

Optimizing Urban Forest Allocation for Enhancing Carbon Uptake Using a Deep Learning-Based NPP Prediction Model

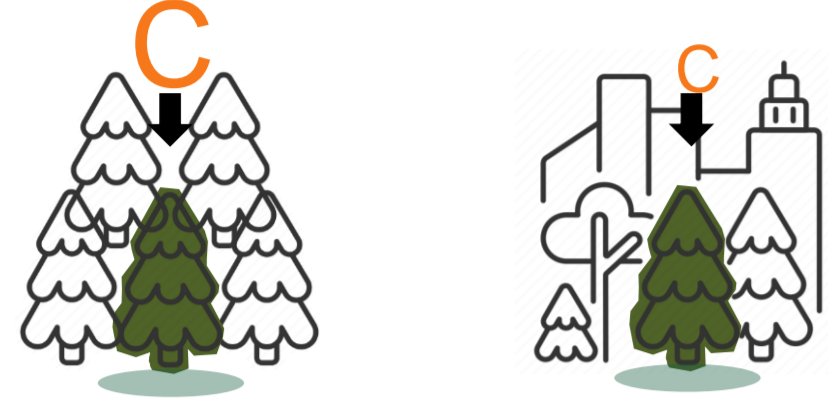
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Introduction



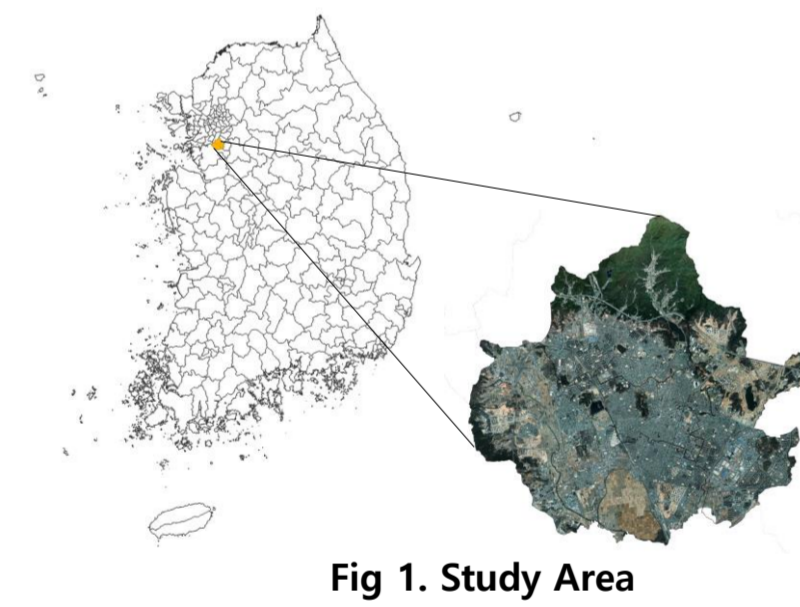
- Carbon uptake performance varies due to factors like topography, climate, and human disturbances (Zhou, Yue, Li, Mu, & Guo, 2021), necessitating decision-support models.
- Optimization algorithms are used in decision-support models for ecosystem services of green infrastructure, relying on simplified formulations due to the high computational demands.
- Models such as SWMM with NSGA and L-THIA-LID 2.1 with NSGA-III optimize green infrastructure for flood reduction and cost minimization, though they are mainly limited to water management.

Aim

- Coupling ANN and Optimization for manage carbon sink
- Propose Optimal Urban Forest Allocation Plan for Enhancing Carbon Uptake
- Evaluate Carbon Sink Allocation plan for Carbon Neutrality

Study Area

- Suwon-si, located in the central-southern region of Gyeonggi-do, South Korea



Results

NPP affected by environmental factors

- Spearman's correlation analysis between the environmental variables and NPP in all grids.

Table 3. Result of correlation analysis

Variable	Correlation coefficient
Elevation	0.630*
Slope	0.557*
Mean temperature	-0.638*
Distance to forest	-0.523*
Distance to urban area	0.585*
Distance to grassland	0.403*
Adjacent Forest area	0.800*
Adjacent Urban area	-0.730*

* p < 0.001

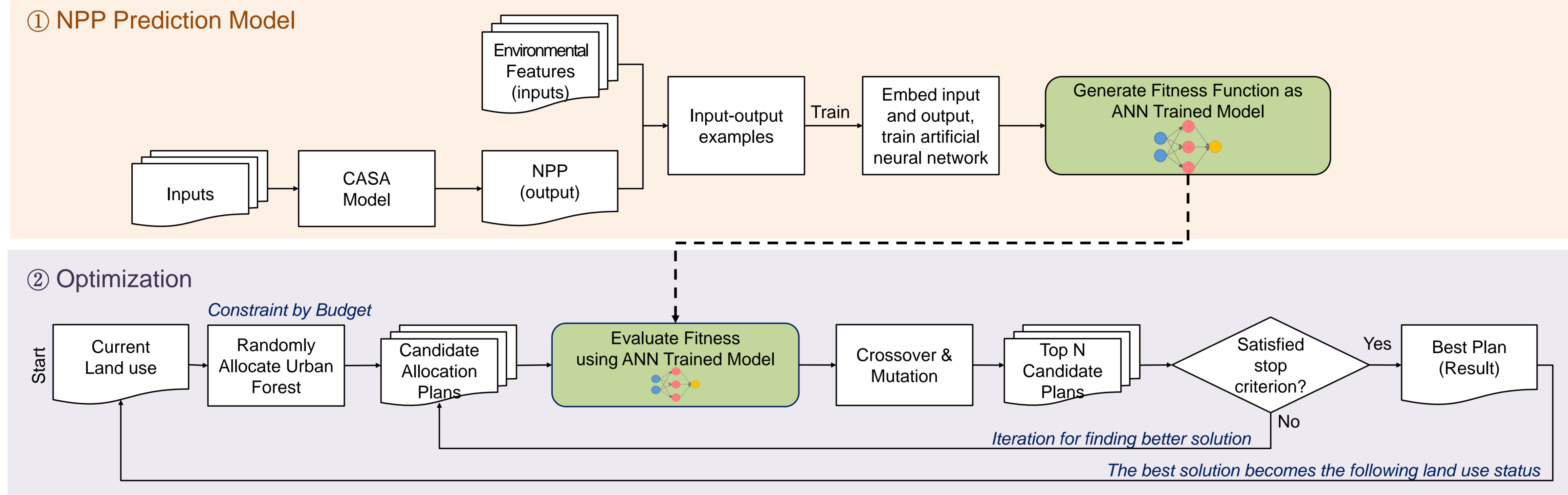
Optimal Urban Forest Allocation Plan

- By 2030, the total carbon absorption from creating additional carbon sink is projected to be 2,314 tCO₂eq.
- Urban forests established in advantageous locations for carbon have achieved an absorption rate of 21.4 tCO₂eq per unit area. However, when established in less optimal areas, this rate declines to 5.7 tCO₂eq per unit area, resulting in reduced efficiency.

Table 4. Result of Optimization urban forest allocation

Year	2022	2023	2024	2025	2030
Area (ha)	84.51	5.4	5.7	5.5	5.13
Total NPP (g C m ⁻²)	28,429	28,550	28,571	28,593	28,629
Increased CO ₂ absorption (tCO ₂ eq)	1810.78	351.12	105.5	46.74	29.22
Increased CO ₂ absorption by unit (tCO ₂ eq/ha)	21.4	65.0	18.5	8.5	5.7

Method



NPP prediction Model

- We used Artificial Neural Network(ANN) regression model to predict Net Primary Productivity(NPP).
- NPP = f(topographic, climate, landuse, location factors)
- NPP(y) of vegetation is estimated using the Carnegie–Ames–Stanford Approach (CASA) model based on satellite remote sensing data.

$$NPP(x,t) = SOL(x,t) \times FPAR(x,t) \times 0.5 \times T_{e1}(x,t) \times T_{e2}(x,t) \times \epsilon_{max}$$

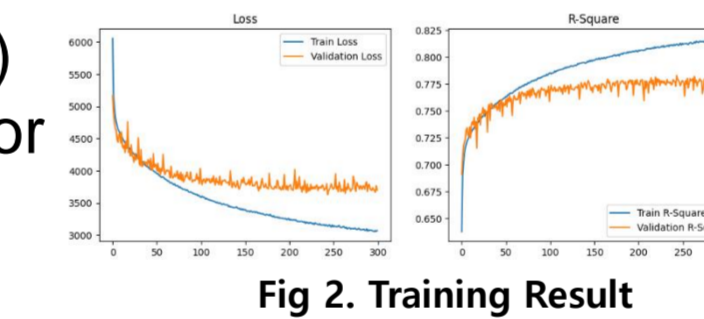
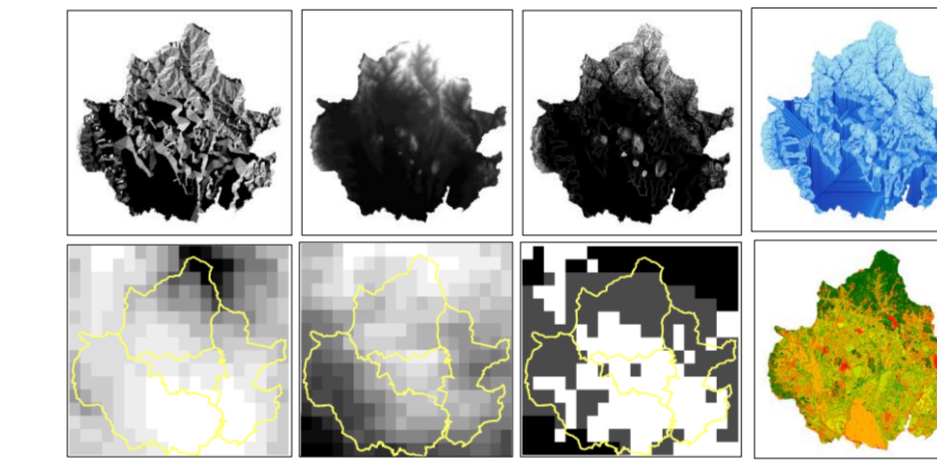
(x grid cell, t period of accumulated NPP)

$SOL(x,t)$ total solar radiation incident
 $FPAR(x,t)$ is the fraction of absorbed photosynthetically active radiation
 T_{e1} and T_{e2} are the temperature stress factors
 ϵ_{max} is the maximum possible efficiency

- Input variables(x) for ANN included topographic, climate, land use, location factors.
- The input variables were structured on a 30meter scale grid, resulting in a dataset comprising a total of 132,906 data.

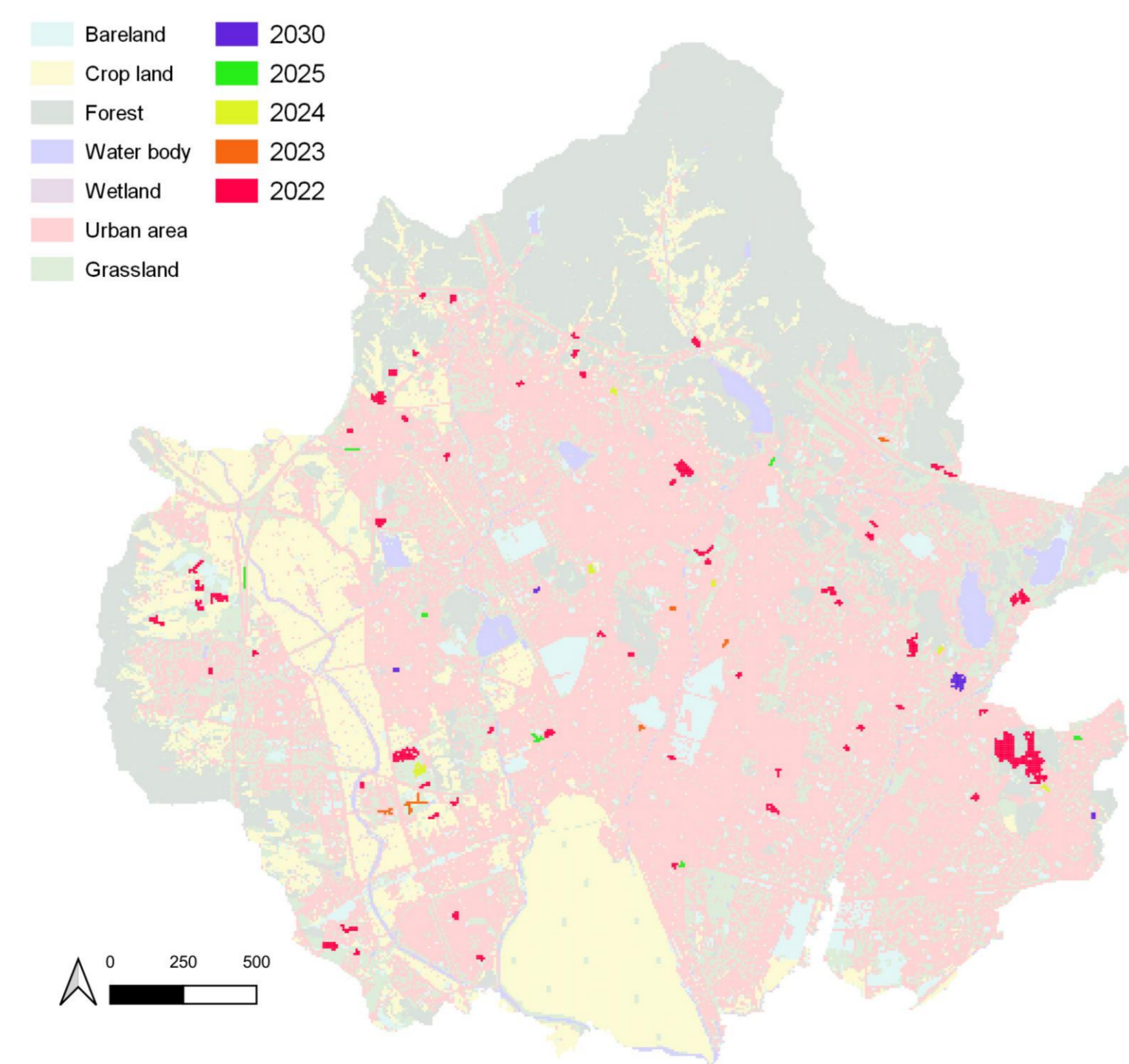
Table 1. Input variables

Input variable	Unit	Predictions
Elevation	m	Unchanged from training data
Aspect	°	Unchanged from training data
Slope	°	Unchanged from training data
Soil type	0 and 1	Unchanged from training data
Mean temperature	°C	Unchanged from training data
Mean precipitation	mm	Unchanged from training data
Current landuse type	0 and 1	Changed from training data
Historical landuse type	0 and 1	Unchanged from training data
Distance to urban	m	Changed
Distance to forest	m	Changed
Distance to cropland	m	Changed
Distance to grassland	m	Changed
Adjacent forest area(-300m)	m	Changed
Adjacent Urban area(-300m)	m	Changed



- We developed 5-hidden-layer model (128-256-64-16-1)
- Use 60% of data for training the model and 40% data for Validation
- Calculate R^2 value to verify accuracy

- As shown in Figure 3, urban forest location aimed at enhancing carbon uptake have been proposed based on annual budgets.
- It has been suggested that urban forests located at higher elevations on the periphery of urban areas are more advantageous for enhancing carbon uptake compared to those in the city center.



- The establishment of urban forests has led to changes in carbon uptake in surrounding land uses. Notably, there has been an observed increase in carbon uptake within the ecosystems of residential areas, grasslands, and uncultivated lands.

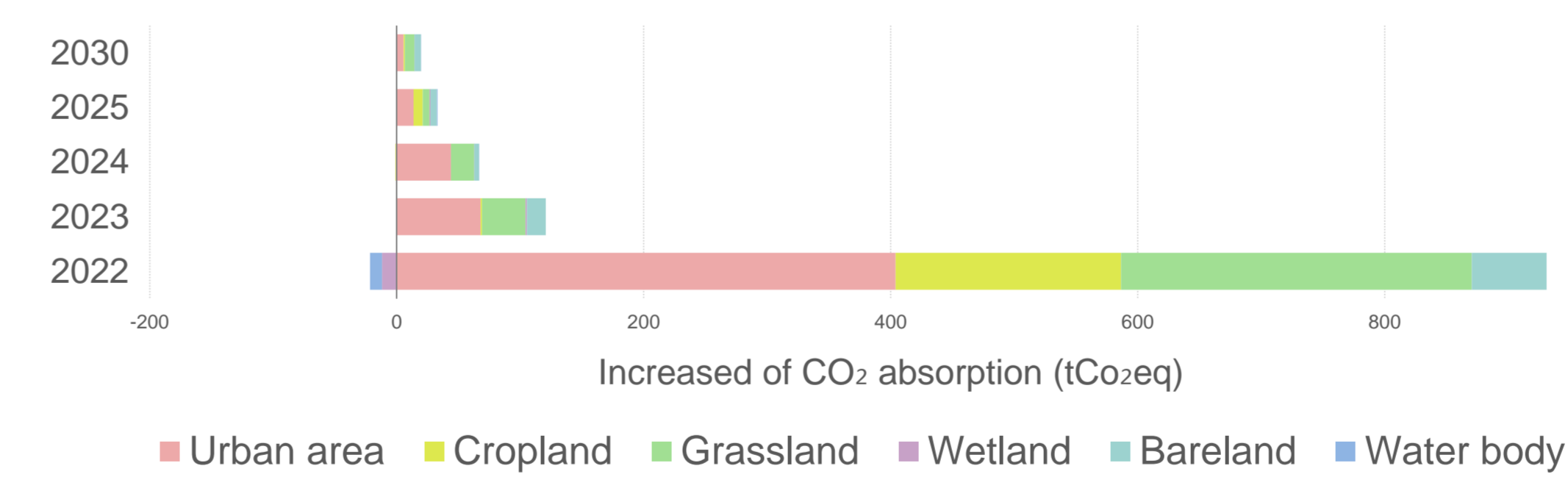
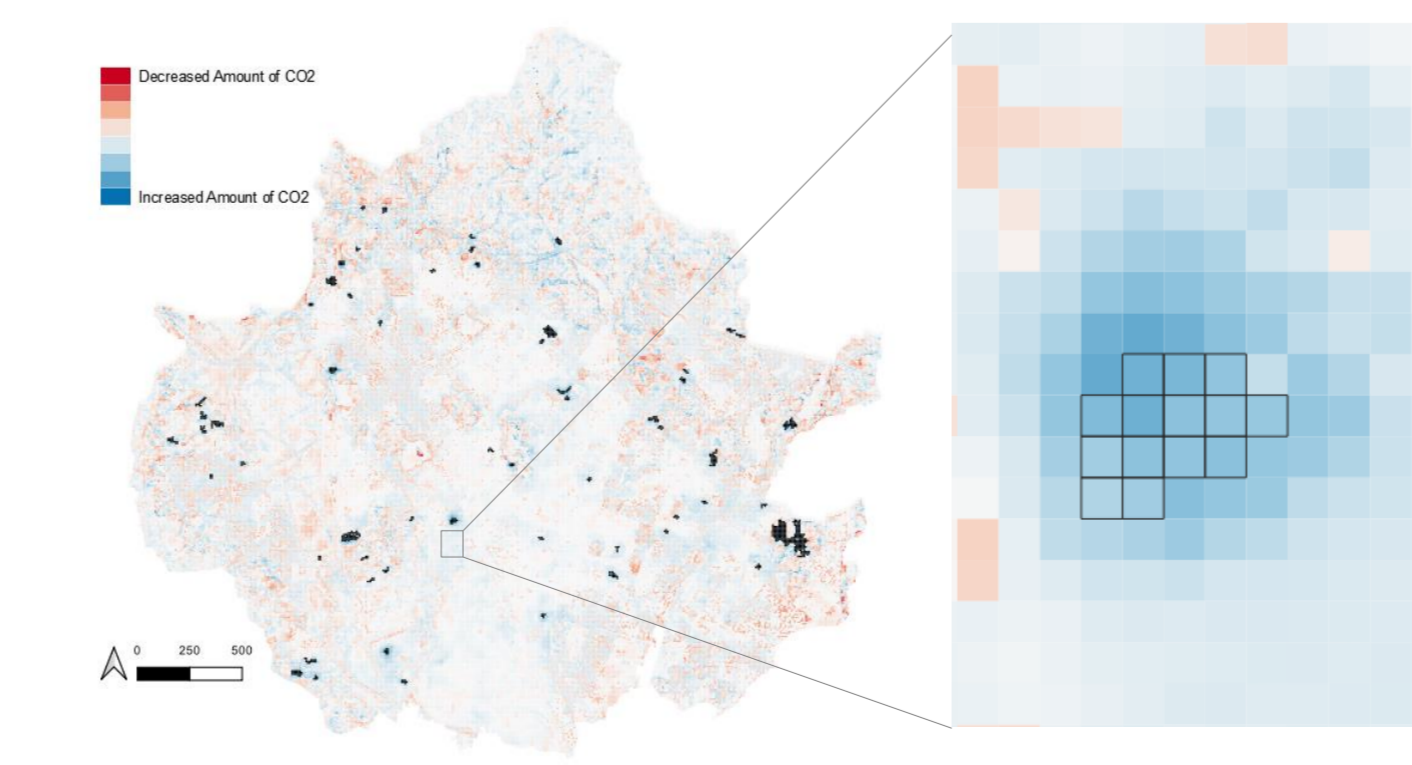


Fig 4. Increased of CO₂ absorption by land use



- Carbon sequestration within a 200-meter buffer zone around the established urban forests increases.
- Among the surrounding land uses, carbon absorption in urban areas shows the greatest increase due to the new urban forests.
- New urban forest enhance the functionality of existing green spaces

Optimization

- We used Genetic Algorithm for optimization
- Decision variable is location of **bare land to be converted to forest**
- Objective is **maximizing NPP**
- Constraint is Urban forest creation area according to the implementation roadmap budget

- The cost of creating an urban forest was set at a hundred million KRW per hectare, and the appropriate size for climate-responsive urban forest was set a minimum 0.5 hectares, as suggested by the Climate Response Urban Forest Construction and Management Field Guide.
- In the carbon sink plan for Suwon-si, the annual budget allocations were considered as constraints in the optimization process

Table 2. annual budget and reduction goal

Year	2022	2023	2024	2025	2030
Required Budget (million KRW)	84800	5873	5873	5873	5873
Carbon Sink Creation for Carbon Neutrality (tCO ₂ eq)	719	939	1117	1240	1860

Calculate CO₂ absorption

- To compare with the reduction targets set by local governments, the annual Net Primary Productivity (NPP) was converted into the corresponding amount of carbon dioxide absorption.

$$S_c = \sum_{i=1}^n NEP_i \times a_i \times \frac{44}{12} \times 10^{-7} \quad R_h = 0.6163R_s^{0.7918}$$

$$NEP = NPP - R_h \quad R_s = 1.55e^{0.031T} \times \frac{P}{P + 0.68} \times \frac{SOC}{SOC + 2.23}$$

S_c total net absorption of CO₂
 NEP is net ecosystem productivity of grid i
 R_h the soil heterotrophic respiration
 R_s is soil respiration
 P and T are the annual precipitation and average temperature

Discussion

- Deep learning predictions model in this study can address the limitations of models that require future parameters(NDVI, vegetation growth, vegetation types)
- The deep learning-based NPP prediction model was utilized by coupling with optimization, addressing the issue of oversimplification in existing optimization fitness functions
- This model can propose optimal urban forest locations to enhance NPP of ecosystem and examine the interaction of surrounding existing land uses' NPP with the establishment of the new urban forest.
- Previous studies have primarily focused on the effects of established green spaces, whereas this model allows for the assessment of interactions among existing land uses resulting from the creation of new green spaces
- This study can provide theoretical guidance and technical support for green space planning that incorporates the effects of newly established green spaces on existing ones

Future Study

- We need to incorporate socio-economic factors and climate variability, which can impact land use changes and affect the predictions made by the model.
- Currently, the model identifies target areas for urban forestation, but many of these include planned development sites. It is important to include potential carbon sinks that can be established in urban environments, such as rooftop greening and street trees.