EV Charging Station Site Selection:
NAJU city with ML

We are JH-Faces, 지훈과얼굴들

07/03/2024 ~ 29/03/2024 (17 days)

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Team leader

Ji Geon, Park
Web App Dev

Ye Won, Lim
Data Analysis

Ji Hoon, Youn
QGis

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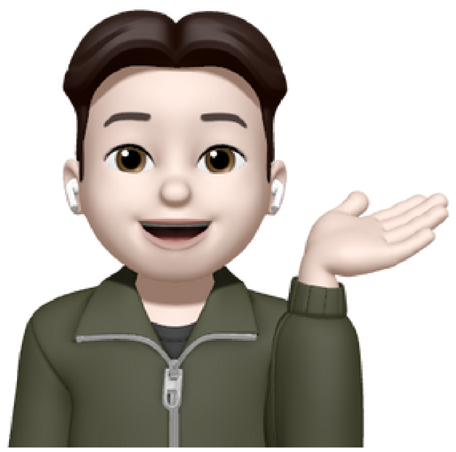

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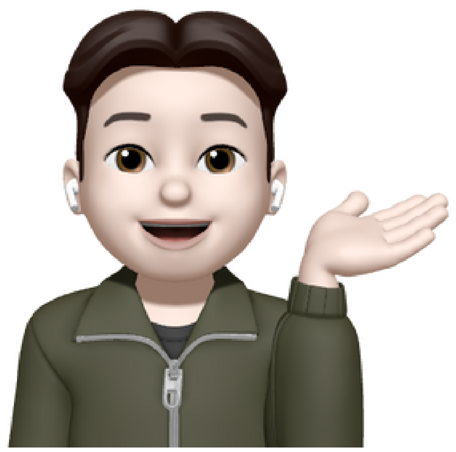

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Data Analysis

01 Analysis Overview

Why EV?

Insufficient EV charging stations

Compared to the high number of EV

Why EV?

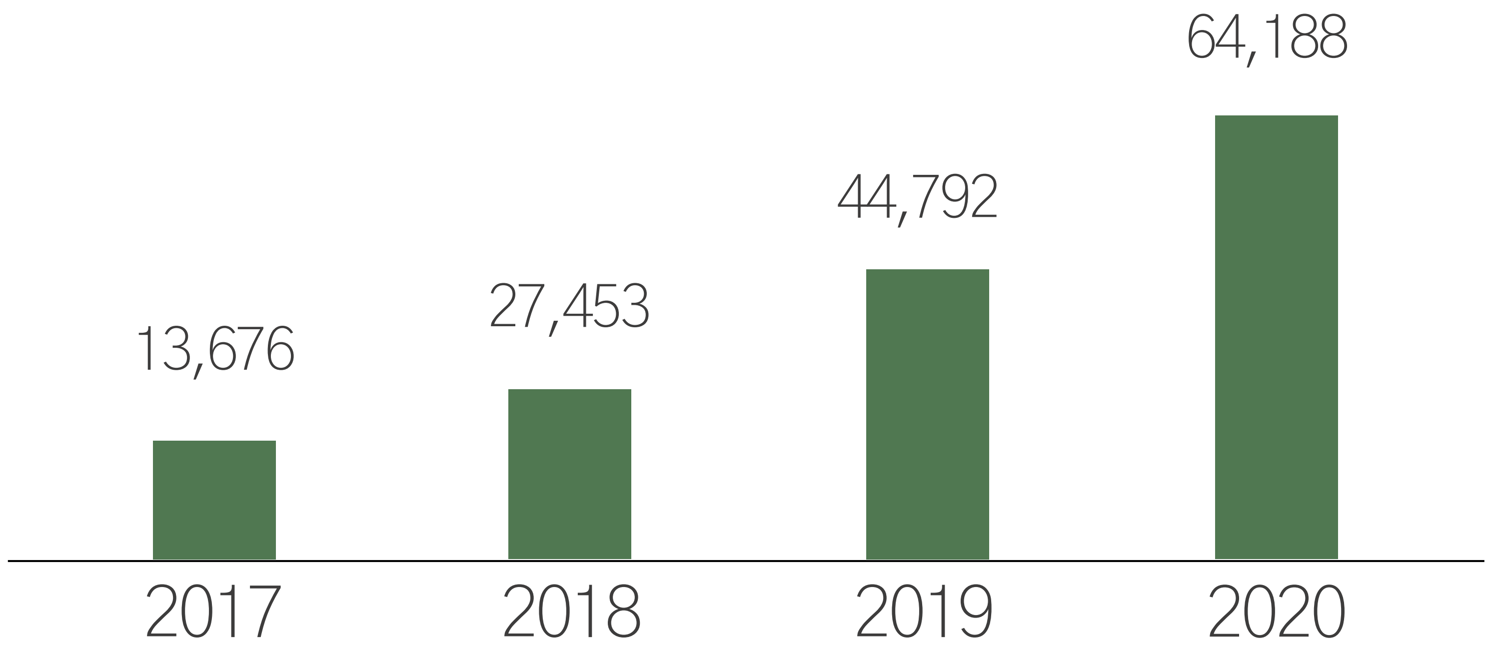
Insufficient EV charging stations

Compared to the high number of EV

Government policy

Massive installation plan for EV charging stations

Why EV?

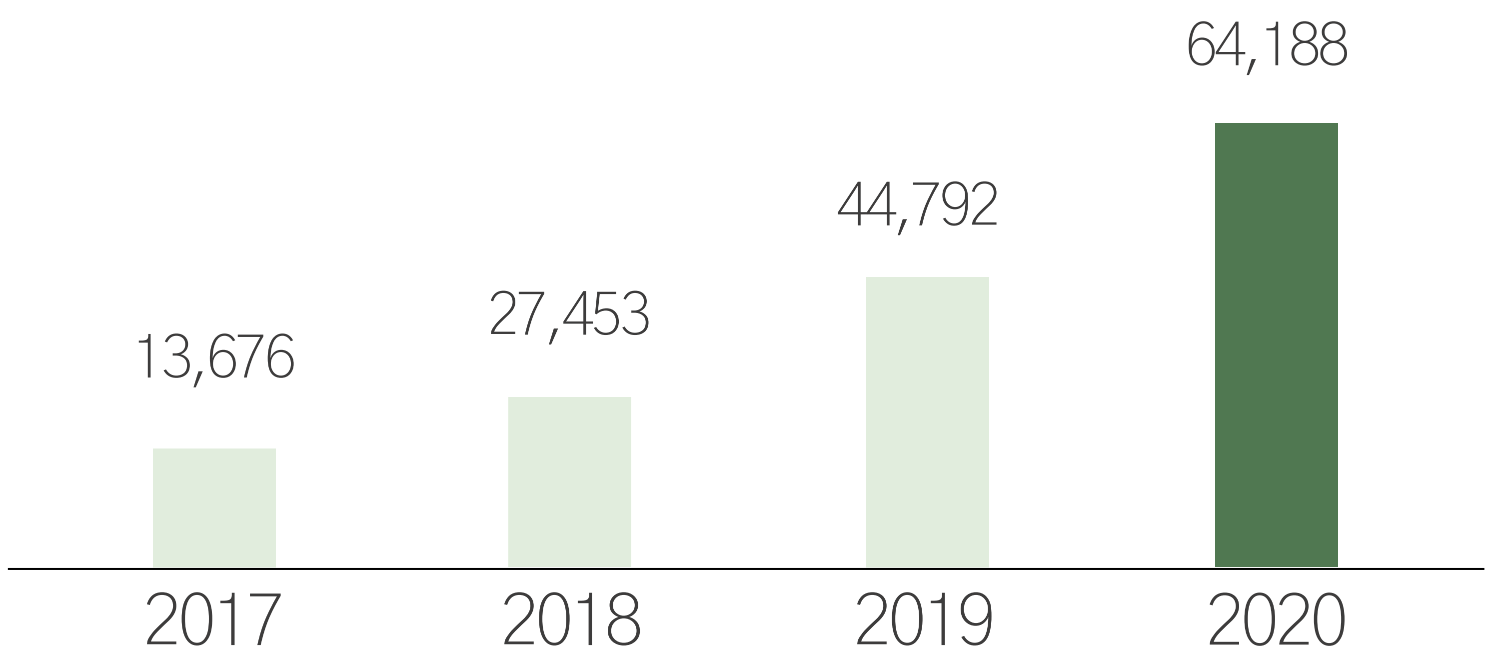


< Number of Electrical Cars >

The number of electric cars has increased FOUR-fold since 2017.

Source : Silly! The answer to EV charging infrastructure is in apartments (TheScoop) / Policy News, South Korea

Why EV?



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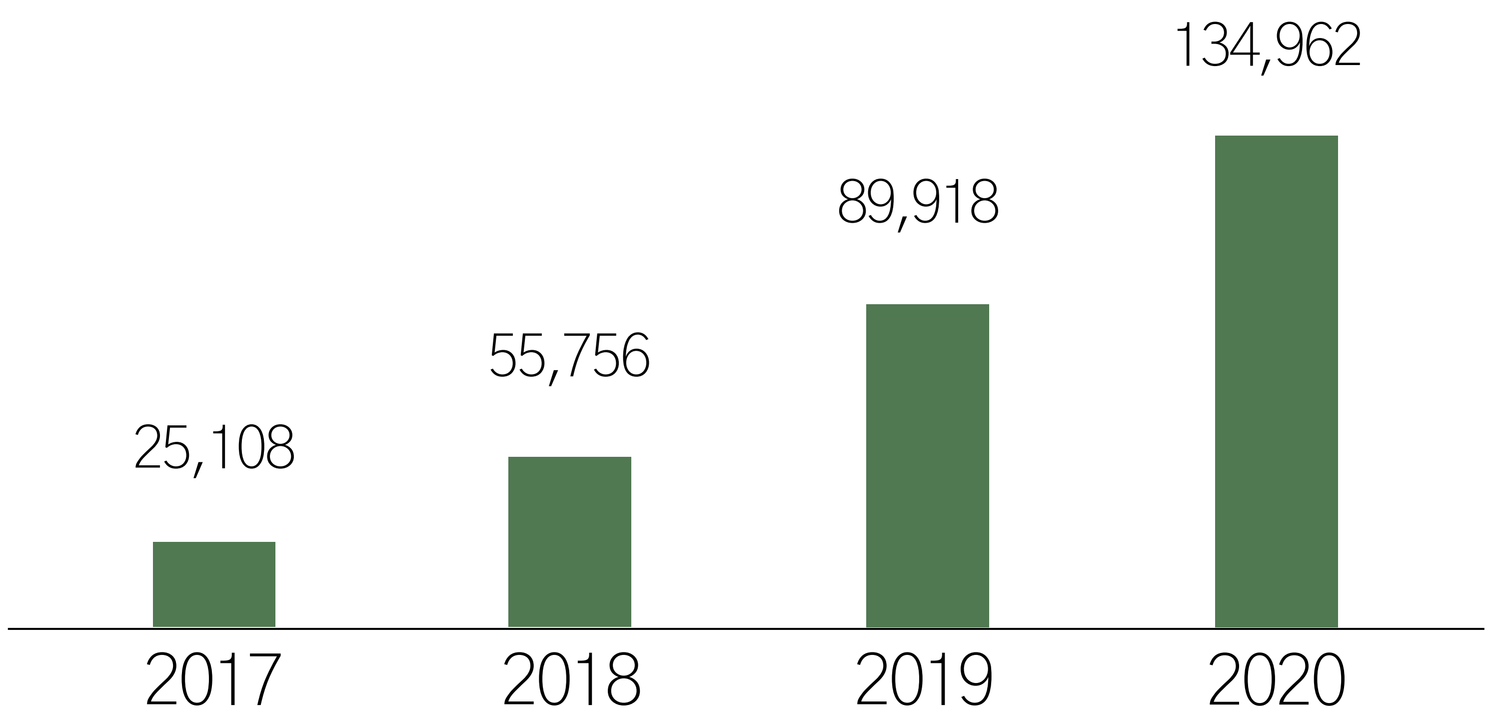
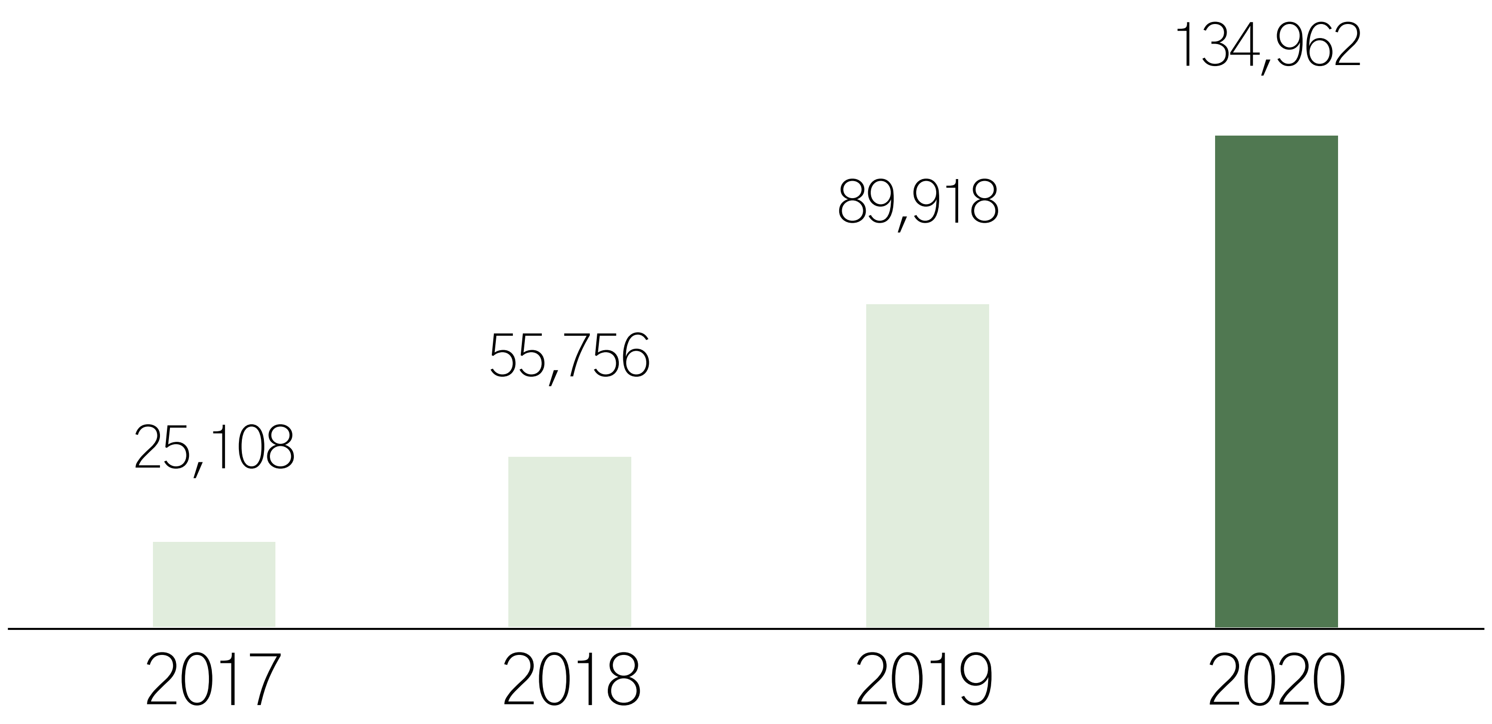


< Underperforming chargers vs. EV spread >

Chargers now handle over FIVE times more electric cars.

Source : Silly! The answer to EV charging infrastructure is in apartments (TheScoop) / Policy News, South Korea

Why EV?



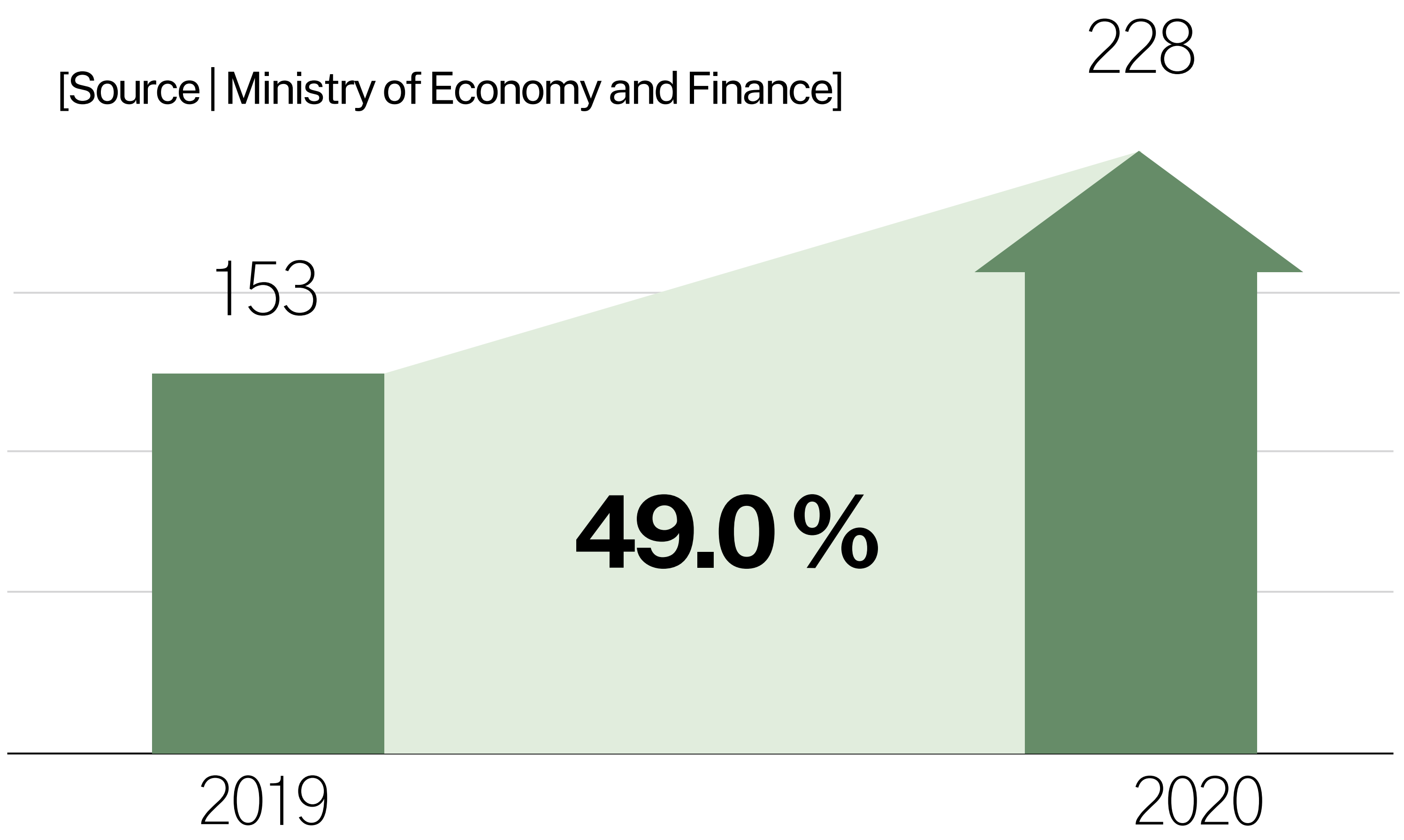
< Underperforming chargers vs. EV spread >

Chargers now handle over FIVE times more electric cars.

Source : Silly! The answer to EV charging infrastructure is in apartments (TheScoop) / Policy News, South Korea

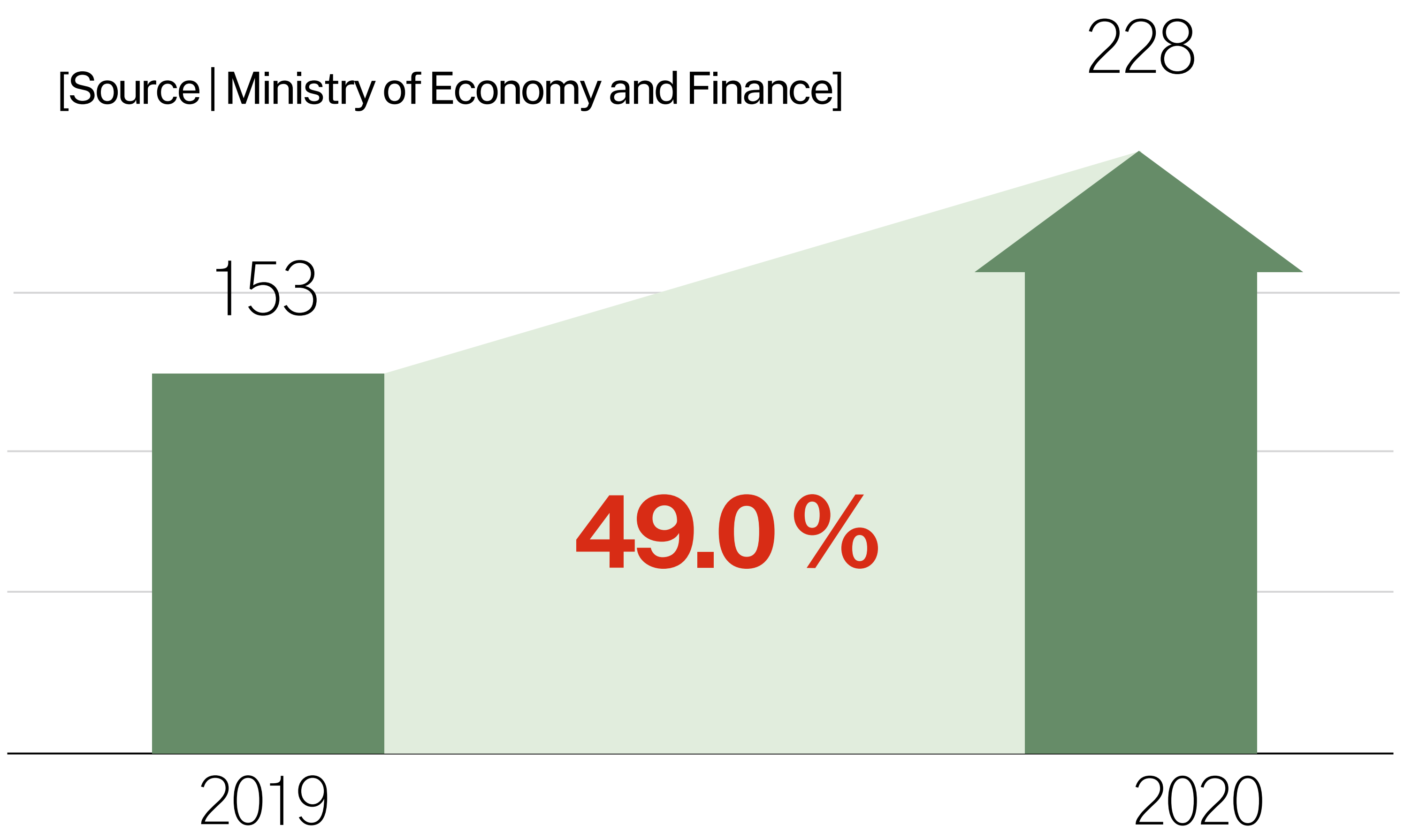
Why EV?

[Source | Ministry of Economy and Finance]



< Rapidly increased complaints regarding EV charger>

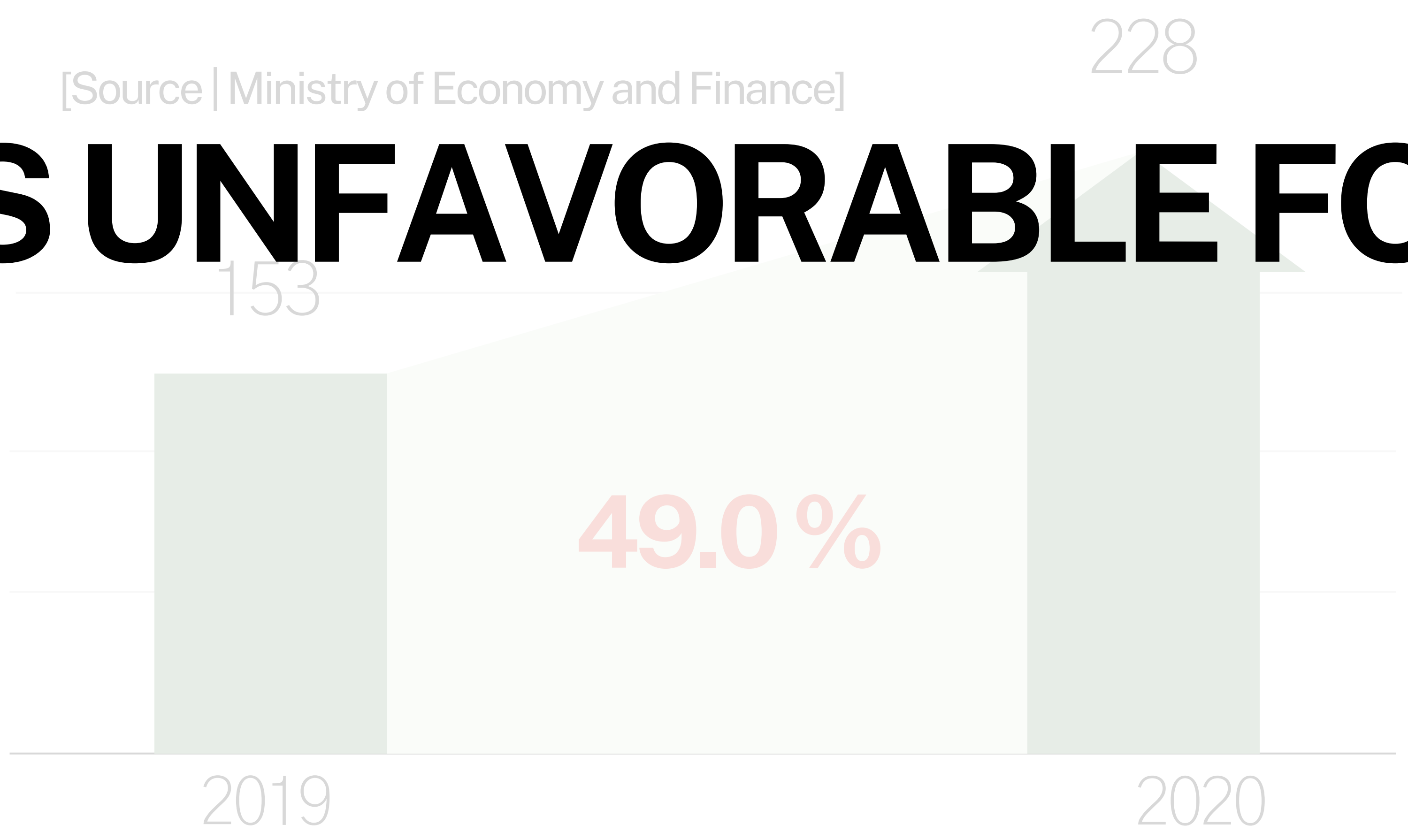
Why EV?



< Rapidly increased complaints regarding EV charger >

Why EV?

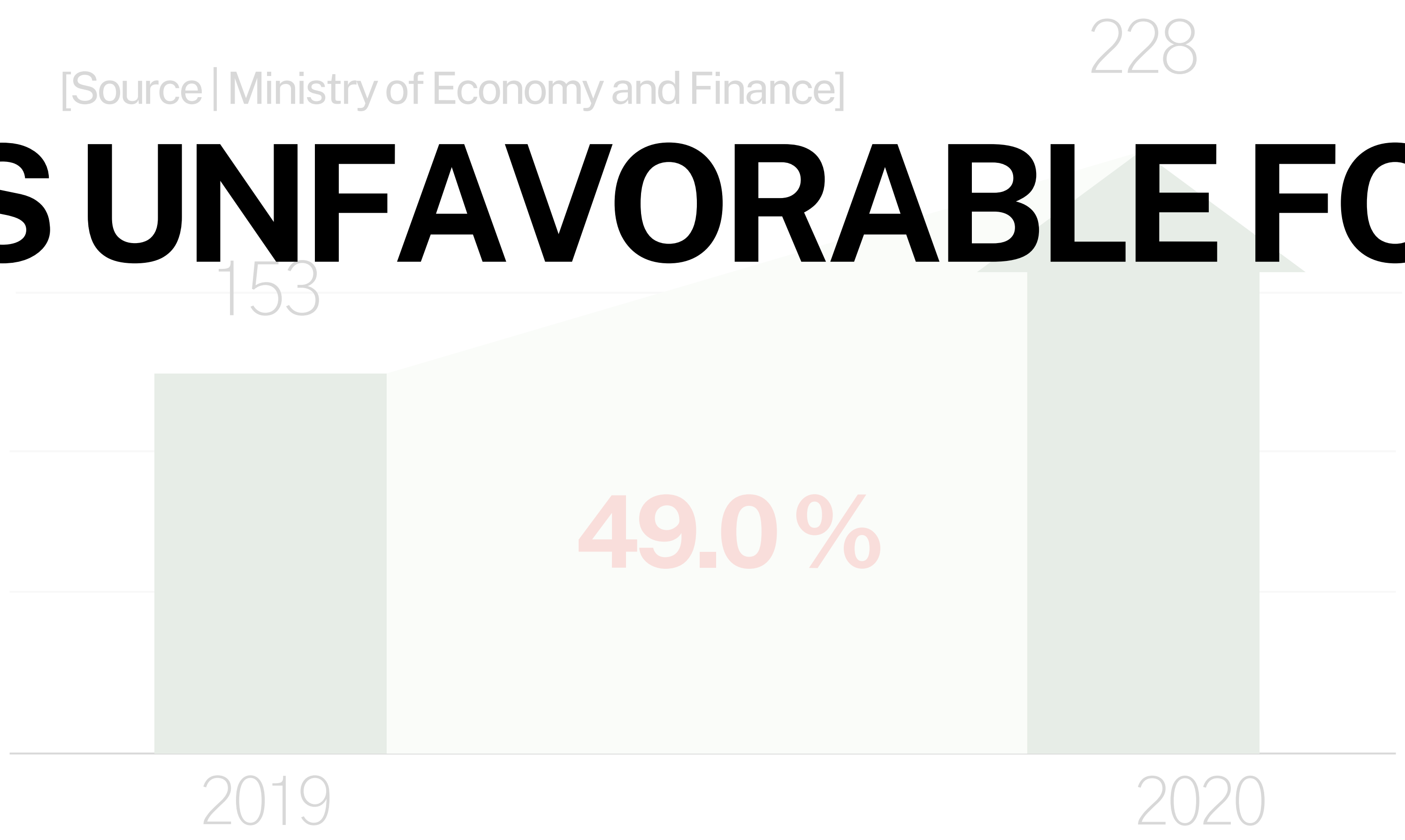
IT IS UNFAVORABLE FOR



< Rapidly increased complaints regarding EV charger >

Why EV?

IT IS UNFAVORABLE FOR COMPANY



< Rapidly increased complaints regarding EV charger >

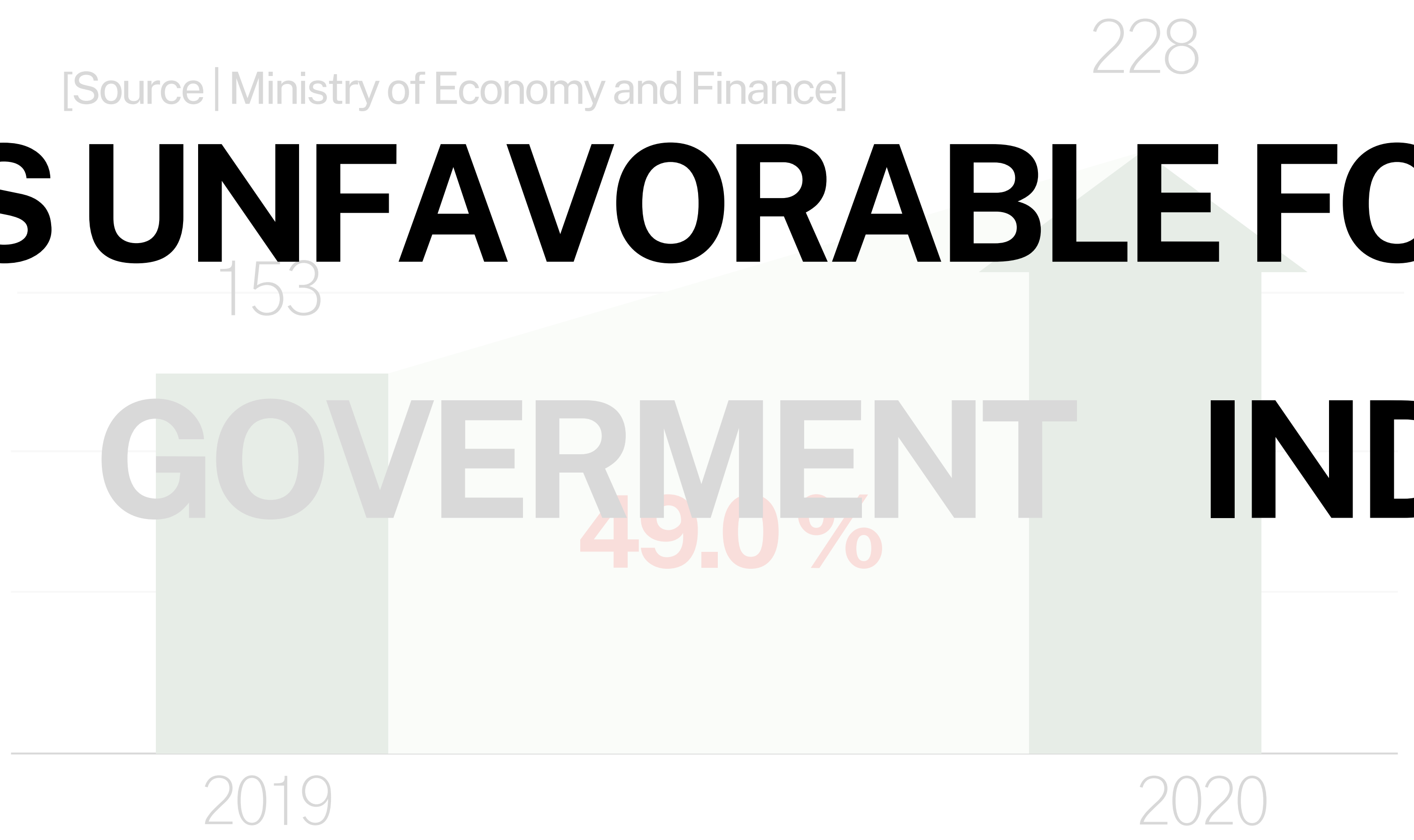
Why EV?

IT IS UNFAVORABLE FOR GOVERMENT

COMPANY

< Rapidly increased complaints regarding EV charger >

Why EV?



IT IS UNFAVORABLE FOR

COMPANY GOVERMENT **INDIVIDUAL.**

< Rapidly increased complaints regarding EV charger >

Why EV?

IT IS UNFAVORABLE FOR

COMPANY **GOVERMENT** INDIVIDUAL.

< Rapidly increased complaints regarding EV charger >

Why EV?

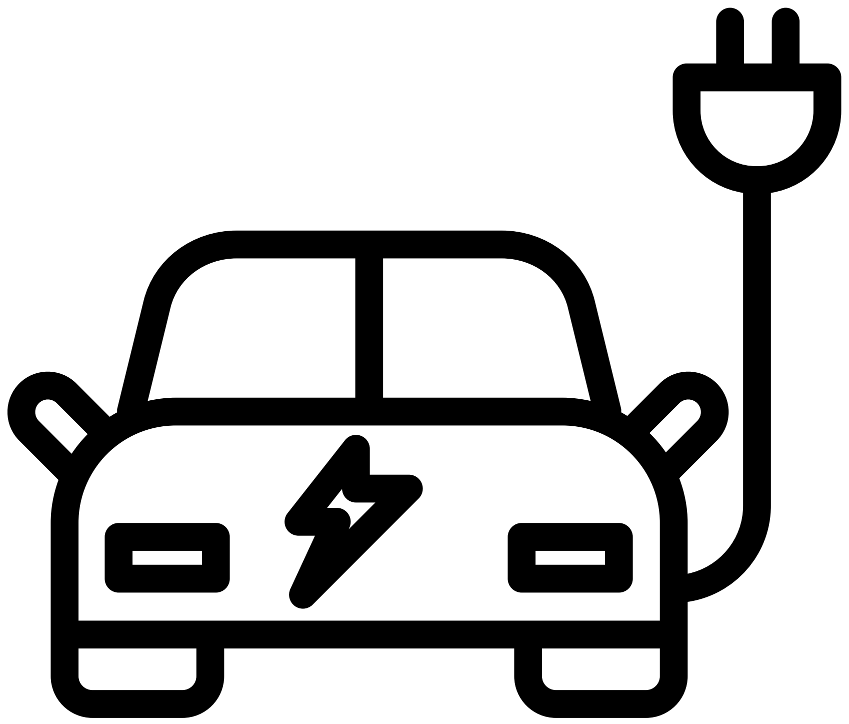
IT IS UNFAVORABLE FOR

COMPANY

GOVERMENT has a Goal !

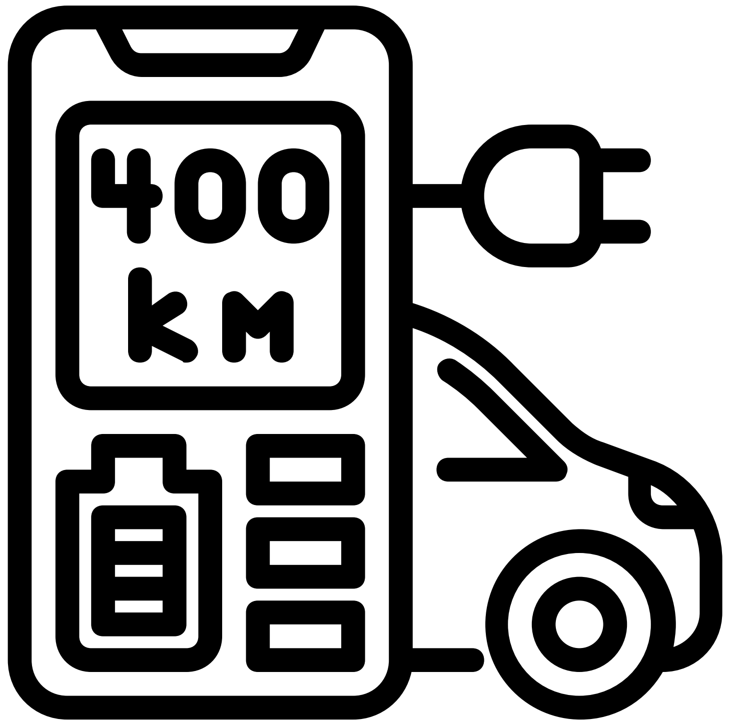
< Rapidly increased complaints regarding EV charger >

Why EV?



By 2030, the goverment plans to supply 4.2 M electirc vehicles.

Why EV?



By 2030, the goverment installs over 1.23 M electirc chargers.

NAJU

[Naju Innovation City 10 Years] 16 Public Institutions Settled...It has a population of 40,000.

Emergence of New Energy Industry Base..."To be a self-sufficient city full of pride".

(Naju = News 1) Reporter Park Young-rae

Comments

Naju Bitgaram Innovation City, which was developed as a Gwangju and Jeonnam, celebrated its 10th anniversary this year. With 16 public institutions, including KEPCO, moving in, the development, reality, and future vision of the innovative city, which has established itself as a base for new energy industries, will be divided into five sessions.

Source: https://www.news1.kr/articles/?5130974

NAJU

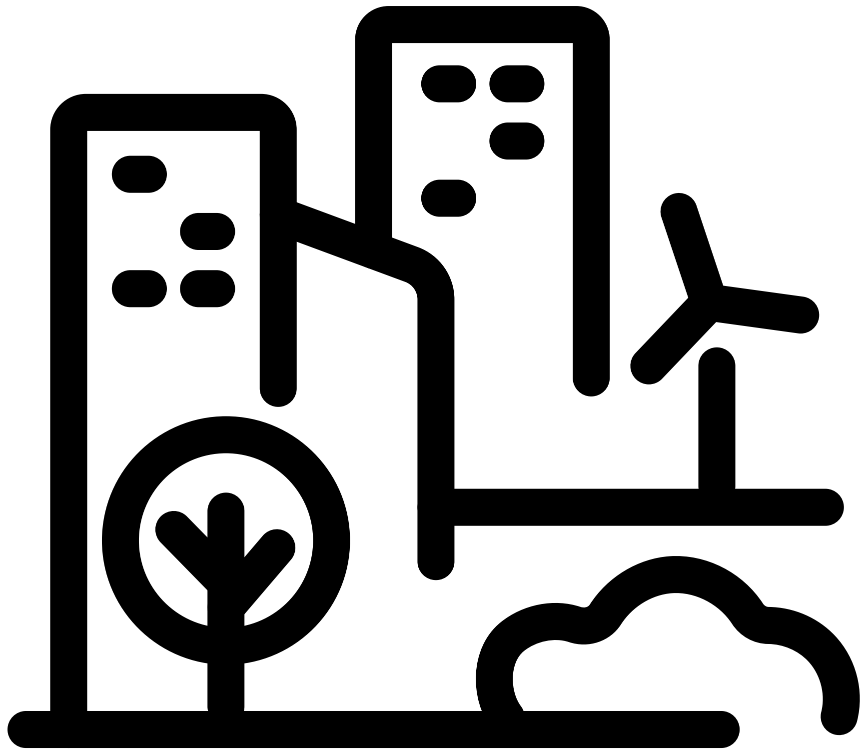
In 2004, Naju City became
an **Innovation City** under national planning.

Source: https://www.news1.kr/articles/?5130974

NAJU

Naju is the only area in Jeollanam-do Province with a growing population.

NAJU



For these reasons , We chose NAJU.

Objetives

To assist decision-makers

in selecting the optimal locations

for installing EV chargers

within Naju

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To assist decision-makers

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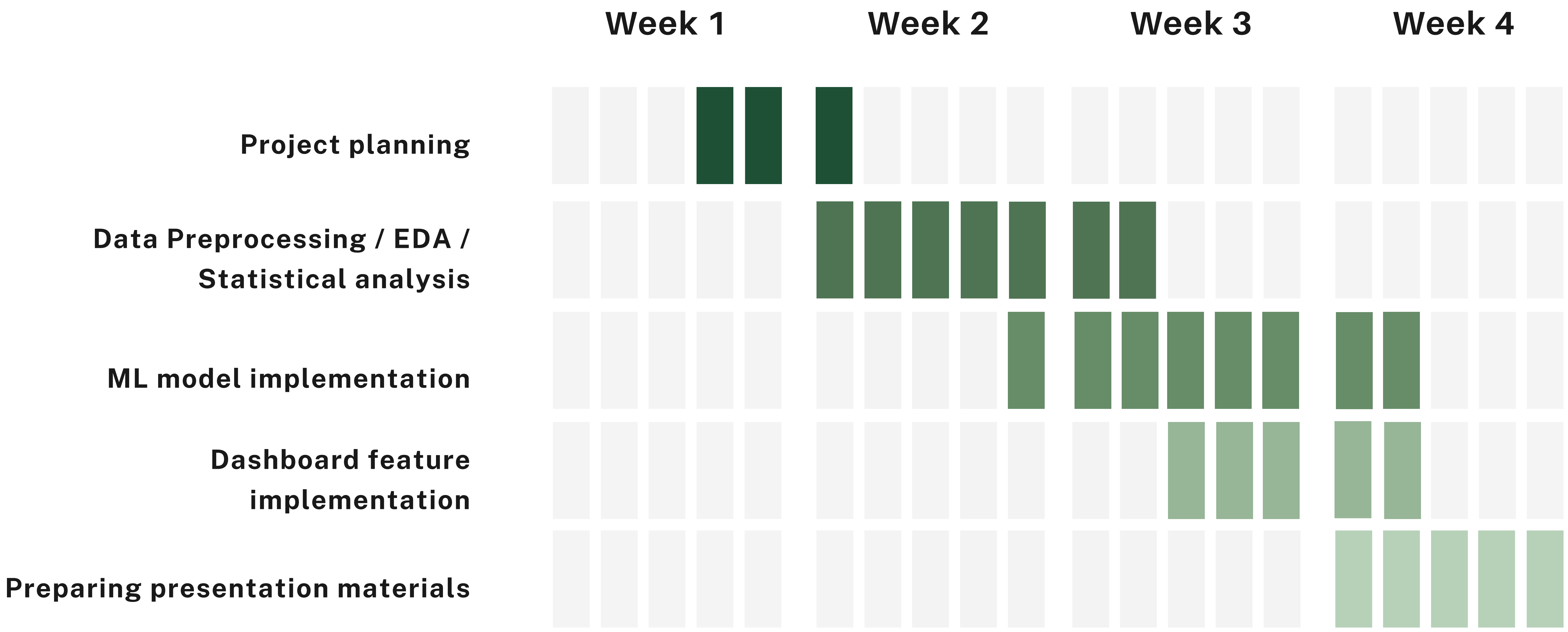
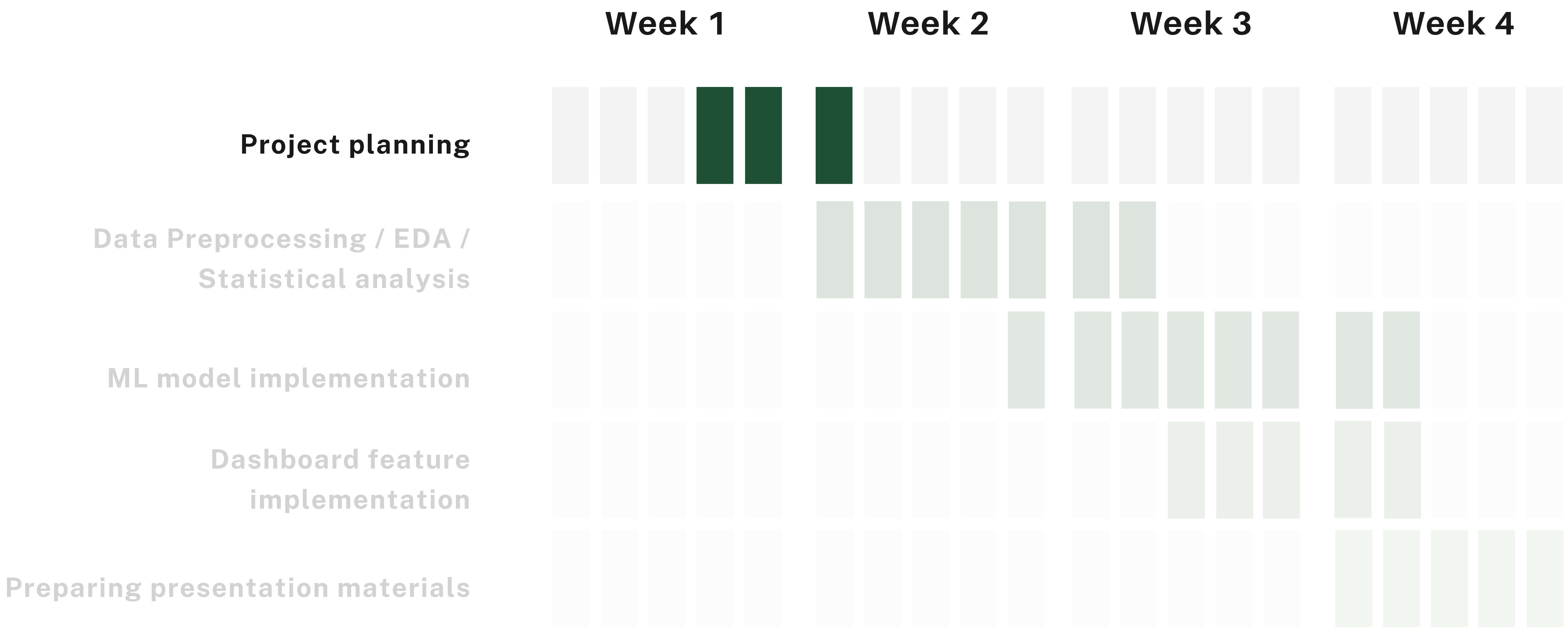
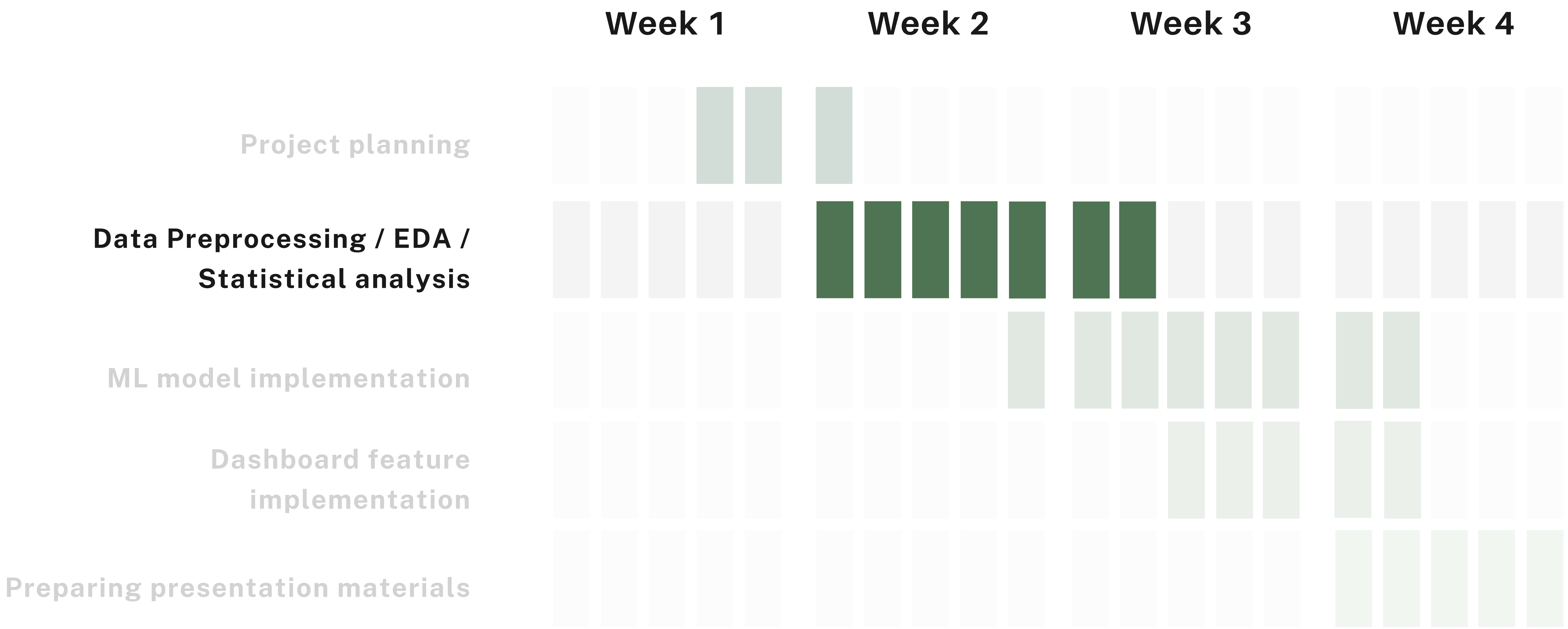
Work Process



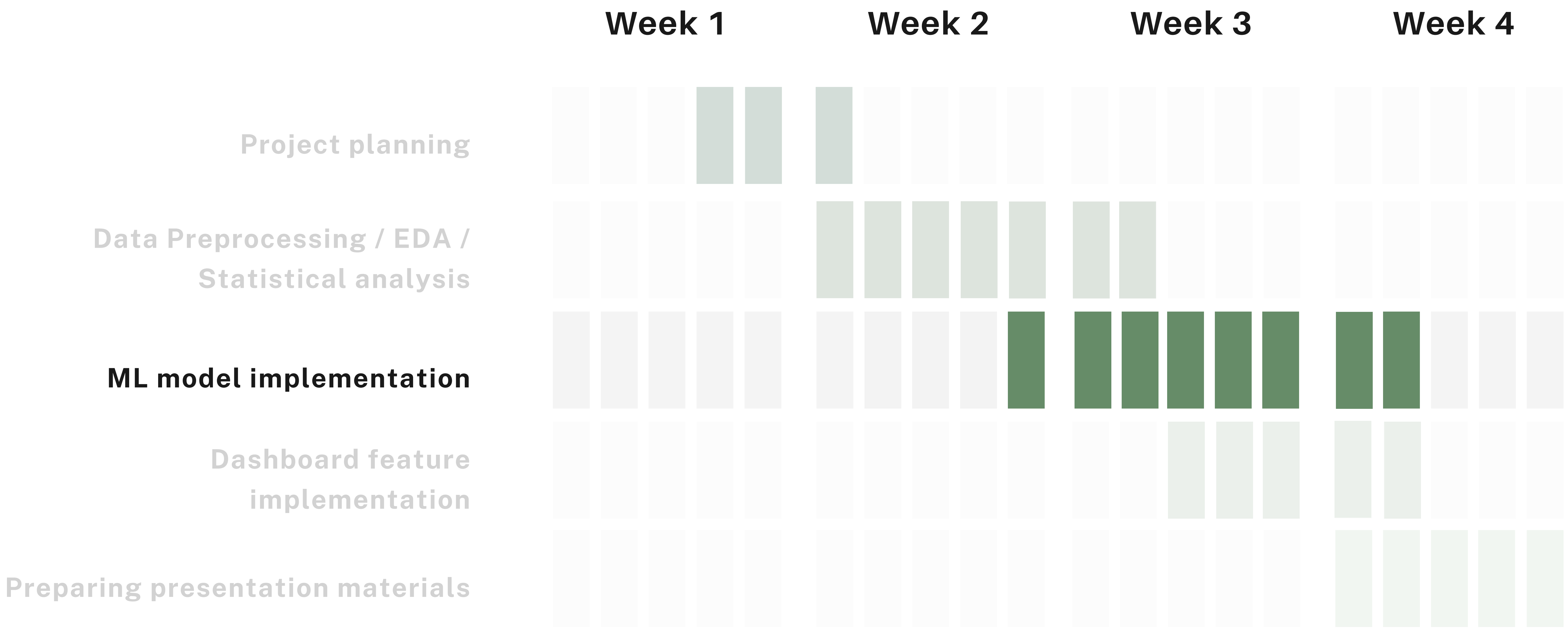
Work Process



Work Process



Work Process



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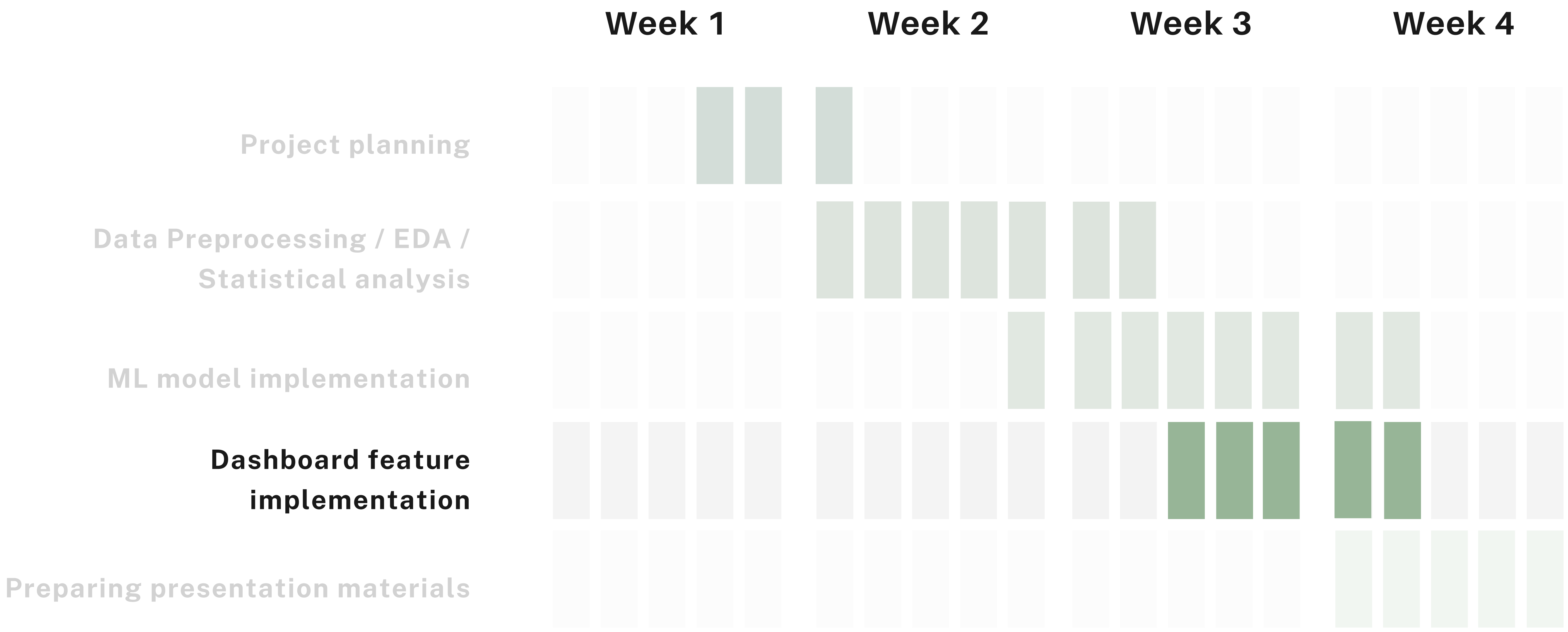

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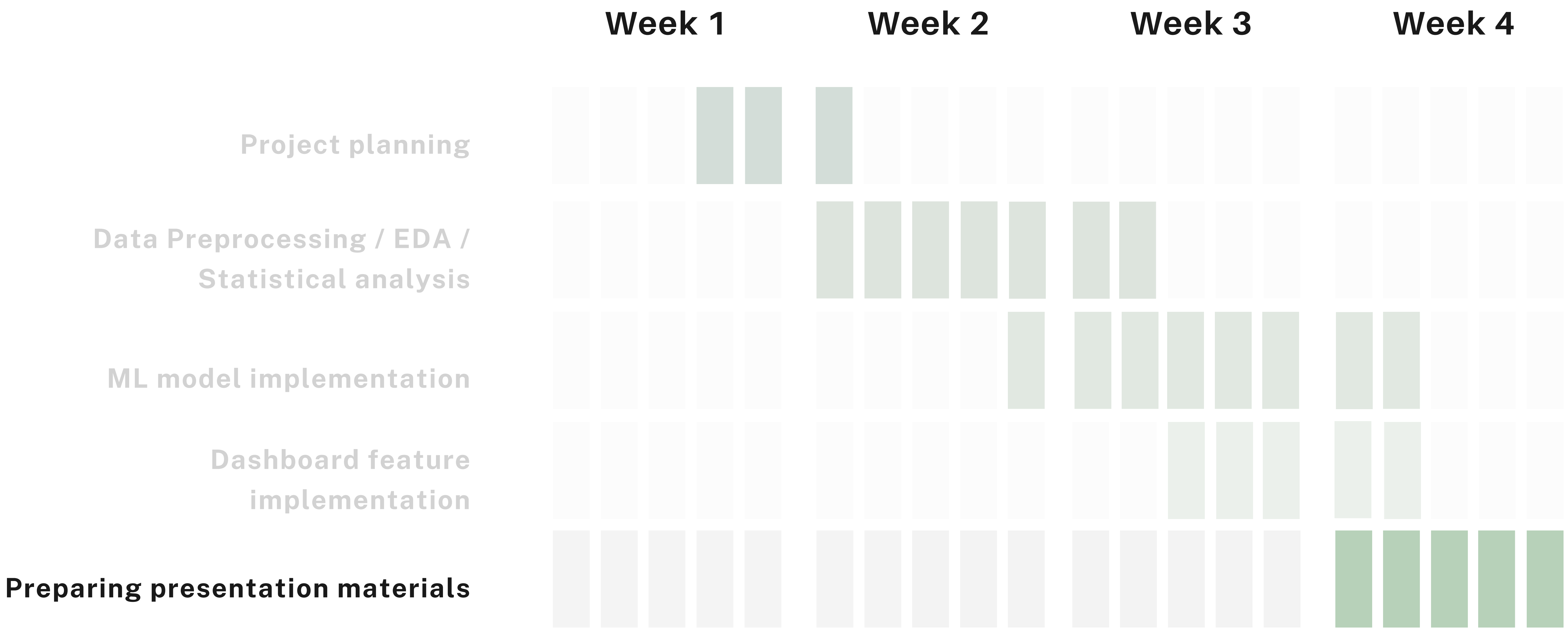
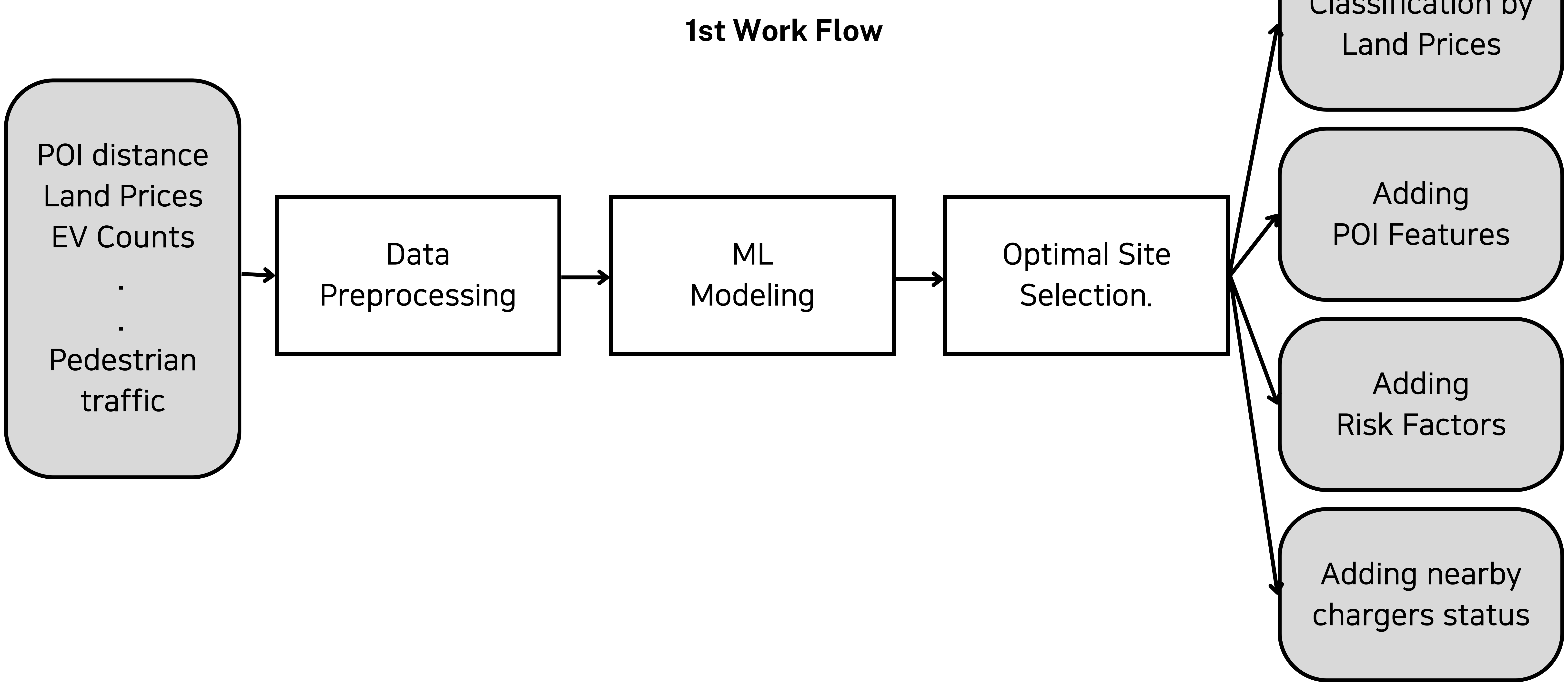
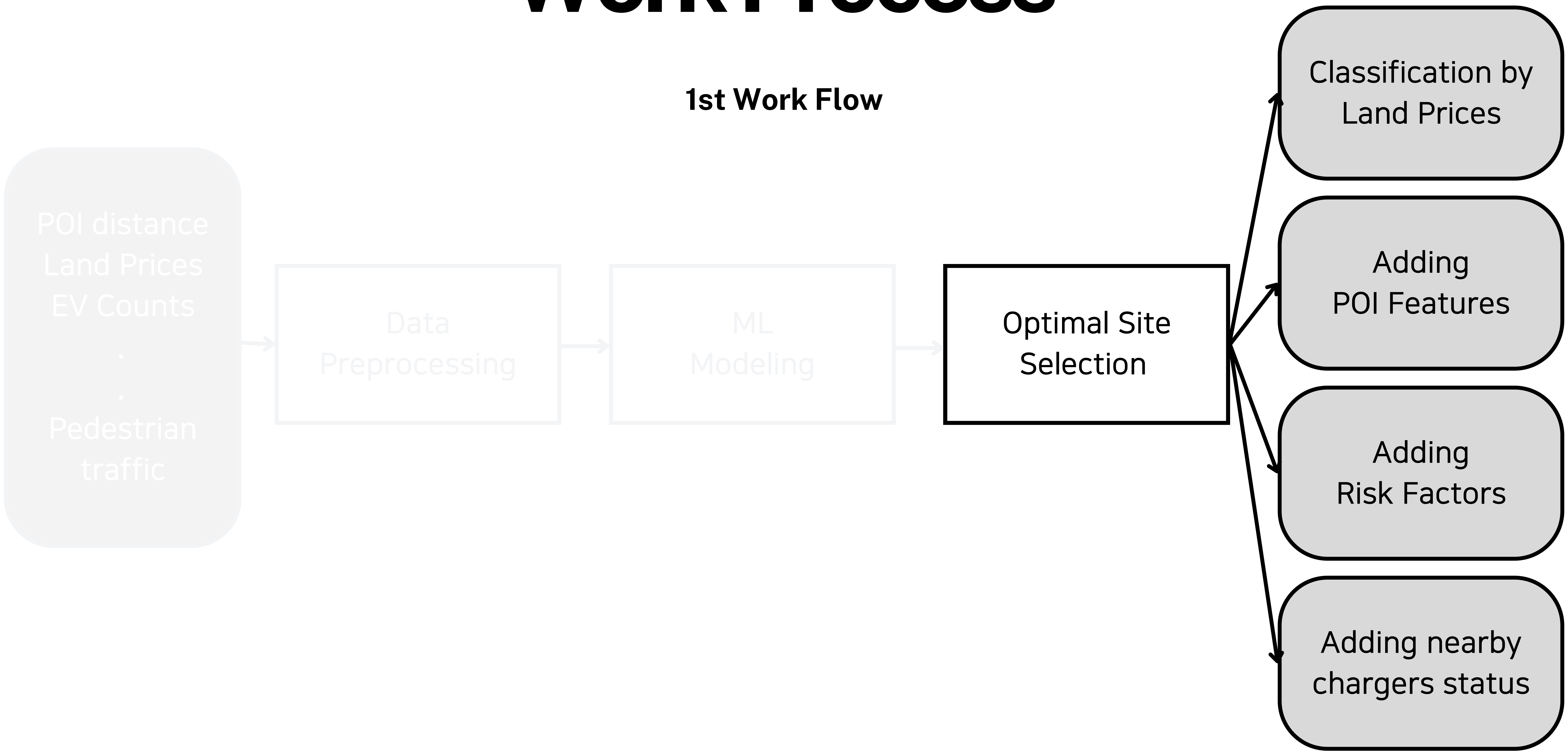


Work Process



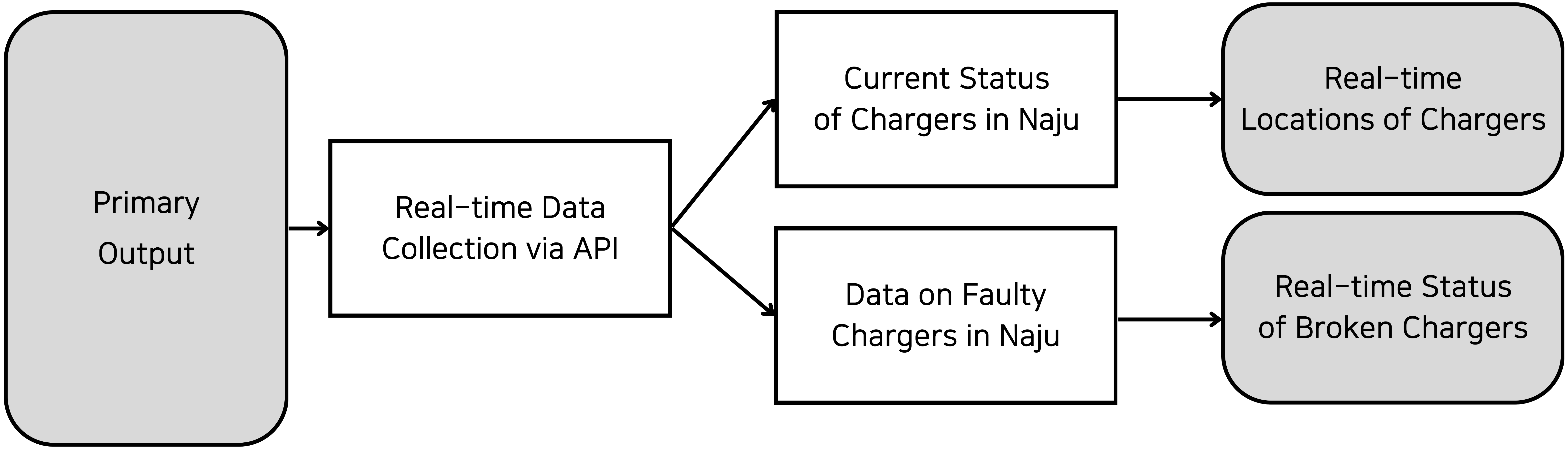
Work Process

1st Work Flow



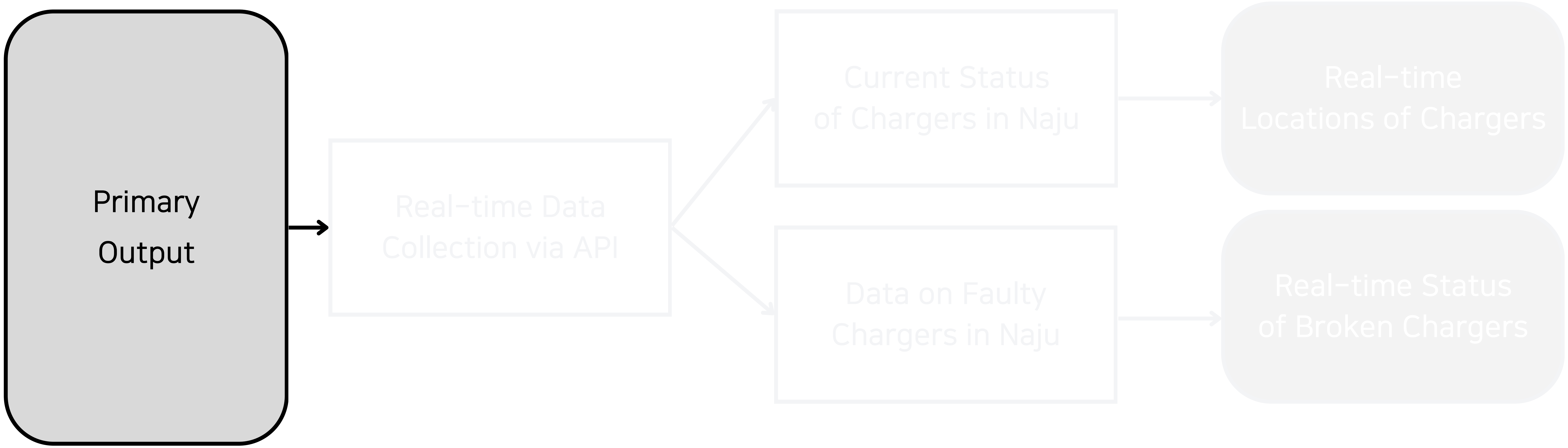
Work Process

2nd Work Flow



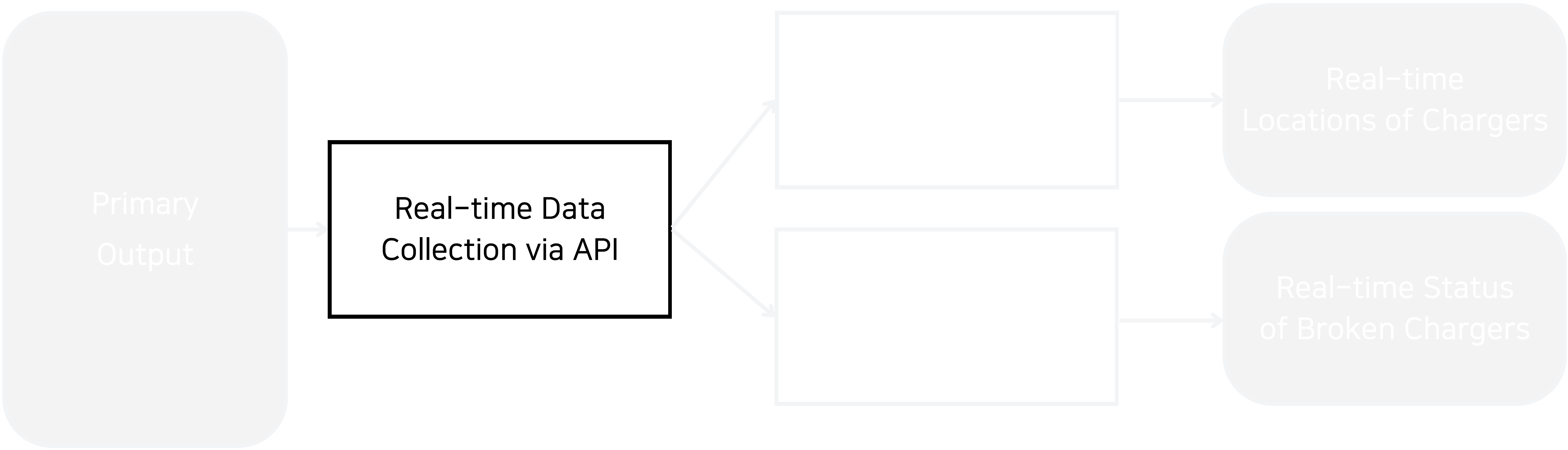
Work Process

2nd Work Flow



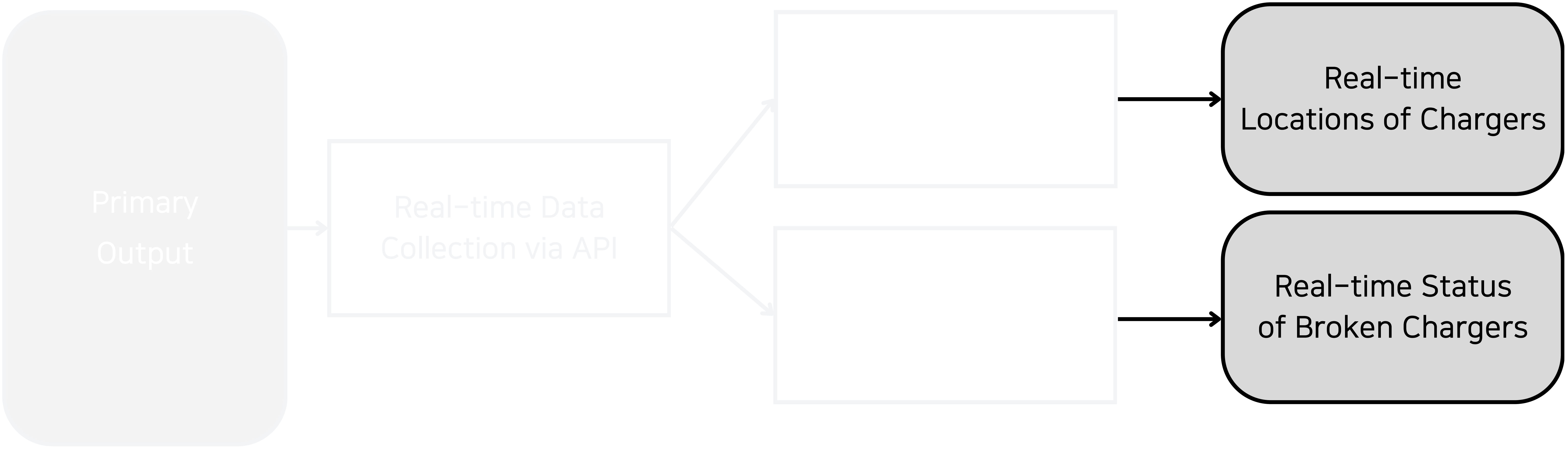
Work Process

2nd Work Flow



Work Process

2nd Work Flow



02 Data Analysis

Data Collection

<table>
<tr><th colspan="4">Data list</th></tr>
<tr><td>Charging station</td><td>• Korean Environment Corporation_Electric Vehicle
• Charging Station Locations and Operating Information</td><td>Land (grid 250m)</td><td>• Assessed land value</td></tr>
<tr><td>Population
(grid 250m)</td><td>• Naju city’s Working Age Population</td><td>etc.</td><td>• Gas station location
• Accessibility to fire station (grid 250m)
• Ministry of Public Administration and Safety_Civil Administration Agency Information Data</td></tr>
<tr><td>Topography</td><td>• Korea Land Information Service (KLIS)_ Continuous Altitude Data Contour Map
• Agricultural land (grid 250m)</td><td rowspan="2">POI (grid 250m)</td><td rowspan="2">• Accessibility to neighborhood park
• Accessibility to Performing arts facility
• Accessibility to Library
• Accessibility to Public sports facility
• Accessibility to Elementary school
• Accessibility to General hospital
• Accessibility to Health facility
• Accessibility to Theme park</td></tr>
<tr><td>National Infrastructure
(grid 250m)</td><td>• Accessibility to Parking lot
• Accessibility to EV charging station</td></tr>
</table>

Data Collection

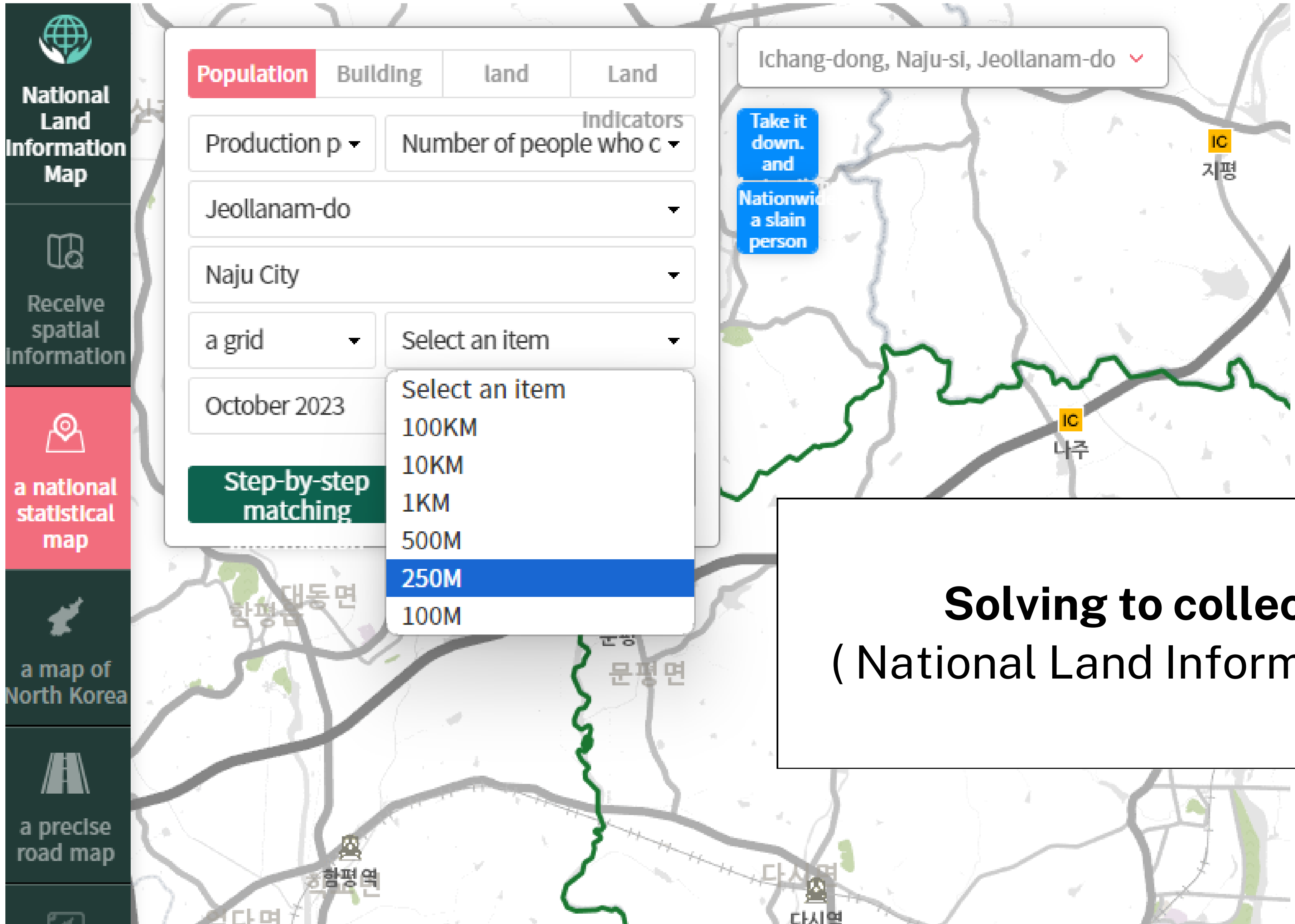
Limitation & Solution

Limitation !

in collecting necessary data for Naju

Data Collection

Limitation & Solution



Solving to collect grid dataset
(National Land Information Map website)

Variable Selection

Independent variables

Dependent variables

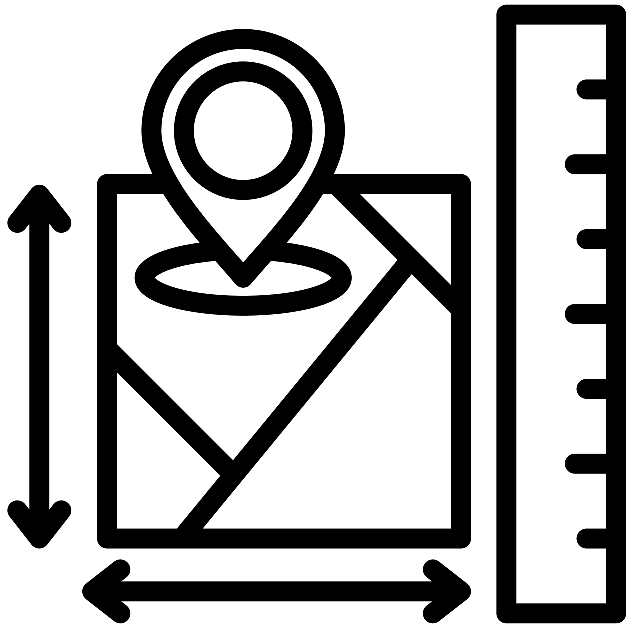
Variable Selection

Independent variables

Dependent variables

Variable Selection

Independent variables



Spatial Data

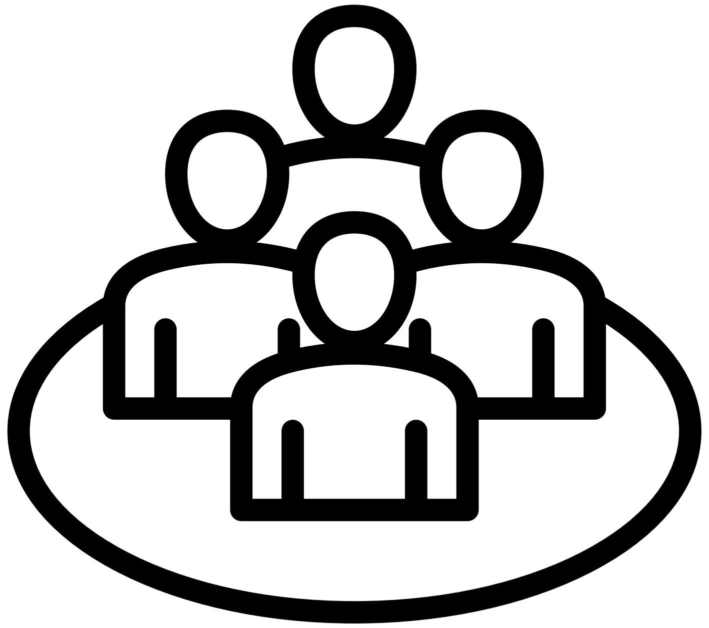
Working Age Population

Land Price

Variable Selection

Independent variables

Spatial Data



Working Age Population

Land Price

Variable Selection

Independent variables

Spatial Data

Working Age Population

Land Price

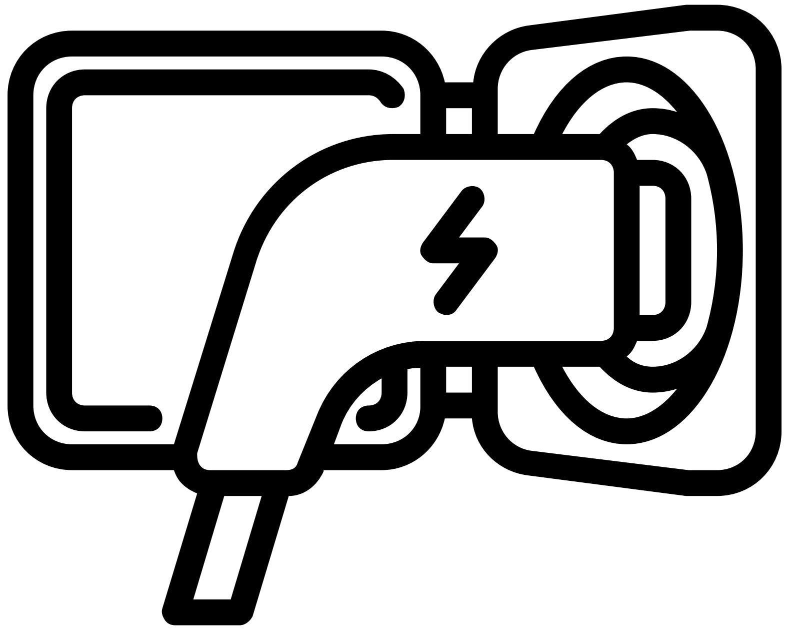
Variable Selection

Independent variables

Dependent variables

Variable Selection

Dependent variables



Presence of fast chargers and slow chargers

(0,1,2,3)

Variable Selection

Dependent variables

None

Slow Charger only

Fast Charger only

Both

Variable Selection

Dependent variables

None

Slow Charger only

Fast Charger only

Both

0

Variable Selection

Dependent variables

None

Slow Charger only

Fast Charger only

Both

1

Variable Selection

Dependent variables

None

Slow Charger only

Fast Charger only

Both

2

Variable Selection

Dependent variables

None

Slow Charger only

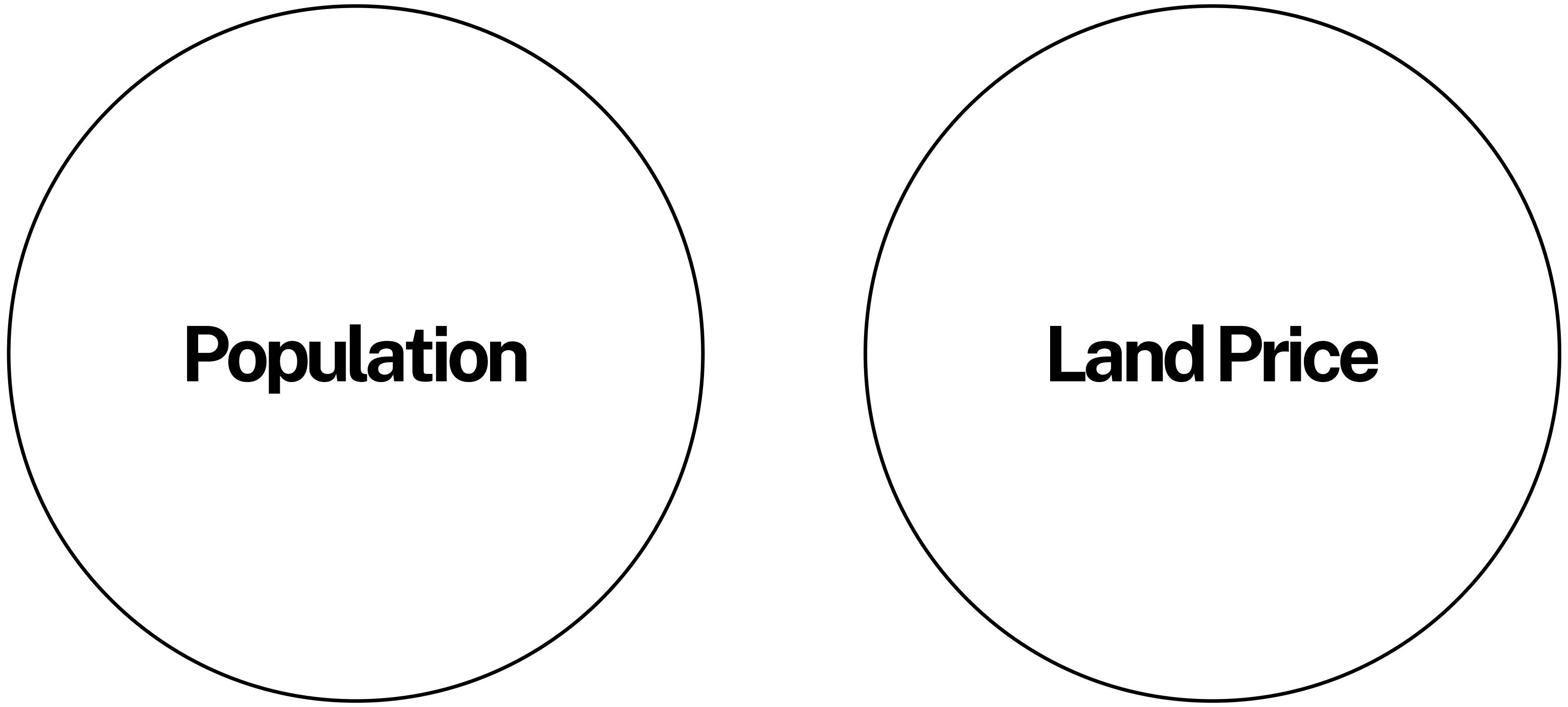
Fast Charger only

Both

3

Issues with Data

2.3.1 Handling missing values



Issues with Data

2.3.1 Handling missing values

Population	→	6443 missing data : Replace with 0
Land Price	→	468 missing data : KNN Imputation

Issues with Data

2.3.1 Handling missing values

Population → 6443 missing data : Replace with 0

Land Price → **468 missing data : KNN Imputation**

Issues with Data

2.3.2 Incorporating coordinates into grid data

Gas Station

Charging Station

Issues with Data

2.3.2 Incorporating coordinates into grid data

Gas Station

Charging Station

Issues with Data

2.3.2 Incorporating coordinates into grid data

Gas Station

Charging Station

including the coordinates
of the additional data into the grid

Feature Engineering

2.4.2 Setting Development Restriction Zone

Average Altitude Column > **Farmland Area Column** > **Stream Column**

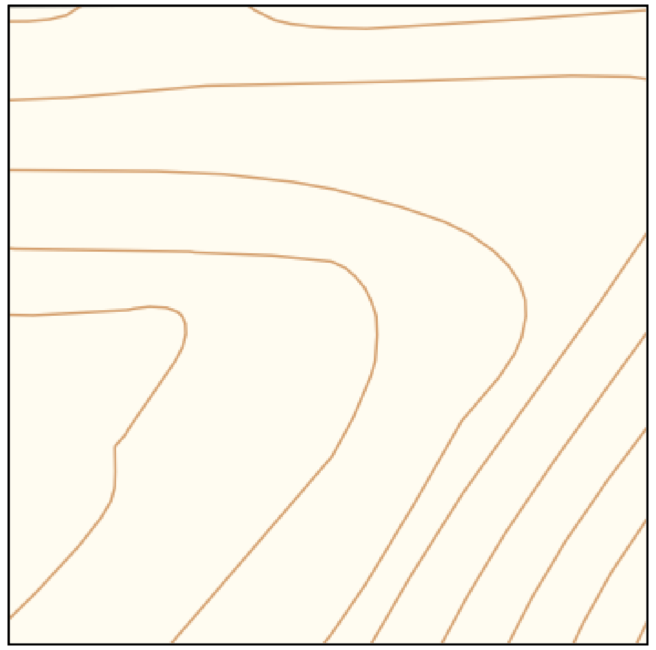
Feature Engineering

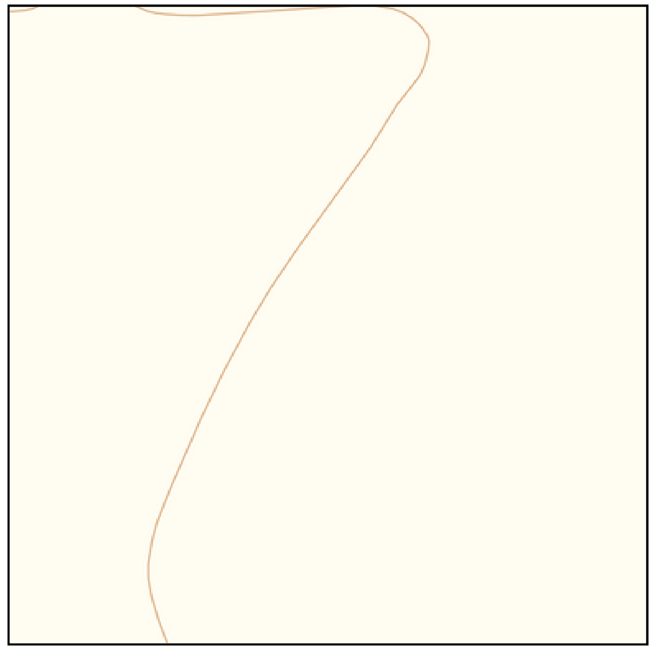
2.4.2 Setting Development Restriction Zone

Average Altitude Column > Farmland Area Column > Stream Column

Feature Engineering

2.4.2 Setting Development Restriction Zone





Establish Contour Average Altitude based on Grid

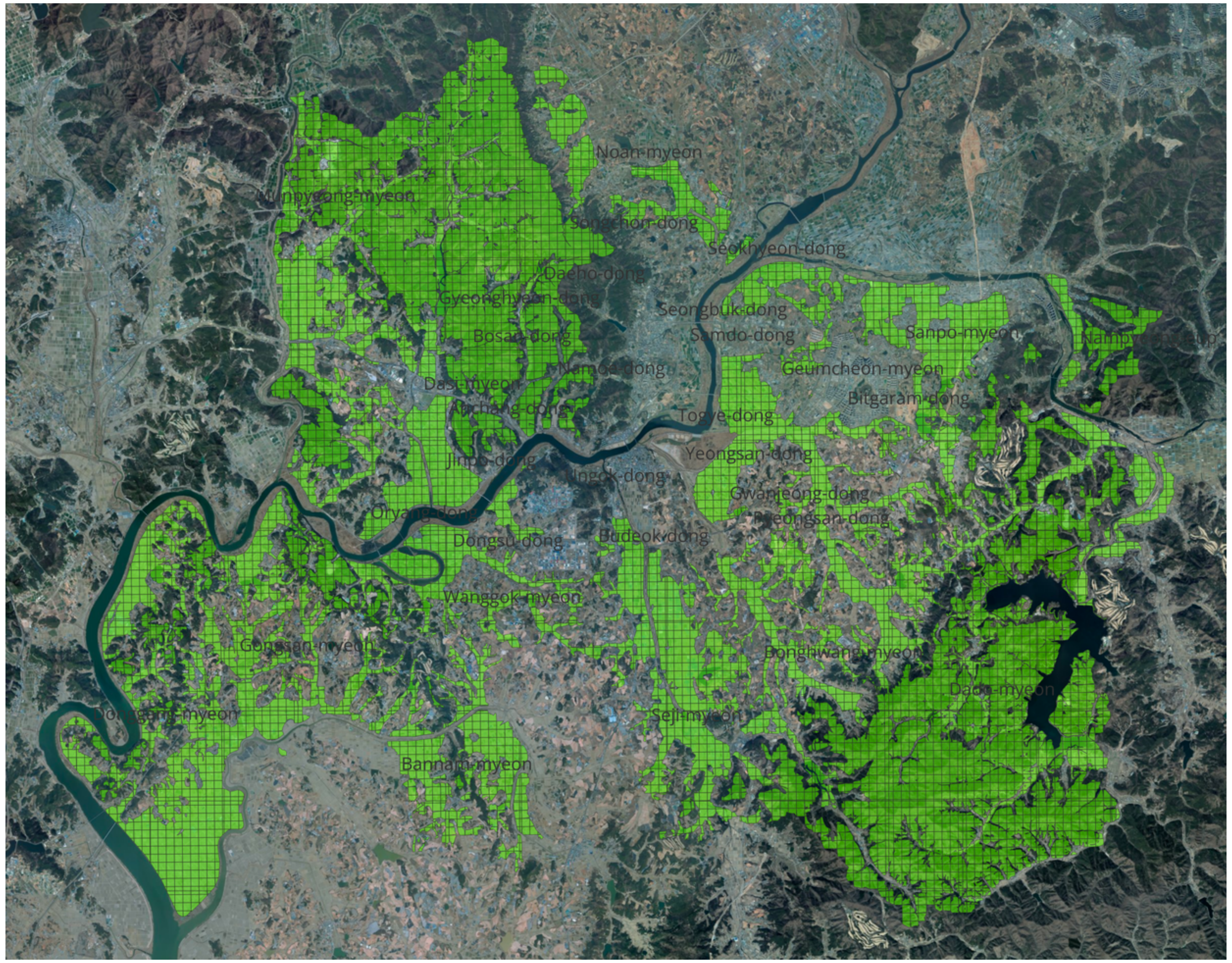
Feature Engineering

2.4.2 Setting Development Restriction Zone

Average Altitude Column > **Farmland Area Column** > Stream Column

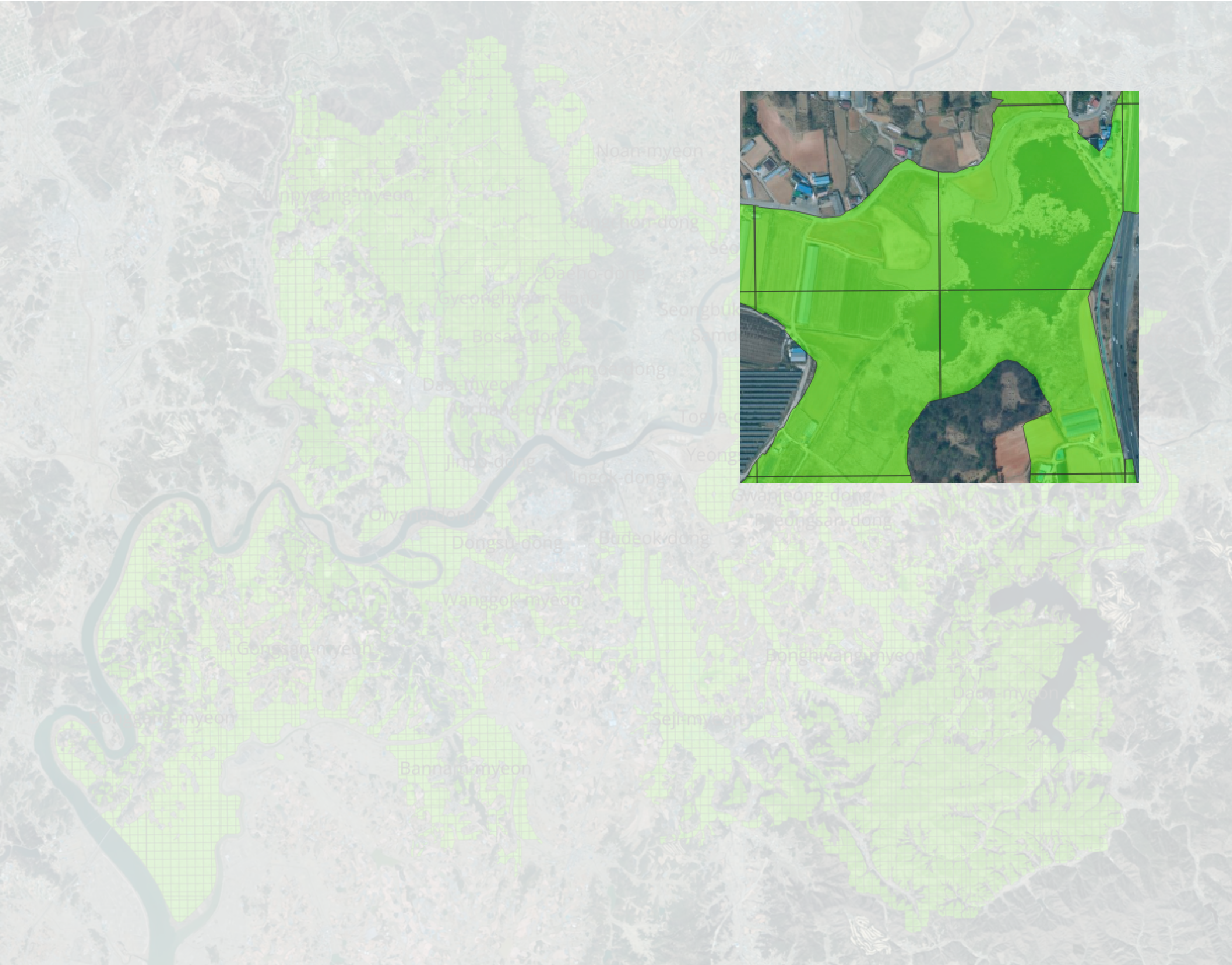
Feature Engineering

2.4.2 Setting Development Restriction Zone



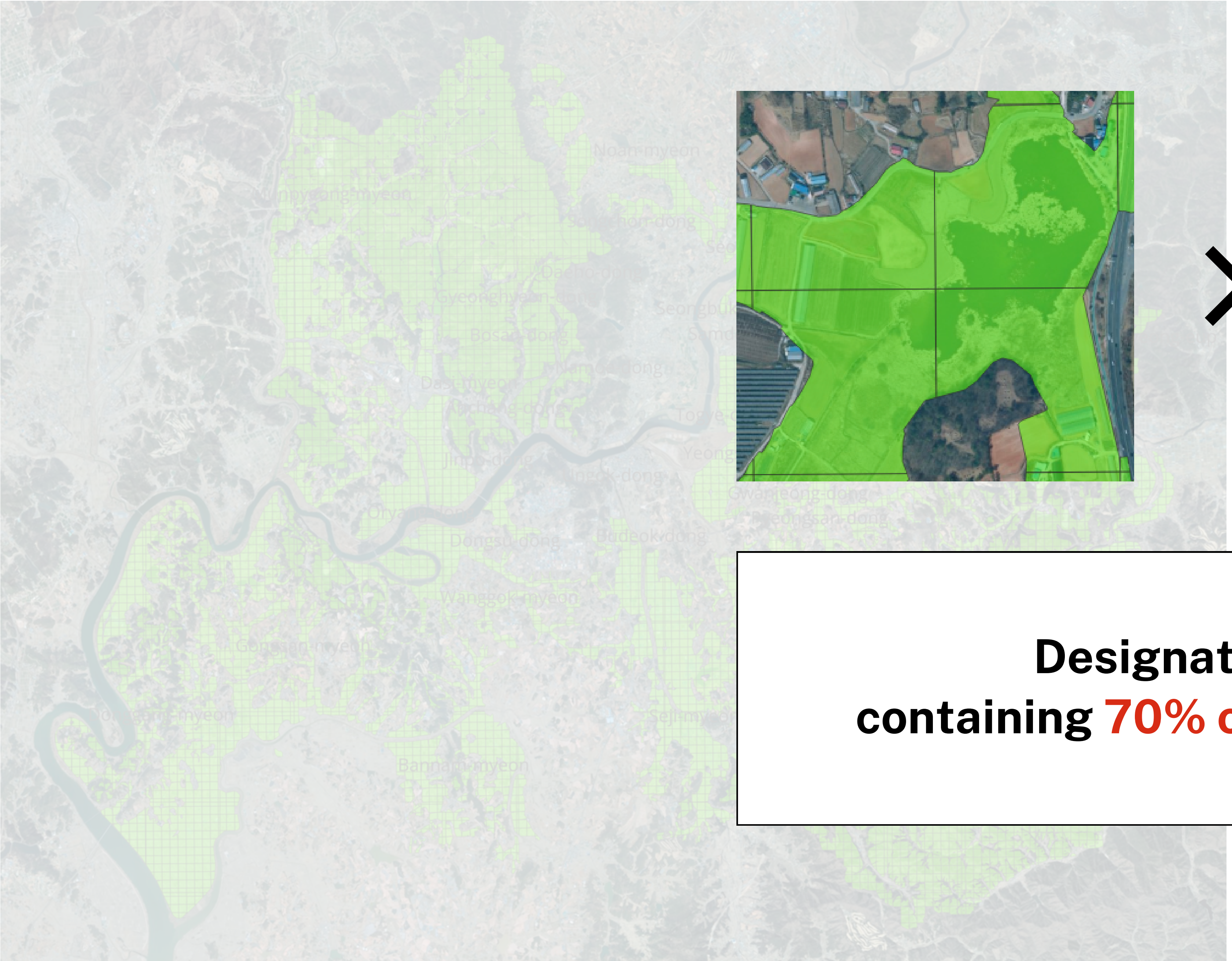
Feature Engineering

2.4.2 Setting Development Restriction Zone



Feature Engineering

2.4.2 Setting Development Restriction Zone



Designated areas containing 70% or more farmland

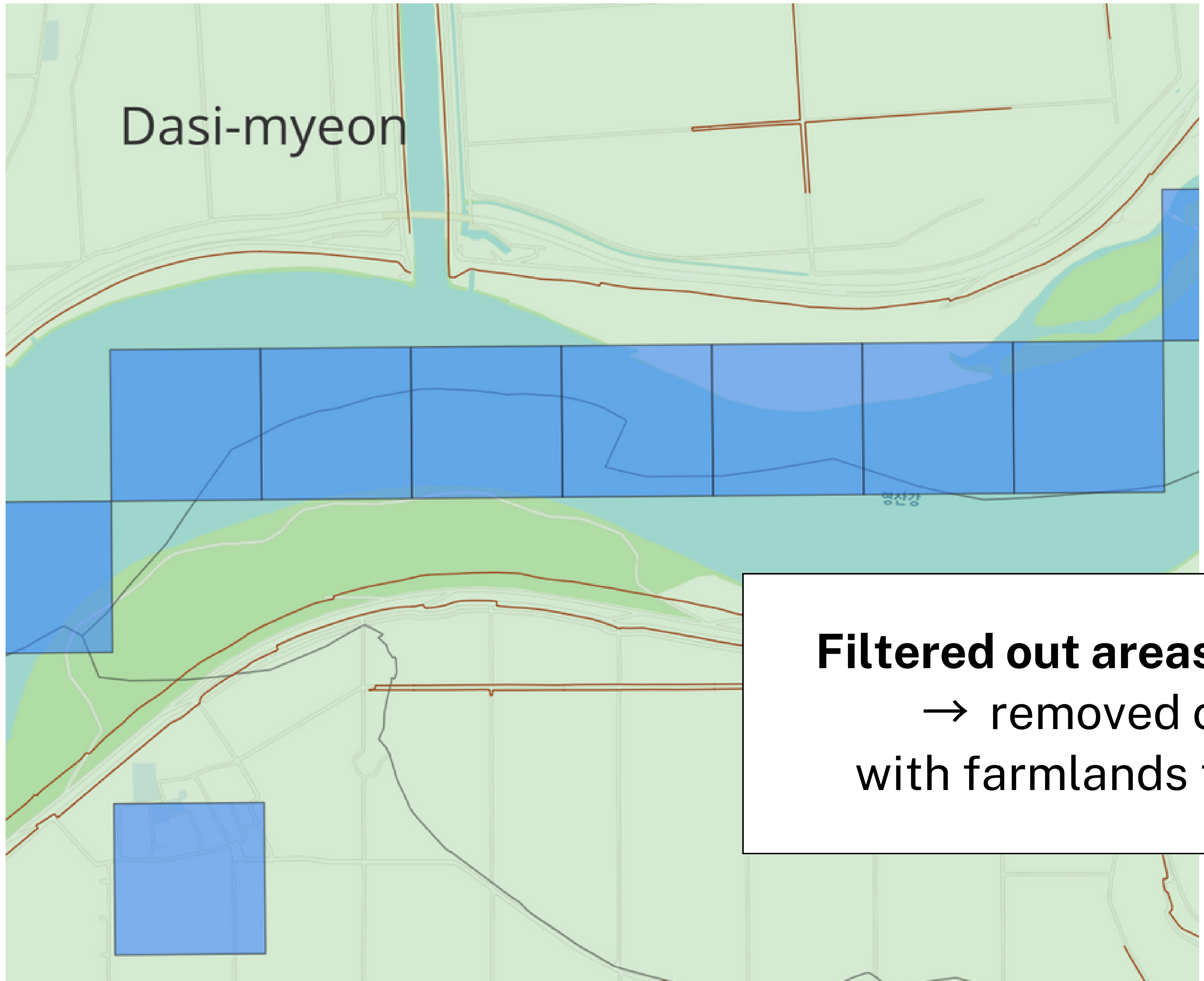
Feature Engineering

2.4.2 Setting Development Restriction Zone

Average Altitude Column > Farmland Area Column > **Stream Column**

Feature Engineering

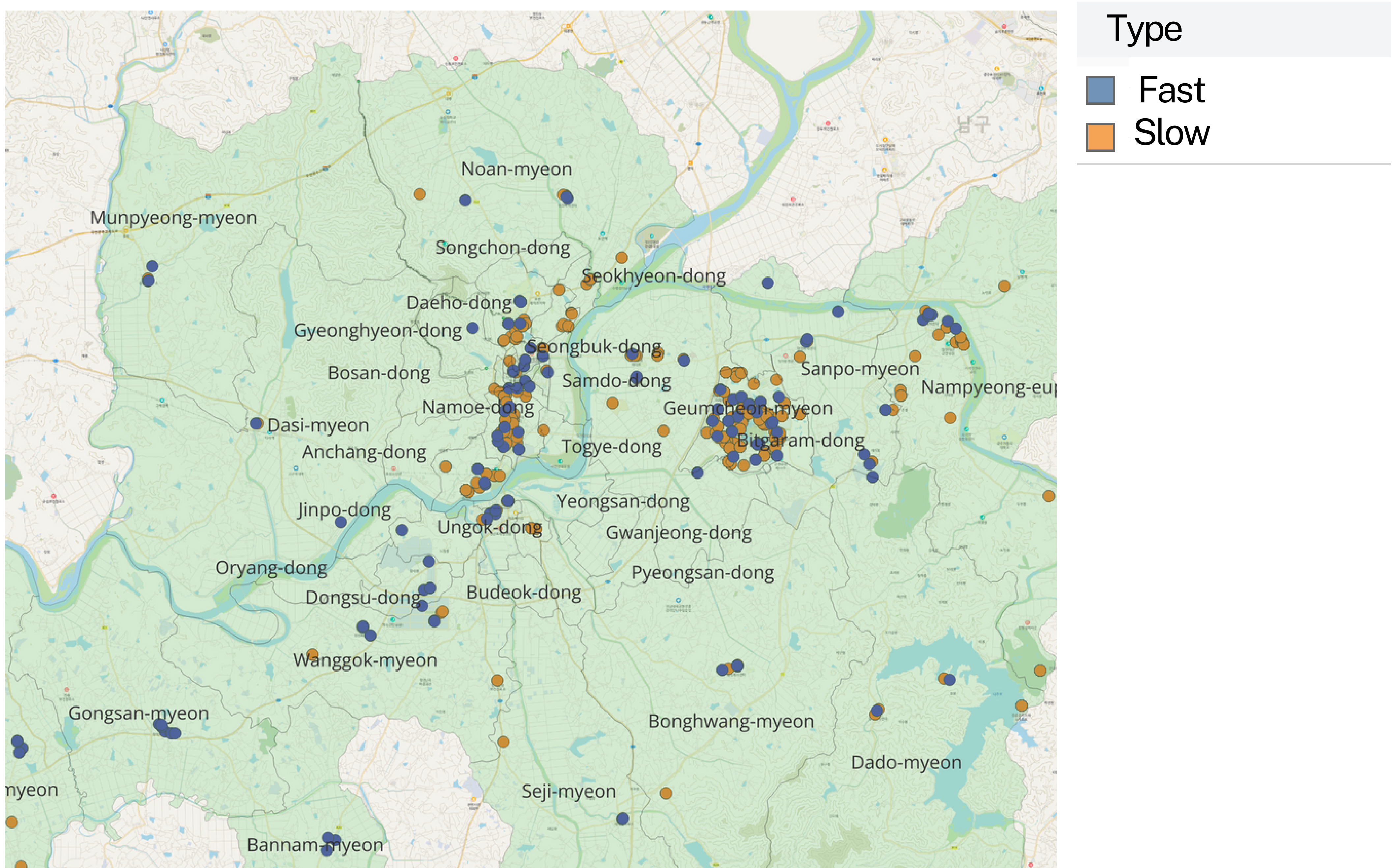
2.4.2 Setting Development Restriction Zone



Filtered out areas with no contour lines
→ removed overlapping areas
with farmlands to seperate streams.

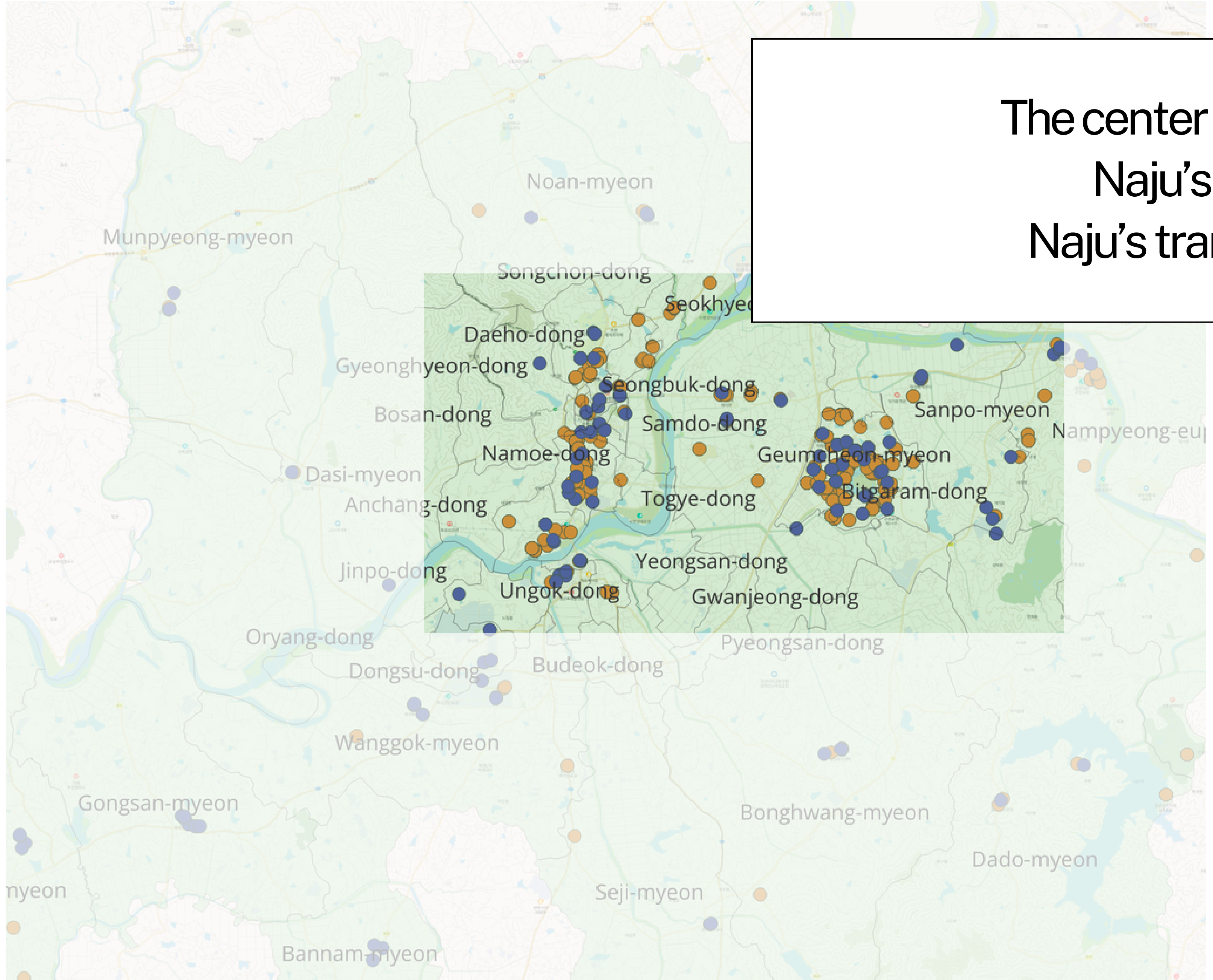
EDA

2.5.1 Charger distribution in Naju city



EDA

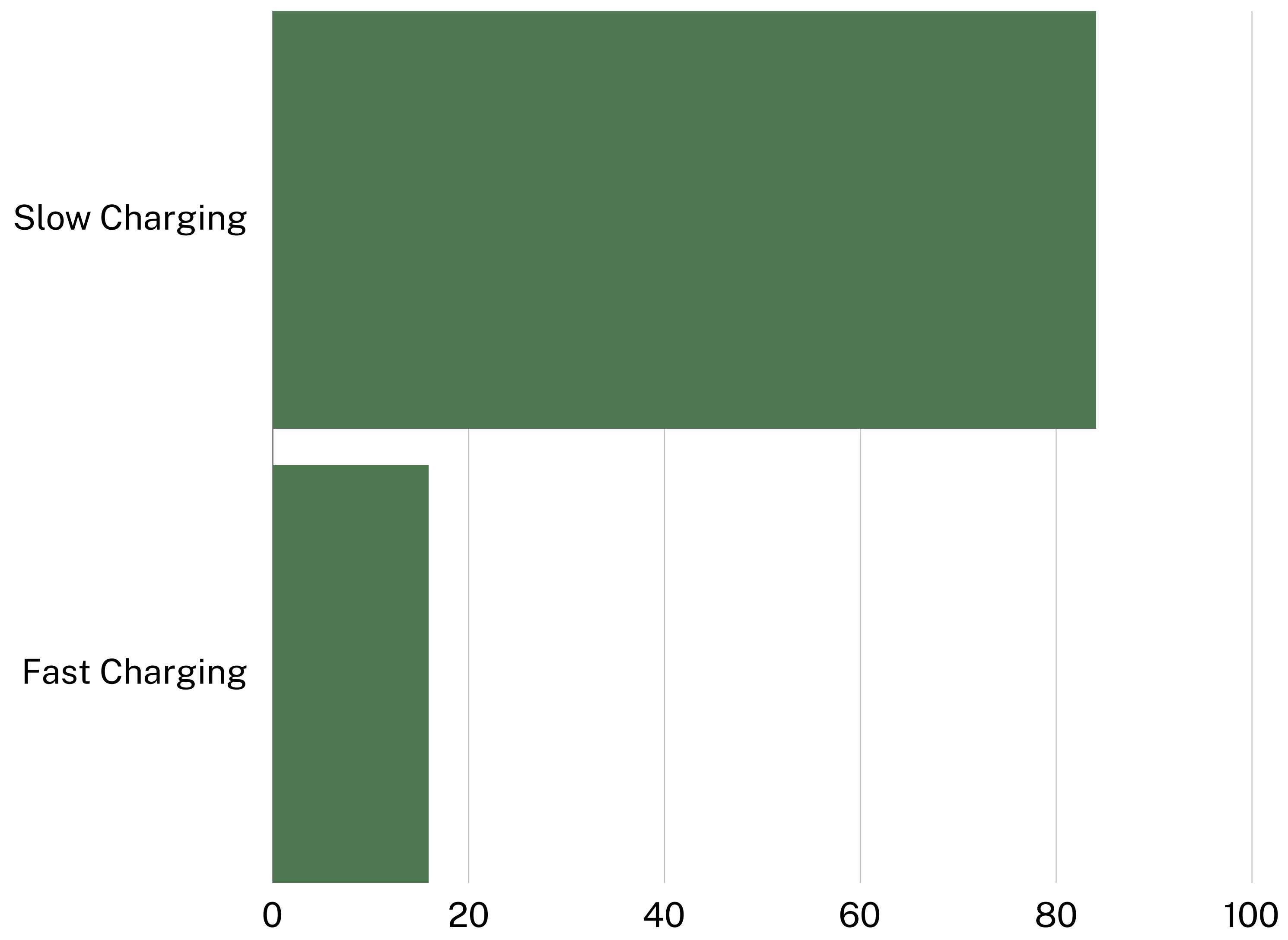
2.5.1 Charger distribution in Naju city



The center of innovation city
Naju's cultural hub
Naju's transportation hub

EDA

2.5.2 Bar chart of EV chargers by type

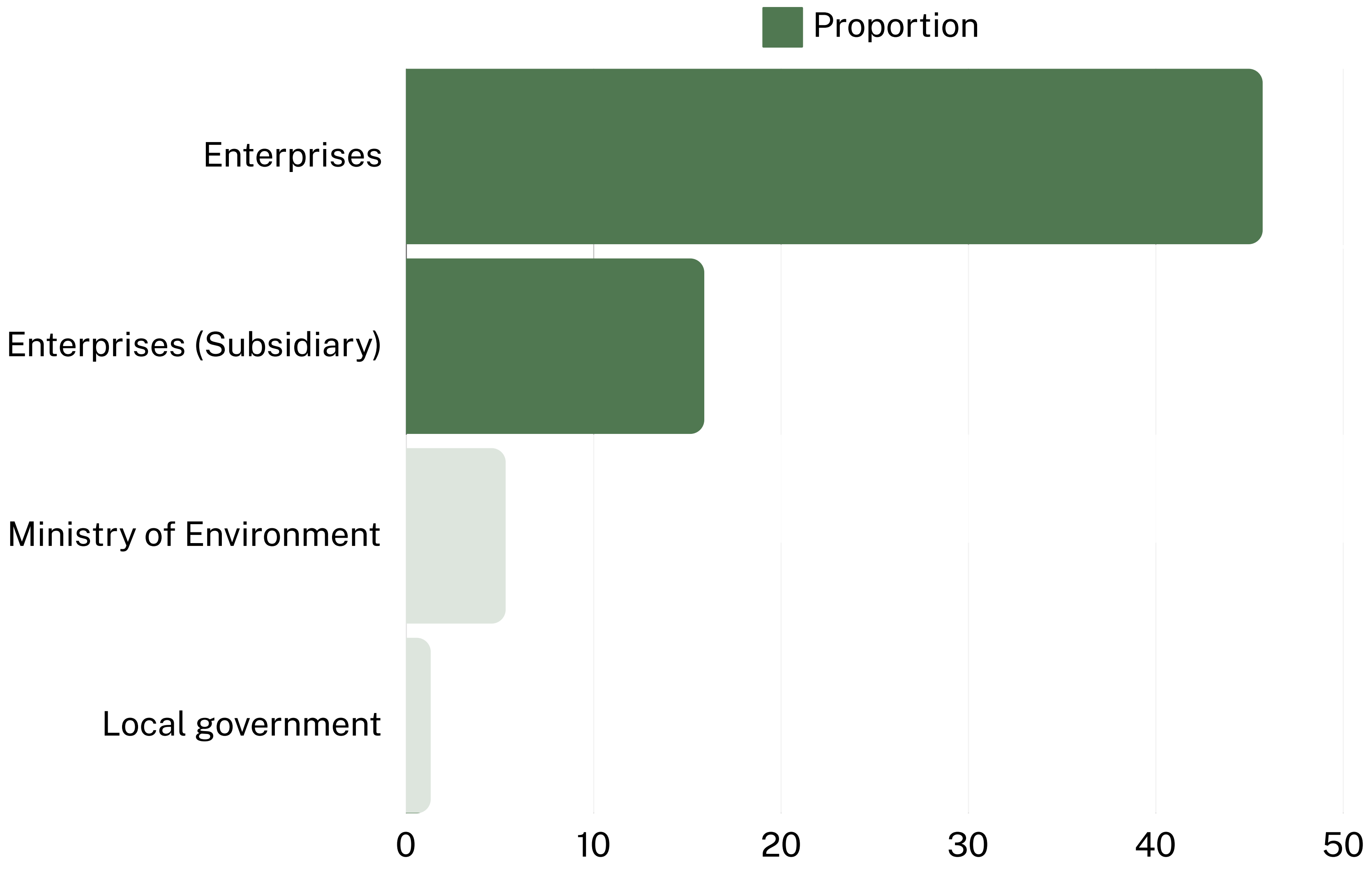


Overall,

Total number of slow chargers are 5 times bigger than fast chargers.

EDA

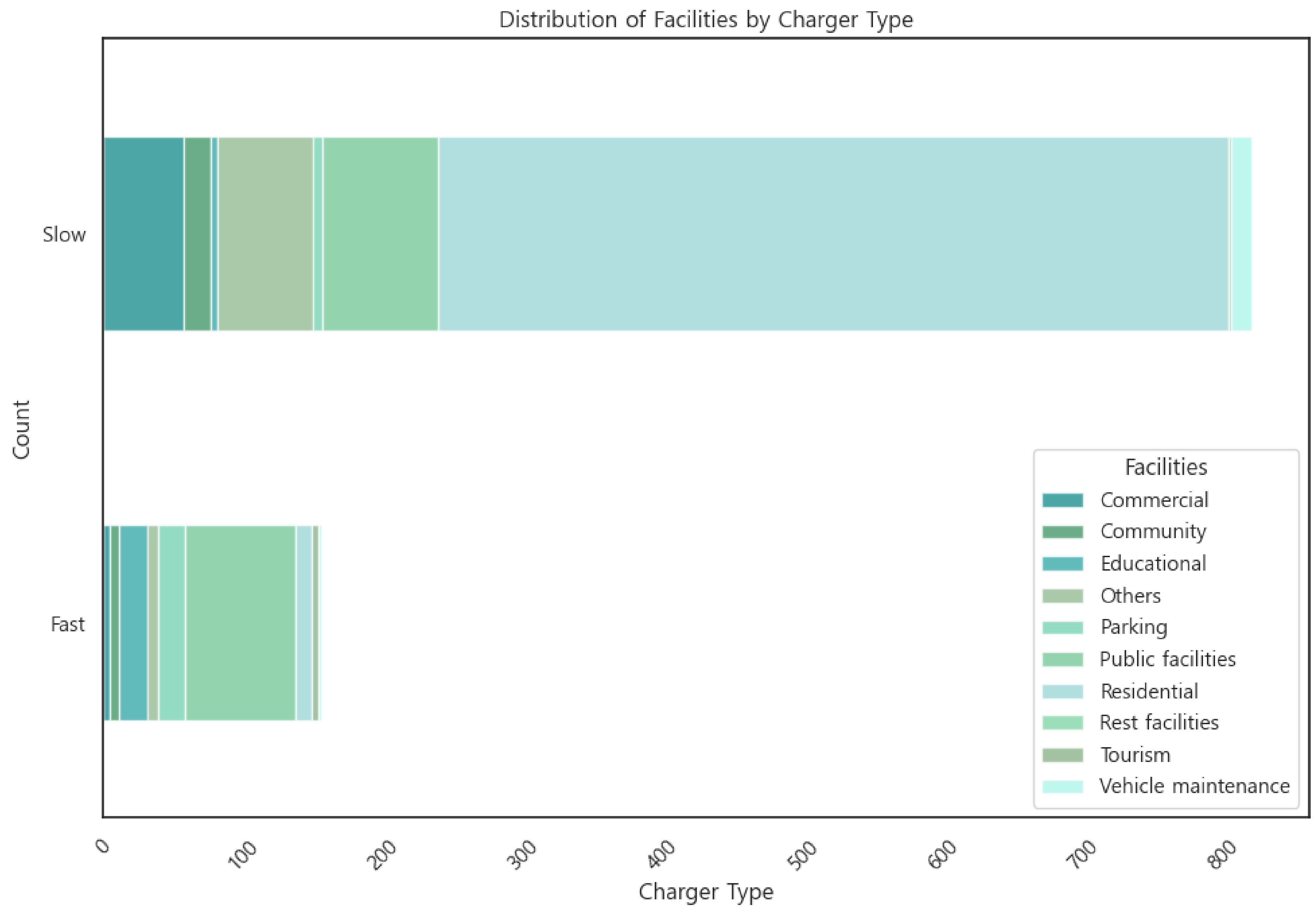
2.5.3 Bar chart of EV chargers by Operating agency



Enterprises showed the largest operating proportion.

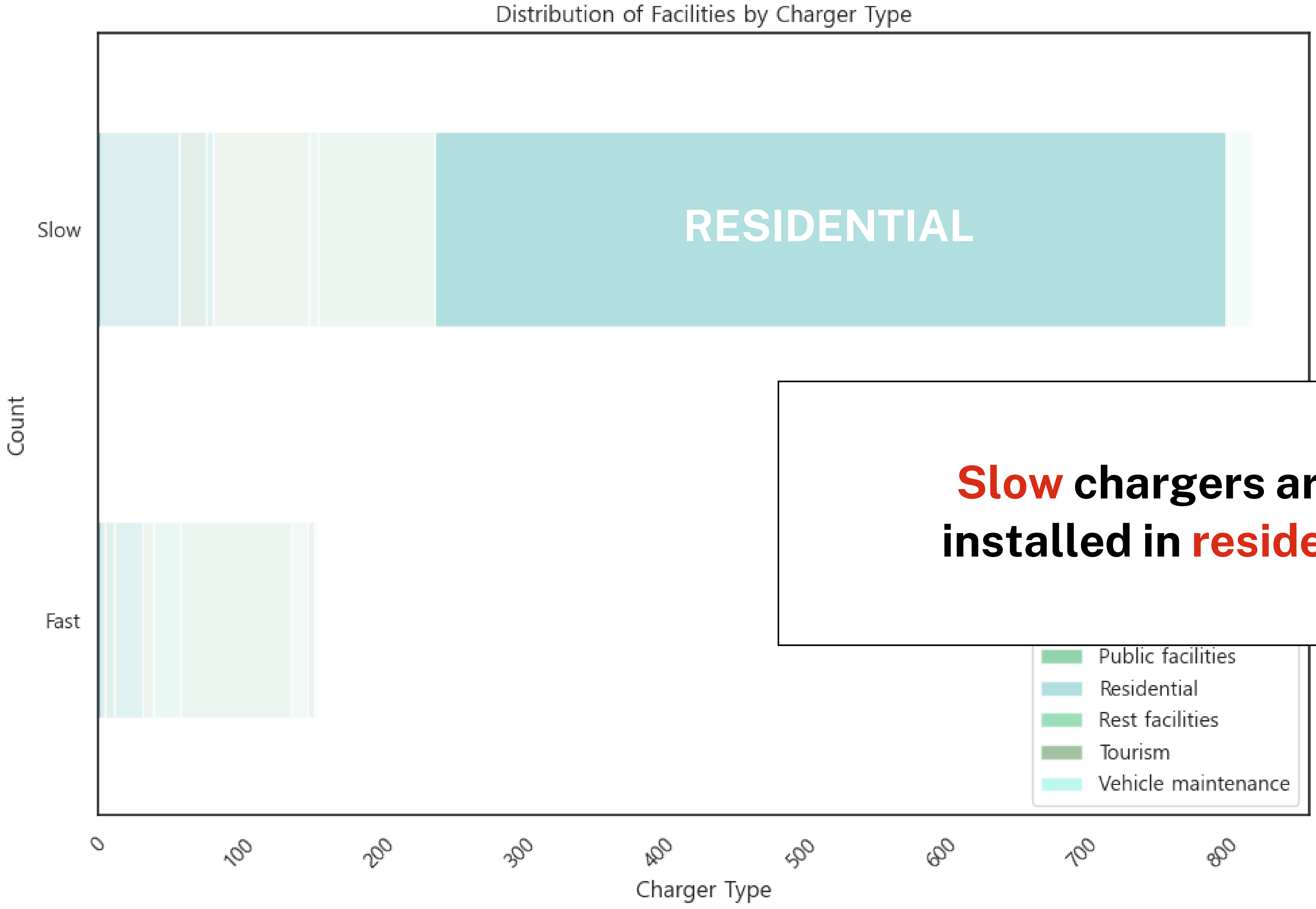
EDA

2.5.4 Bar chart of EV chargers by facility type



EDA

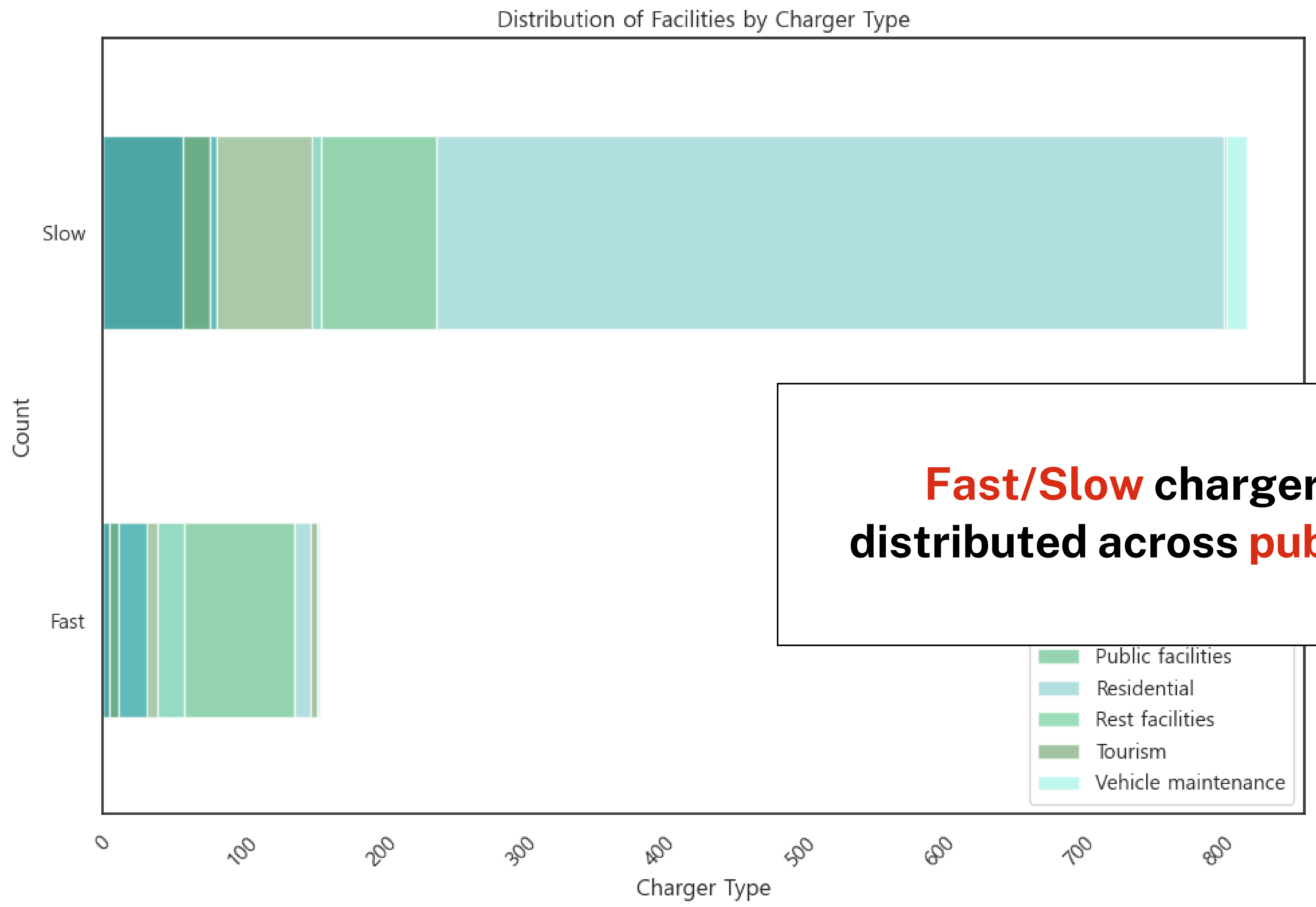
2.5.4 Bar chart of EV chargers by facility type



Slow chargers are primarily installed in residential areas.

EDA

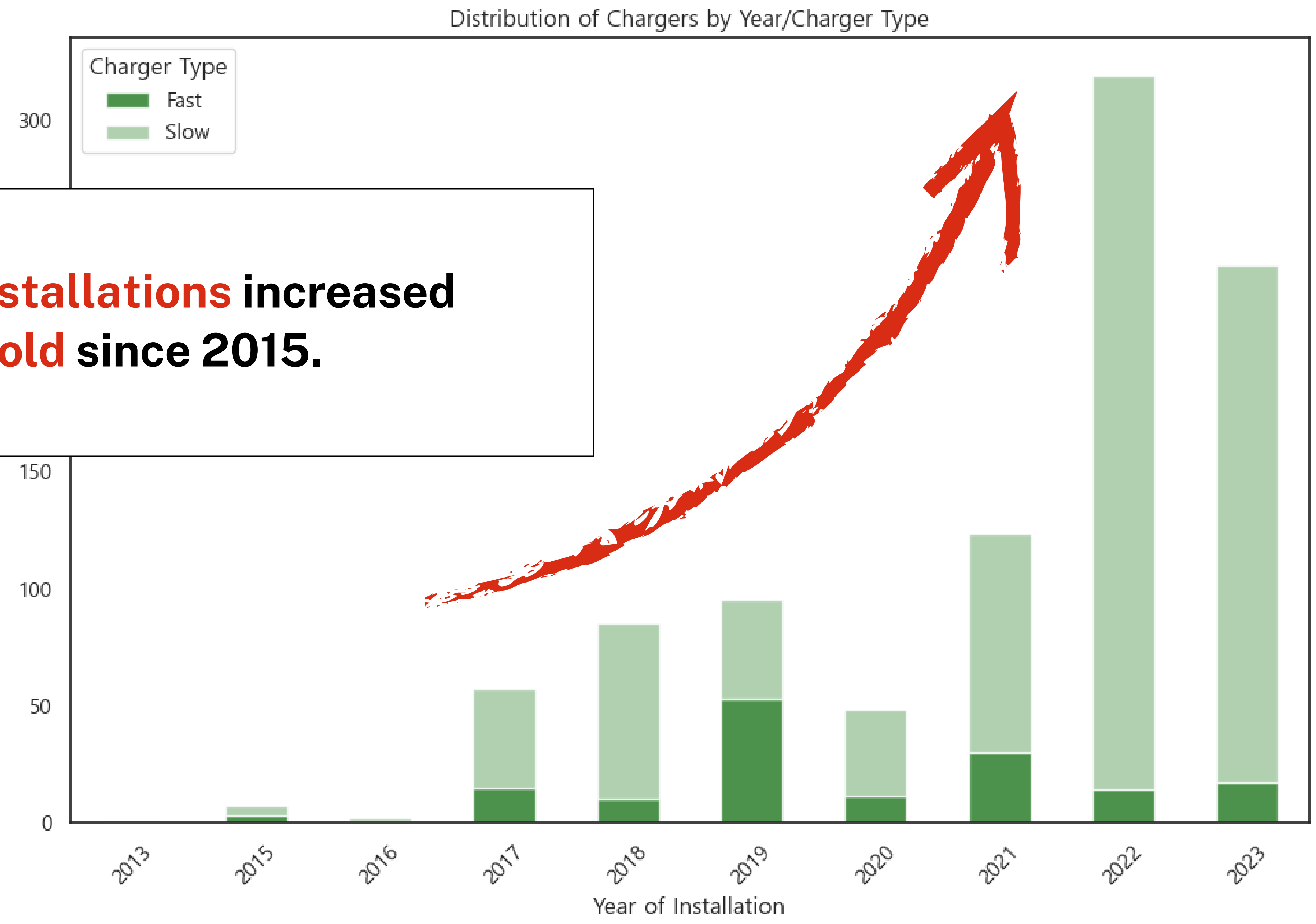
2.5.4 Bar chart of EV chargers by facility type



Fast/Slow chargers are evenly distributed across public institutions.

EDA

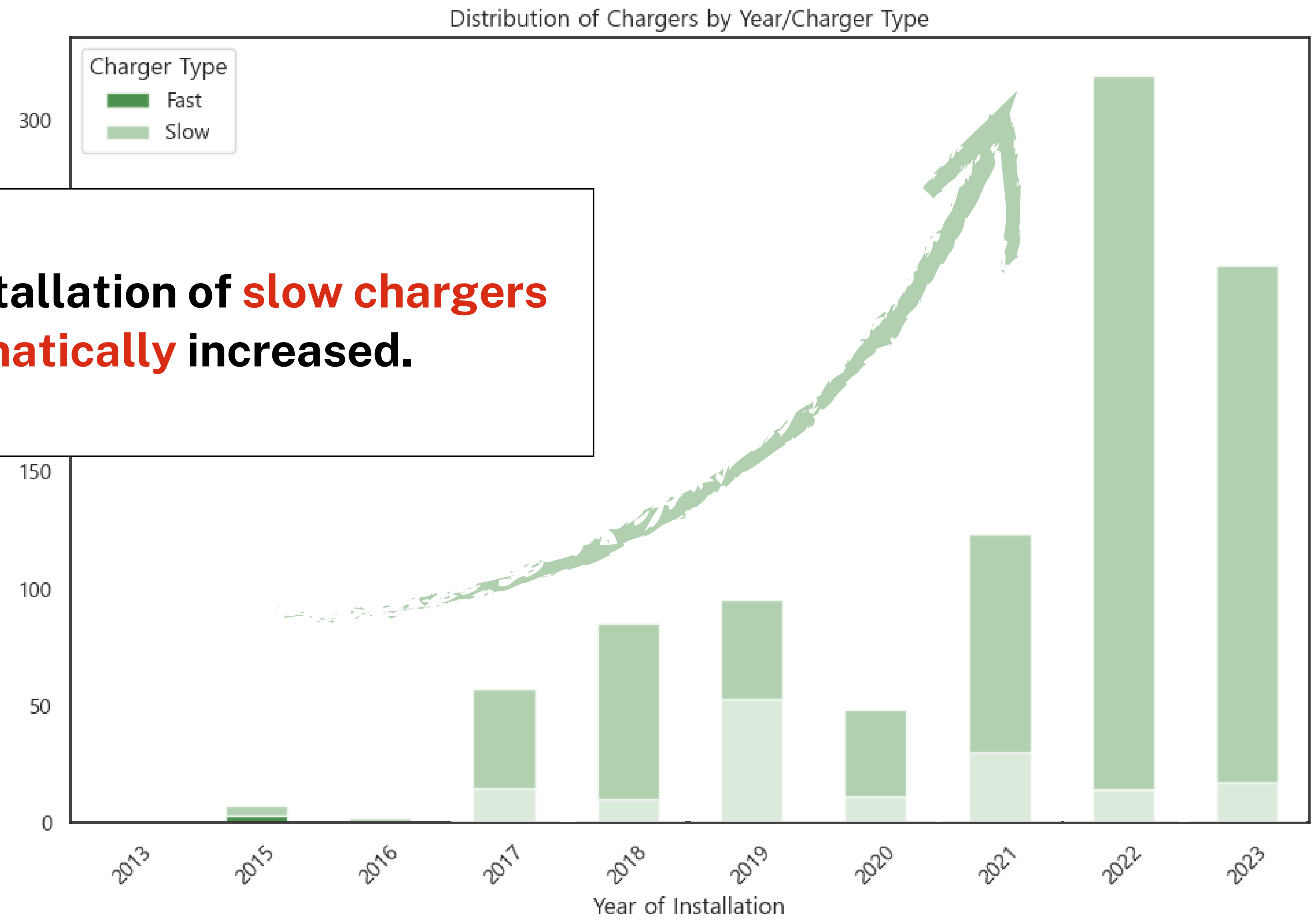
2.5.6 Bar chart of EV chargers by year/facility type



Charger installations increased 30-fold since 2015.

EDA

2.5.6 Bar chart of EV chargers by year/facility type



Especially, Installation of slow chargers has dramatically increased.

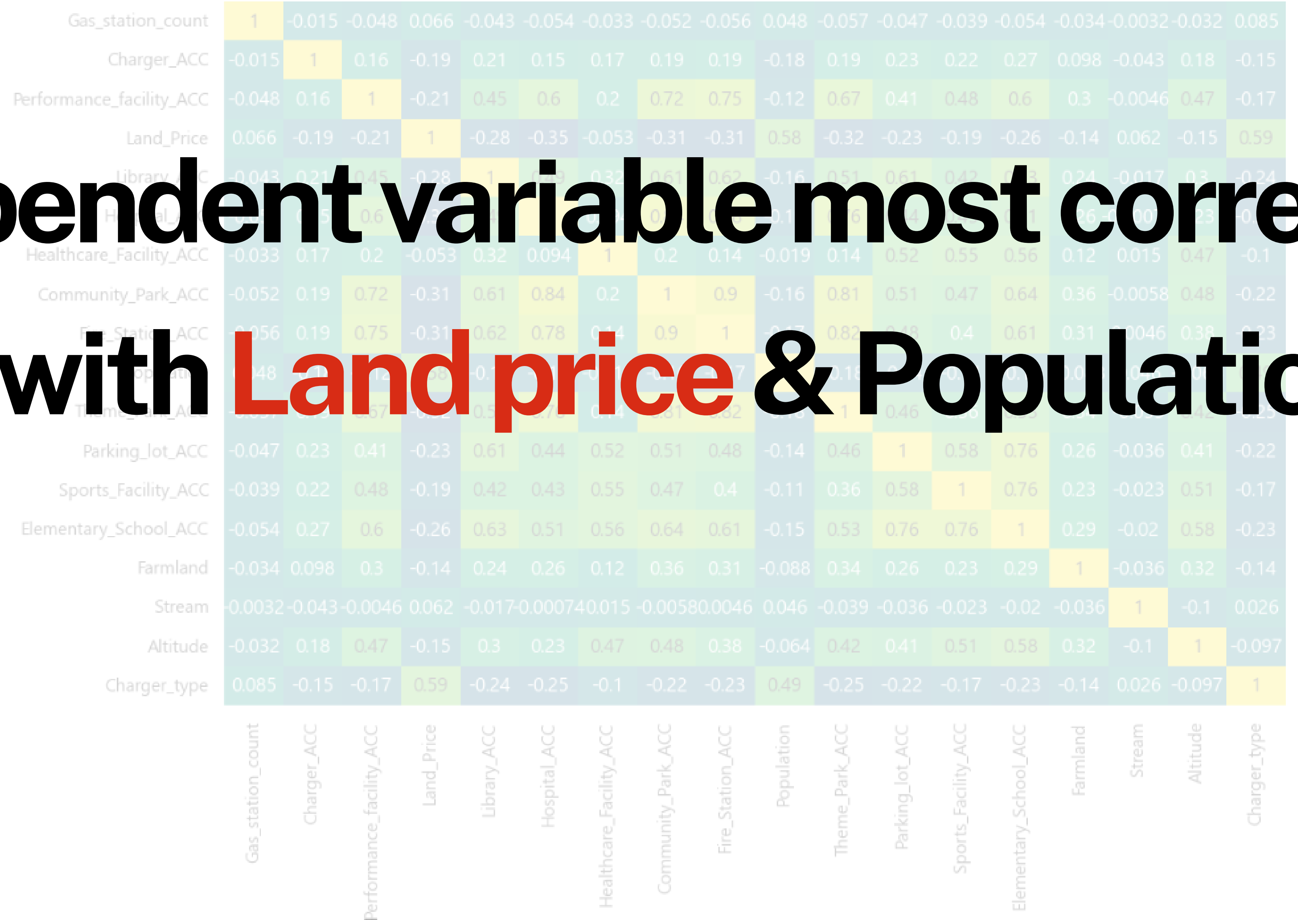
EDA

2.5.8 Correlation among variables

	Gas_station_count	Charger_ACC	Performance_facility_ACC	Land_Price	Library_ACC	Hospital_ACC	Healthcare_Facility_ACC	Community_Park_ACC	Fire_Station_ACC	Population	Theme_Park_ACC	Parking_lot_ACC	Sports_Facility_ACC	Elementary_School_ACC	Farmland	Stream	Altitude	Charger_type
Gas_station_count	1	-0.015	-0.048	0.066	-0.043	-0.054	-0.033	-0.052	-0.056	0.048	-0.057	-0.047	-0.039	-0.054	-0.034	-0.0032	-0.032	0.085
Charger_ACC	-0.015	1	0.16	-0.19	0.21	0.15	0.17	0.19	0.19	-0.18	0.19	0.23	0.22	0.27	0.098	-0.043	0.18	-0.15
Performance_facility_ACC	-0.048	0.16	1	-0.21	0.45	0.6	0.2	0.72	0.75	-0.12	0.67	0.41	0.48	0.6	0.3	-0.0046	0.47	-0.17
Land_Price	0.066	-0.19	-0.21	1	-0.28	-0.35	-0.053	-0.31	-0.31	0.58	-0.32	-0.23	-0.19	-0.26	-0.14	0.062	-0.15	0.59
Library_ACC	-0.043	0.21	0.45	-0.28	1	0.49	0.32	0.61	0.62	-0.16	0.51	0.61	0.42	0.63	0.24	-0.017	0.3	-0.24
Hospital_ACC	-0.054	0.15	0.6	-0.35	0.49	1	0.094	0.84	0.78	-0.19	0.76	0.44	0.43	0.51	0.26	-0.00074	0.23	-0.25
Healthcare_Facility_ACC	-0.033	0.17	0.2	-0.053	0.32	0.094	1	0.2	0.14	-0.019	0.14	0.52	0.55	0.56	0.12	0.015	0.47	-0.1
Community_Park_ACC	-0.052	0.19	0.72	-0.31	0.61	0.84	0.2	1	0.9	-0.16	0.81	0.51	0.47	0.64	0.36	-0.0058	0.48	-0.22
Fire_Station_ACC	-0.056	0.19	0.75	-0.31	0.62	0.78	0.14	0.9	1	-0.17	0.82	0.48	0.4	0.61	0.31	0.0046	0.38	-0.23
Population	0.048	-0.18	-0.12	0.58	-0.16	-0.19	-0.019	-0.16	-0.17	1	-0.18	-0.14	-0.11	-0.15	-0.088	0.046	-0.064	0.49
Theme_Park_ACC	-0.057	0.19	0.67	-0.32	0.51	0.76	0.14	0.81	0.82	-0.18	1	0.46	0.36	0.53	0.34	-0.039	0.42	-0.25
Parking_lot_ACC	-0.047	0.23	0.41	-0.23	0.61	0.44	0.52	0.51	0.48	-0.14	0.46	1	0.58	0.76	0.26	-0.036	0.41	-0.22
Sports_Facility_ACC	-0.039	0.22	0.48	-0.19	0.42	0.43	0.55	0.47	0.4	-0.11	0.36	0.58	1	0.76	0.23	-0.023	0.51	-0.17
Elementary_School_ACC	-0.054	0.27	0.6	-0.26	0.63	0.51	0.56	0.64	0.61	-0.15	0.53	0.76	0.76	1	0.29	-0.02	0.58	-0.23
Farmland	-0.034	0.098	0.3	-0.14	0.24	0.26	0.12	0.36	0.31	-0.088	0.34	0.26	0.23	0.29	1	-0.036	0.32	-0.14
Stream	-0.0032	-0.043	-0.0046	0.062	-0.017	-0.00074	0.015	-0.0058	0.0046	0.046	-0.039	-0.036	-0.023	-0.02	-0.036	1	-0.1	0.026
Altitude	-0.032	0.18	0.47	-0.15	0.3	0.23	0.47	0.48	0.38	-0.064	0.42	0.41	0.51	0.58	0.32	-0.1	1	-0.097
Charger_type	0.085	-0.15	-0.17	0.59	-0.24	-0.25	-0.1	-0.22	-0.23	0.49	-0.25	-0.22	-0.17	-0.23	-0.14	0.026	-0.097	1

EDA

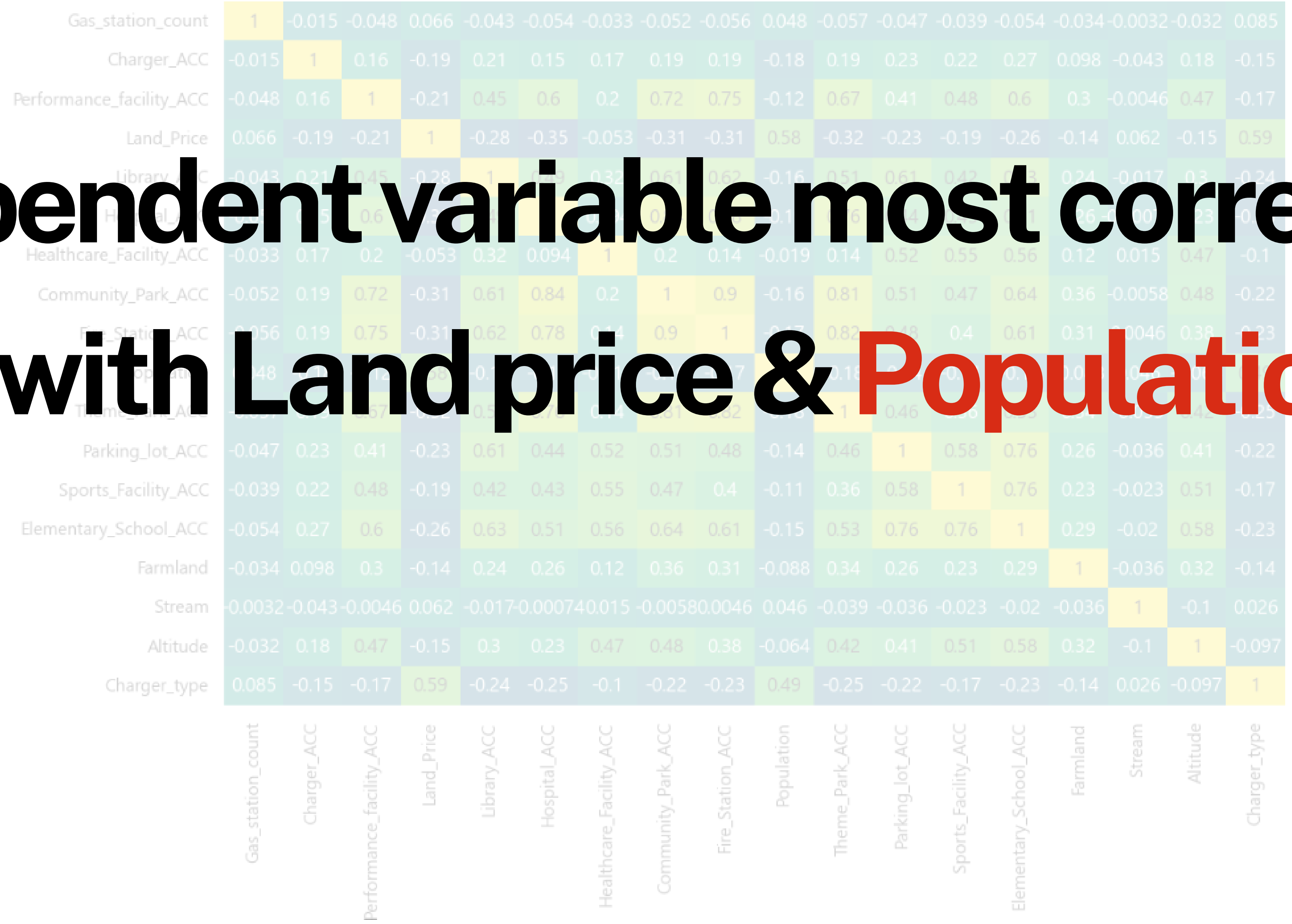
2.5.8 Correlation among variables



Dependent variable most correlated with Land price & Population.

EDA

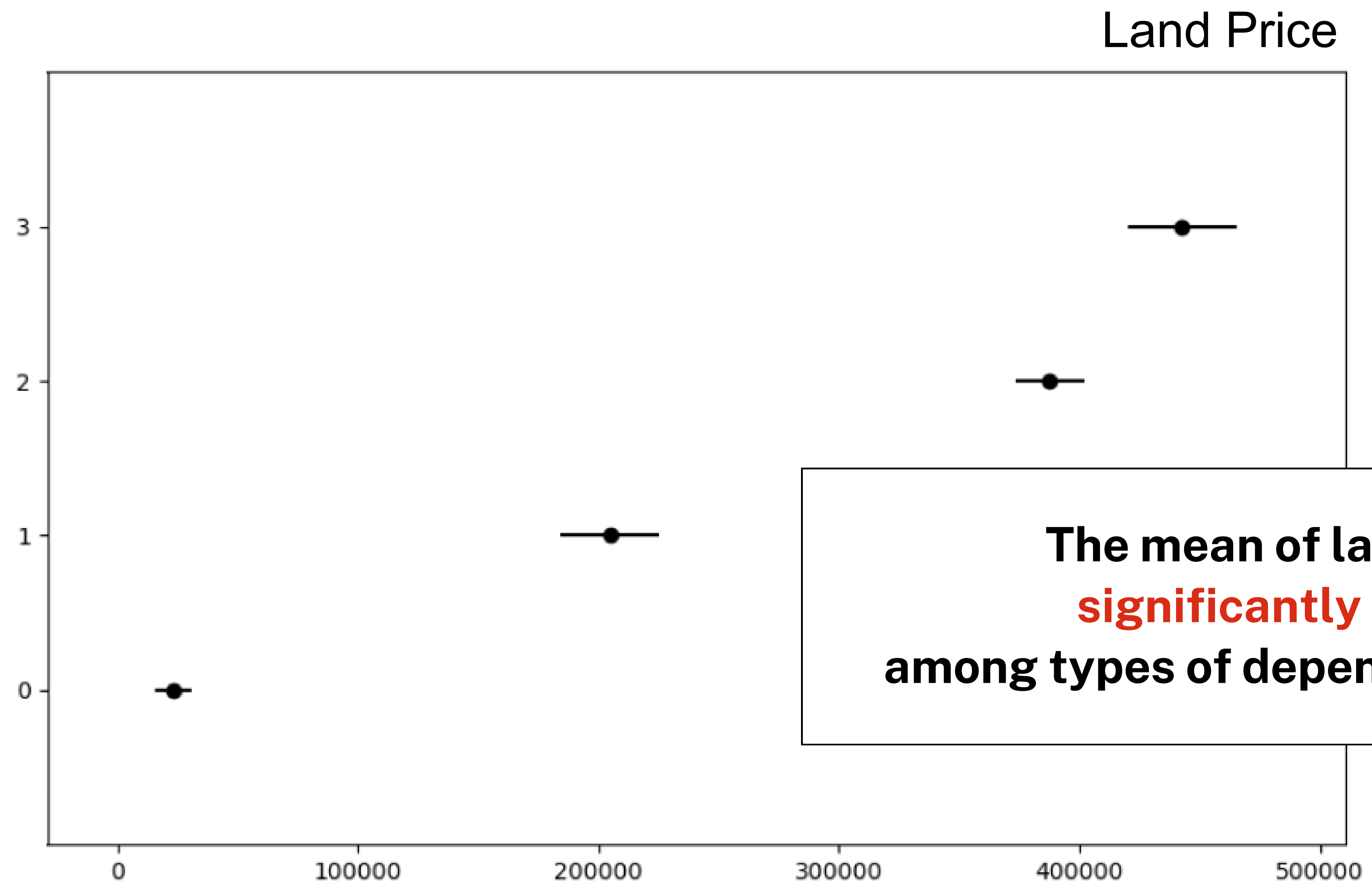
2.5.8 Correlation among variables



Dependent variable most correlated with Land price & Population.

Statistical Analysis

2.6.1 ANOVA (Analysis of Variance)

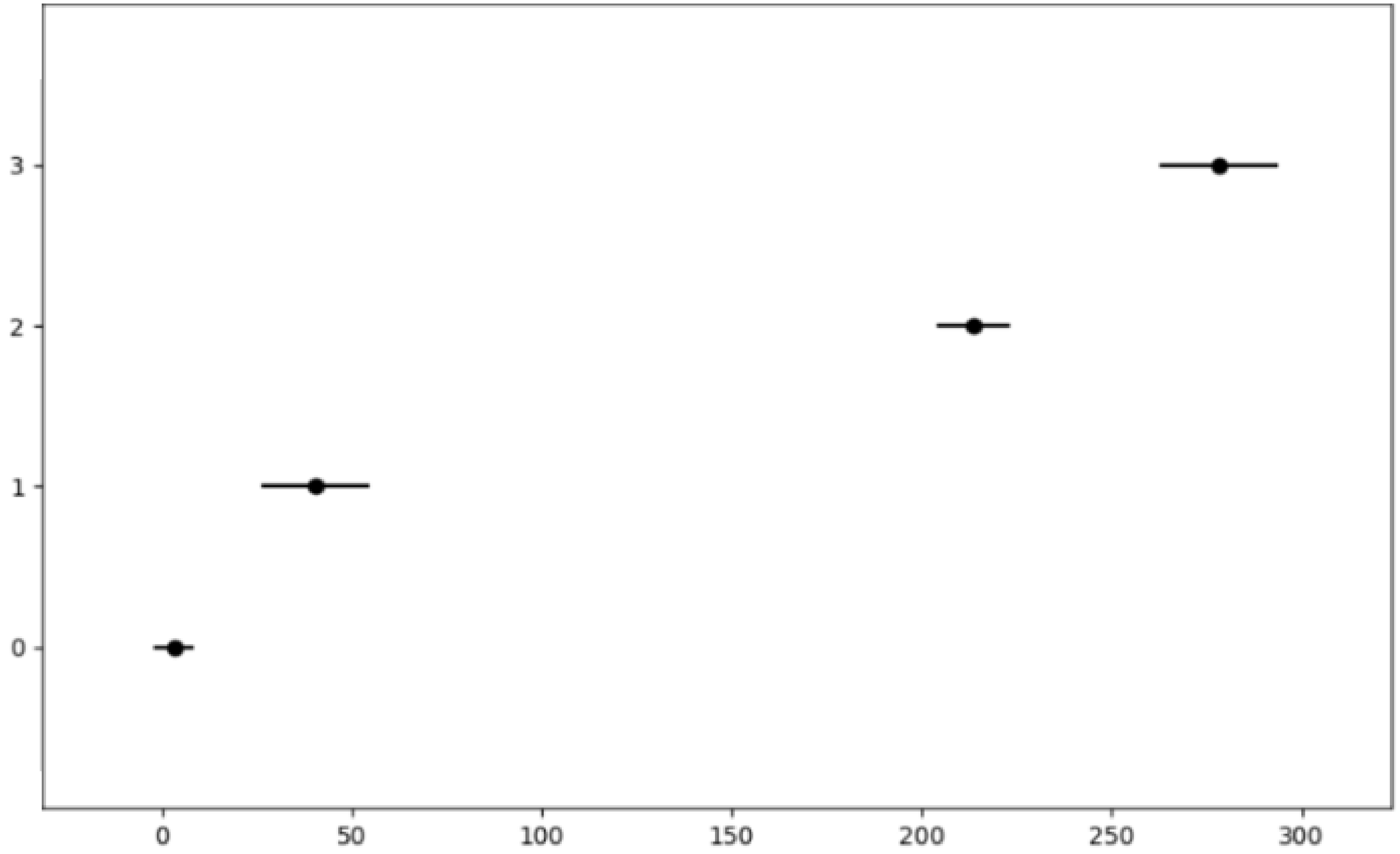


The mean of land price
significantly differs
among types of dependent variables.

Statistical Analysis

2.6.1 ANOVA (Analysis of Variance)

Population



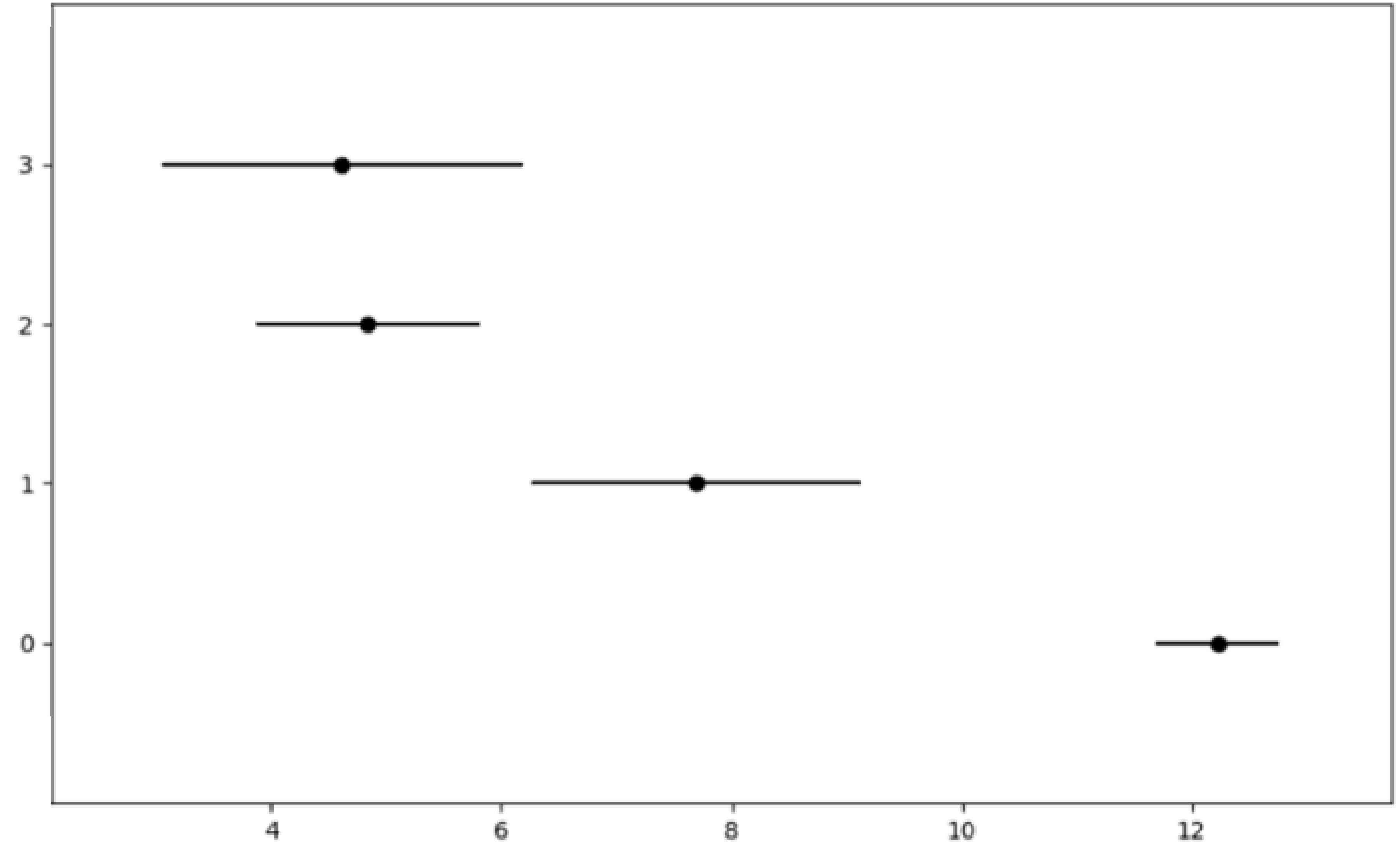
Accessibility to Hospital

Statistical Analysis

2.6.1 ANOVA (Analysis of Variance)

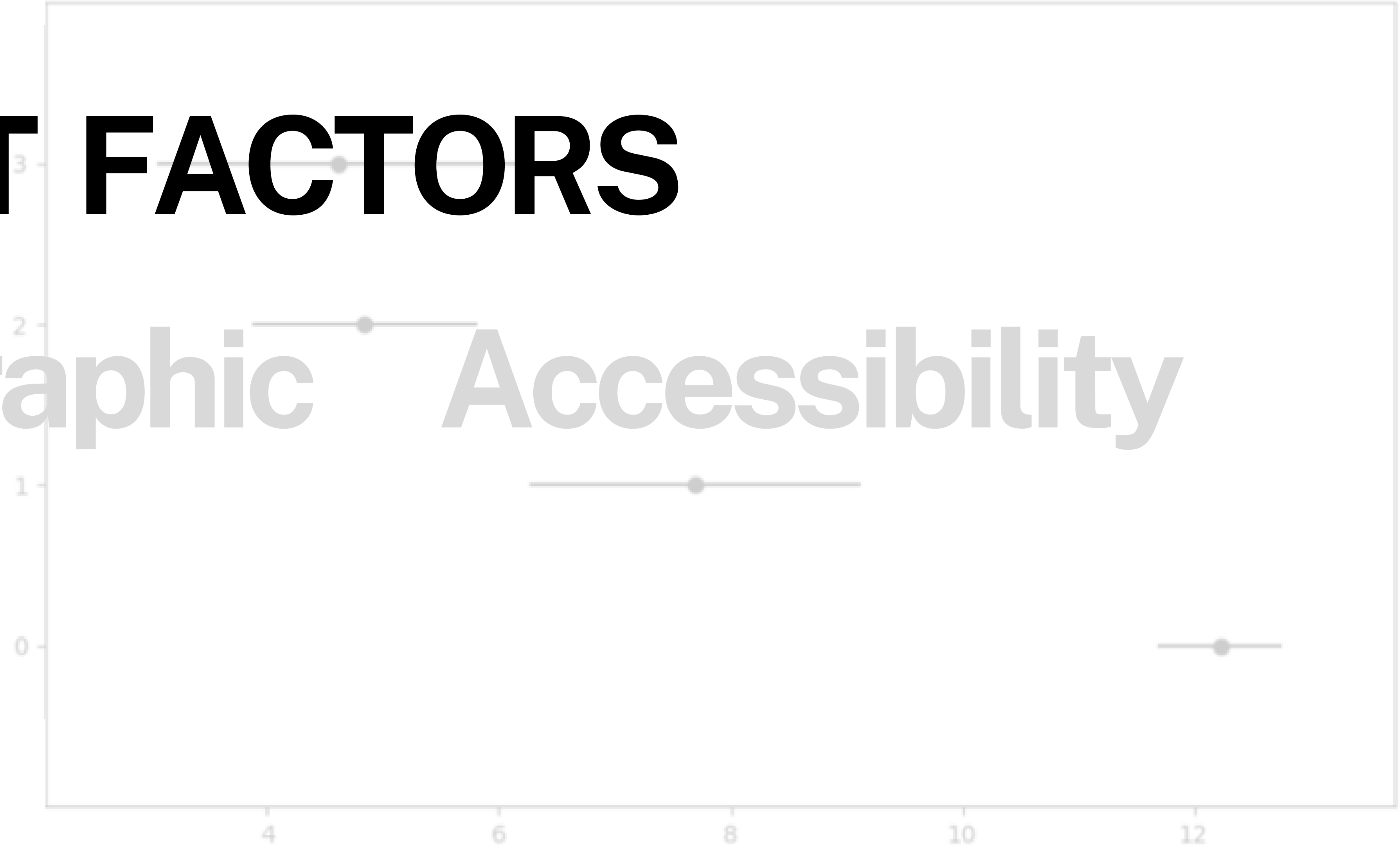
Population

Accessibility to Hospital



Statistical Analysis

2.6.1 ANOVA (Analysis of Variance)



IMPORTANT FACTORS

Econimic

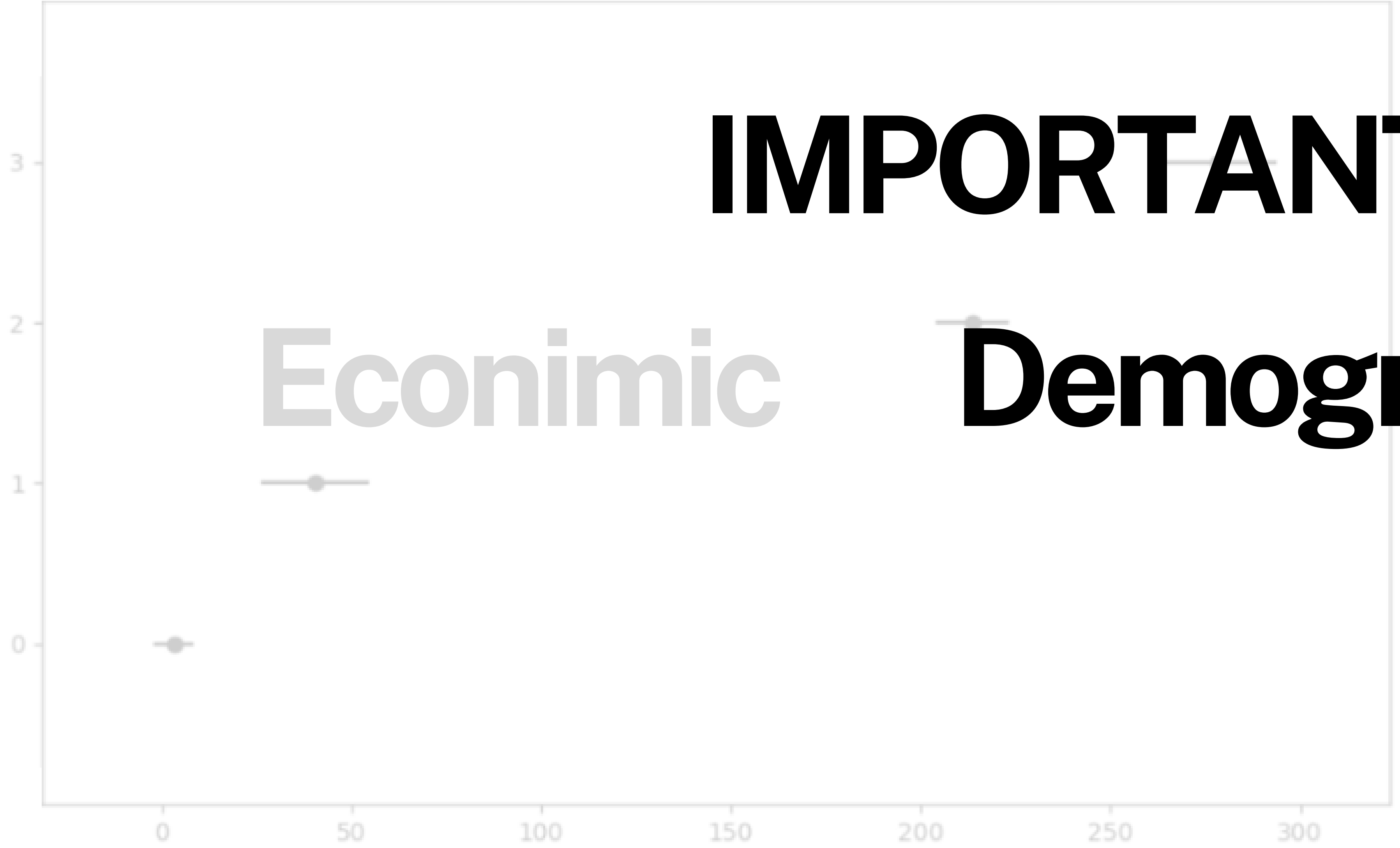
Demographic

Accessibility

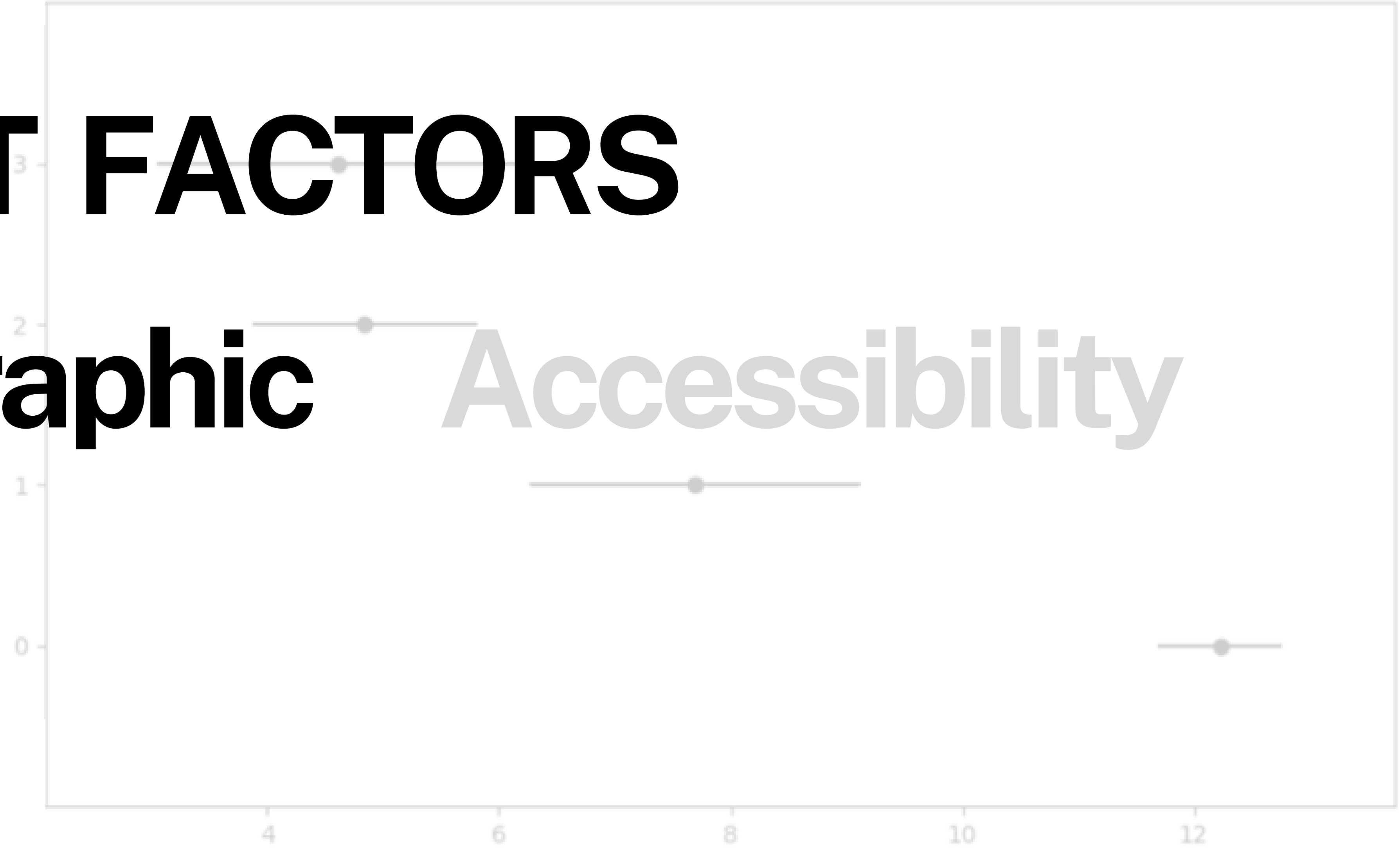
Statistical Analysis

2.6.1 ANOVA (Analysis of Variance)

Population



Accessibility to Hospital



IMPORTANT FACTORS

Econimic **Demographic** Accessibility

Statistical Analysis

2.6.1 ANOVA (Analysis of Variance)

IMPORTANT FACTORS

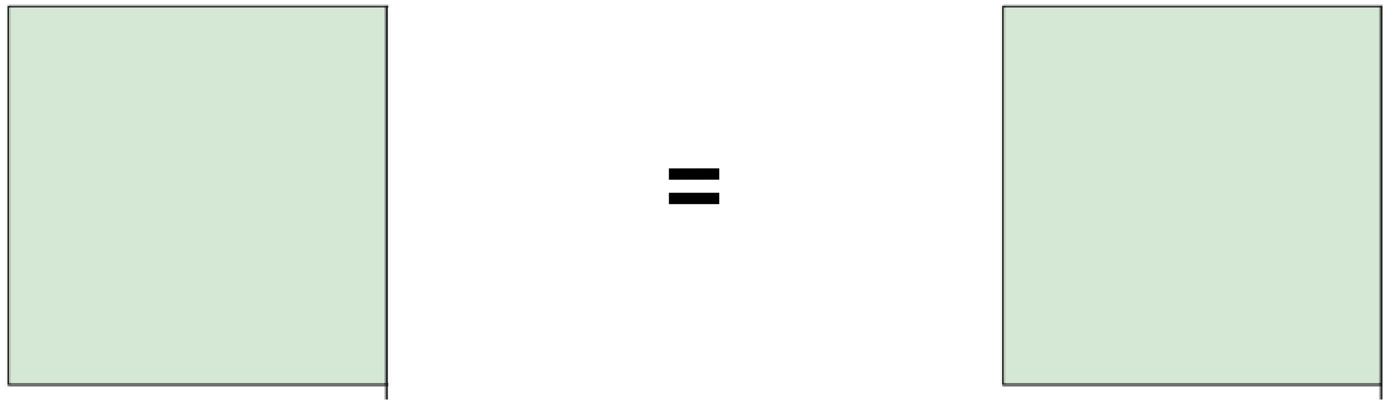
Econimic Demographic **Accessibility**

03 Modeling & Selection

Generation of Train Dataset

3.1 Problem

Train Data(250X250) **Test Data**(250X250)



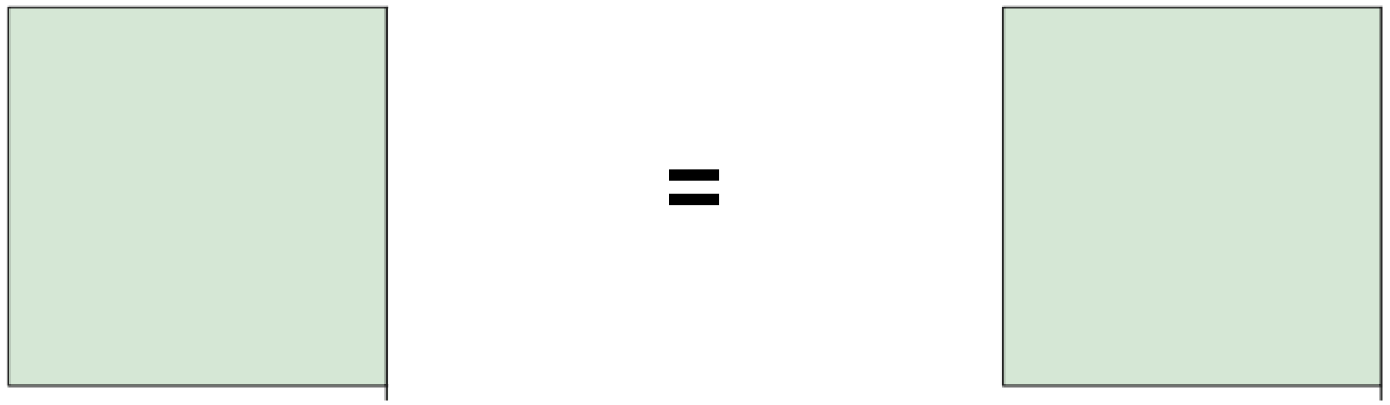
NOT possible to apply machine learning .

Because, train and test data are IDENTICAL .

Generation of Train Dataset

3.1 Problem

Train Data(250X250) **Test Data**(250X250)

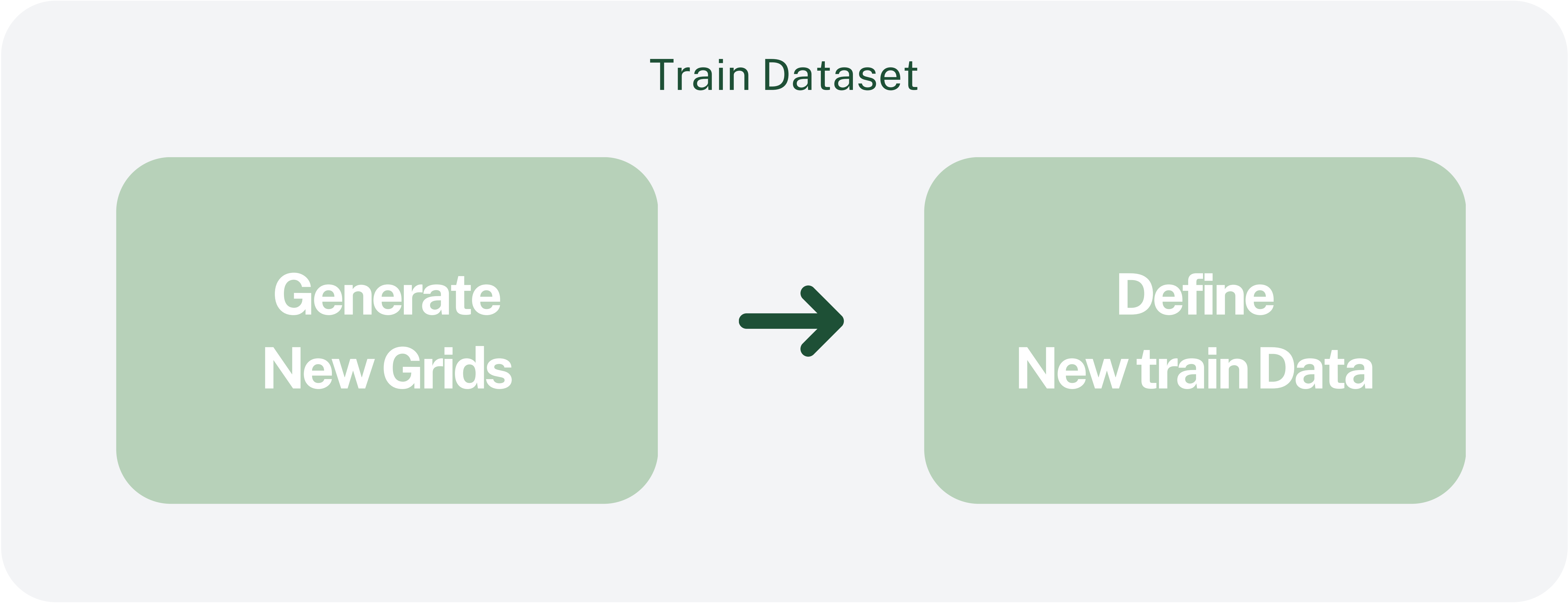


NOT possible to apply machine learning .

Because, train and test data are IDENTICAL .

Generation of Train Dataset

3.1.2 Solution



Generation of Train Dataset

3.1.2 Solution

Train Dataset

Generate New Grids → **Define New train Data**

Generation of Train Dataset

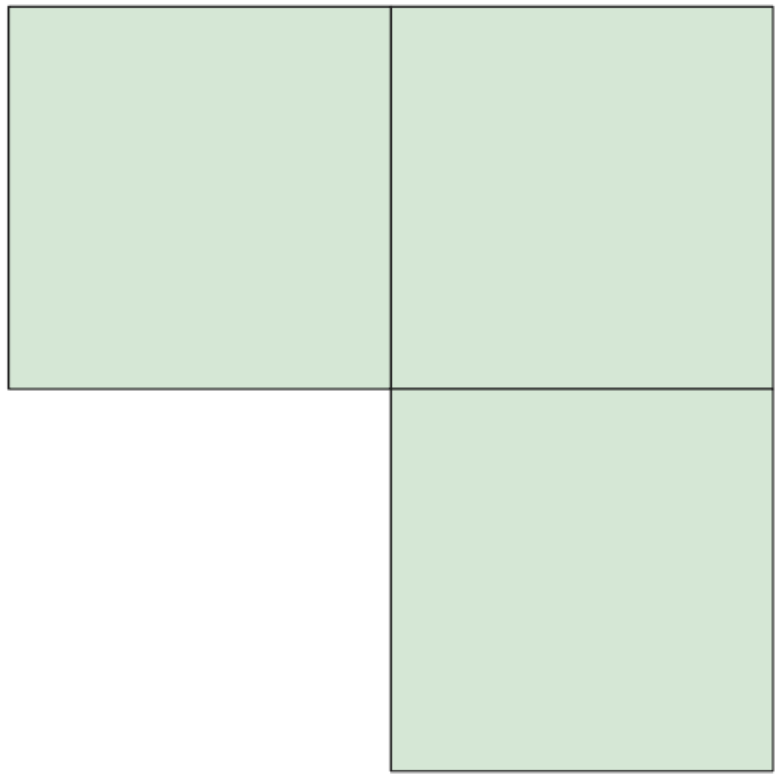
3.1.2 Solution

Train Dataset

Generate New Grids → **Define New train Data**

Generation of Train Dataset

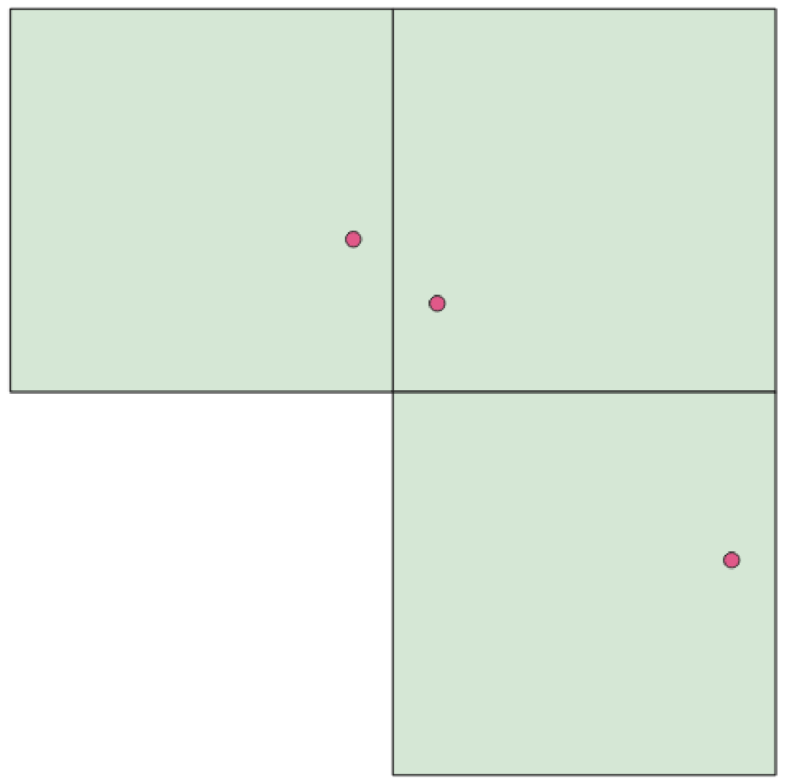
3.1.3 Generation of New Grids



Existing grids to be used for testing

Generation of Train Dataset

3.1.3 Generation of New Grids

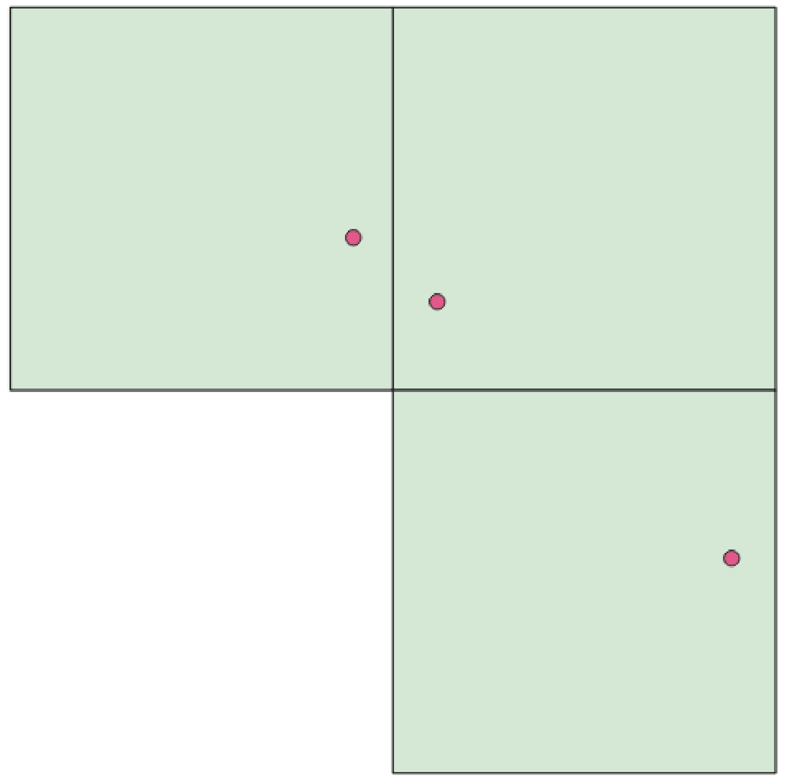


Generate random points within the grid range

NOTICE: For readability, the demonstration in the presentation will be conducted with 1 randomly selected point.

Generation of Train Dataset

3.1.3 Generation of New Grids

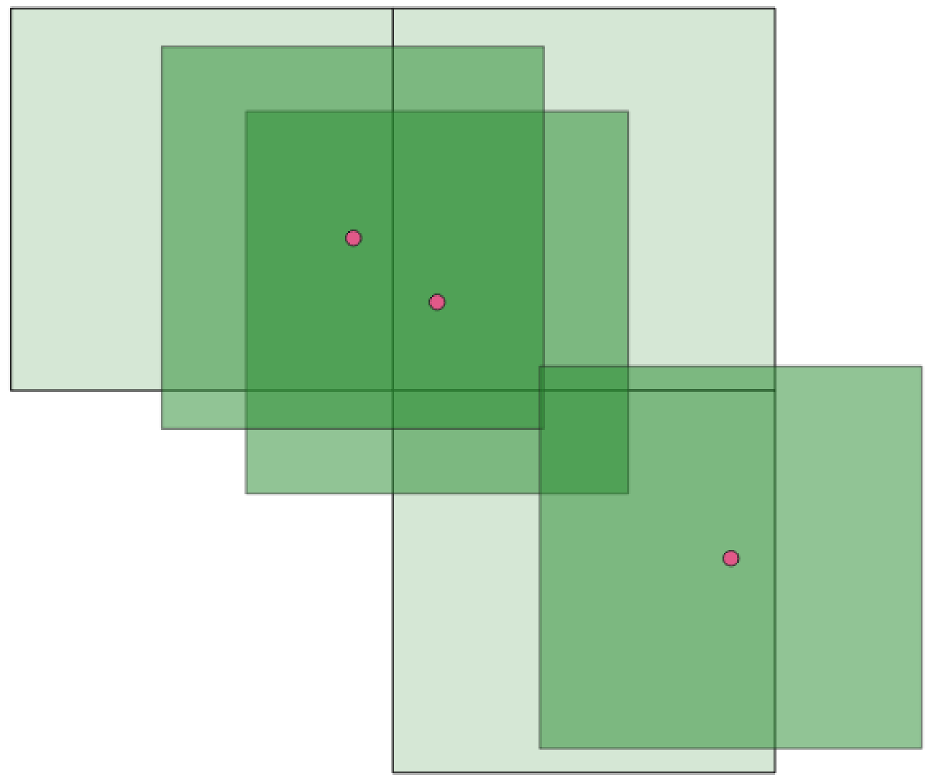


Set the distance between points in the grid to at least 10m

NOTICE: For readability, the demonstration in the presentation will be conducted with 1 randomly selected point.

Generation of Train Dataset

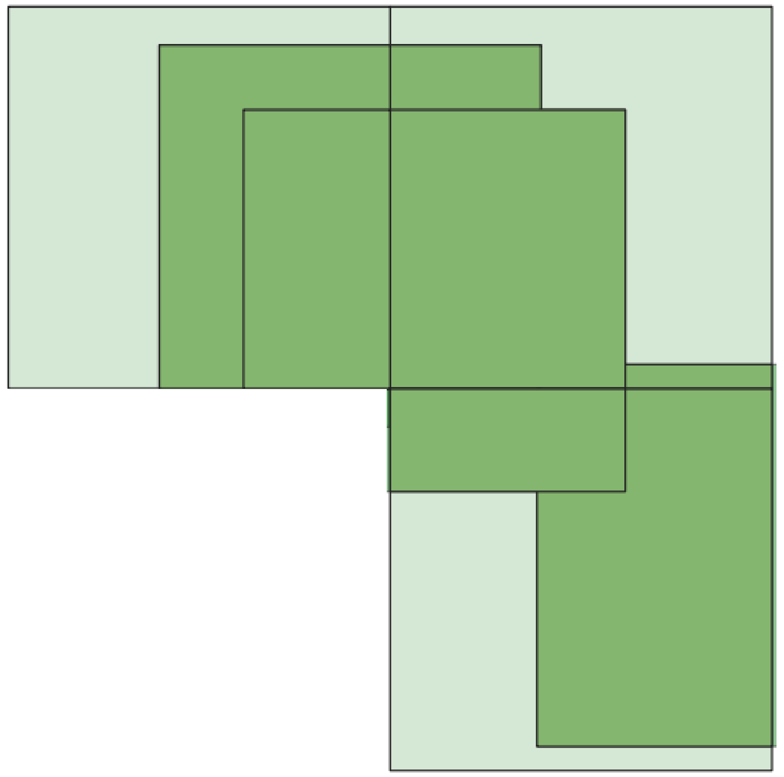
3.1.3 Generation of New Grids



Create new grids centered around the generated random points

Generation of Train Dataset

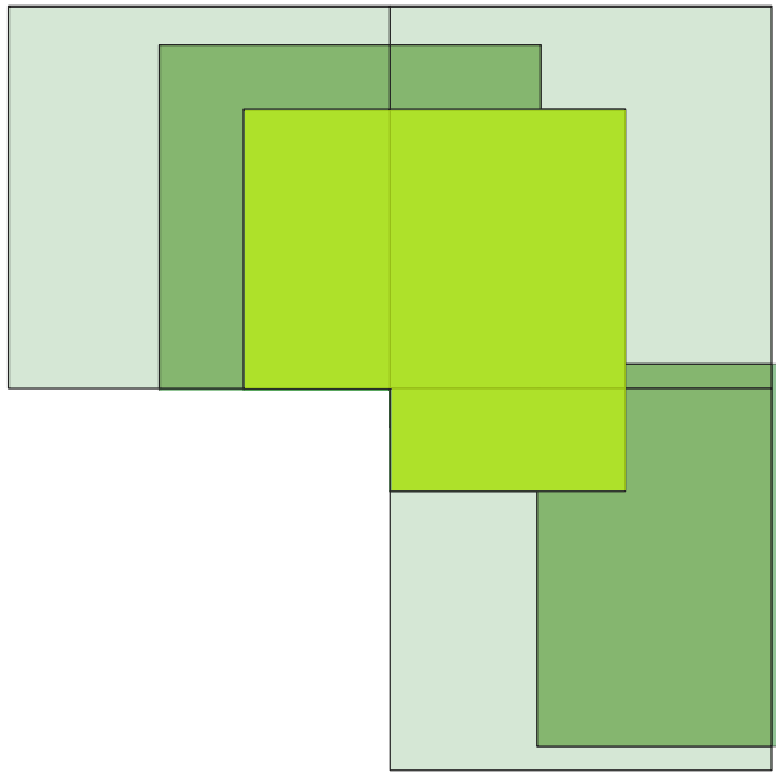
3.1.3 Generation of New Grids



Calculate the intersection area
between the new grid and the existing grid

Generation of Train Dataset

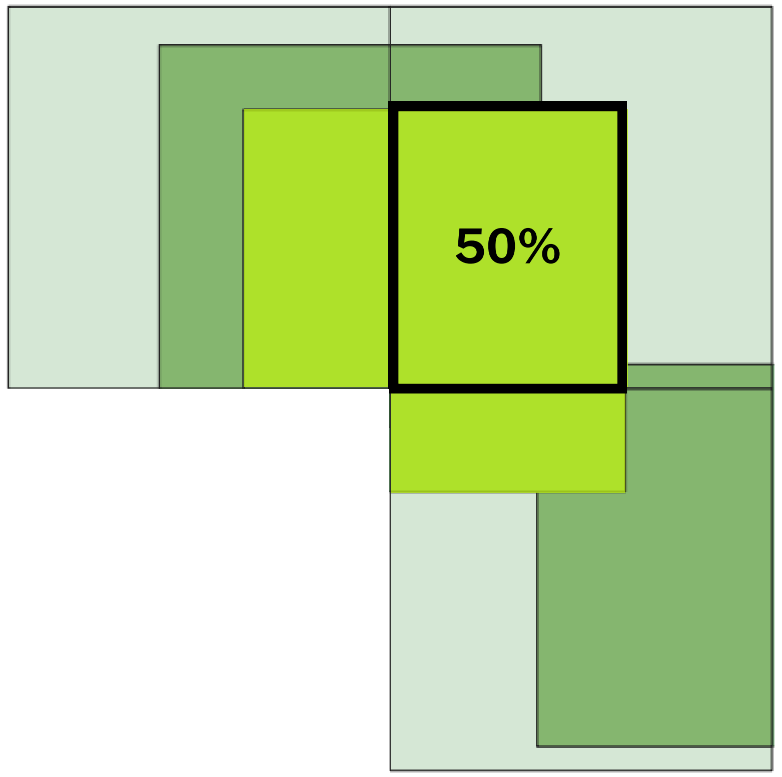
3.2 Defining Data Corresponding to the New Grid



New grids spanning multiple existing grids (targets for data generation)

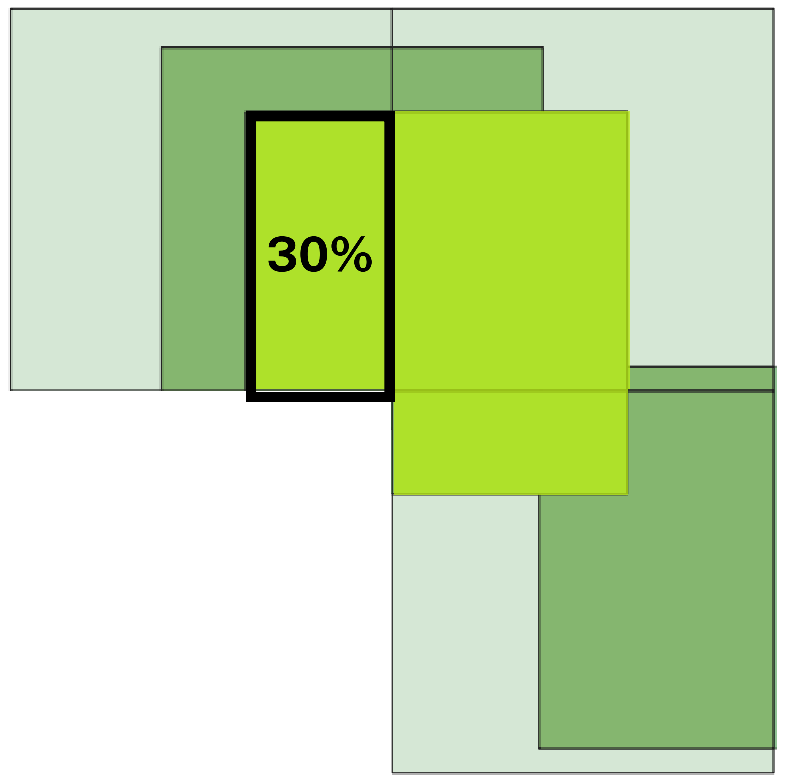
Generation of Train Dataset

3.2 Defining Data Corresponding to the New Grid



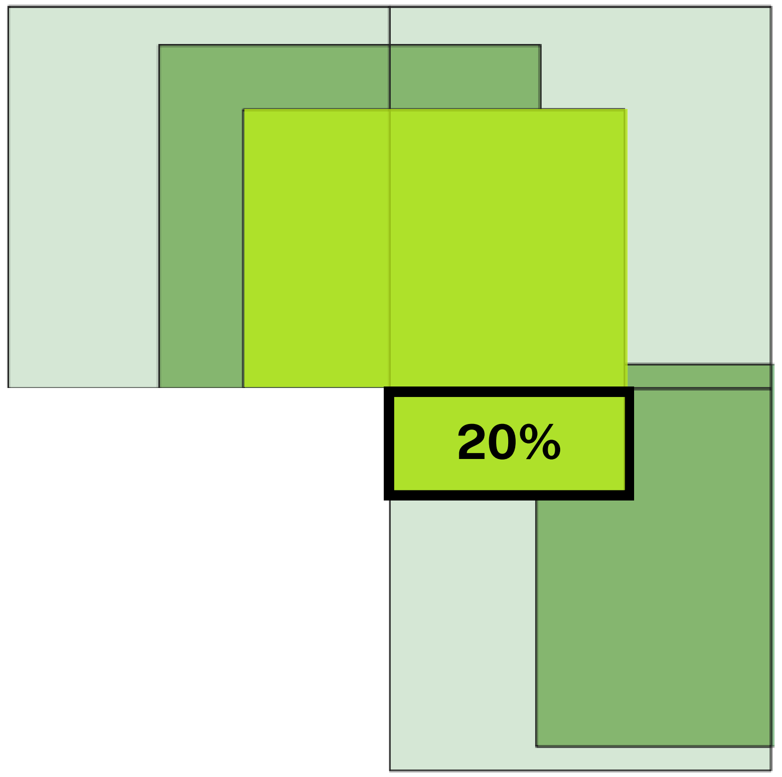
Generation of Train Dataset

3.2 Defining Data Corresponding to the New Grid



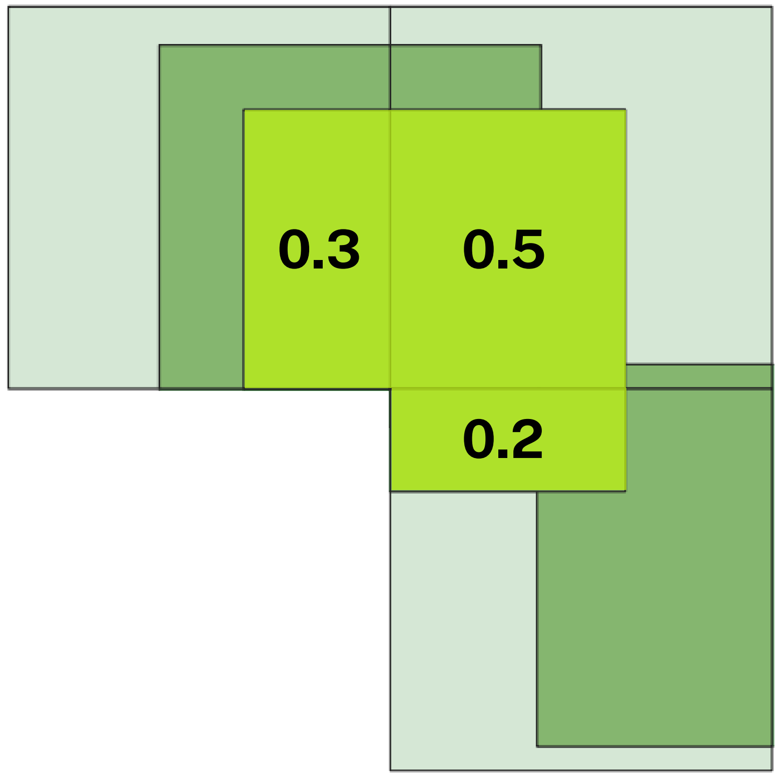
Generation of Train Dataset

3.2 Defining Data Corresponding to the New Grid



Generation of Train Dataset

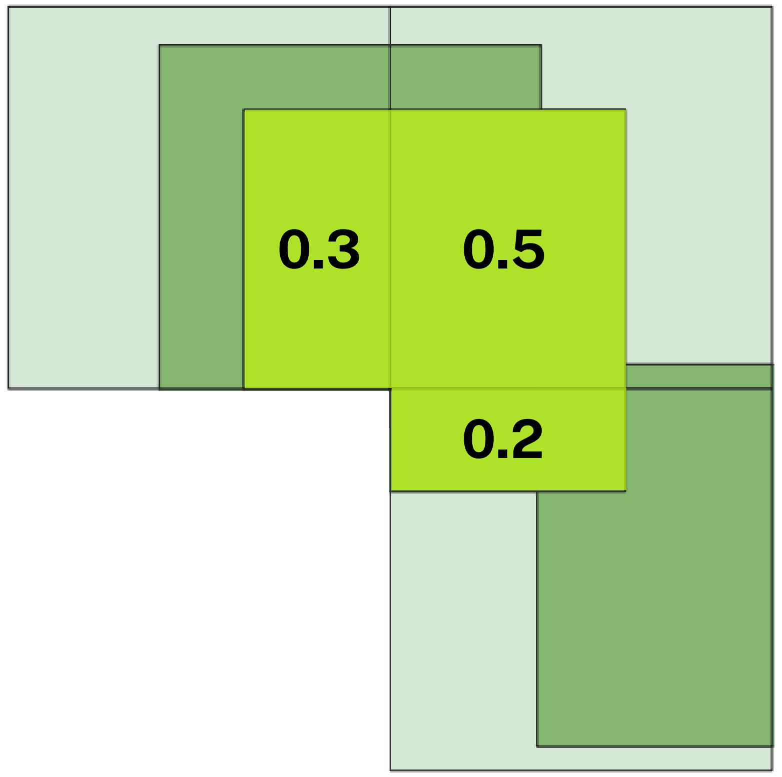
3.2 Defining Data Corresponding to the New Grid



Calculate the ratio of the overlapping area of new grids with existing grids

Generation of Train Dataset

3.2 Defining Data Corresponding to the New Grid



Finally, calculate the ratio to the total area of the grids.

Generation of Train Dataset

3.2 Defining Data Corresponding to the New Grid

$$X_i = \sum_{j=1}^{n} \left(\frac{Area(j)}{Total\ Area} \times X_{ij} \right)$$

X_i : the independent variable of the *i*th grid
X_{ij} : the independent variable value of the *j*th intersection within the *i*th grid
$Area(j)$: the area of the *j*th intersection within the *i*th grid
$Total\ Area$: the total area of the *i*th grid

Generation of Train Dataset

3.2 Defining Data Corresponding to the New Grid

- Accessibility
- Population
  Gas stations
- Streams
  Farmlands
- Altitude
- Charger Type

Generation of Train Dataset

3.2 Defining Data Corresponding to the New Grid

Accessibility

Population
Gas stations

Streams
Farmlands

Altitude

Chrger Type

Weighted processing

Generation of Train Dataset

3.2 Defining Data Corresponding to the New Grid

Accessibility

Population
Gas stations

Streams
Farmlands

Altitude

Chrger Type

Weighted processing -> rounding

Generation of Train Dataset

3.2 Defining Data Corresponding to the New Grid

Accessibility

Population
Gas stations

Streams
Farmlands

Altitude

Chrger Type

Binary representation

Generation of Train Dataset

3.2 Defining Data Corresponding to the New Grid

Accessibility

Population
Gas stations

Streams
Farmlands

Altitude

Chrger Type

Processing according to altitude values

Generation of Train Dataset

3.2 Defining Data Corresponding to the New Grid

Accessibility

Population
Gas stations

Streams
Farmlands

Altitude

Charger Type

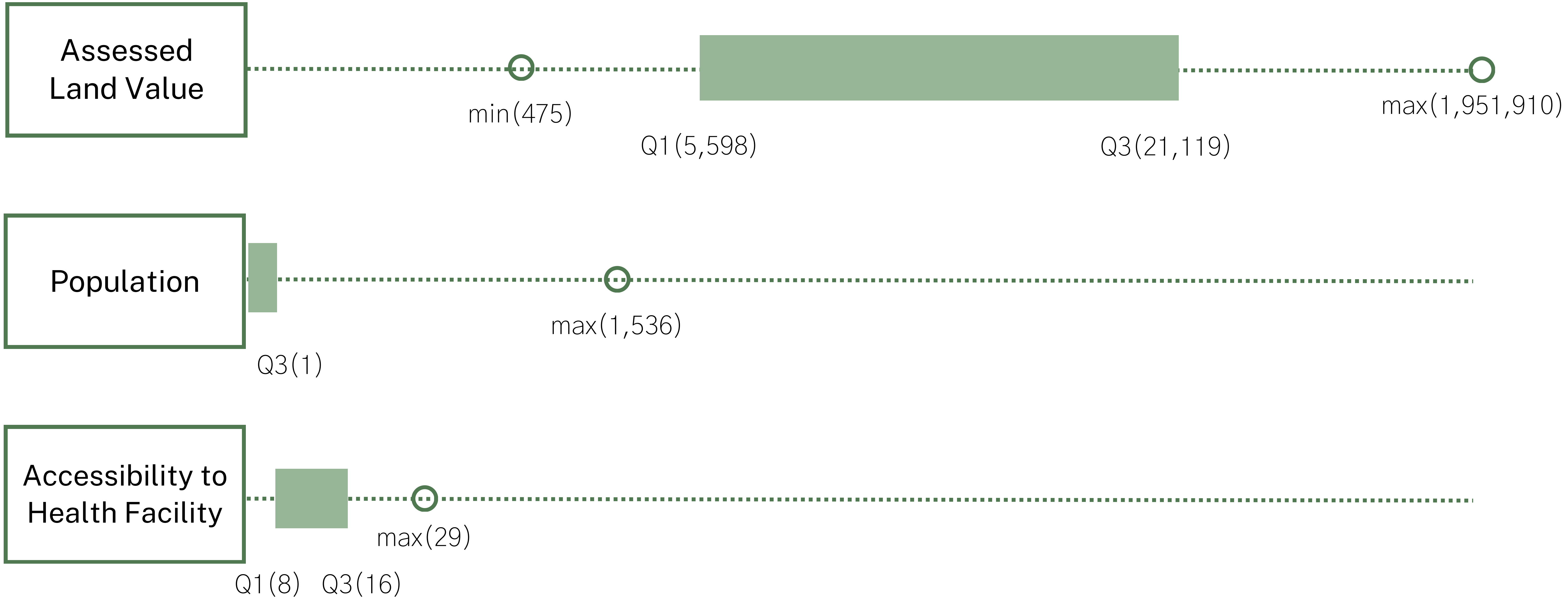
**Remove zeros, then
follow dependent variable rules**

Preprocessing

<table>
<tr><th colspan="4">Column list</th></tr>
<tr><td>Charger Type
(target)</td><td>• Fast, slow, or both</td><td>Land</td><td>• Assessed land value</td></tr>
<tr><td>Population</td><td>• Working Age Population</td><td>Topography</td><td>• Altitude
• Agricultural Land
• Stream Area</td></tr>
<tr><td>POI
(Point of Interest)</td><td>• Accessibility to neighborhood park
• Accessibility to Performing arts facility
• Accessibility to Library
• Accessibility to Public sports facility
• Accessibility to Elementary school
• Accessibility to General hospital
• Accessibility to Health facility
• Accessibility to Theme park</td><td rowspan="2">etc.</td><td rowspan="2">• Gas station location
• Accessibility to fire station (grid 250m)</td></tr>
<tr><td>National Infrastructure</td><td>• Accessibility to Parking lot</td></tr>
</table>

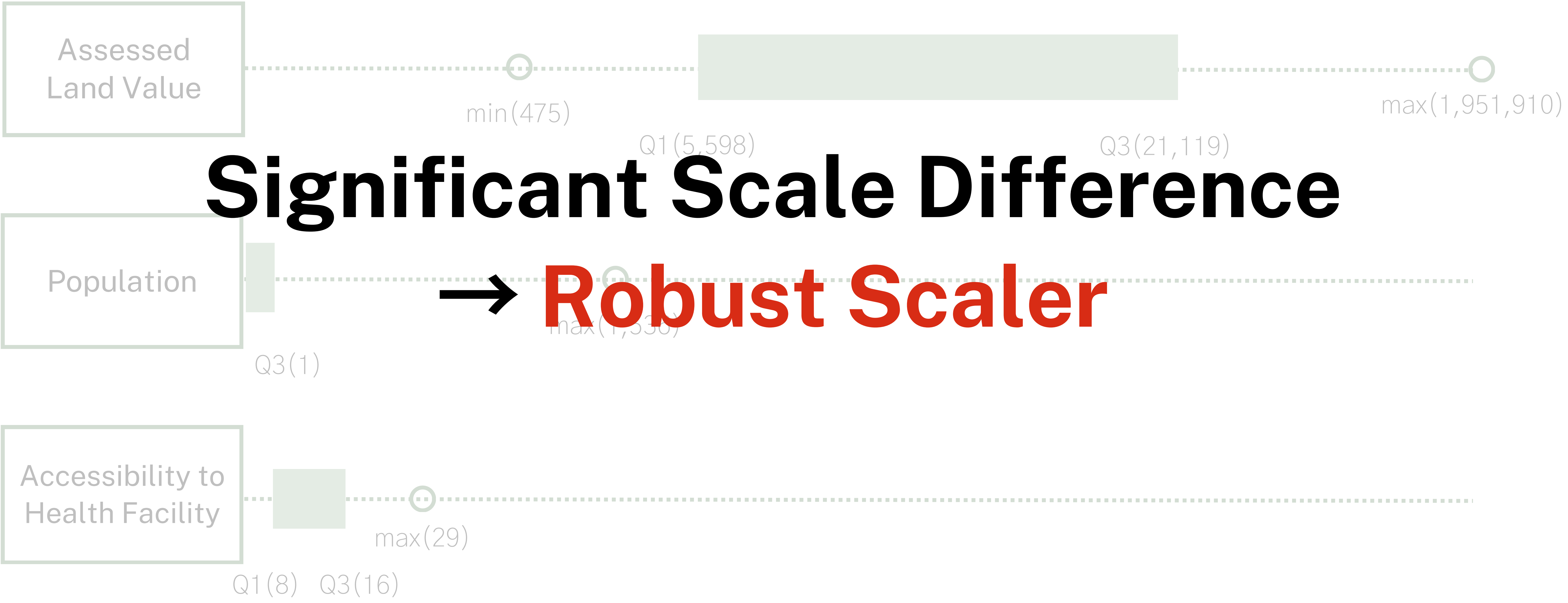
Preprocessing

3.3.1 Scaling



Preprocessing

3.3.1 Scaling

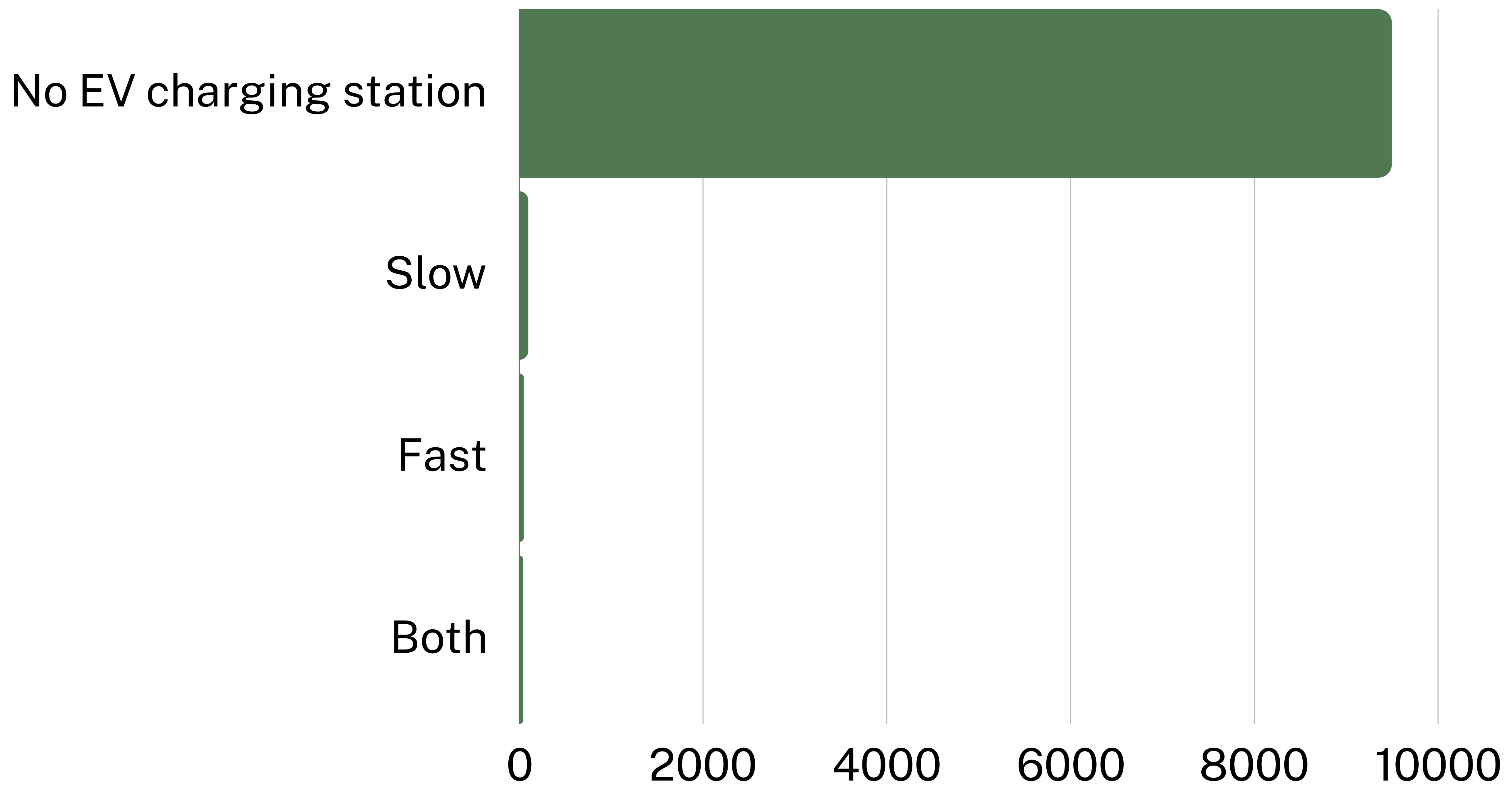


Significant Scale Difference

→ Robust Scaler

Preprocessing

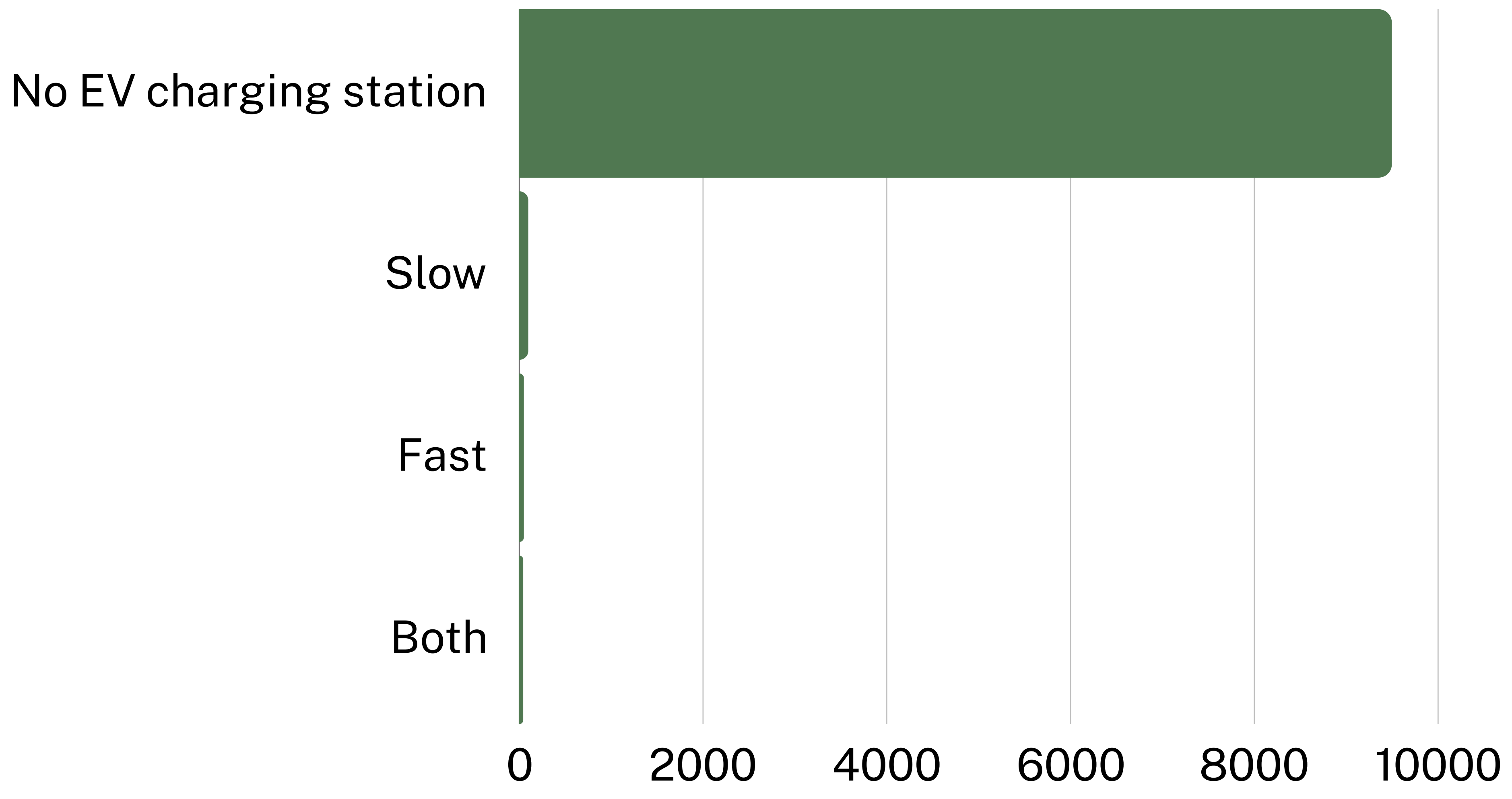
3.3.2 Over-Sampling



Due to severe class imbalance in dependant variable

Preprocessing

3.3.2 Over-Sampling

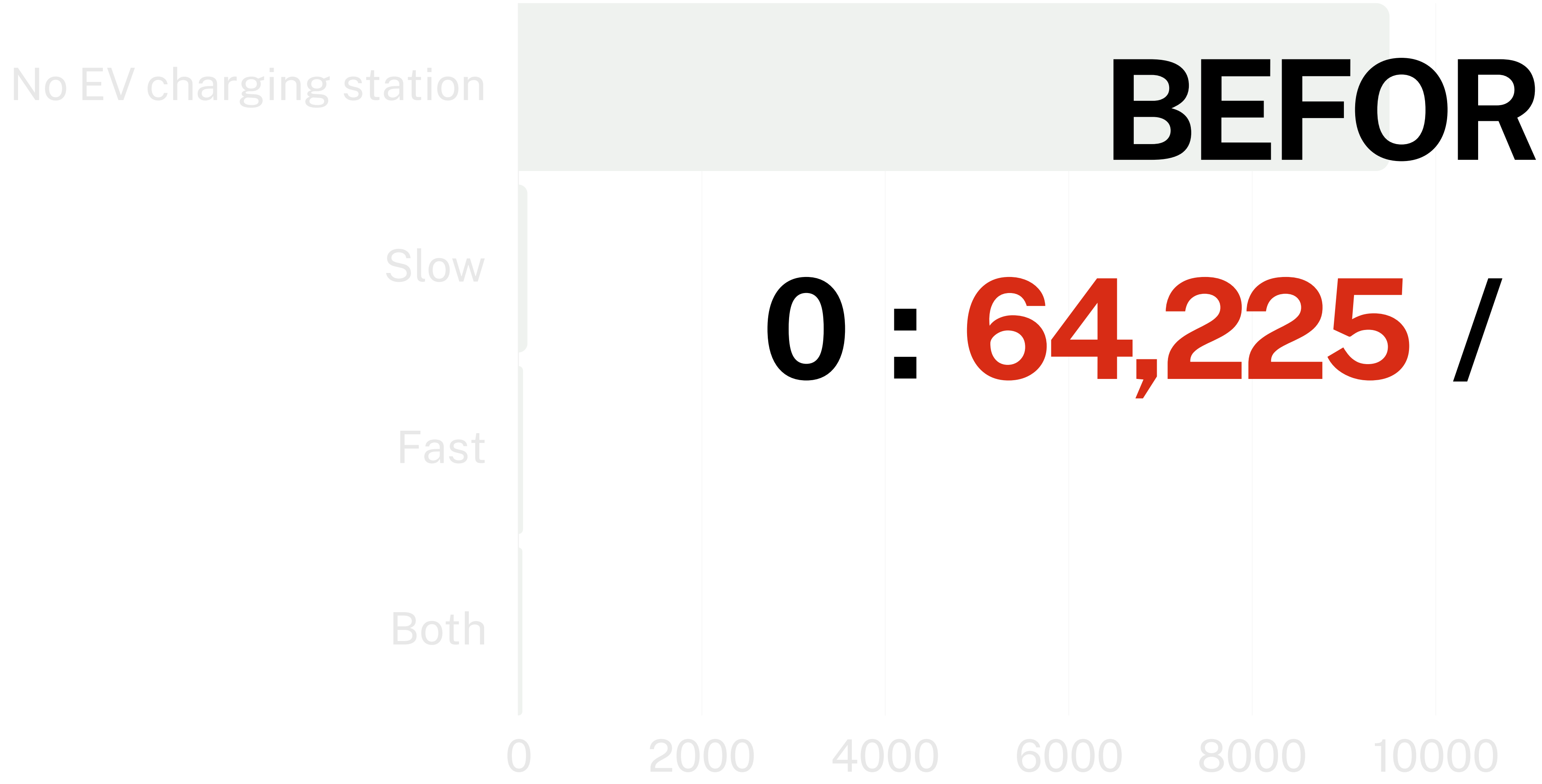


To prevent overfitting,

We used SMOTE !

Preprocessing

3.3.2 Over-Sampling



BEFORE

0 : 64,225 / 67,816

We used SMOTE !

Preprocessing

3.3.2 Over-Sampling

AFTER

All balanced within 67,816

We used SMOTE !

Modeling

F1-wei...	FP	F1-mac...	Recall-...	Imbalan...	Modeling	Scaling	Preprocessing	Encoding	Precision	train 정확도	test 정확도
0.97622	588	0.85667	0.95664	X	로지스틱	StandardScaler	공시지가 구간화	X	0.93564	0.95699	0.95664
0.97	542	0.46	0.94	SMOTE	LightGBM	RobustScaler	X	X (농림지역, 하천 범주형 변환x)	0.98		0.9380677126341
0.83	473	0.768497	0.899159	O	CatBoost	RobustScaler		X	0.687901	0.968057	0.965128
0.831041	472	0.768803	0.900704	O	CatBoost	RobustScaler		O	0.689457	0.967872	0.965202
0.834065	438	0.775373	0.895188	O	LightGBM	StandardScaler		X	0.697990	0.970379	0.967709
0.838171	436	0.780544	0.901768	O	LightGBM	StandardScaler		O	0.702514	0.969715	0.967856
0.94	427(0,1)			SMOTE	LightGBM	RobustScaler	O(공시지가,인구 구간화)	X		0.94	0.90
0.843586	423	0.787281	0.908962	O	CatBoost	StandardScaler		X	0.709287	0.971430	0.968815
0.96	4[illegible]	[illegible]	0.95	SMOTE	XGBoost	RobustScaler	[illegible]	X (농림지역[illegible] 변환x)	0.98		0.9511767134599
0.97	4[illegible]	[illegible]	0.95	[illegible]TE	Voting Classifier	Ro[illegible]Scaler	[illegible]	X (농[illegible]환x)	[illegible]	[illegible]	[illegible]
.846519	4[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	O	[illegible]6194	[illegible]	[illegible]
0.842903	3[illegible]	[illegible]2	0.887816	O	XGBoost	Ro[illegible]er	[illegible]	O	0.722251	0.973494	0.971542
0.843637	379	0.791550	0.886064	O	XGBoost	RobustScaler		X	0.724876	0.973439	0.972058
0.858233	339	0.811591	0.896579	O	XGBoost	StandardScaler		X	0.749754	0.976757	0.975007
0.862084	328	0.816273	0.902956	O	XGBoost	StandardScaler		O	0.753289	0.977107	0.975818
0.96	303	0.55	0.96	SMOTE	RandomForest	RobustScaler	X	X (농림지역, 하천 범주형 변환x)	0.99		0.9632535094962
0.878276	250	0.841257	0.890849	O	RandomForest	RobustScaler		O	0.799430	0.981033	0.981569
0.98209	238	0.42768	0.98245	X	LightGBM	StandardScaler	공시지가 구간화	X	0.98179		0.99663
0.887036	236	0.852648	0.902414	O	RandomForest	RobustScaler		X	0.810480	0.981107	0.982601
0.98	225	0.63	0.98	X	RandomForest	RobustScaler	X	X (농림지역, 하천 범주형 변환x)	0.99		0.976775
0.875905	225	0.836892	0.798595	X	CatBoost	RobustScaler		X	0.884720	0.980406	0.983412
0.875905	225	0.836892	0.798595	X	CatBoost	StandardScaler		X	0.884720	0.980443	0.983412
0.875021	225	0.837680	0.818	X	LightGBM	RobustScaler		O	0.860994	0.981770	0.983412
0.875021	225	0.837680	0.818	X	LightGBM	RobustScaler		X	0.860994	0.981383	0.983412
0.87533	223	0.837224	0.80726	X	CatBoost	RobustScaler		O	0.873275	0.980296	0.983559
0.87533	223	0.837224	0.80726	X	CatBoost	StandardScaler		O	0.873275	0.980591	0.983559
0.877035	221	0.840875	0.824913	X	LightGBM	StandardScaler		X	0.858645	0.981733	0.983707
0.876944	221	0.840065	0.817096	X	LightGBM	StandardScaler		O	0.866910	0.981475	0.983707
0.891706	218	0.859321	0.898739	O	RandomForest	StandardScaler		X	0.824837	0.982526	0.983928
0.98	216	0.57	0.97	X	LightGBM	RobustScaler	X	X (농림지역, 하천 범주형 변환x)	0.99		0.971305

Modeling

F1-wei...	FP	F1-mac...	Recall-...	Imbalan...	Modeling	Scaling	Preprocessing	Encoding	Precision	train 정확도	test 정확도
0.97622	588	0.85667	0.95664	X	로지스틱	StandardScaler	공시지가 구간화	X	0.93564	0.95699	0.95664
0.97	542	0.46	0.94	SMOTE	LightGBM	RobustScaler	X	X (농림지역, 하천 범주형 변환x)	0.98		0.9380677126341
0.83	473	0.768497	0.899159	O	CatBoost	RobustScaler		X	0.687901	0.968057	0.965128
0.831041	472	0.768803	0.900704	O	CatBoost	RobustScaler		O	0.689457	0.967872	0.965202
0.834065	438	0.775373	0.895188	O	LightGBM	StandardScaler		X	0.697990	0.970379	0.967709
0.838171	436	0.780544	0.901768	O	LightGBM	StandardScaler		O	0.702514	0.969715	0.967856
0.94	427(0,1			SMOTE	LightGBM	RobustScaler	O(공시지가,인구 구간화)	X		0.94	0.90
0.843586	423	0.787281	0.908962	O	CatBoost	StandardScaler		X	0.709287	0.971430	0.968815
0.96	420	0.50	0.95	SMOTE	XGBoost	RobustScaler	X	X (농림지역, 하천 범주형 변환x)	0.98		0.9511767134599
0.97	413	0.50	0.95	SMOTE	Voting Classifier	RobustScaler	X	X (농림지역, 하천 범주형 변환x)	0.98		0.9515895953757
0.846519	410	0.791650	0.90846	O	CatBoost	StandardScaler		O	0.716194	0.971559	0.969773
0.842903	386	0.790002	0.887816	O	XGBoost	RobustScaler		O	0.722251	0.973494	0.971542
0.843637	379	0.791550	0.886064	O	XGBoost	RobustScaler		X	0.724876	0.973439	0.972058
0.858233	339	0.811591	0.896579	O	XGBoost	StandardScaler		X	0.749754	0.976757	0.975007
0.862084	328	0.816273	0.902956	O	XGBoost	StandardScaler		O	0.753289	0.977107	0.975818
0.96	303	0.55	0.96	SMOTE	RandomForest	RobustScaler	X	X (농림지역, 하천 범주형 변환x)	0.99		0.9632535094962
0.878276	250	0.841257	0.890849	O	RandomForest	RobustScaler		O	0.799430	0.981033	0.981569
0.98209	238	0.42768	0.98245	X	LightGBM	StandardScaler	공시지가 구간화	X	0.98179		0.99663
0.887036	236	0.852648	0.902414	O	RandomForest	RobustScaler		X	0.810480	0.981107	0.982601
0.98	225	0.63	0.98	X	RandomForest	RobustScaler	X	X (농림지역, 하천 범주형 변환x)	0.99		0.976775
0.875905	225	0.836892	0.798595	X	CatBoost	RobustScaler		X	0.884720	0.980406	0.983412
0.875905	225	0.836892	0.798595	X	CatBoost	StandardScaler		X	0.884720	0.980443	0.983412
0.875021	225	0.837680	0.818	X	LightGBM	RobustScaler		O	0.860994	0.981770	0.983412
0.875021	225	0.837680	0.818	X	LightGBM	RobustScaler		X	0.860994	0.981383	0.983412
0.87533	223	0.837224	0.80726	X	CatBoost	RobustScaler		O	0.873275	0.980296	0.983559
0.87533	223	0.837224	0.80726	X	CatBoost	StandardScaler		O	0.873275	0.980591	0.983559
0.877035	221	0.840875	0.824913	X	LightGBM	StandardScaler		X	0.858645	0.981733	0.983707
0.876944	221	0.840065	0.817096	X	LightGBM	StandardScaler		O	0.866910	0.981475	0.983707
0.891706	218	0.859321	0.898739	O	RandomForest	StandardScaler		X	0.824837	0.982526	0.983928
0.98	216	0.57	0.97	X	LightGBM	RobustScaler	X	X (농림지역, 하천 범주형 변환x)	0.99		0.971305

Modeling

3.4 Model Selection

$$F_1 = 2 \times \frac{precision \times recall}{precision + recall}$$

Precision: the proportion of true positive predictions among all positive predictions made by the model
Recall: the proportion of true positive predictions among all actual positive instances in the dataset

Modeling

3.4 Model Selection

Preprocessing (Scaling + SMOTE) + **Comparison of FP (False Positive)** + **Model Evaluation (F1-score)** = **LightGBM**

Modeling

3.5 Confusion Matrix

		Predicted			
		0	1	2	3
Actual	0	8955	191	211	140
	1	0	33	0	[illegible]
	2	1	2	57	[illegible]
	3	0	0	0	[illegible]

A total of 542 grids:
Candidate grids for EV charger installation

Modeling

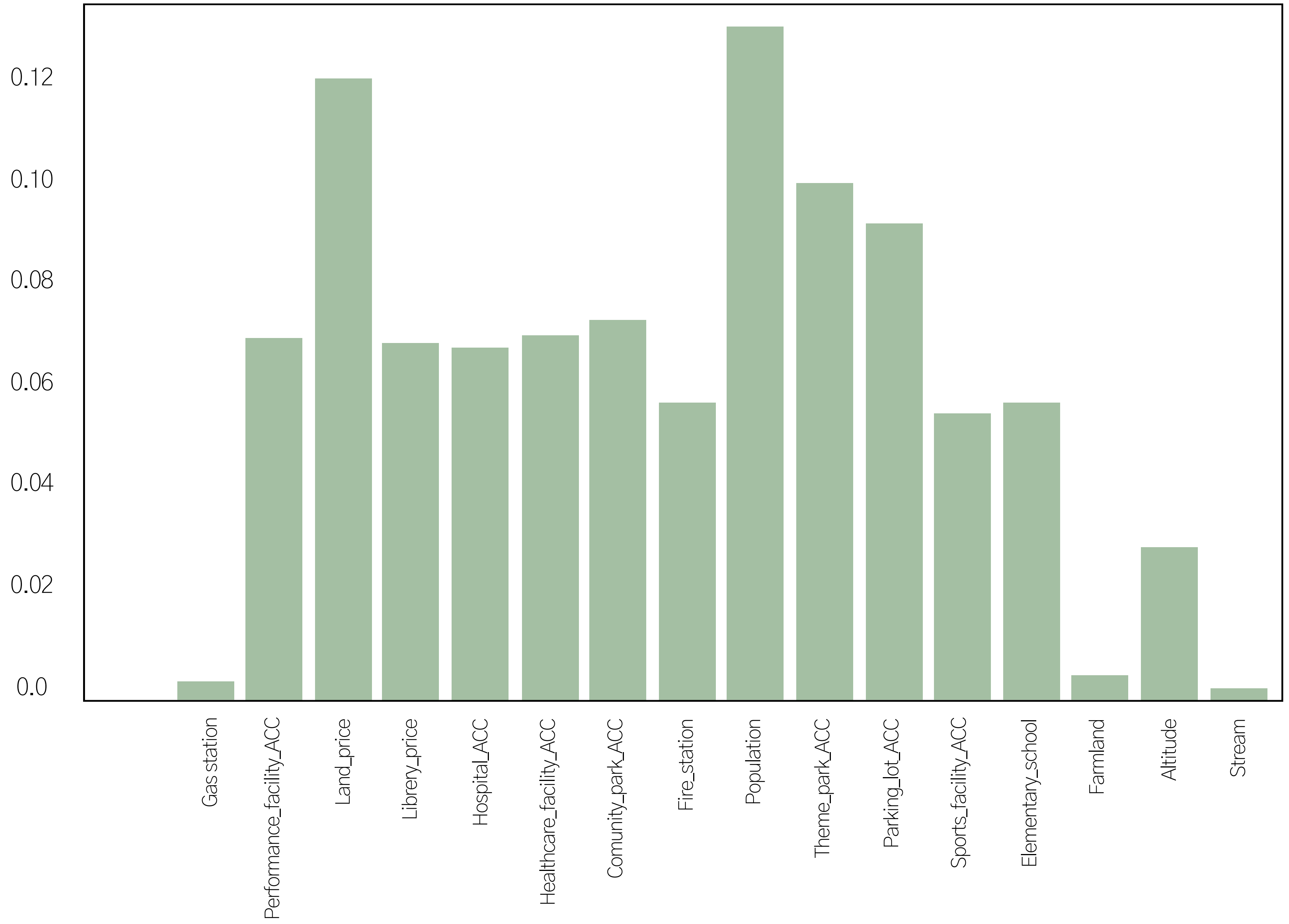
3.5 Confusion Matrix

	Predicted				
Actual		**0**	**1**	**2**	**3**
	0	8955	191	211	140
	1	0	33	0	**17**
	2	1	2	57	**38**
	3	0	0	0	43

Areas for adding both fast/slow charging stations

Modeling

3.6 Feature Imporatnce



High Importance

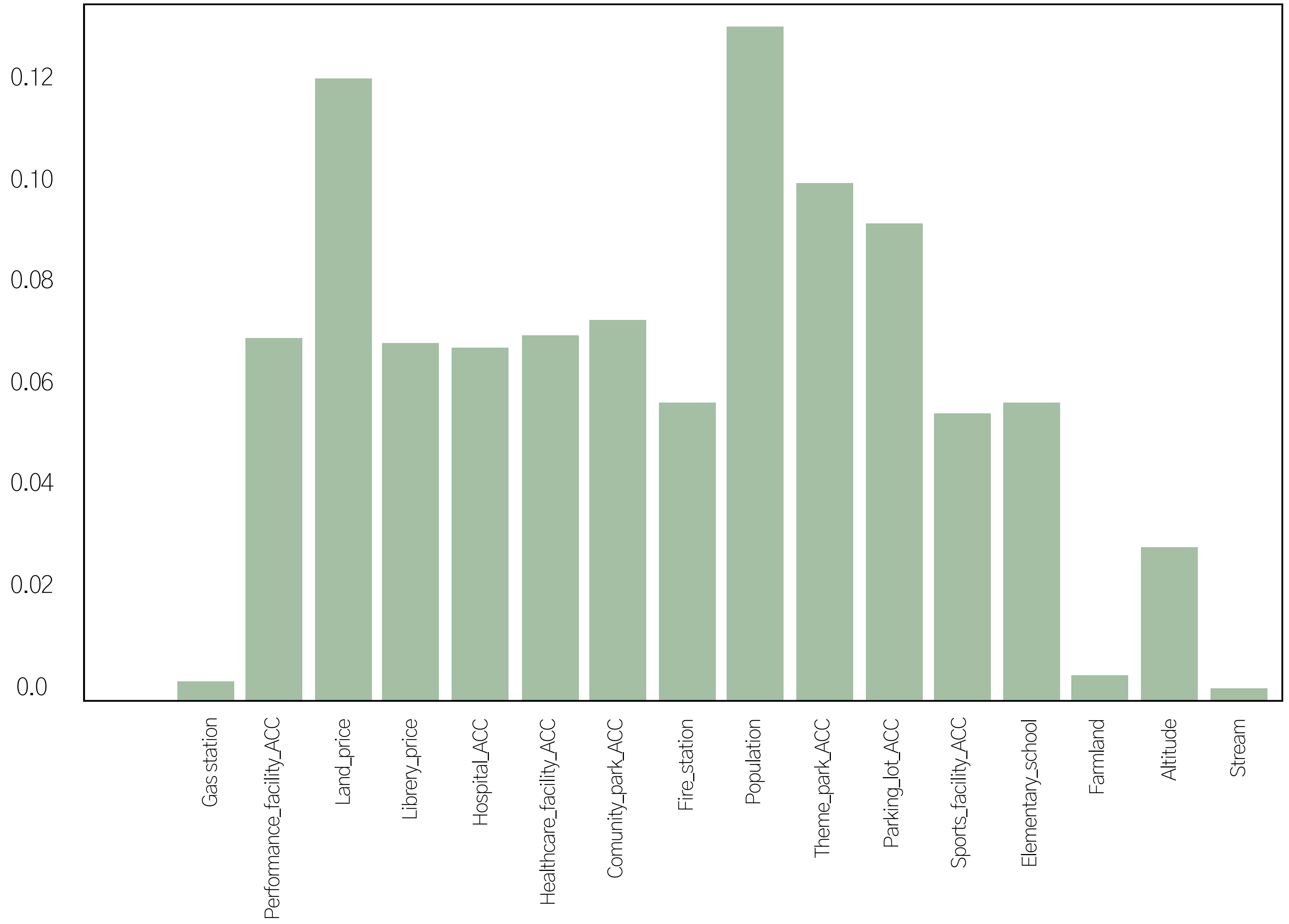
Population, Land price,
Accessibility (Theme Park , Parking Lot)

Low Importance

- **Count of Gas Station. : DELETE**
- **Farmland & Stream. : Keep**

Modeling

3.6 Feature Imporatnce



High Importance

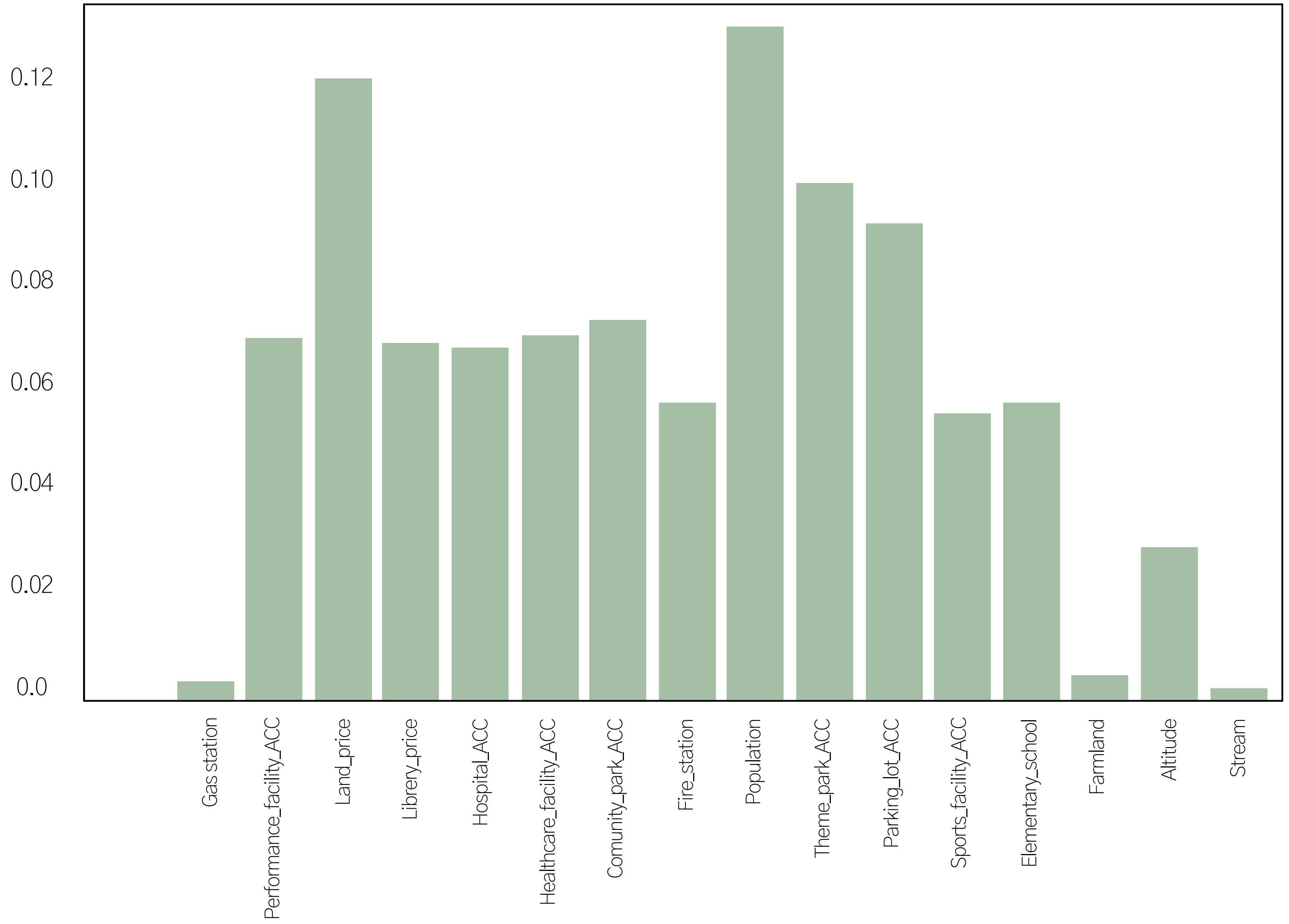
Population, Land price,
Accessibility (Theme Park , Parking Lot)

Low Importance

- Count of Gas Station. : DELETE
- Farmland & Stream. : Keep

Modeling

3.6 Feature Imporatnce



High Importance

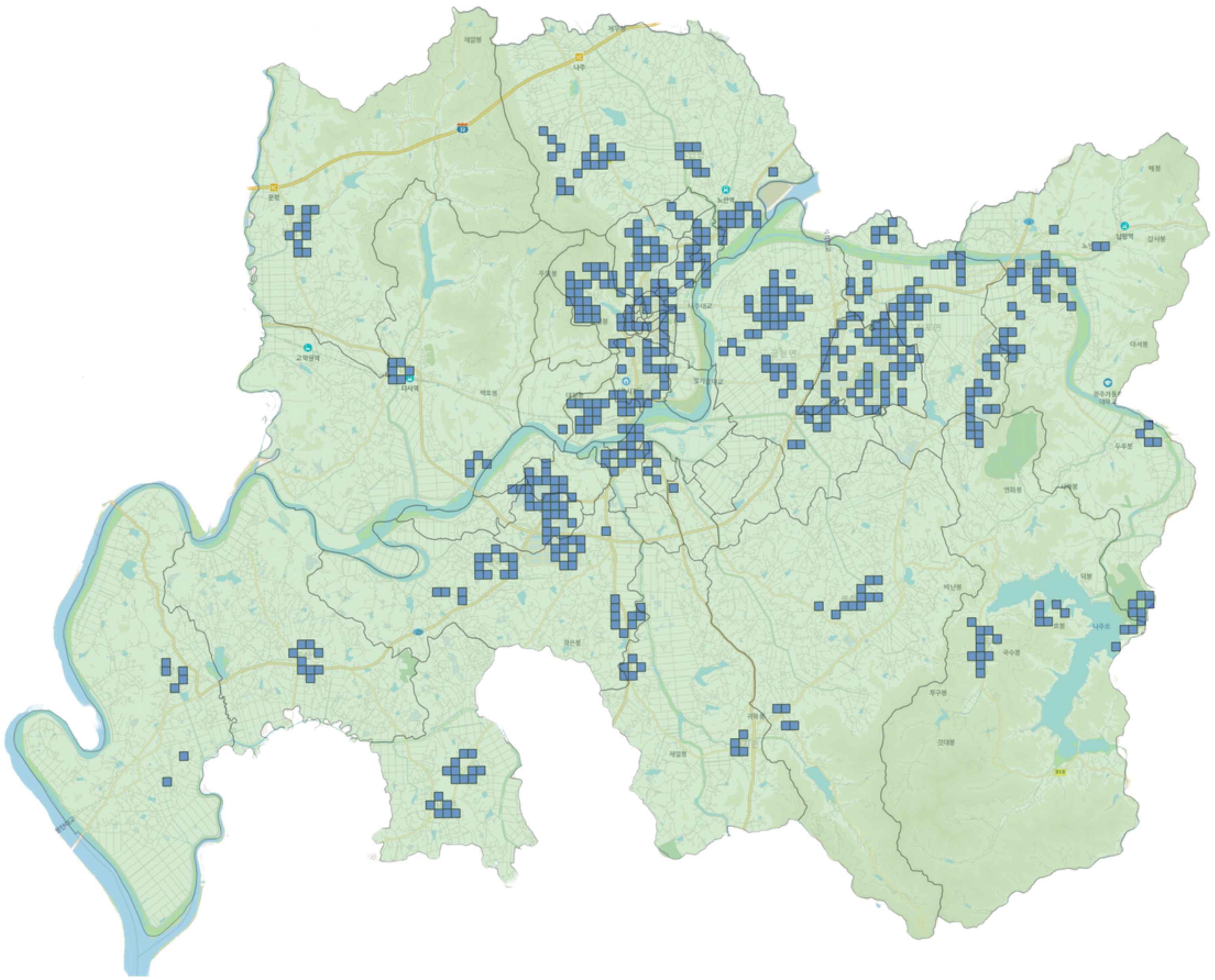
Population, Land price,
Accessibility (Theme Park , Parking Lot)

Low Importance

- **Count of Gas Station. : DELETE**
- **Farmland & Stream. : Keep**

Site Selection

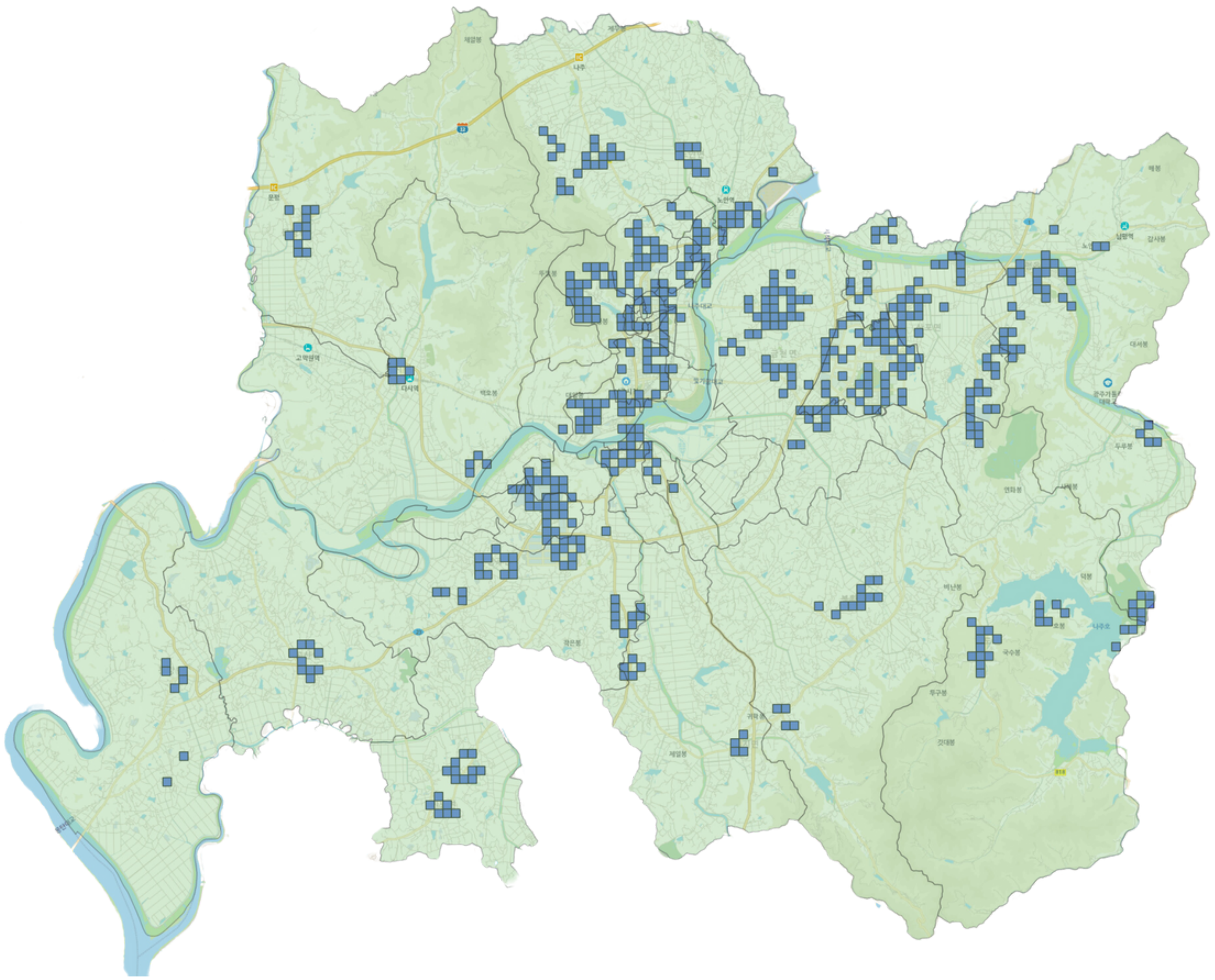
3.7.1 Distribution of Candidate grids



Already excluding
farmlands, forestry and streams

Site Selection

3.7.1 Distribution of Candidate grids



Evaluating performance
with a confusion matrix (0,1,2,3)

Site Selection

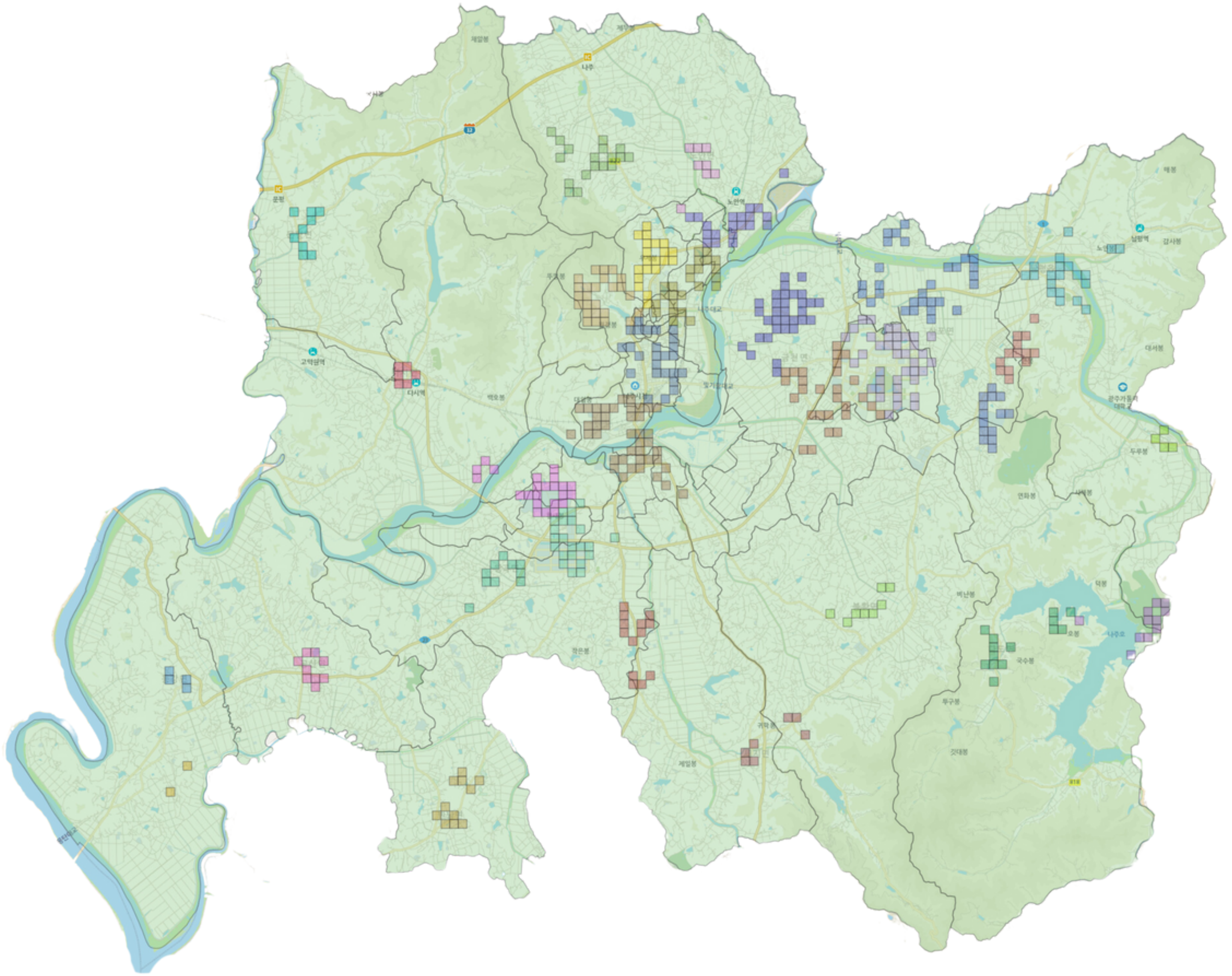
3.7.1 Distribution of Candidate grids

Finally,
We could obtain 542
optimal grids!

Evaluating performance
with a confusion matrix (0,1,2,3)

Site Selection

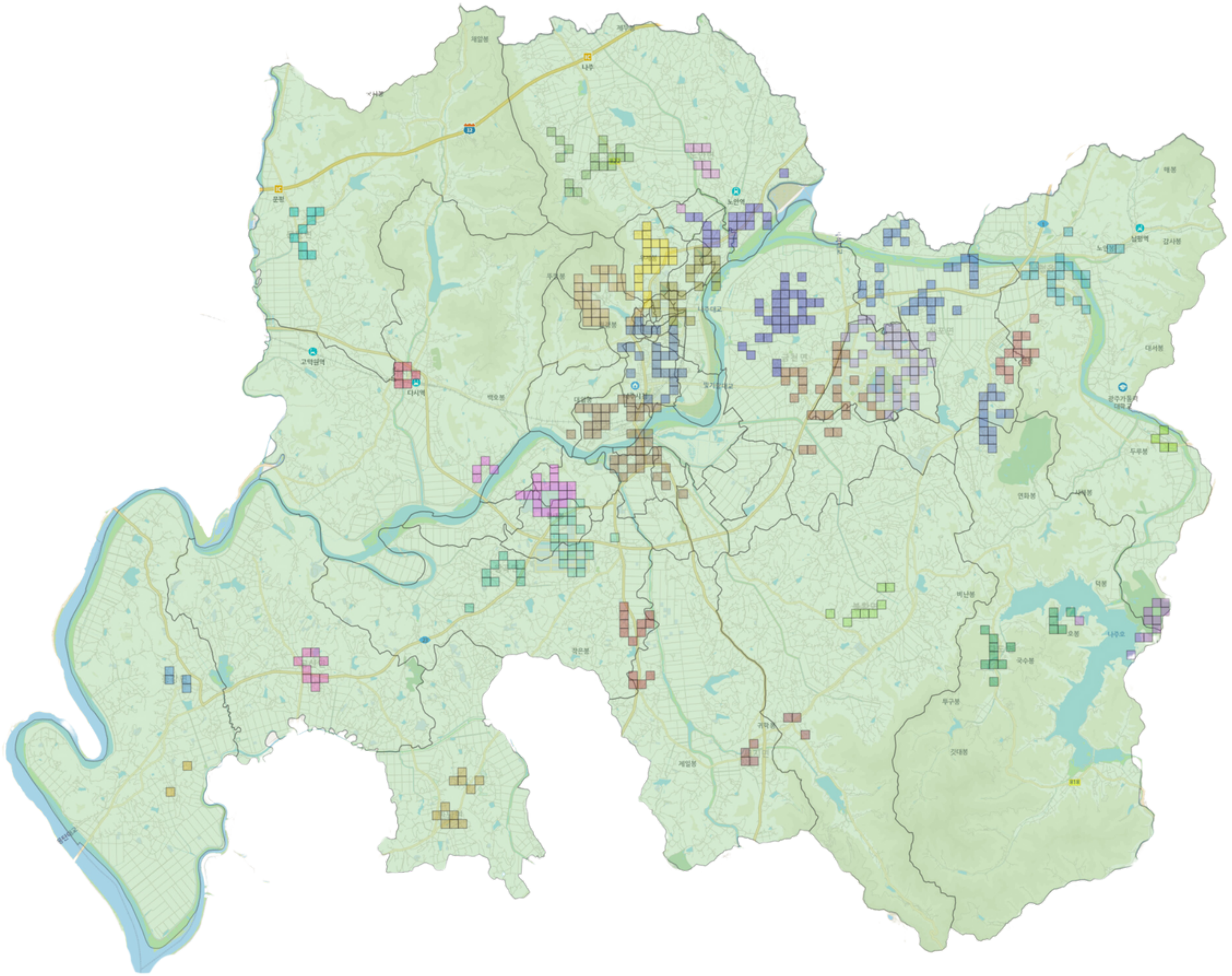
3.7.1 Distribution of Candidate grids



Clustered into 30 clusters

Site Selection

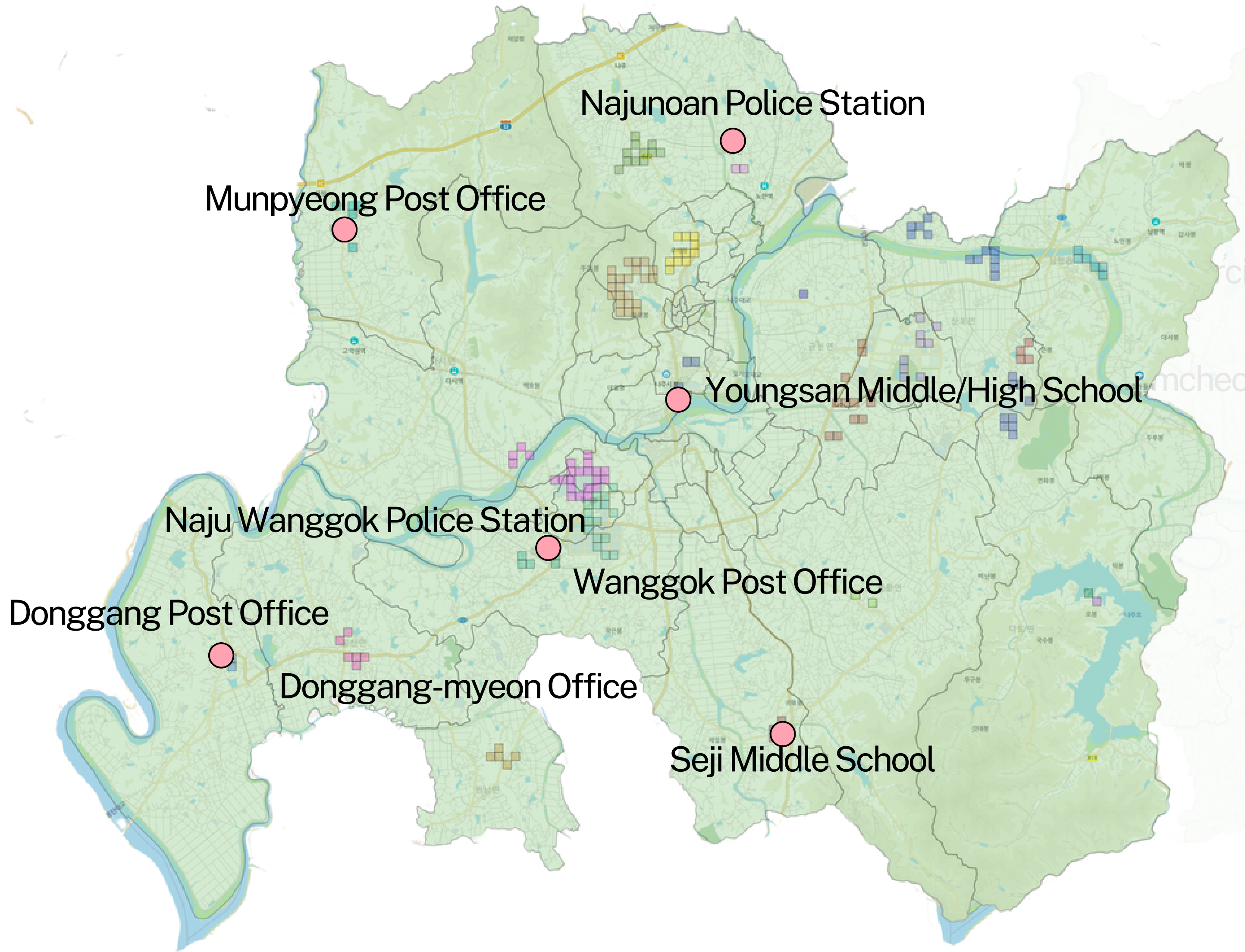
3.7.1 Distribution of Candidate grids

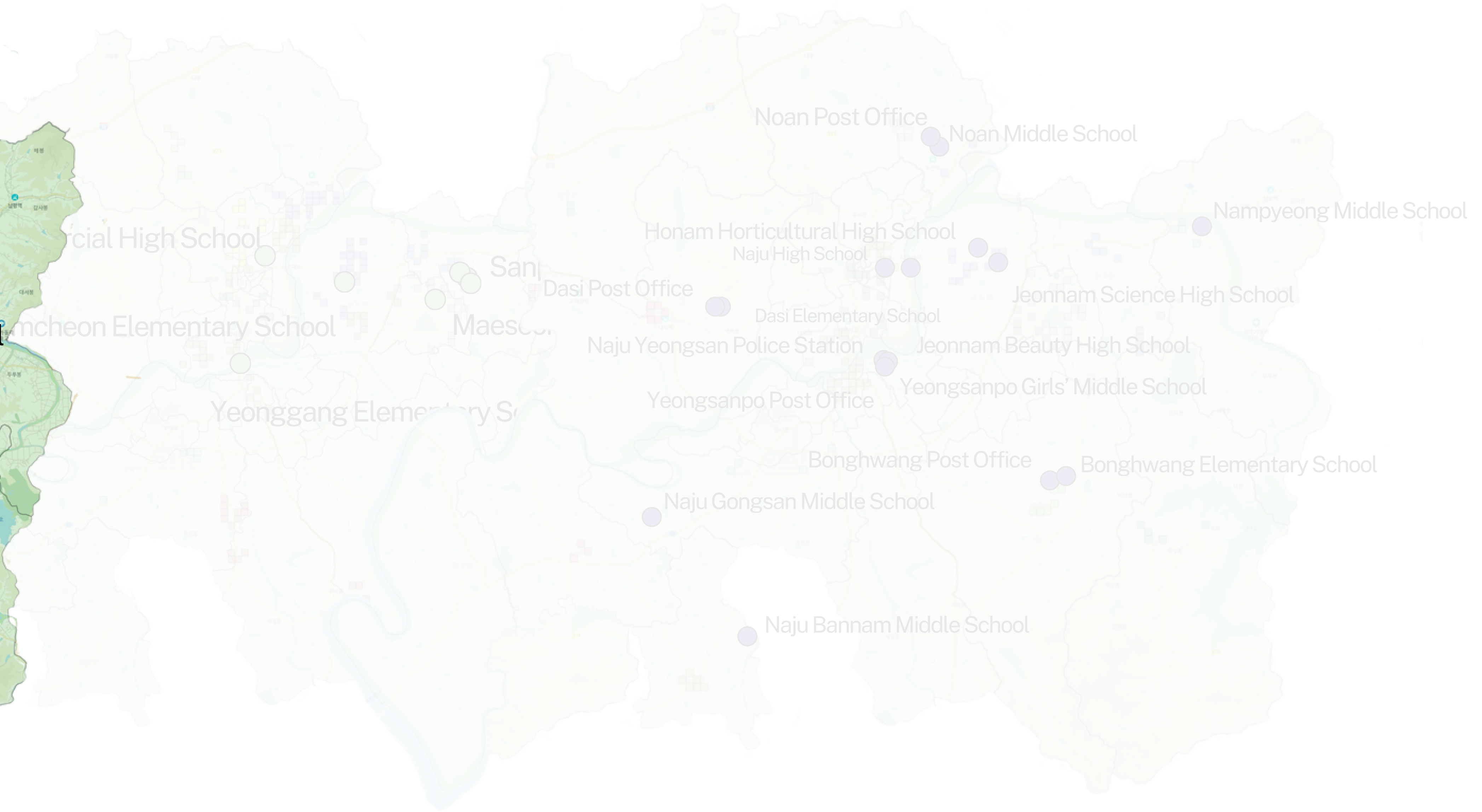


Exclude grids with altitude **above 90m**

Site Selection

3.7.2 Site Selection for Chargers by Type

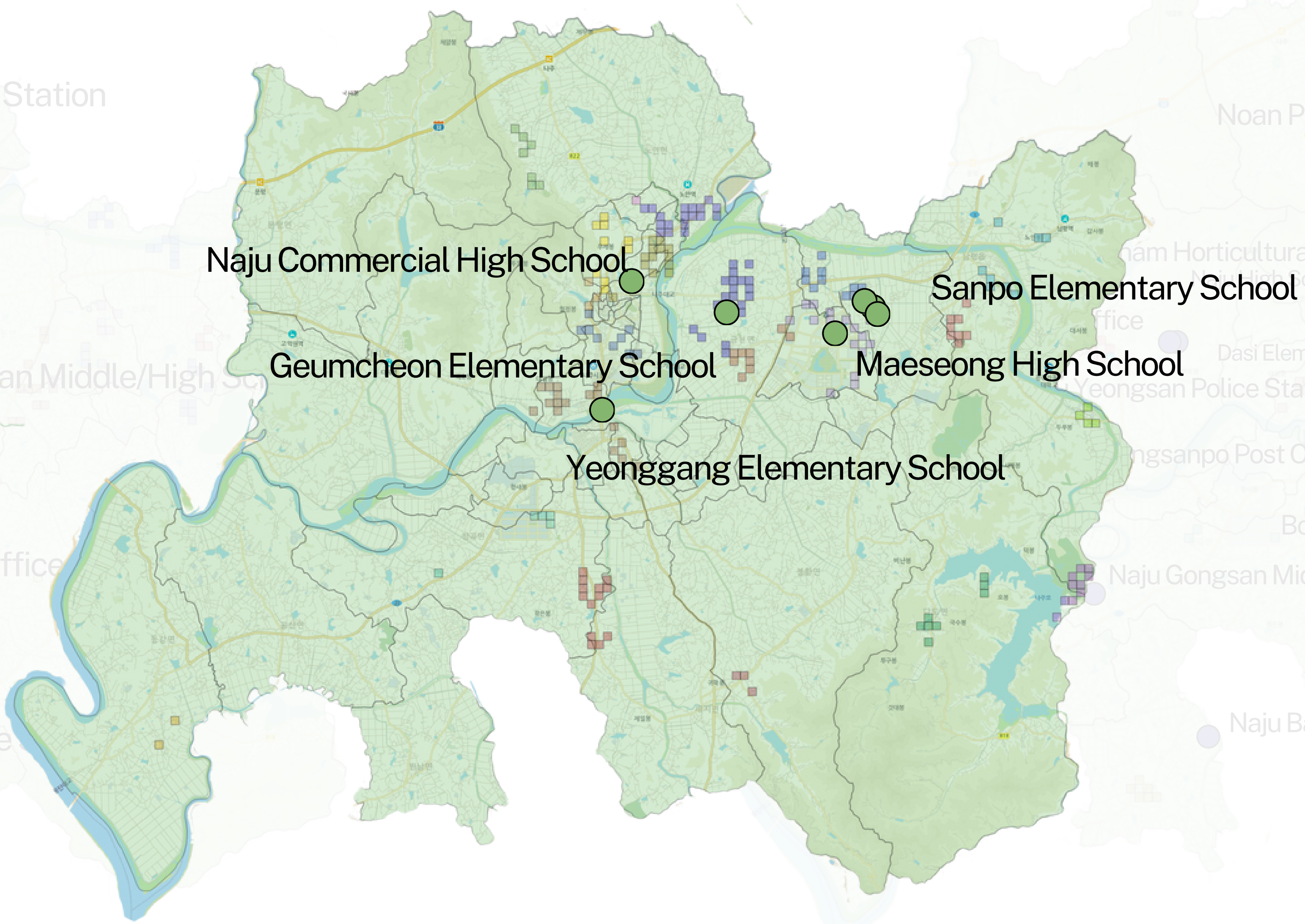




Fast Chargers

Site Selection

3.7.2 Site Selection for Chargers by Type



Slow Chargers

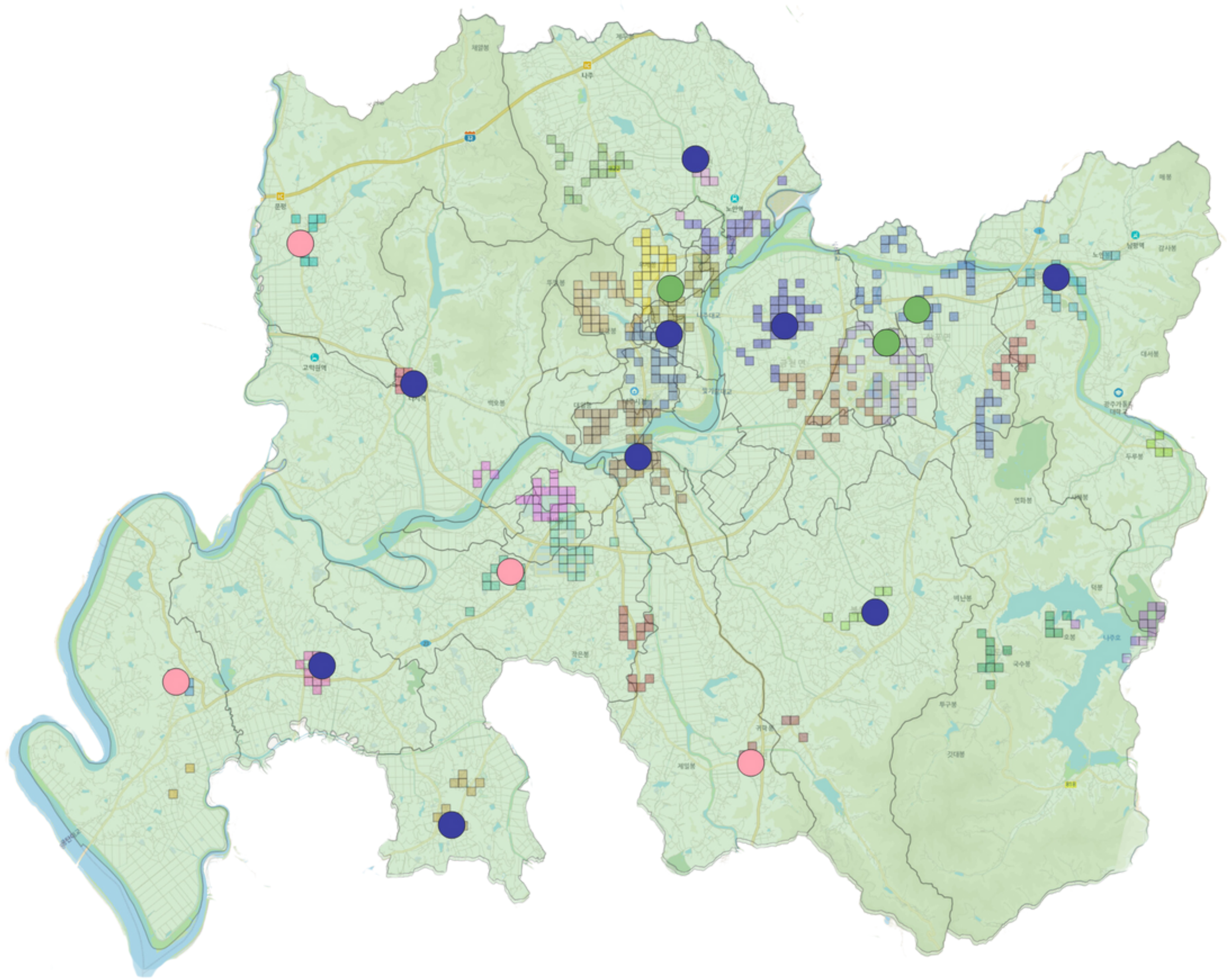
Site Selection

3.7.2 Site Selection for Chargers by Type

Both

Site Selection

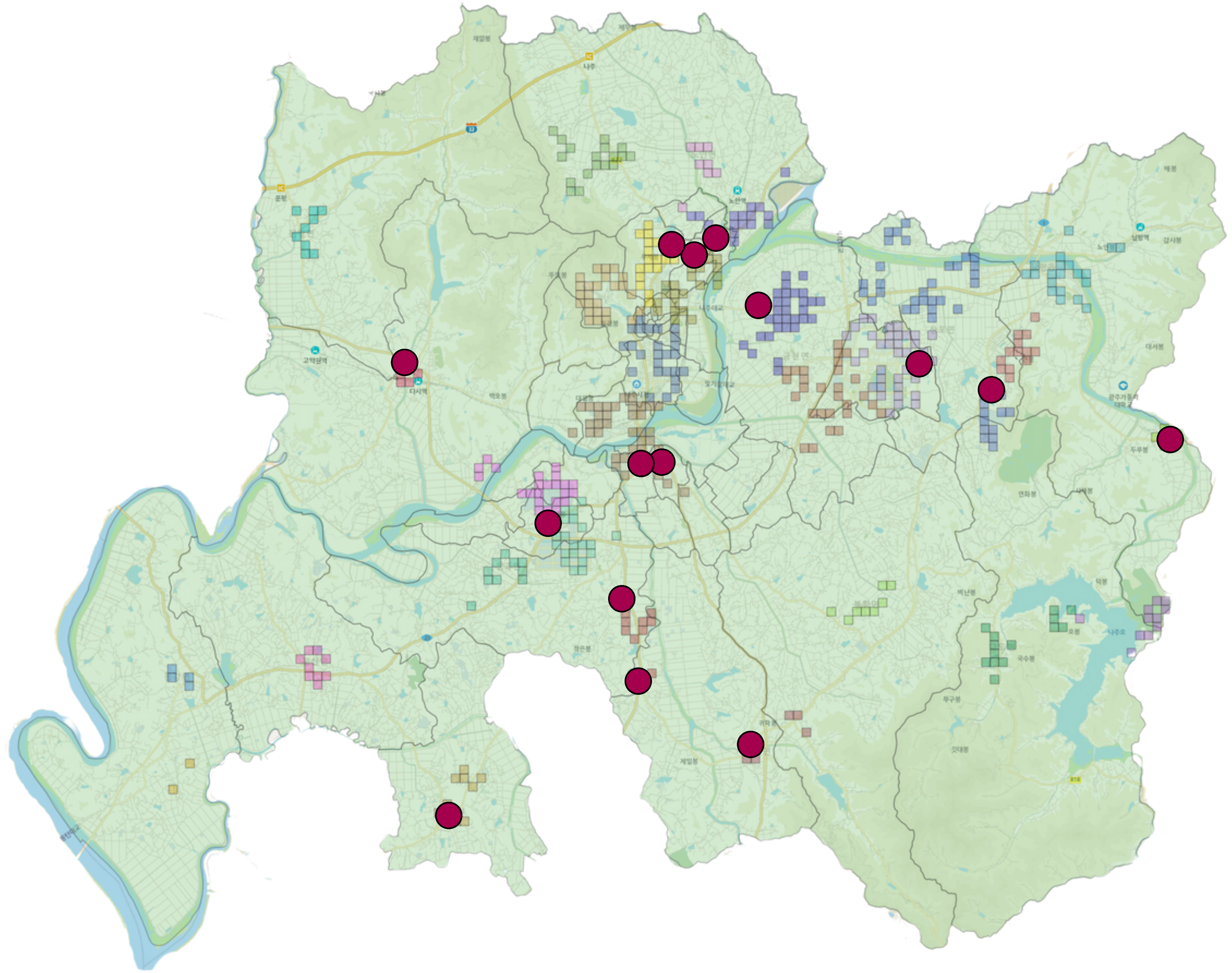
3.7.3 Distribution of Candidate grids



Select the grids with
the lowest land prices

Site Selection

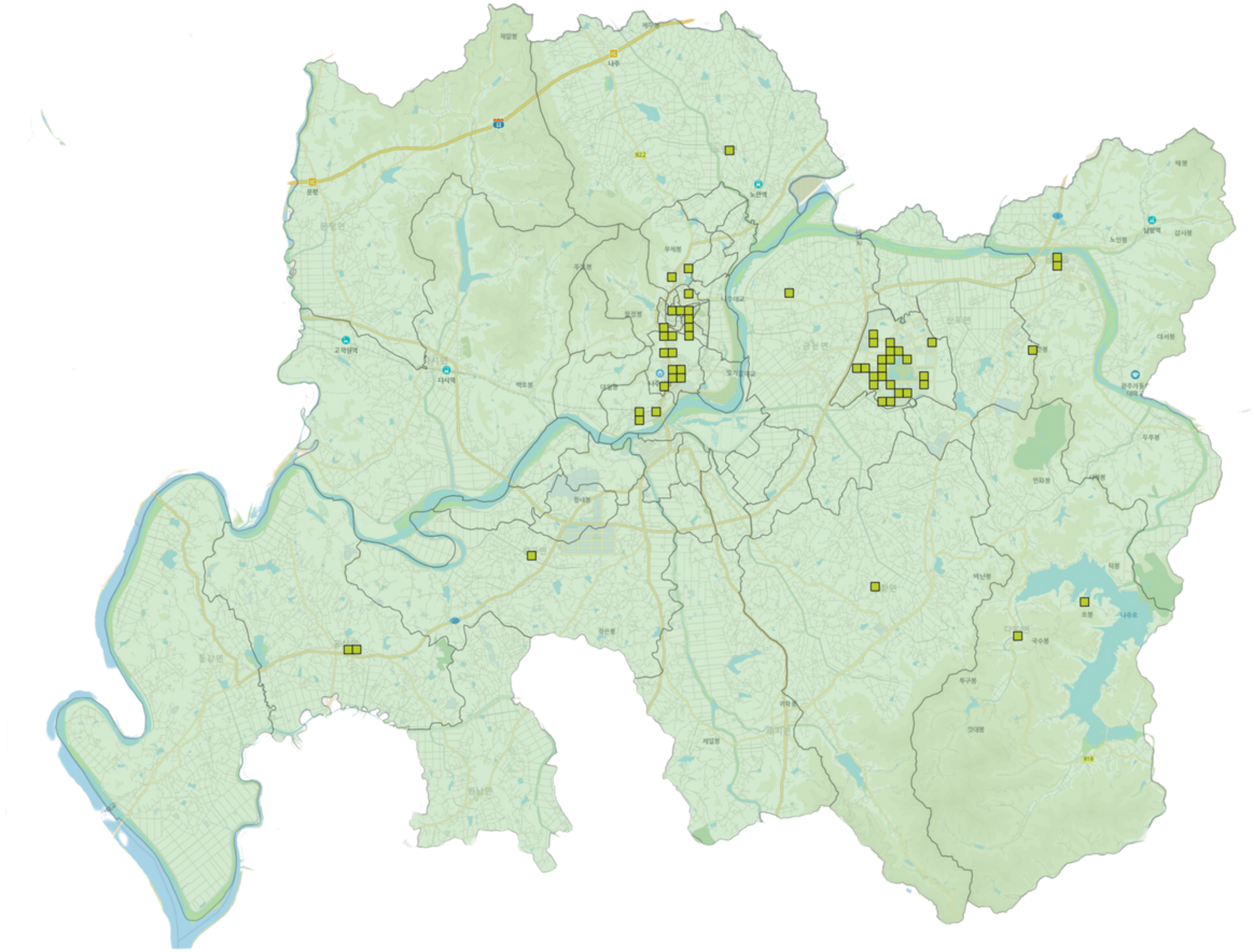
3.7.4 Location of Gas Station



Select a gas station
located within these grids

Site Selection

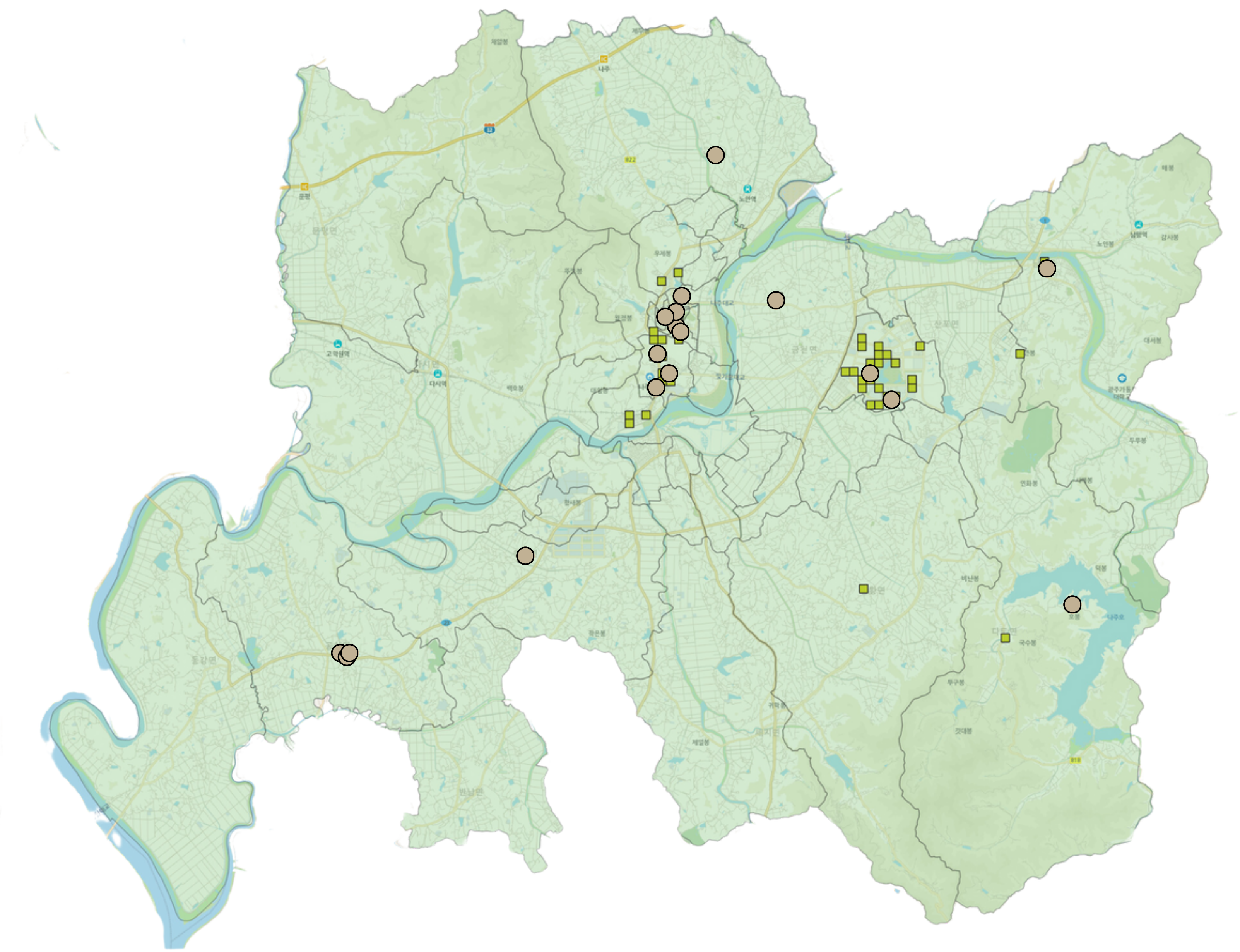
3.7.5 Additional Site Selection



Additionally,
we obtained 55 more grids
([1 to 3], [2 to 3])

Site Selection

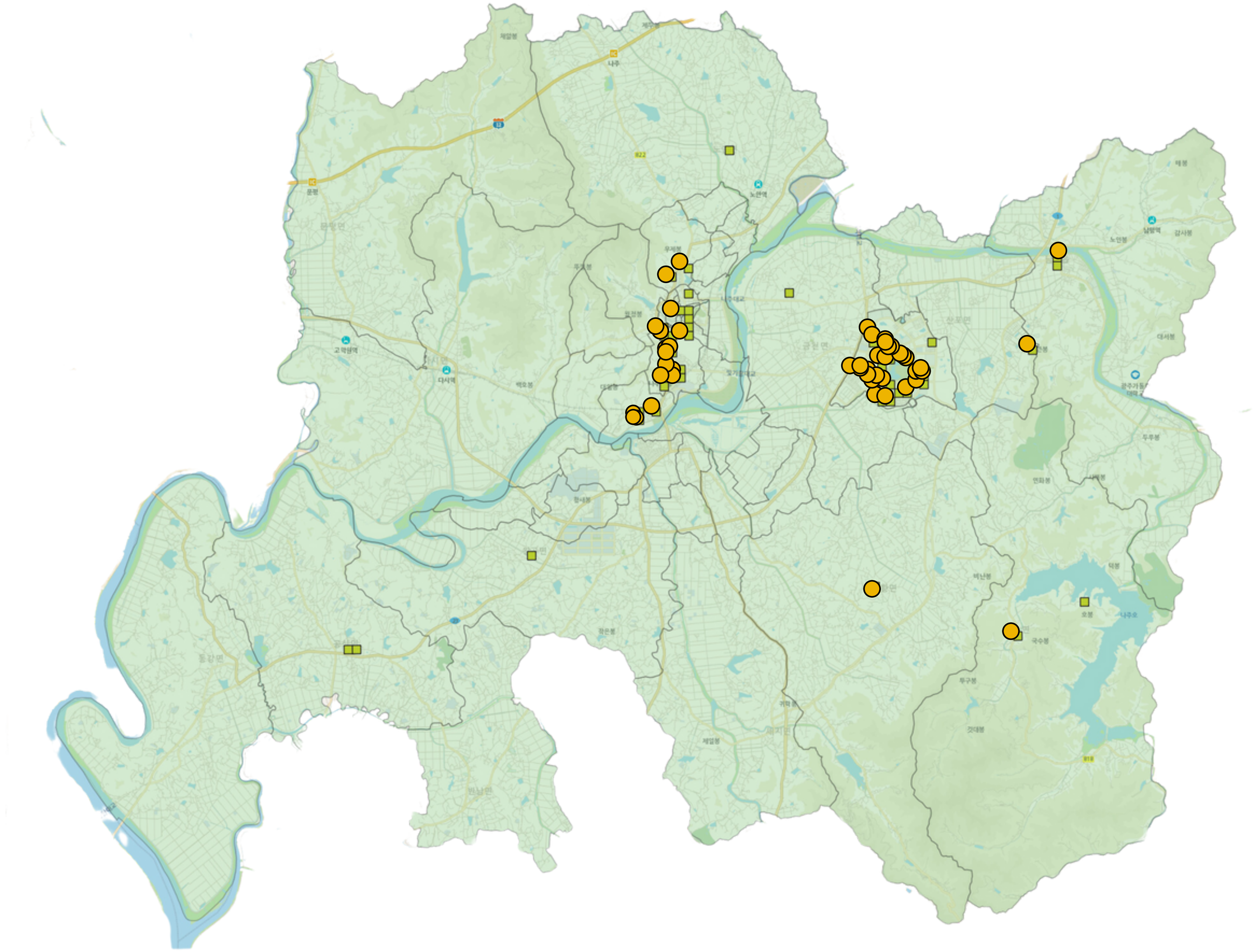
3.7.5 Additional Site Selection



Adding more Slow Charger
to a Pre-Installed(Fast) Grid

Site Selection

3.7.5 Additional Site Selection



Adding more Fast Charger
to a Pre-Installed(Slow) Grid

04 Conclusion

Optimal Sites

4.1.1 Optimal locations for fast chargers

No	Location	Address	Type
1	Munpyeong Post Office	297 Cheam-ro, Munpyeong-myeon, Naju-si, Jeollanam-do	Fast
2	Seji Middle School	112 Dongchang-ro, Semyeon, Naju-si, Jeollanam-do	Fast
3	Donggang-myeon Office	28 Indong-gil, Donggang-myeon, Naju-si, Jeollanam-do	Fast
4	Wanggok Post Office	382 Najuseobu-ro, Wanggok-myeon, Naju-si, Jeollanam-do	Fast

Optimal Sites

4.1.2 Optimal locations for slow chargers

No	Location	Address	Type
1	Naju Commercial High School	23-4 Hambaksan-gil, Naju-si, Jeollanam-do	Slow
2	Maeseong High School	19 Ssangsan 1-gil, Naju-si, Jeollanam-do	Slow
3	Maeseong Middle School	19 Ssangsan 1-gil, Naju-si, Jeollanam-do	Slow
4	Najusanpo Police Station	443-5 Sanpo-ro, Sanpo-myeon, Naju-si, Jeollanam-do	Slow

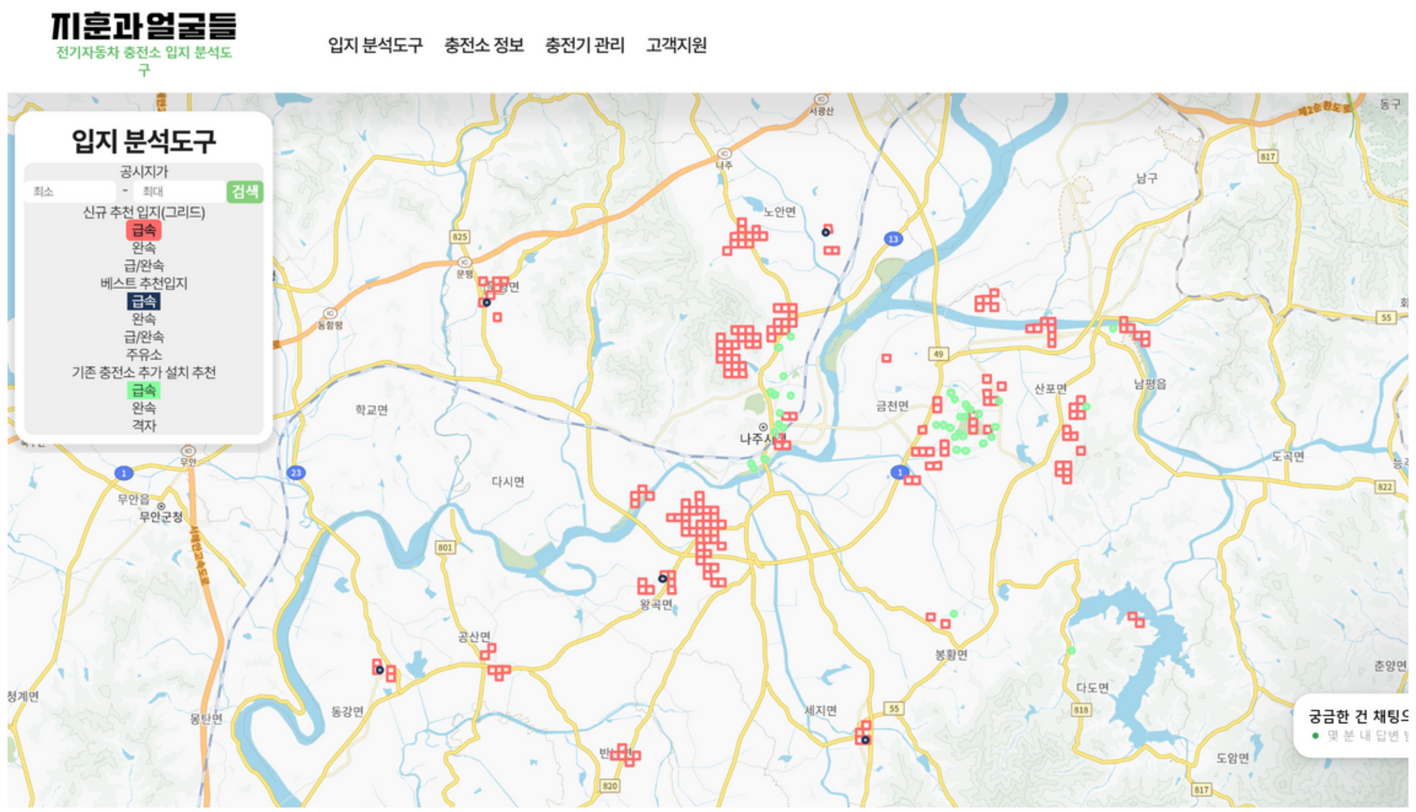
Optimal Sites

4.1.3 Optimal locations for both chargers

No	Location	Address	Type
1	Noan Post Office	29 Geumsan-ro, Noan-myeon, Naju-si, Jeollanam-do	Fast/Slow
2	Nampyeong Middle School	40 Nampyeong 3-ro, Nampyeong-eup, Naju-si, Jeollanam-do	Fast/Slow
3	Naju Middle School	10 Namsan-gil, Naju-si, Jeollanam-do	Fast/Slow
4	Naju Gongsan Middle School	110 Gongsan-ro, Gongsan-myeon, Naju-si, Jeollanam-do	Fast/Slow
5	Naju Bannam Middle School	20-15 Seokcheon-ro, Bannam-myeon, Naju-si, Jeollanam-do	Fast/Slow
6	Bonghwang Elementary School	31 Jukseok-gil, Bonghwang-myeon, Naju-si, Jeollanam-do	Fast/Slow
7	Jeonnam Science High School	33 Ogang-gil, Geumcheon-myeon, Naju-si, Jeollanam-do	Fast/Slow
8	Jeonnam Beauty High School	182-9, Yeongsanpo-ro, Naju-si, Jeollanam-do	Fast/Slow
9	Dasi Elementary School	203, Dashi-ro, Dashi-myeon, Naju-si, Jeollanam-do	Fast/Slow

Web App Demonstration

Location Analysis Tool (▼ Click)



Charging station information (▼ Click)

Limitations

No	Limitations
1	Absense of Naju city's recent data for the number of EV registrations
2	Limited precision of recommended locations for using 250x250 grid size
3	Absence of private/non-private land data
4	Absence of the floating population data
5	Absence of detailed data on buildings other than administrative agencies

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Conclusion

1st KPI

100% COMPLETE

0 100

2nd KPI

100% COMPLETE

0 100

Conclusion

Conclusion

1st KPI

Classification by Land Prices

Adding POI Features

0

100

2nd KPI

0

100

Conclusion

1st KPI	Classification by Land Prices	Adding POI Features	Adding Risk Factors	
	0			100
2nd KPI				
	0			100

Conclusion

1st KPI	Classification by Land Prices	Adding POI Features	Adding Risk Factors	Adding nearby chargers status

0 100

2nd KPI

0 100

Conclusion

1st KPI

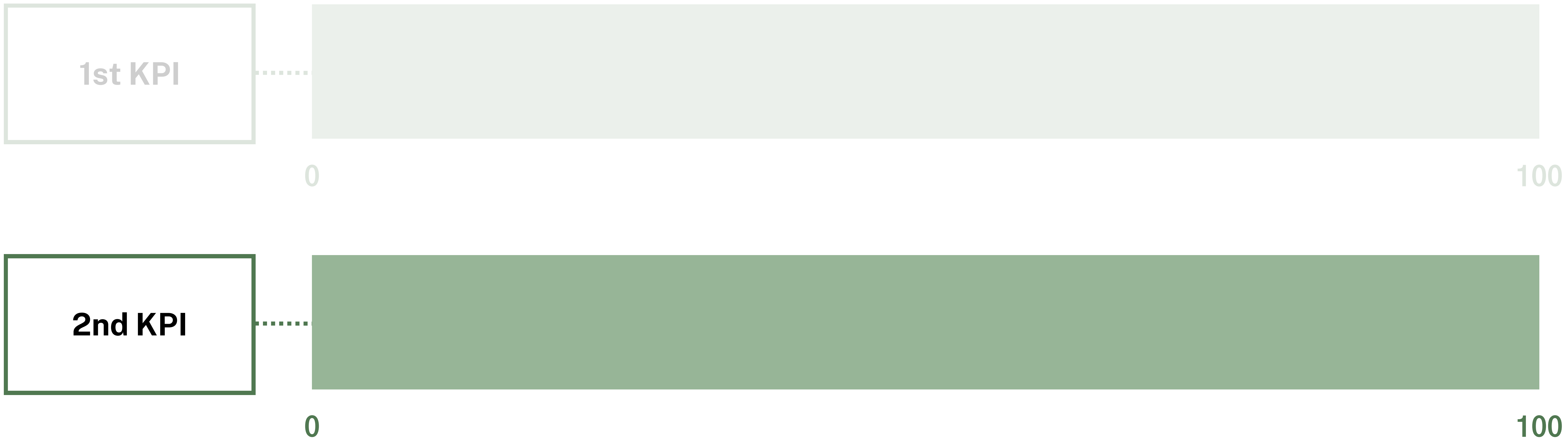
100% COMPLETE

0 100

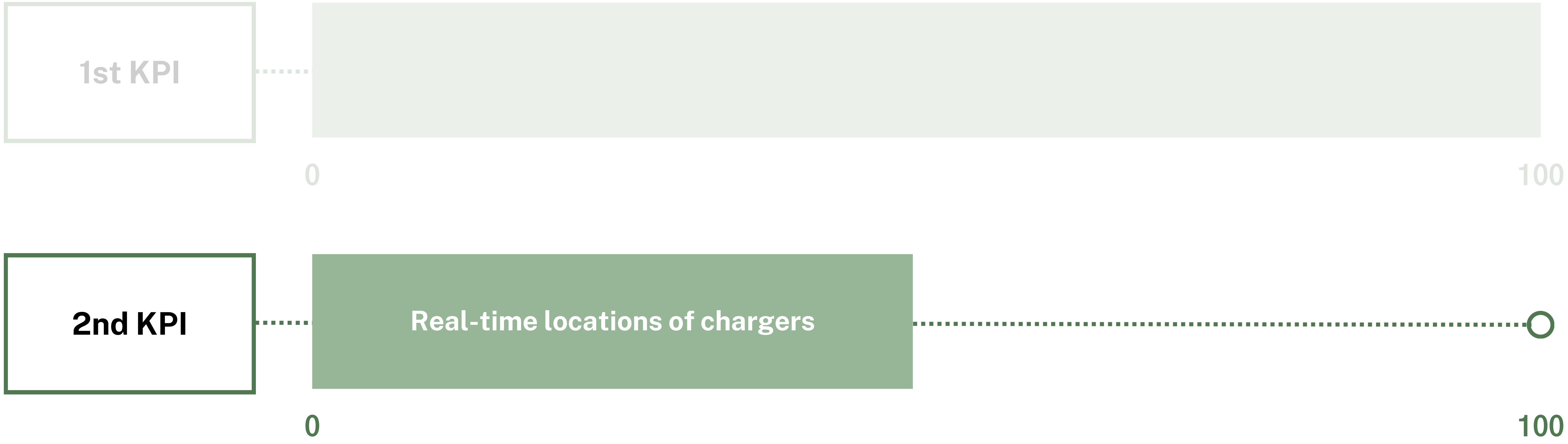
2nd KPI

0 100

Conclusion



Conclusion



Conclusion

1st KPI

0 100

2nd KPI

Real-time locations of chargers

Real-time locations of broken chargers

0 100

Conclusion

1st KPI

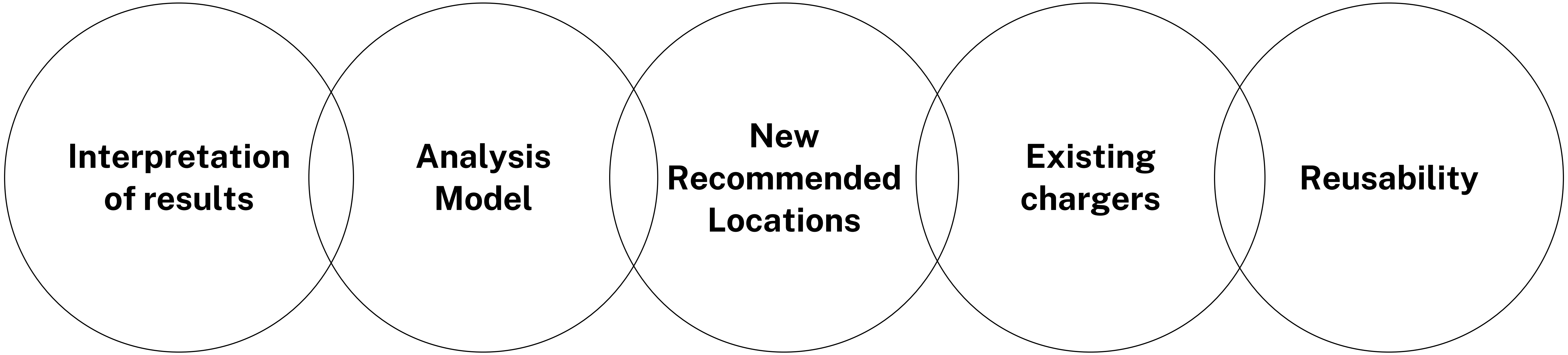
0 100

2nd KPI

100% COMPLETE

0 100

Conclusion


Interpretation of results
Analysis Model
New Recommended Locations
Existing chargers
Reusability

Conclusion

Interpretation of results

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New Recommended Locations

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Interpretation of results

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Existing chargers

Reusability

Conclusion

- Interpretation of results
- Analysis Model
- New Recommended Locations
- Existing chargers
- **Reusability**

EV Charging Station Site Selection:

Q & A

We are JH-Faces, 지훈과얼굴들

⚡ EV Charging Station Site Selection:

Thank you for your attention

We are JH-Faces, 지훈과얼굴들

07/03/2024 ~ 29/03/2024 (17 days)