GIS Portfolio

Harvey Jing, GISP

About Me

- More than **ten years** of strong experience, holding positions of increasing scope and responsibility.
- Strong background in all areas of the GIS process, is thoroughly familiar with **GIS practices, standards, and protocols**, and is proven in consistently meeting the highest in organizational and project expectations.
- Experienced in supporting the software **product life cycle** via timely provision of UX **design, testing, documentation, release, and support**, and works with stakeholders to meet all project goals.

Professional Experience

1. HIKVISION, Hangzhou, Zhejiang, China

- *Product Manager* (2022-Present)

- *Senior GIS Developer* (2019-2022)

2. Esri, Redlands, California

- *Enterprise Specialist* (2017-2019)

- *Enterprise Support Analyst* (2014-2017)

3. Department of Geography, Tuscaloosa, Alabama

- *Graduate Research Assistant* (2012-2014)

Education

THE UNIVERSITY OF ALABAMA, Tuscaloosa, Alabama

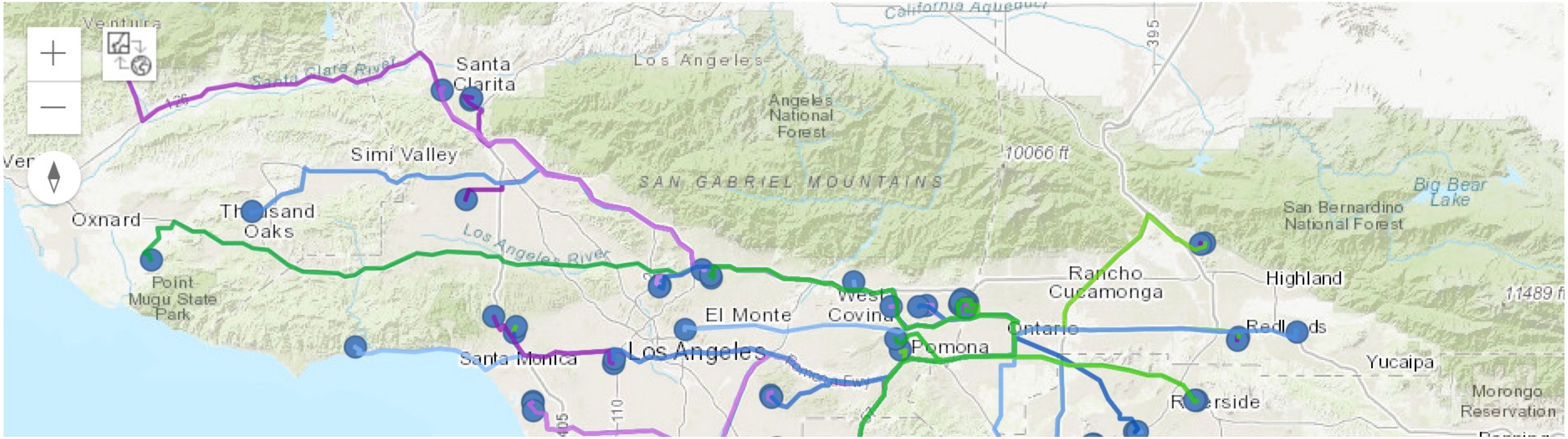
M.S. in Geography

NANJING UNIVERSITY OF POSTS AND TELECOMMUNICATIONS, Nanjing, China

B.S. in Geographic Information Systems

Summary of GIS Projects

- Identify the potential university.
- A camera pose estimation and positioning service.
- Stereo camera-based HD mapping application.
- Land use land cover analysis in Birmingham Metro Area.



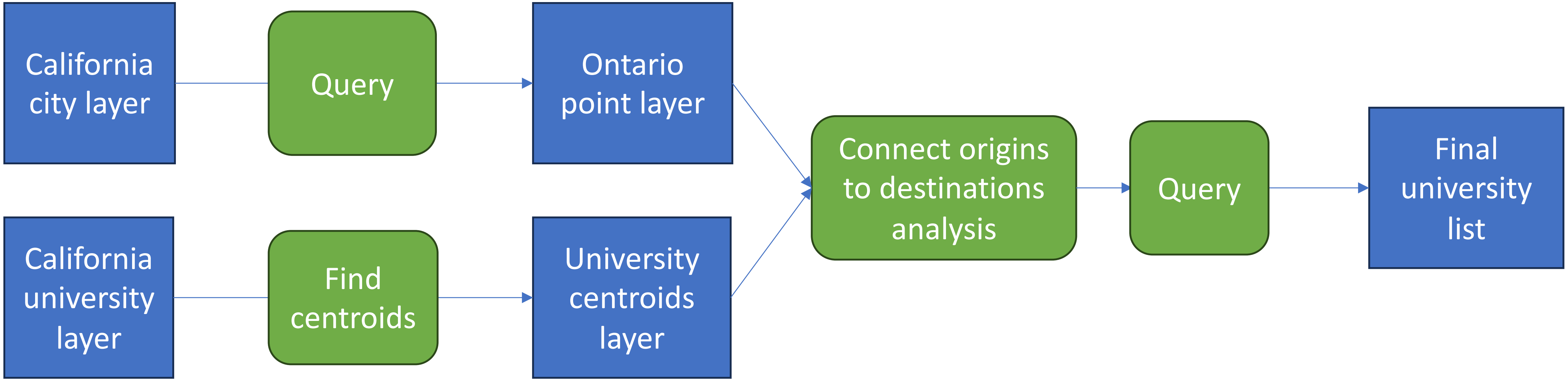
Identifying the Potential Universities

Tools: ArcGIS API for Python.

Skills: Spatial analysis

Objectives

- Identify the universities: The commuting time from Ontario is less than 60 minutes.

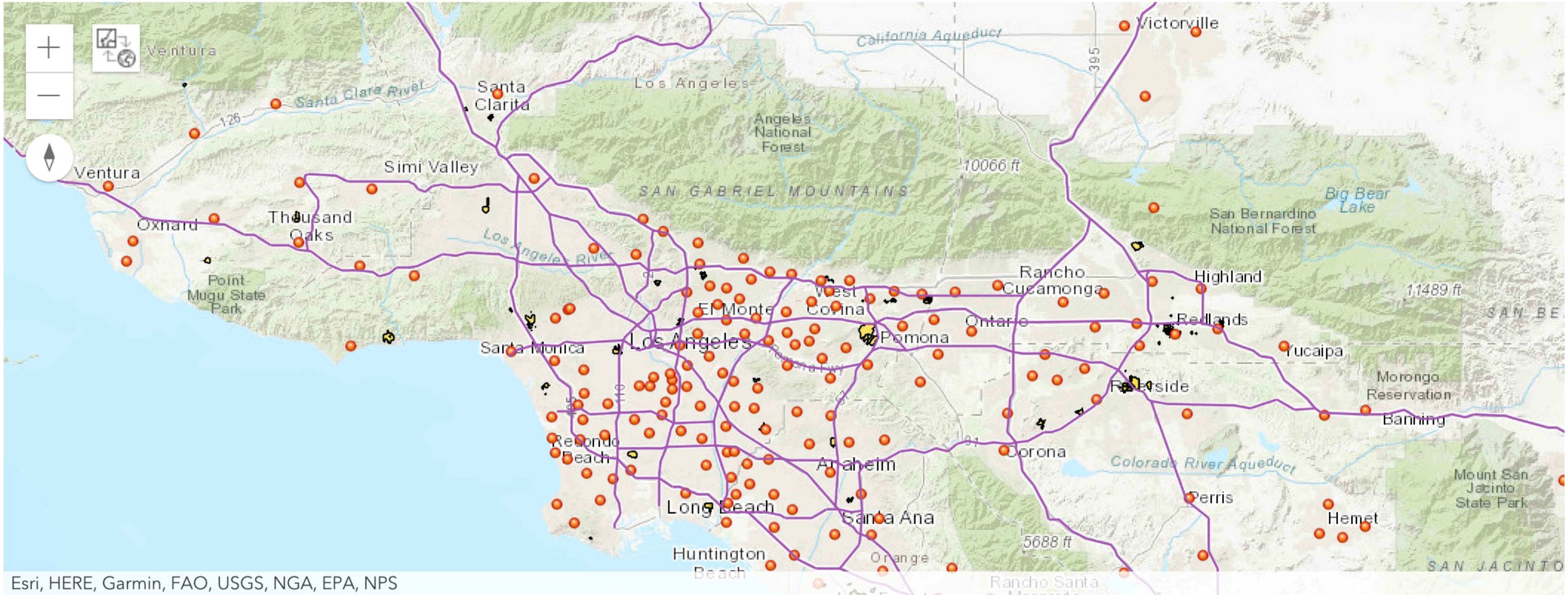


Explore the data for analysis

- **California Cities**: We will query Ontario and use it as origin_layer for connect_origins_to_destinations analysis.
- **California Campus Database 2021**: We will use the university campus layer and calculate the centroids of the campus. We will use these centroids as destination_layer for connect_origins_to_destinations analysis.
- **California Highways**: We will query the interstate highway, display it on the map, and explore the spatial relationship between the interstate highway and the university campus.

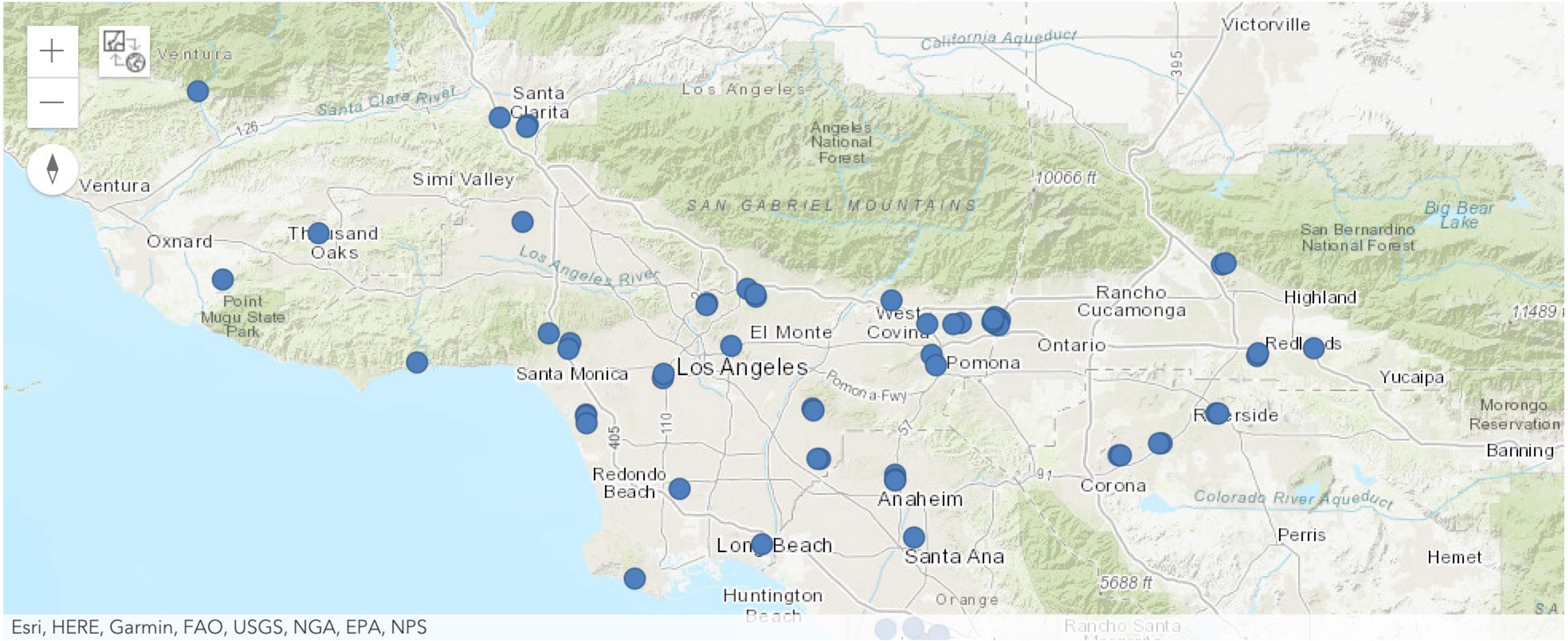
Display data on the map

In [10]:
```python
# Create web map around Rancho Cucamonga
map_all_layers = gis.map('Rancho Cucamonga, California', zoomlevel=9)
map_all_layers
```



Find centroids of universities

```
In [18]: map_for_analysis
```



Query Ontario from California Cities Layer

- The field "AREANAME" stores information on the city name. Let's query using where clause "AREANAME = 'Ontario'".

```
In [21]: ontario_pt_fset = cities_layer.query(where="AREANAME = 'Ontario'")
         ontario_pt_fset

Out[21]: <FeatureSet> 1 features
```

Run Connect Origins to Destinations

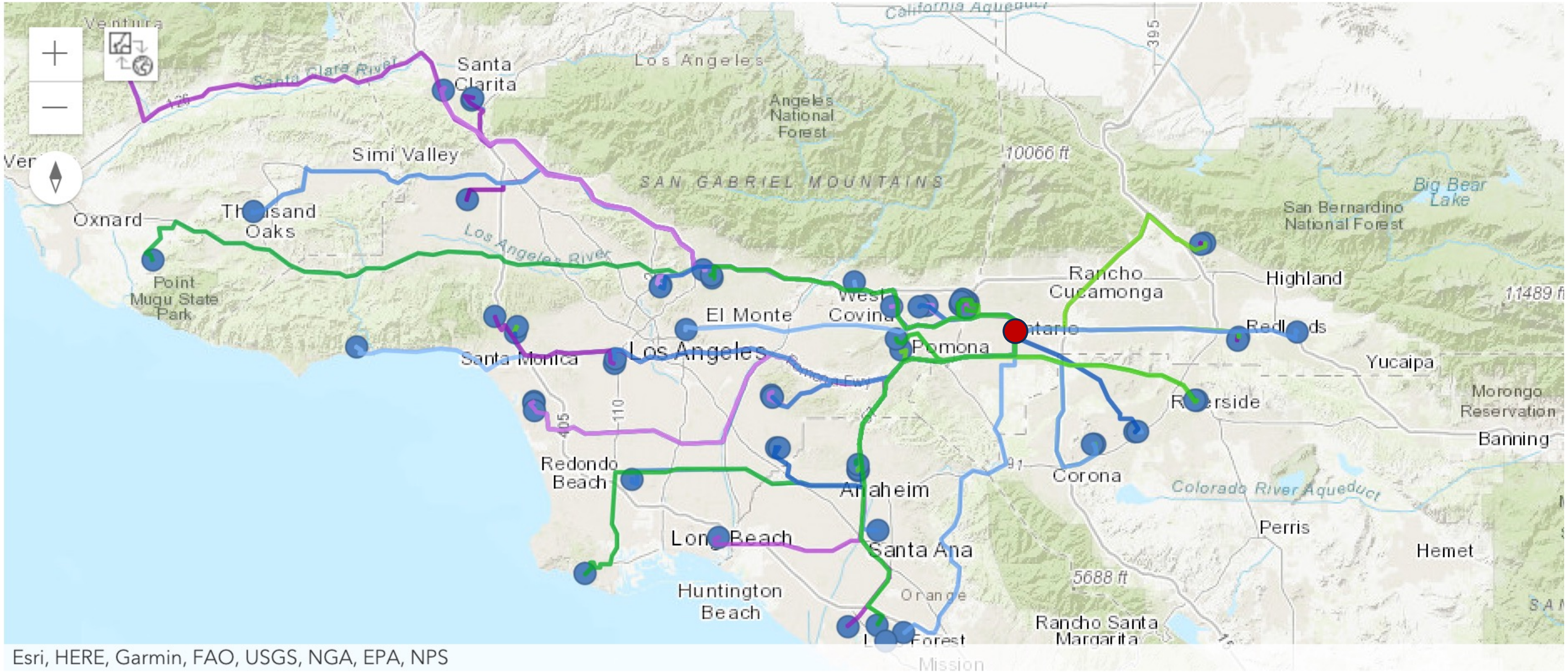
- We will calculate the driving time from Ontario to all university campuses with our analysis extent.
- The origins layer is ontario_pt_fc
- The destination layer is university_centroids_layer.
- The measurement_type is set to 'Driving Time'.

In [ ]:

```python
# Run connect_origins_to_destinations.
from arcgis import features
features.use_proximity.connect_origins_to_destinations(origins_layer=ontario_pt_fc,
                                                       destinations_layer=university_centroids_layer,
                                                       measurement_type='Driving Time',
                                                       origins_layer_route_id_field=None,
                                                       destinations_layer_route_id_field=None,
                                                       time_of_day=None,
                                                       time_zone_for_time_of_day=None,
                                                       include_route_layers=False,
                                                       output_name='connect_od',
                                                       context=context,
                                                       gis=gis,
                                                       estimate=False)
```

Display results of analysis

In [25]:
```
map_for_analysis
```



Routes with driving time less than 60 minutes

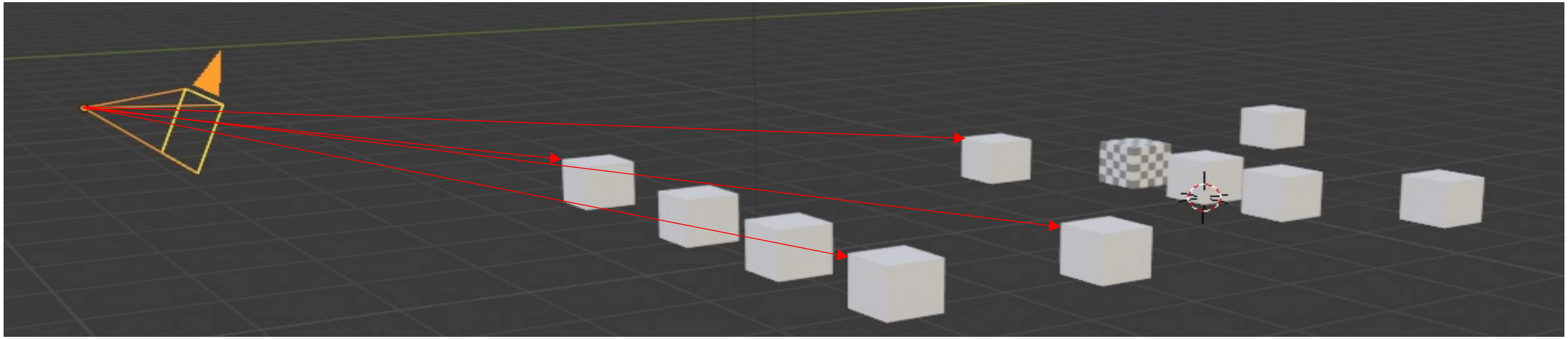
In [31]:
```
# Sort our dataframe, and only select the columsn we are interested in.
connect_od_sdf = connect_od_sdf.sort_values('Total_Minutes')[['RouteName','Total_Minutes']]
# Select routes with Total_Minutes less than 60 minutes
route_lt_60min = connect_od_sdf[connect_od_sdf['Total_Minutes']<=60]
route_lt_60min.head()
```

Out[31]:

	RouteName	Total_Minutes
54	Route 55 - 347 - Claremont McKenna College	16.229716
34	Route 21 - 347 - Claremont McKenna College	16.721673
30	Route 20 - 347 - Pitzer College	17.381815
21	Route 19 - 347 - Pomona College	17.681490
59	Route 54 - 347 - Harvey Mudd College	17.683302

...

	RouteName	Total_Minutes
48	Route 39 - 347 - University of Southern Califo...	55.240155
2	Route 2 - 347 - California State University, L...	56.930925
52	Route 43 - 347 - Occidental College	57.020357
42	Route 28 - 347 - Occidental College	57.237149
29	Route 15 - 347 - University of Southern Califo...	58.963873



A Camera Pose Estimation and Positioning Service

- Tools: ArcGIS Pro, RTK device, Blender
- Skills: Python development, 3d modeling, field work

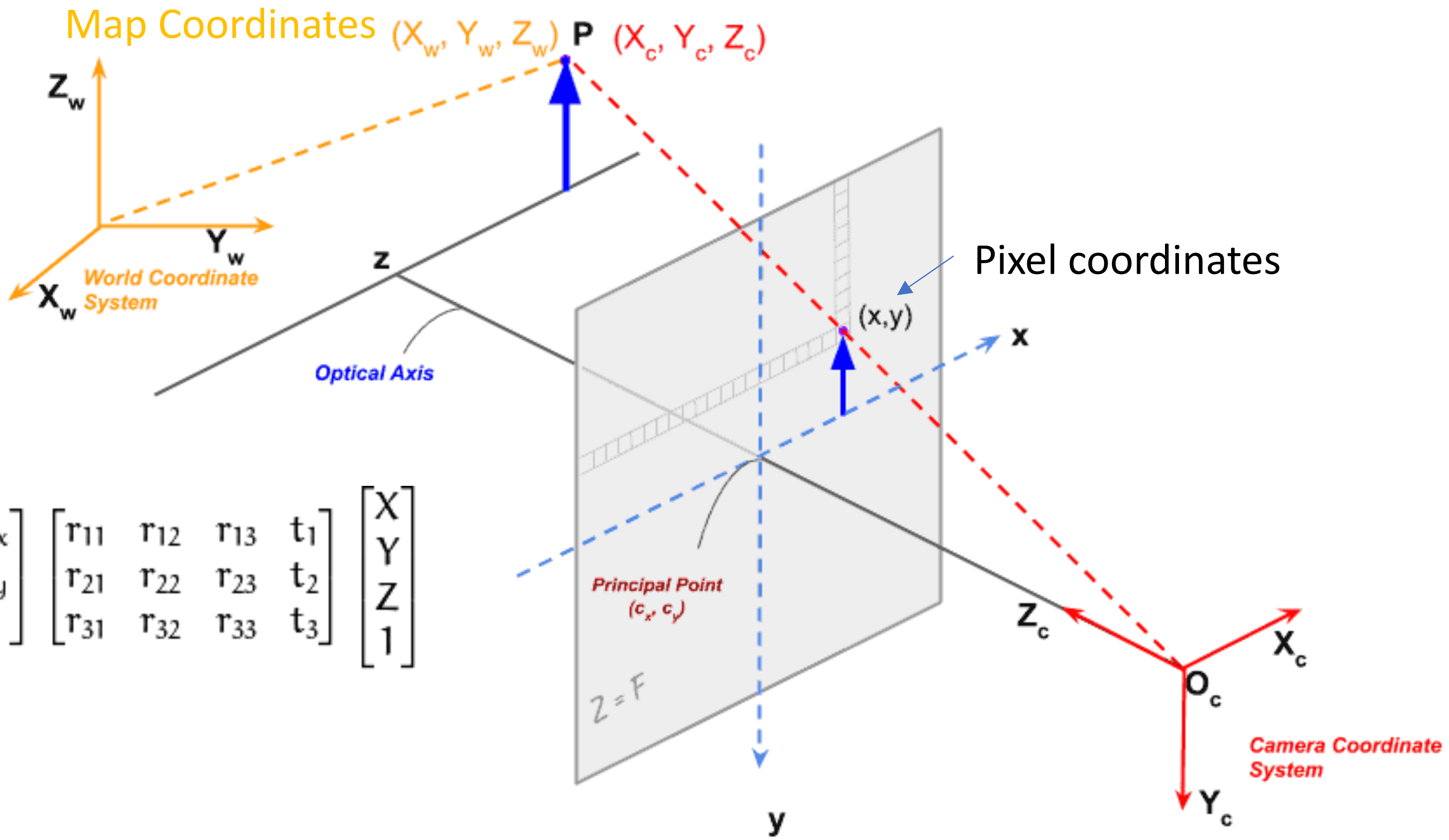
Objectives

- Develop an algorithm that calibrates camera extrinsic parameters using control points.
- Establish relationships between image pixel coordinates and world 2D coordinates.
- Develop various REST APIs that other teams can utilize.

Methodology

1. Review math foundation
2. Camera calibration
3. Test algorithm in a virtual scene
4. Verify algorithm in real world
5. Accuracy assessment
6. Design REST APIs

Methodology – Math foundation



equation

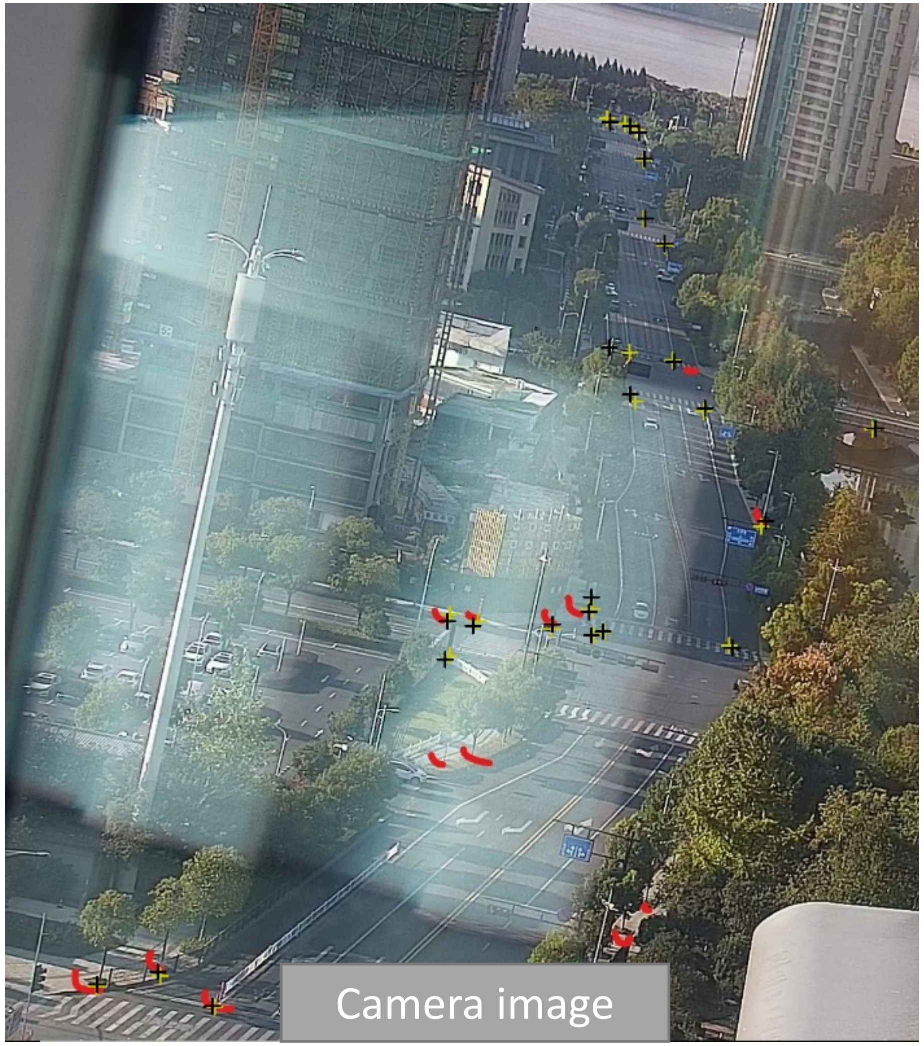
$$s\begin{bmatrix}u\\v\\1\end{bmatrix}=\begin{bmatrix}f_x & 0 & c_x\\0 & f_y & c_y\\0 & 0 & 1\end{bmatrix}\begin{bmatrix}r_{11} & r_{12} & r_{13} & t_1\\r_{21} & r_{22} & r_{23} & t_2\\r_{31} & r_{32} & r_{33} & t_3\end{bmatrix}\begin{bmatrix}X\\Y\\Z\\1\end{bmatrix}$$

Methodology – Camera calibration

$$s\begin{bmatrix}u\\v\\1\end{bmatrix} = \underbrace{\begin{bmatrix}f_x & 0 & c_x\\0 & f_y & c_y\\0 & 0 & 1\end{bmatrix}}_{K} \underbrace{\begin{bmatrix}r_{11} & r_{12} & r_{13} & t_1\\r_{21} & r_{22} & r_{23} & t_2\\r_{31} & r_{32} & r_{33} & t_3\end{bmatrix}}_{\text{Rt (camera pose)}} \begin{bmatrix}X\\Y\\Z\\1\end{bmatrix}$$

- **Camera intrinsic K (Known):** image resolution, focal length, CCD sensor size
- **Camera extrinsic Rt (Need calibration): x, y, z, pitch, yaw, roll, also called camera pose**
- Control points: image pixels – world coordinates
- Least-square optimization to calculate optimized camera pose.

Methodology - Camera calibration

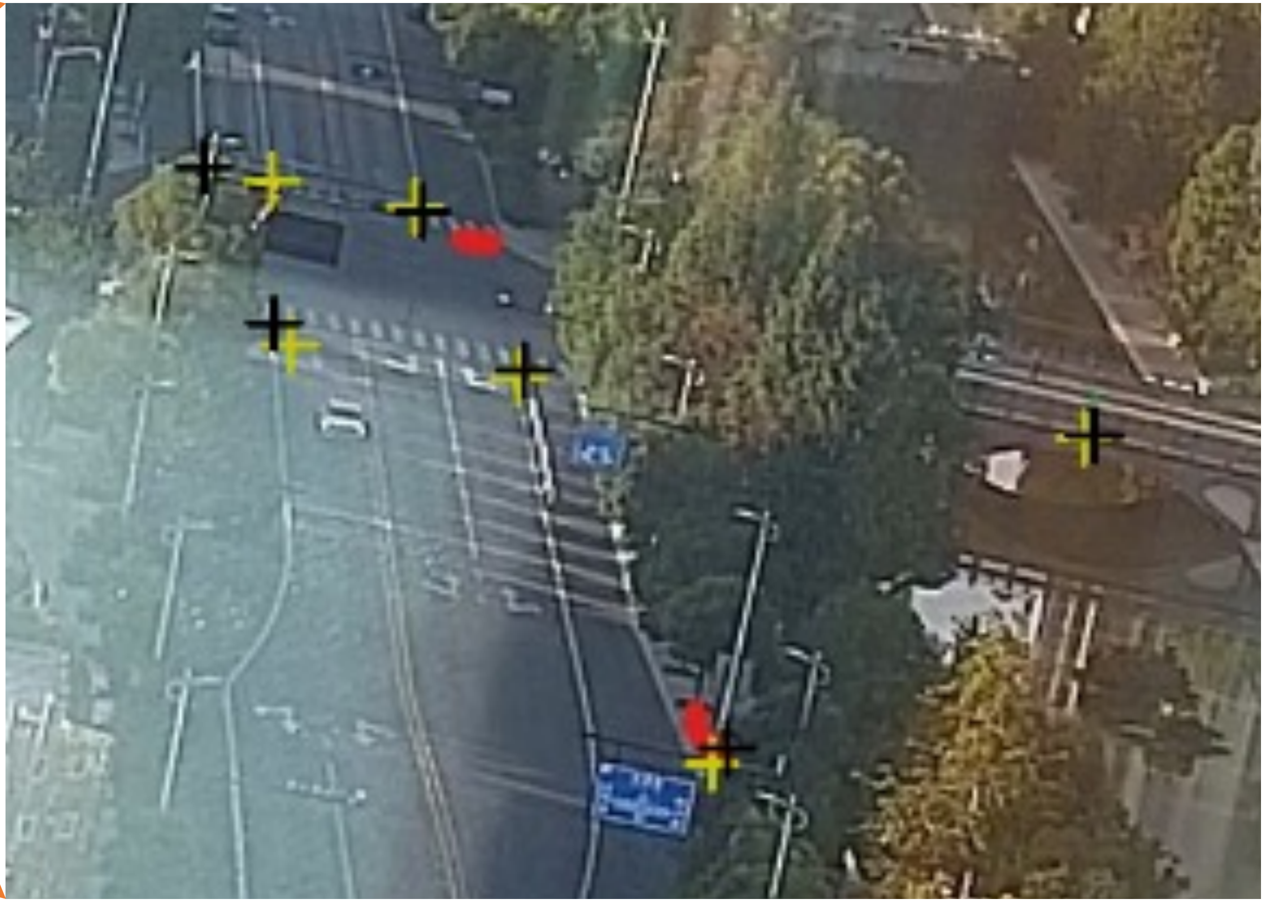

Camera image


Control points map

Label	Lat	Lng	pixel_x	pixel_y
24	30.2146	120.2148	606	839
25	30.21472	120.2146	606	786
26	30.21473	120.2147	642	795
27	30.21483	120.2147	737	805
28	30.21487	120.2147	791	813
29	30.21484	120.2147	804	809
30	30.21492	120.2146	785	779
31	30.21498	120.2146	789	779
32	30.21615	120.2134	844	512
34	30.21649	120.213	837	449
39	30.21989	120.2097	855	202
42	30.22076	120.2088	845	163
43	30.22091	120.2086	831	155
44	30.22086	120.2085	808	148
47	30.2184	120.2112	855	277
49	30.21804	120.2116	882	311
50	30.21655	120.2131	892	459
51	30.21649	120.2136	1149	548
52	30.21622	120.2135	932	525
53	30.2156	120.2142	1006	673
54	30.21498	120.2148	965	826
55	30.2149	120.2153	1424	1017
56	30.21398	120.2156	747	1300
57	30.21387	120.2157	748	1408
58	30.21382	120.2157	684	1429
59	30.21379	120.2155	304	1291
60	30.			1265
61	30			1251

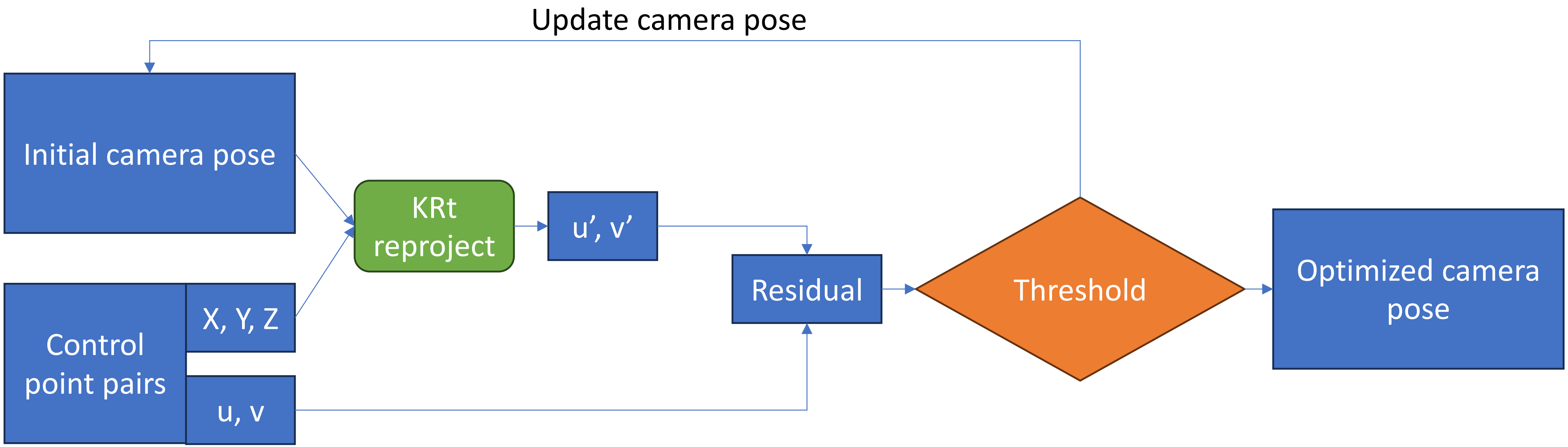
Control points

Methodology - Camera calibration

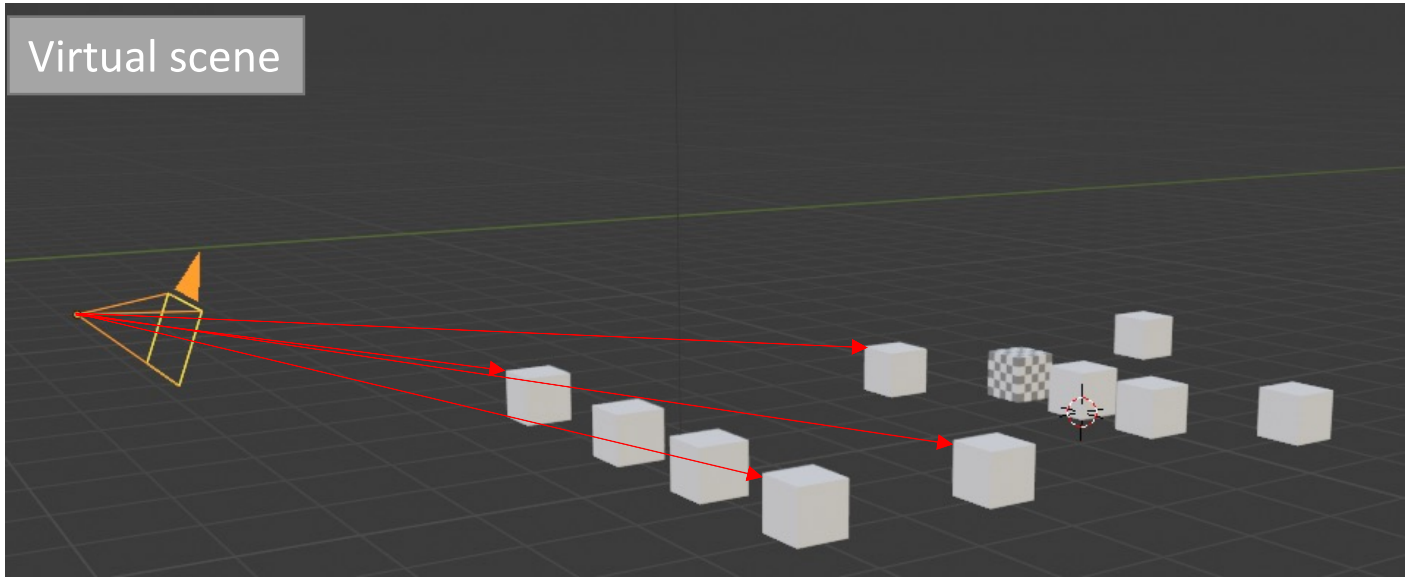


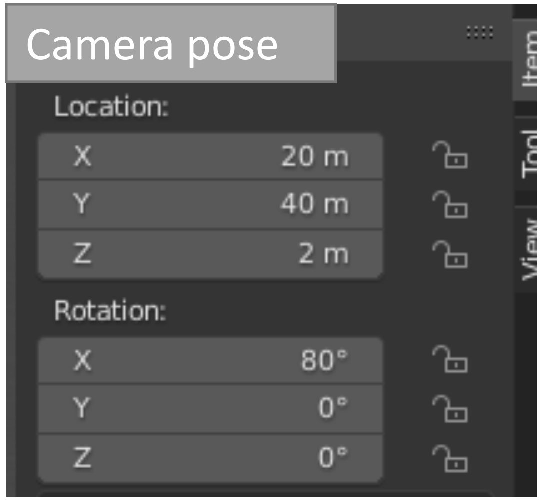
- Reproject world coordinates to pixel coordinates.
- Calculate the residual between the black cross and the yellow cross.
- Update the camera pose to minimize the residual.

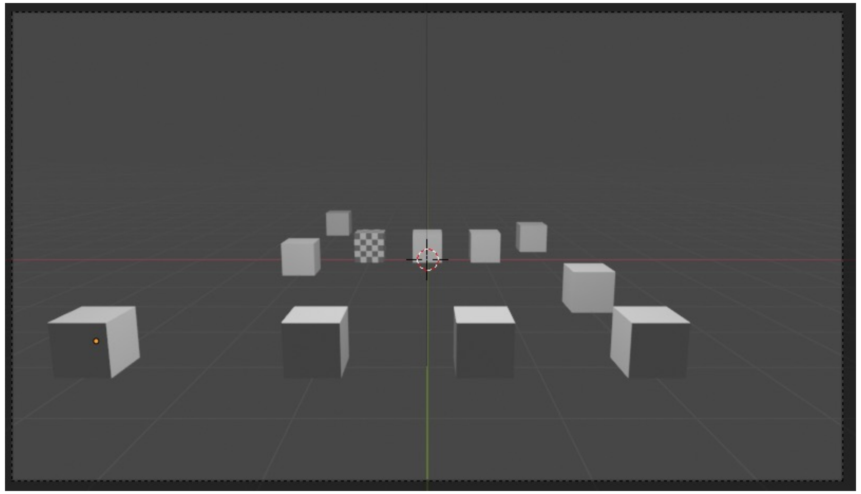
Methodology – Camera calibration (least-square)

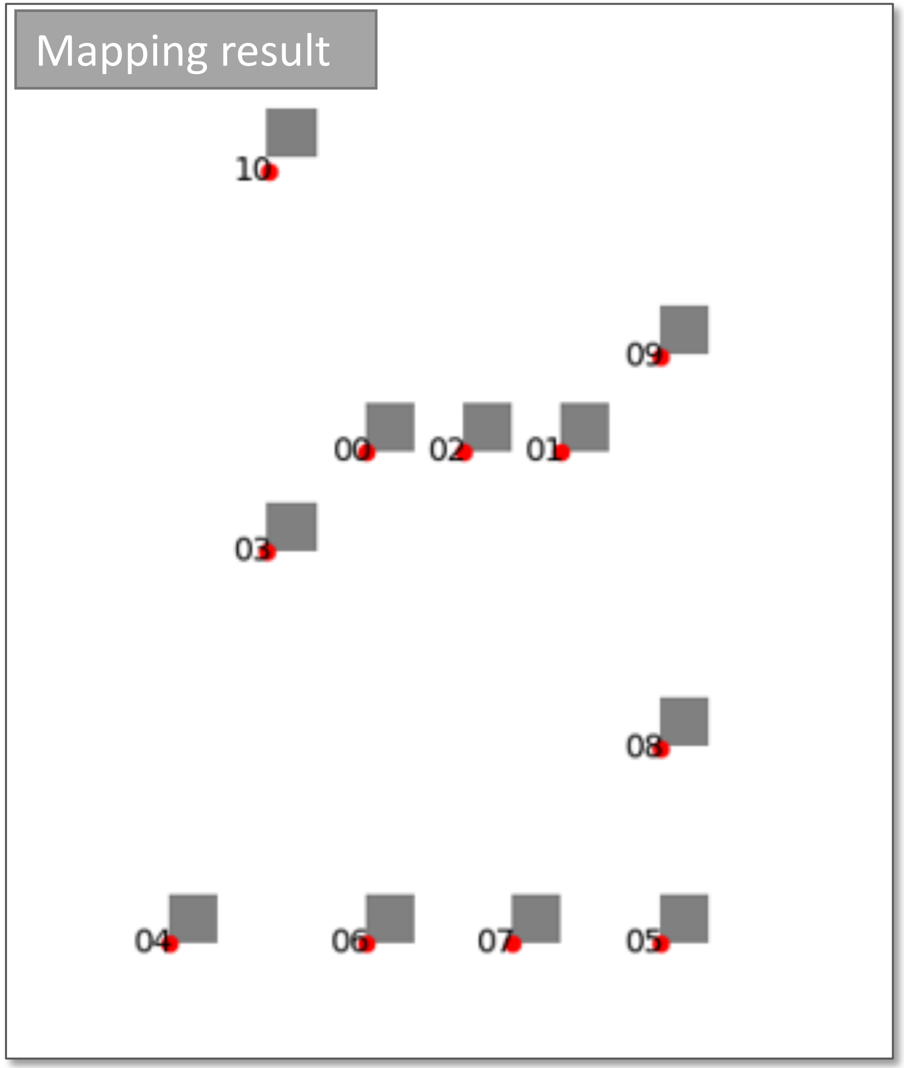


Methodology – Test in virtual scene

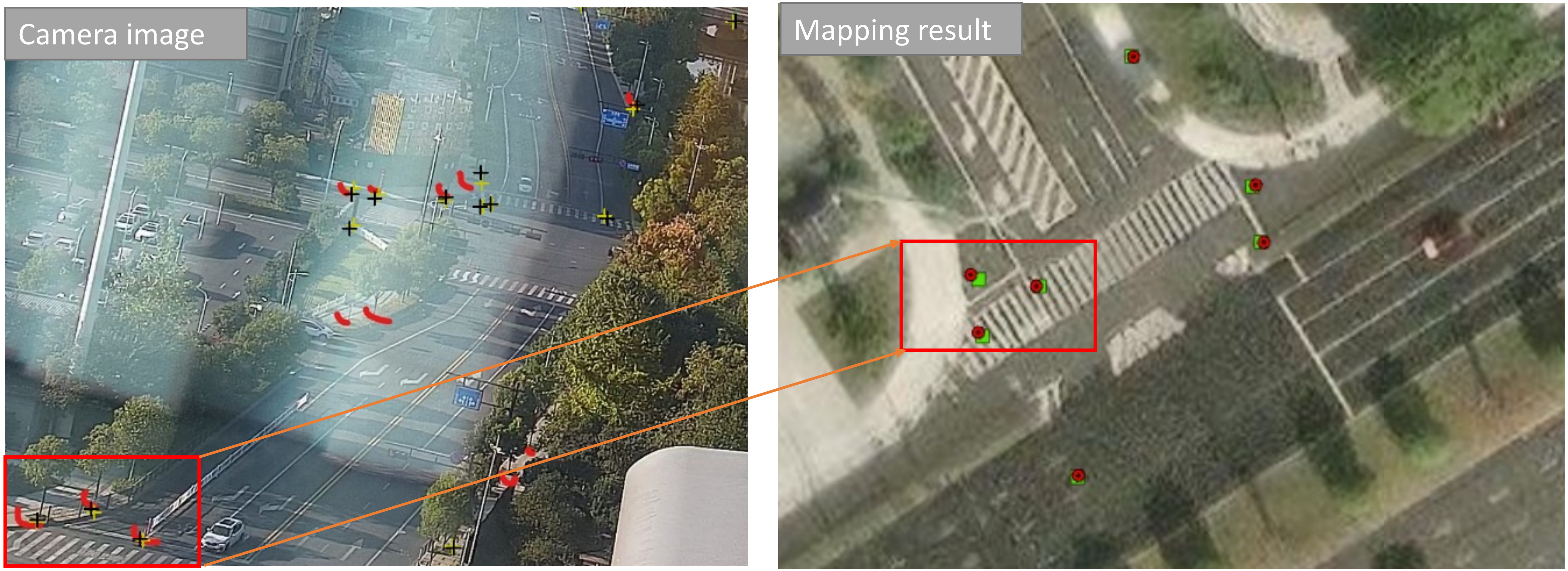






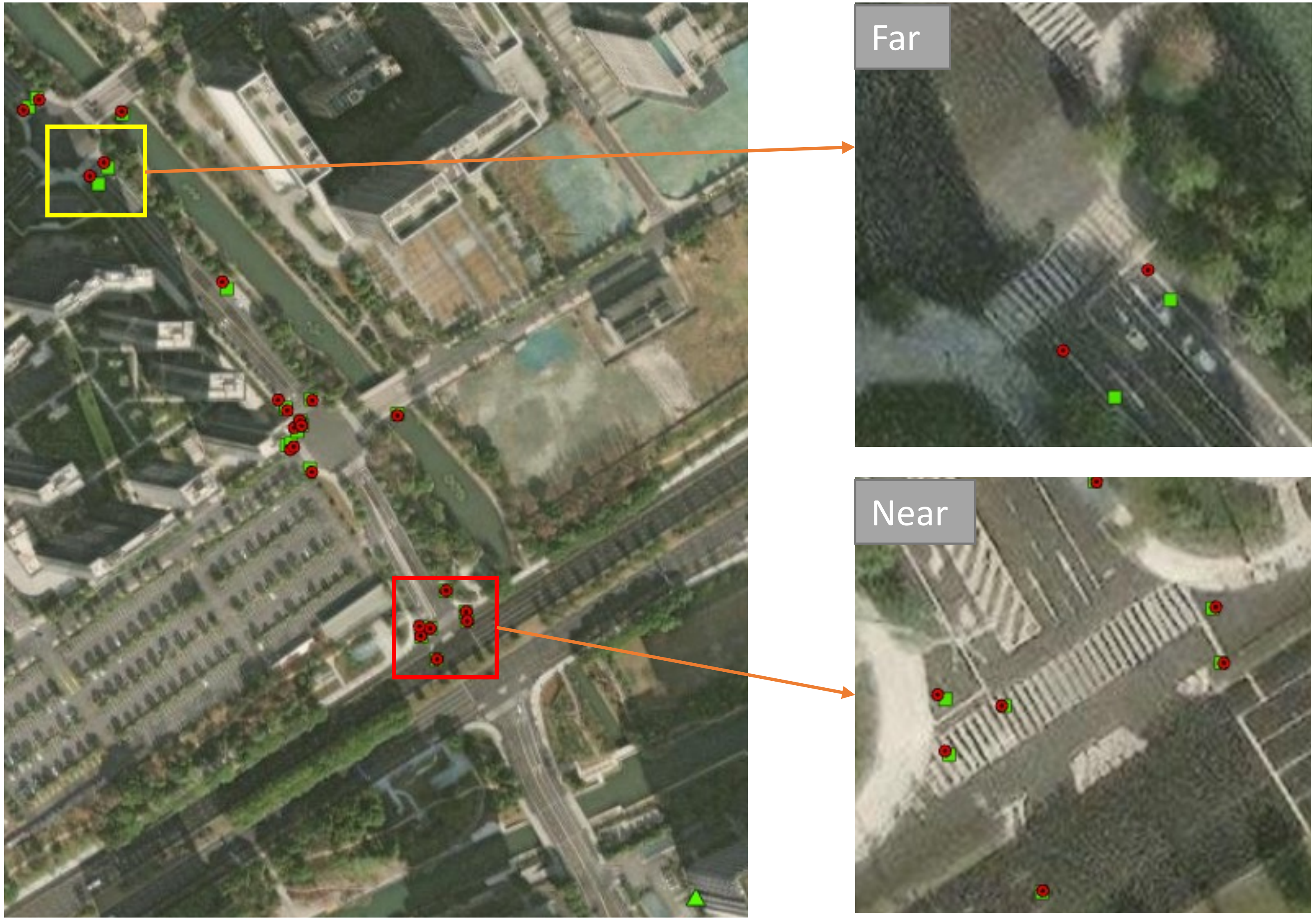


Methodology – Verify in real world



Red dots: control points
Green squares: calculated from pixel coordinates.
They are very close to each other.

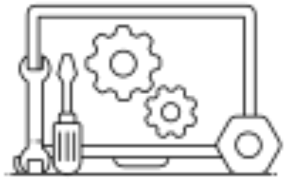
Methodology – Accuracy assessment



- Within 1000 meters, the error is less than 10 meters.
- Acceptable in small-scale applications.
- The accuracy depends on the distance to the camera, the quality of control points, and camera calibration.

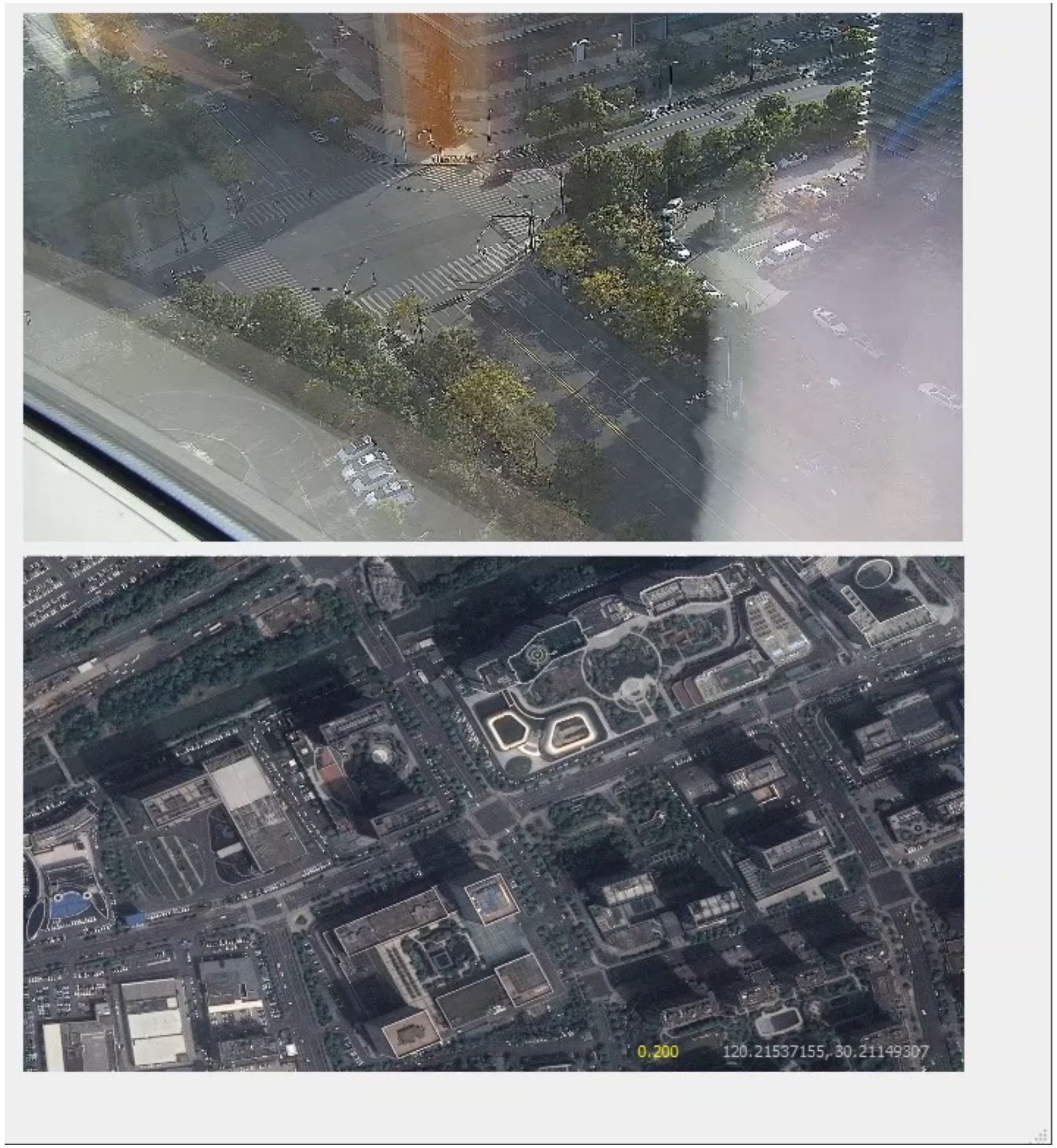
Methodology – REST APIs

- Set up python tornado web services.
- Write REST API documentation.



API Path	Usage
/cvp/reproject	Converts 3d world coordinates to 2d pixel coordinates
/cvp/locate	Converts 2d pixel coordinates to 3d world coordinates
/cvp/calibrate	Calibrates camera extrinsic parameters given set of control points.

Results



The mouse cursor on the map corresponds to a red dot on the video streaming.

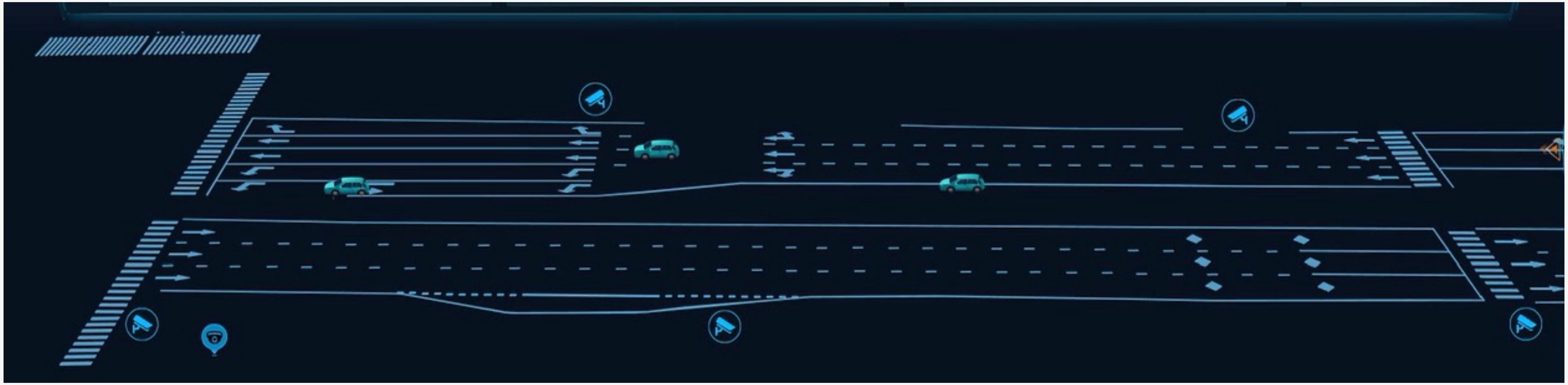
Challenges

Finding the best control point in the field.

- Use RTK devices for better precision
- Control points are evenly distributed
- Avoid trees
- Use road lane markings such as crosswalk markings, and arrows.

Learning the math foundation of computer vision.

- Review matrix calculation and linear algebra
- Learn computer vision basics online and from the textbook.



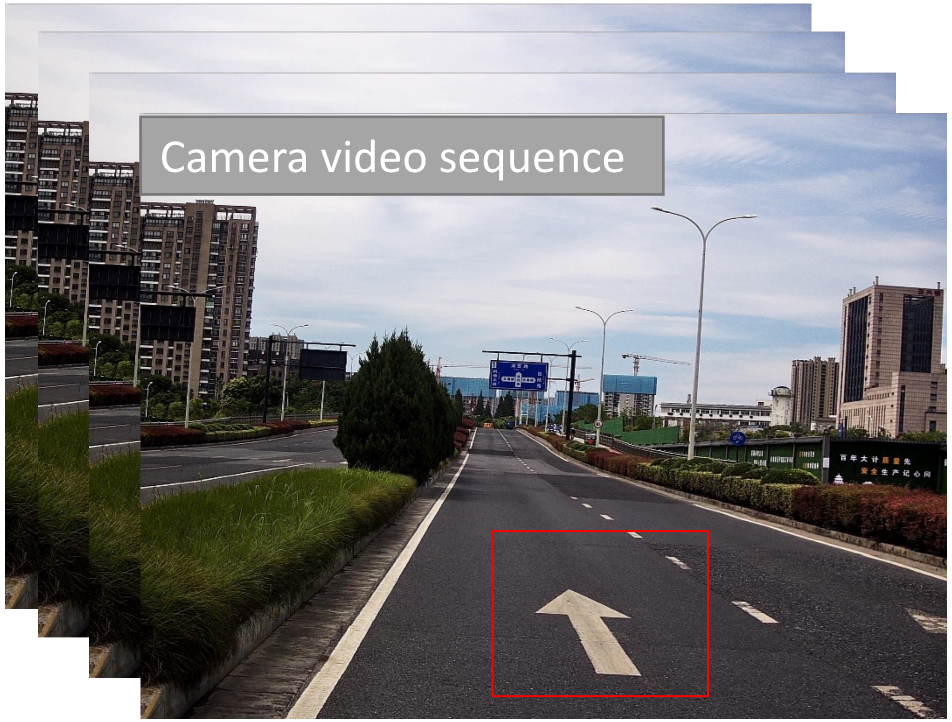
Stereo camera-based HD mapping application

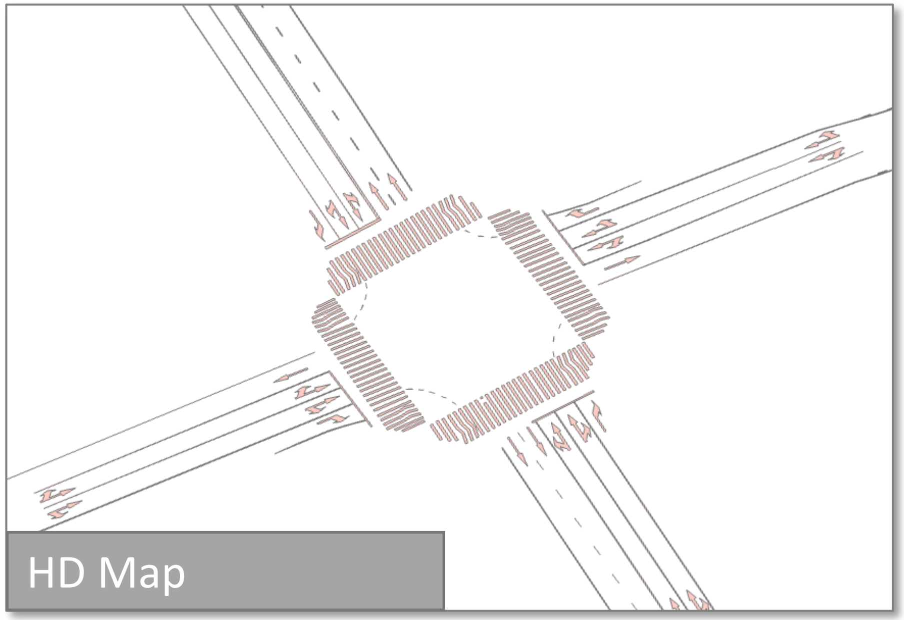
Tools: ArcGIS Pro, QGIS, CloudCompare

Skills: Python development, research, field work

Project Goals

- Extract the road lane marking from the stereo camera video frame.

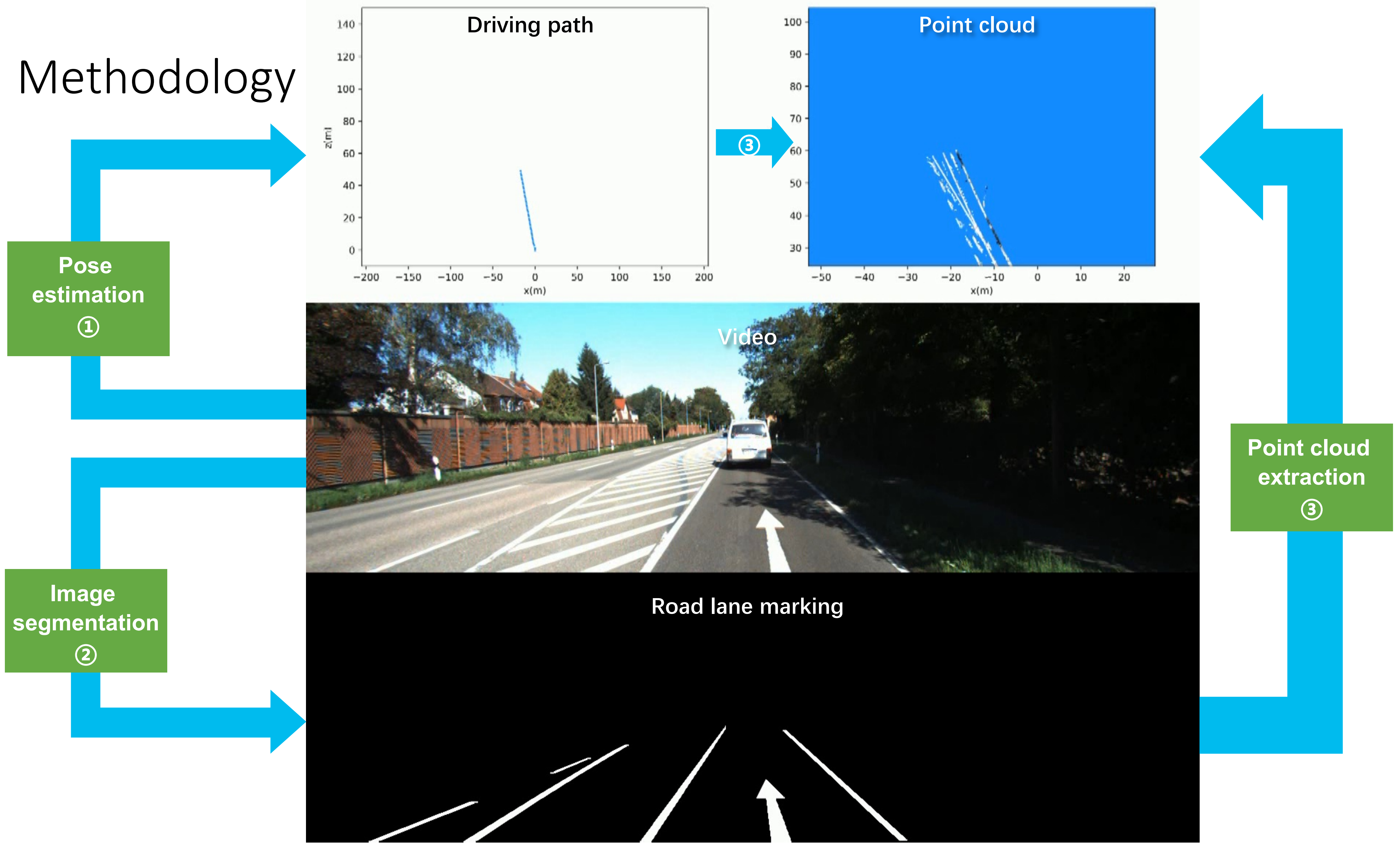




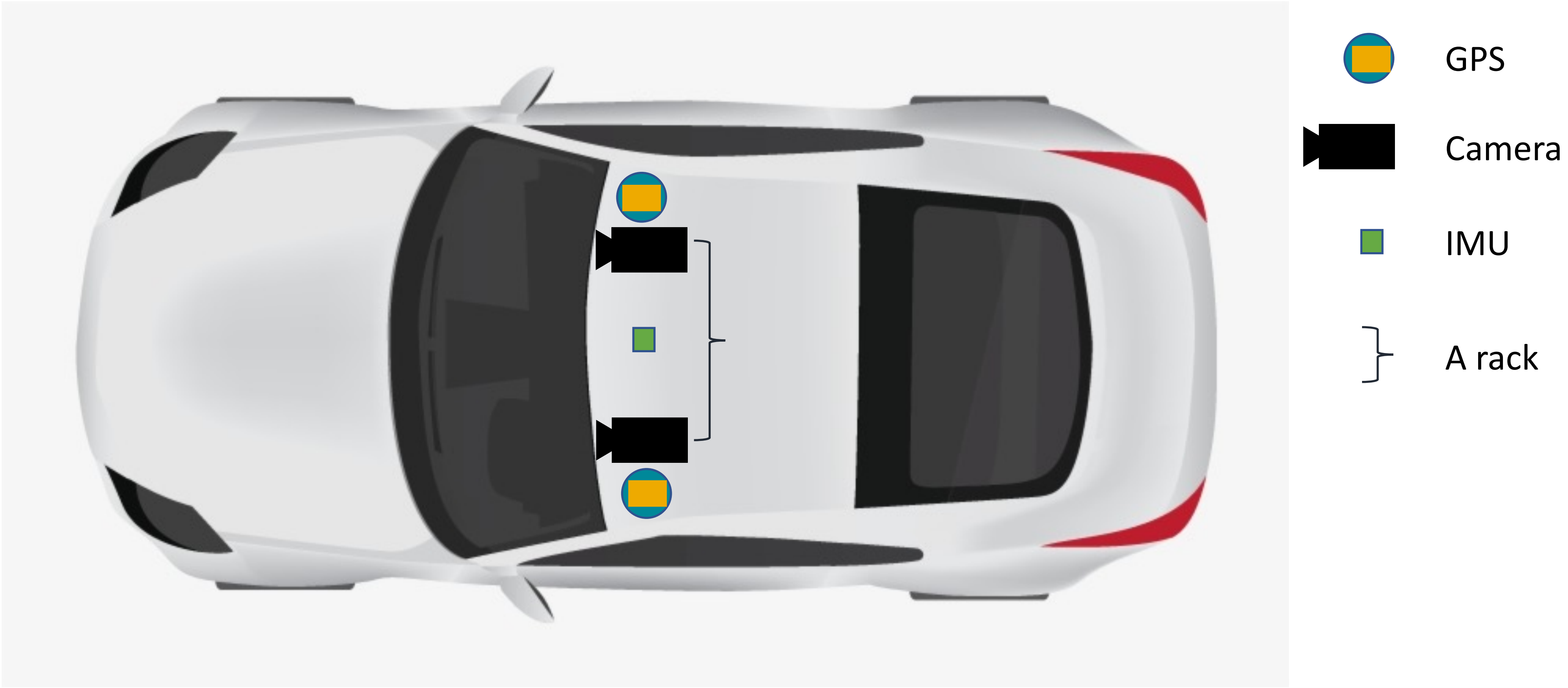
Methodology

1. Design the stereo-camera video-capturing systems.
2. Image segmentation using deep learning.
3. Convert image polygon to map polygon.
4. Spatial Aggregation.
5. Post-processing in ArcGIS Pro.

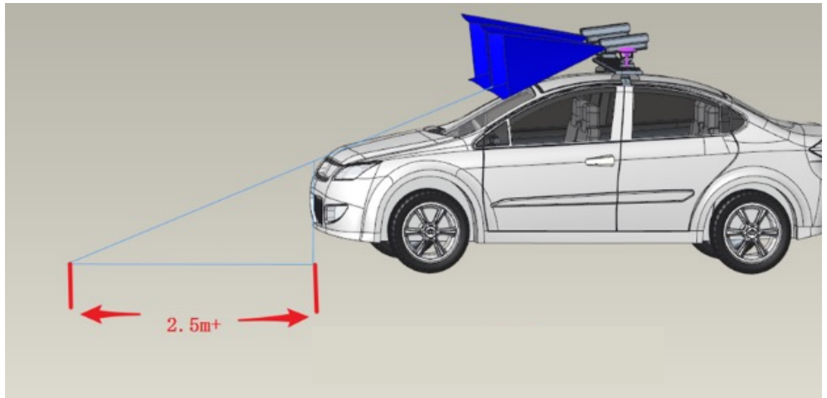
Methodology

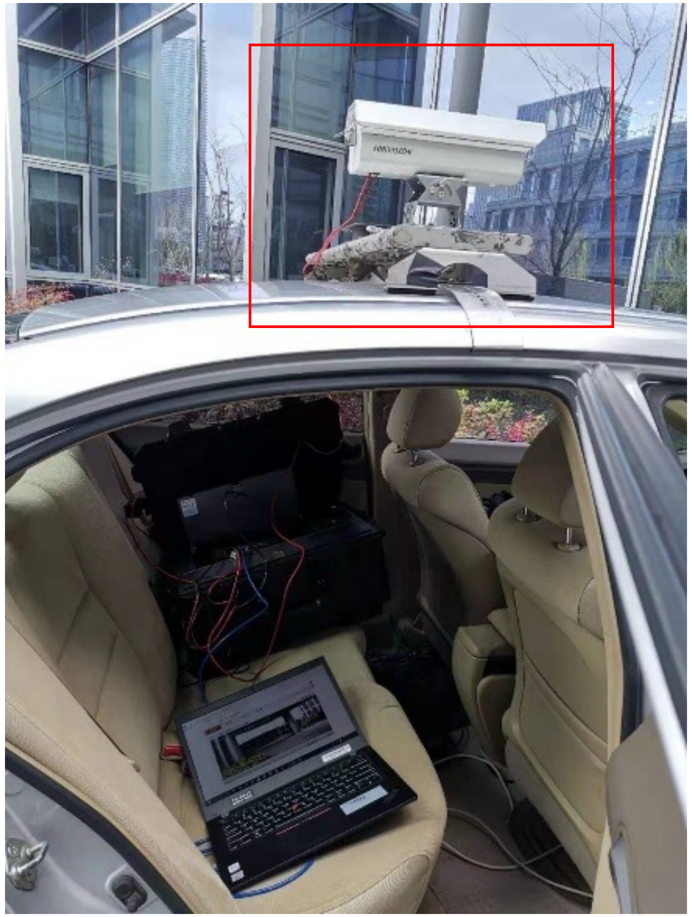


Methodology – Video capturing hardware

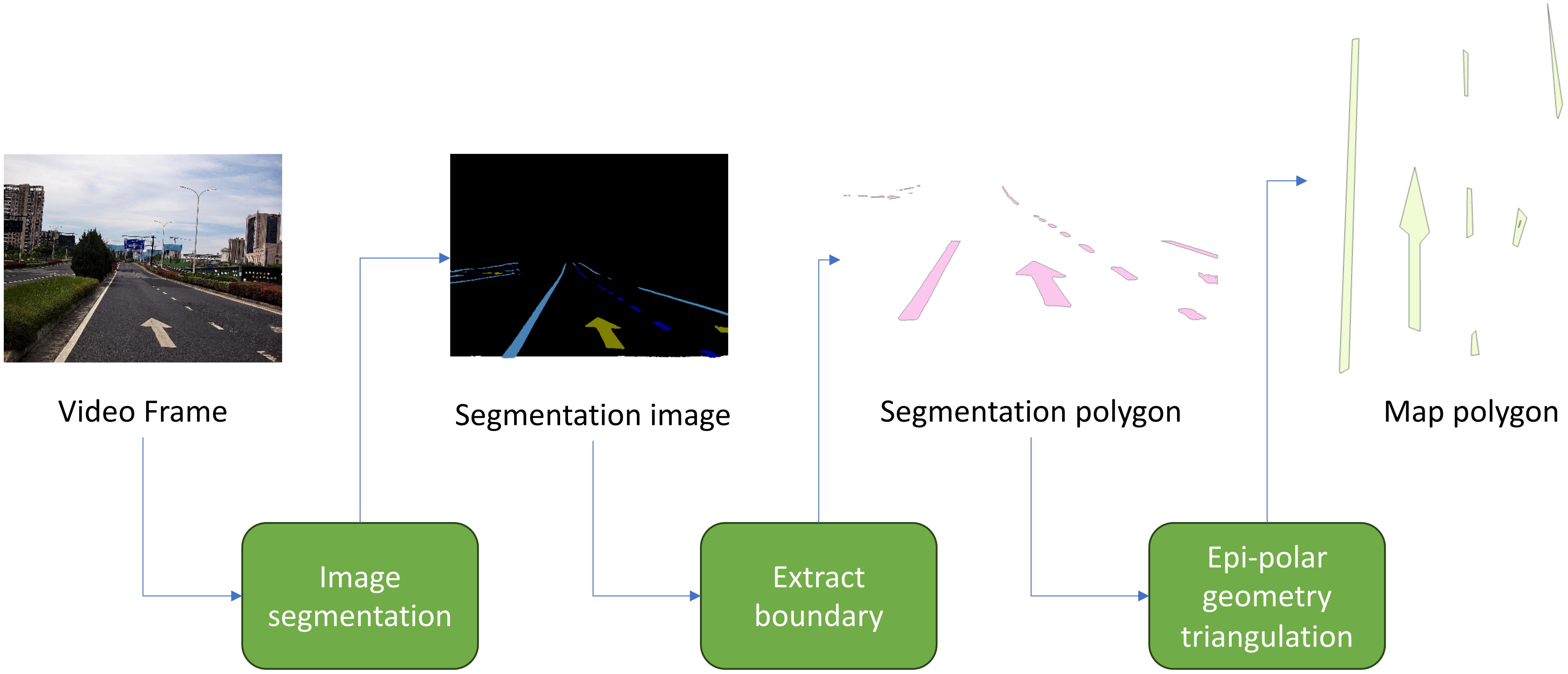


Methodology – Video capturing hardware



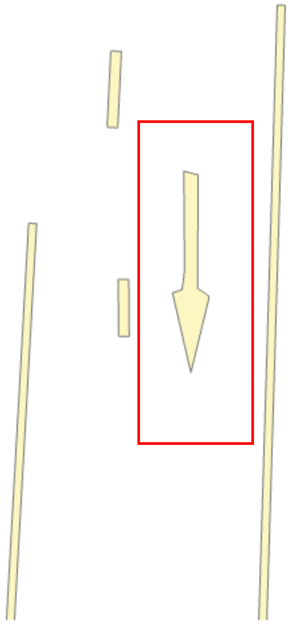


Methodology – Image segmentation and map polygon extraction

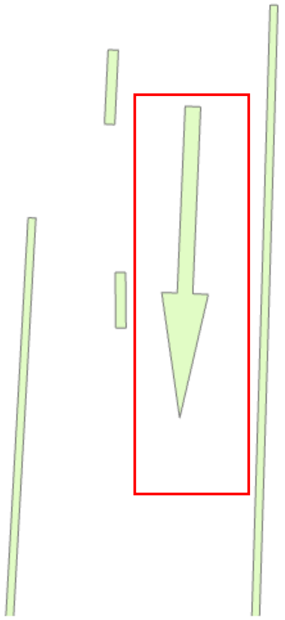


Methodology – Spatial aggregation and post processing

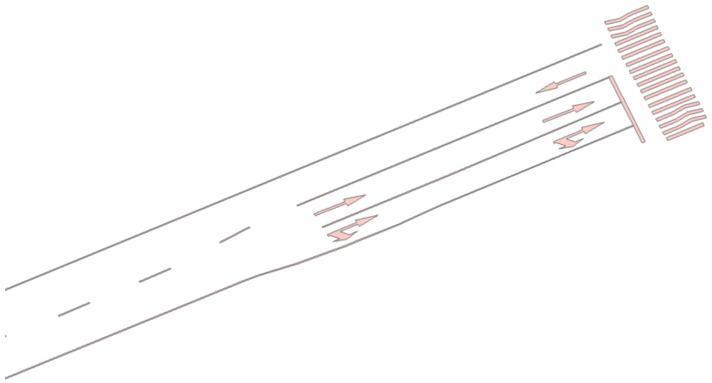
Map polygon of each frame



Spatial aggregation by marking type

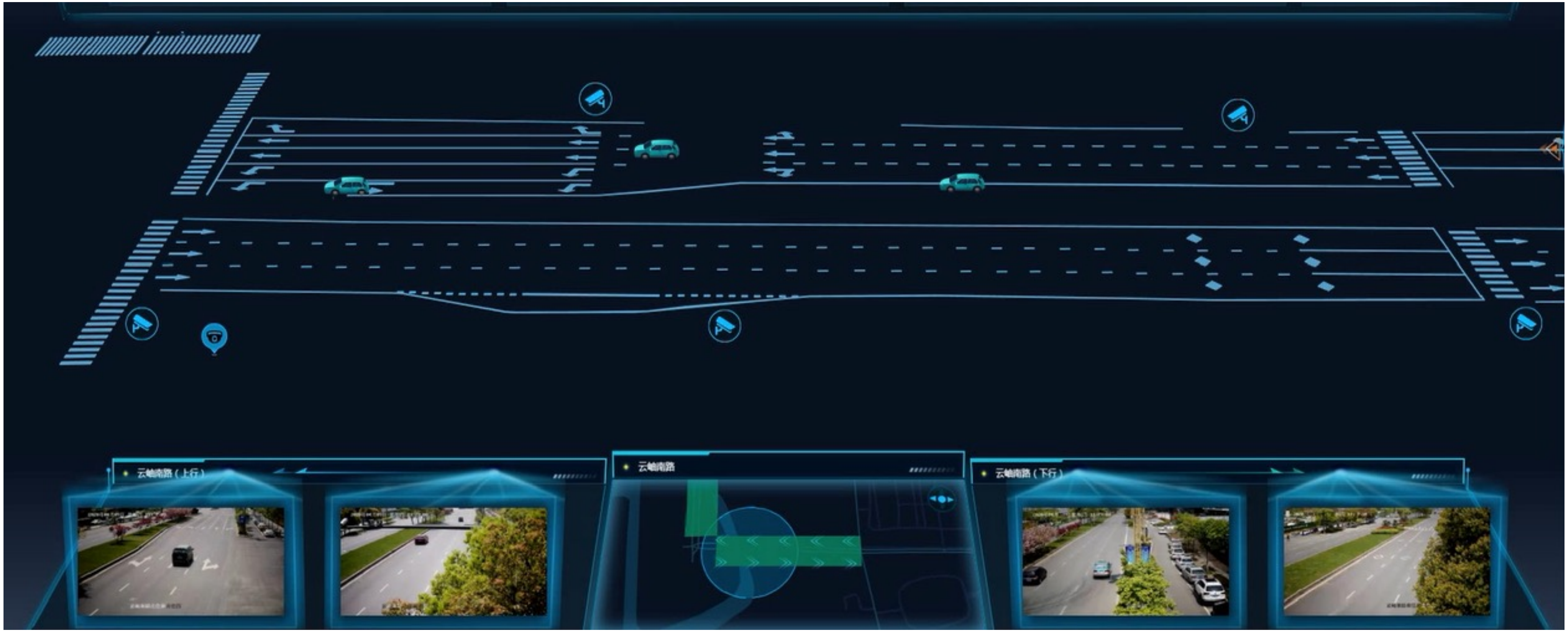


Replace marking with standard templates



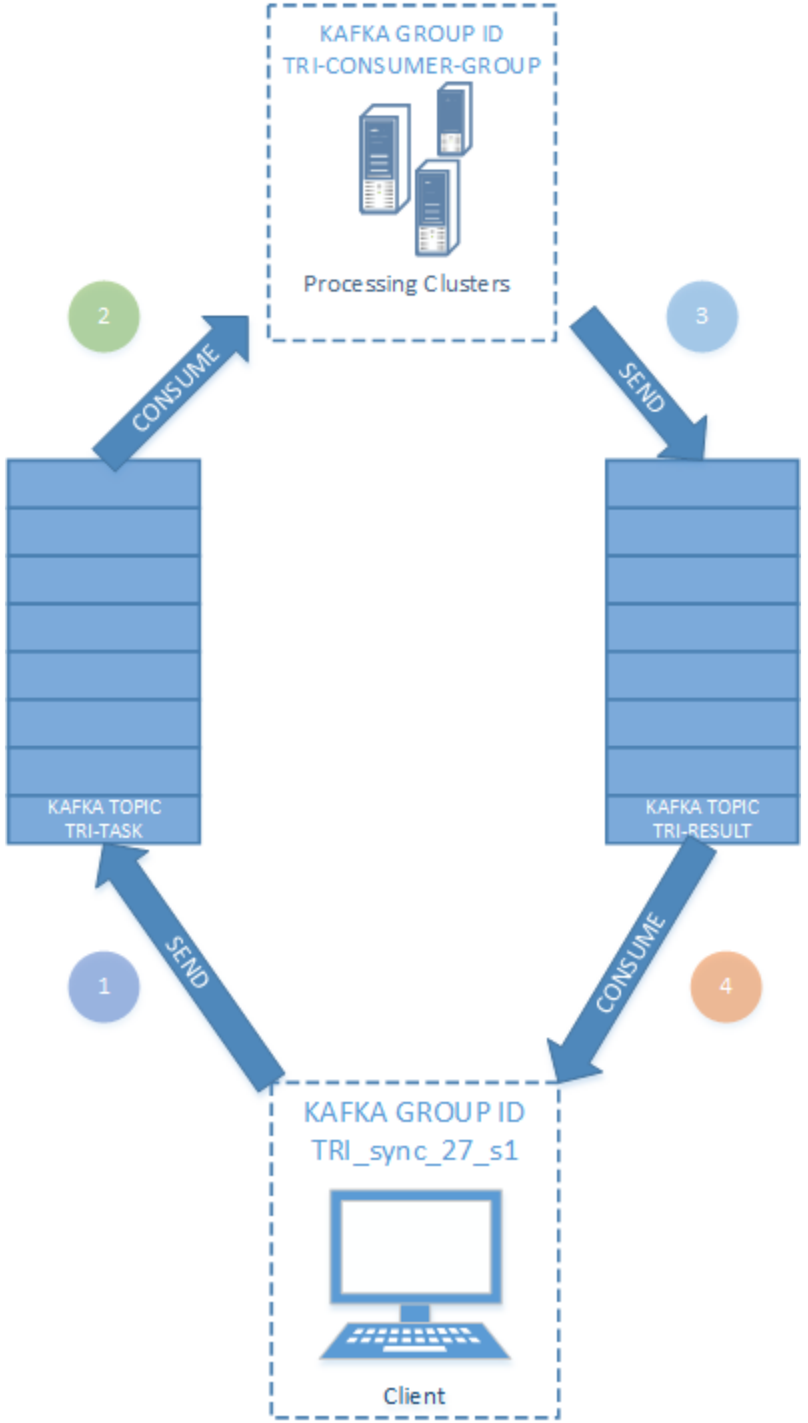
Post-processing in QGIS or ArcGIS Pro

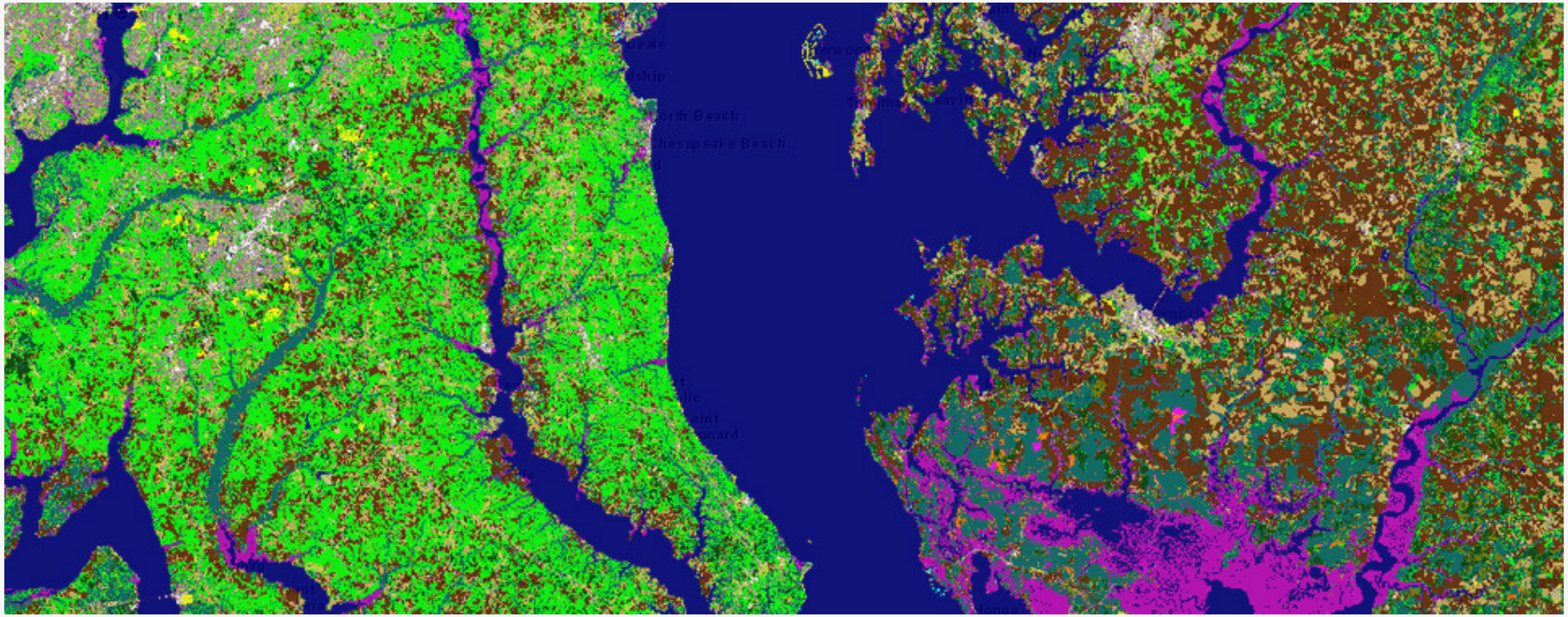
Results – HD Map used in transportation application



Challenges

- The map polygon conversion processing performance is slow.
- We are utilizing the multiple machine deployment and Kafka clusters.
- We improved processing time from 7s to 1s per image.





A Land Use Land Cover Analysis in Birmingham Metro Area

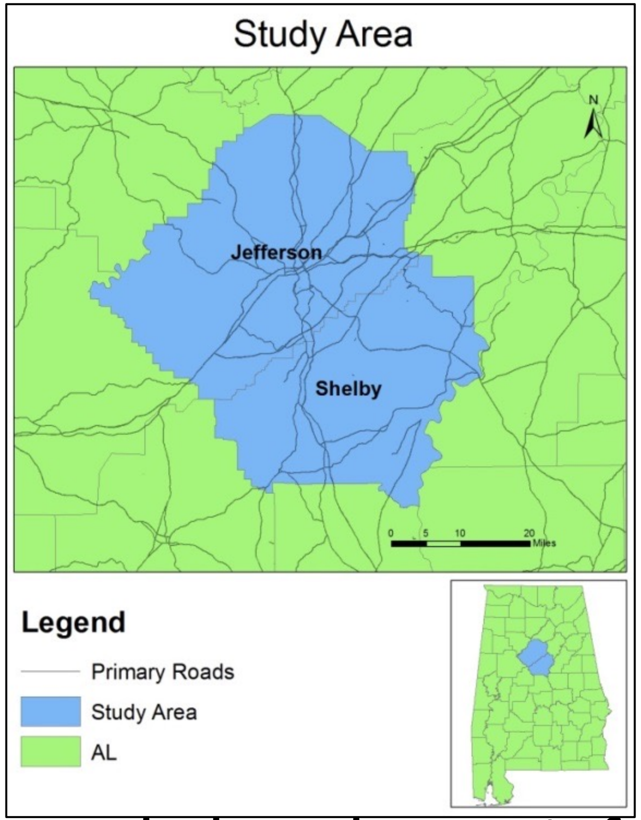
Tools: ArcMap, ERDAS IMAGINE, SLEUTH model

Skills: Supervised classification, accuracy assessment, field work.

Objectives

- To **perform a systematic LULC classification** to show LULC change in study area over the last three decades
- To **perform a change detection** to see where and when the dramatic change was
- To **simulate the landscape pattern** in the next three decades using a cellular automaton model

Study area



- It consists of Jefferson County

and Shelby County

- City area 393 km^2
- City population 212,237
- Population density 540.043 /sq km^2
- Humid subtropical, hot summer, mild winter, and abundant rainfall
- Mean elevation 173 meter, max at 454.73 meter, min at 73.99 meter. Mean slope 11.31%, max at 96.11%
- I-20, I-65, I-59, U.S Hwy 280, and U.S. Hwy 31

Methodology – Supervised classification

- Satellite images
  - Landsat 5 Thematic Mapper (TM)
  - Landsat 8 Operational Land Imager (OLI)/Thermal Infrared Sensor (TIRS)

Spectral bands detail of Landsat 5 TM sensor

Bands number	Wavelength (µm)	Spatial resolution (m)
Band 1 Visible	0.45-0.52	30
Band 2 Visible	0.52-0.60	30
Band 3Visible	0.63-0.69	30
Band 4 Near-Infrared	0.76-0.90	30
Band 5 Near-Infrared	1.55-1.75	30
Band 6 Thermal	10.40-12.50	120
Band 7 Mid-Infrared	2.08-2.35	30

Spectral bands detail of Landsat 8 OLI/TIRS sensor

Bands number	Wavelength (µm)	Spatial resolution (m)
Band 1 Visible	0.43-0.45	30
Band 2 Visible	0.45-0.51	30
Band 3 Visible	0.53-0.59	30
Band 4 Red	0.64-0.67	30
Band 5 Near-infrared	0.85-0.88	30
Band 6 SWIR 1	1.57-1.65	30
Band 7 SWIR 2	2.11-2.29	30
Band 8 Panchromatic	0.50-0.68	15
Band 9 Cirrus	1.36-1.38	30
Band 10 TIRS 1	10.6-11.19	100
Band 11 TIRS 2	11.5-12.51	100

Methodology – Supervised classification

- Satellite images

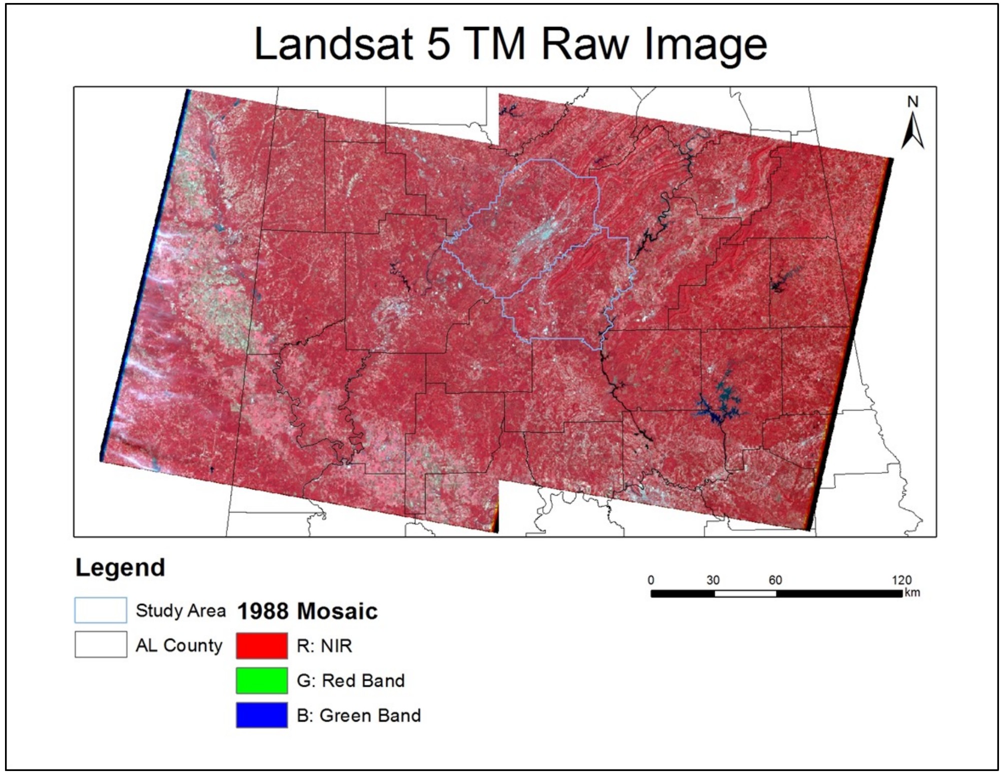
Path: 20/Row: 37	Path: 21/Row: 37	System
October 12, 1988	October 22, 1989	Landsat 5 TM
October 16, 1995		Landsat 5 TM
October 13, 2000	October 4, 2000	Landsat 5 TM
October 14, 2006	October 5, 2006	Landsat 5 TM
October 9, 2010	October 16, 2010	Landsat 5 TM
September 15, 2013	September 6, 2013	Landsat 8 OLI/TIRS

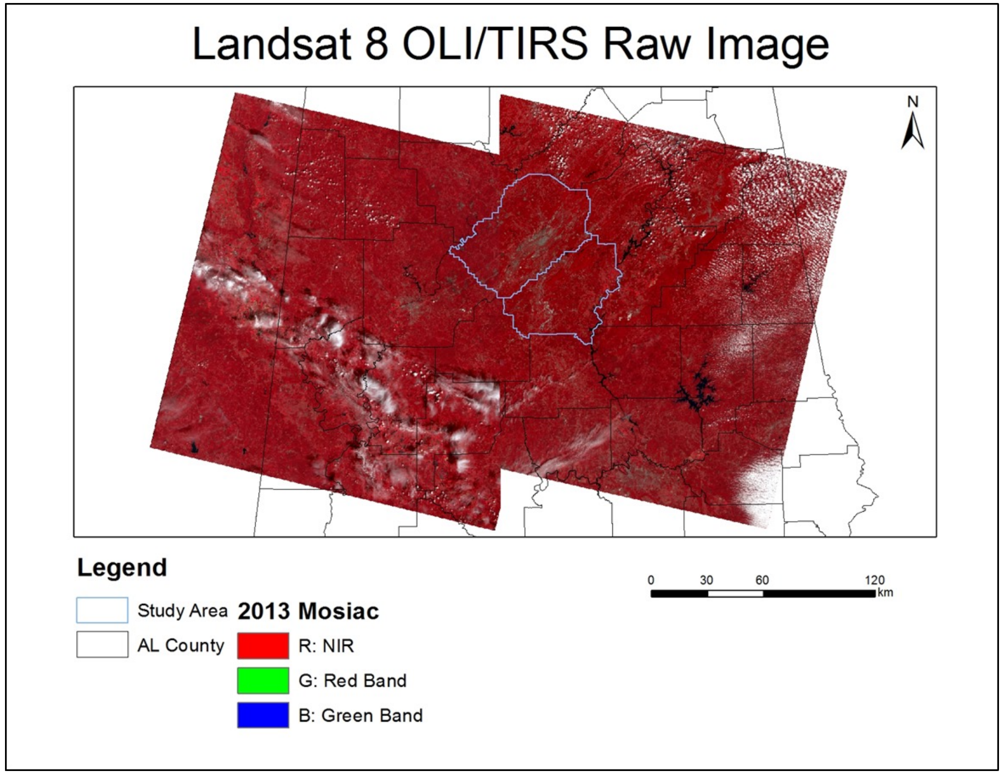
Methodology – Supervised classification

- Collateral data
  - Google Earth
  - The University of Alabama Map Library
  - Census Bureau: TIGER, Population, and income
  - U.S. Geological Survey: Digital Elevation Model (DEM)
  - Department of Transportation: National Transportation Atlas 2010, 2007, 2000
  - National Historical GIS: historical census data

Methodology – Supervised classification

- Image preprocessing
  - Mosaic and subset



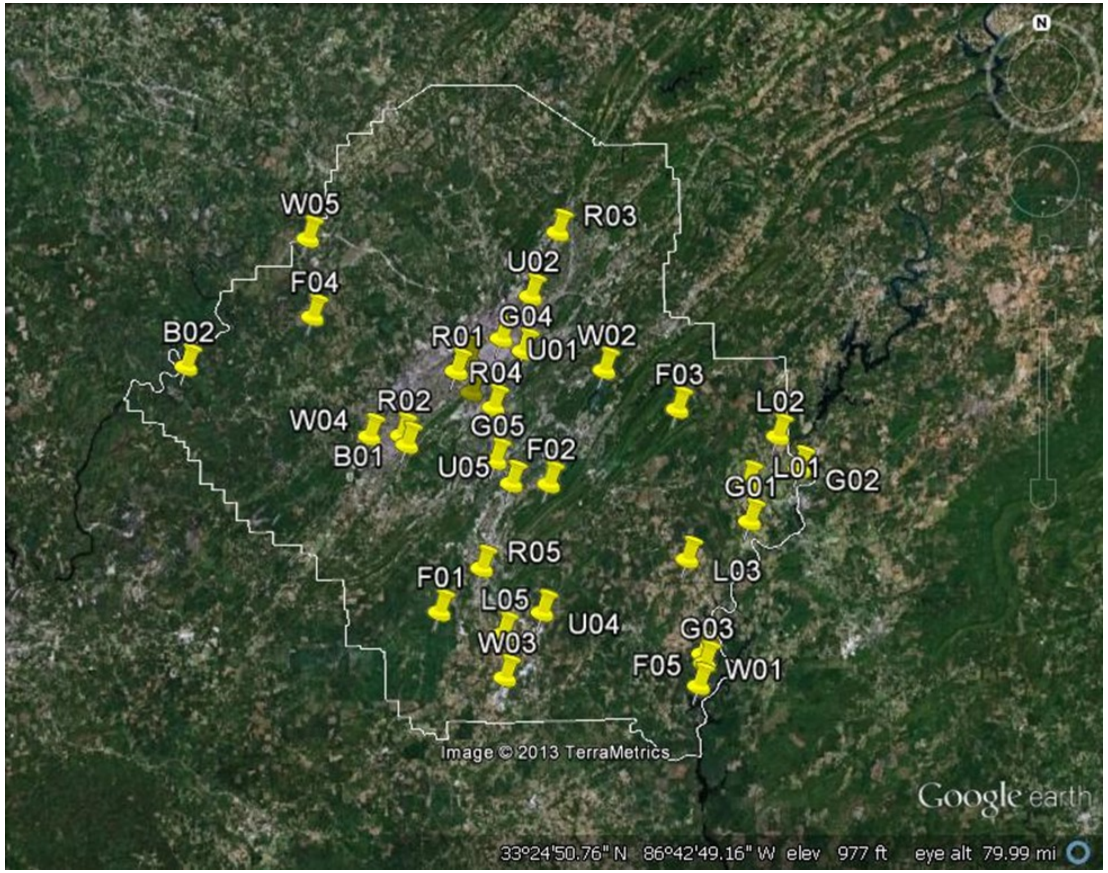


Methodology – Supervised classification

- Supervised classification
- Parametric rule: maximum likelihood
- 6 classes: High Intensity Urban/Developed Land, Low Intensity Urban/Residential, Water, Forest, Growing Vegetation, and Light Vegetation

Methodology – Supervised classification

- Training sites in study area



Methodology – Supervised classification

- Accuracy assessment
  - Stratified random sampling method
  - Errors matrix were created for each classification
  - Kappa statistics, overall accuracy, producer’s accuracy, user’s accuracy, omission error, and commission error

Error matrix

	Reference Data						
Classification	U	R	W	F	L	G	Row Total
U	43	0	0	0	7	0	50
G	0	42	0	1	6	1	50
W	0	0	50	0	0	0	50
F	0	1	1	48	0	0	50
L	1	7	0	6	36	0	50
G	0	0	0	5	5	40	50
Column Total	44	50	51	60	54	41	300

Overall Accuracy = 259/300 = 86.33%

Producer's Accuracy		**User's Accuracy**	
U = 43/44 = 97.73%	2.27% omission error	U = 43/50 = 86.00%	14.00% commission error
R = 42/50 = 84.00%	16.00% omission error	R = 42/50 = 84.00%	16.00% commission error
W = 50/51 = 98.04%	1.96% omission error	W = 50/50 = 100.00%	0.00% commission error
F = 48/60 = 80.00%	20.00% omission error	F = 48/50 = 96.00%	4.00% commission error
L = 36/54 = 66.67%	33.33% omission error	L = 36/50 = 72.00%	38.00% commission error
G = 40/41 = 97.56%	2.44% omission error	G = 40/50 = 80.00%	20.00% commission error

Methodology – Change detection

- Change detection
  - Recode classification map
  - Map algebra
  - 1988-1995, 1995-2006, 2006-2013, 1988-2013

Codes of from-to change detection

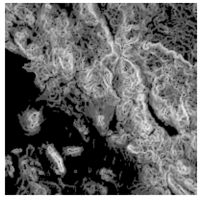
To From	U: 1	R: 2	W: 3	F: 4	L: 5	G: 6
U: 1*10=10	11	12	13	14	15	16
R: 2*10=20	21	22	23	24	25	26
W: 3*10=30	31	32	33	34	35	36
F: 4*10=40	41	42	43	44	45	46
L: 5*10=50	51	52	53	54	55	56
G: 6*10=60	61	62	63	64	65	66

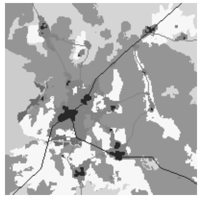
Methodology - SLEUTH

- Introduction
    - SLEUTH Model: Slope, Land use, Exclusion, Urban Extent, Transportation, and Hillshade
    - C program running under UNIX
    - Calibration and forecasting

Methodology - SLEUTH

- Data input
  - Slope
  - Land use
  - Excluded image: area where growth is prohibited
  - Urban extent
  - Transportation network
  - Hillshade

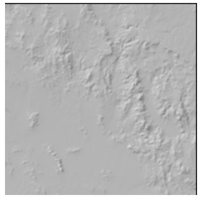

Slope


Land use


Exclusion


Urban extent


Transportation


Hillshade

Methodology - SLEUTH

- Growth rule

Growth rule	Growth coefficient	Growth coefficient value range	Description of simulated growth patterns
Spontaneous new growth	Diffusion	0-100	Randomly selected potential new growth cells. High values for diffusion will result in dispersed urban patterns.
New spreading center growth	Breed	0-100	Creates new clusters of urbanized cells.
Edge growth	Spread	0-100	Growth that occurs along the edges of existing or newly created urban clusters.
Road-influenced growth	Road-gravity, diffusion and breed	0-100	Growth that occurs along the transportation network.
Slope resistance	Slope	0-100	Simulates the effect of slope on reducing the likelihood of urbanization.

Methodology - SLEUTH

- Work flow of simulation

Start
- Historical data and layers
- Working Eenvironment set-up

Coarse
- Default five coefficient (0-100)
- Determine the coefficients for Fine Calibration

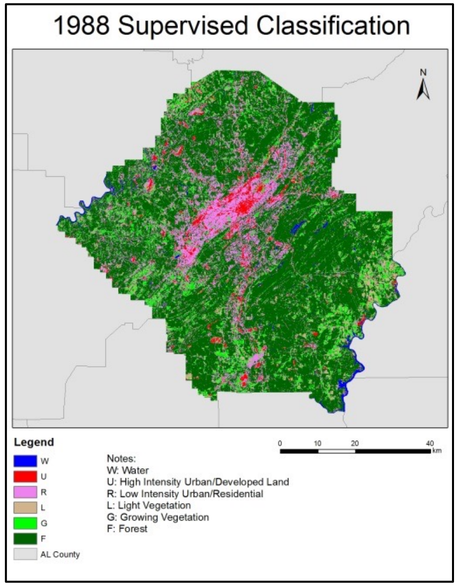
Fine
- Start with smaller range of coefficients
- Determine the coefficents for Final Calibration

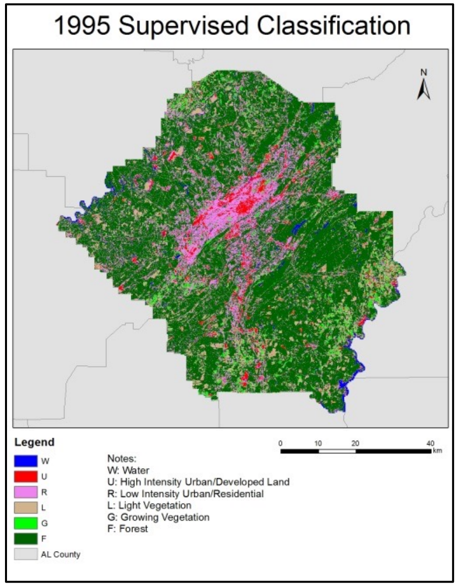
Final
- Start with even better range of coefficients
- determine the coefficients for Derive step

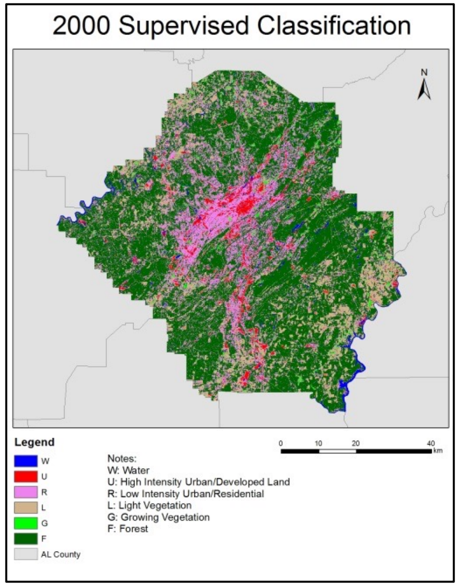
Derive
- Determine the coefficient for prediction

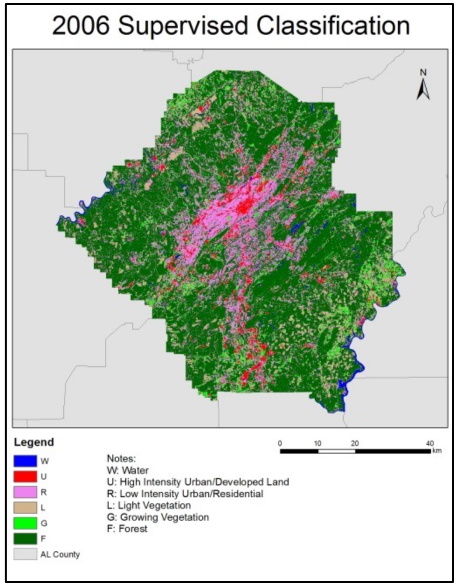
Predieti on
- Predict the future LULC pattern based on best-fit coefficients

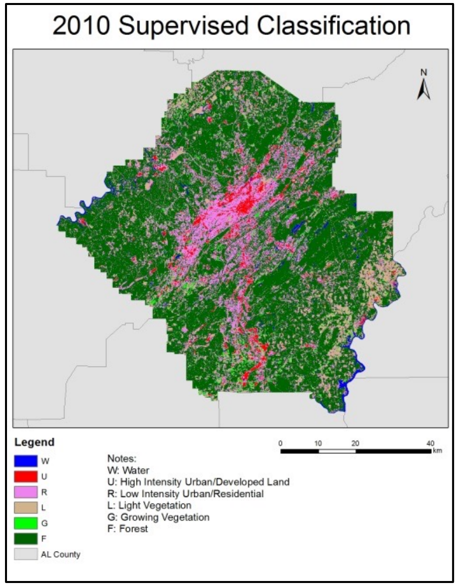
Results – Supervised classification

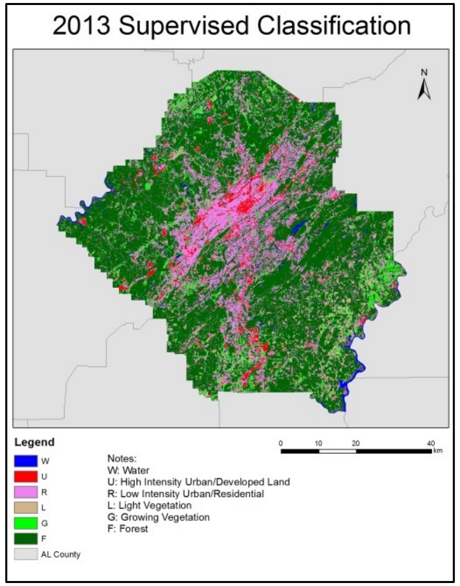




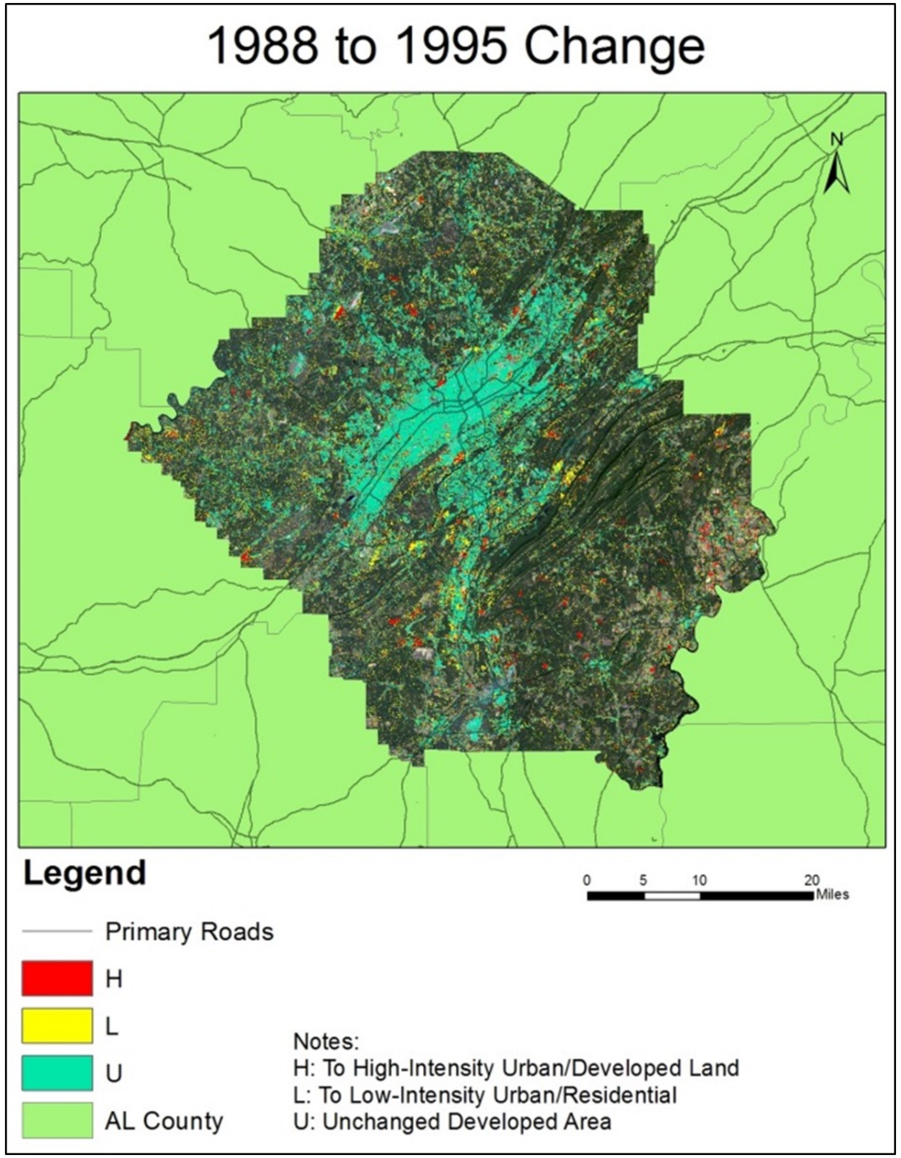


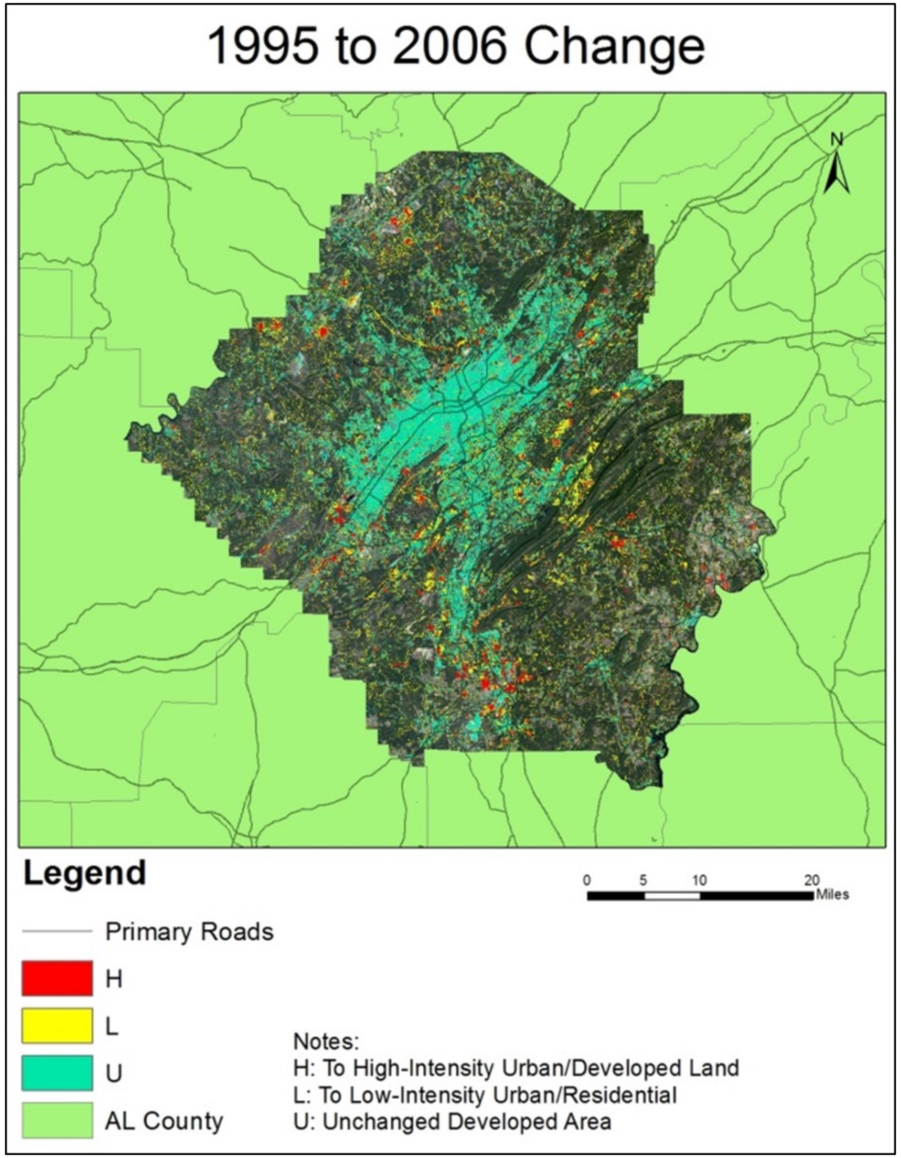




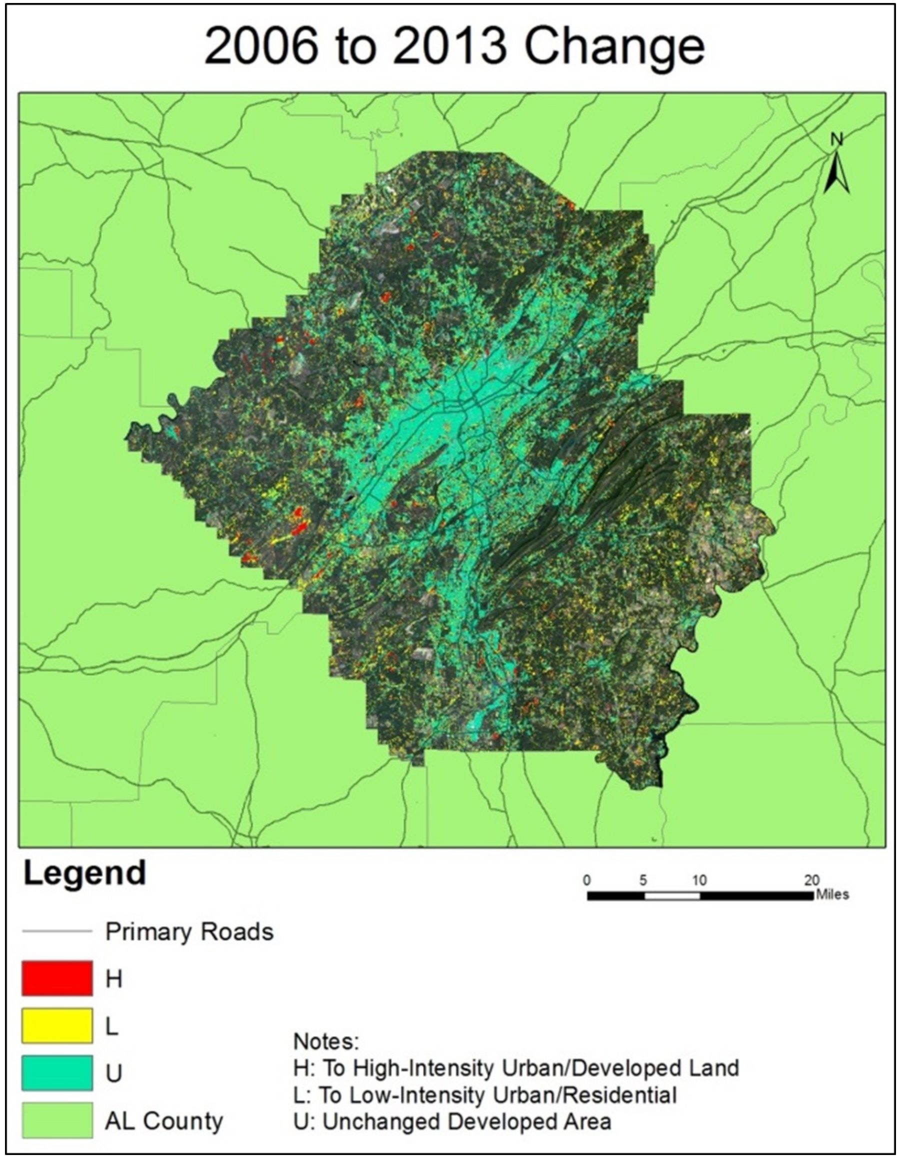


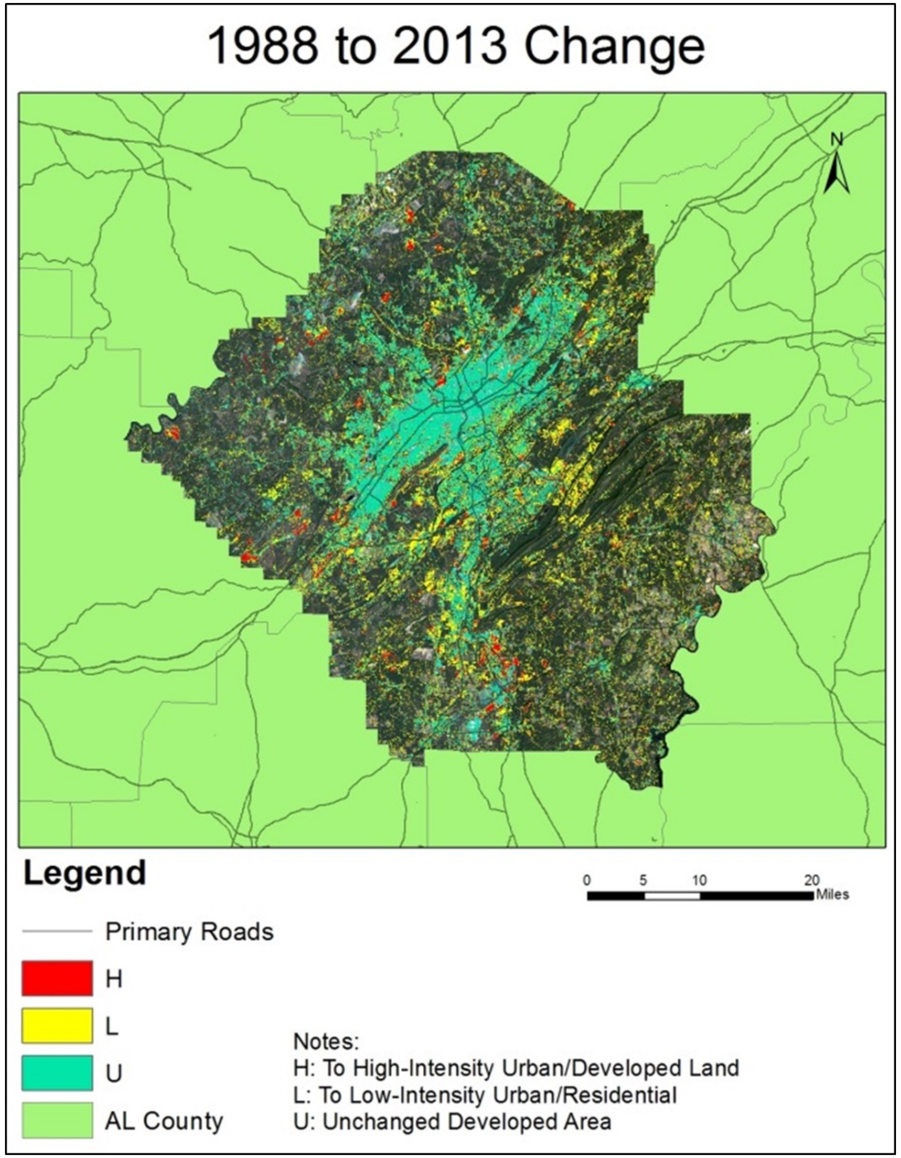
Results - Change detection





Results - Change detection





Results - Change detection

Land use land cover change details between 1988 and 1995

Land Use Land Cover Change	Amount of Change in km^2
High Intensity Urban/Developed Land (no change)	96.978
Low Intensity urban/Residential (no change)	537.665
Forest to High Intensity Urban/Developed Land	36.724
Forest to Low Intensity urban/Residential	236.607
Light Vegetation to High Intensity Urban/Developed Land	14.992
Light Vegetation to Low Intensity urban/Residential	41.694
Growing Vegetation to High Intensity Urban/Developed Land	8.764
Growing Vegetation to Low Intensity urban/Residential	71.394

Land use land cover change details between 1995 and 2000

Land Use Land Cover Change	Amount of Change in km^2
High Intensity Urban/Developed Land (no change)	95.829
Low Intensity urban/Residential (no change)	531.530
Forest to High Intensity Urban/Developed Land	54.403
Forest to Low Intensity urban/Residential	304.665
Light Vegetation to High Intensity Urban/Developed Land	17.239
Light Vegetation to Low Intensity urban/Residential	80.038
Growing Vegetation to High Intensity Urban/Developed Land	9.344
Growing Vegetation to Low Intensity urban/Residential	24.330

Land use land cover change details between 2006 and 2013

Land Use Land Cover Change	Amount of Change in km^2
High Intensity Urban/Developed Land (no change)	120.002
Low Intensity urban/Residential (no change)	686.702
Forest to High Intensity Urban/Developed Land	26.045
Forest to Low Intensity urban/Residential	259.005
Light Vegetation to High Intensity Urban/Developed Land	6.054
Light Vegetation to Low Intensity urban/Residential	74.400
Growing Vegetation to High Intensity Urban/Developed Land	4.561
Growing Vegetation to Low Intensity urban/Residential	81.644

Land use land cover change details between 1988 and 2013

Land Use Land Cover Change	Amount of Change in km^2
High Intensity Urban/Developed Land (no change)	78.218
Low Intensity urban/Residential (no change)	536.511
Forest to High Intensity Urban/Developed Land	54.561
Forest to Low Intensity urban/Residential	411.981
Light Vegetation to High Intensity Urban/Developed Land	8.889
Light Vegetation to Low Intensity urban/Residential	61.306
Growing Vegetation to High Intensity Urban/Developed Land	13.229
Growing Vegetation to Low Intensity urban/Residential	103.842

Results - SLEUTH

- Simulation of LULC

Coarse Calibration

Coefficients	Start value	Stop value	Steps
Diffusion	0	100	25
Breed	0	100	25
Spread	0	100	25
Slope resistance	0	100	25
Road gravity	0	100	25

Fine Calibration

Coefficients	Start value	Stop value	Steps
Diffusion	1	20	5
Breed	1	25	5
Spread	1	20	5
Slope resistance	75	100	5
Road gravity	25	100	15

Final Calibration

Coefficients	Start value	Stop value	Steps
Diffusion	1	1	1
Breed	1	6	1
Spread	1	1	1
Slope resistance	90	100	2
Road gravity	25	55	5

Deriving coefficients

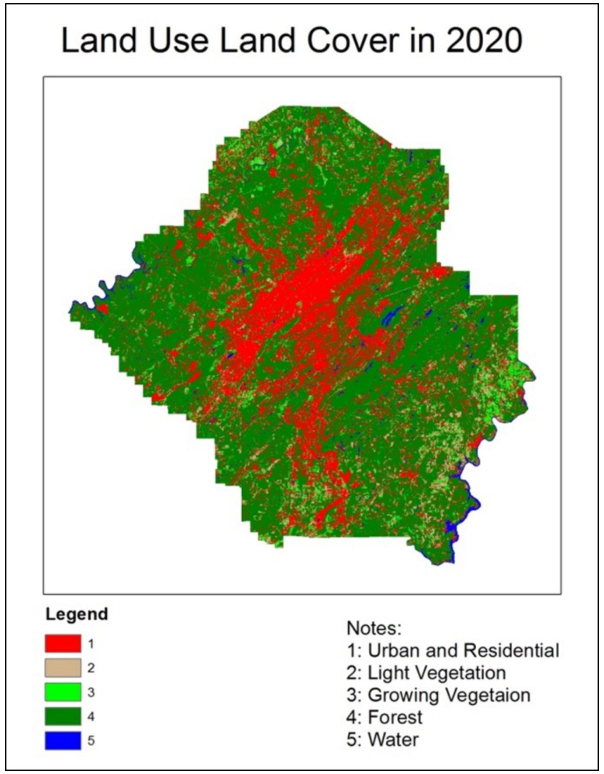
Coefficients	Start value	Stop value	Steps
Diffusion	1	1	1
Breed	6	6	1
Spread	1	1	1
Slope resistance	90	90	1
Road gravity	41	41	1

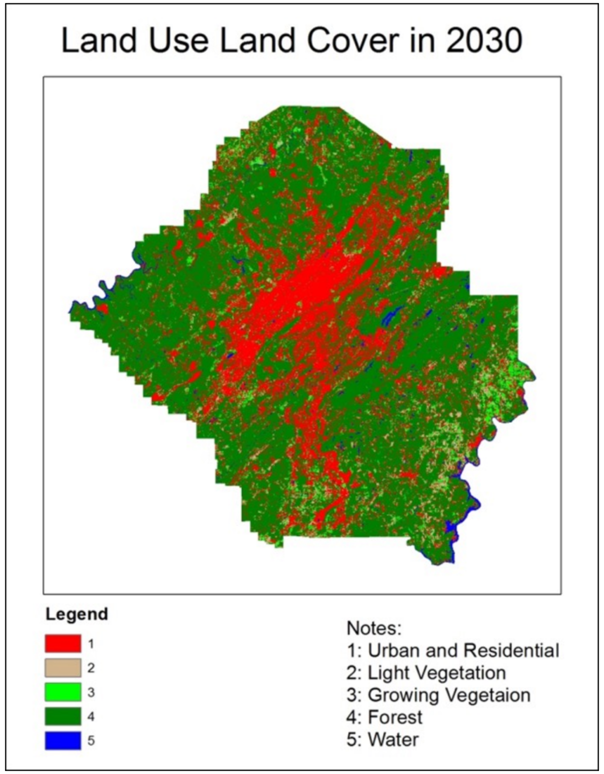
Best fit coefficients

Diffusion	Breed	Spread	Slope resistance	Road gravity
1	1	1	100	40

Results - SLEUTH

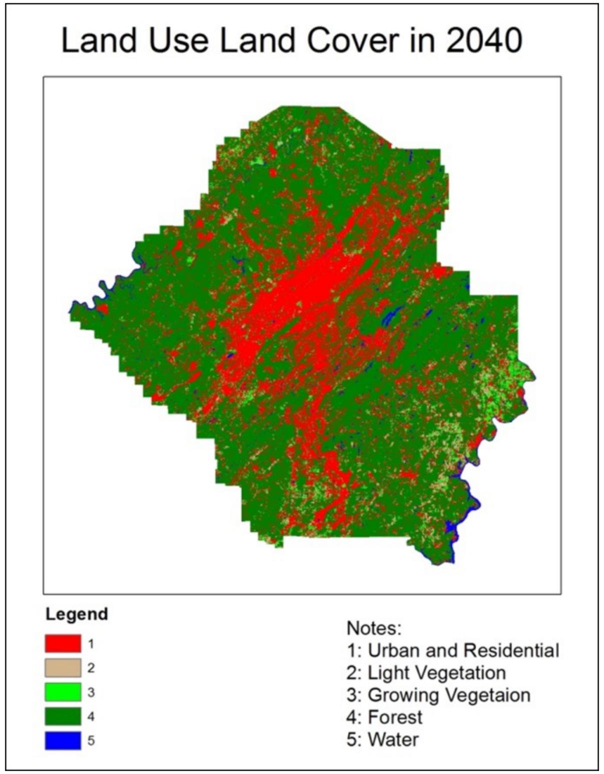
- Simulation of LULC

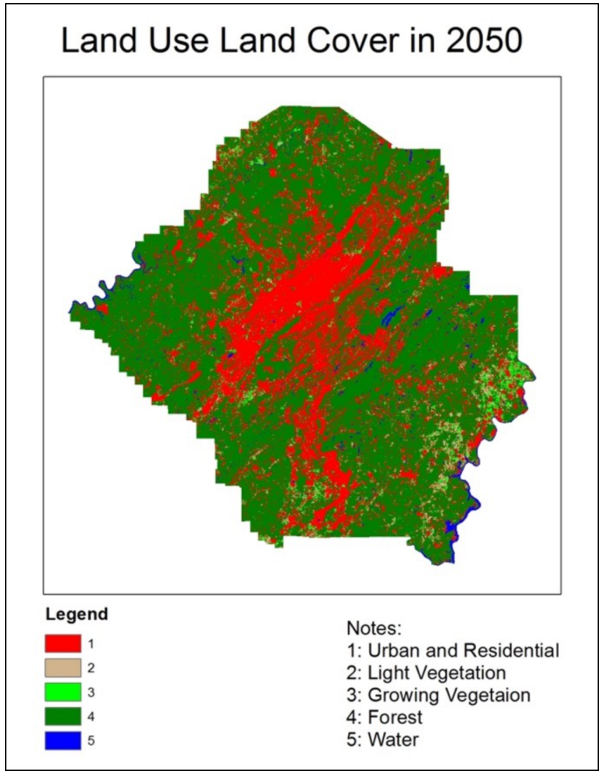




Results - SLEUTH

- Simulation of LULC





Results - SLEUTH

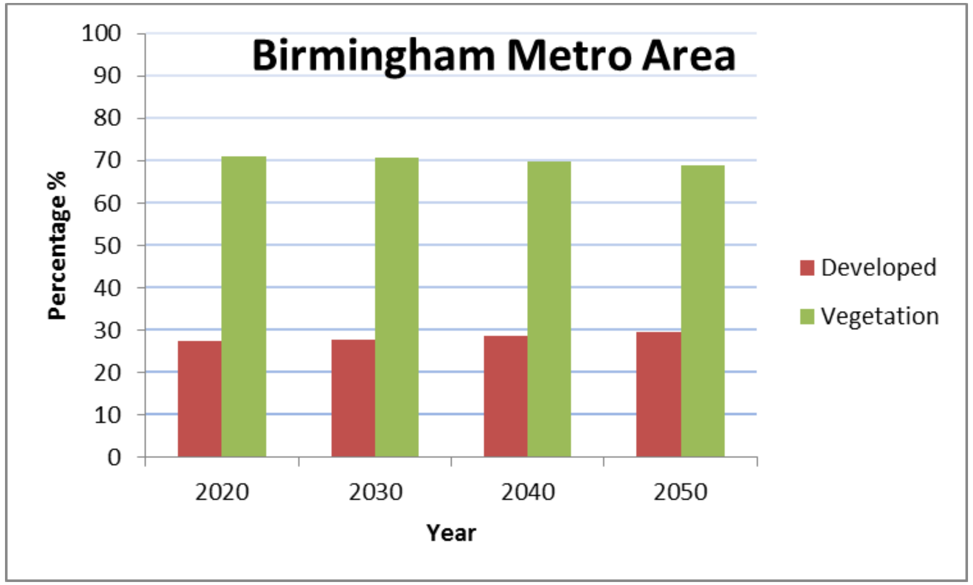
- Simulation of LULC

Pixel counts of predicted LULC classes

LULC	2020	2030	2040	2050
Urban/Residential	381829	387825	397524	411725
Vegetation	988180	982313	972785	958761
Light Vegetation	61330	53670	43993	34810
Growing Vegetation	87624	71865	54517	40741
Forest	839226	856778	874275	883210
Water	21666	21540	21373	21199

Percentage of predicted LULC classes

LULC	2020	2030	2040	2050
Urban/Residential	27.437	27.867	28.564	29.585
Vegetation	71.007	70.585	69.900	68.892
Light Vegetation	4.407	3.856	3.161	2.501
Growing Vegetation	6.296	5.164	3.917	2.927
Forest	60.303	61.564	62.821	63.463
Water	1.557	1.548	1.536	1.523



Contact Me

LinkedIn: https://www.linkedin.com/in/jingxuehan0707/

Email: jingxuehan0707@gmail.com

Phone: 8402109597