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Optimizing urban agriculture for long-term ecosystem services: Integrating scenario-based suitability analysis and the landscape approach

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ABSTRACT

Uncontrolled urban sprawl intensifies socio-ecological pressures, demanding planning strategies that measurably enhance urban ecosystem services. Urban agriculture is a promising lever, yet its long-term ecosystem services contributions remain insufficiently quantified. This study addresses two critical questions: (1) How can suitability analysis guide the spatial integration of urban agriculture to optimize long-term ecological benefits? and (2) How can a landscape approach-based urban agriculture planning strategy be designed to align with ecosystem services enhancement goals? We develop a transparent, reproducible pipeline linking machine-learning suitability modeling (XGBoost with SHAP), deep-learning land use simulation, and monetary ecosystem services valuation. Using Rotterdam as a case study, we simulate three development scenarios for 2030 and 2050: Business-as-Usual (BAU), Suitability-Based Autonomous Transformation, and Suitability-Based Landscape Approach Transformation. Suitability-guided scenarios outperform BAU, with the landscape-approach scenario delivering the most stable multi-decadal outcomes for regulating and cultural services. However, provisioning services can plateau or even decline when ecological protection constraints limit intensive production, revealing the limits of land allocation alone. We conclude by offering thresholds and rules that translate suitability and scenario outputs into a transferable urban agriculture planning model, enabling planners to embed urban agriculture within a landscape approach as part of broader sustainable urban transformation.

1. Introduction

Cities around the world are experiencing rapid urbanization, which often exacerbates challenges such as poverty, inequality, environmental degradation, and public health risks (Roggema, 2020; McMichael, 2000). As cities grapple with escalating socio-ecological challenges driven by rapid urbanization (Elmqvist et al., 2019; Geels, 2002; Hölscher & Frantzeskaki, 2021), enhancing ecosystem services in cities is one of the most significant ways to help cities get out of the woods. The consolidation of ecosystem services contributes to the harmonization of people and nature and promotes the positive and stable development of society (Daily, 1997). Precisely because humans are considered part of nature, natural ecosystems within the urban context cannot be ignored as well (Bolund & Hunhammar, 1999). Therefore, integrating ecosystem services into planning systems for urban transformation is crucial for promoting sustainable urban development (Cortinovis & Geneletti, 2018). In recent years, extensive attention has begun to be paid to the impacts of agroecosystem services on urban dwellers, particularly urban agriculture (Aerts et al., 2016). As an inclusive and integrated concept, urban agriculture is proved to be relevant to almost all urban sustainable development goals (Pradhan et al., 2024). Urban agriculture's influence of ensuring food security, creating employment opportunities, and enhancing habitats has gained significant attention and recognition (Azunre et al., 2019; Ilieva et al., 2022; Waffle et al., 2017). In this way, advocacy for the integration of agriculture into urban ecosystems is proved to address a variety of contemporary issues (Feagan, 2007; Lovell, 2010). Taken together, urban agriculture has achieved substantial progress in the urban transformation process by delivering ecosystem services (Morgan, 2015; Langemeyer et al., 2021; Mackenzie & Davies, 2019).

However, in urban development catalogues, especially urban planning and design, it is the pursuit of long-term resilient provisioning of ecosystem services that promotes human well-being (McPhearson et al., 2015). Because the spatial and temporal response of land use change to ecosystem services in urban transformation and city planning is substantial (Cui et al., 2021), urban agriculture should play a key role as a

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multifunctional land use strategy. Although there is widespread support for urban agriculture to provide provisioning, regulating and cultural values (Zasada, 2011), some of its ecological impacts call into question its ability to provide long-term ecosystem services. For example, intensive urban agricultural development may displace high-value natural habitats or green spaces, potentially harming biodiversity, carbon sequestration, and other regulating services in the long run (Barthel and Isendahl, 2013; Portela and Aguirre, 2000). In addition, the spatial configuration, integration, and management of urban agriculture are fundamental to ensuring its long-term sustainability and its contribution to the ecological fabric of cities (Gómez-Villarino et al., 2021). But some scholars find that although urban agriculture like gardens on vacant lots can improve ecosystem services in the short term, its long-term sustainability remains contentious due to potential trade-offs in resource consumption and landscape transformation (Drake and Lawson, 2014; Padgham et al., 2015). This highlights a key issue: while expanding urban agriculture seems to be an immediate solution, longevity is a major challenge. Therefore, arranging urban agriculture to provide ecosystem services from a long-term perspective in conjunction with a rational spatial logic is a major task in advancing its operability in urban transformation.

From a multi-level perspective, urban transformation models emphasize the institutional embedding of niches, which refers to innovative practices in urban agriculture and serve as the main object for validating changes in ecosystem services (Geels, 2002; Ernst et al., 2016). Within broader landscape structures, institutions are made up of multiple policy and regulatory mechanisms that together determine whether a niche can be implemented and diffused (Hölscher & Frantzeskaki, 2021). From a practical standpoint, multi-perspective and multi-scale approaches to urban transformation highlight the benefits of placemaking, integrated systems thinking, and urban networks. Broader landscape structures highlight the ability of urban agriculture to be integrated into landscape structures across scales and to have a broader impact across cities (Arts et al., 2017; Wu, 2013). These are in line with the principles of the landscape approach, which is a multidimensional, cross-scalar integrative strategy that conceptualizes landscapes as the dynamic interface between human and environmental interactions (Sayer, 2009; Reed et al., 2015; Wascher, 2004). Therefore, considering urban agriculture as a landscape approach to promote urban transformation has great potential in achieving sustainable urban development and enhancing ecosystem services. The landscape approach views cities as coupled human-land-environment systems and advocates the coordination of multiple land uses (e.g. agriculture, conservation and urban development) to achieve synergistic effects on ecosystem services (Arts et al., 2017; Nijhuis, 2022). However, there are two major obstacles in exploring this path. First, few studies have quantitatively assessed the dynamic changes of ecosystem services within the city during urban development under a unified spatial modeling framework (Huan et al., 2024a; Evans et al., 2022; Yuan et al., 2022). This has led scholars and practitioners to remain skeptical and vague about the contribution of urban agriculture to urban transformation. Second, urban agriculture programs are often based on isolated case studies, making it difficult to generalize the research results or use them to guide the planning of the entire city (Pueyo-Ros et al., 2024). These gaps not only limit theoretical advancement but pose a practical bottleneck. Therefore, this urges us to not only validate and assess the exact contribution of urban agriculture to ecosystem services in the dynamics of urban transformation, but also to summarize and propose a universal spatial intervention strategy based on these results.

To this end, this study raises a key research question: how can urban agriculture be embedded in a landscape approach to enhance long-term ecosystem services (Fig. 1)? To address this issue, we construct an integrated research framework for validating and quantifying the dynamics of ecosystem services in different contexts. This not only validates the capacity of the landscape approach in a long-term perspective, but also provides designers with a useable toolkit for spatial practice. Firstly, based on the research gaps suggested by the literature review, we define three different urban development scenarios to visualize the landscape approach and demonstrate its effects, using Rotterdam as the experimental area. Given that the landscape approach emphasizes the suitability assessment of interventions (Nijhuis, 2022), the three scenarios are identified as (1) a Business-as-Usual (BAU) scenario; (2) a Suitability-Based Autonomous Transformation scenario and (3) a Suitability-Based Landscape Approach scenario. Following this, we use the XGBoost algorithm combined with the SHAP interpretability mechanism to conduct a machine learning-based suitability assessment to identify the urban agriculture locations with the greatest development potential. After accurate identification, considering that previous

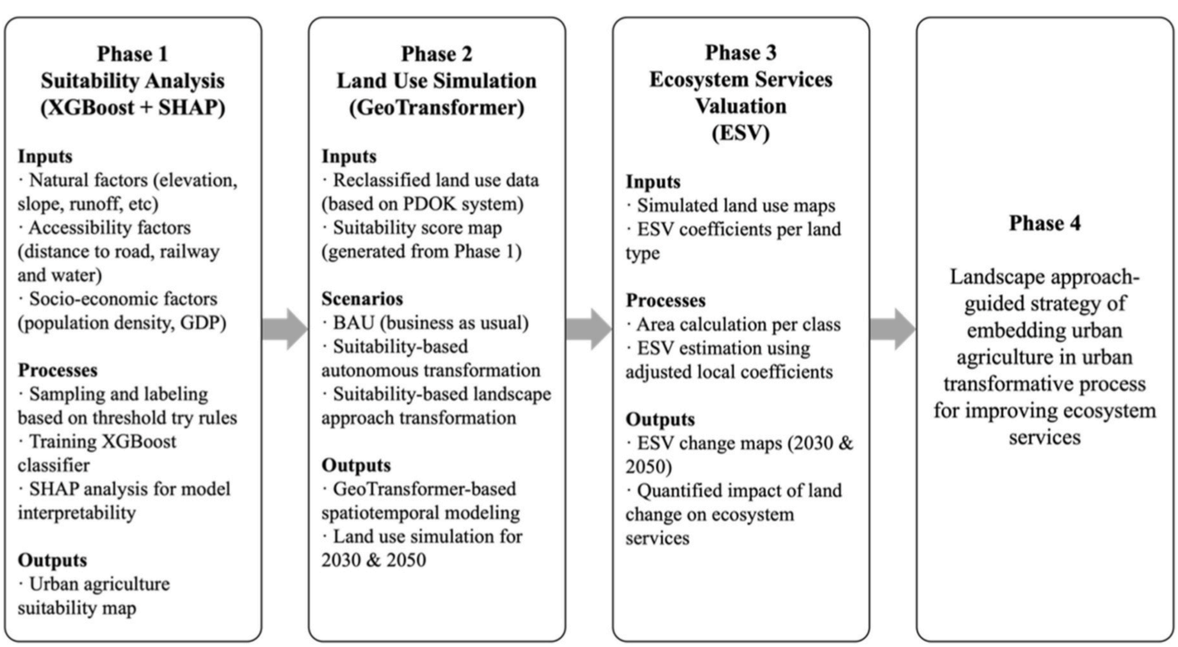

Fig. 1. Workflow of methodology.
Source: By author

models relying on cellular automata or scenario trend analysis cannot incorporate the multidimensional driving factors and spatial dependencies unique to urbanization, we decide to use deep learning-based tool for land use simulation (Liu et al., 2017; Li et al., 2023; Jia et al., 2024). We choose two-time nodes, 2030 and 2050, to represent the short- and long-term scenarios, respectively. Finally, by calculating the ecosystem services valuation, we summarize the contribution of urban agriculture as a landscape approach to inter-temporal provisioning. Subsequently, combining the experimental results, theoretical basis and empirical experience, we propose a 'micro-urban-regional' cross-scale spatial intervention strategy to optimize long-term ecological benefits.

This study is positioned at the intersection of urban planning, landscape ecology, and data-driven spatial simulation. Rather than proposing a new algorithm, this study contributes by: (i) integrating established suitability modelling (XGBoost + SHAP) with deep-learning land-use simulation (GeoTransformer) into a transparent, reproducible pipeline for urban agriculture planning; (ii) providing multi-scenario, multi-decadal evidence on how the landscape approach influences ecosystem services trajectories in Rotterdam; and (iii) translating model outputs into cross-scale planning guidance (local–urban–regional) that practitioners can operationalize. Although the case is based in Rotterdam, the methodological framework and policy-relevant insights are adaptable to cities worldwide that seek to balance land development with ecological performance. The full dataset and code/notebook are openly released with DOIs to support reuse and scrutiny.

2. Methods and materials

The study is carried out specifically after acquiring and preprocessing the data, following the methodology shown in Fig. 1.

2.1. Study area and data source

Rotterdam, located in South Holland, the Netherlands, lies adjacent to the Rhine and Nieuwe Maas Rivers and spans over 200 km^2, with its extensive port district occupying more than 100 km^2. Situated in the low-lying Dutch delta, the city features flat terrain averaging approximately 7 m below sea level, characterized by mild winters, cool summers, and an annual precipitation of around 700 mm. The city's diverse landscape includes expansive estuaries, meandering rivers, and a subsoil composed predominantly of clay, sand, and peat deposits. Beyond serving as a major international hub for agri-food trade, Rotterdam is also an important producer of agricultural goods. Urban agriculture has notably thrived in recent years, benefiting from proactive governmental initiatives and policies established since 2007 to promote sustainable food systems. Rotterdam is selected as a case study for two distinct reasons: the city's abundant, high-quality, publicly accessible data sources including those provided by the Central Bureau of Statistics (CBS) and Public Services on the Map (PDOK), which facilitate precise quantitative analysis; and its established policy framework and substantial municipal investment supporting urban agriculture initiatives. For this study, multiple datasets on urban land use and socio-environmental factors within Rotterdam are analyzed at the neighborhood level. Given that some neighborhoods predominantly consist of water bodies or uninhabited areas, the final analysis focuses specifically on 16 selected neighborhoods (Fig. 2). This combination of robust data availability, mature policy support, and active urban agricultural projects makes Rotterdam an ideal setting for this comprehensive investigation.

To evaluate areas suitable for the development of urban agriculture across Rotterdam, we implement a machine learning-based suitability analysis using the XGBoost model in combination with SHAP interpretability techniques. The dataset is constructed by integrating multiple spatial indicators derived from authoritative sources, including the Central Bureau of Statistics (CBS) and Public Services on the Map (PDOK), and processed using QGIS to achieve consistent resolution and coordinate systems (Table 1). The indicators encompass natural environmental conditions, transportation accessibility, and socioeconomic characteristics. The socio-economic variables include population density and road network density which are known to influence the distribution and potential impact of urban agriculture (Hume et al., 2021; Bellemare & Dusoruth, 2021; Ferreira et al., 2018). Environmental indicators consist of elevation, slope, aspect, surface runoff, proximity to

Fig. 2. Selected scope of the Rotterdam.
Source: By author

Table 1
Land use simulation factors selection and source.

Form	Data name	Year	Source	Resolution
Site data	Boundaries	2010	PDOK	Raster
	Land use	2010, 2017	PDOK + OSM (open street map)	30m
Natural environmental factors	DEM	2024	NASA SRTM	30m
	Slope, Aspect	2024	NASA SRTM	30m
	Arable land	2024	PDOK	Raster
	Forest land	2024	PDOK	Raster
	Wetland	2024	PDOK	Raster
	Vegetation cover	2024	NASA SRTM	30m
	Wind speed	2023	PDOK	Raster
	Runoff	2020	PDOK	30m
Socio-economic factors	Distance to water body	2024	PDOK	Raster
	Distance to railway	2024	PDOK	Raster
	Distance to highway	2024	PDOK	Raster
	Population density	2023	PDOK	1 km
Ecological factor	Nature reserve	2024 PDOK	Raster	

water bodies, and the presence of ecological reserves, which are essential for assessing the viability and sustainability of urban agriculture (Diekmann et al., 2019; Beniston and Lal, 2012; Cui et al., 2018; Raza et al., 2019). Precipitation, temperature, and soil quality data are also collected for the Rotterdam area. However, these variables are excluded from the final suitability analysis due to limited spatial variation (precipitation and temperature) and data gaps in urbanized zones (soil quality). Their exclusion ensures consistency and avoids bias in the modeling framework. A labeled dataset for suitability modeling is created through stratified sampling, assigning binary suitability labels based on threshold-based evaluation of the above factors. XGBoost, an ensemble-based classifier, is trained on this dataset, and model performance is evaluated using standard cross-validation methods. SHAP values are subsequently computed to interpret the influence of each variable on suitability predictions, improving transparency in spatial decision-making.

A consistent suite of spatial predictors is used as driving factors for the GeoTransformer model to maintain scenario comparability. Following previous land use simulation literature (Liang et al., 2021; Li et al., 2023; Lin et al., 2020), we exclude only ecological reserves from the dataset. Spatial predictors include topographical (elevation, slope, aspect), hydrological (runoff, proximity to water bodies), infrastructural (distance to roads), and socio-economic variables (population density, urban greening). Land use data is reclassified into nine categories: agriculture, forest, urban agriculture, urban green/grassland, wetland, water, built-up area, transportation, and unused land. This reclassification follows the PDOK system and is implemented through merging, clipping, and raster transformation operations in QGIS. All layers are spatially aligned and resampled to a common resolution to ensure compatibility within the GeoTransformer simulation framework. This methodological consistency ensures robust and interpretable results across all simulated development scenarios.

2.2. Modelling of land use scenarios for urban transformation

2.2.1. Urban agriculture suitability assessment using XGBoost and SHAP

In this study, we implement a reproducible approach to assess urban agriculture suitability by integrating the eXtreme Gradient Boosting (XGBoost) algorithm with SHapley Additive exPlanations (SHAP). XGBoost constructs an ensemble of weak learners (typically decision trees, Fig. 3) using additive training and regularization to minimize the loss function:

$$\mathscr{L}(\varnothing) = \sum_{i=1}^{n} l(\hat{y}_i, y_i) + \sum_{k=1}^{K} \Omega(f_k), \textit{where } \Omega(f) = \gamma T + \frac{1}{2}\lambda\|\omega\|^2$$

Here, $\hat{y}_i$ is the predicted value, y_i is the observed value, f_k represents each regression tree, and Ω denotes the complexity penalty for regularization (Chen and Guestrin, 2016). This formulation enables XGBoost to efficiently handle large-scale, high-dimensional, and nonlinear relationships common in spatial datasets.

To enhance model interpretability, SHAP (SHapley Additive exPlanations) is integrated post hoc. SHAP values decompose a model's output $f(x)$ into additive contributions from each feature:

$$f(x) = \varnothing_0 + \sum_{i=1}^{M} \varnothing_i$$

Where $\varnothing_0$ is the model's base value and $\varnothing_i$ represents the Shapley value of feature *i*,interpreted as the marginal contribution of feature *i* across all possible feature coalitions (Lundberg and Lee, 2017). This approach satisfies properties of consistency and local accuracy, ensuring reliable interpretation even in complex black-box models.

This combination provides competitive accuracy for screening urban agriculture opportunities and feeds subsequent scenario simulation and ES valuation. This pipeline facilitates interpretable decision-making regarding the spatial allocation of urban agriculture, aligning with recent advancements in explainable artificial intelligence (XAI) applied to spatial planning (Linardatos et al., 2020).

Fig. 4 visualizes the SHAP summary plot, where the x-axis represents the SHAP value (i.e., the impact on the model output), and each point corresponds to an individual prediction. The color gradient indicates feature value (from low in blue to high in red). The model identifies distance to rail, runoff, and population density as the top three

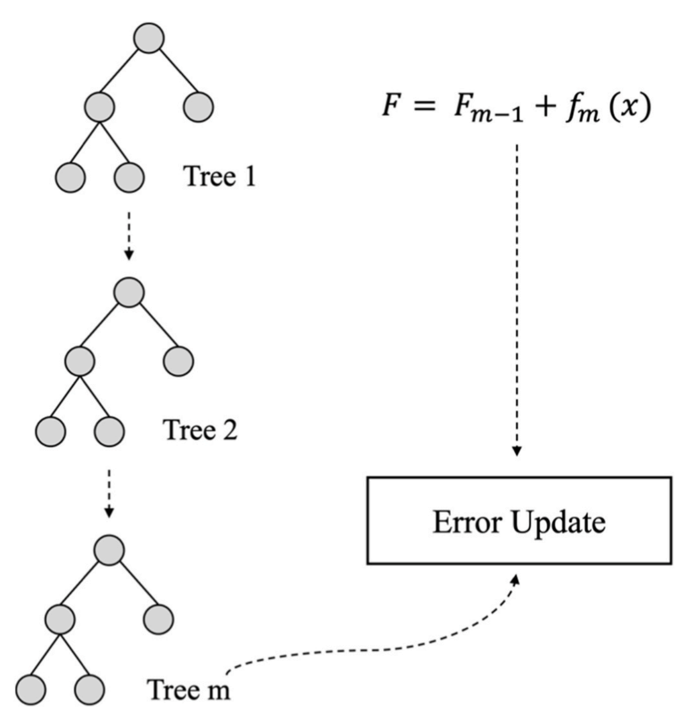

Fig. 3. Schematic representation of the XGBoost architecture. The model iteratively adds decision trees to minimize the residuals from previous predictions. At each iteration m, a new tree $f_m(x)$ is trained to correct the errors of the ensemble F_{m-1} , producing an updated prediction $F = F_{m-1} + f_m(x)$
Source: By author

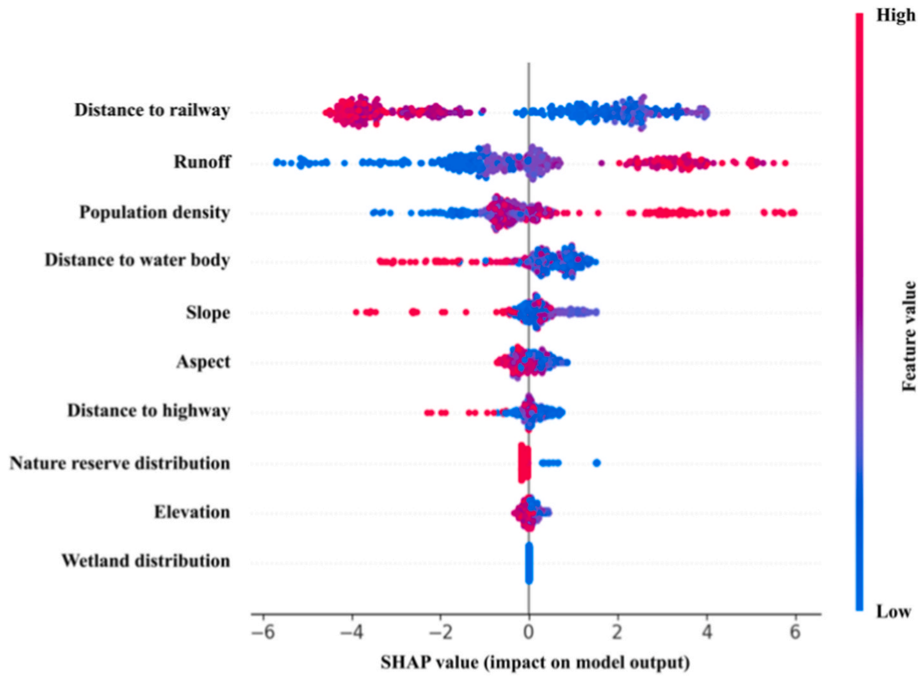

Fig. 4. SHAP dependence plot showing the contribution of each predictor variable to the urban agriculture suitability model. Distance to railway, runoff, and population density exhibit the strongest influence on suitability predictions.
Source: By author

predictors influencing urban agriculture suitability. Shorter distances to rail and higher runoff values consistently increase the probability of a location being suitable, as shown by the clustering of high-value points in the positive SHAP value range. The high influence of 'distance to railway' is attributed to multiple factors. Proximity to railway networks facilitates efficient transportation logistics, reduces operational costs for

Source: By author

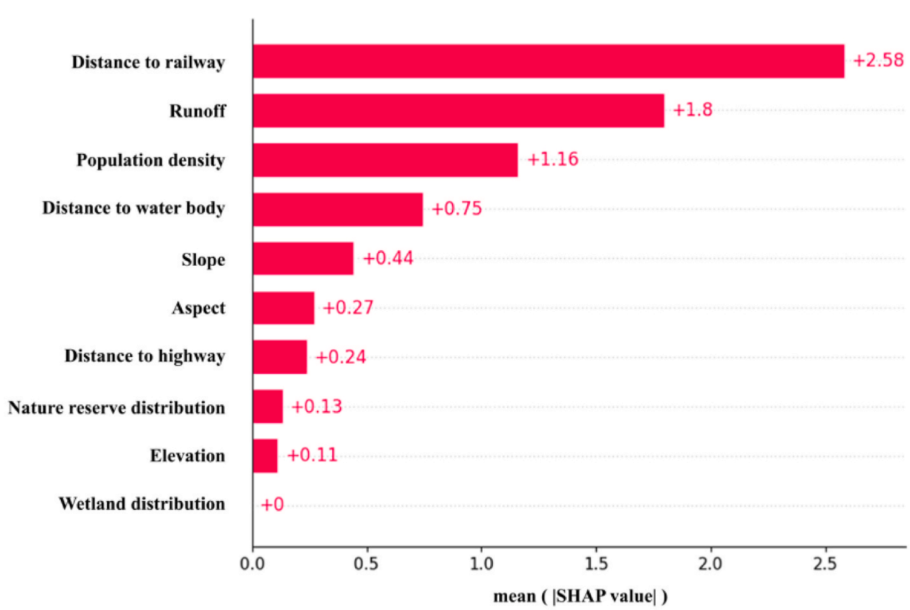

Fig. 5. Mean absolute SHAP value summary plot ranking the relative importance of predictor variables in the urban agriculture suitability model. Distance to railway, runoff, and population density emerge as the top three predictors, indicating that accessibility and hydrological conditions are the dominant drivers of urban agriculture suitability in Rotterdam.
Source: By author

urban farmers, and aligns with municipal policies favoring transit-oriented development. Additionally, areas close to transit infrastructure typically benefit from greater socio-economic accessibility, enhancing community participation in urban agriculture (Haberman et al., 2014; Taylor and Lovell, 2012). Complementing this, Fig. 5 shows the mean absolute SHAP values for all features, offering a global interpretation of feature importance. This bar plot highlights the dominance of distance_rail, runoff, and pop_density, followed by distance_water and slope. Interestingly, features such as elevation and wetland showed minimal influence, suggesting their weaker discriminative power in this specific urban context. These visualizations confirm the relevance of infrastructure proximity and hydrological context in determining the feasibility of urban agriculture development. The interpretability enabled by SHAP supports more transparent decision-making in policy contexts where spatial equity and environmental constraints must be balanced.

To standardize model outputs for spatial comparison, the raw suitability predictions are normalized using min-max scaling, resulting in a continuous scale from 0 to 1. This method commonly refers to as min-max normalization and rescales values according to the minimum and maximum values of the dataset and is widely used in spatial multi-criteria evaluation and machine learning to ensure comparability across heterogeneous indicators (Malczewski, 1999).

$$\textit{Suitability score} = P(y = 1 \mid x) = \frac{e^{f(x)}}{1 + e^{f(x)}}$$

2.2.2. Geotransformer based land use simulation

GeoTransformer is the core tool selected for land use modelling in this study. GeoTransformer's architecture consists of multiple layers of fully connected neurons, positional encoding, and spatial embedding modules, which allow for fine-grained control over location-specific transition probabilities. Its ability to process multi-source spatial drivers in parallel makes it highly scalable and well-suited for modeling rapid land transformations in urban and peri-urban regions. It is a land use simulation framework built upon deep learning architectures, specifically designed to capture spatiotemporal dynamics in complex and heterogeneous landscapes (Jia et al., 2024). The model is inspired by Transformer-based attention mechanisms, which have revolutionized sequential data processing in natural language processing (Vaswani et al., 2017) and have recently been successfully adapted for spatial modeling tasks in remote sensing (Dosovitskiy et al., 2020; Aleissaee et al., 2023). These mechanisms enable GeoTransformer to capture long-range spatial dependencies and context-aware interactions among geospatial variables, significantly outperforming rule-based or cellular automata approaches in urban land simulation scenarios (Zhao et al., 2023).

The core mechanism of the GeoTransformer model is designed to simulate spatiotemporal land use transitions by learning from geospatial context. The model takes as input encoded representations of spatial regions ("query region") and their contextual surroundings ("value regions"), retrieved through sparse matrix indexing. These regions are passed through a multi-head geospatial cross-attention module that computes attention weights based on both spatial proximity and entropy-based importance. The attention mechanism learns the influence of surrounding land patches on the target patch, enabling context-aware prediction. The deep representation is further processed through a stack of transformer blocks, each composed of feed-forward layers, normalization, and linear projection, ultimately producing a predicted land use class. This architecture allows the model to generalize across heterogeneous and non-contiguous spatial data, offering improved accuracy in highly dynamic urban environments.

2.2.3. Transformative scenarios design

Scenario simulation is an essential method for describing ecosystem service dynamics and regional-scale landscape change trajectories (Schröter et al., 2005). To explore the potential pathways of urban transformation, three contrasting land use scenarios are designed (Table 2). The first is the "Business-as-Usual (BAU)" scenario, which assumes continuity in current land use trends and policy frameworks. This scenario functions as a control benchmark and reflects outcomes under minimal intervention conditions. The second scenario is the "Suitability-based autonomous transformation" scenario, which integrates the spatial suitability outputs derived from the XGBoost + SHAP model as soft constraints in the GeoTransformer simulation. Unlike BAU, this scenario allows land use change to evolve more organically, guided by spatially explicit suitability patterns. This form of scenario simulation has gained increasing recognition for its ability to align data-driven insights with future-oriented spatial policy (Batty, 2013). The third scenario is the "Suitability-based landscape approach transformation" scenario. The scenario draws from landscape ecological principles that emphasize multifunctionality, spatial connectivity, and the integration of human-nature relationships across scales (Opdam et al., 2003; Wu, 2013). Landscape approaches offer a temporal perspective that acknowledges that ecological and social processes unfold at different rates, thus supporting adaptive long-term land strategies (Sayer et al., 2013; Nijhuis, 2022). Landscape-based strategies integrate ecological structure, urban form, and cultural values, allowing for resilient and adaptive territorial transformation that aligns long-term landscape goals with short-term planning decisions. The implementation of this scenario supports emerging calls for integrated urban landscape planning in response to climate change and ecological degradation (Ahern, 2013).

2.3. Ecosystem service values

There are numerous quantitative approaches for assessing ES based on land use change. For example, the widely applied InVEST model quantifies ecosystem services such as carbon storage, biodiversity, and soil retention based on land use, climate, and soil data (Ouyang et al., 2016). Similarly, the ARIES model employs artificial intelligence to dynamically simulate ecosystem services (Villa et al., 2014). Although both methods are suitable for regional and larger-scale assessments, they

Table 2
Scenario framework detailing the development logic, guiding mechanisms, and land use transition rules.

Scenario	Development Logic	Guiding Mechanism	Land Use Transition Rule
BAU	Urban land evolves freely without regulatory or ecological constraints.	No suitability analysis considerations	All transitions permitted with no spatial preference; outcomes driven by historical land use patterns and model learning.
Suitability-based autonomous transformation	Urban agriculture expands in areas assessed as suitable by the model.	Suitability derived from XGBoost + SHAP	Land use transitions are more likely in high-suitability areas, but not restricted by landscape approach principles.
Suitability-based landscape approach transformation	Urban agriculture follows both the principles of suitability and landscape approach.	Combines XGBoost + SHAP suitability with hard landscape planning constraints.	Urban agriculture allowed only in suitable areas outside key ecological zones (e.g., forests, wetlands) in which landscape factors are protected.

require large datasets, complex parameterization, and extensive computational processes. Additionally, the InVEST model is designed to evaluate specific ecosystem services rather than providing an integrated assessment, making it challenging to analyze comprehensive ES dynamics. To address these limitations, we seek a simpler approach that facilitates data acquisition and computation, while remaining applicable to both urban and regional scales. After evaluating multiple methods, we select ecosystem service valuation. Ecosystem services value refers to the monetization of ecosystem benefits, capturing the economic, social, and environmental contributions of ecosystem processes (Costanza et al., 1997). Compared to other approaches, ecosystem services value provides a tangible monetary representation of ecosystem significance and can be effectively integrated with land use change analysis (Brander et al., 2024; Costanza et al., 2014). Given the heterogeneity in urban agriculture practices, including rooftop farming, community gardens, and greenhouse horticulture, we refined the ecosystem service valuation by assigning practice-specific coefficients, reflecting distinct ecological and social values derived from recent studies (Langemeyer et al., 2021; Gómez-Villarino et al., 2021). This approach captures more accurately the diversity and specificity of ecosystem services provided by various urban agriculture types. In 2016, Statistics Netherlands and Wageningen University conducted a national assessment of Dutch terrestrial ecosystem services, encompassing crop production, timber production, water filtration, air purification, carbon sequestration, pollination, recreational value, and amenity services (Horlings et al., 2020). Based on this report, we identify ecosystem service values for each land use type (Table 3). However, since urban agriculture is not explicitly listed, but greenhouse agriculture is included, we assume that all urban agriculture land corresponds to greenhouse horticulture. Additionally, we conduct a comparative analysis of specific ecosystem services using their percentage contributions to the total ecosystem services value (Table 4). Finally, we adopt ESV_{Total} to represent the total ecosystem service value, and $ESV_{provisioning}$、 $ESV_{regulating}$ and $ESV_{cultural}$ to denote the values of provisioning, regulating, and cultural services, respectively. The specific relationships are defined as follows:

$$ESV_{Total} = \sum_{i=1}^{n} (ESV_i{*}A_i)$$

$$ESV_{provisioning,regulating,cultural} = \sum_{i=1}^{n} \left(ESV_i{*}A_i{*}p_{pi,ri,ci}\right)$$

where ESV_i represents the unit value per hectare of the ith ecosystem service, A_i represents the area of the ith ecosystem service, $p_{pi,ri,ci}$ represents the percentage of provisioning, regulating and cultural services, respectively, and n is the total number of site types.

3. Results

3.1. Suitability analysis for urban agriculture

This study employs a machine learning-based framework to evaluate the spatial suitability of urban agriculture across the municipality of Rotterdam. Suitability is assessed using an eXtreme Gradient Boosting (XGBoost) classifier trained on spatial predictors representing environmental, infrastructural, and demographic attributes. Each pixel in the study area is assigned a continuous suitability score between 0 and 1, indicating its relative favorability for urban agriculture development under current landscape conditions (Fig. 6).

The spatial distribution of suitability scores reveals a clear differentiation across the municipality. High-suitability areas, predominantly located within and around the central urban districts, are characterized by proximity to dense transportation networks (e.g., roads and railways), moderate slopes, and higher population densities. These factors, as identified by SHAP analysis, collectively contribute to creating favorable conditions for urban agricultural development in these zones. Conversely, low-suitability areas are mainly found in the northwestern port zones and peripheral industrial districts, where extensive land sealing, ecological protection restrictions, or poor accessibility significantly limit agricultural feasibility. This distinct spatial polarization highlights that urban agriculture opportunities in Rotterdam are closely tied to the interplay between infrastructural accessibility, existing land use intensity, and biophysical constraints. It underscores the importance of integrating transportation planning and land recycling strategies when promoting urban agriculture in dense metropolitan contexts.

After obtaining the suitability results for urban agriculture development, we simulate land use spatial distribution outcomes under scenarios with and without suitability constraints (Fig. 7). Simulations for 2030 and 2050 without suitability constraints show: built-up areas continue to expand along major corridor routes and port peripheries, accompanied by scattered residual open spaces. Conversely, under suitability constraints, part of the 2030 growth is reallocated to brownfield and infill development opportunities marked as highly suitable within the central urban area and inner ring corridors. This approach preserves and stitches together the suburban green-blue belts in the south and east. By 2050, this constraint mechanism will form a more coherent urban-rural mosaic pattern of agriculture and green spaces, particularly along riverfronts and secondary road networks. This pattern effectively curbs the encroachment on low-suitability industrial/port zones observed in the unconstrained scenario. Overall, this comparison demonstrates that embedding suitability stratification into allocation rules does not suppress urban expansion. Instead, it guides development toward areas possessing conditions conducive to supporting sustainable urban agriculture. This approach reduces land fragmentation, enhances green corridor connectivity, and minimizes conflicts with high-intensity land uses.

3.2. Scenario-based land use simulation outcomes

This section presents the simulated land use patterns in Rotterdam under three different scenarios: Business-as-Usual (BAU), Suitability-Based Autonomous Transformation, and Suitability-Based Landscape Approach Transformation. As shown in Fig. 8, the BAU scenario maintains the existing land use dynamics, resulting in only marginal expansion of urban agriculture by 2030 and 2050, predominantly confined to isolated parcels with favorable conditions. Under the Suitability-Based Autonomous Transformation scenario, the spatial distribution of urban agriculture significantly broadens, with new urban agriculture parcels emerging not only at the urban periphery but also interspersed within built-up areas where suitability conditions are favorable. This expansion is more spatially fragmented but overall more extensive compared to the BAU projection. The Suitability-Based Landscape Approach Transformation scenario exhibits a more structured pattern. Urban agriculture primarily concentrates along ecological corridors, near urban green spaces, and adjacent to natural reserves, reflecting an intentional integration of ecological connectivity considerations. Compared to other scenarios, this approach results in more compact and strategically positioned agricultural patches.

Spatially, as illustrated in Fig. 9, the evolution of urban agriculture

Table 3
Value of ecosystem services (euro/ha).

Agriculture	Forest	Urban Agriculture	Urban Green/Grassland	Wetland	Water	Built-up area	Transportation	Unused Land
2655	6730	707	4183	3768	787	137	259	229

Table 4
Percentage share of provisioning, regulating and cultural ecosystem services(%).

Type of service	Agriculture	Forest	Urban Agriculture	Urban Green/Grassland	Wetland	Water	Built-up area	Transportation	Unused Land
Provisioning	25.43	1.97	12.50	0	0	0	0	0	0
Regulating	4.43	12.32	0	9.68	4.79	0.95	31.08	17.24	0
Cultural	70.14	85.71	87.50	90.32	95.21	99.05	68.92	82.76	0

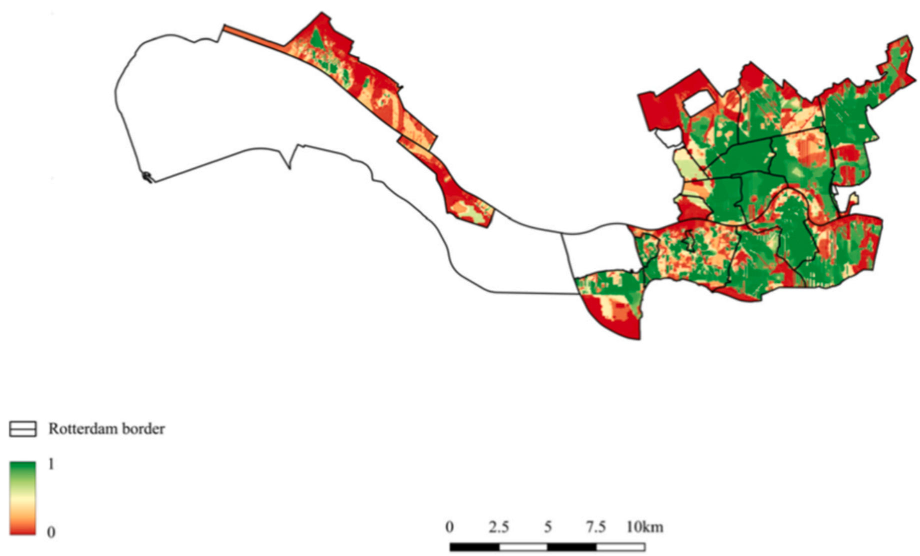

Fig. 6. Results of the suitability analysis of urban agriculture.
Source: By author

under different scenarios demonstrates clear divergence by 2050. While BAU maintains a relatively static and limited distribution, the Suitability-Based scenarios markedly enhance the quantity and spatial integration of urban agriculture, particularly in suburban and peri-urban regions. These outcomes highlight the critical influence of planning strategies in shaping future urban land dynamics and their potential to support sustainable urban agricultural expansion.

3.3. Ecosystem services dynamics under different scenarios

This study quantitatively evaluates the changes in ecosystem services value across the scenarios for 2030 and 2050 (Table 5, Fig. 10). Under the BAU scenario, total ecosystem services value exhibits a continuous decline, dropping from 20.11 million in 2024 to 19.07 million in 2030 and further to 18.77 million in 2050. This downward trend is mainly driven by a substantial reduction in urban green/grassland area (from 9.40 million to 9.05 million) and a marked loss of wetland ecosystems (from 433,056 m^2 to only 29,584 m^2). Simultaneously, built-up areas remain relatively stable, indicating that ecological land loss occurs without a proportional increase in urban densification. In the Suitability-Based Autonomous Transformation scenario, ecosystem services value demonstrates slight overall growth, increasing from 20.04 million in 2030 to 20.18 million in 2050. This stabilization is primarily due to the significant expansion of urban agriculture land (from approximately 978,311 m^2 to 988,556 m^2), which partially offsets the decline in traditional green spaces. However, compared to the landscape approach, this scenario still exhibits moderate reductions in wetland and forest areas, suggesting a limited capacity to fully preserve high-value ecological land. The Suitability-Based Landscape Approach scenario achieves the greatest improvement in ecosystem services value, rising from 21.18 million in 2030 to 21.44 million in 2050. Agricultural land shows a remarkable increase, from approximately 6.90 million m^2 to 6.90 million m^2 (maintained at a high level), and wetland areas are better preserved (around 1.58–1.60 million m^2). In addition, built-up and transportation areas remain relatively constrained, indicating successful ecological prioritization in land conversion processes. This scenario thus most effectively balances urban development demands with ecological conservation objectives.

Comparative analysis reveals that while all scenarios maintain stable water surface areas, the key factors influencing ecosystem services value dynamics are the variations in agricultural land, urban green/grassland, and wetland distribution. The findings emphasize that integrating spatial suitability assessments with landscape ecological frameworks can markedly enhance the resilience and multifunctionality of urban ecosystems over long-term planning horizons.

Moreover, a decomposition of ecosystem services value into cultural, provisioning, and regulating services (Fig. 11a–c) reveals notable differences among scenarios. Cultural services exhibit a consistent decline under the BAU scenario but significantly increase under both suitability-guided pathways, particularly in the Landscape Approach scenario. Provisioning services show modest variations across scenarios, with Scenario 3 achieving the highest provisioning service value by 2050. Regulating services remain relatively stable under BAU and Suitability-Based Autonomous Transformation scenarios but substantially improve under the Landscape Approach scenario by 2050, underscoring its superior capacity to strengthen long-term ecological regulation functions.

4. Discussion

4.1. Landscape approach-based urban agriculture enhances long-term ecosystem services

This research provides empirical evidence supporting the critical role of landscape approach-based urban agriculture in enhancing long-term ecosystem service provision. Compared to other decentralized urban nature-based solutions approaches or sectoral green infrastructure planning, landscape approach uniquely integrates suitability assessment with multifunctional landscape connectivity. While decentralized

Source: By author

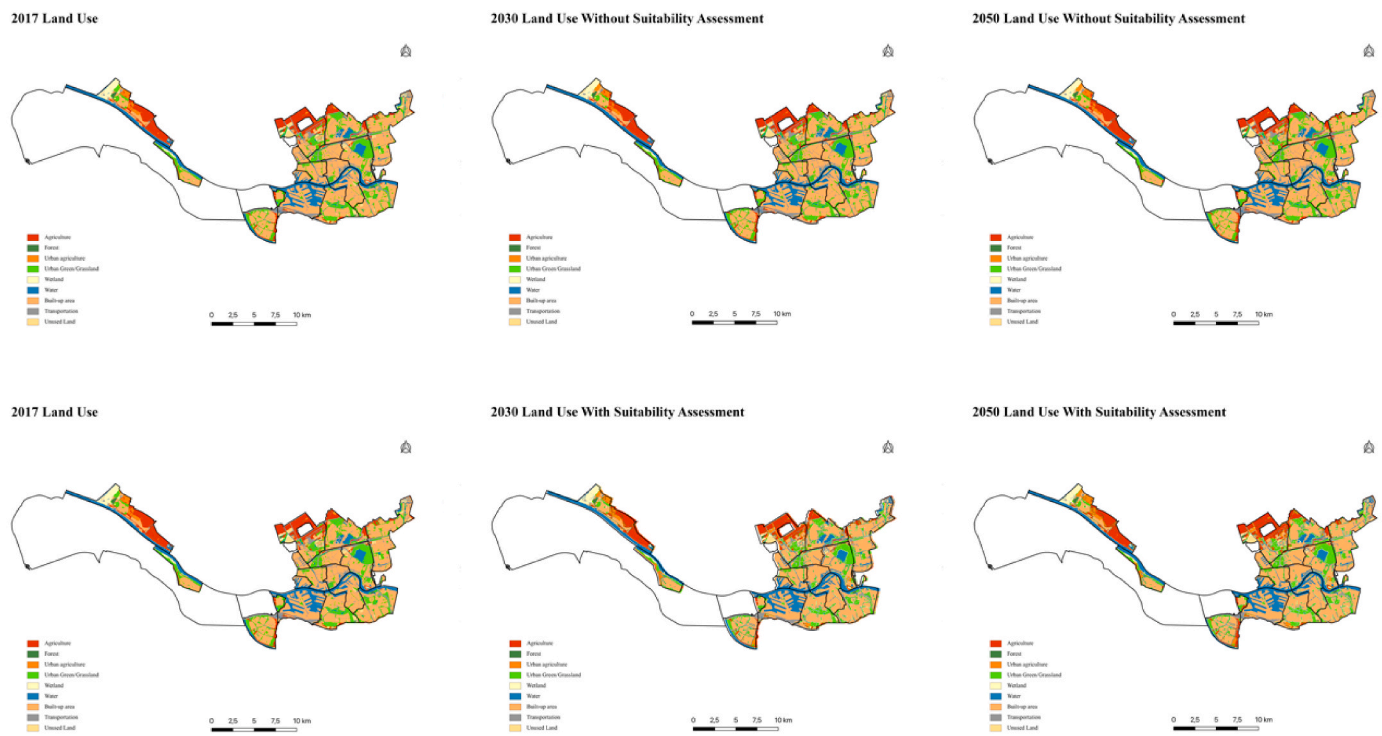

Fig. 7. Land use simulation with/without suitability assessment in 2030 and 2050.
Source: By author

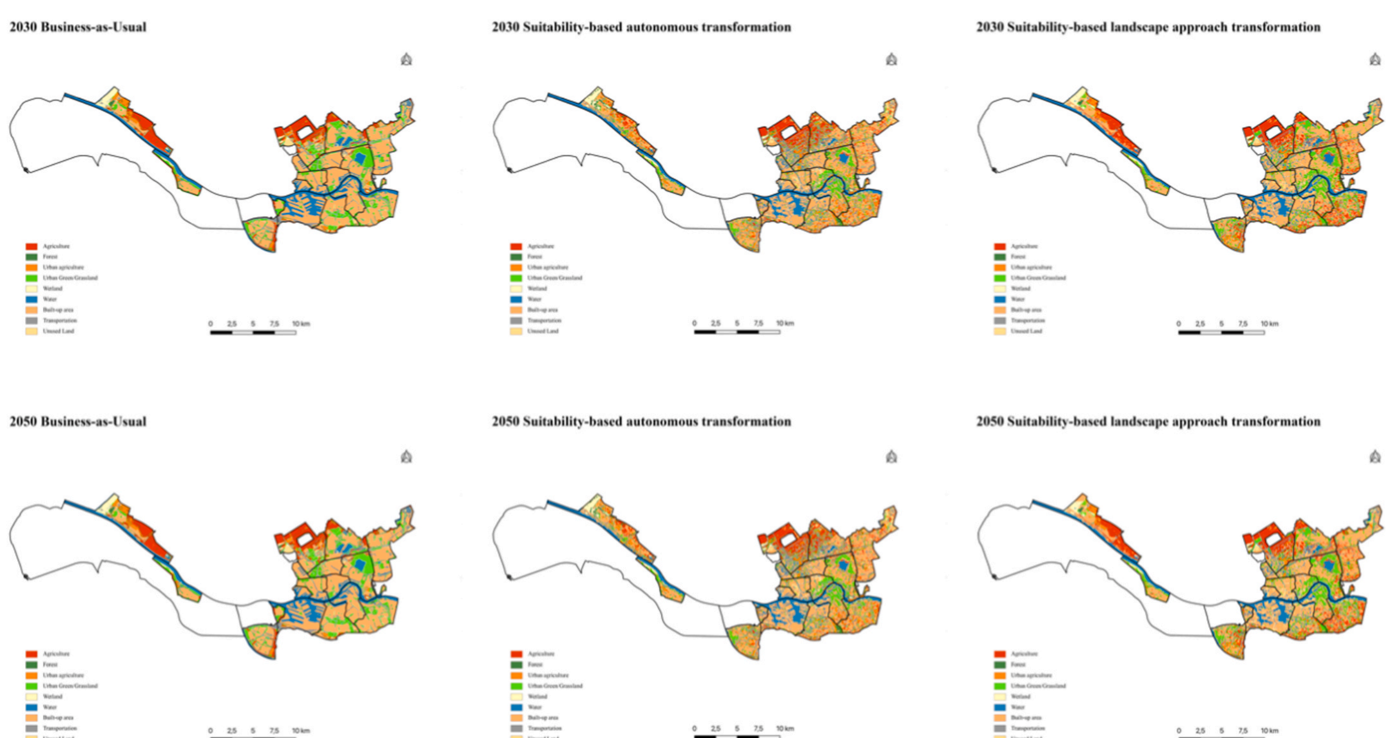

Fig. 8. Simulated land use patterns for Rotterdam under three scenarios (Business-as-Usual, Suitability-Based Autonomous Transformation, and Suitability-Based Landscape Approach Transformation) for the years 2030 and 2050.
Source: By author

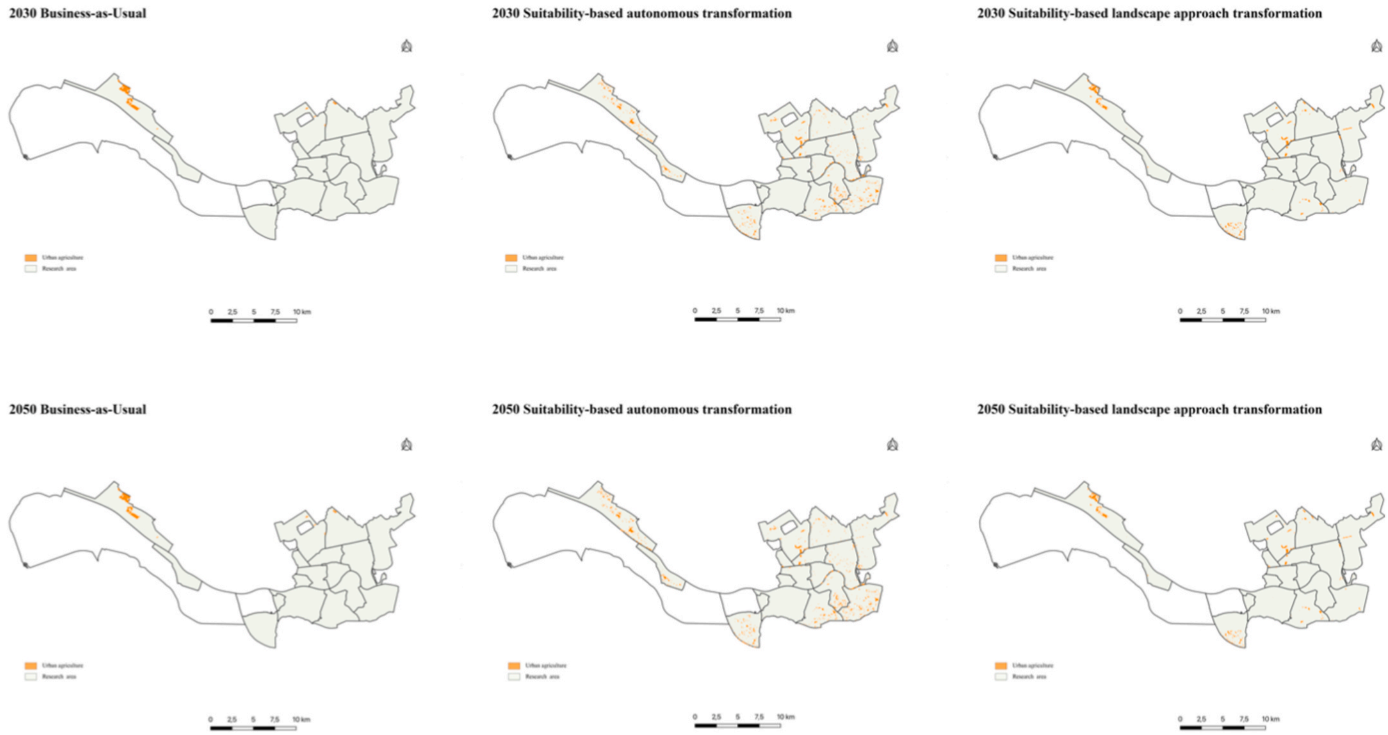

Fig. 9. Spatial distribution of urban agriculture land under three scenarios (Business-as-Usual, Suitability-Based Autonomous Transformation, and Suitability-Based Landscape Approach Transformation) for 2030 and 2050.
Source: By author

Table 5
Area-based ecosystem services value estimations for each land use type under different scenarios and years.

Scenarios	Agriculture	Forest	Urban Agriculture	Urban Green/ Grassland	Wetland	Water	Built-up area	Transportation	Unused Land	Total
BAU 2030	5086050.68	539678.72	300651.75	9399356.53	433056.24	1714936.32	1007028.13	489067.11	98701.29	19068526.77
BAU 2050	5513293.32	540890.11	295179.57	9048456.52	29584.24	1459806.33	996202.35	568810.62	116096.13	18568319.19
Scenario 2 2030	4609823.41	2705661.92	978311.25	6536272.09	1526718.22	1763454.54	804298.23	612330.39	139838.84	19676708.89
Scenario 2 2050	4593813.83	2852241.33	988555.68	6662766.11	1608785.33	1756584.42	795630.24	608274.45	140972.42	20007623.81
Scenario 3 2030	6900398.11	869785.24	334630.17	9041680.02	1585725.11	2014263.52	888364.17	338064.93	101401.21	22074312.48
Scenario 3 2050	6902309.69	881899.18	328330.82	9146338.72	1608446.21	1985346.91	883173.24	336969.36	116116.74	22188930.87

nature-based solutions excel in rapid local implementation, they often lack mechanisms for regional ecosystem services synergy, which is a critical gap identified in urban resilience frameworks. Similarly, sectoral approaches may optimize single ecosystem service but overlook trade-offs inherent to urban agriculture. Our scenario simulations reveal that among 3 conditions, urban agriculture guided explicitly by landscape ecological principles such as multifunctionality, ecological connectivity, and spatial heterogeneity (Sayer et al., 2013), outperform actions that ignore landscape dimensional thinking. Specifically, our results illustrate how adopting a landscape-based approach significantly increases biodiversity, ensures stable delivery of regulating services (e.g., climate regulation and flood mitigation), and enhances overall urban ecological resilience.

Empirical studies from international contexts reinforce these insights. For example, Berlin's city-wide network of dispersed community gardens, explicitly developed under landscape ecological guidelines, has sustainably delivered extensive cultural and ecological services over long periods. These gardens not only maintained ecological connectivity, facilitating species movement and genetic diversity, but also supported various ecosystem services such as microclimate regulation, habitat provision, and cultural engagement (Langemeyer et al., 2021). Similarly, Gómez-Villarino et al. (2021) emphasizes through their empirical work that the strategic spatial configuration of green infrastructure, which incorporates multifunctional and connected green spaces, significantly enhances urban ecosystem functions, reinforcing theoretical assumptions about landscape ecology and spatial sustainability. By combining these empirical validations with our scenario-based simulations, this study confirms and expands upon landscape approach theory as it relates to urban agriculture. Thus, this research not only validates existing theoretical propositions but also provides additional empirical foundations for integrating urban agriculture into broader landscape approach-based planning and management frameworks.

4.2. Suitability analysis as an essential Component within the landscape approach

Our findings underscore that spatial suitability analysis is not merely advantageous but fundamentally necessary within the landscape approach-based planning framework for urban agriculture. The

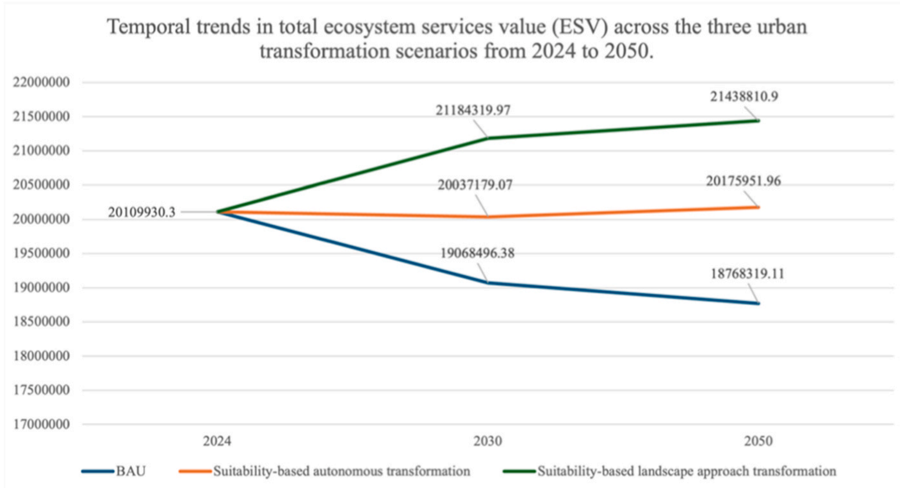

Fig. 10. Temporal trends in total ecosystem services value across the three urban transformation scenarios from 2024 to 2050.
Source: By author

XGBoost + SHAP suitability approach employed in this study significantly improves our ability to systematically identify optimal urban agriculture sites by clearly interpreting the critical environmental, social, and infrastructural factors affecting spatial decisions. These methodological advancements greatly reduce the potential for conflicts, ecological risks, and inefficiencies in urban agriculture implementations, thus setting a firm groundwork for subsequent landscape approach-based spatial interventions. From a theoretical perspective, suitability analysis plays a pivotal role within landscape ecology principles, particularly those articulated by Forman (1995) and Wu (2013). Landscape approach emphasizes spatial configuration, connectivity, and multifunctionality, which require precise spatial assessments to operationalize effectively. Suitability analysis fulfills this role by systematically integrating ecological criteria with socioeconomic factors to optimize spatial decision-making processes. Without robust suitability analysis, landscape approach-based strategies risk becoming spatially fragmented, diminishing their ecological coherence and long-term sustainability.

The necessity of suitability analysis is further reinforced by recent landscape sustainability theories, highlighting its role as a crucial interface between theoretical ecological principles and practical spatial planning (Opdam et al., 2018). Suitability analysis ensures targeted spatial interventions are aligned with broader landscape objectives, translating theoretical insights into practical applications. Thus, it becomes indispensable for achieving landscape-level sustainability, resilience, and spatial equity within contemporary landscape urbanism theories. Conclusively, our empirical analysis demonstrates that suitability analysis is not just methodologically advanced but theoretically essential for landscape approach-based urban agriculture planning. It effectively operationalizes critical landscape approach concepts, providing planners with concrete, evidence-based spatial guidance essential for achieving long-term ecosystem service goals.

4.3. *Long-term effects fatigue and imbalance in specific service types on land use change*

In this study, the three urban agriculture scenario simulations proposed (Business-as-Usual, Suitability-Based Autonomous Transformation, and Suitability-Based Landscape Approach Transformation) provide a detailed comparative analysis of the long-term ecological impacts of urban agriculture. By quantifying the dynamics of ecosystem services under these three scenarios, although the third scenario performs excellently in most ecosystem service types, we also identify a significant decline in its long-term performance. A more in-depth analysis, particularly of the growth rates in provisioning services, reveals concerning trends and suggests that relying solely on land use change cannot fully mitigate the slowdown of long-term effects in urban transformation.

Although Scenario 3 initially performs well, the growth rate significantly slows down over time, and its final growth rate is lower than that of Scenario 2. This finding is especially evident in the growth curve of ecosystem service value, where the ecosystem service value under Scenario 3 almost stagnates by 2050. The observed decline in provisioning services under Scenario 3 is linked to systemic trade-offs inherent in the landscape approach, particularly competition between land allocated for ecological conservation and urban agriculture productivity. Ecological zones prioritized for conservation under landscape planning frameworks often constrain intensive agricultural activities, thereby limiting the scope for provisioning service enhancement (Barthel and Isendahl, 2013; Lovell, 2010). However, Scenario 2 continues to grow at a faster rate. Further examination of the specific service types, in provisioning services, Scenario 3 is the only one which experiences negative growth. In contrast, Scenario 1 shows the best performance in provisioning services, despite its overall lower performance. This phenomenon reveals that urban agriculture cannot effectively cope with the pressures of long-term development, especially in the provisioning service sector when lacking a proper spatial integrated method. For this phenomenon, we draw the following conclusion: The fatigue of long-term effects and the imbalance in specific service types suggest that relying solely on land use change without cross-temporal and spatial thinking is insufficient to ensure balanced growth across all ecosystem service sectors. In the long-term planning process of urban agriculture, it is necessary to combine multi-scale and multi-dimensional strategies, particularly by integrating suitability analysis and precise spatial interventions in specific service areas. This can avoid the slowdown or imbalance in ecosystem service growth caused by the limitations of a single strategy.

4.4. *Landscape approach-based spatial strategies for urban agriculture planning*

Building upon the theoretical insights and empirical findings of this research, Fig. 12 outlines a landscape approach-based spatial strategy for enhancing ecosystem services by urban agriculture. The strategy covers the four levels of policy, assessment, action and impact, closely fitting the layered approach of the landscape approach (Huan et al., 2024b). Central to this strategy is the foundational role of suitability analysis, which systematically informs spatial interventions by

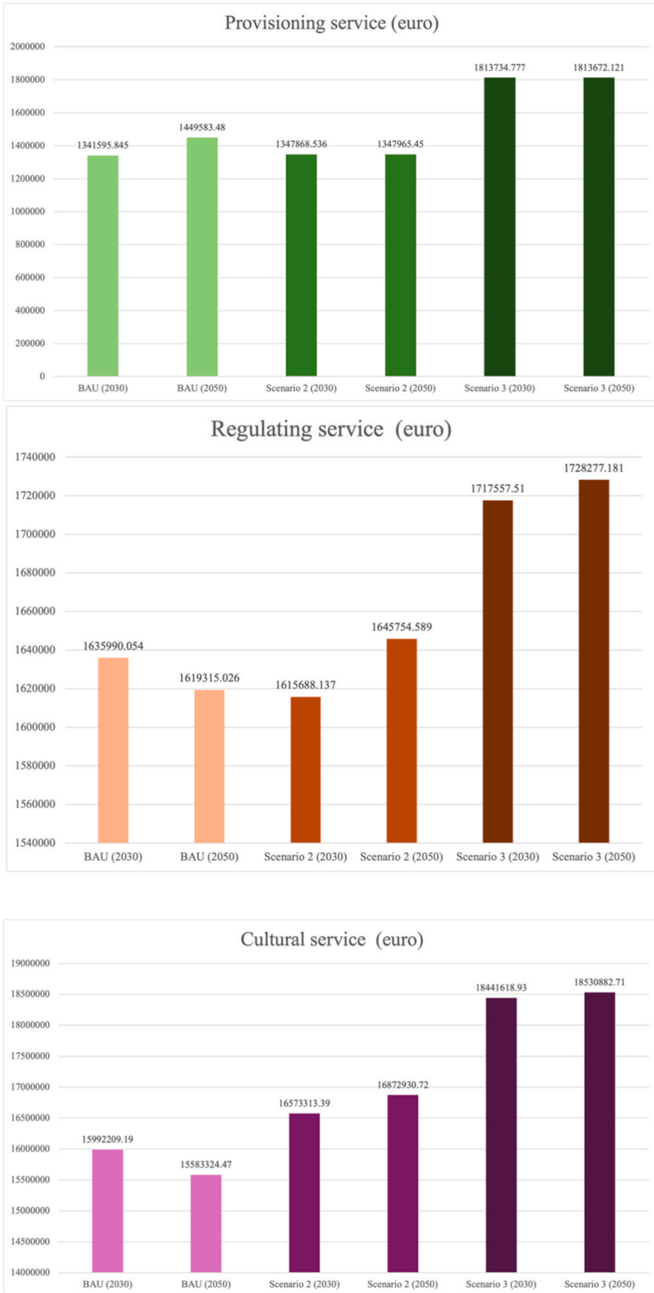

Fig. 11. Provisioning(a), Regulating(b), Cultural(c) ecosystem service value under the Business-as-Usual (BAU), Suitability-Based Autonomous Transformation (Scenario 2), and Suitability-Based Landscape Approach (Scenario 3) scenarios for 2030 and 2050.

identifying optimal locations and ensuring targeted ecological and socioeconomic outcomes. Toronto has successfully integrated diverse forms of urban agriculture within a hierarchical spatial network, aligning with city-wide green infrastructure initiatives (Nasr & Komisar, 2012). Therefore, summarizing and developing a spatial strategy with universal applicability is of extreme operational importance.

The strategy is explicitly structured at three spatial scales. At the local scale, the strategy emphasizes building-integrated urban agriculture solutions, such as rooftop farms, vertical gardening, and indoor hydroponics. These practices optimize spatial efficiency, reduce pressure on urban green space, and enhance urban food system resilience. Such targeted local interventions effectively operationalize landscape approach principles by embedding multifunctionality within dense urban fabrics, facilitating immediate and tangible ecological benefits. At the urban scale, the strategy proposes a systematic transformation of urban infrastructure and open spaces to integrate multifunctional agricultural uses. Spatial interventions include green corridors, multifunctional parks, and ecological buffers. These practices strategically enhance ecosystem services such as flood regulation, urban heat mitigation, and biodiversity conservation, while simultaneously revitalizing underutilized urban spaces. Urban agriculture at this scale becomes a critical tool for achieving landscape-level connectivity and multifunctionality, key objectives articulated within landscape ecological frameworks. At the regional scale, the strategy promotes interconnected networks of urban agriculture sites, forming cohesive ecological and social landscapes. By integrating peri-urban agricultural sites with urban centers through systematic spatial planning, this scale of intervention strengthens ecological corridors, fosters biodiversity at broader scales, and enhances regional ecosystem resilience. Such comprehensive regional integration exemplifies the landscape method's emphasis on cross-scale ecological coherence and social connectivity.

Additionally, to operationalize the proposed multi-scale spatial strategy, we recommend governance instruments such as zoning adjustments to safeguard agricultural areas, economic incentives to promote UA integration in urban infrastructure, participatory planning processes involving local communities, and cross-sectoral coordination frameworks. These governance mechanisms provide actionable pathways to effectively mediate competing land-use priorities, ensuring both housing and urban agriculture coexist sustainably (Mansfield and Mendes, 2013; Azunre et al., 2019). In summary, by integrating systematic suitability analysis with multi-scale spatial interventions, our proposed strategy provides urban planners with a practical and theoretically robust framework. It operationalizes critical landscape approach theories and transforms them into scalable planning practices, significantly contributing to sustainable urban transformations and resilient urban ecosystems.

5. Conclusion

This research demonstrates that embedding urban agriculture within a landscape approach can significantly enhance the long-term provision of ecosystem services, while also revealing important considerations for sustainable urban planning. Rather than introducing a new algorithm, we contribute a reproducible, evidence-backed workflow that links suitability, scenario simulation, and monetary ecosystem services valuation. Through an integrative methodology, our study provides empirical evidence that a landscape approach-guided strategy for urban agriculture outperforms a conventional trend in maintaining ecosystem services over multiple decades. In the Rotterdam case, the Suitability-Based Landscape Approach scenario led to greater biodiversity support, improved regulating functions (such as climate regulation and flood mitigation), and higher cultural service values by 2050 compared to a BAU scenario. These findings validate the theoretical assertions of landscape ecology that spatially coordinated, multifunctional land-use planning can yield superior ecological outcomes and extend them by quantifying long-term benefits in an urban context.

Importantly, our results also highlight that while a landscape approach markedly boosts ecosystem services, it is not a panacea for all aspects of sustainability. We observed a diminishing growth rate of total ecosystem service value in the later decades under the landscape-focused scenario, with provisioning services eventually plateauing. This “long-term effects fatigue” suggests that relying solely on optimized land use allocation has limits; continuous gains across all service categories may stall without complementary interventions. Urban agriculture's contribution to provisioning services may decline over time if not bolstered by innovations in practice or policy. Therefore, planners should adopt multi-scale and adaptive strategies: combining site-level technological improvements and community engagement, city-level green infrastructure integration, and regional landscape connectivity

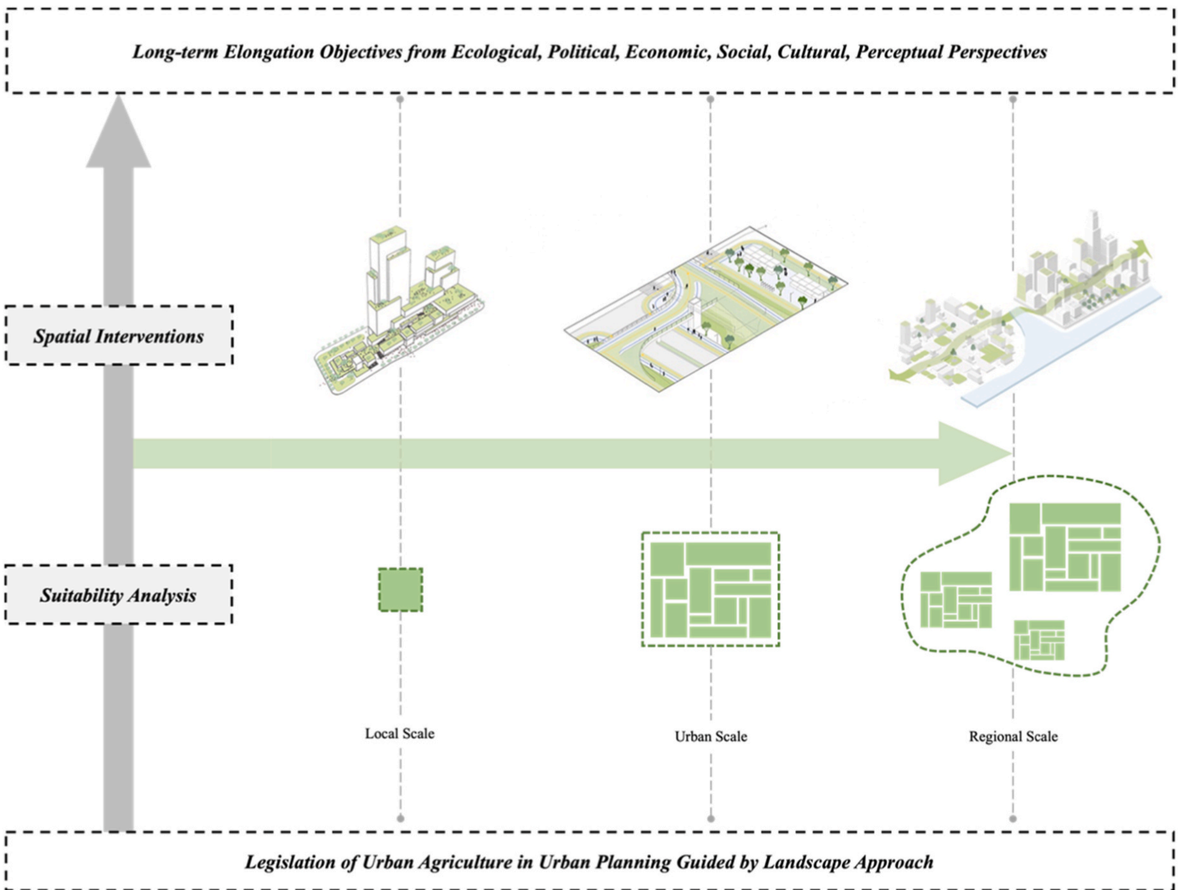

Fig. 12. A conceptual spatial strategy paradigm of urban transformation guided by urban agriculture in the perspective of landscape approach.
Source: By author

to sustain growth in ecosystem services.

Building on these insights, we propose a cross-scale landscape-based planning framework for urban agriculture. At the local scale, incorporating urban agriculture into buildings and underutilized spaces (e.g., rooftop farms, vertical gardens) can deliver immediate benefits without consuming scarce land. At the city scale, establishing green corridors and networks of agricultural parks enhances connectivity and multifunctionality, amplifying regulating and cultural services. At the regional scale, linking urban agriculture with peri-urban farms and natural areas creates a cohesive ecological network that supports biodiversity and broad resilience. This tiered strategy operationalizes the landscape approach principles across scales, ensuring that urban agriculture contributes to ecosystem services in a balanced and sustained manner over time.

In conclusion, our study not only introduces a machine learning-based methodological framework for planning urban agriculture, but also provides generalizable knowledge and practical guidance for urban sustainability. By quantitatively confirming the long-term value of a landscape approach to urban agriculture, we address a critical gap in the literature and offer planners a robust toolset for ecosystem-based urban transformations. While this study focuses on Rotterdam, the integrated approach developed herein is not specific. The combination of suitability modeling, scenario simulation, and cross-scale planning can be adapted to diverse urban contexts worldwide, provided that local ecological, social, and institutional factors are considered. Cities with varying levels of urbanization, green infrastructure, and planning capacity can tailor this framework to support evidence-based decisions that align urban agriculture with long-term sustainability goals. In doing so, our approach contributes not only to academic discourse but also to globally relevant planning practices under the evolving pressures of climate adaptation, land competition, and food system resilience.

CRediT authorship contribution statement

Yu Huan: Writing – original draft, Visualization, Software, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization. **Steffen Nijhuis:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Conceptualization. **Nico Tillie:** Writing – review & editing, Supervision, Project administration, Conceptualization.

Data and code availability

All processed data used in this study (12 GeoTIFF files) are publicly available on the Zenodo (dataset https://doi.org/10.5281/zenodo.17251210, access: https://doi.org/10.5281/zenodo.17251210). The analysis code and a Colab-ready notebook are openly available on Zenodo (code https://doi.org/10.5281/zenodo.17243851; access: https://doi.org/10.5281/zenodo.17243851), with a maintained mirror on GitHub (huanyuhuanyuhuanyu-arch/UA_Geotransformer_for_ES). The repository includes requirements.txt, environment.yml, a Reproducibility Setup cell, and a Data Download (no checksum) cell that fetches the 12 rasters from the dataset DOI; direct file links are additionally listed in data/README.md.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Yu Huan reports financial support was provided by CSC. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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