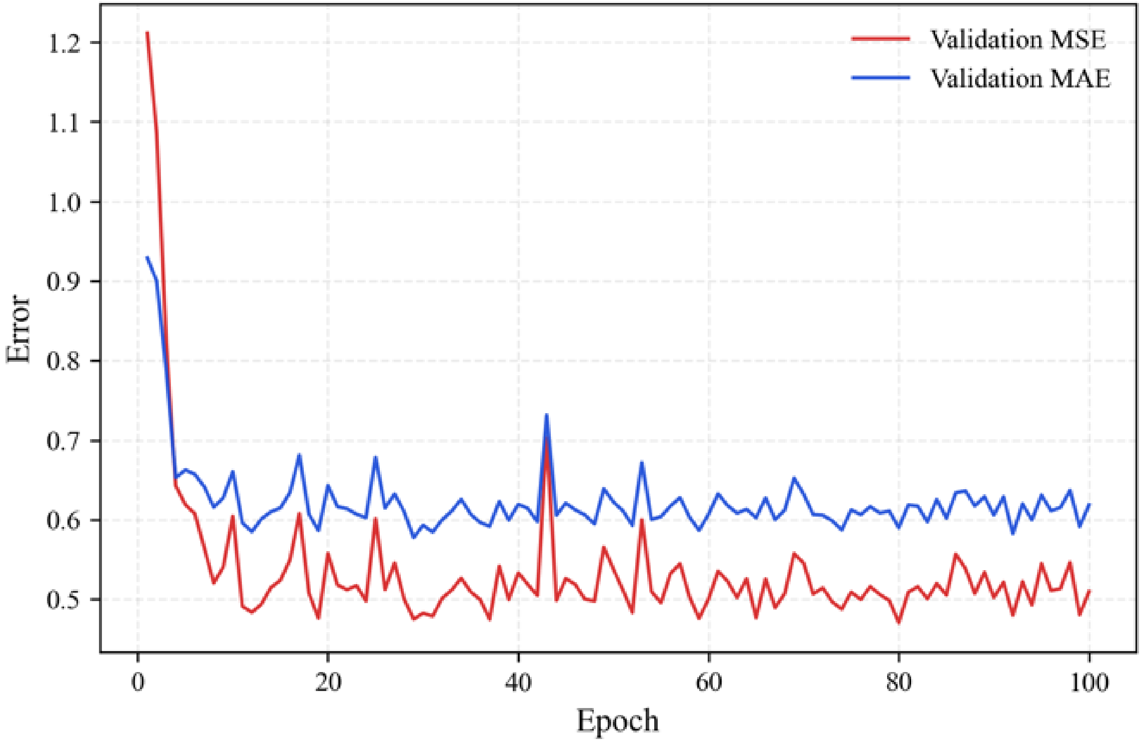
- R^2： Goodness of fit, $R^2 \leq 1$. Closer to 1 means better prediction
- where $\bar{y}$ is the mean of the observed vacant house counts.
  An R^2 value closer to 1 indicates stronger explanatory power,
- while values near 0 suggest limited predictive capability.

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{N}(y_i - \bar{y})^2}$$

4.3 Model Training and Evaluation

- The MSE is around 0.5, and the MAE is around 0.6.



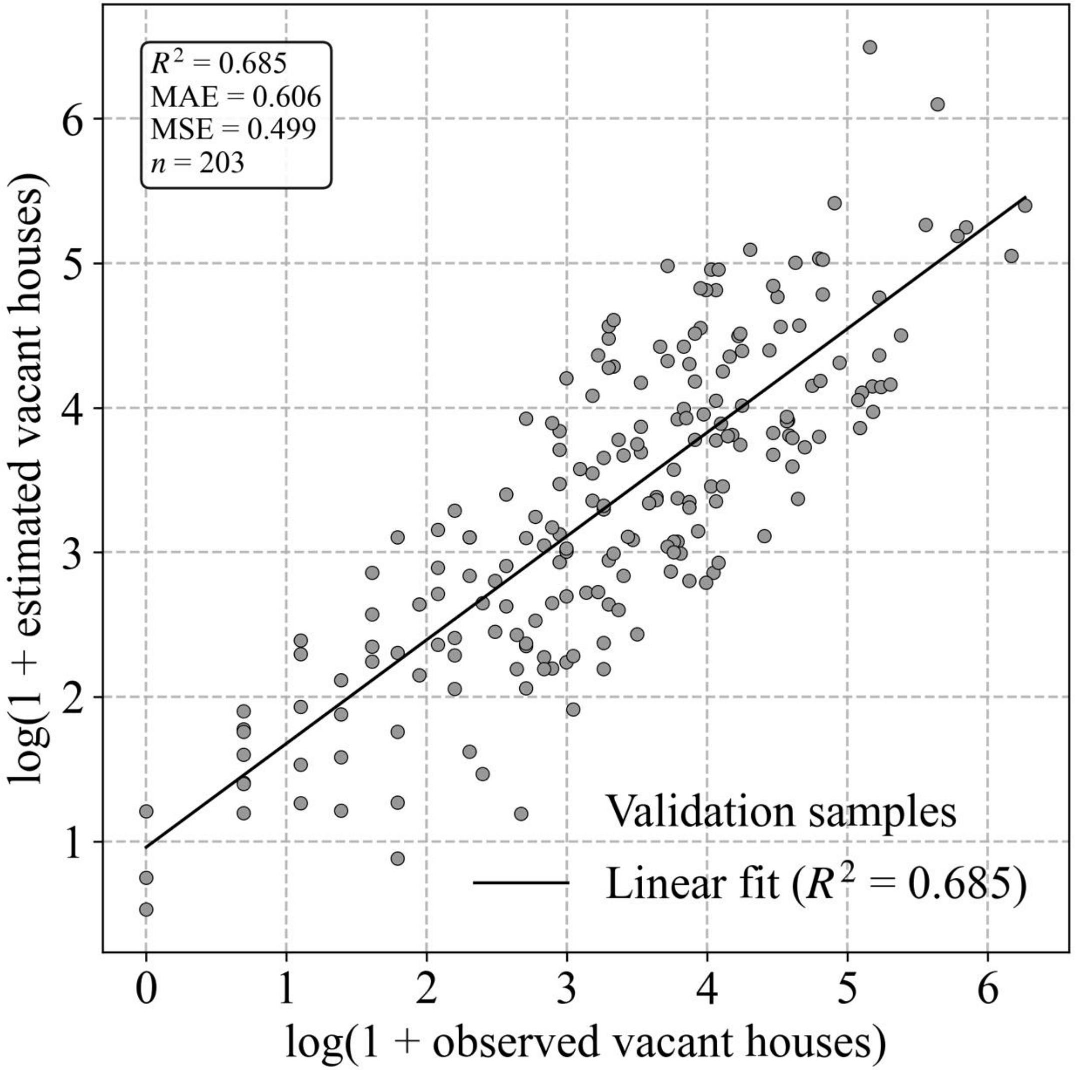


4.3 Model Training and Evaluation

- The input data **lack strong proxies** such as **water** or **electricity usage**

- A Model performance at the **block level** is stable and reasonable.

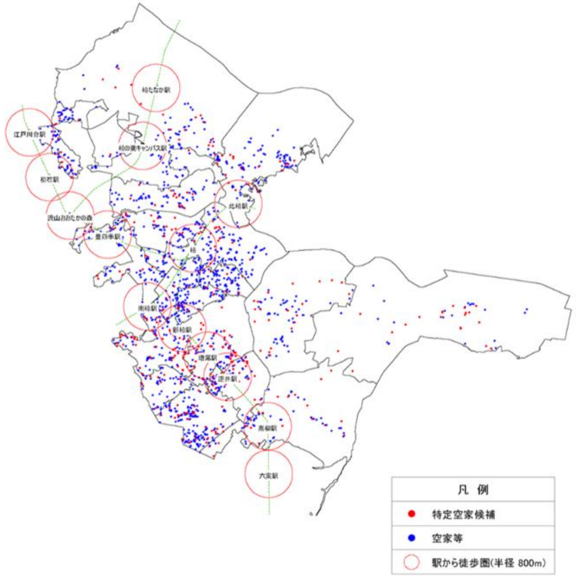
- An **R^2** of approximately **0.69 is reasonable**. Indicating that the model captures the dominant spatial variation in vacant house intensity across blocks.



5. Model Validation in Kashiwa City

5.1 Overview of vacant houses in Kashiwa city
5.2 Block-level estimation results in Kashiwa city
5.3 Error-based Pattern Analysis with Field Survey
5.4 Summary of Findings

5.1 Overview of vacant houses in Kashiwa

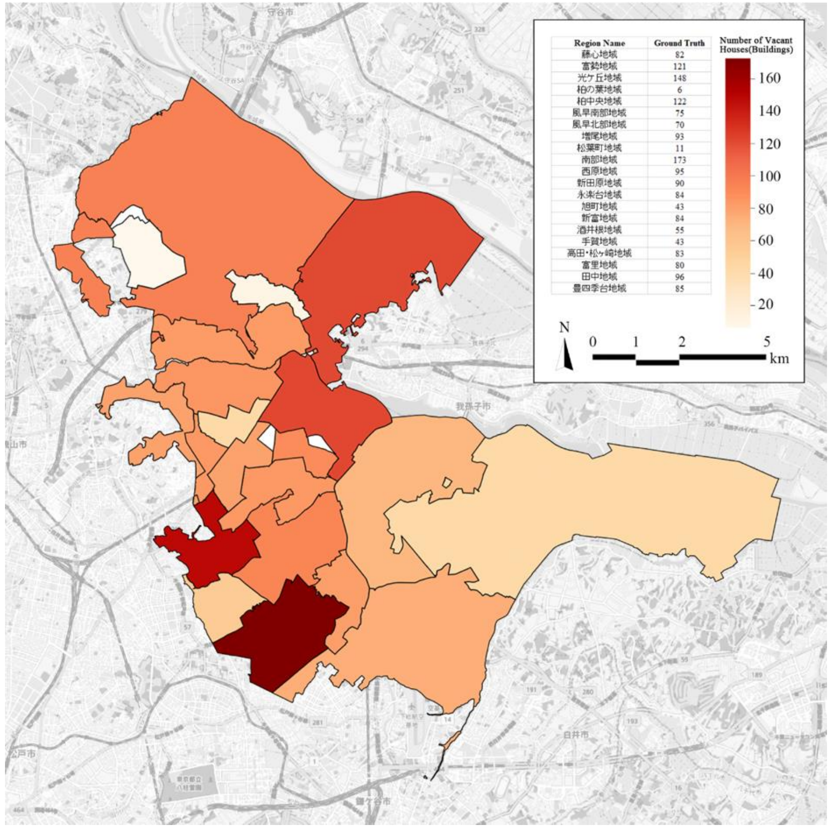


	空家等総数	空家等	特定空家等候補
平成２９年度	1,６３１件	1,４０５件 （８６.1％）	２２６件 （1３.９％）
令和４年度	1,７３９件	1,367 件 （７８.6％）	372 件 （２1.4％）
増　　減	+1０８件 （+６.６％）	−38 件 （−2.7％）	+146 件 （+64.6％）

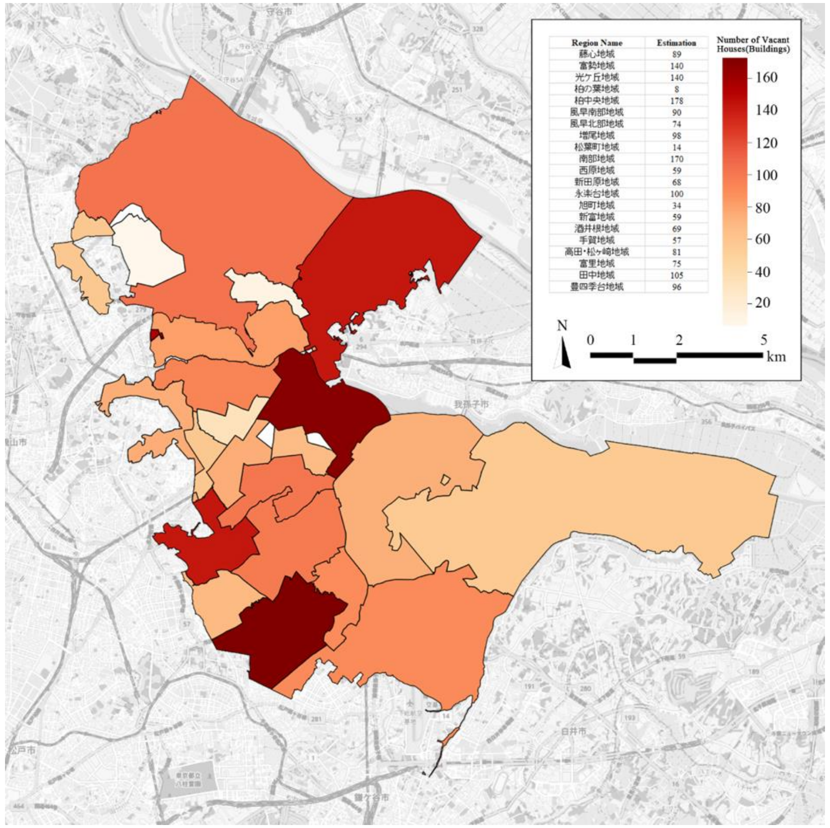
Source: Vacant House Condition Survey, Kashiwa City, 2023

- **A typical suburban city in Tokyo**
- **Common housing structures and vacancy patterns.**
- Suitable for testing **model generalizability** rather than case-specific performance.

Ground Truth



Model Estimation



- Captured the trend
- Similar overall color pattern
- Consistent hotspot locations

Region Name	Ground Truth	Estimation	Error
藤心地域	82	89	7
富勢地域	121	140	19
光ケ丘地域	148	140	-8
柏の葉地域	6	8	2
柏中央地域	122	178	56
風早南部地域	75	90	15
風早北部地域	70	74	4
増尾地域	93	98	5
松葉町地域	11	14	3
南部地域	173	170	-3
西原地域	95	59	-36
新田原地域	90	68	-22
永楽台地域	84	100	16
旭町地域	43	34	-9
新富地域	84	59	-25
酒井根地域	55	69	14
手賀地域	43	57	14
高田・松ヶ崎地域	83	81	-2
富里地域	80	75	-5
田中地域	96	105	9
豊四季台地域	85	96	11
Average:	82.81	85.90	13.57

Surveyed Areas

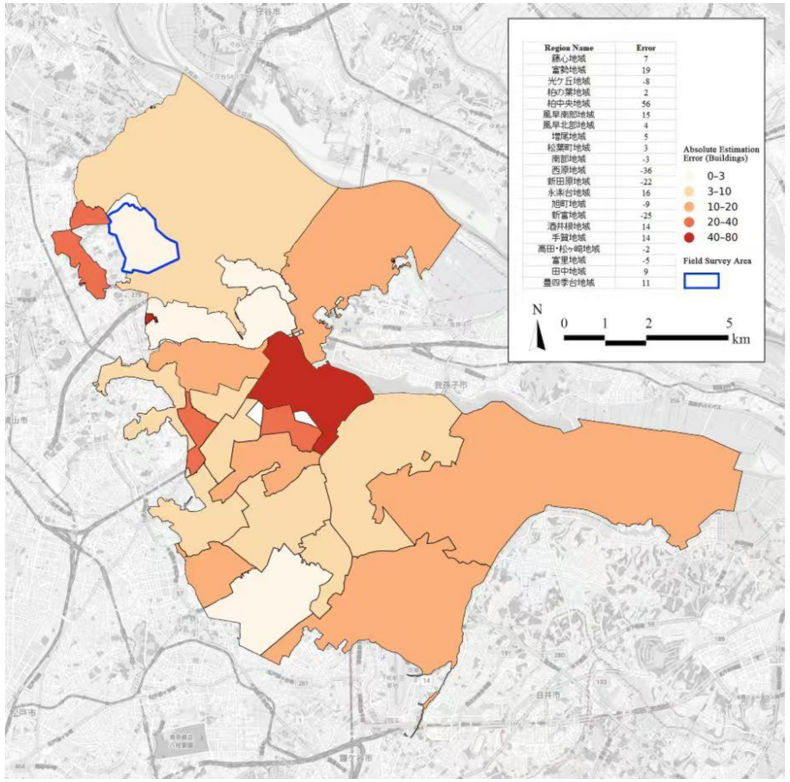
Correct Estimation
Kashiwanoha (3 vacant houses)

Small Error
Toyoshikidai (12 vacant houses)

Large Error
Kashiwa Chuo (15 vacant houses)

5.3.1 Correct Estimation： Kashiwanoha Area

Vacant Houses: Few



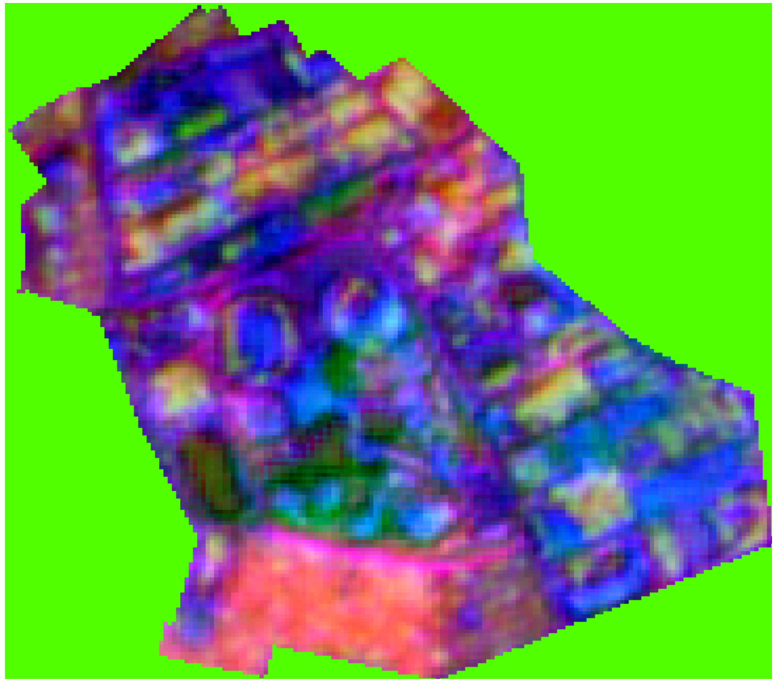
Spatial Patterns:

- Highly scattered distribution
- Low diversity in buildings

Interpretation:

- The model captures low-frequency, block-level patterns
- Such patterns match the model’s representation capacity

5.3.1 Correct Estimation： Kashiwanoha Area



Satellite embedding

Traditional satellite image

- **Low building density**
- **Simple structure**
- **Lead to a small number of vacant houses**

Ground-truth： 6
Estimation： 8
Error： +2

Sample 1	
Latitude: 35.890671	Longitude: 139.244845

Plan View (GIS-based) and Field Photo Location

Sample 2	
Latitude: 35.886847	Longitude: 139.939422

Plan View (GIS-based) and Field Photo Location

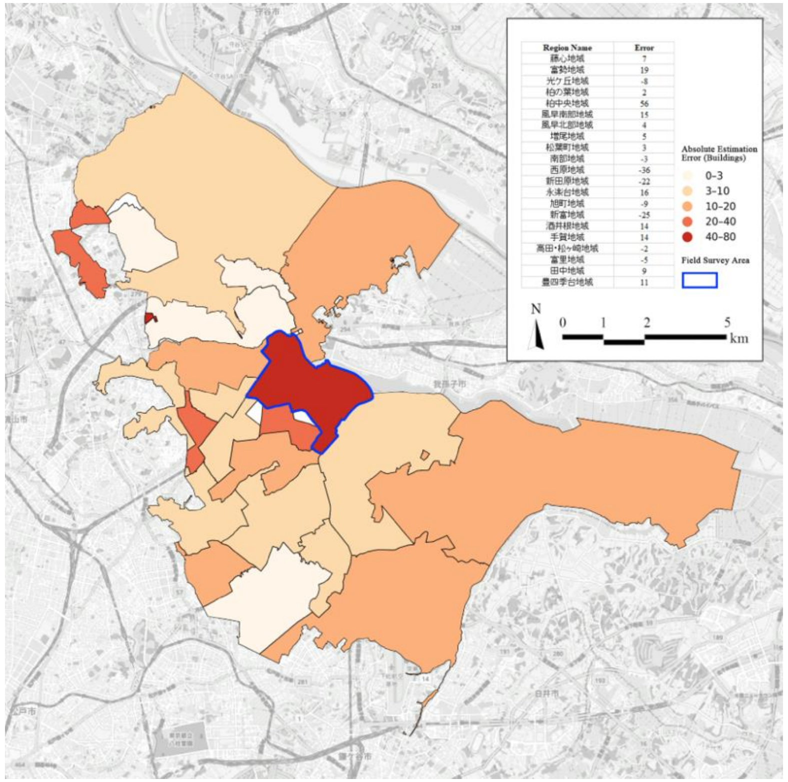
Sample 3	
Latitude: 35.879916	Longitude: 139.940622

Plan View (GIS-based) and Field Photo Location

Many human activity   Well-maintained surroundings

5.3.3 Large Error： Kashiwa Chuo Area

Vacant Houses: Many



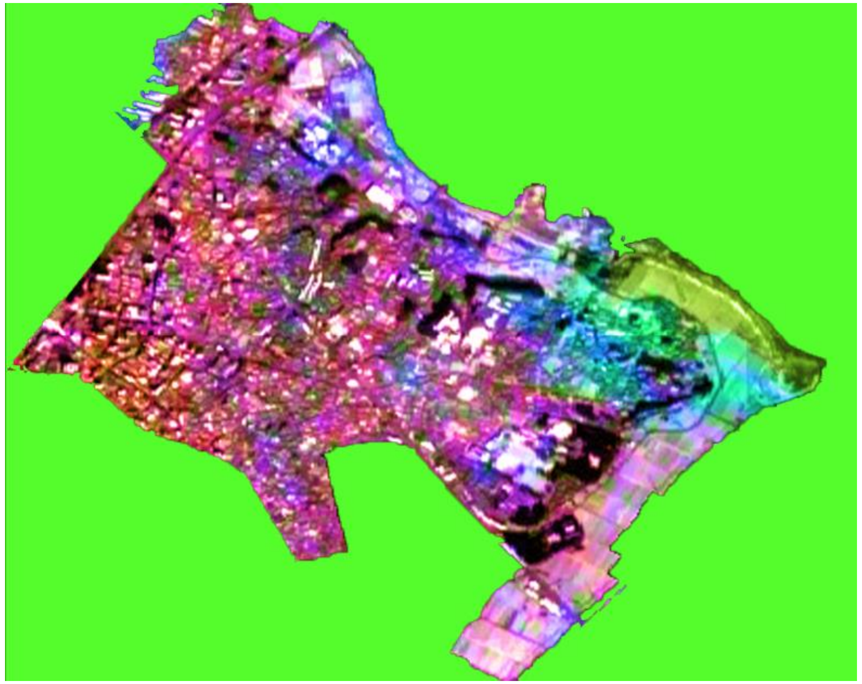
Spatial Patterns:

- Strong spatial clustering
- Homogeneous large-scale residential areas
- High vacancy concentration

Interpretation:

- High-frequency local patterns dominate
- Block-level aggregation amplifies local bias
- Spatial patterns exceed the model’s representation capacity

5.3.3 Large Error： Kashiwa Chuo Area


Satellite embedding


Traditional satellite image

High building density
Complex structure

Ground-truth： 122
Estimation： 178
Error： +56

Sample 12	
Latitude: 35.854069	Longitude: 139.993024
Plan View (GIS-based) and Field Photo Location 	
	

Sample 14	
Latitude: 35.8542966	Longitude: 139.9909842
Plan View (GIS-based) and Field Photo Location 	
	

Sample 16	
Latitude: 35.8557305	Longitude: 139.9868279
Plan View (GIS-based) and Field Photo Location 	
	

Dense buildings

Narrow streets

Mixed land use

5.4 Summary of Findings

Input dataset: Embeddings

contain block-level spatial information, including

- land use
- building density
- human activity pattern
- surrounding environment etc.

Model: ResNet-18

- The architecture of ResNet-18 mainly capture low-frequency patterns
- Hard to handle complex information

5.4 Summary of Findings

Correct estimation

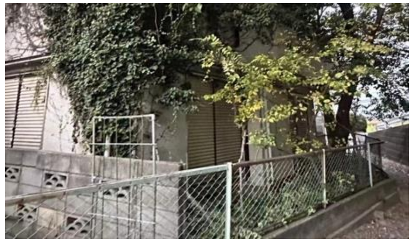
- low-density areas
- stable spatial patterns




Struggles in

- High-density
- Complex environments

Block-level aggregation also increase local errors

6. Conclusion and Future Strategy

Conclusion

- An open and free data-based framework for vacant house estimation at the block level in Japan.
- This study shows that satellite embeddings can be applied to vacant house estimation.

Limitations

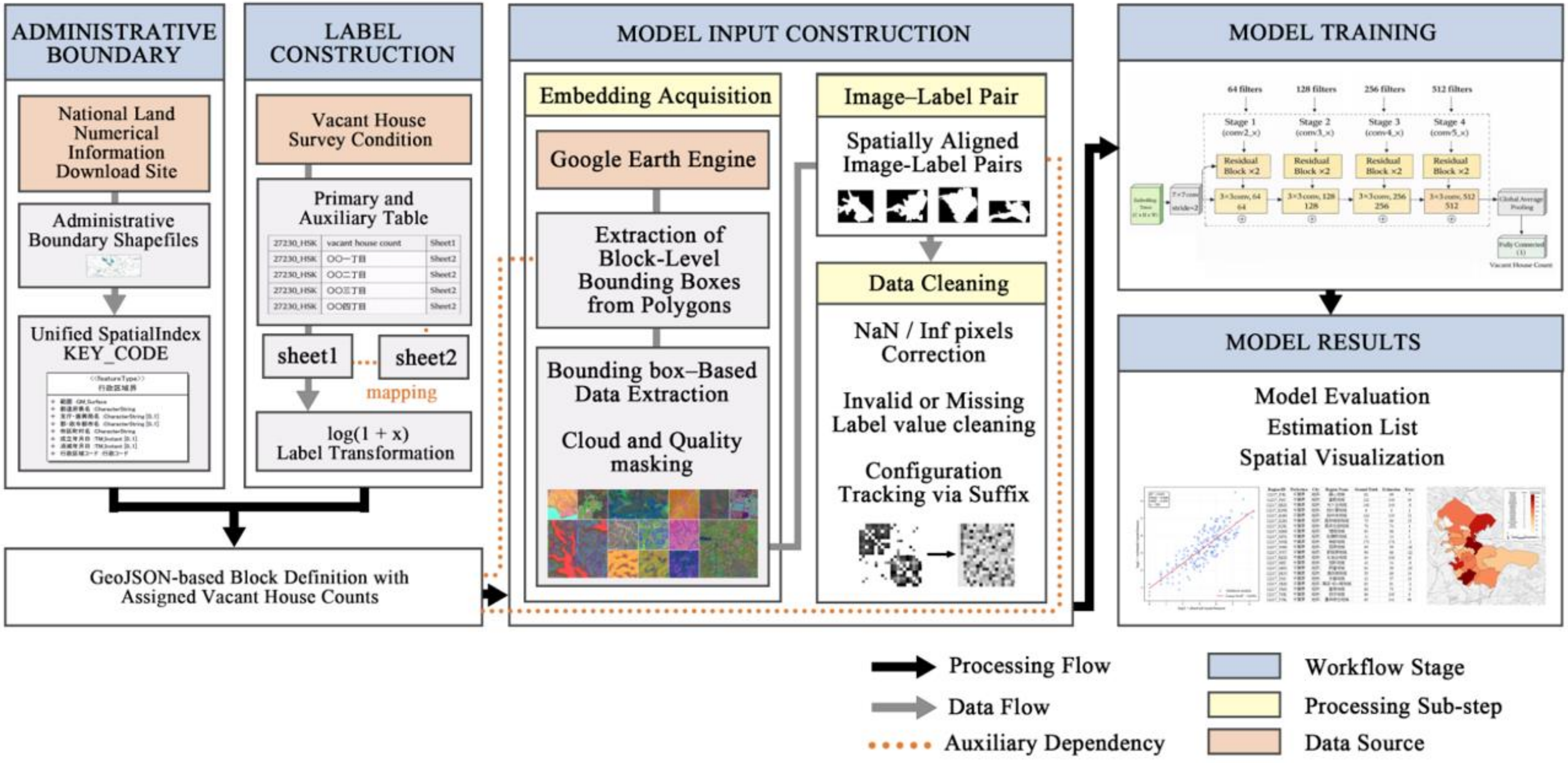
- Estimation limitations in accuracy.

Future Strategy

- Extend the framework to building-level estimation.
- Increase the amount of training data.
- Use more advanced models.

Supplementary Information

Framework


ADMINISTRATIVE BOUNDARY
National Land Numerical Information Download Site
Administrative Boundary Shapefiles
Unified SpatialIndex KEY_CODE
LABEL CONSTRUCTION
Vacant House Survey Condition
Primary and Auxiliary Table
sheet1
sheet2
mapping
log(1 + x) Label Transformation
GeoJSON-based Block Definition with Assigned Vacant House Counts
MODEL INPUT CONSTRUCTION
Embedding Acquisition
Google Earth Engine
Extraction of Block-Level Bounding Boxes from Polygons
Bounding box–Based Data Extraction
Cloud and Quality masking
Image–Label Pair
Spatially Aligned Image-Label Pairs
Data Cleaning
NaN / Inf pixels Correction
Invalid or Missing Label value cleaning
Configuration Tracking via Suffix
MODEL TRAINING
MODEL RESULTS
Model Evaluation
Estimation List
Spatial Visualization
Processing Flow
Data Flow
Auxiliary Dependency
Workflow Stage
Processing Sub-step
Data Source

Sheet 1 (Primary Table)

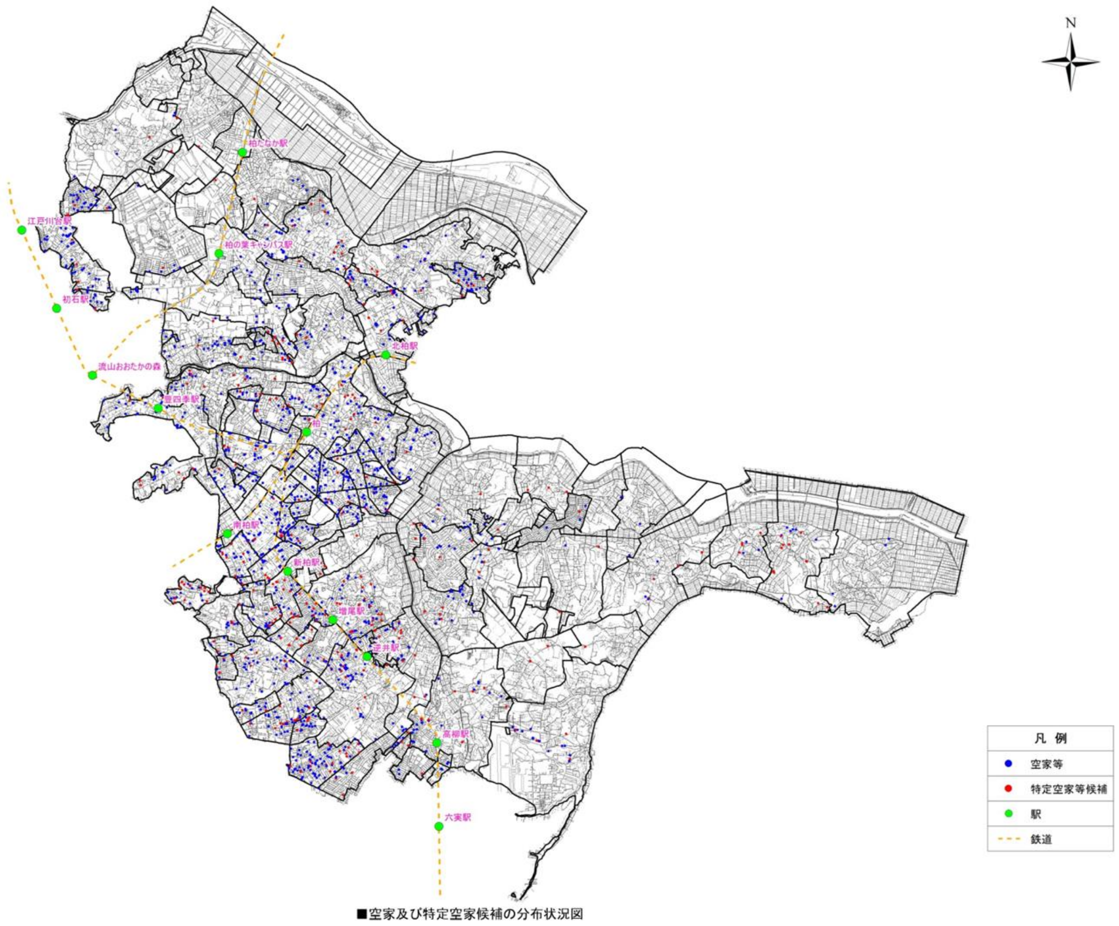
region_id	prefecture	city	region_name	region_type	vacant_count	survey_date	level_of_detail
11229	埼玉県	和光市	和光市	city	208	2022	2
28223_KSB	兵庫県	丹波市	柏原地域	district	177	2022	2.5
014060010	北海道	古平町	大字沖町	chome	12	2024	3

mapping

Sheet 2 (Auxiliary Table)

region_id	gis_code_name	gis_code	prefecture	city	region_name
11229	白子一丁目	11229001001	埼玉県	和光市	和光市
11229	白子二丁目	11229001002	埼玉県	和光市	和光市
11229	白子三丁目	11229001003	埼玉県	和光市	和光市
11229	白子四丁目	11229001004	埼玉県	和光市	和光市
…	…	…	…	…	…
28223_KSB	柏原町柏原屋敷	28223001001	兵庫県	丹波市	柏原地域
28223_KSB	柏原町柏原新町	28223001002	兵庫県	丹波市	柏原地域
28223_KSB	柏原町柏原古市場	28223001003	兵庫県	丹波市	柏原地域
…	…	…	…	…	…

5.3 Error-based Pattern Analysis with Field Surveys



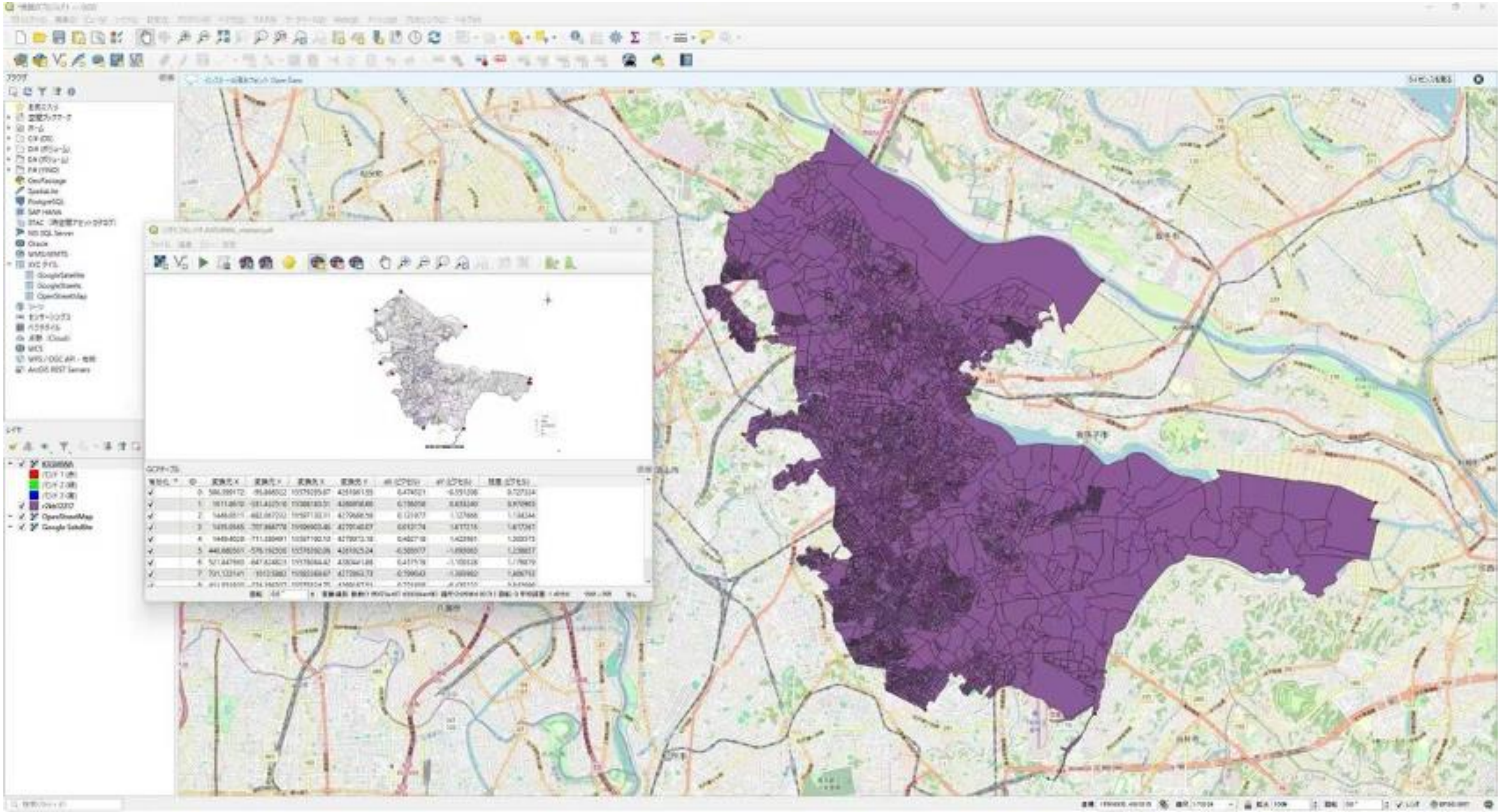
Source: Vacant House Condition Survey of Kashiwa City

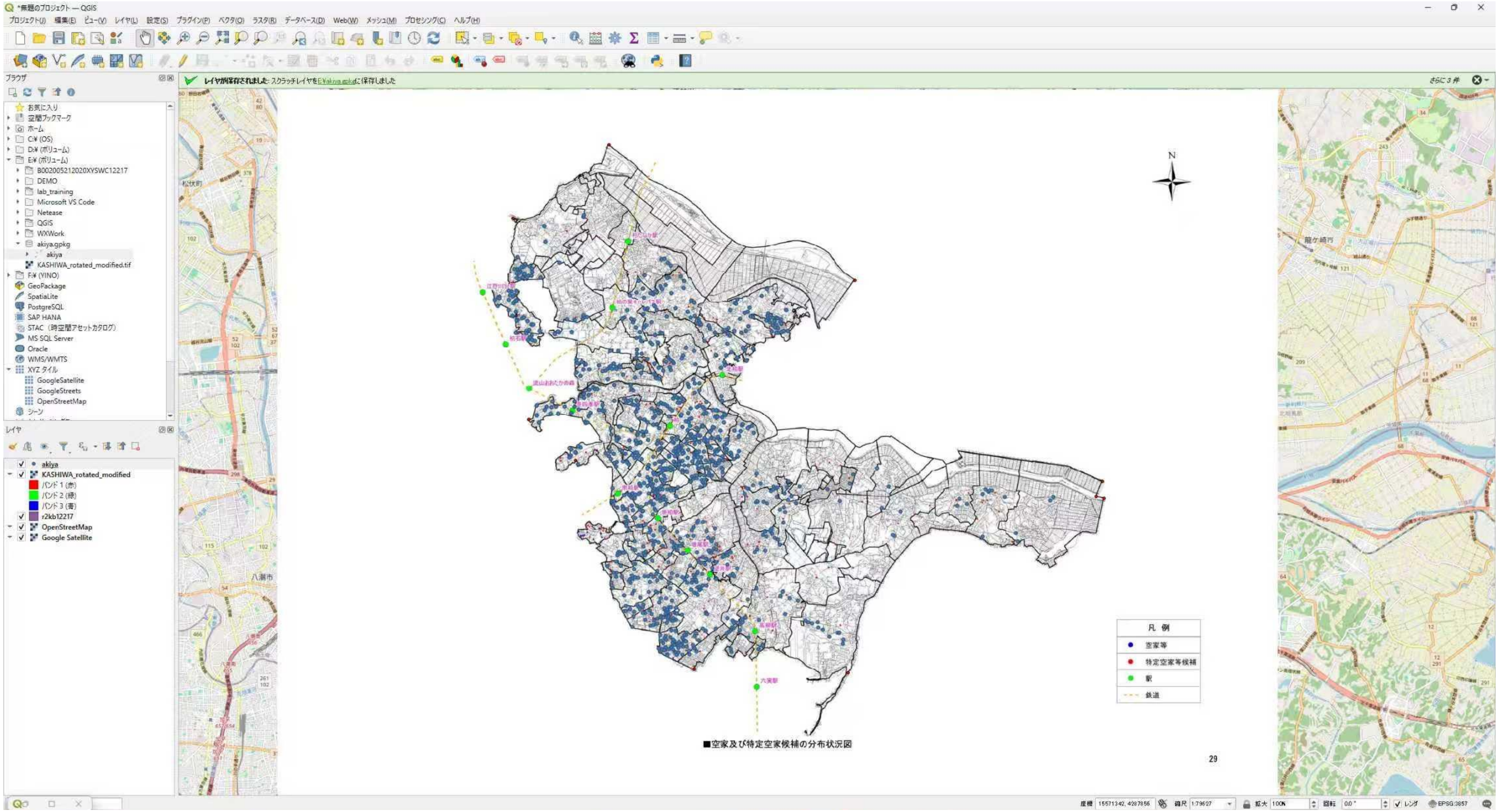
Photos are not used as model input

Purpose of Field Validation：

- Used to understand model errors and identify feature patterns.

- Identifying vacant houses that can be spatially located using GIS.




*無題のプロジェクト — QGIS
akiya
KASHIWA_rotated_modified
r2kb12217
OpenStreetMap
Google Satellite
N
凡 例
空家等
特定空家等候補
駅
鉄道
■空家及び特定空家候補の分布状況図
29