RESEARCH ARTICLE

A hybrid simulation-optimization model for assessing and enhancing carbon sequestration in urban parks

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Urban parks play a vital role in mitigating the negative effects of urbanization by serving as essential carbon sinks. As cities face increasing pressure to reduce greenhouse gas emissions, it is crucial to precisely measure and optimize the carbon sequestration ability of these green spaces. This research proposed a hybrid simulation-optimization model to evaluate and enhance the carbon sequestration potential of urban parks. The simulation component incorporated spatial data from various sources including vegetation indices, satellite imagery, and structural factors obtained from Light Detection and Ranging (LiDAR) sensors. To ensure the accuracy of the data, the Savitzky-Golay filter was applied to remove noise from the sensing data. The Hybrid Coral Reefs Optimizer-driven Scalable Random Forest (HCRO-SRF) algorithm was used to classify biotopes within the park followed by the estimation of net primary productivity and biomass to quantify carbon sequestration from 2019 to 2024. The dynamic assessment captured spatial-temporal patterns and the influence of vegetation changes over time. The Coral Reefs Optimizer (CRO) model identified optimal configurations for species selection, planting density, and spatial layout, aimed at maximizing carbon sequestration while maintaining ecological diversity and park functionality. The results demonstrated that the proposed model could improve carbon sequestration by a lower MAE of 10.16, RMSE of 12.03, and R^2 of 0.94, providing actionable strategies for policymakers, urban ecologists, and landscape architects. This research contributed to advancing climate-resilient urban design through integrated environmental modeling and optimization.

Keywords: carbon sequestration; urban parks; hybrid optimization; remote sensing; machine learning.

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Introduction

Urbanization at an accelerating rate worldwide leads to magnified environmental challenges that primarily affect air quality, together with climate change [1]. It includes a growing pattern of greenhouse gases accumulation (GHA), particularly CO_2, in earth's atmosphere, which is essential. These urban green spaces have arisen as essential climate change combat assets, which act as important carbon sinks that absorb atmospheric carbon and store it [2]. Urban parks achieve two objectives by establishing natural spaces, both to protect biodiversity and provide advantages to their local community. Urban parks show great importance, but current knowledge lacks effective and completive assessment methods to determine and enhance their carbon sequestration efficiency [3]. An urban park has carbon sequestration potential while improving its capacity, which uses precise ecological process simulation and optimized calculation methods to investigate the effects of new park design on carbon capture rates [4]. At present, it demands that city developers prioritize environmental sustainability while achieving emissions reduction targets. The spatial environmental data integration from multiple sources serves as a basis to achieve its core operation. The simulation phase combines vegetation indices extracted from space-based images together with structural light detection and ranging (LiDAR)-derived data, as well as additional geographical information to describe the park environment [5].

Accurate evaluation of carbon sequestration requires precise quantification of both net primary productivity (NPP) and biomass [6]. Scientists have examined species adaptation patterns together with seed dispersal formations to determine their capability for carbon capture [7]. The hybrid approach completes its objective by uniting three concurrent targets including optimizing carbon sequestration, supporting biodiversity, and optimizing operational system. The iterative feedback system performs real-time assessment integration as part of the hybrid model structure [8]. The simulated carbon flux patterns led to the creation of a decision-making system that enhances urban park designs to increase their carbon storage abilities. Data-based methods create new understanding about climate-resilient urban design procedures through maximizing the carbon reduction potential of green infrastructure [9]. An effective method to enhance urban park carbon storage capacity will simultaneously lower climate change effects on humans and nature [10]. Previous research has applied diverse modeling approaches to evaluate carbon sequestration in urban green spaces. Several studies have analyzed vegetation composition, canopy structure, and soil interactions to estimate CO_2 absorption efficiency [11]. Empirical and statistical assessments have demonstrated that vegetation diversity and spatial heterogeneity strongly influence carbon storage in public parks [12, 13]. Remote sensing and geospatial analyses have been extensively used to quantify biomass and monitor landscape patterns, highlighting the value of LiDAR-derived canopy metrics and satellite-based vegetation indices such as normalized difference vegetation index (NDVI) [14–16]. Machine learning has also emerged as a powerful tool for environmental prediction and carbon modeling. Ensemble-based methods such as random forest (RF) and extreme gradient boosting (XGBoost) have achieved superior accuracy in modeling ecosystem functions and predicting carbon dynamics across urban ecosystems [17, 18]. However, these methods typically operate as static, single-model frameworks with limited adaptability to heterogeneous park conditions. Despite increasing global interest in carbon-neutral urban development, existing assessment frameworks often lack precision and adaptability for complex city ecosystems. Conventional approaches either rely solely on empirical field data or use simplified statistical assumptions, which restrict their accuracy in heterogeneous landscapes. Therefore, a scientifically grounded, data-driven modeling system is required to capture the spatial and temporal variability of carbon sequestration in urban parks.

This study proposed a hybrid coral reefs optimizer–scalable random forest (HCRO–SRF) model that integrated ecological simulation, remote sensing, and optimization-based learning to dynamically adjust vegetation structure and spatial configuration and maximize carbon sequestration efficiency, thereby offering a scalable and adaptive framework for sustainable urban-park management and accurately quantification and enhancement of carbon sequestration potential in urban parks. The research classified biotopes within the park and estimated net primary productivity and biomass, which not only advanced methodological integration between ecological simulation and optimization techniques but also provided a transferable framework to support urban carbon-management policies and climate-resilient city planning.

Materials and methods

Data collection

The data of this research was collected from urban parks within Qiqihar City, Heilongjiang, China (47.34° N, 123.91° E) from 2019 – 2024 through satellite imagery, LiDAR processed using PDAL library (https://pdal.io/) and visualized in CloudCompare (https://www.danielgm.net/cc/), NDVI derived from Sentinel-2 data *via* the Google Earth Engine (https://earthengine.google.com/), NPP model adapted from the InVEST Carbon Storage and Sequestration module (https://naturalcapitalproject.stanford.edu/software/invest) and biomass data were also collected through field examinations and environmental monitoring stations. Additionally, park design features such as species selection and planting density were analyzed through onsite observations and municipal park planning documents. LiDAR canopy data, Sentinel-2 NDVI imagery, soil and land-use geographic information system (GIS) layers, and meteorological variables were harmonized to a 10 m resolution under world geodetic system (WGS) 84 for consistent spatial analysis.

Data preprocessing using Savitzky-Golay filter

All data were preprocessed using the Savitzky-Golay (SG) filter implemented using the SciPy library in Python (https://scipy.org/) for noise reduction of environmental park sensor data while maintaining key pattern detection. The integration of noise elimination techniques with data form preservation could optimize the data's utilization of patterns while effectively minimizing random image data variations. The SG filter moved the window to filter data by using the least squares combining approach. A window array was created with the origin w_j at its centre that contained $2N+1$ sample points for fitting using the N sampling points surrounding the original data w. The fitted polynomial M was shown as below.

$$o(m) = \sum_{l=0}^{M} b_l m^l - N \leq m \leq N, M \leq 2N+1 \quad (1)$$

where m^l was a data point within the window. $2N+1$ was the breadth of the chosen fitting window. Each filtering window's convolution coefficients for the data m^l were given by b_l. The filtered result was $o(m)$as follows.

$$\varepsilon_M = \sum_{m=-N}^{M}(o(m) - w[m])^2 = \sum_{m=-N}^{N}(\sum_{l=0}^{M} b_l m^l - w[m])^2 \quad (2)$$

By adjusting the window array, all the original data's fitted points were found. The noise component in the fitting process fluctuated a lot compared to the normal value. The initial sequence entered run through the SG filter in the data preparation module to obtain polynomial solutions that matched the local data of the chosen window, therefore, smoothing the data.

HCRO-SRF

The HCRO-SRF was a novel AI-based framework designed to enhance carbon sequestration in urban parks by utilizing global search mode from coral reefs optimizer (CRO) and predictive power from scalable random forest (SRF) to optimize plant composition arrangements and environmental conditions, which maximized CO_2 absorption. The model was implemented in Python based on open-source metaheuristic frameworks (https://github.com/). This iterative learning and hybrid optimization system established sustainable urban planning by discovering powerful green strategies and boosting environmental strength. The data-advanced system delivered quantitative procedures to urban policymakers for optimization of green infrastructure functions and sustainably addressing climate change challenges in urban regions.

SRF

SRF functions was a tool for urban park carbon sequestration analysis through examination of various ecological and spatial and climatic data, which had adaptability for handling massive urban data collections to enhance the selection of tree species and improve methods for soils and plan vegetation management. SRF aided in optimizing urban greening strategies to maximize carbon capture and support sustainable city development. Random forest (RF) was a combinatorial classifier for sub-datasets creation by extracting additional samples from the original samples *via* Bootstrap re-sampling [19]. The variety was then increased by creating a basic decision tree and training it with randomly chosen characteristics for every node. Bootstrap verification was then used to merge the decision trees, and the classification outcomes were voted for better performance. The essential step of RF algorithm was node splitting. The nodes could be divided to create a full decision tree. A set of splitting rules determined every tree's branch formation. These guidelines primarily consisted of the lowest Gini index, the maximum information gain, and the maximum information gain rate. An attribute was then selected to be divided. Depending on its division, the decision tree's branch development was achieved. As the partitioning process proceeded, the purity of the nodes continuously increased, which meant that the samples included belonged to the same category as much as possible. The adaptive parameter selection procedure was used to carry out the decision tree node splitting. Decision trees generated by various node-splitting techniques differed in their characteristics. Choosing the optimal attribute to separate nodes and breaking the method up into a linear combination was the optimal solution. Due to the integration of iterative dichotomiser 3 (ID3) and classification and regression tree (CART) executed using the Scikit-learn library (https://scikit-learn.org/) with the random forest method, node splitting optimization was taken into consideration for both techniques. The information gain and Gini index were derived through dividing the sample set C by characteristics and were displayed using node splitting as follows.

$$Gain(C,b) = Ent(C) - \sum_{u=1}^{U} \frac{|C^u|}{|C|} Ent(C^u) \quad (3)$$

$$Gini(C,b) = \sum_{u=1}^{U} \frac{|C^u|}{|C|} Gini(C^u) \quad (4)$$

where C^u denoted that every sample in the C with an amount of u, b on the characteristic was contained in the b^u branch node as presented below.

$$Ent(C) = -\sum_{l=1}^{|z|} o_l log_2 o_l \quad (5)$$

$$Gini(C) = \sum_{l=1}^{|z|} \sum_{l' \neq l} olol' = 1 - \sum_{l=1}^{|z|} ol^2 \quad (6)$$

Node splitting should be based on the greater purity of the dataset after division. Therefore, the combination of the nodes splitting and the adaptive parameter selection procedure was shown below.

$$G = \min_{\alpha,\beta \in Q} E\{C,b\} = \alpha Gini(C,b) - Gain(C,b) \begin{cases} \alpha + \beta = 1 \\ 0 \leq \alpha, \beta \leq 1 \end{cases} \quad (7)$$

where α and β were the weight factors of attribute splitting. Meanwhile, G had a very low value. To find the ideal combination of parameters, the adaptive selection of parameters was used, which indicated that the best node partitioning criteria to enhance the classification impact were ID3 and CART. Performance was evaluated for assessing and enhancing carbon sequestration. The sample C's classification error rate and the accuracy rate were shown as follows.

$$F(e;C) = \frac{1}{n} \sum_{j=1}^{n} JJ\left(e(w_j) \neq z_j\right) \quad (8)$$

$$acc(e;C) \frac{1}{n} \sum_{j=1}^{n} JJ\left(e(w_j) = z_j\right) = 1 - F(e;C) \quad (9)$$

The structural design of the scalable random forest (SRF) involved multiple decision trees trained on bootstrapped datasets with randomly selected feature subsets. The final classification was obtained by majority voting among all trees, enhancing robustness and reducing overfitting.

HCRO

The hybrid coral reefs optimizer (HCRO) was applied to optimize ecological and spatial parameters influencing carbon sequestration within urban parks. Although biologically inspired by coral reef formation, in this context each “coral” represented a candidate solution that defined vegetation type, planting density, and spatial arrangement in the park. The “reef” denoted the solution space containing all feasible combinations of ecological parameters, and the "health function" evaluated each configuration based on its predicted carbon-sequestration efficiency derived from the simulation model. Through iterative adaptation and replacement of less efficient solutions, the HCRO progressively refined vegetation configurations to maximize CO_2 absorption and biodiversity retention. This algorithm supported data-driven park design and complemented the SRF predictive model by enhancing optimization accuracy and convergence stability.

Model validation

The proposed HCRO-SRF model was validated by comparing with the traditional models of RF implemented *via* the Scikit-learn library (https://scikit-learn.org/) and XGBoost (https://xgboost.ai/) algorithms. RF was an ensemble learning method that constructed multiple decision trees to improve prediction accuracy and control overfitting, while XGBoost was an optimized distributed gradient boosting framework widely used for high-performance predictive modeling. Model accuracy was evaluated using three standard statistical indicators including coefficient of determination (R^2) measuring the proportion of variance in observed data explained by model predictions, root mean square error (RMSE) quantifying the average magnitude of prediction errors with the lower values indicating higher accuracy, mean absolute error (MAE) representing the mean of absolute deviations between predicted and observed values. These metrics jointly assessed the predictive reliability and robustness of the HCRO-SRF model compared with other methods.

Results and discussion

Improvement in carbon sequestration

The proposed HCRO-SRF model integrated spatial data including vegetation indices, satellite imagery, and LiDAR, classified biotopes, and estimated carbon sequestration by analyzing vegetation features like shrubs and small trees. The dynamic assessment revealed a 20% improvement in carbon sequestration by 2024, demonstrating the model's effectiveness in optimizing urban park planning for climate resilience. The temporal analysis of carbon sequestration from 2019 to 2024 revealed a consistent improvement following model-based optimization. The results demonstrated that the baseline conditions in 2019 showed moderate sequestration across most park areas. After the first optimization cycle in 2021, carbon capture performance increased noticeably, and by 2024, a ~20% enhancement was observed across all monitored parks. These results confirmed that the proposed HCRO-SRF model effectively improved vegetation composition and spatial layout to enhance long-term carbon storage capacity in urban ecosystems.

Biomass in urban parks

From 2019 to 2024, urban parks demonstrated a steady increase in NPP and biomass, reflecting enhanced carbon uptake. NPP rose from 3.2 to 4.5 tons C/ha/year, while biomass grew from 45.8 to 57.0 tons C/ha (Figure 1). Carbon sequestration efficiency improved from 75% to 88%, indicating better ecosystem performance. To optimize this trend, the HCRO-SRF model was applied to integrate evolutionary optimization with scalable machine learning and identify key ecological and management factors driving sequestration, supporting targeted interventions and sustainable strategies for maximizing carbon capture in urban green spaces.

Model validation

The fraction of variability in urban carbon sequestration efficiency explained by model parameters was represented by the R^2 values for biomass accumulation and CO_2 absorption rates. The proposed HCRO-SRF model achieved an R^2 of 0.94, outperforming existing methods of RF model with an R^2 of 0.83 and the XGBoost model with an R^2 of 0.89, demonstrating its superior capability in optimizing ecosystem services and carbon capturing potential in urban park environments (Figure 2A). The RMSE value in the context of urban carbon sequestration modeling

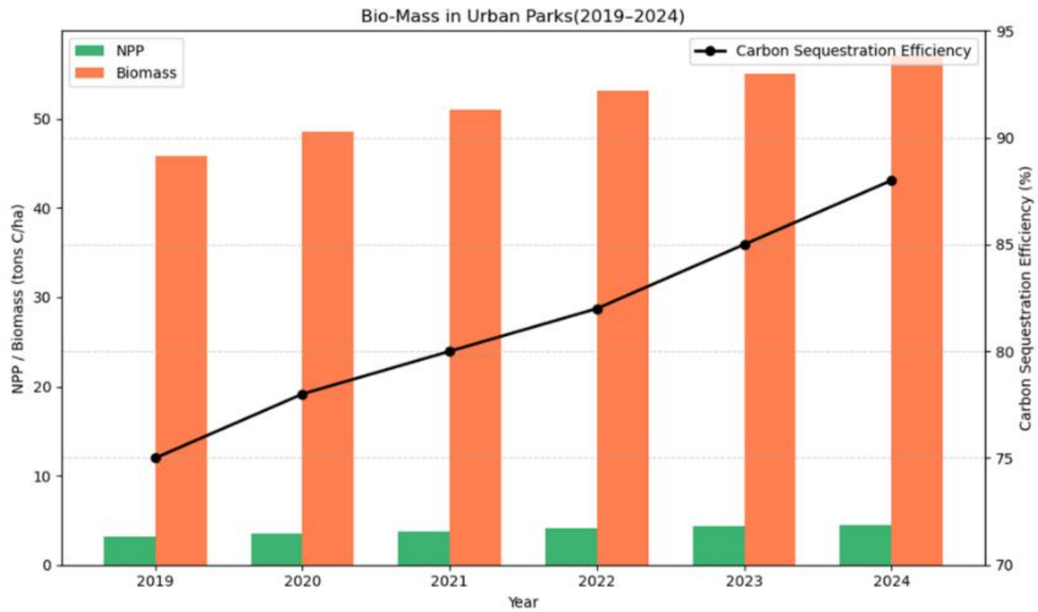

Figure 1. Biomass in urban parks.

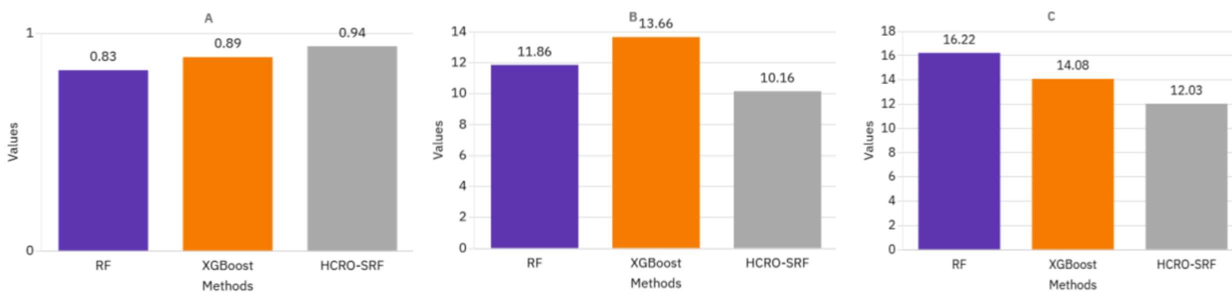

Figure 2. Performance comparison of different models in evaluating urban-park carbon sequestration. **A**. coefficient of determination (R^2). **B**. mean absolute error (MAE). **C**. root mean square error (RMSE).

reflected the accuracy of predictive assessments related to vegetation growth, CO_2 absorption rates, and ecosystem services within urban parks. The proposed HCRO-SRF model achieved an RMSE of 12.03 tons per hectare (t/ha), significantly outperforming the baseline RF and XGBoost approaches, which recorded a higher RMSE of 16.22 and 14.08, demonstrating the model's superior capability in accurately capturing complex ecological interactions for maximizing carbon sequestration in urban green spaces (Figure 2B). The MAE for the real-time edge computing model quantified the average absolute differences between predicted and actual carbon sequestration values in urban park ecosystems, reflecting the system's accuracy in processing environmental sensor data and modeling vegetation dynamics. The proposed HCRO-SRF model achieved an MAE of 10.16, outperforming RF's 11.86 and XGBoost's 13.66, thereby enhancing estimation accuracy, supporting data-driven urban greening strategies, and improving operational efficiency in sustainable urban planning and carbon management (Figure 2C). These results confirmed that the proposed HCRO-SRF model provided more accurate and stable estimates of carbon dynamics in urban-park ecosystems compared with conventional machine-learning approaches.

The hybrid simulation–optimization framework (HCRO-SRF) proposed in this study successfully integrated remote sensing, ecological modeling, and intelligent optimization to enhance the carbon-sequestration capacity of urban parks. By combining LiDAR, vegetation indices, and spatiotemporal modeling from 2019 to 2024, the proposed model achieved high predictive accuracy. The optimized planting configurations identified by the HCRO-SRF algorithm demonstrated measurable improvements in biomass accumulation and net primary productivity. These findings provided actionable insights for urban planners seeking to balance ecological functions and emission reduction targets. Future developments may incorporate real-time sensor networks and multi-agent landscape planning systems to further enhance adaptability and resilience in urban-green-infrastructure management.

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