

International Conference of Environmental &  
Public Health Issues in Asian Mega-cities 2024

# Predicting urban tree locations: A case study of Daegu

By Joonwoo Lee, Hyeyun Kang, and Chulmin Jun\*

# Contents

## 01 Introduction

- Climate Crisis & Carbon Neutrality
- Importance of Carbon Sink Estimation
- Objectives

## 02 Methodology

- Flow Chart
- Data
- Structured Data Generation Process
- XGBoost
- Transfer Learning
- SHapley Additive exPlanations

## 03 Results

- Street Tree Prediction Model of Seoul
- Street Tree Prediction Model of Daegu
- Tree Prediction on Daegu
- Evaluation
- Model Insight

## 04 Conclusion

- Conclusion

# 01

## Introduction

Accurate estimation of carbon sinks within urban settlements is crucial

- Intensifying climate crisis
  - The earth is facing a global climate emergency
  - IPCC 6<sup>th</sup> Assessment Report indicates:
    - A 1.1 °C increase in global surface temperature since 1850–1900s due to human activities
    - A 54% rise in carbon emissions since 1990s
- Global commitment to action
  - 2015 Paris Agreement(United Nations) adopted by 195 countries, including South Korea
    - Replace the Kyoto Protocol
  - Emphasizes:
    - The critical role of forests and vegetations as carbon sinks
    - The importance of transparent greenhouse gas emission and absorption statistics

# Importance of Carbon Sink Estimation

- Role of urban vegetation in carbon neutrality
  - Achieving carbon neutrality requires precise estimation of carbon emissions and absorptions
  - Urban vegetation serve as significant carbon sinks
  - Accurate location data of individual trees in urbanized area is essential for estimation
- Challenges in South Korea
  - Lack of a clear definition for “settlements” or urban areas
  - LULUCF sector greenhouse gas inventory:
    - Calculation methods not fully adapted to domestic conditions
    - Insufficient location data for accurate estimations in the settlement sector<sup>1)</sup>
    - Leads to gaps in greenhouse gas statistics
- Need for improved estimations methods
  - Satellite imagery and vegetation indices offer potential solutions

<sup>1)</sup> Choi, W. J., Han, S. H. & Ahn, S. J. (2022). Current status and implications of the LULUCF calculation system for building a greenhouse gas inventory. *NIGT Brief*, 1–14.

## Estimating the location of carbon sinks within urban areas:

Focus on urbanized cities



Utilize vegetation indices derived from satellite imagery



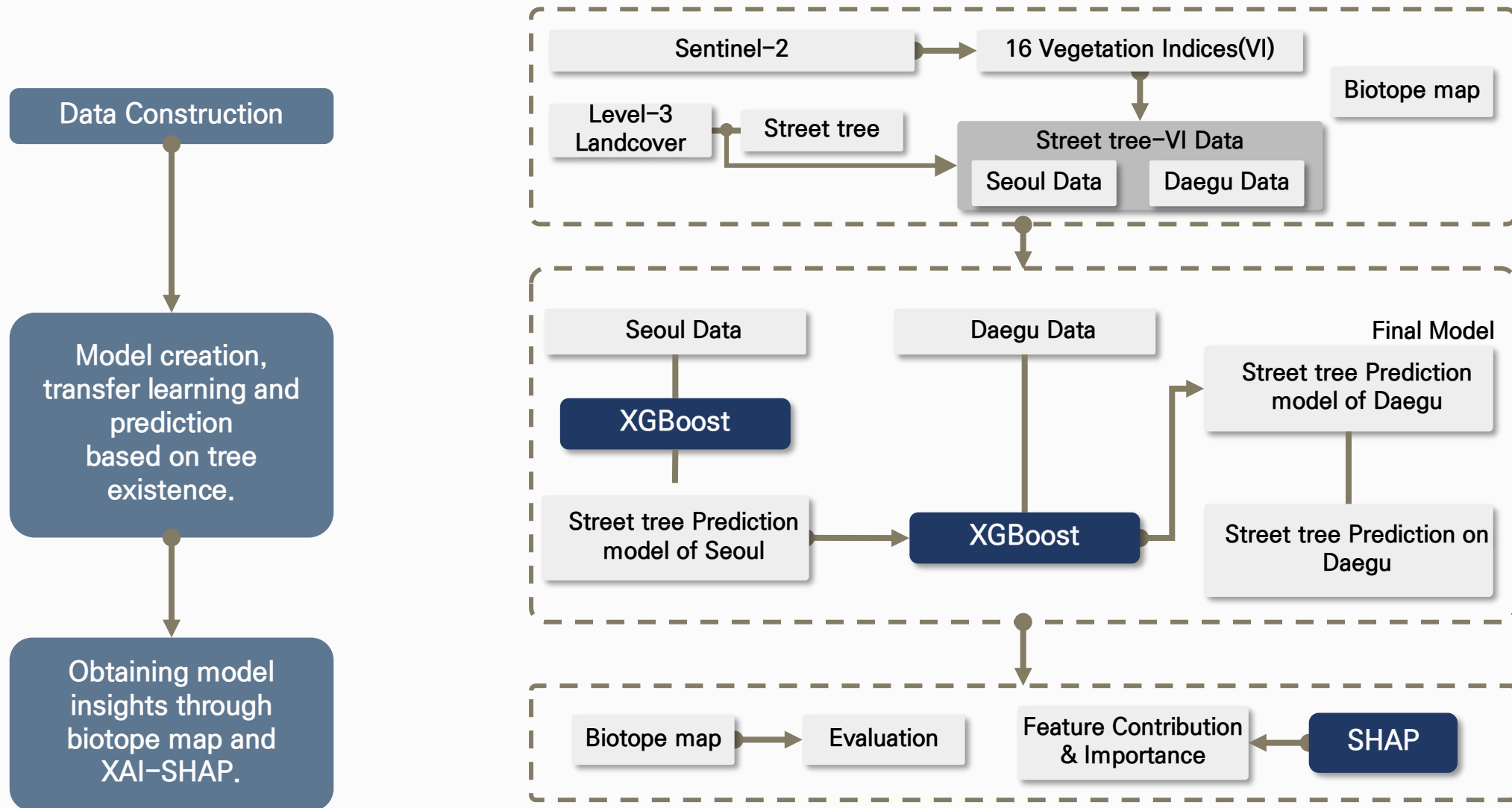
Understand the relationship between vegetation indices and carbon sinks

Utilizing  
advanced modeling to reveal  
urban carbon sink potential

# Methodology

02

# Flow Chart





- Focuses on two major urban areas in South Korea — Seoul and Daegu.
- Due to the lack of a clear definition for “settlements” in South Korea, administrative boundaries were used to delineate study areas in both Seoul and Daegu



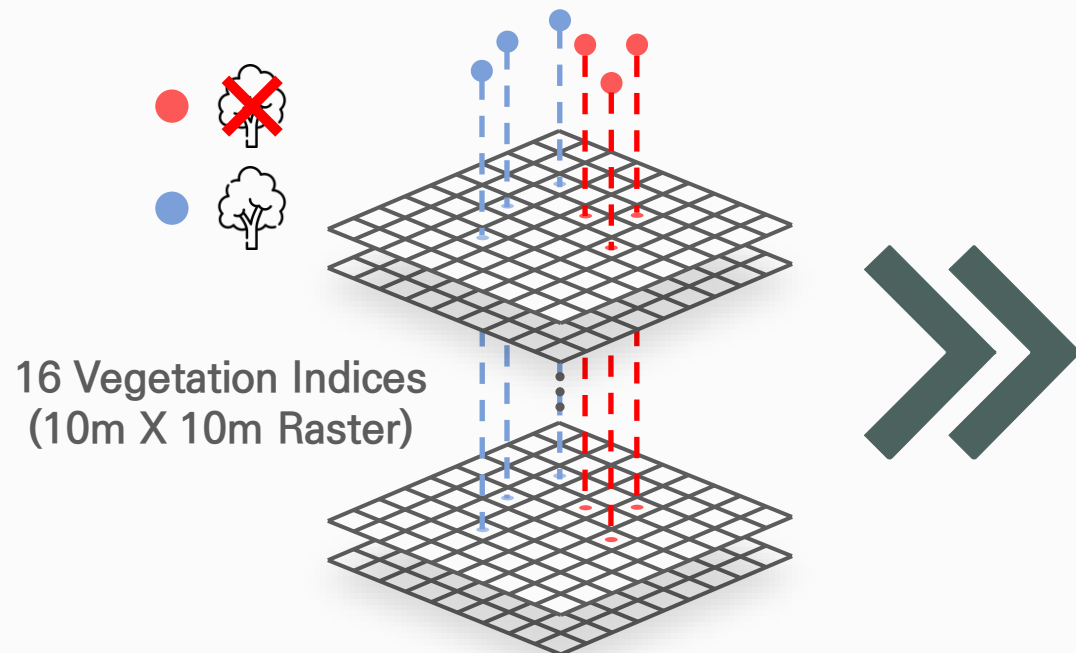
- Street tree location data in Seoul(planted in 2002–2003)
- Street tree location data in Daegu(planted in 2002–2003)
- Subdivision Land Cover Map (2023)
- Biotope Map(Daegu, 2024)
- Satellite images (Sentinel-2, captured in 2024)

## • 16 Vegetation Indices

Vegetation Index	Formula	Vegetation Index	Formula
PSRI	$\frac{Band\ 8}{Band\ 4}$	EVI	$\frac{2.5 \times (Band\ 8 - Band\ 4)}{(Band\ 8 + 6 \times Band\ 4 - 7.5 \times Band\ 2) + 1}$
RVI	$\frac{Band\ 4}{Band\ 8}$	SAVI	$\frac{Band\ 8 - Band\ 4}{(Band\ 8 + Band\ 4 + 0.428) \times 1.428}$
NDVlre1	$\frac{Band\ 8 - Band\ 5}{Band\ 8 + Band\ 5}$	NDMI	$\frac{Band\ 8 - Band\ 11}{Band\ 8 + Band\ 11}$
NDVlre2	$\frac{Band\ 8A - Band\ 5}{Band\ 8A + Band\ 5}$	MSI	$\frac{Band\ 11}{Band\ 8}$
NDVlre3	$\frac{Band\ 8A - Band\ 6}{Band\ 8A + Band\ 6}$	NDWI	$\frac{Band\ 3 - Band\ 8}{Band\ 3 + Band\ 8}$
NDVlre4	$\frac{Band\ 8A - Band\ 7}{Band\ 8A + Band\ 7}$	GCI	$\frac{Band\ 9}{Band\ 8} - 1$
NDVI	$\frac{Band\ 8 - Band\ 4}{Band\ 8 + Band\ 4}$	LCI	$\frac{Band\ 8 - Band\ 5}{Band\ 8 + Band\ 2}$
NDRE	$\frac{Band\ 8 - Band\ 7}{Band\ 8 + Band\ 7}$	SIPI	$\frac{Band\ 8 - Band\ 4}{Band\ 8 + Band\ 2}$

# Structured Data Generation Process

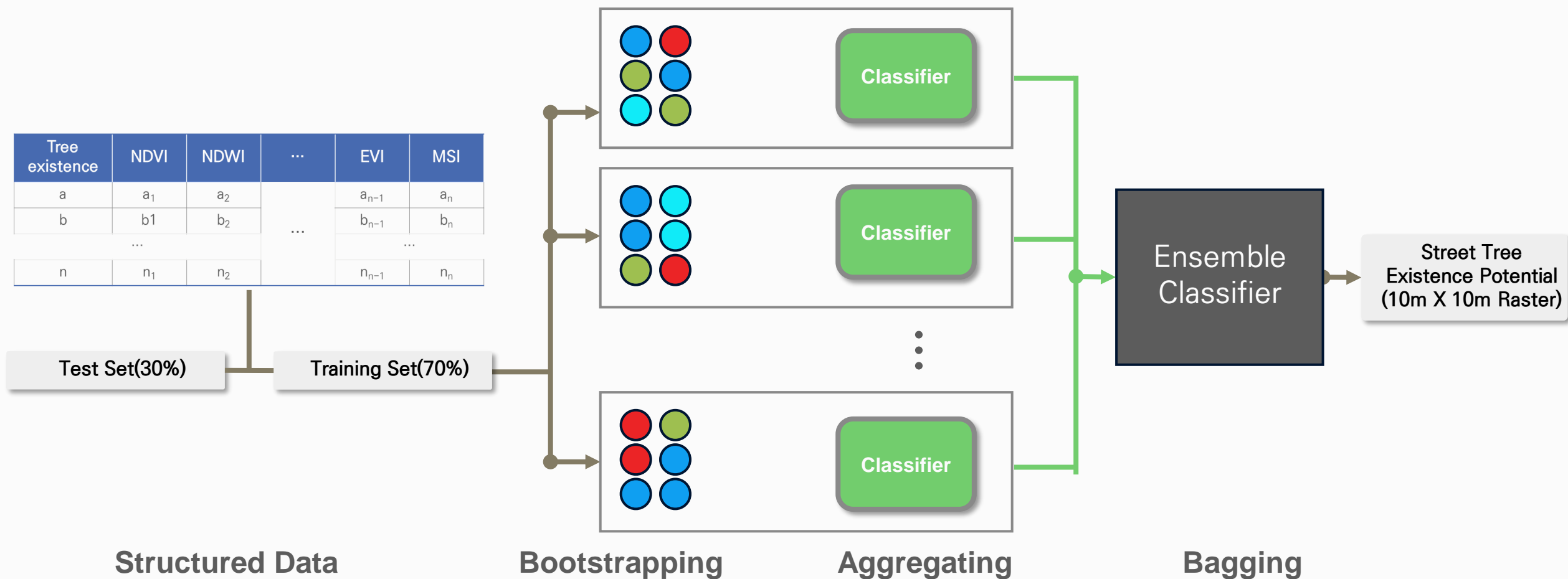
- Create locations without street tree using subdivision land cover map
- Spatial Join vegetation indices values to both street tree locations and non-street tree locations
- Generate data where tree existence is the dependent variable, and vegetation indice values are independent variables
- Seoul: 108943 locations, Daegu: 12627 locations



Structured Data

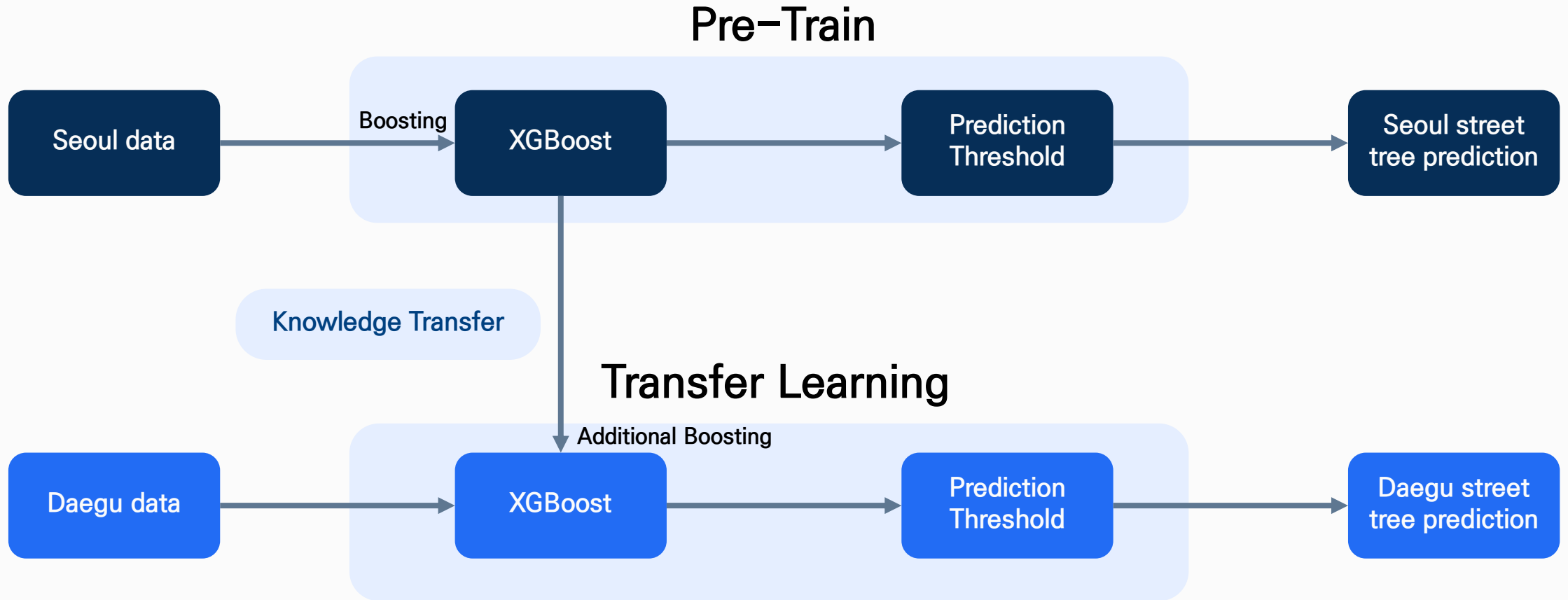
Tree existence	NDVI	NDWI	...	EVI	MSI
0	$a_1$	$a_2$	...	$a_{n-1}$	$a_n$
1	$b_1$	$b_2$		$b_{n-1}$	$b_n$
...				...	
1	$n_1$	$n_2$		$n_{n-1}$	$n_n$

- Basic architecture of XGBoost classifier



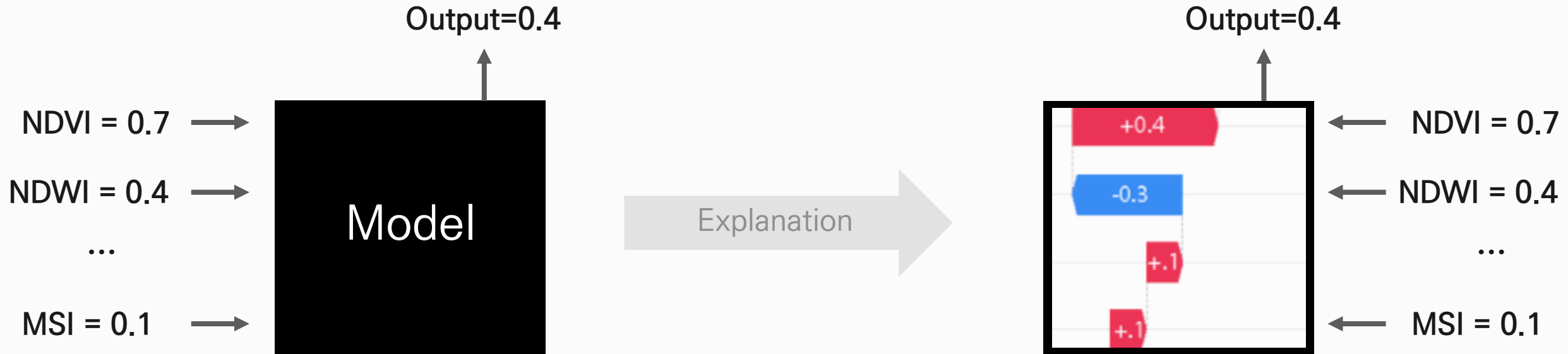
# Transfer Learning

- Transfer learning process used in this study



# SHapley Additive exPlanations

- XAI-SHAP



- XAI method that uses Shapley values to analyze the impact of features on the model
- Deterministic method, considering even the negative impact of features on the model
- Vulnerable to outliers

# Results

# 03

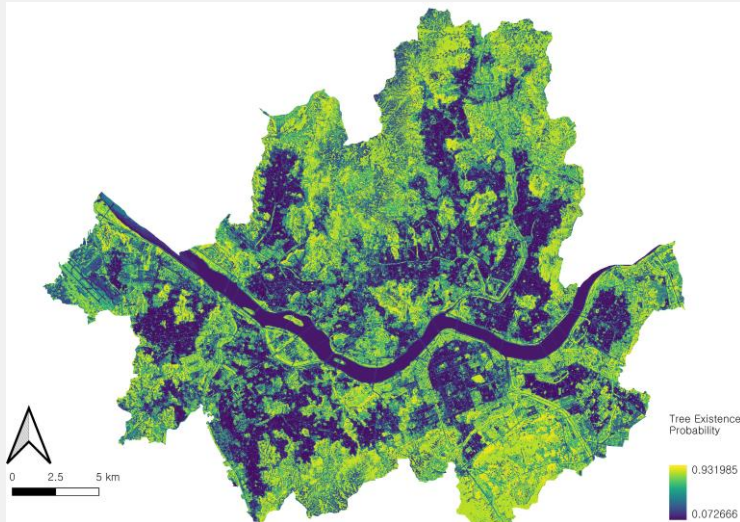
Delivering insights through precise urban  
carbon sink predictions



# Street Tree Prediction Model of Seoul

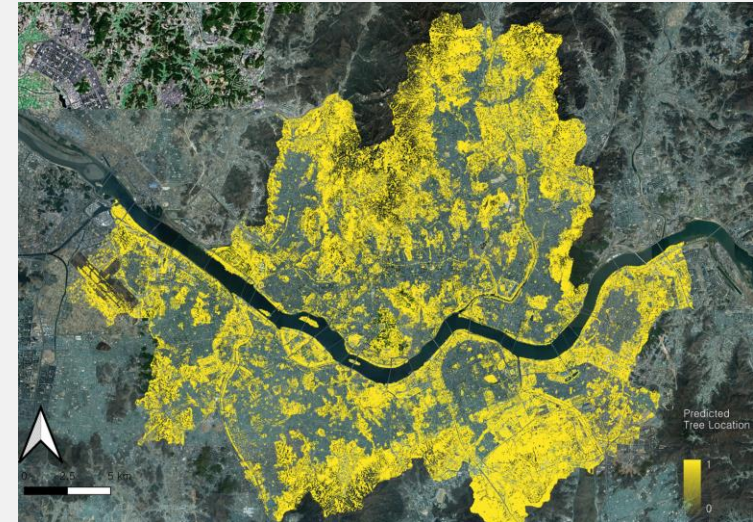
Results

- XGBoost classifier model training results
  - Boosting: 100
  - Accuracy: 0.8383
  - Precision: 0.8226
  - F1-Score: 0.8378
- Probability of tree existence predicted using the XGBoost model trained only on Seoul data



Street Tree Existence Probability of Seoul

- To predict tree existence based on probability of tree existence, a threshold between 0.5 and 0.9 was compared and analyzed
- Final threshold of 0.6 was applied to generate the tree existence prediction map for Seoul

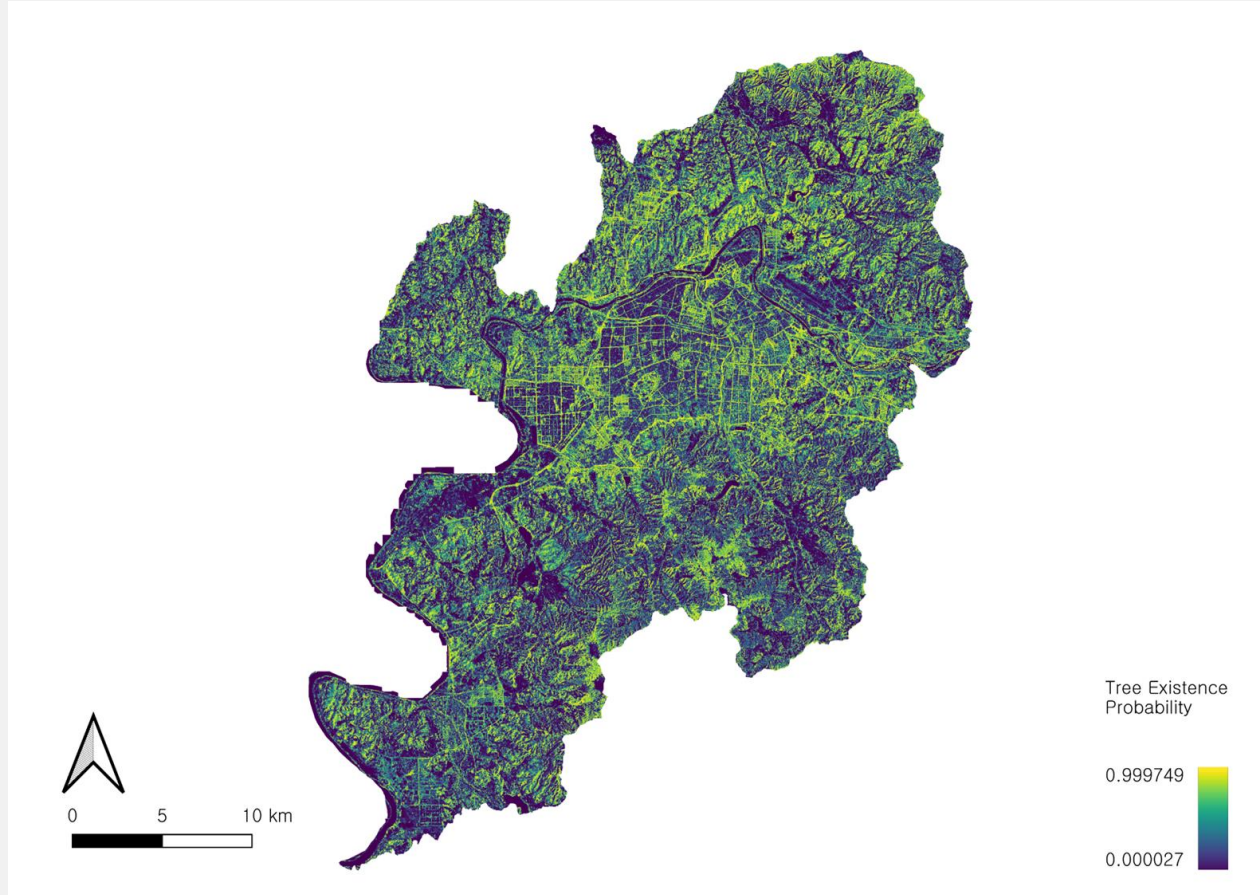


Predicted Street Tree Location of Seoul



# Street Tree Prediction Model of Daegu

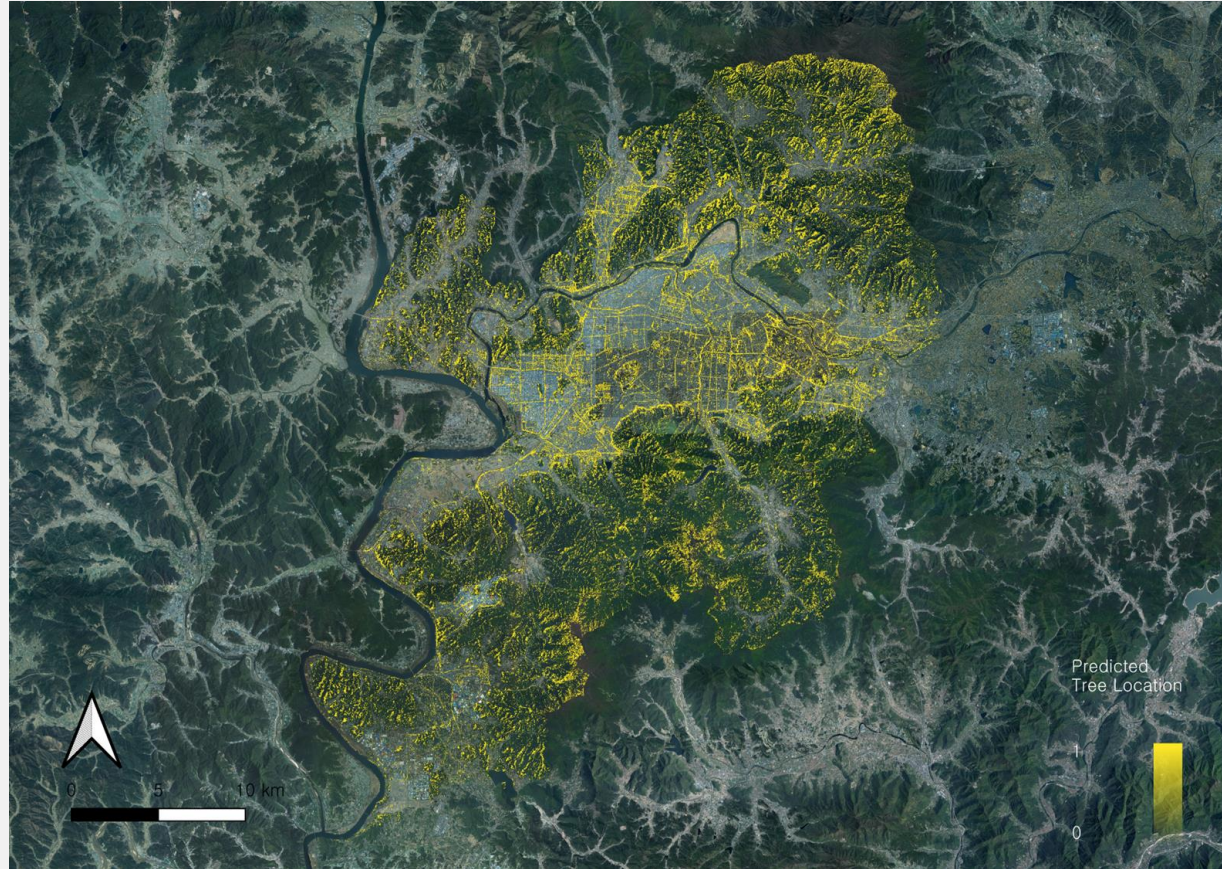
Results



Street Tree Existence Probability of Daegu

- Transfer Learning Results
  - Boosting: 100
  - Accuracy: 0.8232
  - Precision: 0.7978
  - F1-Score: 0.8145
- The left image shows the predicted probability of tree presence in Daegu City, using a final XGBoost model trained through transfer learning.
- While there was no significant improvement over the pre-trained model, the model demonstrated consistent performance post-transfer learning, indicating reliable consistency

# Tree Prediction on Daegu



Predicted Tree Location of Daegu

- The left image shows the estimated locations of street trees in Daegu City using a threshold value of 0.6
- Validation of predicted map was limited through high proportion of non-urban areas within Daegu's administrative bound and lack of ground-truth data
- Concentrating on urban areas, evaluation was conducted through biotope map of Daegu City





(A) Daegu's Urban Ecological Maps (biotope map)



(B) Example of Green Belt and Predicted Carbon Sinks

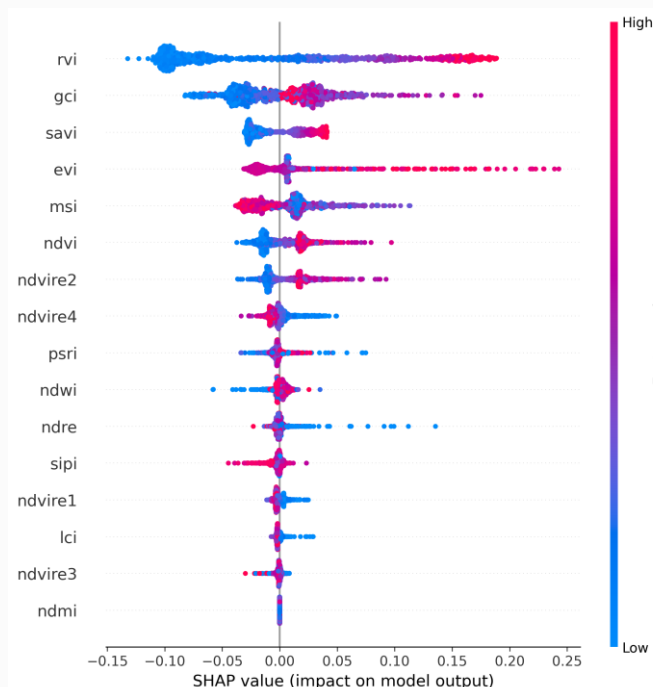
Constructe d Green Space	Road Green Space	Green Belt
17%	31%	50%

(C) Area Ratio of Estimated Carbons Sinks in Biotope Map

- Street trees in the biotope map are classified as constructed green space (major category), road green space (sub-category), and green belt (detailed category)
- To verify the estimation performance of street tree estimation map, the area ratio of estimated as a carbon sink for each biotope category has been calculated
- Constructed and road green spaces within settlements include various biota, excluding street trees, which limits the predicted area of carbon sinks to be high-proportion
- Although 50% of green belt areas were predicted as carbon sinks, slight location errors, due to shrub-centered spatial settings, resulted in some areas not being predicted as carbon sinks
- some limitations exist due to different spatial settings and other factors, the model was relatively effective in identifying street tree locations

## Evaluation through Biotope map of Daegu

## Pre-Trained Model



### Postive Correlation

- RVI, GCI, SAVI, NDVI, NDVire2

### Negative Correlation

- MSI, NDVire4, NDRE, NDVire1, LCI

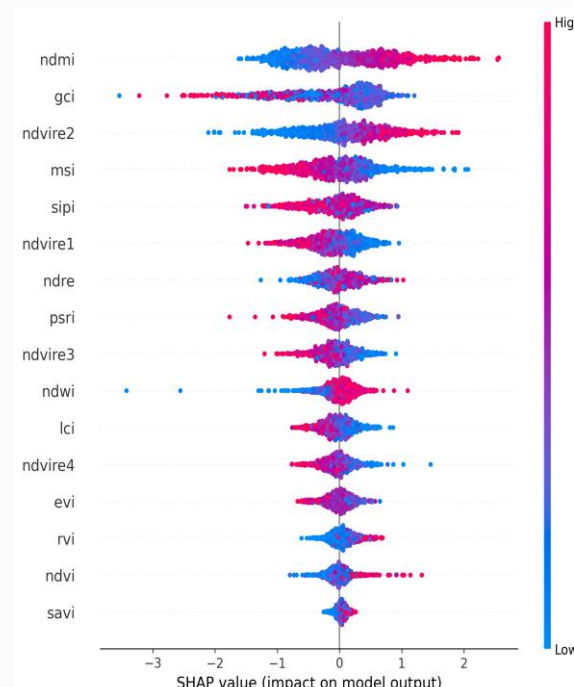
### Low Contribution

- NDMI, NDVire3, LCI, NDVire2

### Additional Analysis Needed

- GCI, SAVI, etc.

## Final Model



### Postive Correlation

- NDMI, NDVire2, NDWI, RVI, NDVI

### Negative Correlation

- GCI, MSI, NDVire1, PSRI, LCI, NDVire4

### Low Contribution

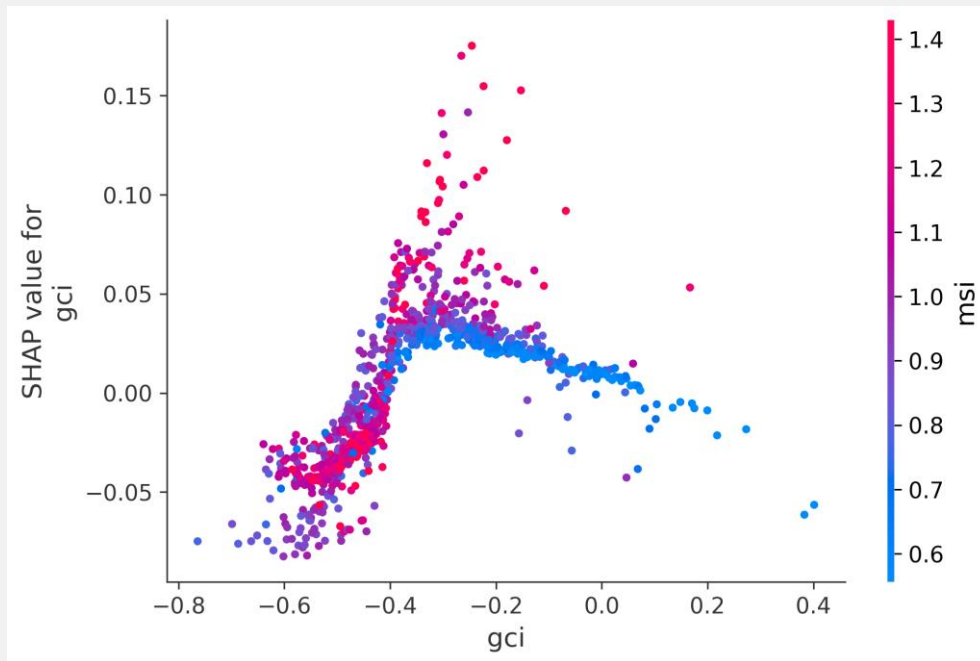
- SAVI, NDVI, RVI, EVI

### Additional Analysis Needed

- SIPI, NDRE, etc.

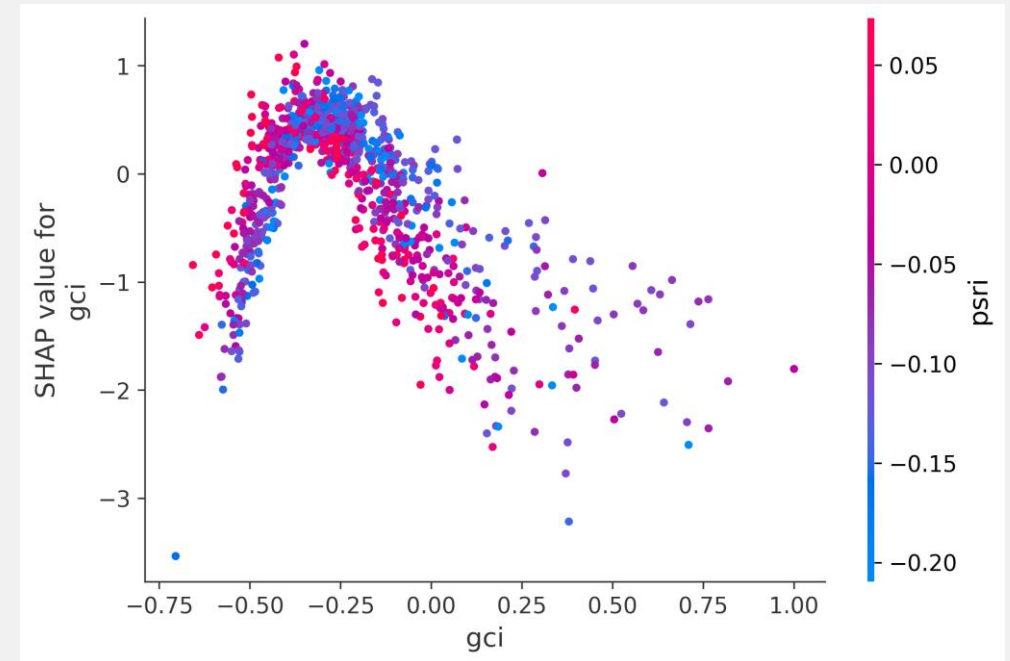
- Pre-Trained Model

- Relationship between GCI and SHAP value is more linear than final model



- Final Model

- Distinct non-linear pattern emerges, showing more complex interactions involving GCI



# 04

## Conclusion

Driving forward with data-driven strategies for a sustainable future

# Conclusion

- **Significance of Urban Carbon Sink Estimation:** Accurate prediction of carbon sinks in urban areas is essential for achieving carbon neutrality and addressing climate change. Urban vegetation plays a crucial role, requiring reliable estimation methods
- **Model Performance & Adaptability:** The XGBoost model demonstrated strong predictive capabilities, with consistent accuracy across Seoul and Daegu datasets. Transfer learning proved effective, highlighting the model's adaptability to various urban environments
- **Key Insights & Future Directions:** Vegetation indices like NDMI, NDVIre2, and RVI showed positive correlations with carbon sinks, while indices like GCI and MSI revealed complex, non-linear interactions. Further analysis of specific indices will enhance model precision
- **Next Steps:** Expanding validation efforts with additional ground-truth data, refining vegetation index analysis, and exploring advanced machine learning techniques can further improve urban carbon sink estimation accuracy

# Acknowledgment

This research was supported by the Carbon Neutrality, a specialized program of the Graduate School through the Korea Environmental Industry & Technology Institute(KEITI) funded by Ministry of Environment (MOE, Korea)



# Thank you for listening

Joonwoo Lee, Hyeyun Kang, Chulmin Jun\*

- Tel: 02-6490-5456
- Email: [leejoon924@uos.ac.kr](mailto:leejoon924@uos.ac.kr)