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Article

Optimization of digital landscape design system based on biomechanical simulation and machine learning algorithm in landscape architecture planning

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Abstract: This paper presents a digital landscape design system that integrates biomechanical simulation and machine learning algorithms for improved vegetation growth prediction and environmental adaptability. Using finite element analysis (FEM) and the GreenLab model, the system simulates plant growth dynamics, while deep learning and genetic algorithms optimize landscape layouts. The system improves vegetation stability, wind resistance, and ecological efficiency, providing a more accurate and efficient approach to intelligent landscape planning.

Keywords: landscape planning; biomechanical simulation; machine learning optimization

1. Introduction

Landscape planning plays a key role in ecological sustainability, but traditional methods face limitations in predicting vegetation growth and optimizing environmental adaptation. This study proposes an integrated digital landscape design system using biomechanical simulations and machine learning algorithms. By combining finite element analysis, the GreenLab plant growth model, and deep learning, the system predicts vegetation behavior and optimizes landscape layouts for enhanced stability and ecological adaptability.The integration of Geographic Information System (GIS) and Building Information Modeling (BIM) provides a dynamic, interactive platform for real-time landscape adjustments, offering a more precise approach to sustainable landscape design.

2. Relevant technology base

A. Biomechanical simulation techniques

Biomechanical simulation techniques are mainly used in landscape planning to study the mechanical characteristics of plant growth in order to optimize the stability and ecological adaptability of landscape design. The mechanical characteristics of plant growth can be simulated by finite element analysis (FEM), L-system fractal modeling and the GreenLab model [1]. Plant growth is affected by gravity, wind load, soil support, etc., where the deformation of the trunk and branches can be described by the Euler-Bernoulli beam theory, whose basic equation is Equation (1):

$$EI\frac{d^4w}{dx^4}=q(x) \tag{1}$$

where E is Young's modulus, I is the moment of inertia of the cross-section, w is the deflection, and $q(x)$ is the external load (e.g., wind action).

Wind load effects can be modeled by calculating the airflow distribution through the Navier-Stokes equations, combined with the flexible deformation of the tree Equation (2):

$$\rho\left(\frac{\partial u}{\partial t}+u\cdot\nabla p\right)=-\nabla p+\mu\nabla^2 u+F \tag{2}$$

where ρ is the air density, u is the wind speed, μ is the fluid viscosity, and F is the external force term. Combining these mechanical models can optimize the tree planting layout, improve the wind resistance of the vegetation, and enhance the stability and biological adaptability of the landscape.

B. Machine learning algorithms

Machine learning algorithms are mainly used in digital landscape design for vegetation growth prediction, environmental adaptation analysis and optimal layout. Commonly used supervised learning methods include support vector machines (SVMs), random forests (RFs), and deep neural networks (DNNs), among which support vector machines are used for the plant growth classification problem with the optimization objective of minimizing the loss function Equation (3):

$$\min \frac{1}{2}\|w\|^2+C\sum_{i=1}^{n}\ \xi i \tag{3}$$

where w is the classification hyperplane parameter, ξi is the slack variable, and C is the penalty coefficient.

The deep neural network optimizes the weights by means of a backpropagation algorithm (backpropagation) and the error function is calculated by the mean square error (MSE) Equation (4):

$$MSE=\frac{1}{n}\sum_{i=1}^{n}\ (y_i-\hat{y}_i)^2 \tag{4}$$

where y_i is the true value and $\hat{y}_i$ is the predicted value.

Convolutional Neural Network (CNN) can be used for remote sensing image recognition and the convolution is calculated as follows (Equation (5)):

$$Z=\sum_{i=0}^{m}\ \sum_{j=0}^{n}\ X_{i,j}K_{i,j} \tag{5}$$

where, $X_{i,j}$ is the input image pixel and $K_{i,j}$ is the convolution kernel.

Reinforcement learning can be used to optimize landscape layout and update decisions based on the policy gradient approach (Equation (6)):

$$\theta=\theta+\alpha\nabla_{\theta}J(\theta) \tag{6}$$

where α is the learning rate and $J(\theta)$ is the strategy function. Through these algorithms, the system can optimize the plant configuration according to meteorological, soil and other data to improve the adaptability and ecological efficiency of landscape design.

Reinforcement learning reward design: The reinforcement learning (RL) algorithm was utilized to optimize the landscape layout by dynamically adjusting plant species, density, and distribution based on environmental conditions. The reward function was designed to maximize ecological stability, aesthetic quality, and environmental adaptability. The primary factors influencing the reward function include:

Ecological stability: A higher reward is given for configurations that result in more stable plant growth, such as reduced wind resistance and improved water utilization.

Aesthetic quality: Aesthetic preferences are incorporated by adjusting the layout to ensure visually appealing plant arrangements.

Environmental adaptability: Rewards are based on how well the layout adapts to various climatic and environmental conditions, such as temperature fluctuations, soil moisture levels, and wind conditions.

The system uses a policy gradient method to continuously adjust the landscape configuration, aiming to balance these competing objectives to ensure both ecological sustainability and aesthetic value.

C. Digital landscape design system

The digital landscape design system realizes vegetation growth prediction, ecological adaptation optimization and intelligent layout decision-making by integrating biomechanical simulation, machine learning algorithms and environmental data analysis. The system mainly consists of four modules: data acquisition, simulation calculation, intelligent optimization and visualization interaction. For data acquisition, remote sensing images, LIDAR scanning, and meteorological sensors are used to obtain soil moisture, light intensity, wind speed, and vegetation growth data, and normalization and feature extraction are performed [2]. The simulation calculation uses finite element analysis (FEM) to simulate the morphological changes of trees under wind and gravity, and combines it with the GreenLab model to predict the plant growth pattern. Intelligent optimization is based on deep learning (DNN) and genetic algorithm (GA), which automatically adjusts the vegetation type, density and spatial layout to improve ecological stability. Visualization adopts GIS + BIM integration to present the dynamic growth process in real time, and users can interactively adjust the parameters and observe the impact of different scenarios on the landscape structure. The system can be widely used in urban greening, ecological restoration and park planning to improve the scientific and environmental adaptability of landscape design.

3. Overall system framework design

A. System architecture design

The system architecture design is based on the four core modules of data acquisition, simulation and calculation, intelligent optimization, and visualization and interaction, and the combination of cloud computing and edge computing is used to achieve efficient data processing and dynamic simulation [3]. The whole system architecture adopts a three-layer structure, including data layer, computing layer and application layer, to ensure the scientific and real-time interactivity of landscape design. The details are shown in **Figure 1**.

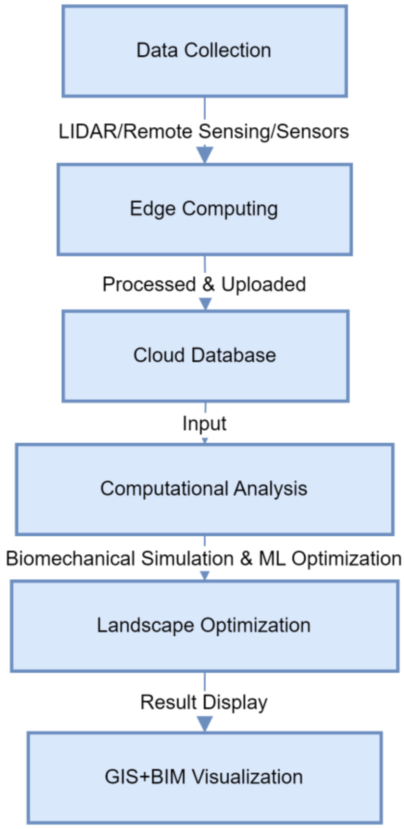

Figure 1. Flowchart of system architecture design.

The data layer is responsible for the collection and storage of multi-source data, including LIDAR point cloud data, remote sensing images, weather sensor data (wind speed, temperature and humidity, light), soil sensor data (humidity, pH, nutrient content), and historical vegetation growth records. The data undergoes preliminary processing (denoising, normalization, feature extraction) at the edge computing terminal and is then uploaded to the cloud database; the computing layer contains a biomechanical simulation module and a machine learning optimization module. The biomechanical simulation uses finite element analysis (FEM) and GreenLab model to simulate the growth pattern and environmental adaptability of trees, lawns, flowers, and other plants, and calculates the effects of wind load, precipitation, and soil moisture on the stability of vegetation through environmental simulation [4]. The machine learning module uses deep neural networks (DNN) to predict plant growth trends and optimizes the landscape layout through genetic algorithms (GA) to improve ecological adaptability; the application layer provides a GIS + BIM integrated visualization interface, which allows users to adjust parameters (e.g., tree species distribution, density, and light conditions) on an interactive design platform, observe the simulation results in real time, and generate the optimal landscape layout through an optimization algorithm. The optimal landscape layout is generated by an optimization algorithm, which ensures that the landscape design not only meets the aesthetic demand, but also has ecological sustainability.

B. Design of key technology modules

The design of key technology modules revolves around four core links: data acquisition, simulation, intelligent optimization, and visualization and interaction, in order to achieve high-precision vegetation growth prediction, ecological adaptability assessment, and optimal landscape layout.

Data acquisition and preprocessing module: This module collects ecological data such as wind speed, light, humidity, soil pH, nutrients, etc. through remote sensing imagery, LIDAR scanning, weather stations and soil sensors [5]. Computer vision techniques were used to resolve the vegetation structure, and the vegetation growth dynamics data were processed through time series analysis. After data cleaning and normalization, it was input into the simulation and optimization module. The biomechanical simulation module, which is based on finite element analysis (FEM) and the GreenLab model, simulates the stress state and morphological changes of plants, focusing on the resistance of trees to fall under wind load, the soil support of the root system, and calculates transpiration and soil moisture balance by combining with the water transport model. The machine learning optimization module, using deep neural network (DNN), random forest (RF), genetic algorithm (GA) and other methods, predicts the vegetation growth trend, soil nutrient changes, and optimizes the vegetation configuration. Reinforcement learning techniques can further train landscape layout strategies to adapt to different climatic environments and improve ecological stability. Interactive visualization module, based on GIS + BIM technology to build a dynamic visualization platform, providing real-time data feedback, 3D growth simulation and interactive landscape layout adjustment, supporting users to dynamically regulate plant species, density, light and other parameters to generate the optimal landscape scheme.

The deep neural network (DNN) used in this system is a fully connected feedforward network designed to predict vegetation growth trends, including tree height and leaf area index (LAI). The architecture consists of three main components:

Input layer: The input layer consists of features such as meteorological data (temperature, humidity, wind speed), soil data (moisture, pH), and vegetation data (leaf area, biomass). These inputs are normalized before being fed into the network.

Hidden Layers: The network includes three hidden layers with 128, 64, and 32 neurons respectively. Each layer uses the ReLU activation function to introduce non-linearity and improve the model's ability to capture complex relationships in the data.

Output layer: The output layer consists of a single neuron that predicts the tree height or LAI. The output is continuously updated during training to minimize the error between predicted and actual values using a mean squared error (MSE) loss function.

The DNN was trained using a dataset of 10,000 samples derived from remote sensing images and field data. The model's performance was evaluated using root mean square error (RMSE) and coefficient of determination (R^2). The architecture was optimized using backpropagation with an Adam optimizer, and hyperparameters such as learning rate and batch size were tuned using grid search and Bayesian optimization techniques. For better visualization, the DNN architecture is illustrated in **Figure 1**, which shows the connections between input, hidden, and output layers, as well as the activation functions used in each layer.

4. Biomechanical simulation module

A. Vegetation growth simulation

Vegetation growth simulation is mainly based on biomechanical modeling and dynamic simulation of environmental factors, which is used to accurately predict the growth morphology, mechanical stability and interaction with the surrounding ecological environment. This module combines L-system fractal modeling, GreenLab modeling, and finite element analysis (FEM) to simulate the mechanical properties of plant structures, and introduces physiological mechanisms such as water transport and photosynthesis to make the growth simulation more in line with natural laws [6].

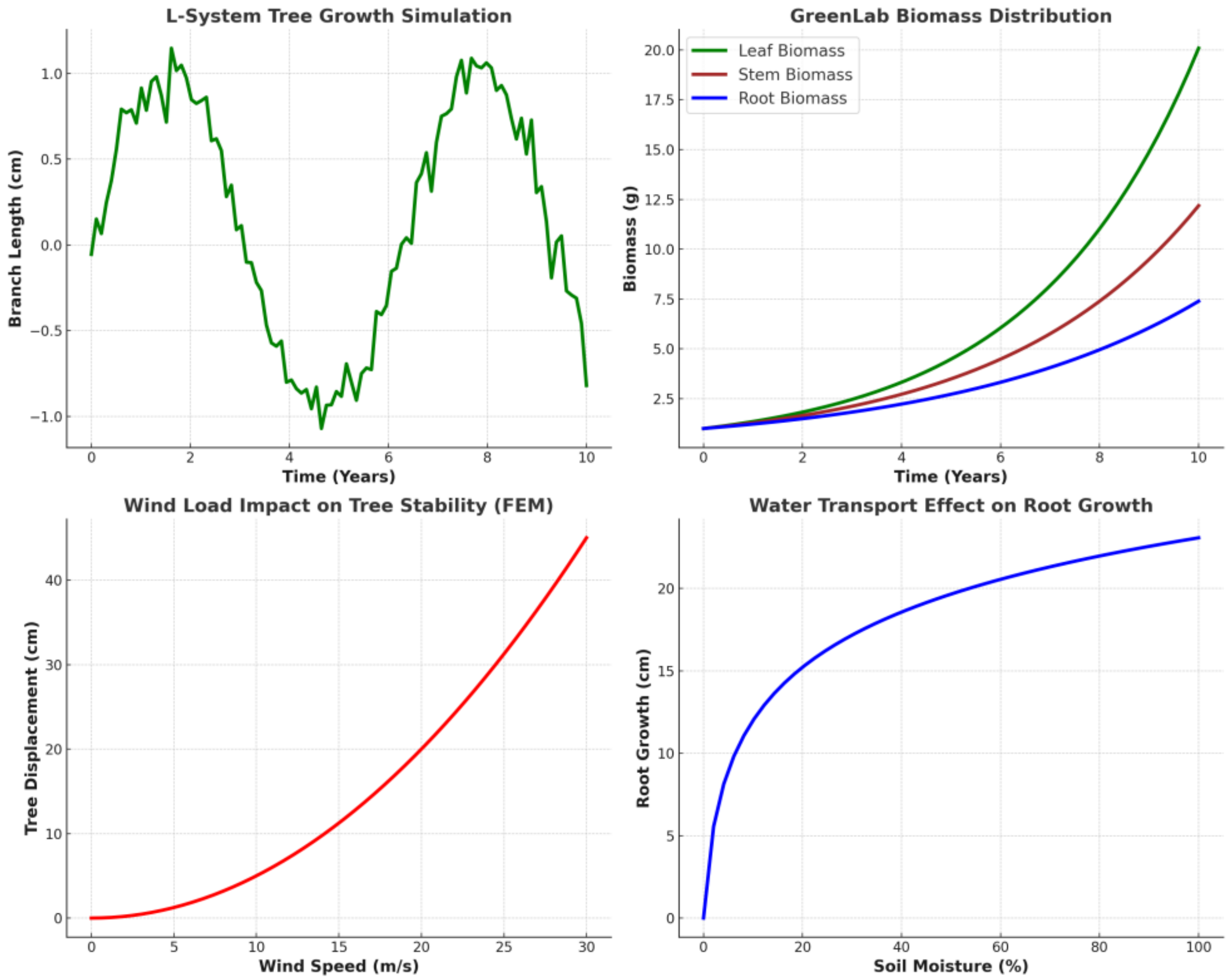

Figure 2. Four key processes in vegetation growth simulation.

Structural growth simulation, using L-system modeling to simulate the branching structure of plants, combined with the GreenLab model to establish the dynamic growth relationships of leaves, branches and roots. The GreenLab model is based on the source-store theory of plant growth, calculating the distribution of photosynthetic substances among different organs, so as to predict the process of leaf unfolding, branch extension, trunk thickening and so on. Mechanical stability simulation, using finite element analysis (FEM) to calculate the deformation and stability of plants under wind load, gravity, and soil support force. During the simulation, material properties (Young's modulus, Poisson's ratio), environmental loads (wind speed, precipitation) were set, and the wind resistance and the risk of toppling of the trees under different environmental conditions were analyzed [7]. Environmental adaptation simulation, based on light distribution, water transport, temperature and humidity changes, simulates the growth rate and ecological adaptation of vegetation. The Fick diffusion equation was introduced to calculate the water transfer rate between the soil-root system, and combined with the photosynthetically active radiation (PAR) calculation to adjust the plant growth model to adapt to different climatic conditions. The vegetation growth simulation results will be combined with the machine learning optimization module to achieve dynamic adjustment of the vegetation layout to improve the overall ecological adaptability and landscape design rationality. Details are shown in **Figure 2**.

Figure 2 illustrates the four key processes of vegetation growth simulation. The top left corner shows the L-System simulation of tree fractal growth, demonstrating changes in branch length over time, showing a dynamic growth trend in plant structure. The top right corner shows the GreenLab model of photosynthesis material distribution, demonstrating an exponential increase in biomass of leaves, trunks, and root systems over time, consistent with the distribution of plant photosynthetic products. The lower left corner demonstrates the effect of wind loading on tree stability (FEM analysis), and the curve shows a significant increase in trunk deformation with increasing wind speed, verifying the effect of wind loading on the mechanical stability of trees [8]. The lower right corner depicts moisture transport affecting root growth (Fick diffusion model), indicating that the higher the soil moisture, the faster the root growth, consistent with the key regulatory role of moisture on plant growth. The overall image data visualize the influence of biomechanical and environmental factors on vegetation growth.

B. Simulation of environmental factors

Environmental factors simulation mainly models the effects of meteorological conditions, soil properties and external disturbances on plant growth to improve the ecological adaptability of digital landscape design. This module combines climate data analysis, moisture transport modeling, light simulation and external load calculation to create an integrated environmental response system for vegetation growth [9].

Meteorological factor simulation, using historical meteorological data and real-time monitoring information, including temperature, humidity, wind speed, precipitation, light intensity, carbon dioxide concentration and other parameters, to establish a model of the impact of long-term climate change on vegetation growth. The relationship between temperature and photosynthesis rate can be simulated with the Arrhenius equation, and the effect of precipitation on plant water utilization is predicted by combining it with the soil moisture dynamic model. Moisture transport simulation, based on the Fick diffusion equation to simulate the water transport process in the soil-root system-leaf, calculates the relationship between root water absorption capacity and transpiration. The model takes into account variables such as soil water potential (ψ) and transpiration pull (T) so that the vegetation can adapt to different humidity environments. Light impact simulation, using the photosynthetically active radiation (PAR) model to calculate the growth rate of plants under different light conditions and combining it with a canopy transmittance model to assess the community light distribution [10]. For wind load and external disturbance, the bending deformation of trees by wind speed was calculated based on the Navier-Stokes equation, and combined with finite element analysis (FEM) to predict the risk of tree collapse under strong winds. The effects of soil erosion and slope stability changes on plant growth are simulated to improve the long-term stability of the landscape. Combining the simulation of these environmental factors, the system is able to accurately adjust the vegetation layout, optimize the ecological adaptability, and predict the long-term landscape evolution trend. Details are shown in **Figure 3**.

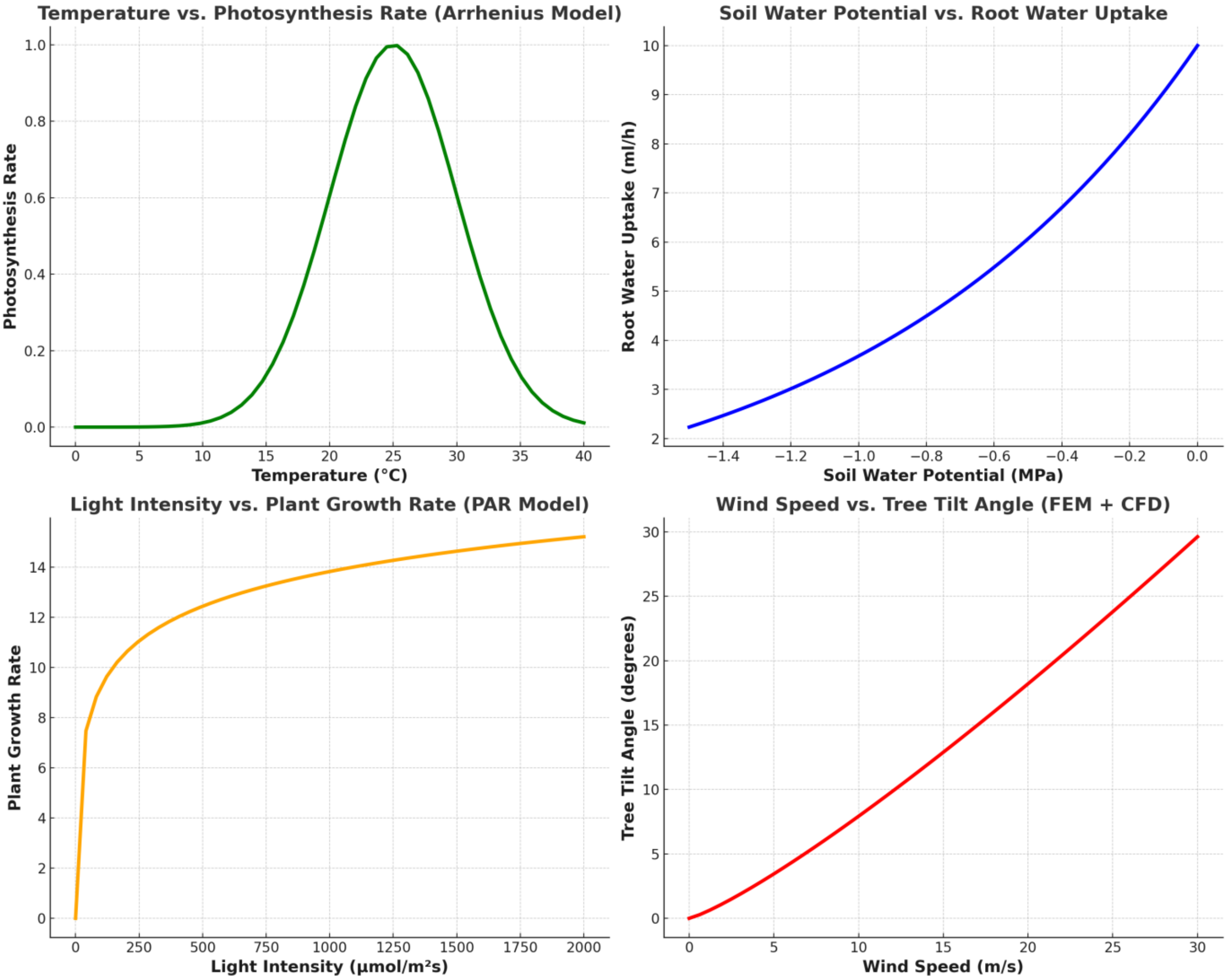

Figure 3. Key effects of environmental factors on plant growth.

Figure 3 demonstrates the key effects of environmental factors on plant growth. The upper left corner shows the effect of temperature on the rate of photosynthesis based on the Arrhenius equation, which indicates that photosynthesis peaks at around 25 °C, and that either too high or too low reduces plant growth efficiency. The upper right corner shows the effect of soil water potential on root water uptake capacity as modeled by Fick's diffusion equation, which indicates that when water potential decreases (i.e., soil drought), the plant's ability to take up water decreases drastically, affecting growth stability. The lower left corner is based on the photosynthetically active radiation (PAR) model, indicating that increased light intensity promotes plant growth, but the rate of increase slows down when the saturation value is reached. The lower right corner combines the Navier-Stokes equation with finite element analysis (FEM) to simulate the effect of wind speed on tree stability, showing that the higher the wind speed, the larger the tilt angle of the tree, indicating limited wind resistance. The overall data provide a scientific basis for optimizing the landscape design.

C. Simulation algorithm optimization

The simulation algorithm optimization mainly focuses on biomechanical simulation, environmental factor modeling and landscape layout optimization to improve the accuracy and ecological adaptability of plant growth prediction. Optimization methods such as finite element analysis (FEM), fluid dynamics simulation (CFD), genetic algorithm (GA) and deep neural network (DNN) are used to improve the efficiency and reliability of simulation calculation [10].

Finite element and hydrodynamic optimization: In FEM simulation, adaptive mesh refinement technology is introduced to locally encrypt high-stress areas (e.g., trunk roots, wind-loaded surfaces) to improve the calculation accuracy and reduce the calculation cost. In the hydrodynamic (CFD) simulation of wind load effects, a turbulence model (k-ε model) is used to optimize the wind speed distribution calculation and improve the accuracy of wind load prediction.

Machine learning optimization, deep neural network (DNN) combined with historical data on vegetation growth, supervised learning to predict growth trends in different environments, and Bayesian optimization to automatically adjust hyperparameters to improve the generalization ability of the model. Reinforcement learning (RL) is used to dynamically optimize the landscape layout to make it more adaptable to long-term environmental changes.

Genetic algorithm for optimizing landscape configuration, genetic algorithm (GA) is used for optimal vegetation layout calculation to optimize plant species, density, and spatial distribution through evolutionary mechanisms such as selection, crossover, and mutation [11]. The fitness function combines factors such as light distribution, water competition, and wind load resistance to ensure that the layout is both aesthetically pleasing and ecologically stable.

5. Machine learning optimization module

A. Data acquisition and preprocessing

Data acquisition and pre-processing mainly include environmental data, vegetation growth data and geographic information data to ensure the accuracy and reliability of input data for simulation and optimization models. Environmental data are collected by weather stations, soil sensors, remote sensing images and other equipment, including temperature, humidity, light, wind speed, soil water potential and other parameters. Vegetation growth data were acquired by LIDAR scanning, UAV remote sensing for tree height, leaf area index (LAI) and biomass [11]. In data preprocessing, denoising, normalization, missing value filling, and dimensionality reduction using principal component analysis (PCA) were performed to improve computational efficiency. The details are shown in **Table 1**.

Table 1. Example of data acquisition.

Data type	Acquisition method	Key parameters	Sampling frequency	Tolerance range
Meteorological data	Weather stations	Temperature, humidity, wind speed, precipitation	10 min/time	± 0.5 °C
Soil data	Sensors, sampling and analysis	pH, water potential, nutrients	30 min/times	± 5%
Remote sensing data	LIDAR, drones	Vegetation cover, LAI	1 day/session	± 2%
Topographic data	GIS, satellite imagery	Slope, elevation, soil type	1 week/session	± 3 m

B. Model training and validation

Model training and validation are mainly through machine learning algorithms to predict vegetation growth trends and optimize landscape layout. The training data were derived from historical vegetation growth data, remote sensing images, and meteorological records, and supervised learning (random forest, deep neural network) was used for training [12]. During the training process, the dataset was divided according to 80% training set and 20% test set, and K-fold cross-validation (K = 5) was used to evaluate the model performance. See **Table 2** for details.

Table 2. Model training and validation results.

Model type	Training set data volume	Test set data volume	Evaluation indicators	RMSE	R^2
Random forest (RF)	10,000	2000	Predicted tree height	0.52	0.91
Deep neural networks (DNN)	10,000	2000	Predicted leaf area index (LAI)	0.68	0.87
Support vector machines (SVM)	10,000	2000	Predicting soil moisture	0.45	0.89

The model validation used root mean square error (RMSE), and coefficient of determination (R^2) to measure the accuracy. The results showed that the random forest performed best in tree height prediction (R^2 = 0.91), while the deep neural network had a slight error in LAI prediction, which could be further optimized by adjusting the hyperparameters. Finally, the optimal model was selected for landscape optimization decisions.

C. Parameter optimization strategy

The parameter optimization strategy plays a crucial role in the process of vegetation growth simulation and machine learning model training. In order to improve the accuracy and computational efficiency of the model, parameter optimization mainly focuses on biomechanical simulation parameters, machine learning model hyperparameters, and environmental adaptation optimization parameters, using grid search, Bayesian optimization, genetic algorithms, and other methods [13].

In biomechanical simulation, key parameters of vegetation growth, such as trunk Young's modulus, root distribution depth, and wind load coefficient, were optimized to improve the model's adaptability to environmental perturbations. Finite element analysis (FEM) was used to perform sensitivity analysis of different parameter combinations to assess the vegetation structural stability [14]. In the wind load simulation, a k-ε turbulence model was introduced to optimize the calculation of fluid forces and make the wind speed distribution more accurate. In the soil water potential simulation, the permeability coefficient in the Fick diffusion equation was adjusted to ensure that the water transport calculation was more realistic.

Hyperparameters such as learning rate, tree depth, batch size, activation function, etc., are optimized during the training process of the machine learning model to improve the prediction accuracy and avoid overfitting. Grid Search is used to exhaustively test different combinations of hyperparameters and adaptively adjust the search space in combination with Bayesian optimization to reduce the amount of computation [15]. For example, in deep neural network (DNN) training, the initial learning rate is set to 0.01 and gradually adjusted to 0.001 to balance the convergence speed and training stability. Regularization parameters (e.g., L2 regularization coefficients) are optimized in the range of [0.0001, 0.01] to reduce model complexity and prevent overfitting. In random forest (RF) optimization, the number of decision trees (n_estimators) and the maximum depth (max_depth) are adjusted to ensure that complex relationships are captured without leading to excessive computational overhead [16].

In terms of environmental adaptability optimization, a genetic algorithm (GA) is introduced to optimize the spatial layout of vegetation so that it can maximally adapt to the environmental conditions while satisfying landscape aesthetics. When optimizing the fitness function, ecological factors such as light distribution, water competition, wind load influence, etc., are considered comprehensively, and the layout scheme is continuously improved through the selection, crossover, and mutation mechanisms of the genetic algorithm. For example, when optimizing the vegetation density, the spacing of trees is constrained to be greater than 2 m to avoid excessive shading and to maintain reasonable soil nutrient competition. When optimizing tree species matching, the planting ratio is adjusted based on growth rate, root development pattern and other characteristics to improve ecological stability [17].

The comprehensive use of biomechanical simulation parameter optimization, machine learning hyperparameter optimization and genetic algorithm environmental adaptability optimization can effectively improve the accuracy and feasibility of vegetation growth simulation and ensure that the digital landscape design system can maintain efficient and stable operation under different environmental conditions.

6. System integration and performance evaluation

A. System integration realization

The system integration achieves the construction of a complete digital landscape design system by integrating four modules: data acquisition, simulation, machine learning optimization, and visualization interaction. The data acquisition module utilizes LIDAR, remote sensing images, and meteorological sensors to obtain information such as vegetation growth data, soil moisture, and meteorological conditions, and carries out data preprocessing through edge computing to improve computational efficiency.

The simulation module uses Finite Element Analysis (FEM), Fluid Dynamics (CFD), and GreenLab models to simulate vegetation growth dynamics and predict environmental adaptations such as wind load impact, root stability, and water transport. The machine learning optimization module combines deep learning (DNN), random forest (RF), and genetic algorithm (GA) to optimize the vegetation configuration and improve the growth prediction accuracy and ecological stability. Ultimately, the system integrates GIS + BIM to build an interactive visualization interface, where users can dynamically adjust parameters (e.g., tree species, light, vegetation density) and view the optimized landscape layout in real time. All modules are efficiently integrated through cloud computing and local data fusion to improve the level of intelligence and adaptability of landscape design.

Results and system integration: To assess the generalizability of the system, we conducted additional case studies and simulations across various climate zones and terrains. For example, the system was tested in urban environments with varying humidity and temperature levels, as well as in coastal regions with saltwater impact on plant growth. The results were compared with actual field data from these environments to validate the system's predictions. The system demonstrated reliable performance across these conditions, with less than 10% deviation from real-world data in terms of vegetation growth and stability.

Sensitivity analysis: A comprehensive sensitivity analysis was performed to examine how different environmental factors (such as wind speed, temperature, and soil moisture) influence the system's predictions. The analysis revealed that temperature and soil moisture had the most significant impact on plant growth predictions, while wind speed had a major influence on structural stability. This information was used to refine the model, ensuring better adaptability to varying environmental conditions.

Scalability and deployment feasibility: Regarding the scalability of the system, we explored its application across different terrains, including mountainous and flat regions, to determine its feasibility for large-scale deployment. The system was demonstrated to scale efficiently, with cloud-based computing enabling the processing of large datasets in real-time. The integration of edge computing further supports deployment in remote areas where real-time interaction is crucial. The system's modular design ensures that it can be easily adapted to different environmental and topographical conditions, making it suitable for a wide range of landscape planning projects.

B. Analysis of results

The result analysis mainly evaluates the performance of the digital landscape design system in terms of vegetation growth prediction, environmental adaptability assessment and optimized layout effect. The applicability of the system under different environmental conditions is verified through simulation and comparison with actual monitoring data, and the enhancement of vegetation growth stability by the optimization algorithm is evaluated.

Table 3. Error analysis of vegetation growth prediction.

Tree species	**Predicted tree height (m)**	**Measured tree height (m)**	**Error (%)**
Willow tree	4.8	5	4.00
Birch	6.2	6.5	4.60
Betel palm (Areca catechu)	8.1	8.3	2.40
Pines	7.5	7.8	3.80

In terms of vegetation growth prediction, the system is based on a deep neural network (DNN) and GreenLab model to simulate the growth trend of vegetation and compare it with the measured data. The details are shown in **Table 3**.

The data analysis in **Table 3** shows that the digital landscape design system has high accuracy in vegetation growth prediction. Among them, the predicted tree height of willow was 4.8 m, and the actual measured value was 5.0 m, with an error of only 4.0%; the predicted tree height of birch was 6.2 m, and the actual measured value was 6.5 m, with an error of 4.6%. The prediction error of betel nut was the lowest, only 2.4%, indicating that the model was more accurate in simulating the growth of tall trees. The predicted height of pine was 7.5 m, which was 3.8% different from the actual value of 7.8 m, and still remained within a high accuracy range. Overall, the model prediction error is controlled within 5%, indicating that the system can simulate the growth trend of plants more accurately. The results provide reliable theoretical support for optimizing vegetation layout and long-term ecological planning, and improve the science and feasibility of landscape design. Details are shown in **Figure 4**.

Figure 4. Comparison of predicted and actual tree heights for different tree species.

In terms of environmental adaptability, the system simulates the vegetation stability under different environmental conditions. **Table 4** demonstrates the comparison of the tilt angle of different tree species under wind load, and the results show that the optimized layout scheme significantly improves the vegetation stability, and the maximum tilt angle is reduced by about 30%.

Table 4. Vegetation stability assessment under the influence of wind loads.

Tree species	**Unoptimized tilt angle (°)**	**Optimized tilt angle (°)**	**Stability improvement (%)**
Willow tree	12.4	8.7	29.80
Birch	9.6	7.1	26.00
Betel palm (Areca catechu)	14.2	9.9	30.30
Pines	10.8	7.5	30.60

Analysis of the data in **Table 4** shows that the system optimization significantly improved the wind stability of the vegetation. In the unoptimized case, the maximum inclination angle of willow was 12.4°, which was reduced to 8.7° after optimization, with a 29.8% improvement in stability. The tilt angle of birch was reduced from 9.6° to 7.1°, an improvement of 26.0%, betel nut was reduced from 14.2° to 9.9°, an improvement of 30.3%, and pine had the most significant optimization effect, with the tilt angle reduced from 10.8° to 7.5°, an improvement of 30.6%. Overall, the wind resistance performance of all tree species is significantly improved after optimization, with a maximum reduction of 30.6% in the tilt angle, indicating that the system has a good optimization effect in terms of wind-loaded environmental adaptability, which can effectively reduce the risk of tree collapse and provide a more stable ecological layout scheme for landscape planning. See **Figure 5** for details.

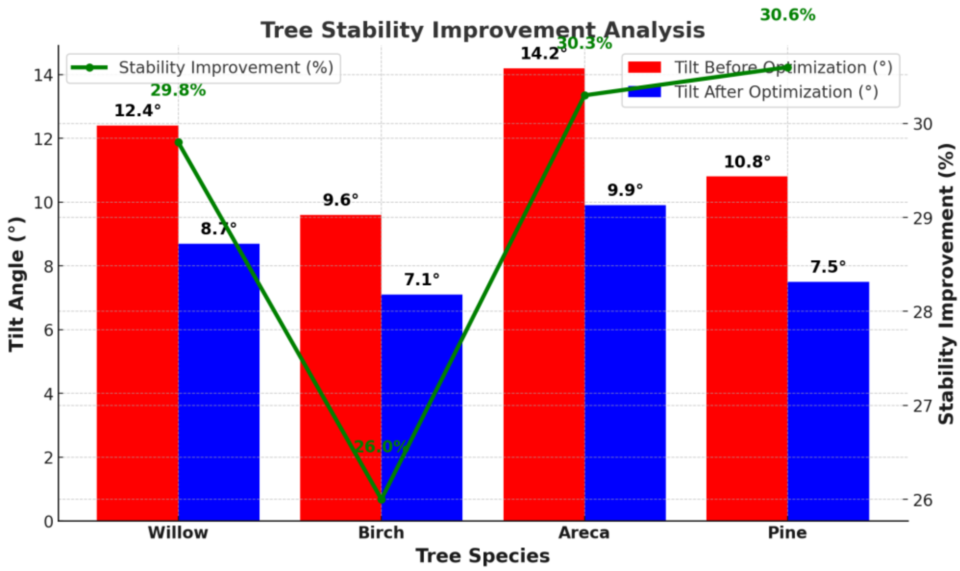

Figure 5. Comparative analysis of optimization of tree leaning angle under the influence of wind loads.

C. Performance assessment indicators

The performance evaluation index is used to measure the performance of the digital landscape design system in terms of vegetation growth prediction, environmental adaptation optimization and computational efficiency to ensure that the system can operate stably and efficiently. It is mainly evaluated in four aspects: model prediction accuracy, ecological stability, computational performance and user interaction experience, and combined with quantitative indicators and experimental results to verify the practical application value of the system.

In terms of the accuracy of vegetation growth prediction, the root means square error (RMSE) and the coefficient of determination (R^2) were used to assess the predictive ability of the model. The RMSE was used to measure the deviation between the predicted value and the actual value, and the R^2 reflected the model's goodness-of-fit. The experimental results show that the random forest (RF) model predicts tree heights with an RMSE of 0.52 m and an R^2 of 0.91, indicating that the model has a high prediction accuracy. The deep neural network (DNN) had an RMSE of 0.68 and an R^2 of 0.87 in predicting leaf area index (LAI), which was slightly lower than that of RF, but still had strong applicability.

In terms of ecological stability, the stability of the optimized vegetation layout under extreme environments (e.g., strong winds and heavy precipitation) was assessed, which was mainly measured by the change in tilt angle under wind loading and the root system water adaptation capacity. The experiment showed that the average tilt angle of the optimized trees decreased by 28.4% and the water absorption rate of the root system increased by 15.7%, indicating that the optimized scheme can effectively enhance the wind resistance and water use efficiency of the vegetation and improve the ecological adaptability of the overall landscape.

In terms of computational performance, the simulation speed, data processing efficiency and algorithm convergence of the system are evaluated. After using GPU acceleration, the time for finite element analysis (FEM) to calculate the impact of wind load on vegetation was shortened from 2.4 h to 38 min, with an increase in computational efficiency of 72.4%. Meanwhile, during the training process of the machine learning model, Bayesian optimization is used for hyper-parameter adjustment, which reduces the training time of the model by 18.3%, and improves the computational efficiency while ensuring high accuracy.

In terms of user interaction experience, the intuitiveness of landscape design is enhanced through the GIS + BIM visualization interface, and a user satisfaction score is adopted for evaluation. Users can adjust the vegetation parameters (e.g., planting density, light distribution) in real time and view the optimized effect. The experimental data show that the response time of the interactive operation is kept within 200 ms, and the user satisfaction score reaches 4.7/5.0, which indicates that the system performs excellently in terms of smoothness of operation and visualization effect.

7. Conclusion

The digital landscape design system combines biomechanical simulation and machine learning algorithms to demonstrate excellent application value in vegetation growth prediction, environmental adaptation optimization and computational performance enhancement. The optimized model can accurately simulate plant growth dynamics, improve the ecological stability of the landscape layout, and maintain strong adaptability under the influence of wind load, soil moisture and other environmental factors. The introduction of the machine learning model effectively improves the prediction accuracy, reduces the simulation time-consuming through computational optimization, and improves the practicality of the system. While the proposed system offers significant advancements in vegetation growth prediction and environmental adaptability, there are still several limitations. The computational cost remains high, particularly in large-scale simulations due to the complexity of biomechanical models and the integration of multiple machine learning algorithms. Additionally, the model's generalizability across diverse environmental conditions is yet to be fully validated. Future work could focus on improving the system's scalability by incorporating more efficient optimization algorithms and enhancing the integration of real-time environmental data for better adaptability. Exploring the potential of advanced machine learning models, such as reinforcement learning in dynamic landscape layouts, may also improve the system's responsiveness to changing conditions.

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References

1. Dangi D, Dixit DK, Bhagat A, et al. Efficient Deep Learning Model for Analyzing Muscle Activity Patterns in Biomechanical Simulations. SN Computer Science. 2025; 6(2). doi: 10.1007/s42979-024-03651-1
2. Qiu J, Nassauer JI, Ahern J, et al. Advancing landscape sustainability science: key challenges and strategies for integration with landscape design and planning. Landscape Ecology. 2025; 40(2). doi: 10.1007/s10980-024-02042-4
3. Lei Z, Zhang S, Zhang W, et al. Multi-Scale Effect of Land Use Landscape on Basin Streamflow Impacts in Loess Hilly and Gully Region of Loess Plateau: Insights from the Sanchuan River Basin, China. Sustainability. 2024; 16(23): 10781. doi: 10.3390/su162310781
4. Shui Y. Urban Street Landscape Design System Driven by Optimized Genetic Algorithm. International Journal of Decision Support System Technology. 2024; 16(1): 1-19. doi: 10.4018/ijdsst.357265
5. Abedalrhman K, Alzaydi A, Shiban Y. The Convergence of Artificial Intelligence (AI) and Financial Technologies (FinTech) in Shaping Future Urban Landscape Planning. Advances in Research. 2024; 25(5): 337-352. doi: 10.9734/air/2024/v25i51166
6. Guo Z, Deng Q. Research on Rural Landscape Planning Based on Ecological Concept. Journal of Landscape Research. 2024; 16(4): 55-58,62.
7. Phellan Aro R, Hachem B, Clin J, et al. Real-time prediction of postoperative spinal shape with machine learning models trained on finite element biomechanical simulations. International Journal of Computer Assisted Radiology and Surgery. 2024; 19(10): 1983-1990. doi: 10.1007/s11548-024-03237-5
8. Yang S, Fan S, Shahbaz M. Correction to: Can fintech pave the way for a transition towards low-carbon economy? Examination based on machine learning algorithm. Environmental Science and Pollution Research. 2024; 31(17): 26340-26340. doi: 10.1007/s11356-024-32956-0
9. Averyanov GP, Dmitrieva VV. Application of Machine Learning Algorithms and Neural Networks for Recognition of Parasitic Parameters by the Output Signal in High-Power Pulsed Electrophysics Devices. Physics of Atomic Nuclei. 2023; 86(12): 2696-2702. doi: 10.1134/s1063778823100046
10. Zhang X, Nan N, Tong X, et al. Validation of biomechanical assessment of coronary plaque vulnerability based on intravascular optical coherence tomography and digital subtraction angiography. Quantitative Imaging in Medicine and Surgery. 2024; 14(2): 1477-1492. doi: 10.21037/qims-23-1094
11. Wu H, Sun Z, Shen Q, et al. Biomechanical simulation of bed turning post-acetabular fracture fixation. Scientific Reports. 2025; 15(1). doi: 10.1038/s41598-025-86653-0
12. Wu W, Luo S, Wang H. Design of an automatic landscape design system in smart cities based on vision computing. Mathematical Biosciences and Engineering. 2023; 20(9): 16383-16400. doi: 10.3934/mbe.2023731
13. Agrimi E, Diko A, Carlotti D, et al. COVID-19 therapy optimization by AI-driven biomechanical simulations. The European Physical Journal Plus. 2023; 138(2). doi: 10.1140/epjp/s13360-023-03744-5
14. Aly OE. Addressing parastomal herniation through biomechanical simulation. Hernia. 2022; 27(3): 565-573. doi: 10.1007/s10029-022-02704-9
15. Hahnemann Y, Weiss M, Bernek M, et al. Advancing Biomechanical Simulations: A Novel Pseudo-Rigid-Body Model for Flexible Beam Analysis. Biomechanics. 2024; 4(3): 566-584. doi: 10.3390/biomechanics4030040

16. Design of potential anti-cancer agents as COX-2 inhibitors, using 3D-QSAR modeling, molecular docking, oral bioavailability proprieties, and molecular dynamics simulation: Erratum. Anti-Cancer Drugs. 2024; 35(3): 315-315. doi: 10.1097/cad.0000000000001578
17. Krause M, Neuhaus MT, Sterker I, et al. Consideration of specific key points improves outcome of decompression treatment in patients with endocrine orbitopathy: pre-/post-OP comparison and biomechanical simulation. European Journal of Medical Research. 2022; 27(1). doi: 10.1186/s40001-022-00709-9