ACM SIGSPATIAL 2024

Session 6: Prediction and forecasting

GraphParcelNet: Predicting Parcel-Level Imperviousness from Geospatial Vector Data using Graph Neural Networks

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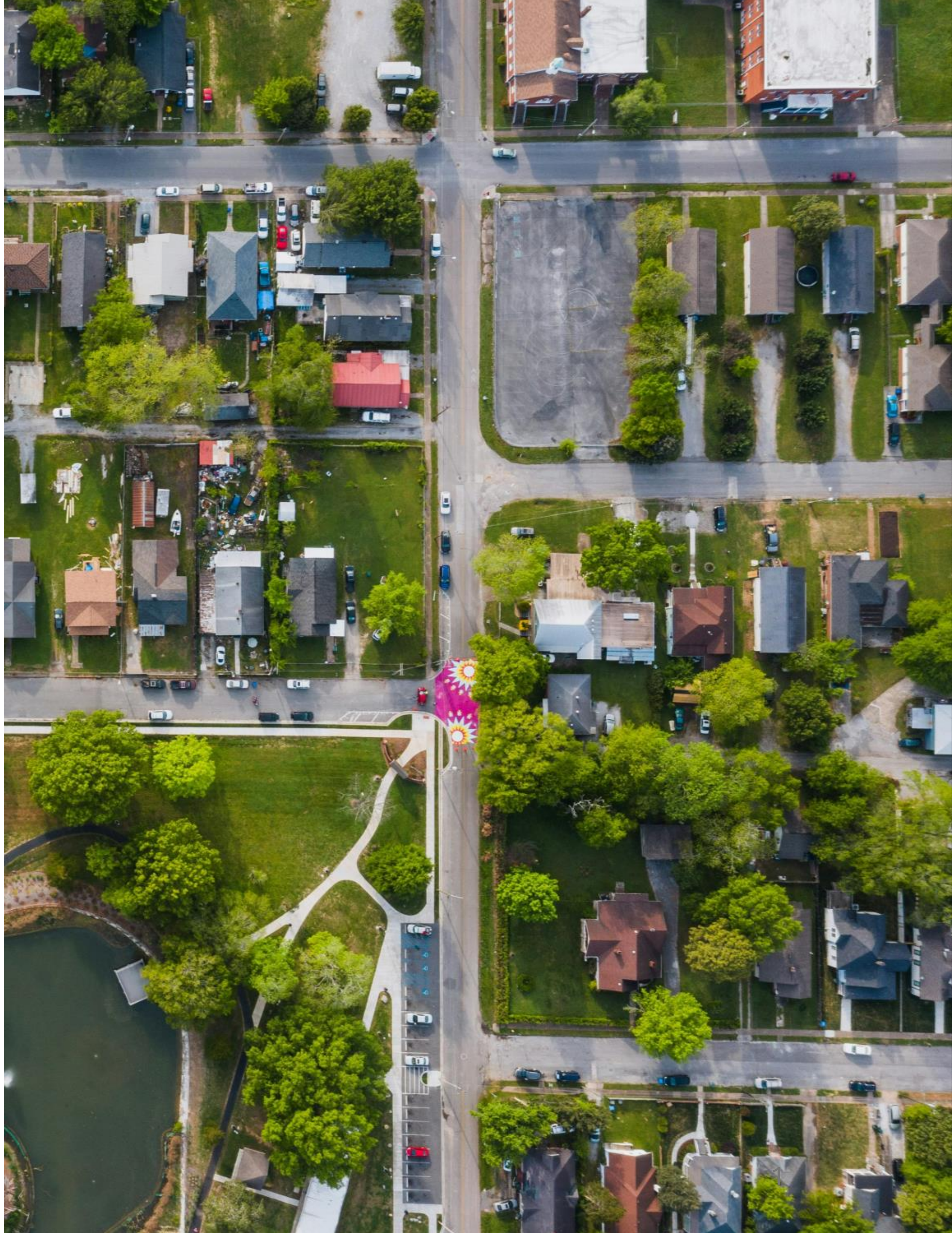
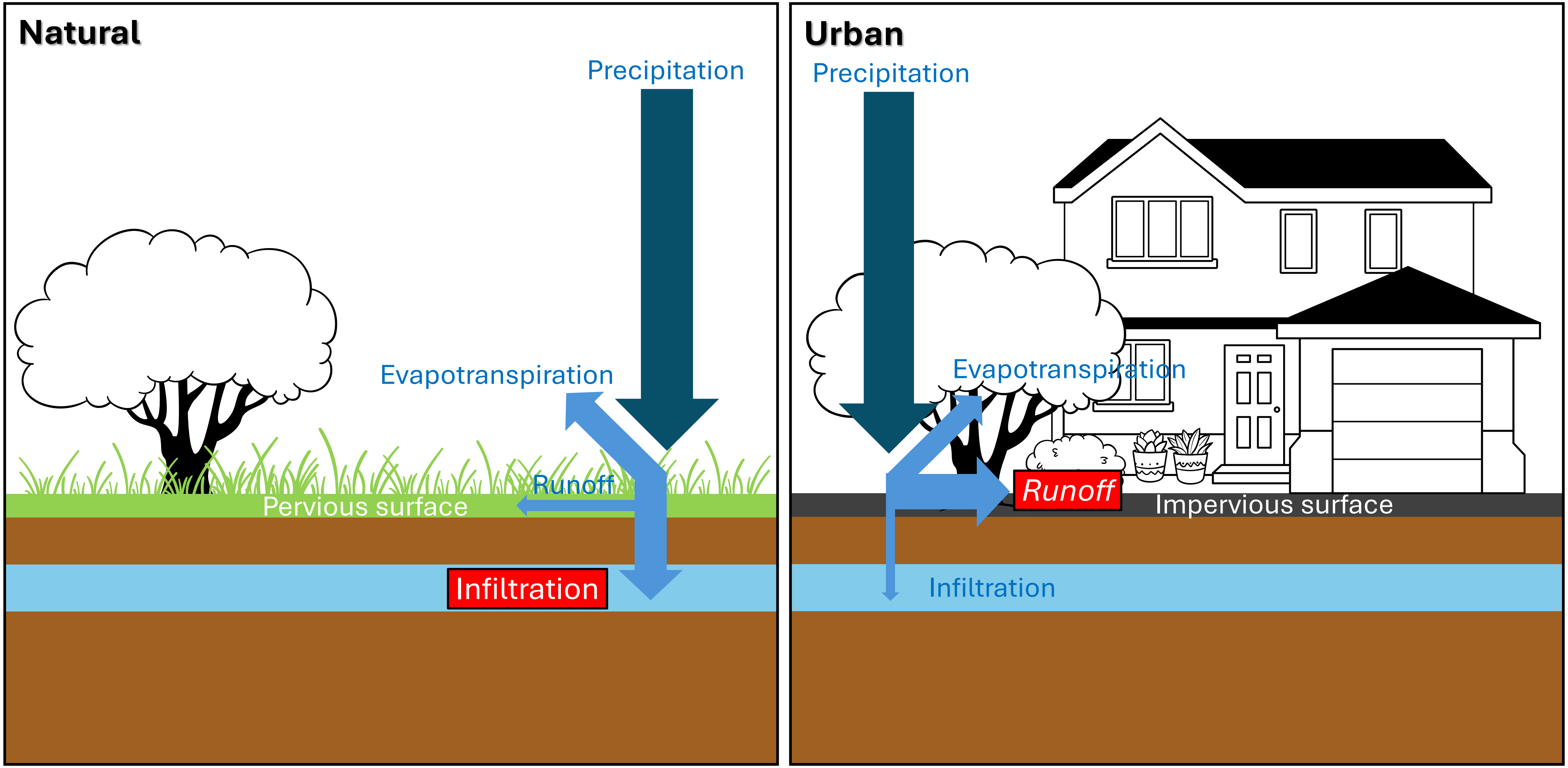
NSF



Pervious and Impervious Surfaces in Urban Areas

(Image ref: Binyamin Mellish)

How Cities Shape the Movement of Water



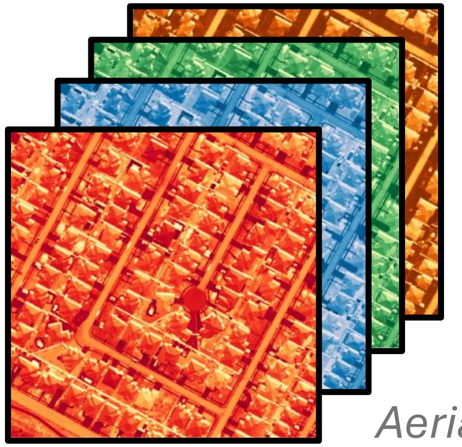
Equivalent residential units(ERUs) VS Tiered

Case study – City of Corpus Christi, Texas

Source: https://experience.arcgis.com/experience/07f98a4be33844668470fdad51fdf869

From Raster to Vector: Introducing GraphParcelNet

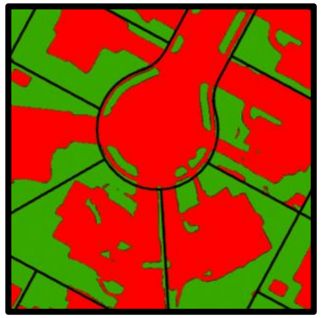
Traditional procedure



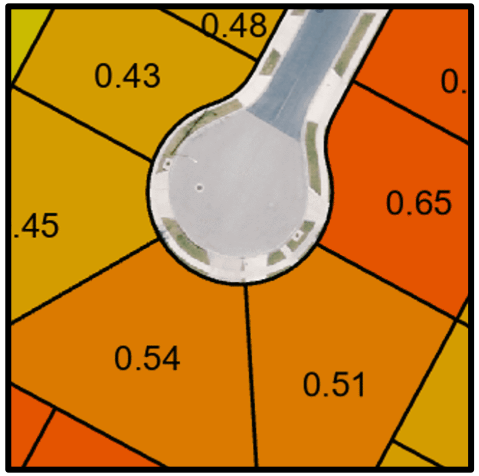
Aerial images

Pixel classification

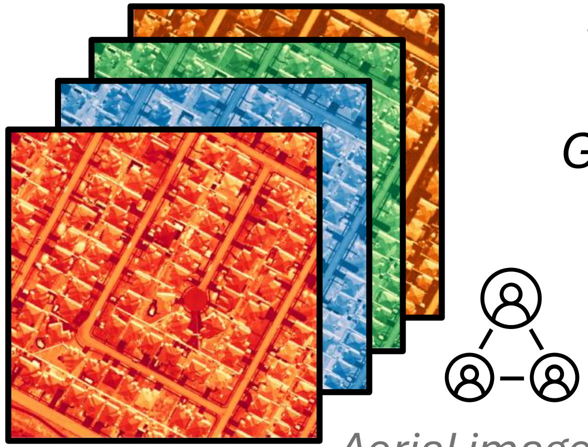
Raster



Spatial statistics

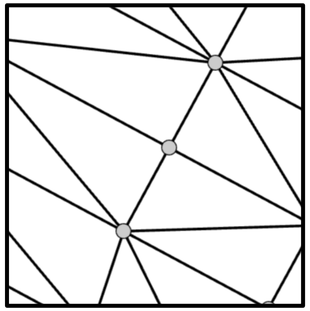


Proposed procedure



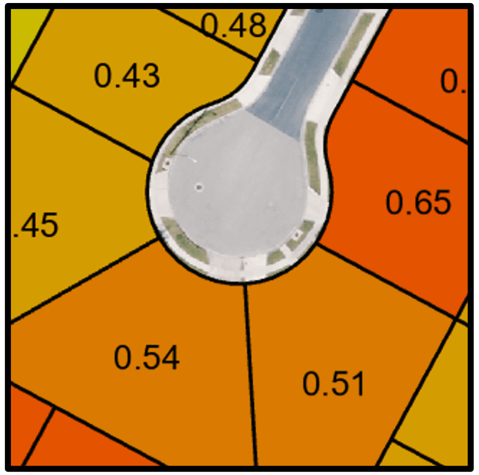
Aerial images + Demographic

Spatial statistics, Vectorization, Graph construction



Graph neural network

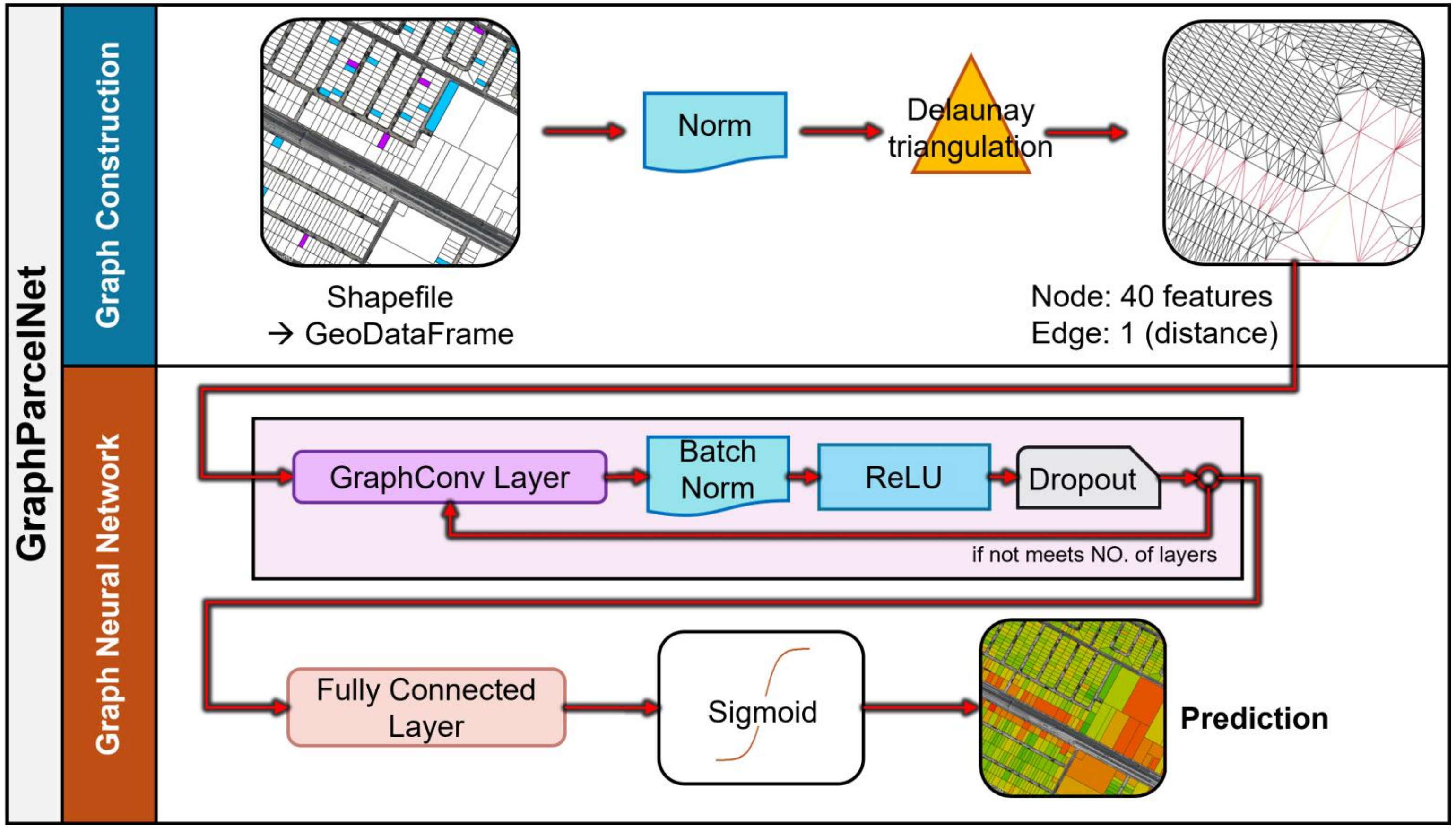
Vector



Proposed method

Phase 1: Graph Construction

- Input features from aerial imagery and ACS demographic data.
- Features are normalized (MinMax scaling from -1.0 to 1.0).
- Parcel system is represented as a graph G=(N,E) where:
  - **N**: Nodes (individual parcels).
  - **E**: Edges (spatial relationships).
- **Delaunay triangulation** used to define edges (distance as features).
- Data divided into training, validation, and testing subsets.



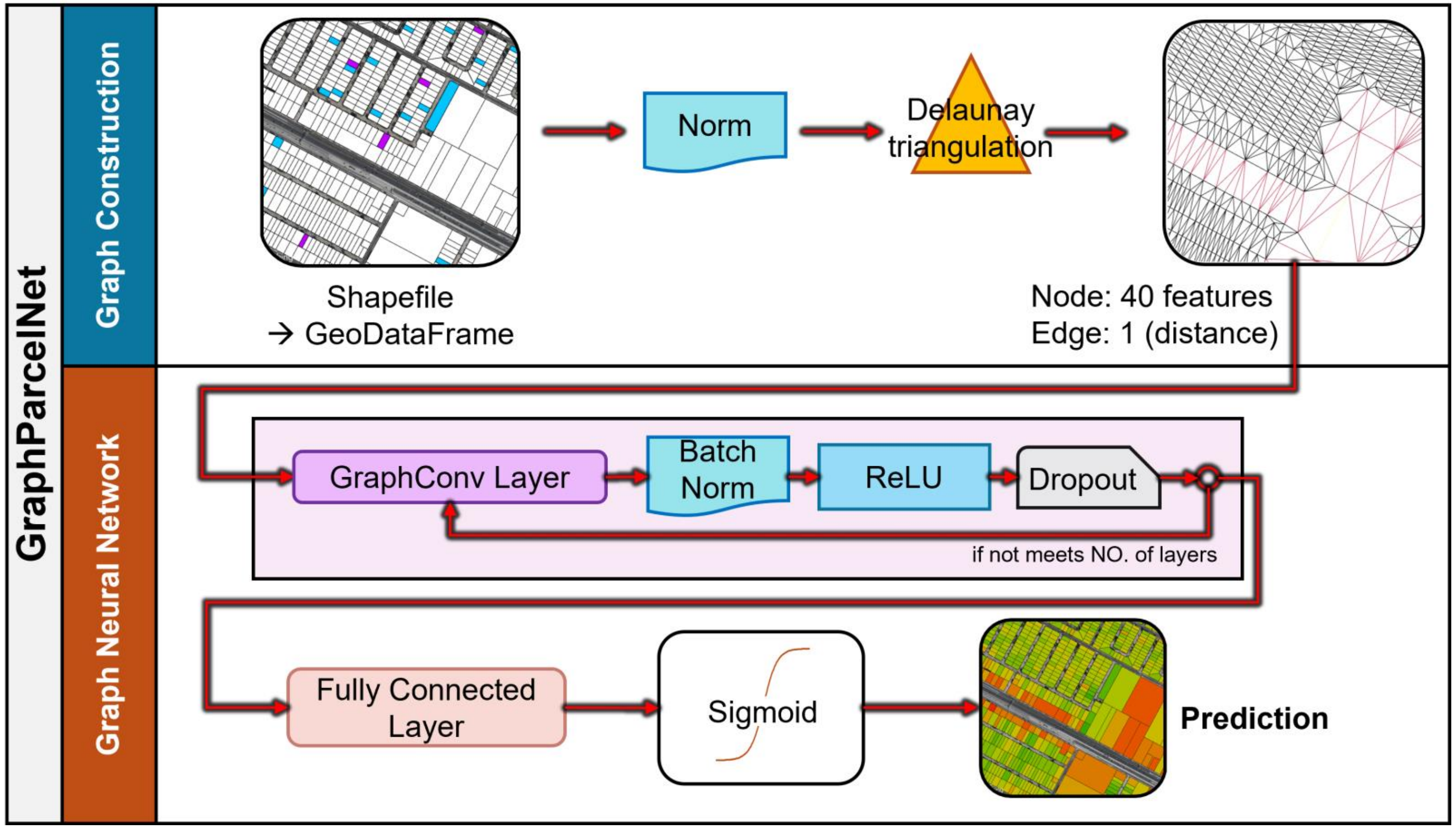
Proposed method

Phase 2: Graph Neural Network

- GraphConv Layer: Aggregates node features, capturing dependencies between parcels.
- Residual block: ReLU activation, batch normalization, dropout.
- Fully Connected Layer
- Sigmoid function ensures output is [0.00-1.00]

$$\mathrm{GNN} = \sigma\left(\mathrm{DBN}(\mathrm{GraphConv}(H^{(k)}))\Big|_{k=1}^{n}\right)$$

Final Output:
- Prediction of impervious surface ratio using **MAE** as the loss function.



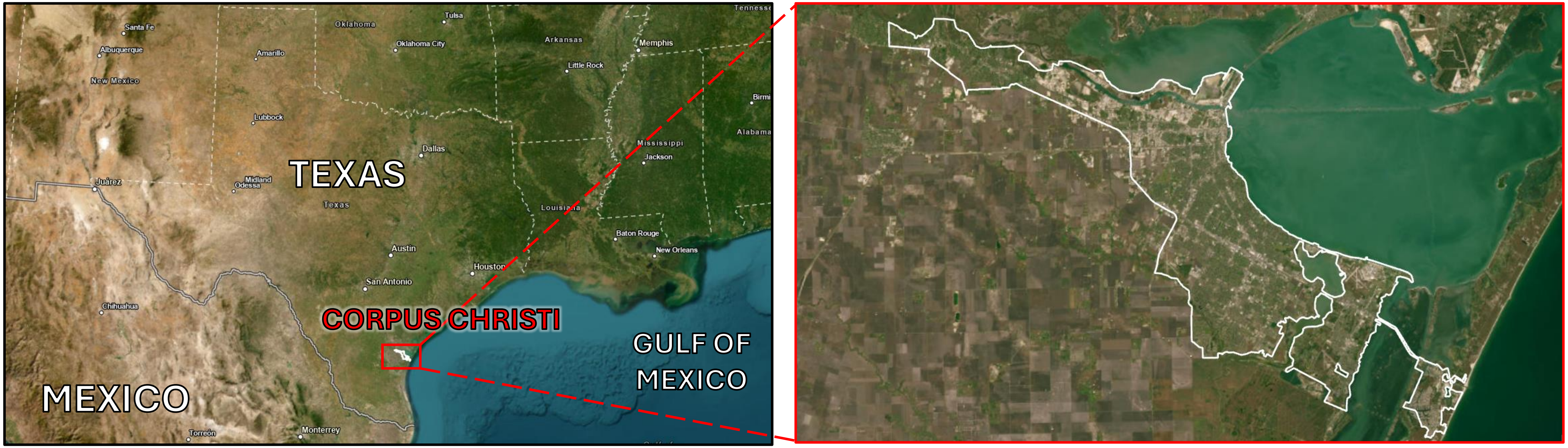
Experiments

Datasets

Location: Corpus Christi, Texas, USA

Data Overview:

- Total parcels: 103,828



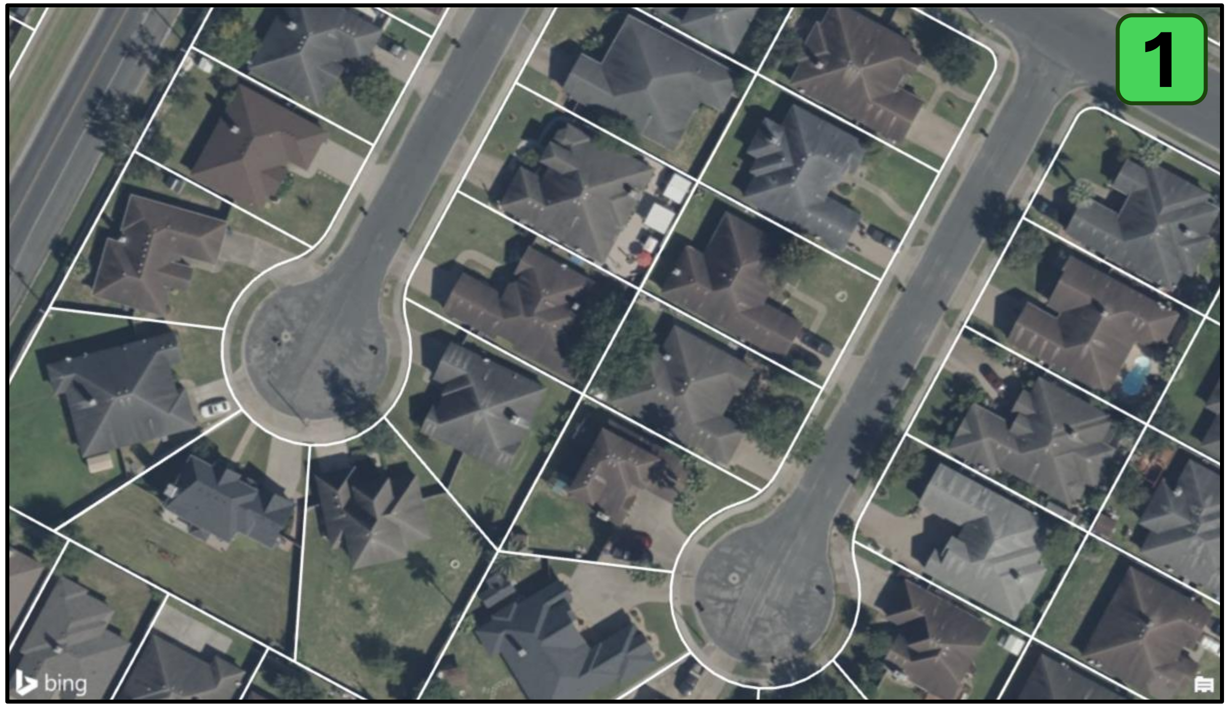
Experiments

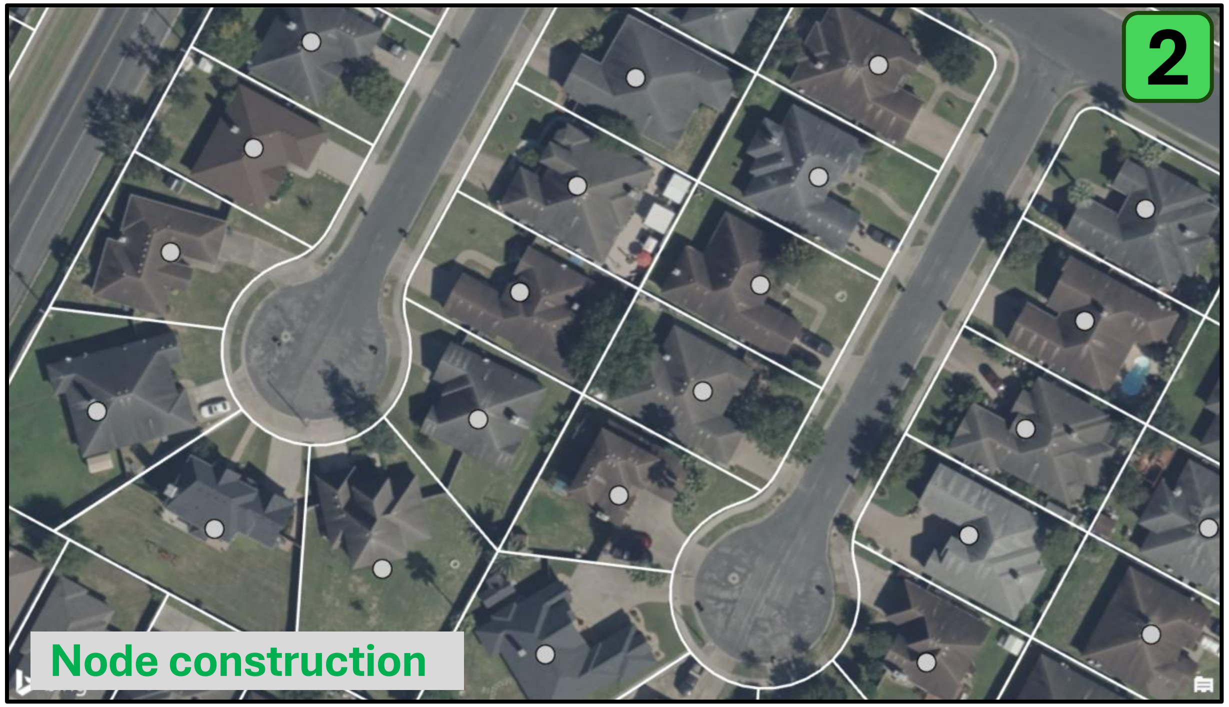
Datasets

Location: Corpus Christi, Texas, USA
Node Features: Spectral indices, Demographic, Land parcel data
Target Feature: Impervious surface ratio [0.00 - 1.00]

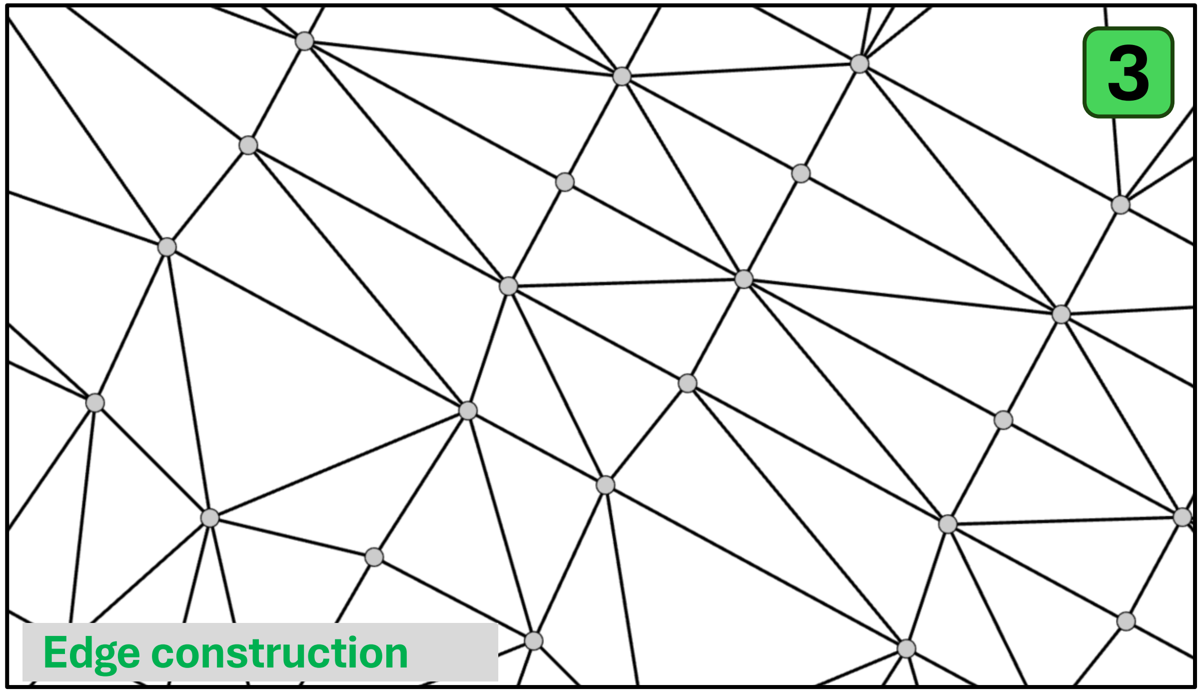
Data Overview:

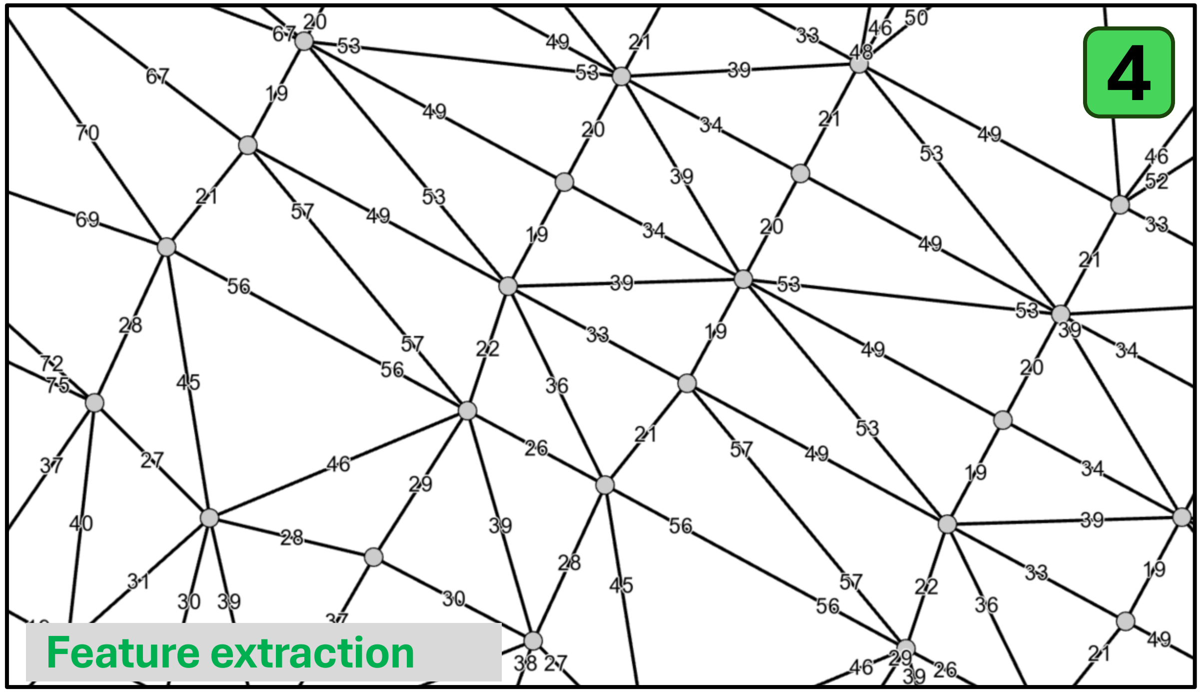
- Total parcels: 103,828
- Training set: 5,000 parcels
- Validation set: 1,000 parcels
- Test set: 97,828 parcels





Experiments



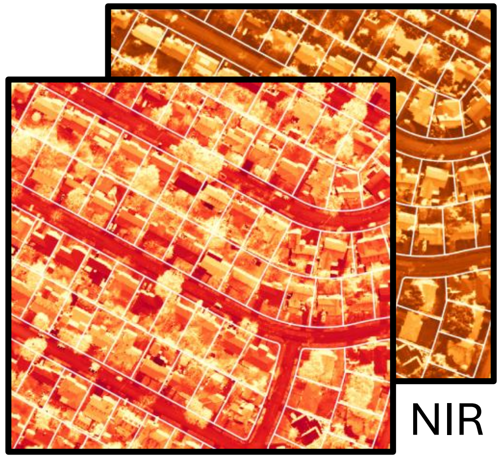


Experiments

Node features and their descriptions (32 spectral indices+ 8 demographic features)

Features	Variants	Description
NDVI	Mean, Std, Min, Max, Range, Sum, Median, Pct90	Vegetation index derived from visible and near-infrared light reflected by vegetation.
NDWI		Water index for moisture/liquid water content of soil and vegetation.
MTVI2		Enhanced vegetation index to correct soil and atmospheric influences.
VARI		Index for visualizing vegetation in RGB imagery.

Example: Mean of NDVI

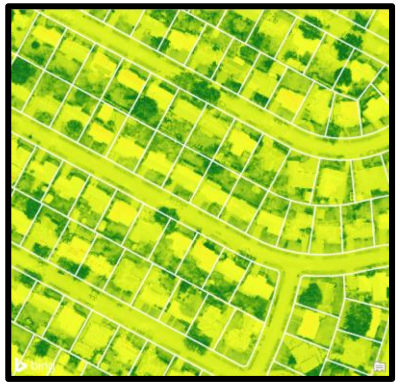


NIR

Red

NDVI

$$\mathrm{NDVI} = \frac{\mathrm{NIR} - \mathrm{RED}}{\mathrm{NIR} + \mathrm{RED}}$$



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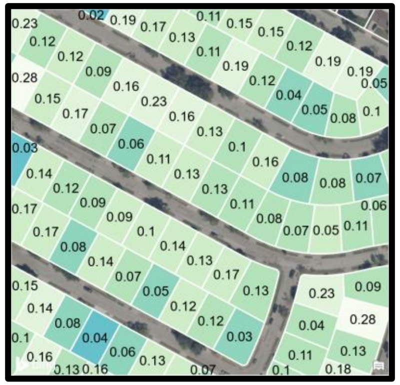
Spatial statistics

Mean



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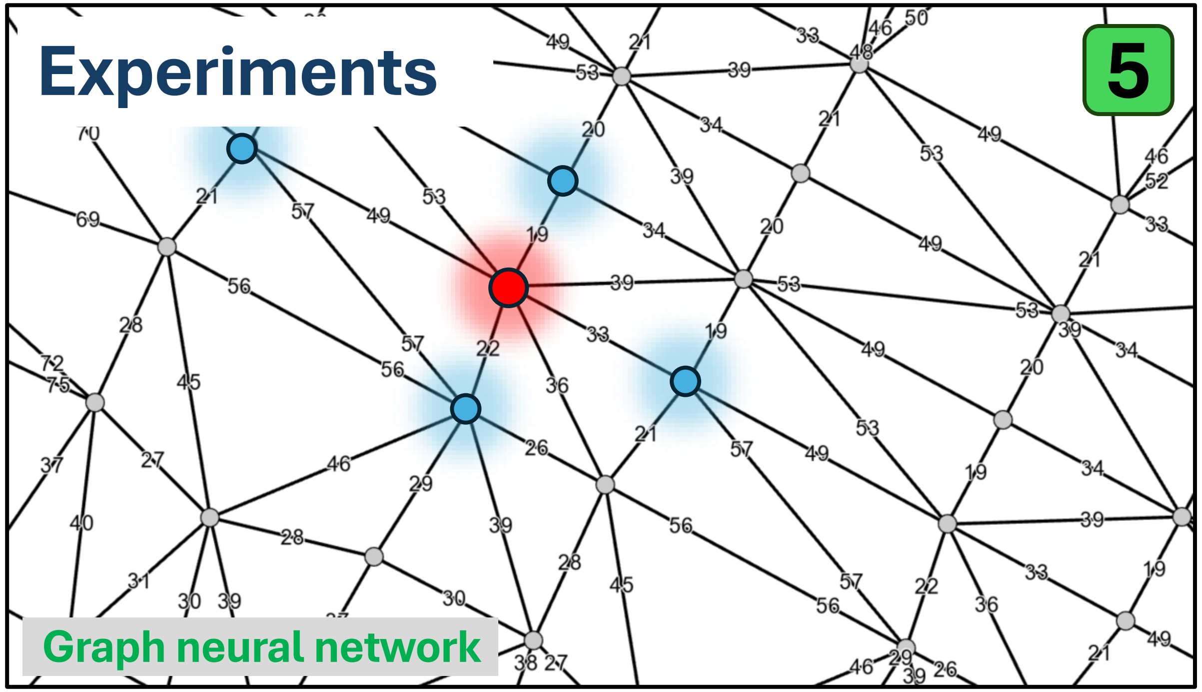
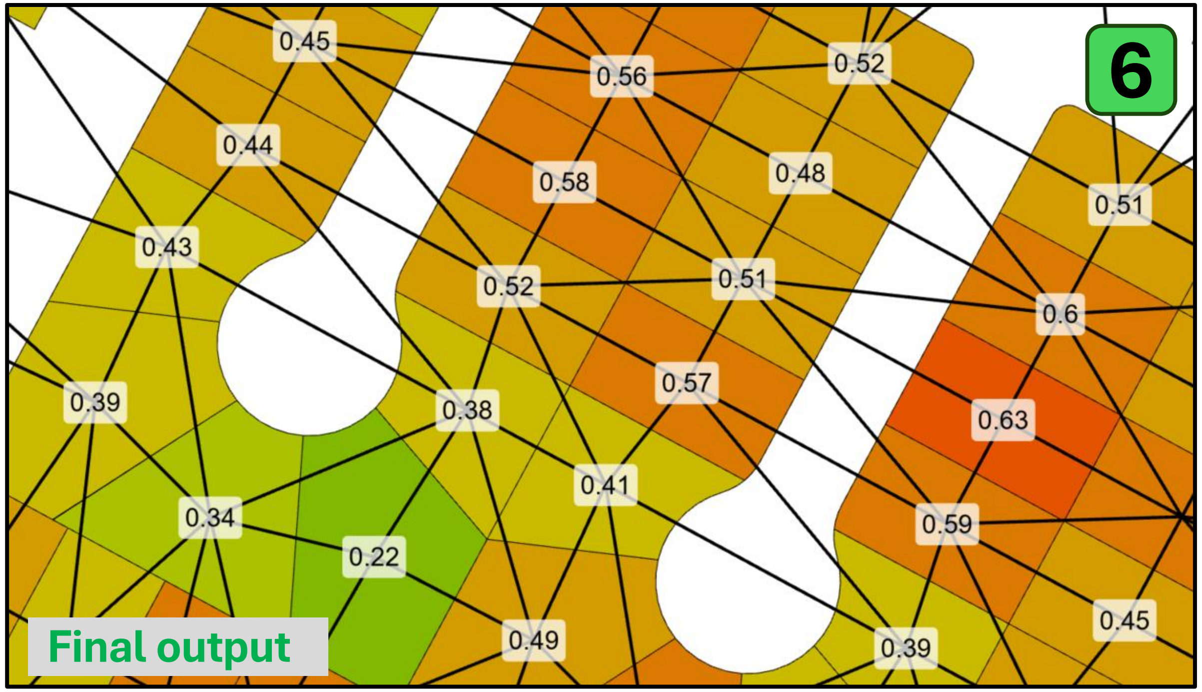
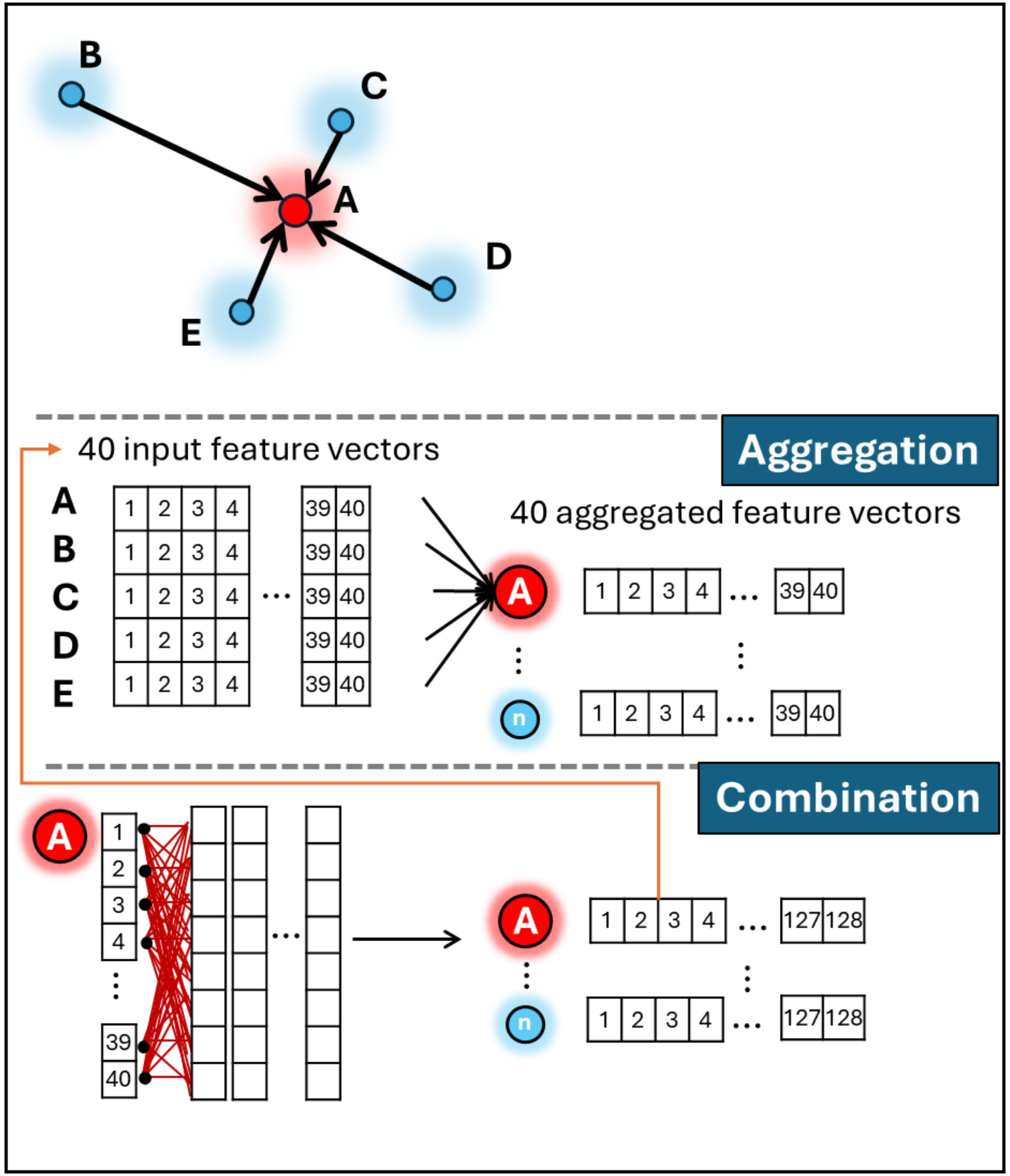
VARI		Index for visualizing vegetation in RGB imagery.
Demographics	Census track, Population density, Average home price, Average family income	Demographic information at block group level.
Coordinates	X, Y	Projected coordinates of the parcel.
Shape	Length, Area	Geometric measurements of the parcel shape.

Experiments







Evaluation (Training and Validation results)

Optimal Configuration:

- **Learning Rate**: 0.001
- **Layers**: 2 GraphConv
- **Hidden Dimension**: 128
- **Dropout Rate**: 0.5
- **Weight Decay**: 0.00001

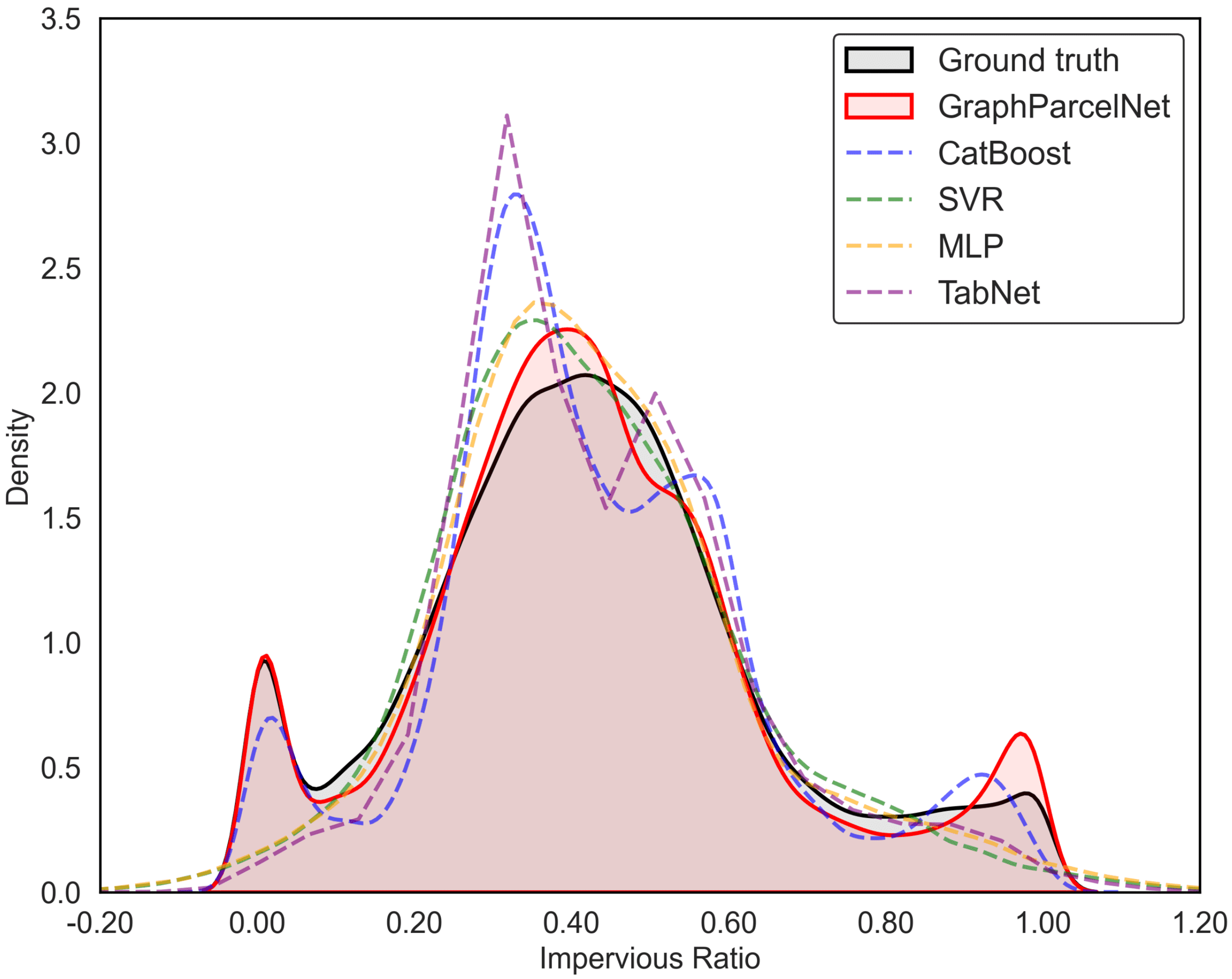
Performance (Averaged over 10 iterations):

- **Training Loss**: 0.0486
- **Validation Loss** (MAE): 0.0548
- Validation MSE: 0.0070

Model	Validation Loss MAE
TabNet	0.0806
MLP	0.0731
SVR	0.0732
CatBoost	0.0573
GraphParcelNet	**0.0548**

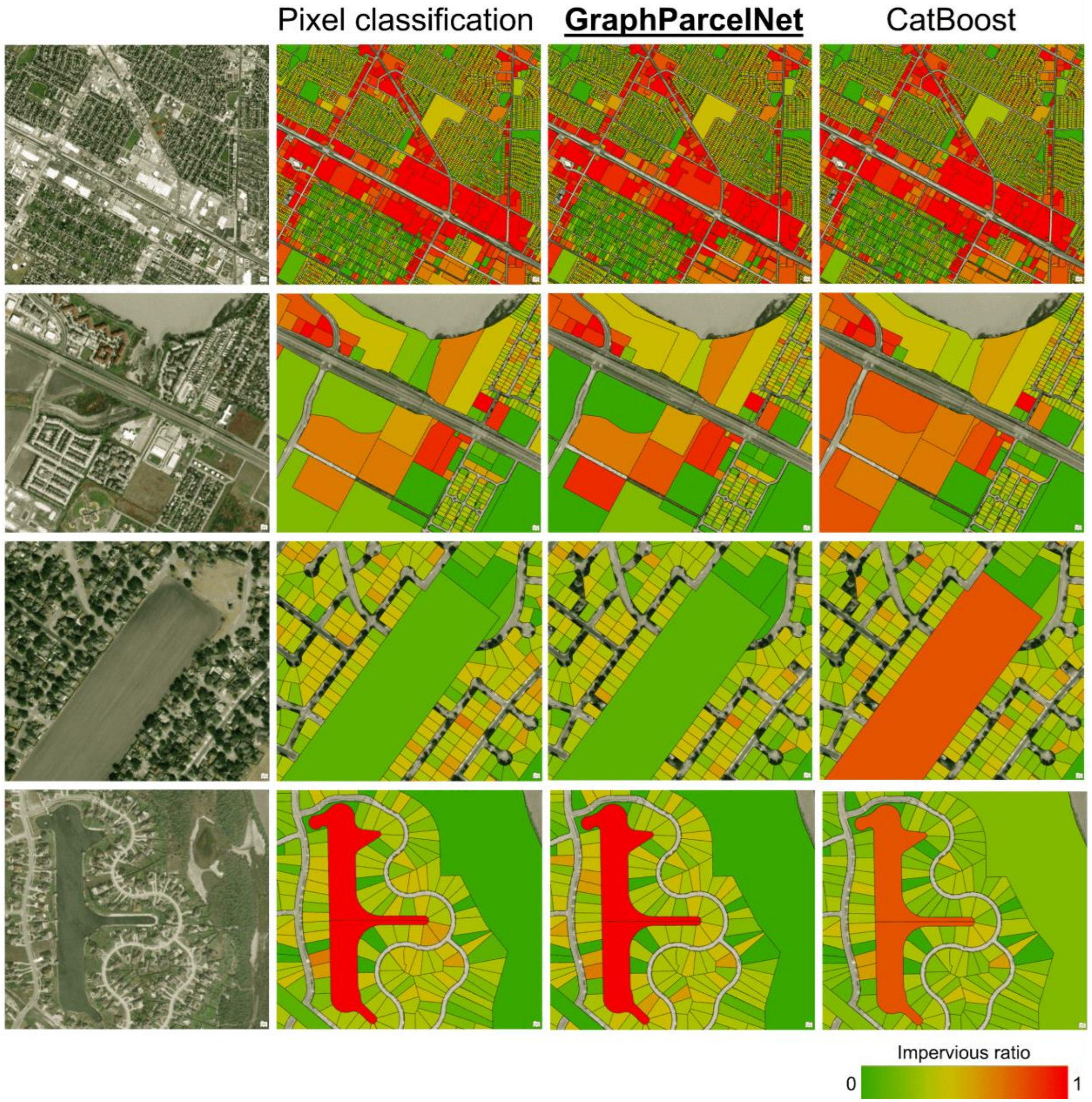
Evaluation (Testing result, 97,828 parcels)

Metric	TabNet	MLP	SVR	CatBoost	GraphParcelNet
MAE					✓
MSE				✓	
Median AE					✓
Quantile Loss				✓	✓
EMD					✓
KS Statistic					✓
Min					✓
Max					✓
Mean			✓		
Median		✓			✓
Std					✓
Mode					✓
IQR					✓
Skewness				✓	
Kurtosis					✓
CV					✓



(EMD: Earth Mover's Distance, KS Statistic: Kolmogorov-Smirnov Statistic, IQR: Interquartile Range, CV: Coefficient of Variation)

Evaluation (Testing result, 97,828 parcels)



Example 1:

- Both models capture high imperviousness in commercial zones (buildings, parking lots).

Example 2:

- Accurate residential predictions by both models.
- CatBoost: Misclassifies undeveloped land (orange) as impervious.

Example 3:

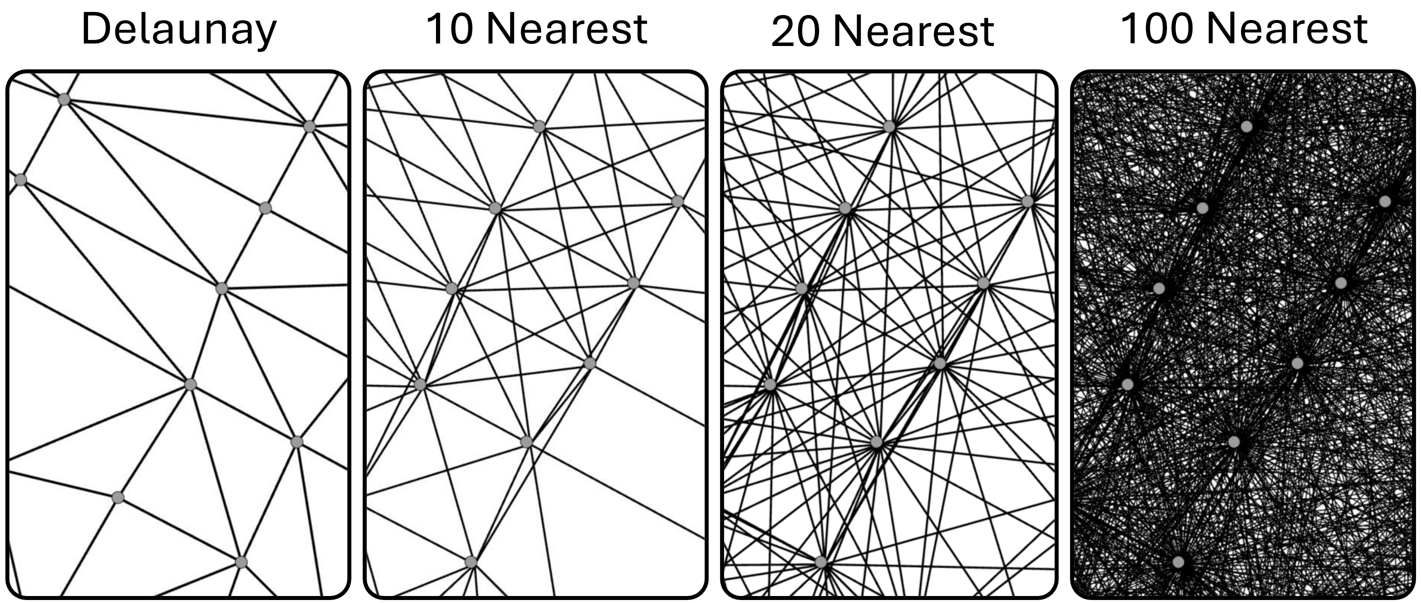
- CatBoost: Overestimated imperviousness of large undeveloped parcel, unrealistic values.

Example 4:

- GraphParcelNet: Correctly predicts 1.00 impervious ratio for retention pond.

Ablation Study

- Using alternative algorithms to construct graphs



312 km^2 study area size

Model	Graph Construction		Training/Validation		Testing		Evaluation	
	Time (s)	Memory (MB)	Time (s)	Memory (MB)	Time (s)	Memory (MB)	MAE	MSE
Vector Domain								
1. Delaunay	**132.20**	1254.69	**33.81**	**1127.00**	**0.07**	**1166.72**	**0.0548**	**0.0070**
2. 10 Nearest Neighbors	134.09	**1229.54**	64.18	1358.91	0.20	**1476.41**	0.0570	0.0076
3. 20 Nearest Neighbors	134.38	1240.91	107.53	1214.88	0.36	1426.82	0.0563	0.0073
4. 100 Nearest Neighbors	**141.10**	**1380.72**	**434.13**	**1423.29**	**1.53**	1400.41	**0.0608**	**0.0084**
Raster Domain								
Pixel Classification [15 cm pixel size]	-	-	36000	-	439200	-	-	-

Conclusions

1. **Efficiency:** GraphParcelNet significantly reduces prediction time from days to seconds, making vector-based prediction more efficient than traditional raster methods.

2. **Scalability:** Delaunay triangulation ensures fast, memory-efficient processing for large urban areas.

3. **Performance:** While closely matching pixel classification in accuracy, GraphParcelNet surpasses regression models such as CatBoost, MLP, SVR, and TabNet in most metrics.

4. **Spatial Insight:** GNNs effectively capture complex spatial relationships between parcels, improving prediction reliability and accuracy.

5. **Versatility:** The framework can be applied to other geospatial tasks, offering potential beyond impervious surface predictions and stormwater management.

COMPUTER-AIDED CIVIL AND INFRASTRUCTURE ENGINEERING

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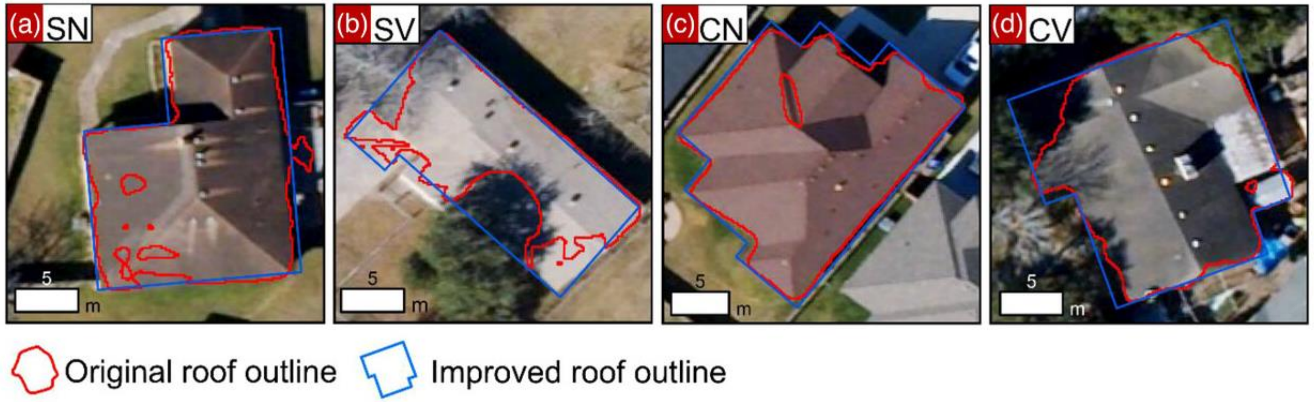
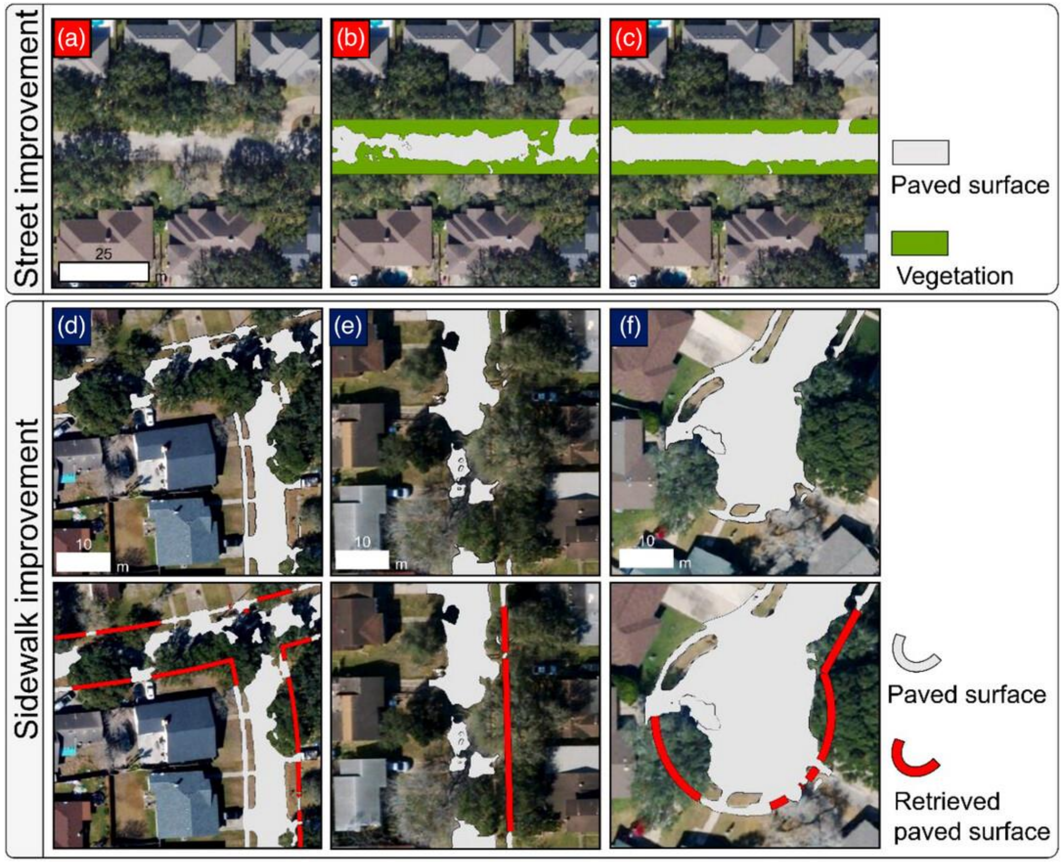
Integrated urban land cover analysis using deep learning and post-classification correction

Lapone Techapinyawat, Aaliyah Timms, Jim Lee, Yuxia Huang, Hua Zhang

First published: 27 May 2024 | https://doi.org/10.1111/mice.13277 | Citations: 1





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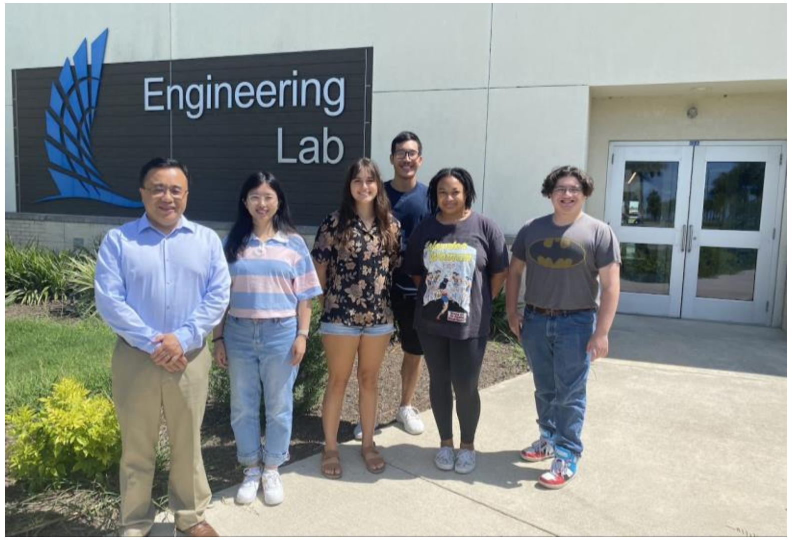
Abstract Number H21A-08
Session Number: H21A
Date & Time: Tuesday, 10 December 2024, 09:40 – 09:50 EST
Location: Convention Center, 140 A-B





Thank-you

More information:

https://laponet.github.io
www.linkedin.com/in/laponet
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