

Application and Prospects of LiDAR in Nature-Based Solutions: A Bibliometric Analysis

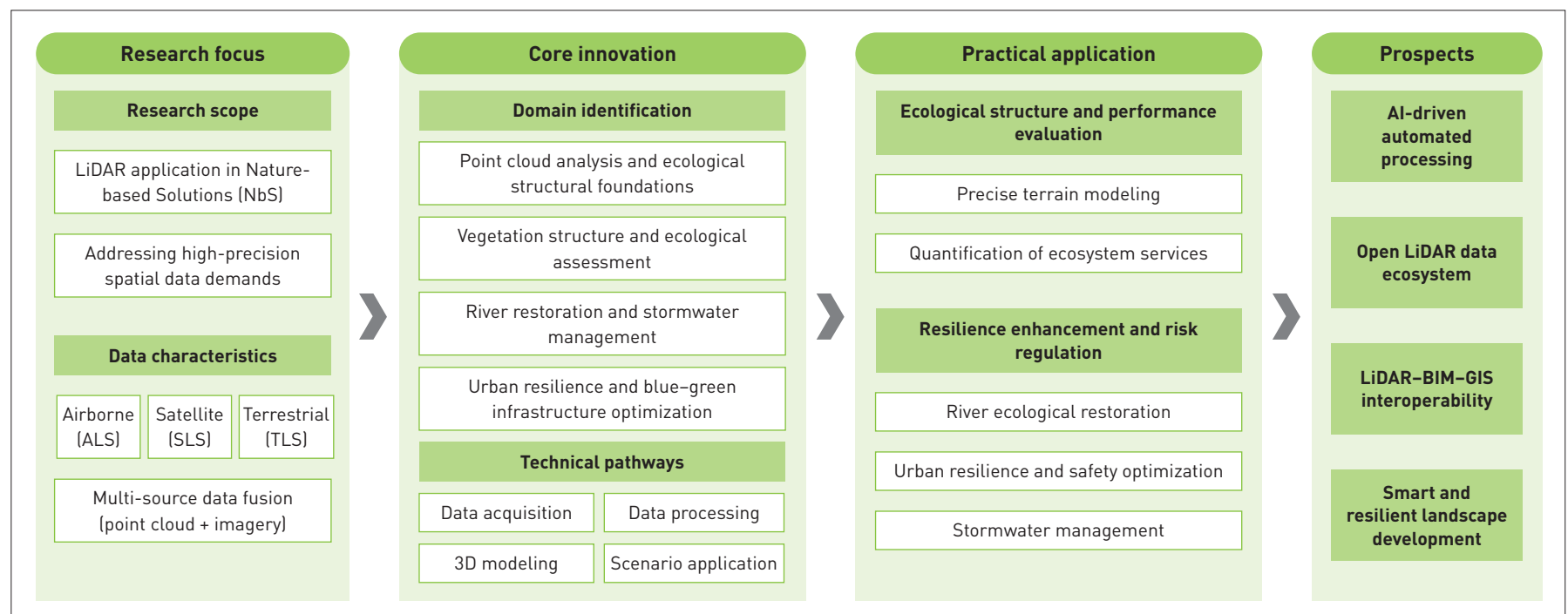
Songtao WU¹, Shipeng WEN¹, Xiao PENG^{1,*}, Guolin ZHANG²

¹ School of Architecture and Design, Harbin Institute of Technology, Harbin 150001, China
² College of Architecture and Landscape, Peking University, Beijing 100871, China

*CORRESPONDING AUTHOR

Address: Room D305, Mingde Building, Harbin Institute of Technology, No. 92 West Dazhi Street, Nangang District, Harbin 150001, China
Email: pengxiao@hit.edu.cn

GRAPHICAL ABSTRACT



ABSTRACT

Nature-based Solutions (NbS) have emerged as critical strategies for addressing global climate change and ecological crises. Light Detection and Ranging (LiDAR) technology offers high-precision 3D data that could significantly enhance NbS implementation, yet its integration into planning and design workflows faces technical barriers. We employed a bibliometric approach to systematically review 4,275 publications from the Web of Science Core Collection (2000–2024), using CiteSpace and Bibliometric R package with Pathfinder algorithm optimization to identify research clusters and evolutionary patterns. Four core application domains were identified: 1) ecological structural analysis, 2) vegetation assessment, 3) river

restoration, and 4) urban resilience. LiDAR significantly enhances NbS site selection, spatial scaling, and performance evaluation by translating geometric-structural information into computable ecological metrics. However, challenges regarding data processing complexity, toolchain fragmentation, and interdisciplinary barriers continue to impede the full realization of LiDAR's potential. To address these gaps, we propose an integrated development pathway comprising three aspects: 1) open data sharing platforms to lower application thresholds, 2) AI-driven automation processing to overcome semantic understanding bottlenecks, and 3) standardized interoperability to bridge toolchain fragmentation.

This pathway aims to transform LiDAR from a high-precision measurement tool into digital public infrastructure for evidence-based NbS design and governance, facilitating the digital and intelligent transformation of landscape planning and design.

KEYWORDS

LiDAR; Nature-based Solutions; Bibliometric Analysis; Point Cloud Processing; Landscape Planning and Design; Ecological Restoration; Stormwater Management; Urban Resilience; Blue-Green infrastructure

HIGHLIGHTS

- Systematically analyzed 4,275 publications to map LiDAR application trends in NbS (2000–2024)
- Identified four core domains: ecological structure analysis, vegetation assessment, river restoration, and urban resilience
- Proposed “Open Data + AI + Standardization” pathway to bridge technology-design gaps

RESEARCH FUNDS

- Heilongjiang Provincial Postdoctoral Science Foundation (No. LBH-Z23164)
- Joint Guidance Project of the Natural Science Foundation of Heilongjiang Province (No. LH2024E051)

1 Introduction

Nature-based Solutions (NbS) have emerged as critical strategies for addressing global climate change, biodiversity loss, and environmental degradation^[1]. By leveraging ecosystem services, NbS address these challenges through the protection, restoration, and sustainable management of natural or modified ecosystems^[2-3]. This approach offers high cost-effectiveness, significant co-benefits, and broad social acceptance^[4-5]. However, effective NbS implementation faces a critical bottleneck: the need for high-precision 3D structural data to support spatial and environmental modelling^[6-7]. Traditional data collection methods (e.g., field surveys, 2D remote sensing)

exhibit limited precision and efficiency in complex terrains, dense vegetation, and urban environments, making it difficult to satisfy the requisite demand^[8-10]. Particularly in critical applications such as stormwater management, urban heat island (UHI) mitigation, and ecological restoration, precise data on topography, vegetation structure, and surface characteristics are indispensable for supporting decision-making in site selection, scale control, and performance evaluation^[11-13].

Light Detection and Ranging (LiDAR) technology offers a transformative solution to aforementioned data acquisition challenge. As an active remote sensing technology, LiDAR can penetrate vegetation canopies to acquire high-precision 3D structural information, including topography, canopy architecture, and surface features^[14]. LiDAR operates by emitting laser pulses and measuring return signals to calculate the distance between the sensor and the target, generating high-fidelity 3D point cloud data^[15]. This capability enables effective surface information acquisition in complex environments, including dense forests and urban areas^[16]. Furthermore, LiDAR technology has evolved into multiple operational platforms—including satellite (SLS), airborne (ALS), terrestrial (TLS), and mobile (MLS) laser scanning^[17]—providing comprehensive data support for quantitative NbS assessment and targeted design. In recent years, LiDAR applications in NbS have expanded across critical domains, including ecosystem restoration, stormwater management, and urban resilience enhancement^[18-19]. However, the absence of a systematic review of LiDAR applications in NbS obscures the overall research trajectory, evolutionary patterns, and technical bottlenecks that constrain broader adoption.

To address these knowledge gaps, this study employed bibliometric analysis to systematically review LiDAR applications in NbS from 2000 to 2024. The specific objectives are to: 1) identify the core application domains of LiDAR in NbS and their technical characteristics; 2) analyze the primary bottlenecks and challenges in technical integration; and 3) propose technical development pathways oriented towards design practice. The findings would provide a comprehensive reference for promoting the integration of LiDAR technology with landscape planning and design, facilitating the digital and intelligent transformation of NbS practices.

2 Data and Methods

2.1 Data Acquisition

Data collection was conducted using the Web of Science Core Collection, employing a search strategy that combined LiDAR technology and NbS application scenario terms. Drawing upon

established research frameworks^[20-24], a comprehensive search system was constructed, encompassing four core dimensions (Table 1): 1) ecosystem restoration and biodiversity conservation, 2) hydrological regulation and flood control, 3) urban resilience and blue-green infrastructure, and 4) climate regulation and ecosystem service assessment.

The inclusion criteria were established as follows: 1) time span ranged between January 1, 2000 and December 31, 2024; 2) document types restricted to articles and review articles; and 3) language limited to English. Data retrieval was completed on October 6, 2025. By pooling the four search sets, a unified dataset was generated. The dataset was deduplicated based on unique Digital Object Identifiers (DOIs) and further validated through a preliminary manual review of titles and abstracts to ensure topical relevance. Ultimately, a total of 4,275 valid publications were confirmed and included to construct the dataset for macro-trend analysis.

2.2 Bibliometric Analysis Methods

This study employed CiteSpace and the Bibliometric R package to conduct a comprehensive bibliometric analysis^[25]. The analytical framework comprised three key procedures: 1) topological optimization of the co-occurrence network via the Pathfinder algorithm, which prunes redundant and non-significant links

while preserving global network connectivity to delineate core research clusters; 2) mapping the technological trajectory through temporal citation analysis; and 3) systematically synthesizing the core functions, developmental trends, and challenges of LiDAR within the NbS domain. To mitigate the inherent limitations of quantitative metrics, this study incorporated secondary validation through supplementary literature review and expert consultation. This qualitative assessment focuses on technical application characteristics, workflow integration bottlenecks, and implementation pathways for planning and design practice, ensuring both scientific rigor and targeted relevance of the research conclusions.

3 Application Progress and Core Domains of LiDAR in NbS

3.1 Research Trends and Hotspot Evolution

3.1.1 Publication Trends

The temporal distribution of publications reveals three distinct developmental stages in LiDAR applications within the NbS domain (Fig. 1): 1) the technology accumulation phase (2000–2006), characterized by limited publication volume but the establishment of foundational technologies; 2) the rapid growth phase (2007–2015),

Table 1: Data collection strategy and retrieved literature quantity

Search set	NbS domain	Search query	Number of publications
#1	Ecosystem restoration and biodiversity conservation	TS = ("lidar" OR "light detection and ranging" OR "laser scanning" OR "point cloud") AND TS = ("ecological restoration" OR "habitat restoration" OR "ecosystem restoration" OR "biodiversity conservation" OR "forest management" OR "reforestation" OR "afforestation")	1,442
#2	Hydrological regulation and flood control	TS = ("lidar" OR "light detection and ranging" OR "laser scanning" OR "point cloud") AND TS = ("flood" OR "inundation" OR "watershed management" OR "river basin management" OR "river restoration" OR "erosion control" OR "coastal protection" OR "wetland restoration" OR "stormwater" OR "sponge city" OR "sustainable drainage" OR "low impact development")	1,596
#3	Urban resilience and blue-green infrastructure	TS = ("lidar" OR "light detection and ranging" OR "laser scanning" OR "point cloud") AND TS = ("green infrastructure" OR "blue-green infrastructure" OR "urban resilience" OR "urban green space" OR "urban park" OR "corridor" OR "tree canopy" OR "heat island" OR "carbon sequestration" OR "biodiversity" OR "green-blue infrastructure")	2,427
#4	Climate regulation and ecosystem service assessment	TS = ("lidar" OR "light detection and ranging" OR "laser scanning" OR "point cloud") AND TS = ("ecosystem service*" OR "carbon sequestration" OR "temperature change" OR "microclimate" OR "climate adaptation" OR "climate regulation" OR "environmental monitoring")	1,278
#5	NbS	#1 OR #2 OR #3 OR #4	4,275

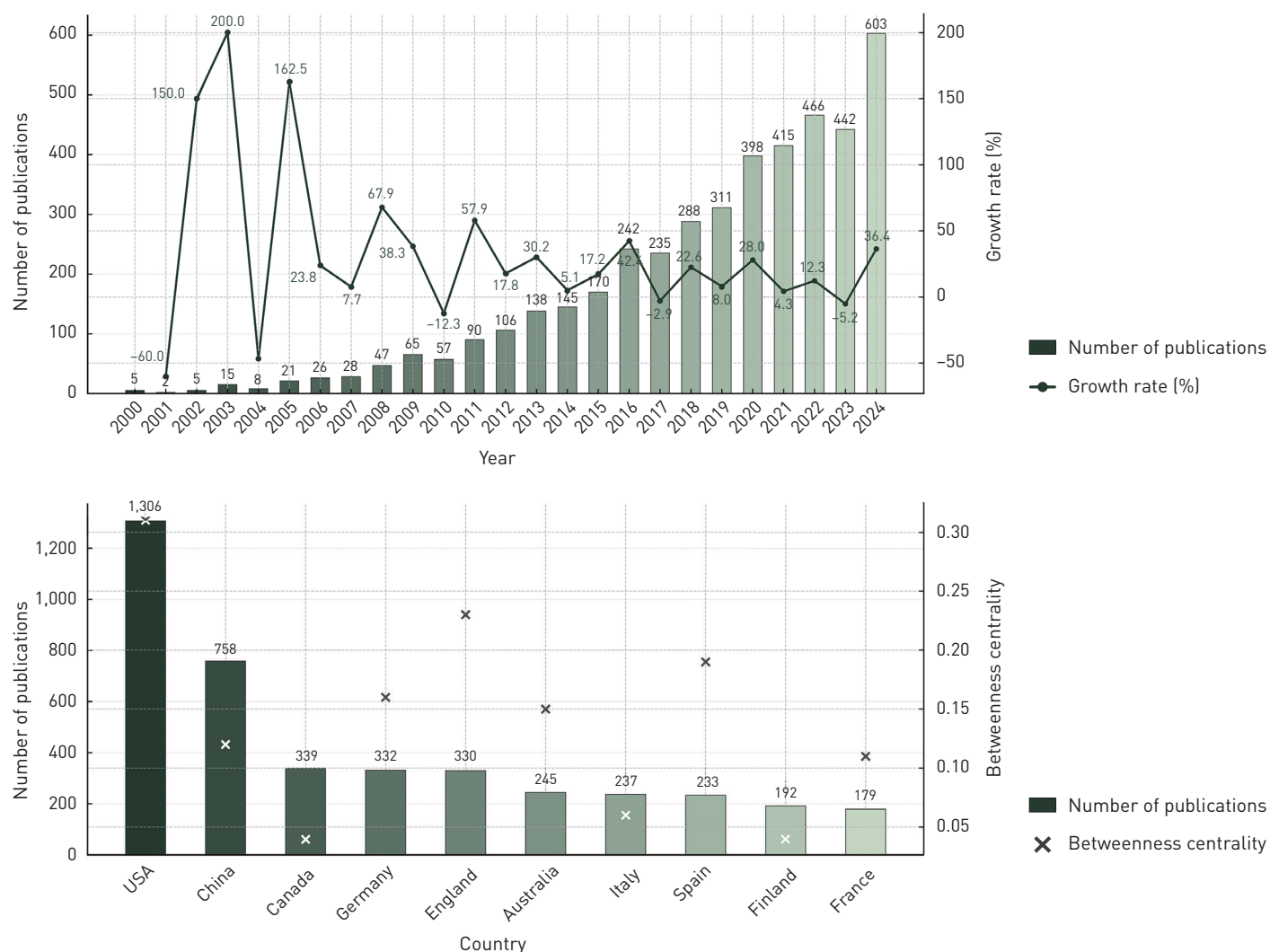


Fig. 1 Annual publication trends (2020–2024) and the total publications and network centrality by country.

marked by a significant surge in annual output that expanded the disciplinary influence and broadened cross-domain applications; and 3) the high-quality development phase (2016–present), where annual publication volume has consistently exceeded 200 papers and maintained a continuous upward trend, indicating the progressive maturation of the field. Geographically, North American and European nations maintain a dominant position in publication output. The USA ranks first with 1,306 publications and exhibits the highest betweenness centrality in the international collaboration network. This metric underscores the pivotal hub role of the USA in connecting disparate research clusters and integrating global scientific resources. China ranks second with 758 publications, with its volume rapidly approaching that of traditional research powerhouses, signifying the swift emergence of Asia-Pacific nations. European nations such as England, Germany, and Spain demonstrate high centrality despite trailing the USA and China in total volume, highlighting their critical bridging function within the global collaborative network.

3.1.2 Research Hotspot Evolution

The temporal visualization of keywords reveals a distinct development trajectory in LiDAR application within the NbS domain, characterized by a “technology–application–intelligence” progress (Fig. 2). Corresponding to the initial technology accumulation phase, research primarily focused on digital elevation model (DEM) generation and topographic mapping (cluster #2), aiming to resolve fundamental technical issues related to the precise acquisition and filtering of surface 3D information and laying the data foundation for subsequent applications. As the field entered the rapid growth phase, research hotspots extended toward ecological parameter retrieval, forming application clusters represented by forest inventory (cluster #0) and sediment transport (cluster #1). This phase marked a transition from single structural parameter extraction to complex biomass estimation and habitat assessment. In the current high-quality development phase, keyword clusters such as deep learning (cluster #3) and UHI (cluster #7) have become dominant in the high-frequency co-occurrence network. This shift

CiteSpace, v. 6.4.R1 (64-bit) Advanced
 October 7, 2025, 9:20:34 PM CST
 WoS: C:\Users\shipe\Desktop\BaiduSyncdisk\01论文\3SUBMISSION\LIDAR\1过程数据\bb_wos\cs_wos_1006\data
 Timespan: 2000-2024 (Slice Length=2)
 Selection Criteria: g-index (k=25), LRF=2.5, L/N=10, LBY=5, e=1.0
 Network: N=650, E=2501 (Density=0.0119)
 Largest 1 CCs: 631 (97%)
 Nodes Labeled: 1.0%
 Pruning: Pathfinder
 Modularity Q=0.4586
 Weighted Mean Silhouette S=0.7154
 Harmonic Mean(Q, S)=0.5589
 Excluded:

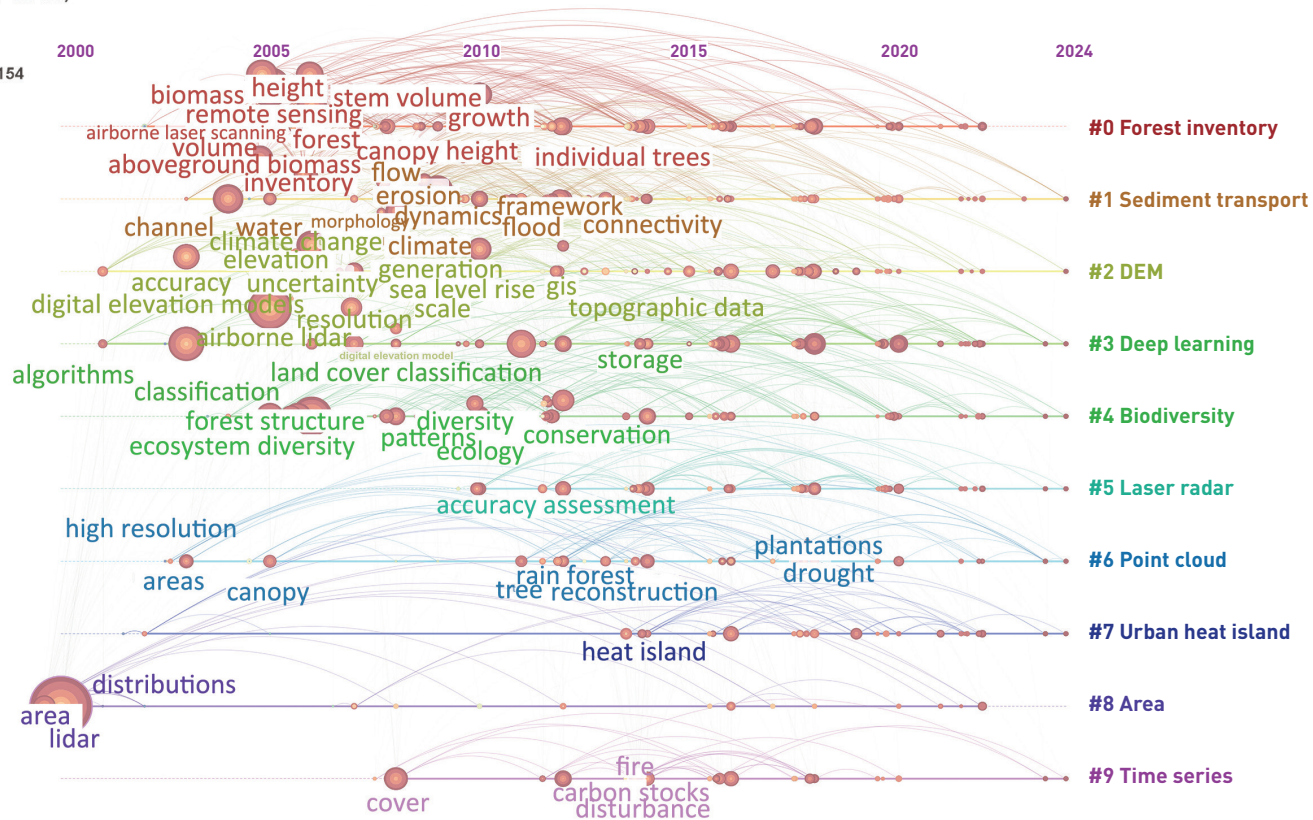


Fig. 2 Keyword frequency trends in LiDAR applications for NbS.

© Songtao Wu, Shipeng Wen, Xiao Peng, Guolin Zhang

indicates that current research is accelerating toward intelligent and refined directions, including semantic segmentation, multi-source data fusion, and urban resilience modeling.

3.2 Identification of Core Application Domains

3.2.1 Cluster Analysis and Visualization

The dataset was analyzed using annual time slicing, with cited references and keywords serving as network nodes. The g-index threshold was set at $k = 25$ ^[25]. As an enhanced algorithm over the h-index, the g-index accounts for the cumulative contribution of highly cited papers, assigning greater weight to high-impact nodes. This approach filtered out low-impact information while preserving core knowledge units within each time slice. Based on this parameter setting, the initial co-citation network was constructed and optimized via the Pathfinder algorithm. The resulting network comprises 1,196 nodes and 1,789 links, from which 19 sub-clusters with a size greater than 30 were extracted. The network modularity ($Q = 0.9045$) and weighted mean silhouette score ($S = 0.9442$) indicate that the clustering structure is highly reliable and robust (Fig. 3).

CiteSpace, v. 6.4.R1 (64-bit) Advanced
 October 7, 2025, 9:04:38 PM CST
 WoS: C:\Users\shipe\Desktop\BaiduSyncdisk\01论文\3SUBMISSION\LIDAR\1过程数据\bb_wos\cs_wos_1006\data
 Timespan: 2000-2024 (Slice Length=2)
 Selection Criteria: g-index (k=25), LRF=2.5, L/N=10, LBY=5, e=1.0
 Network: N=1196, E=1789 (Density=0.0025)
 Largest 1 CCs: 1047 (87%)
 Nodes Labeled: 1.0%
 Pruning: Pathfinder
 Modularity Q=0.8494
 Weighted Mean Silhouette S=0.9442
 Harmonic Mean(Q, S)=0.8943
 Excluded:

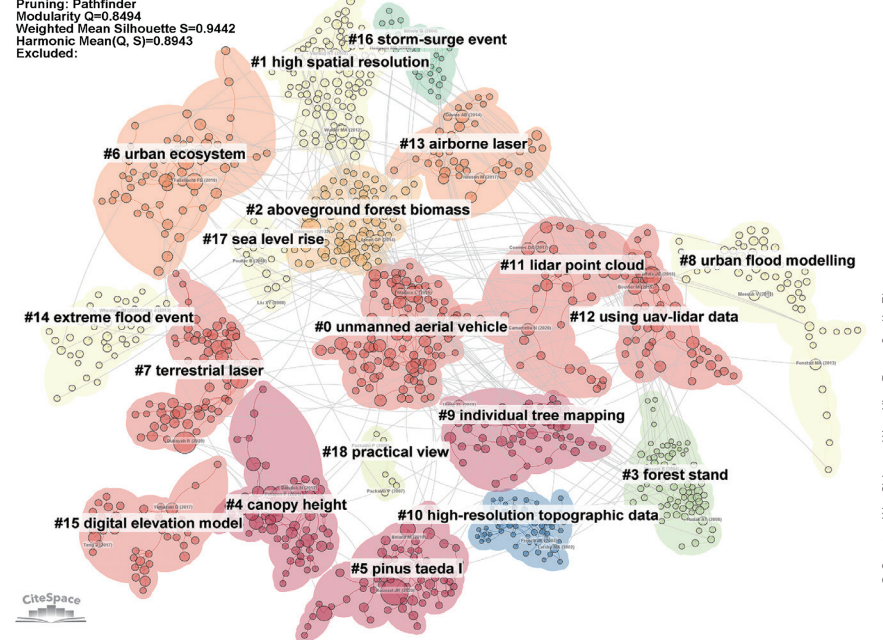


Fig. 3 Co-citation network clusters of LiDAR application in NbS.

© Songtao Wu, Shipeng Wen, Xiao Peng, Guolin Zhang

3.2.2 Core Application Domains

Based on Latent Semantic Indexing (LSI) labels and Log-Likelihood Ratio (LLR) optimization, combined with an analysis of highly cited references and burst years, the sub-clusters were synthesized into four core application domains (Table 2). 1) Point cloud analysis and ecological structural foundations: this domain focuses on critical processes such as semantic segmentation, point cloud segmentation, and terrain reconstruction using airborne, terrestrial, and mobile LiDAR data, providing structured data support for high-precision 3D modeling of watershed and urban ecosystems. 2) Vegetation structure and ecological assessment: this domain encompasses aboveground biomass retrieval, tree species classification, canopy structure, and biodiversity assessment, achieving the quantitative characterization of vegetation from morphological features to ecological functions, and represents a core direction for evaluating the ecosystem service benefits of NbS. 3) River restoration and stormwater management: underpinned by LiDAR-supported topographic mapping and hydrological modeling, this domain focuses on floodplain evolution, flood risk analysis, and

watershed ecological restoration, emphasizing disaster prevention and mitigation strategies driven by natural processes. 4) Urban resilience and blue-green infrastructure (BGI) optimization: this domain centers on UHI effects and climate regulation mechanisms, utilizing LiDAR data to quantify urban green volume, ventilation corridors, and microclimate characteristics, and provides a scientific basis for optimizing BGI layout and climate-adaptive design.

3.3 Technical Analysis of Representative Application Domains

3.3.1 Point Cloud Analysis and Ecological Structural Foundations

(1) Point cloud processing and terrain modeling

LiDAR terrain modeling typically adheres to a technical workflow of “data preprocessing–feature extraction–3D modeling,” transforming raw point cloud data into digital models suitable for NbS applications (Fig. 4).

1) Data preprocessing phase. Based on raw point clouds, this phase constructs the digital terrain model (DTM), encompassing noise removal and ground point separation^[16]. Noise removal eliminates outliers and anomalies caused by sensor errors,

Table 2: Core domain clusters of the co-citation network

Domain	Cluster	Size	Silhouette	Labels	Burst year
Point cloud analysis and ecological structural foundations	#1	122	0.981	Airborne laser scanning; semantic segmentation; point cloud segmentation; spatial resolution	2017
	#7	63	0.932	Topographic mapping; surface reconstruction	2018
	#9	38	0.974	Automated detection; ground point classification	2014
Vegetation structure and ecological assessment	#3	94	0.936	Aboveground biomass; forest structural complexity; carbon storage	2016
	#4	76	0.954	Tree species classification; crown structure; biological invasion	2015
	#5	68	0.935	Canopy structure; multi-layered structure; ecosystem services	2012
	#8	59	0.928	Biodiversity; landscape pattern	2014
River restoration and stormwater management	#0	118	0.890	River geomorphology; ecological restoration	2010
	#2	102	0.988	Urban flood modeling; flood risk; hydrological simulation	2018
Urban resilience and BGI optimization	#6	87	0.917	UHI; climate regulation; urban green volume	2017
	#3	64	0.936	Carbon storage; ventilation corridors; urban ecosystem services	2016

NOTE

Cluster #3 was categorized into two domains due to its dual attributes.

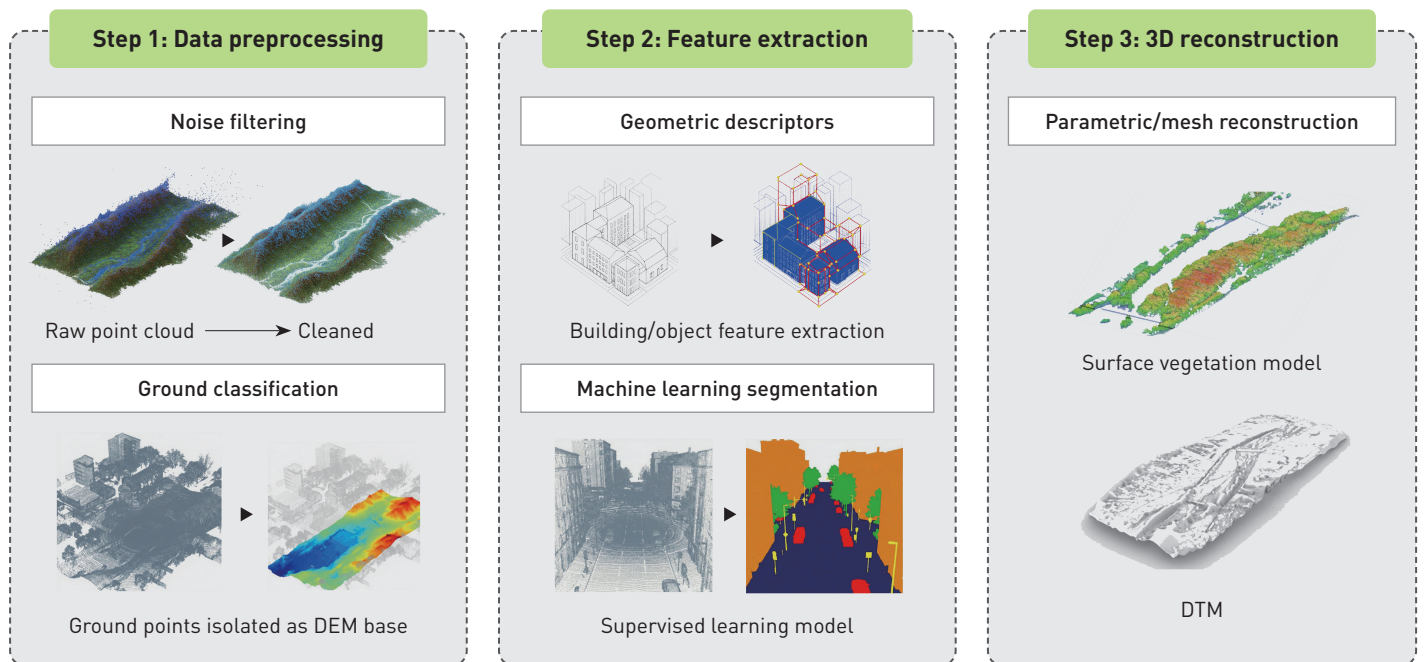


Fig. 4 Standardized workflow for LiDAR point cloud processing in NbS applications.

environmental interference, or data acquisition constraints, thereby enhancing overall data quality. Ground point separation utilizes algorithms to distinguish ground points from non-ground points (e.g., vegetation, buildings, vehicles), preserving the authentic undulations of the terrain surface. Common algorithms include Cloth Simulation Filtering (CSF)^[26-27], Progressive Morphological Filter (PMF), and Simple Morphological Filter (SMRF)^[28]. However, manual intervention and editing remain necessary in areas with abrupt terrain changes, complex feature types, or severe noise interference.

2) Feature extraction phase. This phase transforms the geometric and reflectance attributes of point clouds into structured information. Traditional methods typically rely on geometric features such as normal vectors, curvature, and height thresholds for preliminary separation^[29-30]. Data-driven supervised learning algorithms, e.g., Random Forest (RF), Support Vector Machine (SVM), k-Nearest Neighbors (kNN), Decision Trees, can integrate multidimensional features, including intensity, return number, and waveform width, to accomplish finer-grained classification and semantic segmentation^[31-34]. Moreover, deep learning approaches can directly process unstructured point sets, improving robustness in complex scenarios such as urban environments and under-canopy areas^[35].

3) 3D modeling phase. DEMs are generated via Delaunay triangulation or voxelization^[27,36]. Parametric variables such as canopy height models (CHM), roughness, canopy porosity, and slope can be derived using DEMs, providing a 3D data foundation for hydrological analysis and ecological assessment^[14,37-39]. In

contrast to traditional 2D imagery, LiDAR's active ranging and high-density sampling maintain geometric continuity within complex environments, significantly enhancing data quality. At the macro scale, airborne LiDAR-derived DEMs are extensively applied in regional ecological restoration^[19,40-41], natural disaster assessment, and flood simulation coupled with hydrodynamic models^[42-44]. At the micro scale, high-precision DTMs/DEMs provide sub-meter or even millimeter-level spatial references for infrastructure layout, vertical design, earthwork calculation, and construction stakeout^[16,45].

(2) Characterization of land cover features

The refined characterization of land cover and ecological features serves as a pivotal link bridging 3D structure and ecological function, typically achieved through multi-source data fusion. The integration of LiDAR and hyperspectral imaging (HSI) consolidates geometric and spectral information. By leveraging the spectral dimension for species discrimination and surface moisture detection, this approach enhances identification accuracy and model generalization in areas with complex vegetation and mixed surfaces^[46-47], achieving robust land cover recognition across multiple scales^[48-49].

LiDAR-based land cover analysis technologies can effectively address the practical demands of NbS governance. At the macro scale, this technology enables the precise classification of complex heterogeneous surfaces, e.g., urban-rural transitional zones^[50]. Combined with multi-temporal data to monitor dynamic ecological processes such as secondary forest succession^[51], it provides high-precision baseline data and continuous monitoring evidence for simulating urban expansion boundaries and delineating ecological

protection red lines^[52-53]. At the micro scale, the synergistic integration of multi-source remote sensing data enables the accurate retrieval of soil moisture and erosion dynamics^[10,32,39]. This facilitates the identification of key site-scale units for soil and water conservation, providing a scientific basis for the layout and optimization of low impact development (LID) facilities, e.g., ecological swales and rain gardens^[11].

3.3.2 Vegetation Structure and Ecological Assessment

(1) Urban vegetation structure monitoring

Within the NbS framework, LiDAR technology has emerged as a fundamental pillar for the inventory and dynamic management of urban vegetation structures. Unlike traditional 2D spectral remote sensing, LiDAR's active ranging capability enables effective penetration of canopy layers to acquire comprehensive 3D structural information^[20,54]. This technological advantage facilitates consistent output of multi-scale structural data ranging from individual tree to community, providing a reliable data foundation for subsequent ecosystem service assessments^[55-57].

At the individual tree scale, algorithms such as density-based clustering and region growing effectively facilitate single-tree segmentation and crown reconstruction^[58-59]. Recent advances in deep learning, particularly Graph Convolutional Networks (GCNs), have significantly improved the accuracy of tree species identification^[60]. The incorporation of multi-source imagery and novel segmentation frameworks (e.g., Segment Anything Model) has further enhanced the system adaptability to complex urban scenarios^[61]. Additionally, multi-view scanning techniques combined with crowdsourced annotation methods have expanded survey coverage of urban green spaces while significantly improving model robustness and cross-domain transferability^[62-63].

Regarding structural parameters and biomass retrieval, LiDAR technology enables direct and stable extraction of core structural parameters, including tree height, diameter at breast height (DBH), leaf area index (LAI), and CHM^[64-65]. Through DBH prediction models and LAI quantification methods based on canopy profiles^[66-69], high-precision structural data layers can be constructed^[70-72], providing a unified data basis for biomass estimation at both individual tree and stand levels. Besides, the integration of multi-platform data (e.g., MLS-ALS) significantly reduces uncertainties caused by occlusion, scale discrepancies, and sampling angle variations compared with single-platform observation. The synergistic fusion of LiDAR and hyperspectral features demonstrates superior explanatory power and robustness in species/functional group discrimination and structure-physiology coupling analysis, reflecting a technological

trend toward "geometry-spectrum-scale" integration^[19,73].

For carbon sequestration and temporal monitoring, the combined application of LiDAR and high-resolution remote sensing effectively maps the spatial distribution patterns of carbon density^[74]. Sub-pixel modeling techniques combined with biomass expansion factors (BEF) significantly mitigate the impact of mixed pixel effects^[75]. Multi-temporal point clouds shift carbon cycle assessment from static analysis to dynamic time-series analysis, offering deep insights into the response mechanisms between urban forest carbon storage and climatic disturbances^[76]. Additionally, emerging 3D carbon models have achieved a preliminary "observation-simulation-validation" cycle through parameter transfer and uncertainty optimization, providing critical data support for climate-adaptive planning and urban carbon neutrality pathway analysis^[77].

(2) Ecosystem service assessment

Building on refined vegetation structure characterization, current research increasingly quantifies LiDAR-derived 3D structural variables as ecosystem service indicators. These indicators delineate key dimensions (e.g., risk regulation, habitat provision, health exposure, social equity) and are integrated into decision-making workflows to underpin site prioritization, scale control, and performance evaluation for NbS^[63,78-79]. LiDAR serves not merely to visualize vegetation structure but to establish a traceable "structure-function-governance" linkage, enabling the spatialized and quantitative integration of ecosystem services into urban and regional governance practices^[78].

For risk prevention and resilience management, LiDAR-derived 3D forest models play a pivotal role in urban forest planning and disaster management^[57]. Leaf-off point cloud data significantly enhances vertical structure analysis precision by reducing parameter uncertainty^[80]. The dynamic mapping of coarse woody debris (CWD) using bi-temporal point clouds provides temporal evidence for targeted renewal and patrol strategies, improving the resilience and timeliness of urban forest governance^[81-82]. By integrating spatial metrics such as canopy cover and patch connectivity, fire risk models for the wildland-urban interface can spatially visualize ecological safety assessments^[83].

Regarding habitat provision and biodiversity, LiDAR's paramount value lies in revealing vertical canopy stratification, gap patterns, and spatial heterogeneity across various heights. These structural features are significantly correlated with species richness, habitat quality, and habitat preferences of terrestrial fauna, particularly birds^[84-85]. Within urban parks, corridors, and fringe habitats, LiDAR-derived metrics (e.g., canopy height distribution, layer thickness, horizontal heterogeneity) offer superior explanatory power for bird

species richness and distribution patterns compared with traditional 2D coverage indices, effectively identifying green patches that structurally approximate high-quality habitats^[58,86-87]. Specifically, stands exhibiting distinct vertical stratification alongside horizontal heterogeneity provide multifunctional niches for shelter, foraging, and nesting, thereby enhancing overall biodiversity^[84-85,87].

For health benefits and environmental equity, LiDAR concurrently characterizes environmental stressors and spatial distribution of ecosystem services, directly linking public health and social vulnerability with vegetation structure^[78-79]. Regarding thermal exposure, LiDAR characterizes 3D features (e.g., tree height, canopy thickness, continuity) at the block scale, enabling quantitative comparison with land surface temperature (LST) and near-surface thermal loads^[88]. Neighborhoods with taller, contiguous canopies exhibit more pronounced cooling effects than those explained by 2D green coverage alone. Additionally, LiDAR-derived individual tree parameters (e.g., height, crown width, lean angle) can be integrated with species traits and local meteorological data to identify potentially unstable trees and high-risk green infrastructure under extreme weather, providing a spatial basis for precision maintenance and renewal prioritization^[89-90]. Urban-scale analysis reveals that low-income or historically marginalized communities often feature lower tree heights, fragmented canopy continuity, and diminished shading capacity, placing them at a systemic disadvantage regarding heat exposure, environmental stress, and accessibility to buffering services^[91]. LiDAR's significance lies in both unveiling and quantifying these disparities and localizing them to specific units, providing a targeted spatial decision-making foundation for NbS interventions.

3.3.3 River Restoration and Stormwater Management

(1) River geomorphological restoration

Floodplain systems are characterized by the inextricable “geometry–connectivity–habitat” coupling, where LiDAR technology serves as a foundational tool for river ecological restoration. LiDAR's active ranging capability and high-density 3D sampling enable the stable reconstruction of baseline topography in river reaches obscured by dense canopy cover or complex gravel micro-topography. This provides a consistent data foundation for identifying connectivity bottlenecks and estimating retention potential^[92-93]. Specifically, applying hydrologic enforcement to multi-platform DTMs effectively eliminates spurious sinks and restores continuous flow paths. This process rectifies connectivity misinterpretations caused by artificial barriers (e.g., roads, levees) being incorrectly identified as impediments to flow^[92]. On this

basis, key metrics, including sinuosity, width-to-depth ratio, bank breaklines, and roughness, can be extracted to precisely locate lateral depressions, paleo-channels, and floodways requiring priority reconnection^[93-94]. Furthermore, by leveraging canopy height and gap distribution to characterize the vertical structure of riparian zones, the “morphology–habitat” coupling degree can be quantified using the probability of connectivity and integral indices of connectivity, effectively identifying severe fragmentation points^[94].

Regarding the spatial scaling of restoration, LiDAR-constrained relationships between threshold water levels and inundation, along with that between area/volume and water level, enable direct estimation of available flood storage volumes and peak reduction potential under varying design water levels. These metrics facilitate reverse calculation of geometric control parameters such as setback width, excavation depth, and bench elevation, providing a scientific basis for site selection and scaling of interventions including levee setbacks, lateral expansion, compound wetlands, reconnected channels, and ecological embankments^[93,95-96]. Compared with traditional 2D imagery or sparse cross-section extrapolation, this LiDAR-based quantitative workflow significantly shortens the inference chain from morphology to function, reduces reliance on empirical roughness coefficients and coarse-resolution DEMs, and enhances the scientific rigor and operability of restoration schemes.

For performance verification and adaptive management, multi-temporal LiDAR facilitates the comparison of sediment erosion and deposition volumes and bankline retreat at both event-based and inter-annual scales. Furthermore, point cloud-based statistical tests (e.g., M3C2-EP) are employed to assess the statistical significance of topographic changes, distinguishing authentic morphological evolution from measurement errors^[95]. The integration of topobathymetric LiDAR and full-waveform ALS for inundation extent identification enables evidence-based reconstruction of flood processes and the verification of connectivity pathways^[96-97], supporting the long-term monitoring and adaptive management of river ecological restoration.

(2) Urban stormwater management

NbS advocates a stormwater management philosophy anchored in source reduction, on-site infiltration, hierarchical retention, and peak attenuation^[98]. LiDAR technology serves as a foundational tool for urban flood simulation and regulation by translating micro-topography, underlying surface characteristics, roughness, and canopy structure into physical parameter layers that can be seamlessly integrated into hydrodynamic models. This significantly mitigates the reliance on empirical parameterization and low-resolution terrain data^[97,99]. Hydrologically enforced LiDAR-

DEMs enable the identification of curbs, stormwater inlets, micro-depressions, and drainage channels at the centimeter-to-decimeter level. When integrated with CHM and land cover information to derive key parameters such as Manning's roughness, imperviousness, and canopy interception, this approach significantly enhances the simulation of flow paths, inundation duration, and retention nodes^[11,99].

For model integration, LiDAR-derived parameters can be coupled with hydrologic models (e.g., SWMM, HEC-HMS) and 1D/2D hydrodynamic models (e.g., HEC-RAS, CityCAT) to establish a comparative assessment workflow^[11,97,99]. Hydrodynamic models driven by LiDAR-constrained DTMs and digital surface models (DSMs) significantly outperform traditional remote sensing topographic basemaps in reconstructing inundation extents, peak flow processes, and block-scale flow paths^[10,99]. Supplementary local elevation data from LiDAR can further elevate precision and interpretability of ultra-high-resolution scenario assessments^[97,99]. Simultaneously, the direct parameterization of roughness and sub-grid topographic variability from LiDAR geometry incorporates the coupling of "morphology-roughness-hydraulic resistance" into the computational framework, improving stability and reliability of 2D hydrodynamic solutions^[11,100].

In terms of LID and sustainable drainage systems (SuDS) configuration and optimization, LiDAR-driven parameters can drive scenario analysis at both street and catchment scales. This facilitates comparative analysis of performance improvements—such as peak reduction, lag time increase, and node overflow frequency—offered by interventions like rain gardens, sunken green belts, permeable pavements, and retention ponds. Utilizing a multi-objective Pareto framework, this process outputs a definitive list of critical vulnerability and priority intervention units^[99]. Overall, by leveraging technical advantages of parameter traceability, indicator quantifiability, and scalar interoperability, LiDAR propels urban NbS stormwater governance from empirical practice toward an structure-framed and evidence-based engineering-oriented framework.

3.3.4 Urban Resilience and BGI Optimization

(1) UHI effect and climate regulation

For NbS-oriented urban climate optimization, the critical objective is to translate 3D geometric structural information directly into interpretable thermal environment control variables, not merely to increase green coverage. LiDAR technology provides essential technical support for mitigating the UHI effect and regulating local climates. DSMs, DTMs, and CHM derived from airborne or terrestrial LiDAR facilitate the stable derivation of key parameters,

including sky view factor (SVF), canopy height/thickness, street canyon aspect ratio, and roughness. When integrated with thermal infrared (TIR) data and building vector data, these parameters enable mechanistic interpretation and correction of LST and near-surface air temperature^[101-104]. Specifically, utilizing LiDAR-derived SVF to refine the SVF-based urban effective emissivity (UEM-SVF) and LST retrieval accuracy significantly mitigates biases induced by the radiation trapping effect within street canyons^[101]. Furthermore, continuous SVF fields computed by LiDAR demonstrate high consistency with hemispherical photography, maintaining spatial continuity and methodological reproducibility in complex, mixed vegetation-building environments^[105]. When coupled with airborne thermal imagery, LiDAR also enables error control in single- or multi-band temperature retrieval^[104].

For vegetation cooling pathways, vertical canopy structure can be directly measured by LiDAR. A case study in Tampa, Florida, revealed that LiDAR-extracted vegetation height possesses greater explanatory power for LST than 2D coverage, indicating that the vertical height of trees is more determinant of cooling magnitude than horizontal canopy extent^[88]. For building morphology, the joint analysis of LiDAR and airborne TIR data demonstrates a significant correlation between 3D morphological metrics (e.g., building height, volume, fractal dimension) and LST. This correlation exhibits heterogeneity across different functional zones, providing a quantitative basis for zoning and regulation^[102].

Overall, the technical advantages of LiDAR in mitigating UHI and regulating climate are manifested in three aspects: 1) direct vertical structure observation, where SVF, shading, and canopy layering are derived from a unified measurement system, minimizing cross-source co-registration errors^[101,103-104]; 2) shortened parameter-performance linkage, which allows design variables (e.g., aspect ratio, tree height, canopy gaps) to be directly mapped to temperature and thermal exposure indicators^[88,102]; and 3) cross-scale scalability, enabling a unified parametric framework to be extrapolated from the block scale to district and city scales, facilitating identification of hotspots and priority intervention units^[88,102,104].

(2) Ventilation corridors and ecosystem services

Ventilation corridors are conceptualized as critical spatial networks connecting source areas (with strong cooling and purification capacities) to high-heat, high-exposure neighborhoods, aiming to enhance the dilution and transport efficiency of heat and pollutants within high-density built environments^[106-107]. LiDAR's core contribution lies in providing a homologous data foundation for 3D morphology and vegetation structure. This enables the construction of roughness/resistance fields and SVF/openness

layers, reducing reliance on empirical parameterization and low-resolution data for corridor identification^[108-109]. A case study in Hong Kong, China, utilized airborne LiDAR to calculate the frontal area index (FAI) of buildings and trees, combined with least cost path (LCP) analysis, identified optimal ventilation corridors under dominant wind directions. Existing comparisons with computational fluid dynamics (CFD) results demonstrated consistency in corridor location and ventilation accessibility, validating the reliability and operability of the LiDAR-based method^[109].

Regarding data and assessment, LiDAR-derived building height fields and canopy thickness can be directly parameterized into ventilation resistance grids, while SVF supplements radiative openness information, jointly constructing ventilation potential maps and resistance maps^[110-111]. Furthermore, novel metrics such as the tree canopy view factor (TC-VF) and potential impact intensity grade (PIIG), calculated from airborne LiDAR 3D point clouds, have shown significant correlations with thermal risk and energy consumption^[112]. These metrics measure the localized interplay of shading, heat dissipation, and ventilation, thereby facilitating the identification of high-resistance bottlenecks, ventilation interruptions, and candidate corridors with modification potential. Consequently, this provides a spatial basis for removing aerodynamic obstacles, connecting flow paths, and expanding ventilation inlets in cold source areas (e.g., waterfronts, open green spaces)^[112].

In terms of monitoring and verification, Doppler LiDAR can reconstruct urban vertical wind profiles, enabling site-scale independent verification and model calibration for corridor accessibility and cooling efficacy, significantly enhancing the evidence base for corridor planning^[113]. Furthermore, LiDAR-based 3D footprints of buildings and tree canopies facilitate the rapid construction of roughness and openness indices required for urban climate maps (UCM). These indices support corridor alignment, prioritization, and phased implementation between waterfront cold sources, open green spaces, and high-heat exposure blocks^[114,105].

4 Challenges and Prospects of LiDAR in NbS Applications

4.1 Technical Challenges and Constraints

4.1.1 Data Quality and Precision Limitations

The foremost challenge confronting LiDAR technology in NbS applications pertains to data quality and precision. In complex terrains, point cloud preprocessing procedures (e.g., filtering, resampling, surface fitting) often result in the loss of critical geometric information. Specifically, filtering algorithms, while removing noise, may inadvertently eliminate micro-topographic

features sensitive to hydrological processes, including flow paths, micro-depressions, and terraced structures. This “over-smoothing” phenomenon directly compromises the accuracy of hydrological models, introducing systematic biases when translating geometric morphology into ecological functions^[10]. Furthermore, data acquisition under dense vegetation cover presents inherent limitations. Restricted laser penetration within dense forests or multi-layer canopies constrains extraction of parameters (e.g., individual tree identification, crown delineation, DBH, tree height), which rely on penetration rates, point density, and waveform characteristics. Even with advanced deep learning segmentation models, complete elimination of omission and commission errors remains unachievable^[8]. This data incompleteness restricts the efficacy of LiDAR in ecological assessments.

4.1.2 Multi-source Data Fusion Barriers

Multi-source remote sensing data fusion is essential for enhancing the efficacy of LiDAR applications; however, it faces significant technical challenges. The synergistic application of LiDAR with hyperspectral or multispectral, TIR, and synthetic aperture radar (SAR) data necessitates resolving fundamental issues such as geometric registration, scale matching, and feature space mapping^[115]. Discrepancies in data formats, spatial resolutions, and temporal baselines across different sensors underscores a lack of unified fusion standards and uncertainty assessment frameworks. More critically, there is a deficit in standardized methodologies for validating and accurately assessing of fused data products. Consequently, quantifying data uncertainty and establishing robust confidence propagation mechanisms have become technical bottlenecks constraining the effective application of multi-source data in NbS.

4.1.3 Semantic Understanding and Automated Processing Bottlenecks

The semantic understanding of point cloud data remains a core challenge in LiDAR applications. Because raw point clouds lack inherent semantic information, feature recognition and classification require complex feature engineering and extensive manual criteria^[116]. Although deep learning technologies have significantly improved automation in point cloud processing, model training still relies heavily on massive, high-quality annotated datasets, and cross-scene generalization capability remain limited^[30,117-118]. In NbS applications, this semantic gap hinders the direct translation of point cloud data into design parameters. Throughout the “point cloud–semantics–design indicators” chain, information loss and

uncertainty accumulation at each stage comprises the reliability and efficiency of data-driven design.

4.2 Workflow Integration and Engineering Challenges

4.2.1 Fragmented Toolchains and Data Silos

Current LiDAR applications are hindered by highly fragmented toolchains. Point cloud data processing and analysis rely heavily on specialized remote sensing software (e.g., CloudCompare, MeshLab), whereas planning and design workflows predominantly operate within CAD/BIM environments^[119-120]. This fragmentation often leads to format incompatibility, precision degradation, and semantic information loss during data migration across platforms. Although standard frameworks such as CityGML, Industry Foundation Classes (IFC), and GeoBIM are advancing, technical difficulties persist regarding geometric consistency, topological integrity, and semantic mapping^[119-120]. The absence of unified data exchange standards renders LiDAR-derived parameters difficult to reuse directly within design software, thereby impeding data-driven design iteration and optimization.

4.2.2 Cost-Benefit and Accessibility Challenges

Cost remains a pivotal factor constraining the widespread adoption of LiDAR. The acquisition costs for high-precision LiDAR systems range from tens of thousands to hundreds of thousands of yuan. When compounded with the expenses of specialized personnel training and computational resources for data processing, these costs become prohibitive for small-to-medium-scale projects^[121]. The data processing phase necessitates high-performance computing infrastructure and professional software; and the entire workflow may span weeks to months, making it challenging to meet the rapid-response demands of planning and design projects. Furthermore, the high professional threshold of LiDAR technology necessitates operators with multidisciplinary backgrounds in remote sensing, geographic information science, and computer vision. This skill

requirement restricts the broader application of the technology, particularly within traditional planning and design domains.

4.3 Future Prospects and Development Pathways

Building on the preceding analysis and practical insights, this section outlines the future trajectory of LiDAR technology in the NbS domain, focusing on data platform construction, intelligent algorithm research, and interoperability enhancement. Recommendations for professional capacity building and cross-disciplinary collaboration are also proposed.

4.3.1 Open Data and Artificial Intelligence Empowerment

Looking forward, constructing open data sharing platforms, utilizing artificial intelligence (AI) to empower point cloud processing, and unifying data exchange standards are critical for promoting the widespread application of LiDAR technology in the NbS domain (Fig. 5).

Open data sharing is a vital pathway to reducing barriers to entry for LiDAR technology, necessitating concerted efforts from governments, academic institutions, and industry stakeholders^[122]. Currently, platforms such as OpenTopography provide open-access LiDAR data covering diverse landforms alongside online processing services^[123]. Additionally, city-scale open point clouds like DublinCity offer benchmark data for multi-scale analysis^[124]; while high-quality benchmark datasets such as WHU-TLS have advanced algorithm evaluation and model training^[125]. Future efforts should focus on constructing a more comprehensive open data ecosystem, encompassing data standardization, quality control, and metadata management.

AI technologies are key to address the challenges in LiDAR application. Deep learning models can automatically recognize landscape elements such as vegetation, buildings, and pavements, significantly reducing reliance on specialized skills^[18]. For instance, large-scale annotated benchmarks like Semantic3D and Paris-

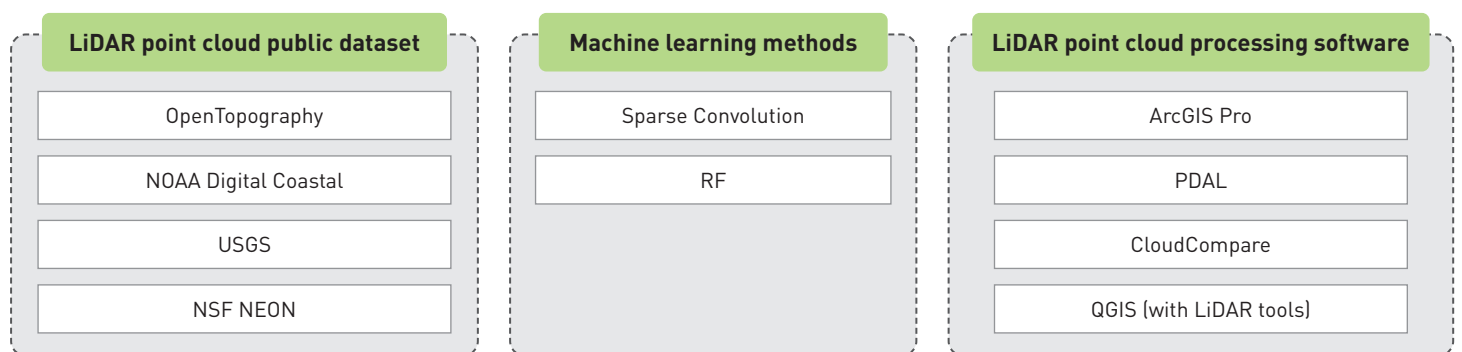


Fig. 5 A development pathway for LiDAR applications in NbS: open data sharing and AI empowerment.

Lille-3D have facilitated standardized evaluation for segmentation or classification in complex urban scene^[18]. Moreover, few-shot learning and transfer learning techniques can enhance the cross-scene generalization capabilities of point cloud segmentation and classification models^[30]. End-to-end point cloud networks, such as PointNet/PointNet++, have reduced dependency on traditional feature engineering^[126]. Future research should prioritize weakly supervised and self-supervised learning methods to minimize the need for extensive manual annotation, thereby enhancing model practicality and scalability.

Establishing unified data standards and interface specifications is fundamental to promoting LiDAR technology adoption. Lightweight semantic mapping based on CityGML/CityJSON and IFC can advance GeoBIM workflows, enabling the seamless integration of LiDAR-derived parameters into design software^[119-120]. This process effectively links manipulable spatial control variables with quantifiable performance indicators, allowing design adjustments to be tracked, compared, and validated. The next critical step lies in unifying cross-platform data standards and APIs to ensure interoperability among LiDAR data, environmental assessment models, and design software, thereby reducing format conversion costs and enhancing decision-making transparency.

4.3.2 Professional Capacity Building and Cross-Disciplinary Collaboration

To implement NbS effectively, the landscape architecture profession must cultivate talents who combine ecological and computational thinking with digital proficiency. Designers should master spatial data analysis and integrate LiDAR results into NbS design workflow. Higher education curricula should systematically incorporate modules on geospatial data analysis, digital tools, ecological process modeling, and parametric design. Through interdisciplinary collaboration, these programs should empower designers to use LiDAR data for NbS site selection, scale regulation, and performance assessment.

Cross-disciplinary collaboration in NbS must evolve from ad-hoc, project-based approaches to systematic, institutionalized mechanisms. Implementing NbS requires the deep integration of ecology, hydrology, landscape architecture, and remote sensing. This integration requires clear protocols for data acquisition, iterative design charrettes, and interdisciplinary workshops. These mechanisms facilitate the translation of ecological process insights into actionable design interventions. Future work should establish standardized cross-disciplinary collaboration workflows for NbS, encompassing ecological data quality control, ecosystem service

assessment validation, and knowledge dissemination mechanisms. Fostering long-term partnerships and shared platforms will promote deep integration across relevant disciplines, ultimately elevating the precision and ecological benefits of LiDAR-based NbS designs. Such collaborative efforts provide scientific evidence-based support for the quantitative assessment of ecological benefits and the construction of climate-adaptive landscapes^[127].

5 Conclusions

Using a bibliometric approach, this study systematically analyzed LiDAR applications in NbS from 2000 to 2024, identifying four core application domains: point cloud analysis and ecological structural foundations, vegetation structure and ecological assessment, river restoration and stormwater management, and urban resilience and BGI optimization. The findings reveal that leveraging its high precision, 3D capability, and multi-platform adaptability, LiDAR consistently translates geometric and structural information into computable ecological metrics. It significantly outperforms traditional 2D remote sensing in observability, spatial continuity, and cross-scale consistency within complex environments. LiDAR thus provides a robust data support for NbS site selection, spatial scaling, and performance evaluation. However, the widespread adoption of LiDAR in NbS still faces challenges including cumbersome data processing, barriers in multi-source data fusion, fragmented toolchains, and cost-benefit imbalances.

To address these challenges, this study proposes a development pathway centered on open data sharing, AI-driven automation, and standardized interoperability, aiming to facilitate the integration of LiDAR technology with NbS practices. The role of LiDAR in NbS should evolve from being merely a high-precision measurement tool to serving as a public infrastructure for evidence-based design and governance. By establishing a complete workflow from data acquisition to design application, LiDAR can support precise implementation of NbS goals, including disaster risk reduction, climate adaptation, biodiversity conservation, and equitable distribution of ecosystem services. With rapid advancement of AI, cloud computing, and the Internet of Things (IoT), LiDAR-empowered NbS practices will drive the landscape planning and design toward a more digital, intelligent, and sustainable development.

Competing interests | The authors declare that they have no competing interests.

REFERENCES

- [1] Albert, C., Brillinger, M., Guerrero, P., Gottwald, S., Henze, J., Schmidt, S., Ott, E., & Schröter, B. (2021). Planning nature-based solutions: Principles, steps, and insights. *Ambio*, 50(8), 1446–1461.
- [2] Seddon, N., Chausson, A., Berry, P., Girardin, C. A. J., Smith, A., & Turner, B. (2020). Understanding the value and limits of nature-based solutions to climate change and other global challenges. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 375(1794), 20190120.
- [3] Cohen-Shacham, E., Walters, G., Janzen, C., & Maginnis, S. (2016). *Nature-based solutions to address global societal challenges*. IUCN.
- [4] Seddon, N., Smith, A., Smith, P., Key, I., Chausson, A., Girardin, C., House, J., Srivastava, S., & Turner, B. (2021). Getting the message right on nature-based solutions to climate change. *Global Change Biology*, 27(8), 1518–1546.
- [5] Nesshöver, C., Assmuth, T., Irvine, K. N., Rusch, G. M., Waylen, K. A., Delbaere, B., Haase, D., Jones-Walters, L., Keune, H., Kovacs, E., Krauze, K., Külvik, M., Rey, F., van Dijk, J., Vistad, O. I., Wilkinson, M. E., & Wittmer, H. (2017). The science, policy and practice of nature-based solutions: An interdisciplinary perspective. *Science of The Total Environment*, 579, 1215–1227.
- [6] Laforteza, R., Chen, J., van den Bosch, C. K., & Randrup, T. B. (2018). Nature-based solutions for resilient landscapes and cities. *Environmental Research*, 165, 431–441.
- [7] Raymond, C. M., Frantzeskaki, N., Kabisch, N., Berry, P., Breil, M., Nita, M. R., Geneletti, D., & Calfapietra, C. (2017). A framework for assessing and implementing the co-benefits of nature-based solutions in urban areas. *Environmental Science & Policy*, 77, 15–24.
- [8] Michałowska, M., & Rapiński, J. (2021). A review of tree species classification based on airborne LiDAR data and applied classifiers. *Remote Sensing*, 13(3), 353.
- [9] Passalacqua, P., Belmont, P., Staley, D. M., Simley, J. D., Arrowsmith, J. R., Bode, C. A., Crosby, C., DeLong, S. B., Glenn, N. F., Kelly, S. A., Lague, D., Sangireddy, H., Schaffrath, K., Tarboton, D. G., Wasklewicz, T., & Wheaton, J. M. (2015). Analyzing high resolution topography for advancing the understanding of mass and energy transfer through landscapes: A review. *Earth-Science Reviews*, 148, 174–193.
- [10] Muhadi, N. A., Abdullah, A. F., Bejo, S. K., Mahadi, M. R., & Mijic, A. (2020). The use of LiDAR-derived DEM in flood applications: A review. *Remote Sensing*, 12(14), 2308.
- [11] Meesuk, V., Vojinovic, Z., Mynett, A. E., & Abdullah, A. F. (2015). Urban flood modelling combining top-view LiDAR data with ground-view SfM observations. *Advances in Water Resources*, 75, 105–117.
- [12] Sofia, G., & Nikolopoulos, E. I. (2020). Floods and rivers: A circular causality perspective. *Scientific Reports*, 10(1), 5175.
- [13] Kafy, A. A., Crews, K. A., & Thompson, A. E. (2024). Exploring the cooling potential of green roofs for mitigating diurnal heat island intensity by utilizing LiDAR and artificial neural network. *Sustainable Cities and Society*, 116, 105893.
- [14] Hamraz, H., Contreras, M. A., & Zhang, J. (2017). Vertical stratification of forest canopy for segmentation of under-story trees within small-footprint airborne LiDAR point clouds. *ISPRS Journal of Photogrammetry and Remote Sensing*, 130, 385–392.
- [15] Dong, P., & Chen, Q. (2017). *LiDAR Remote Sensing and Applications*. CRC Press.
- [16] Meng, X., Currit, N., & Zhao, K. (2010). Ground filtering algorithms for airborne LiDAR data: A review of critical issues. *Remote Sensing*, 2(3), 833–860.
- [17] Guo, Q., Su, Y., & Hu, T. (2023). *LiDAR Principles, Processing and Applications in Forest Ecology*. Academic Press.
- [18] Tao, S., Wang, D., Xie, H., Zhang, W., Zhang, Z., Dong, X., Chen, Y., Qi, J., Cheng, K., Yang, Z., Qi, Z., Li, W., Su, Y., Hu, T., Ma, Q., Li, Y., Cai, S., Wang, B., Yang, H., Ren, Y., Jin, S., Zhang, X., Bai, H., Yang, Z., Hu, X., Asadilla, Y., Huang, H., Xu, Q., & Guo, Q. (2025). Review and prospects of the development of LiDAR in ecology and geosciences. *National Remote Sensing Bulletin*, 29(6), 1963–2004.
- [19] Takhtkeshha, N., Mandlbürger, G., Remondino, F., & Hyypä, J. (2024). Multispectral light detection and ranging technology and applications: A review. *Sensors*, 24(5), 1669.
- [20] Fu, H. (2023). A comprehensive review of nature-based solutions: Current status and future research. *AIMS Environmental Science*, 10(5), 677–690.
- [21] Buma, B., Gordon, D. R., Kleisner, K. M., Bartuska, A., Bidlack, A., DeFries, R., Ellis, P., Friedlingstein, P., Metzger, S., Morgan, G., Novick, K., Sanchirico, J. N., Collins, J. R., Eagle, A. J., Fujita, R., Holst, E., Lavalley, J. M., Lubowski, R. N., Melikov, C., Moore, L. A., Oldfield, E. E., Paltseva, J., Raffeld, A. M., Randazzo, N. A., Schneider, C., Uludere Aragon, N., & Hamburg, S. P. (2024). Expert review of the science underlying nature-based climate solutions. *Nature Climate Change*, 14(4), 402–406.
- [22] Johnson, B. A., Kumar, P., Okano, N., Dasgupta, R., & Shivakoti, B. R. (2022). Nature-based solutions for climate change adaptation: A systematic review of systematic reviews. *Nature-Based Solutions*, 2, 100042.
- [23] Dunlop, T., Khojasteh, D., Cohen-Shacham, E., Glamore, W., Haghani, M., van den Bosch, M., Rizzi, D., Greve, P., & Felder, S. (2024). The evolution and future of research on nature-based solutions to address societal challenges. *Communications Earth & Environment*, 5(1), 132.
- [24] Martin, J. G. C., Scolobig, A., Linnerooth-Bayer, J., Irshaid, J., Aguilera Rodriguez, J. J., Fresolone-Caparrós, A., & Oen, A. (2025). The nature-based solution implementation gap: A review of nature-based solution governance barriers and enablers. *Journal of Environmental Management*, 388, 126007.
- [25] Chen, C. (2006). CiteSpace II: Detecting and visualizing emerging trends and transient patterns in scientific literature. *Journal of the American Society for Information Science and Technology*, 57(3), 359–377.
- [26] Zhang, W., Qi, J., Wan, P., Wang, H., Xie, D., Wang, X., & Yan, G. (2016). An easy-to-use airborne LiDAR data filtering method based on cloth simulation. *Remote Sensing*, 8(6), 501.

- [27] Sohn, G., & Dowman, I. J. (2008). A model-based approach for reconstructing a terrain surface from airborne LIDAR data. *The Photogrammetric Record*, 23(122), 170–193.
- [28] Pingel, T. J., Clarke, K. C., & McBride, W. A. (2013). An improved simple morphological filter for the terrain classification of airborne LIDAR data. *ISPRS Journal of Photogrammetry and Remote Sensing*, 77, 21–30.
- [29] Axelsson, P. (2000). DEM generation from laser scanner data using adaptive TIN models. *International Archives of Photogrammetry and Remote Sensing*, 33(4), 110–117.
- [30] Guo, Y., Wang, H., Hu, Q., Liu, H., Liu, L., & Bennamoun, M. (2021). Deep learning for 3D point clouds: A survey. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 43(12), 4338–4364.
- [31] Turner, R., Panciera, R., Tanase, M. A., Lowell, K., Hacker, J. M., & Walker, J. P. (2014). Estimation of soil surface roughness of agricultural soils using airborne LiDAR. *Remote Sensing of Environment*, 140, 107–117.
- [32] Kempainen, J., Niittynen, P., Riihimäki, H., & Luoto, M. (2018). Modelling soil moisture in a high-latitude landscape using LiDAR and soil data. *Earth Surface Processes and Landforms*, 43(5), 1019–1031.
- [33] Stevens, C. W., & Wolfe, S. A. (2012). High-resolution mapping of wet terrain within discontinuous permafrost using LiDAR intensity. *Permafrost and Periglacial Processes*, 23(4), 334–341.
- [34] Mountrakis, G., Im, J., & Ogole, C. (2011). Support vector machines in remote sensing: A review. *ISPRS Journal of Photogrammetry and Remote Sensing*, 66(3), 247–259.
- [35] Krisanski, S., Taskhiri, M. S., Gonzalez Aracil, S., Herries, D., Muneri, A., Gurung, M. B., Montgomery, J., & Turner, P. (2021). Forest structural complexity tool—An open source, fully-automated tool for measuring forest point clouds. *Remote Sensing*, 13(22), 4677.
- [36] Gonizzi Barsanti, S., Marini, M. R., Malatesta, S. G., & Rossi, A. (2024). Evaluation of denoising and voxelization algorithms on 3D point clouds. *Remote Sensing*, 16(14), 2632.
- [37] Mandlbürger, G., & Jutzi, B. (2019). On the feasibility of water surface mapping with single photon LiDAR. *ISPRS International Journal of Geo-Information*, 8(4), 188.
- [38] Domlija, P., Gazibara, S. B., Arbanas, Z., & Arbanas, S. M. (2019). Identification and mapping of soil erosion processes using the visual interpretation of LiDAR imagery. *ISPRS International Journal of Geo-Information*, 8(10), 438.
- [39] Sanchez-Crespo, F. A., Gomez-Villarino, M. T., Gallego, E., Fuentes, J. M., Garcia, A. I., & Ayuga, F. (2023). Monitoring of water and tillage soil erosion in agricultural basins, a comparison of measurements acquired by differential interferometric analysis of Sentinel TopSAR images and a terrestrial LIDAR system. *Land*, 12(2), 408.
- [40] Mandlbürger, G. (2022). A review of active and passive optical methods in hydrography. *The International Hydrographic Review*, 28, 8–52.
- [41] Kastdalen, L., Stickler, M., Malmquist, C., & Heggenes, J. (2024). Evaluating methods for measuring in-river bathymetry: Remote sensing green LIDAR provides high-resolution channel bed topography limited by water penetration capability. *River Research and Applications*, 40(4), 467–482.
- [42] Fernandez-Diaz, J. C., Carter, W. E., Glennie, C., Shrestha, R. L., Pan, Z., Ekhtari, N., Singhanian, A., Hauser, D., & Sartori, M. (2016). Capability assessment and performance metrics for the Titan multispectral mapping LiDAR. *Remote Sensing*, 8(11), 936.
- [43] Yan, W. Y., Shaker, A., & LaRocque, P. E. (2018). Water mapping using multispectral airborne LiDAR data. *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, XLII-3, 2047–2052.
- [44] Abalharth, M., Hassan, M. A., Klinkenberg, B., Leung, V., & McCleary, R. (2015). Using LiDAR to characterize logjams in lowland rivers. *Geomorphology*, 246, 531–541.
- [45] Shan, J., & Toth, C. K. (2018). *Topographic Laser Ranging and Scanning: Principles and Processing (2nd ed.)*. CRC Press.
- [46] Dalponte, M., Bruzzone, L., & Gianelle, D. (2012). Tree species classification in the Southern Alps based on the fusion of very high geometrical resolution multispectral/hyperspectral images and LiDAR data. *Remote Sensing of Environment*, 123, 258–270.
- [47] Debes, C., Merentitis, A., Heremans, R., Hahn, J., Frangiadakis, N., Kasteren, T., Liao, W., Bellens, R., Pizurica, A., Gautama, S., Philips, W., Prasad, S., Du, Q., & Pacifici, F. (2014). Hyperspectral and LiDAR data fusion: Outcome of the 2013 GRSS data fusion contest. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 7(6), 2405–2418.
- [48] Xu, X., Li, W., Ran, Q., Du, Q., Gao, L., & Zhang, B. (2018). Multisource remote sensing data classification based on convolutional neural network. *IEEE Transactions on Geoscience and Remote Sensing*, 56(2), 937–949.
- [49] Hu, Y., He, H., & Weng, L. (2022). Hyperspectral And Lidar Data Land-Use Classification Using Parallel Transformers. In: *2022 IEEE International Geoscience and Remote Sensing Symposium (IGARSS)* (pp. 703–706). IEEE.
- [50] Mo, Y., Zhong, R., Sun, H., Wu, Q., Du, L., Geng, Y., & Cao, S. (2019). Integrated airborne LiDAR data and imagery for suburban land cover classification using machine learning methods. *Sensors*, 19(9), 1996.
- [51] Szostak, M. (2020). Automated land cover change detection and forest succession monitoring using LiDAR point clouds and GIS analyses. *Geosciences*, 10(8), 321.
- [52] Williams, D. A. R., Matasci, G., Coops, N. C., & Gergel, S. E. (2018). Object-based urban landcover mapping methodology using high spatial resolution imagery and airborne laser scanning. *Journal of Applied Remote Sensing*, 12(4), 046020.
- [53] Marsoner, T., Simion, H., Giombini, V., Egarter Vigl, L., & Candiago, S. (2023). A detailed land use/land cover map for the European Alps macro region. *Scientific Data*, 10(1), 468.
- [54] Lefsky, M. A., Cohen, W. B., Parker, G. G., & Harding, D. J. (2002). Lidar remote sensing for ecosystem studies: Lidar, an emerging remote sensing technology that directly measures the three-dimensional distribution of plant canopies, can accurately estimate vegetation structural attributes and should be of particular interest to forest, landscape, and global ecologists. *BioScience*, 52(1), 19–30.
- [55] Ma, Q., Lin, J., Ju, Y., Li, W., Liang, L., & Guo, Q. (2023). Individual

- structure mapping over six million trees for New York City USA. *Scientific Data*, 10(1), 102.
- [56] Shrestha, R., & Wynne, R. H. (2012). Estimating biophysical parameters of individual trees in an urban environment using small footprint discrete-return imaging LiDAR. *Remote Sensing*, 4(2), 484–508.
- [57] Muenzinger, M., Prechtel, N., & Behnisch, M. (2022). Mapping the urban forest in detail: From LiDAR point clouds to 3D tree models. *Urban Forestry & Urban Greening*, 74, 127637.
- [58] Panagiotidis, D., Abdollahnejad, A., & Slavík, M. (2022). 3D point cloud fusion from UAV and TLS to assess temperate managed forest structures. *International Journal of Applied Earth Observation and Geoinformation*, 112, 102917.
- [59] Zięba-Kulawik, K., Hawryło, P., Wężyk, P., Matczak, P., Przewoźna, P., Ingłot, A., & Mączka, K. (2021). Improving methods to calculate the loss of ecosystem services provided by urban trees using LiDAR and aerial orthophotos. *Urban Forestry & Urban Greening*, 63, 127195.
- [60] Li, X., Wang, L., Guan, H., Chen, K., Zang, Y., & Yu, Y. (2023). Urban tree species classification using UAV-based multispectral images and LiDAR point clouds. *Journal of Geovisualization and Spatial Analysis*, 8(1), 5.
- [61] Ferreira, M. P., dos Santos, D. R., Ferrari, F., Filho, L. C. T. C., Martins, G. B., & Feitosa, R. Q. (2024). Improving urban tree species classification by deep-learning based fusion of digital aerial images and LiDAR. *Urban Forestry & Urban Greening*, 94, 128240.
- [62] Anderson, K., Hancock, S., Casalegno, S., Griffiths, A., Griffiths, D., Sargent, F., McCallum, J., Cox, D. T. C., & Gaston, K. J. (2018). Visualising the urban green volume: Exploring LiDAR voxels with tangible technologies and virtual models. *Landscape and Urban Planning*, 178, 248–260.
- [63] Zhang, X., Qi, J., Lin, E. S., Tan, P. Y., Ho, R., Sia, A., Song, X. P., Waykool, R., & Olszewska-Guizzo, A. (2024). Towards healthy cities: Modeling restorative potential of urban environments by coupling LiDAR-derived 3D metrics with panorama-based online survey. *Environmental Impact Assessment Review*, 106, 107497.
- [64] Heo, H. K., Lee, D. K., Park, J. H., & Thorne, J. H. (2019). Estimating the heights and diameters at breast height of trees in an urban park and along a street using mobile LiDAR. *Landscape and Ecological Engineering*, 15(3), 253–263.
- [65] Brede, B., Calders, K., Lau, A., Raunonen, P., Bartholomeus, H. M., Herold, M., & Kooistra, L. (2019). Non-destructive tree volume estimation through quantitative structure modelling: Comparing UAV laser scanning with terrestrial LIDAR. *Remote Sensing of Environment*, 233, 111355.
- [66] Hosoi, F., & Omasa, K. (2006). Voxel-based 3-D modeling of individual trees for estimating leaf area density using high-resolution portable scanning LiDAR. *IEEE Transactions on Geoscience and Remote Sensing*, 44(12), 3610–3618.
- [67] Takeda, T., Oguma, H., Sano, T., Yone, Y., & Fujinuma, Y. (2008). Estimating the plant area density of a Japanese larch (*Larix kaempferi* Sarg.) plantation using a ground-based laser scanner. *Agricultural and Forest Meteorology*, 148(3), 428–438.
- [68] Zheng, G., & Moskal, L. M. (2012). Computational-geometry-based retrieval of effective leaf area index using terrestrial laser scanning. *IEEE Transactions on Geoscience and Remote Sensing*, 50(10), 3958–3969.
- [69] Umemi, K., & Inoue, A. (2024). A model for predicting mean diameter at breast height from mean tree height and stand density. *Journal of Forest Research*, 29(3), 186–195.
- [70] Oh, S., Jung, J., Shao, G. F., Shao, G., Gallion, J., & Fei, S. (2022). High-resolution canopy height model generation and validation using USGS 3DEP LiDAR data in Indiana, USA. *Remote Sensing*, 14(4), 935.
- [71] Mielcarek, M., Sterenczak, K., & Khosravipour, A. (2018). Testing and evaluating different LiDAR-derived canopy height model generation methods for tree height estimation. *International Journal of Applied Earth Observation and Geoinformation*, 71, 132–143.
- [72] Zhou, L., Meng, R., Tan, Y., Lv, Z., Zhao, Y., Xu, B., & Zhao, F. (2022). Comparison of UAV-based LiDAR and digital aerial photogrammetry for measuring crown-level canopy height in the urban environment. *Urban Forestry & Urban Greening*, 69, 127489.
- [73] Luo, S., Wang, C., Xi, X., Pan, F., Peng, D., Zou, J., Nie, S., & Qin, H. (2017). Fusion of airborne LiDAR data and hyperspectral imagery for aboveground and belowground forest biomass estimation. *Ecological Indicators*, 73, 378–387.
- [74] Schreyer, J., Tigges, J., Lakes, T., & Churkina, G. (2014). Using airborne LiDAR and QuickBird data for modelling urban tree carbon storage and its distribution—A case study of Berlin. *Remote Sensing*, 6(11), 10636–10655.
- [75] Lee, Y., Son, B., Im, J., Zhen, Z., & Quackenbush, L. J. (2024). Two-step carbon storage estimation in urban human settlements using airborne LiDAR and Sentinel-2 data based on machine learning. *Urban Forestry & Urban Greening*, 94, 128239.
- [76] Brilli, L., Chiesi, M., Brogi, C., Magno, R., Arcidiaco, L., Bottai, L., Tagliaferri, G., Bindi, M., & Maselli, F. (2019). Combination of ground and remote sensing data to assess carbon stock changes in the main urban park of Florence. *Urban Forestry & Urban Greening*, 43, 126377.
- [77] Mitchell, M. G. E., Johansen, K., Maron, M., McAlpine, C. A., Wu, D., & Rhodes, J. R. (2018). Identification of fine scale and landscape scale drivers of urban aboveground carbon stocks using high-resolution modeling and mapping. *Science of The Total Environment*, 622–623, 57–70.
- [78] Ziter, C. D., Pedersen, E. J., Kucharik, C. J., & Turner, M. G. (2019). Scale-dependent interactions between tree canopy cover and impervious surfaces reduce daytime urban heat during summer. *Proceedings of the National Academy of Sciences*, 116(15), 7575–7580.
- [79] Locke, D. H., Hall, B., Grove, J. M., Pickett, S. T. A., Ogden, L. A., Aoki, C., Boone, C. G., & O'Neil-Dunne, J. P. M. (2021). Residential housing segregation and urban tree canopy in 37 US Cities. *npj Urban Sustainability*, 1(1), 15.
- [80] Gu, H., & Townsend, P. A. (2017). Mapping forest structure and uncertainty in an urban area using leaf-off LiDAR data. *Urban Ecosystems*, 20(2), 497–509.
- [81] Tanhuanpää, T., Kankare, V., Vastaranta, M., Saarinen, N., & Holopainen, M. (2015). Monitoring downed coarse woody debris through appearance of canopy gaps in urban boreal forests with bitemporal ALS data. *Urban Forestry & Urban Greening*, 14(4), 835–843.

- [82] Harmon, M. E., Franklin, J. F., Swanson, F. J., Sollins, P., Gregory, S. V., Lattin, J. D., Anderson, N. H., Cline, S. P., Aumen, N. G., Sedell, J. R., Lienkaemper, G. W., Cromack, K., Jr., & Cummins, K. W. (1986). Ecology of coarse woody debris in temperate ecosystems. In: A. MacFadyen & E. D. Ford (Eds.), *Advances in Ecological Research* (Vol. 15, pp. 133–302). Academic Press.
- [83] Sankey, T. T., Tango, L., Tatum, J., & Sankey, J. B. (2024). Forest fire, thinning, and flood in wildland-urban interface: UAV and LiDAR-based estimate of natural disaster impacts. *Landscape Ecology*, 39(3), 58.
- [84] Goetz, S., Steinberg, D., Dubayah, R., & Blair, B. (2007). Laser remote sensing of canopy habitat heterogeneity as a predictor of bird species richness in an eastern temperate forest, USA. *Remote Sensing of Environment*, 108(3), 254–263.
- [85] Simonson, W. D., Allen, H. D., & Coomes, D. A. (2014). Applications of airborne LiDAR for the assessment of animal species diversity. *Methods in Ecology and Evolution*, 5(8), 719–729.
- [86] Carrasco, L., Giam, X., Papēs, M., & Sheldon, K. S. (2019). Metrics of LiDAR-derived 3D vegetation structure reveal contrasting effects of horizontal and vertical forest heterogeneity on bird species richness. *Remote Sensing*, 11(7), 743.
- [87] Sasaki, T., Imanishi, J., Fukui, W., & Morimoto, Y. (2016). Fine-scale characterization of bird habitat using airborne LiDAR in an urban park in Japan. *Urban Forestry & Urban Greening*, 17, 16–22.
- [88] Yu, Q., Acheampong, M., Pu, R., Landry, S. M., Ji, W., & Dahigamuwa, T. (2018). Assessing effects of urban vegetation height on land surface temperature in the City of Tampa, Florida, USA. *International Journal of Applied Earth Observation and Geoinformation*, 73, 712–720.
- [89] Moravčik, L., Vincúr, R., & Rózová, Z. (2021). Analysis of the static behavior of a single tree on a finite element model. *Plants*, 10(7), 1284.
- [90] Jackson, T., Shenkin, A., Wellpott, A., Calders, K., Origo, N., Disney, M., Burt, A., Raunonen, P., Gardiner, B., Herold, M., Fourcaud, T., & Malhi, Y. (2019). Finite element analysis of trees in the wind based on terrestrial laser scanning data. *Agricultural and Forest Meteorology*, 265, 137–144.
- [91] Schwarz, K., Fragkias, M., Boone, C. G., Zhou, W., McHale, M., Grove, J. M., O’Neil-Dunne, J., McFadden, J. P., Buckley, G. L., Childers, D., Ogden, L., Pincetl, S., Pataki, D., Whitmer, A., & Cadenasso, M. L. (2015). Trees grow on money: Urban tree canopy cover and environmental justice. *PLOS ONE*, 10(4), e0122051.
- [92] Lindsay, J. B. (2016). Efficient hybrid breaching-filling sink removal methods for flow path enforcement in digital elevation models. *Hydrological Processes*, 30(6), 846–857.
- [93] Cavalli, M., Tarolli, P., Marchi, L., & Dalla Fontana, G. (2008). The effectiveness of airborne LiDAR data in the recognition of channel-bed morphology. *CATENA*, 73(3), 249–260.
- [94] Lallias-Tacon, S., Liébault, F., & Piégay, H. (2017). Use of airborne LiDAR and historical aerial photos for characterising the history of braided river floodplain morphology and vegetation responses. *CATENA*, 149, 742–759.
- [95] Peña-Arancibia, J. L., Ticehurst, C. J., Yu, Y., McVicar, T. R., & Marvanek, S. P. (2024). Feasibility of monitoring floodplain on-farm water storages by integrating airborne and satellite LiDAR altimetry with optical remote sensing. *Remote Sensing of Environment*, 302, 113992.
- [96] Ciotti, D. C., McKee, J., Pope, K. L., Kondolf, G. M., & Pollock, M. M. (2021). Design criteria for process-based restoration of fluvial systems. *BioScience*, 71(8), 831–845.
- [97] Mandlbürger, G., Hauer, C., Wieser, M., & Pfeifer, N. (2015). Topobathymetric LiDAR for monitoring river morphodynamics and instream habitats—A case study at the Pielach River. *Remote Sensing*, 7(5), 6160–6195.
- [98] Palermo, S. A., Turco, M., Pirouz, B., Presta, L., Falco, S., De Stefano, A., Frega, F., & Piro, P. (2023). Nature-based solutions for urban stormwater management: An overview. *IOP Conference Series: Earth and Environmental Science*, 1196(1), 012027.
- [99] Trepekli, K., Balstrøm, T., Friborg, T., Fog, B., Allotey, A. N., Kofie, R. Y., & Møller-Jensen, L. (2022). UAV-borne, LiDAR-based elevation modelling: A method for improving local-scale urban flood risk assessment. *Natural Hazards*, 113, 423–451.
- [100] Abu-Aly, T. R., Pasternack, G. B., Wyrick, J. R., & Barker, R. (2014). Effects of LiDAR-derived, spatially distributed vegetation roughness on two-dimensional hydraulics in a gravel-cobble river at flows of 0.2 to 20 times bankfull. *Geomorphology*, 206, 468–482.
- [101] Yang, J., Wong, M. S., Menenti, M., & Nichol, J. (2015). Study of the geometry effect on land surface temperature retrieval in urban environment. *ISPRS Journal of Photogrammetry and Remote Sensing*, 109, 77–87.
- [102] Chen, C., Bagan, H., Yoshida, T., Borjigin, H., & Gao, J. (2022). Quantitative analysis of the building-level relationship between building form and land surface temperature using airborne LiDAR and thermal infrared data. *Urban Climate*, 45, 101248.
- [103] Chajaei, F., & Bagheri, H. (2024). Machine learning framework for high-resolution air temperature downscaling using LiDAR-derived urban morphological features. *Urban Climate*, 57, 102102.
- [104] Mandanici, E., Conte, P., & Girelli, V. A. (2016). Integration of aerial thermal imagery, LiDAR data and ground surveys for surface temperature mapping in urban environments. *Remote Sensing*, 8(10), 880.
- [105] Kidd, C., & Chapman, L. (2012). Derivation of sky-view factors from LiDAR data. *International Journal of Remote Sensing*, 33(11), 3640–3652.
- [106] Wang, W., Wang, D., Chen, H., Wang, B., & Chen, X. (2022). Identifying urban ventilation corridors through quantitative analysis of ventilation potential and wind characteristics. *Building and Environment*, 214, 108943.
- [107] Suder, A., & Szymanowski, M. (2014). Determination of ventilation channels in urban area: A case study of Wrocław (Poland). *Pure and Applied Geophysics*, 171(6), 965–975.
- [108] Yang, J., Wong, M. S., Menenti, M., & Nichol, J. (2015). Modeling the effective emissivity of the urban canopy using sky view factor. *ISPRS Journal of Photogrammetry and Remote Sensing*, 105, 211–219.
- [109] Peng, F., Wong, M. S., Wan, Y., & Nichol, J. E. (2017). Modeling of urban wind ventilation using high resolution airborne LiDAR data. *Computers, Environment and Urban Systems*, 64, 81–90.
- [110] Wong, M. S., Nichol, J. E., Ng, E. Y. Y., Guilbert, E., Kwok, K. H., To, P.

- H., & Wang, J. Z. (2010). GIS techniques for mapping urban ventilation, using frontal area index and least cost path analysis. *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, 38, 586–591.
- [111] Eldesoky, A. H. M., Colaninno, N., & Morello, E. (2020). Mapping urban ventilation corridors and assessing their impact upon the cooling effect of greening solutions. *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, XLIII-B4-2020, 665–672.
- [112] An, S. M., Kim, B., Lee, H. Y., Yi, C. Y., Joshi, N., & Wende, W. (2024). Views rather than radiosity: A study on urban cover view factor mapping and utilization. *Remote Sensing*, 16(24), 4618.
- [113] He, Y., Yuan, C., Ren, C., & Ng, E. (2022). Urban ventilation assessment with improved vertical wind profile in high-density cities—Comparisons between LiDAR and conventional methods. *Journal of Wind Engineering and Industrial Aerodynamics*, 228, 105116.
- [114] An, S. M. (2023). A study on urban-scale building, tree canopy footprint identification and sky view factor analysis with airborne LiDAR remote sensing data. *Remote Sensing*, 15(15), 3910.
- [115] Kahraman, S., & Bacher, R. (2021). A comprehensive review of hyperspectral data fusion with LiDAR and SAR data. *Annual Reviews in Control*, 51, 236–253.
- [116] Grilli, E., Menna, F., & Remondino, F. (2017). A review of point clouds segmentation and classification algorithms. *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, XLII-2/W3, 339–344.
- [117] Hackel, T., Savinov, N., Ladicky, L., Wegner, J. D., Schindler, K., & Pollefeys, M. (2017). Semantic3D.net: A new large-scale point cloud classification benchmark. *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, IV-1/W1, 91–98.
- [118] Qi, C. R., Su, H., Mo, K., & Guibas, L. J. (2017). PointNet: Deep learning on point sets for 3D classification and segmentation. In *2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)* (pp. 77–85). IEEE.
- [119] Noardo, F., Arroyo Otori, K., Biljecki, F., Ellul, C., Harrie, L., Krijnen, T., Eriksson, H., van Liempt, J., Pla, M., Ruiz, A., Hintz, D., Krueger, N., Leoni, C., Leoz, L., Moraru, D., Vitalis, S., Willkomm, P., & Stoter, J. (2021). Reference study of CityGML software support: The GeoBIM benchmark 2019—Part II. *Transactions in GIS*, 25(2), 842–868.
- [120] Biljecki, F., Stoter, J., Ledoux, H., Zlatanova, S., & Çöltekin, A. (2015). Applications of 3D city models: State of the art review. *ISPRS International Journal of Geo-Information*, 4(4), 2842–2889.
- [121] Ciobotari, I., Príncipe, A., Oliveira, M. A., & Silva, J. N. (2024). LiDAR data acquisition and processing for ecology applications. *arXiv*.
- [122] Natural Resources Canada. (2024, March 12). *Canada Centre for Mapping and Earth Observation*.
- [123] OpenTopography. (n.d.). *About | OpenTopography*.
- [124] V-SENSE. (2019, July 25). *DublinCity: Annotated LiDAR point cloud and its applications*.
- [125] WHU-USI3DV. (2025). *WHU-USI3DV/WHU-TLS*. GitHub.
- [126] Qi, C. R., Yi, L., Su, H., & Guibas, L. J. (2017). PointNet++: Deep hierarchical feature learning on point sets in a metric space. In: I. Guyon, U. V. Luxburg, S. Bengio, H. Wallach, R. Fergus, S. Vishwanathan, & R. Garnett (Eds.), *Advances in Neural Information Processing Systems* (Vol. 30). Curran Associates, Inc.
- [127] Bai, Y., Liu, G., Wu, M., Huo, Z., Yan, N., Meng, F., Yang, Q., Lu, Z., & Cristiano, S. (2025). Research on the potential of urban green-blue infrastructure in carbon reduction benefits. *Landscape Architecture Frontiers*, 13(2), 12–24.

基于文献计量分析的激光雷达在基于自然的解决方案中的应用与展望

吴松涛¹, 文师鹏¹, 彭晓^{1*}, 张国林²

¹ 哈尔滨工业大学建筑与设计学院, 哈尔滨 150001

² 北京大学建筑与景观设计学院, 北京 100871

*通信作者

地址: 哈尔滨市南岗区西大直街92号哈尔滨工业大学

明德楼D305室

邮编: 150001

邮箱: pengxiao@hit.edu.cn

摘要

在全球应对气候变化和生态危机的背景下, 基于自然的解决方案 (Nature-based solutions, NbS) 已成为实现可持续发展的重要途径。激光雷达 (LiDAR) 技术因其能够提供高精度三维数据, 在推进 NbS 实施中展现出巨大潜力, 但将 LiDAR 技术与相关规划设计工作流进行整合仍存在技术壁垒。本研究采用文献计量学方法, 系统回顾了 2000—2024 年间 Web of Science 核心库中的 4 275 篇相关文献, 结合 CiteSpace 与 Bibliometrix R 语言包, 并通过 Pathfinder 算法优化识别研究聚类与演进模式。研究揭示了四大核心应用领域: 点云分析与生态结构基础、植被结构与生态评估、河流生态修复与雨洪管理, 以及城市韧性与蓝绿基础设施优化。研究发现, LiDAR 通过将几何-结构信息转译为可计算的生态指标, 显著提升了 NbS 的选址、尺度控制和绩效评估精度。然而, 数据处理繁琐、工具链割裂和跨学科协作壁垒等挑战仍限制了 LiDAR 技术潜力的充分发挥。为此, 本研究提出了包含三项内容的综合发展路径: 通过数据开放共享平台降低准入门槛; 通过人工智能驱动的自动化处理突破语义理解瓶颈; 通过标准化互操作弥合工具链割裂。该路径旨在推动 LiDAR 从高精度测量工具转型为支撑循证 NbS 设计与治理的数字基础设施, 助力景观规划设计行业的数字化与智能化转型。

关键词

激光雷达; 基于自然的解决方案; 文献计量分析; 点云处理; 景观规划设计; 生态修复; 雨洪管理; 城市韧性; 蓝绿基础设施

文章亮点

- 系统梳理了 2000—2024 年间的 4 275 篇文献, 揭示了 LiDAR 在 NbS 领域的应用趋势
- 识别出四大核心应用领域: 生态结构分析、植被评估、河流修复、城市韧性
- 提出了“数据开放+AI赋能+标准化互操作”的发展路径, 以弥合技术与设计壁垒

基金项目

- 黑龙江省博士后面上资助项目 (编号: LBH-Z23164)
- 黑龙江省自然科学基金联合引导项目 (编号: LH2024E051)