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Smart Cities and Data Enrichment: The Role of LiDAR and Point Cloud Upsampling in Sustainable Urban Management

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Geospatial data with high resolution and spatio-temporal accuracy can further support sustainable infrastructure and optimise urban services to improve the quality of life of city residents. LiDAR-based technologies are commonly used to produce 3D urban models and can include terrestrial laser scanning (TLS), mobile mapping systems (MMS), and airborne platforms such as photogrammetric drones. Point cloud datasets can be utilised for transportation planning and management, utility management, green infrastructure evaluation, and emergency response. Despite the utility of these point cloud datasets, the intrinsic incompleteness or sparsity due to the costs of surveying, the characteristics of the sensors, and environmental occlusion are significant limitations for effective precision modelling at the urban scale. Point cloud upsampling appears to be an innovative modelling gap for synthetically increasing point density, while preserving geometric accuracy. Deep learning–based networks demonstrably reduced the quantified improvements of the point cloud upsampling method. Previous studies have shown that reduced point-to-surface deviation from ~0.146 to ~0.140 (10^{-2} scale; 6.11 % improvement), and improved distribution uniformity from 0.315 to 0.219 (30.55 % improvement), and frequency-selective geometry upsampling provided up to 4.4×s less point-to-point compared to PU-Net and at 4× upsampling factors These results demonstrate that advanced point cloud upsampling methods would reasonable improve the accuracy or precision of derived products such as digital terrain models (DTMs), canopy height models (CHMs), and other ecological indices that are generally sensitive to point density. This paper reviews the latest upsampling algorithms and proposes a way of thinking and structuring data science that can scale into urban monitoring processes.

1. Introduction

One of the fundamental preconditions of sustainable urban development is the need to balance the use of the elements' natural environment with the urban built environment, in which green infrastructure, including trees, parks, green roofs, and green corridors, plays an important part. These green spaces support the urban microclimate, soften the heat island effect, enhance air quality, provide natural drainage for rainfall, and also provide aesthetic and recreational value.
However, to ensure smart, sustainable urban management, detailed, accurate and up-to-date spatial information is needed for municipalities, urban planners and environmental consultants to make better-informed decisions (Costa et al., 2024). Remote sensing technologies, specifically Light Detection and Ranging (LiDAR)-based surveys, provide incredible capabilities for spatial mapping of urban green spaces, developing 3D point cloud data.
A point cloud is a set of data points in space where each point is defined by the X, Y, and Z coordinates that together represent the outer surfaces of objects, structures, vegetation, or terrain features (Lokugam et al., 2022). Data that are derived from 3D point cloud (PC) can be used to conduct detailed analyses of vegetation cover using the extent, structure, density and height of the vegetation cover. Increasing LiDAR system power

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technologies notwithstanding, PCs can be a product of external factors such that they cannot be completed, denoised or upsampled to include the spatial density required to accurately model green infrastructure details such as canopy structure and foliage shading. Point cloud upsampling (PU), meaningfully, refers to the ability to synthetically increase the number of points in a point cloud dataset to reconstruct finer geometric details, fill data holes, and improve spatial resolution.

Recent advancements in PU methods allow for the capability to synthetically densify an existing PC while retaining local geometrical structures or reconstructing new details. PU in an urban environment has applications not only to improve spatial accuracy but also enables the estimation of green infrastructure parameters that can be linked to indicators of sustainability. The purpose of this study is to formulate the meaningfulness of PU for the GIS monitoring of urban green spaces, particularly as it relates to initiating sustainable urban management. The outlining of the AI-based densification process adopted in this study (Figure 1) produces results to enhance or improve the embedded LiDAR data for the purpose of creating a green infrastructure model. The resulting data are more appropriate for the construction of urban digital twins, monitoring changes in green areas and the implementation of environmental decision support systems. By providing a detailed and dynamic spatial representation of green areas, these techniques can also support urban planning processes, including park renovation projects, health-based tree management, and the optimisation of green space distribution for future developments.

2. Background and Related Work

Urban sustainability has emerged as a central aspiration among cities around the world, as they seek to balance economic development, environmental sustainability, and social equity. As a component of urban sustainability, green infrastructure protects and restores urban environmental systems, can reduce the urban heat island effect, improve air quality, increase biodiversity, and provide recreational opportunities for residents (Wang et al., 2024). However, the monitoring and management of urban green space relies on precise and comprehensive spatial data that can accurately report on the complexity of green structures and the dynamic conditions that change over time. Traditional 3D mapping techniques are insufficient for these needs, particularly in higher-density built environments where vegetation is layered vertically and spatially merged with built structures.

LiDAR systems generate 3D PC data that accurately represent the shape and size of trees, vegetation patches and natural features within the urban fabric (Shen et al., 2024). These datasets have become a valuable resource for mapping and monitoring the detailed spatial characteristics of urban green areas. PC data facilitates the measurement of key ecological indicators such as tree canopy height, vegetation density, and Leaf Area Index (LAI), all of which are critical for the health and functional assessment of urban green infrastructure (Díaz-Varela and González-Ferreiro, 2021). With this technology, local governments can make better-informed, evidence-based decisions on how to allocate resources, plan green areas, and determine when to intervene for the protection of vegetation.

However, generating PCs from LiDAR technology is not without challenges. Urban environments are exceptionally complex, thus they are characterised by a heterogeneous mix of buildings, vegetation and varied terrain. As a result, the captured datasets may contain occlusions and data gaps. Factors such as the angle of the sensor, the flight altitude and the presence of densely inhabited areas may contribute to inconsistencies and deficiencies in the datasets. Policymakers are reliant on comprehensive, high-quality datasets in the service of sustainable urban management. This contributes to mitigating the risk of misinterpretation and to preventing suboptimal interventions. Unaddressed, low-quality PC data might lead to underestimation of canopy cover, misclassification of land cover types, or even failure to detect critical vulnerabilities in urban green infrastructure if it is not properly managed.

PU was invented as an advanced data enrichment method to address these limitations. The aim of PU is to densify existing datasets synthetically. This process fills in missing details and enhances the representation of fine-scale features. Quantitative evaluations have established the practice improvements possible with deep learning–based upsampling (Figure 2). In the case of PU-Net, point-to-surface deviation was improved from ~0.146 to ~0.140 (10^{-2} scale; 6.1 % improvement), and point distribution uniformity improved from 0.315 to 0.219 (30.5 % improvement) (Yu et al., 2018). More recently, frequency-selective geometry upsampling achieved as much as 4.4 times less point-to-point variance than PU-Net for the same upsampling factors (Heimann et al., 2022). PU networks significantly enhance the accuracy of green urban environment models. Thus, the estimation of ecosystem services has become more precise, including shading potential, carbon sequestration capacity and stormwater retention capabilities.

A few advanced cities have already successfully used LiDAR-based models in their systems for urban planning and management. Notably, in Helsinki, a 3D geospatial model was created for environmental simulations and smart city experimentation (Hämäläinen, 2021). Singapore has a very similar focus, part of their Smart Nation initiative, which incorporates point cloud data to help optimise green space in the city and coolness strategies (Gobeawan et al., 2018). Recent studies have also demonstrated the potential of PC analysis in building diagnostics and condition assessment (Szurös et al., 2024). Enriched PC data provides a stronger spatial layer for urban planners and managers by improving the spatial resolution and eliminating the data gaps normally present in traditional urban data sources or datasets. Improved detail in point PC will ultimately help urban planners and managers improve the ability of their cities to make effective decisions to plan for climate change adaptation and mitigation. Improperly processed synthetic densification can create uncontrollable gross distortions due to the incapacity errors falling outside of the calibrated error limits. On top of data accuracy, processing and storing units of urban data come with significant computing resources, and have limitations on the prerequisites they are able to execute. Although both of these challenges exist, technological advancements continue to develop within the discipline, suggesting that geospatial datasets can become indispensable elements of planning and managing sustainable urban ecosystems. Integrating details and high-resolution PC datasets in a regulatory framework, and in policy-making, is pivotal to greening, smartening and creating resilient urban cities. In conclusion, previous research has demonstrated the role of LiDAR PC data for urban modelling and green infrastructure assessment. However, a limited number of studies have systematically investigated how PU improve the accuracy of sustainability indicators or provides real-time environmental management at the city level. This gap demonstrates the need for a structured, AI-based upsampling framework which can enrich LiDAR datasets for smart city purposes. The current study addresses this gap with the proposal of a conceptual and methodological framework linking PC densification to sustainable urban management goals.

3. Scientific Hypothesis and Conceptual Framework

PU is a possible avenue to deal with the low density of Airborne Laser Scanning (ALS) datasets and improve the accuracy and robustness of ecological and environmental trajectory modelling. The consequences for generating digital terrain models (DTMs), canopy height models (CHMs) and other ecological indices based on point density, with respect to maintaining the geometric accuracy and surface continuity of the higher point density, are unequivocal. The reasoning behind the above hypotheses relates to the technical characteristics of the PU methodologies. Conventional interpolation techniques can produce local over-smoothing of structures when applied to complex environments and urban landscapes containing environmental noise. Optimisation-based techniques have much greater uniformity over surfaces, but often lack characteristics identifying them at a fine-scale resolution with heterogeneous landscapes. However, there has been some exciting recent development in the methods used for deep learning (DL)-based PU methodologies that allow local geometric reconstruction, continuity of structure, and the propagation of non-geometric information. These technical capabilities also support the conclusions that PU methods lend themselves well to providing representations of ALS data when the ALS data describes heterogeneous environments having irregular spatial sampling and through vegetated occlusion in sample speck thickness with great variation in point density. The overall workflow is modular, beginning with ALS data collection and preprocessing (recognising that all ALS data has to be processed to have a usable and consistent input), processing the ALS data using the methods upscaling, and lastly, post-processing to remove artefacts and impose distribution consistency. The up-scaled datasets have also been validated with independent reference data and apply high-density PC within environmental applications; forestry, watershed assessments and conservation planning.
In summary, the main scientific hypothesis investigated in this study is that point cloud upsampling provides a density of ALS datasets that results in better temporal accuracy and reliability, as well as the accuracy of ecological and urban indicators derived from their processing. PU would provide a denser density for determining vegetation metrics, canopy height distribution, and surface continuity, preserving local geometric quality through syntactic reconstruction of missing features. The research hypotheses are that geometric density at the data level provides specificity that further reduces uncertainty in ecological indices or spatial planning decisions. The hypothesis is based on the implicit assumption that an improvement in geometric accuracy at the data level coincides with a subsequent reduction in uncertainty in ecological indicators for spatial planning decision-making.

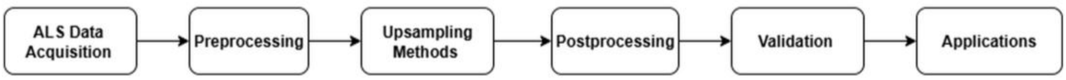

Figure 1: Workflow of the point cloud upsampling process for sustainable urban management (Source: own creation)

4. Proposed Methodological Framework

For the efficient and forward-focused management of urban green infrastructure, organisations need spatially-precise, high-quality data that describes the existing conditions and provides information to inform predictive planning and adaptive management (Korkou et al., 2023). There is an emerging demand within sustainable urban development for digital solutions that will provide dynamic, 3D typologies of green components throughout cities. These dynamic, 3D solutions can not only advance the preservation of existing vegetation but also the creation and growth of green networks that contribute to ecological resilience, thermal comfort, and livability in urban contexts. This framework outlines a framework for integrating PC spatial data, upsampling approaches, and sustainability-focused on green space indicators, which can be integrated into municipal decision-making.
The first component of this framework considers the acquisition of data on urban green areas with current sensing techniques available, such as terrestrial laser scanning, mobile mapping systems, and LiDAR or photogrammetry with UAVs, which will likely continue to become more accessible. These techniques allow for more detailed 3D surveys of urban landscapes that can capture beyond traditional 2D remote. However, PC datasets can be impacted by issues of irregular density, occlusions, and gaps in data due to the nature of urban environments, line-of-sight variability, and varying density of built-up infrastructure. These issues can significantly affect the reliable estimates of key variables such as canopy cover or vertical vegetation profiles that are important for planning for sustainability.
To mitigate these challenges, the second stage of the framework proposes that PU methods for PCs introduced from artificial intelligence (AI) are used. In these algorithms, the PC density increases synthetically through the generation of new points that match local geometric characteristics in the original PC dataset (Kwon et al., 2023). The proposed PU recommended in the second stage of the framework can improve spatially enhanced representations and provide better delineation of green structures on a fine scale, like tree crowns, hedgerows, and vegetation on rooftops. PU can also help to reduce the uncertainty associated with occlusions and incomplete scans to produce data that is better for future sustainability analysis.
The third element of the framework is the extraction of sustainability-relevant indicators from the upsampled dataset. Sustainability-relevant indicators may include metrics based on spatially explicit data, such as total canopy area, vertical vegetation distribution, shading levels, Leaf Area Index, or vegetation health indicators that can be derived from fused multispectral data, etc. Accessibility is also important in terms of sustainable features. This was similarly demonstrated by She (2024). She surveyed urban green space accessibility in Hong Kong through transportation-based GIS network analysis and kernel density analysis. The results underscore the need to incorporate an accessibility assessment into green infrastructure monitoring frameworks that incorporate spatial, green infrastructure planning, design, distribution, and use of urban greenery. These features will be vital indicators to assess urban ecosystems and their roles in heat abatement, biodiversity support, water retention and quality, and air quality. Where clear, consistent, and maintained evaluations can be calculated and maintained over time, these evaluations can be deployed to assess changes over time, when those change patterns begin to cause degradation, and for testing the success of urban greening programs.
The fourth part of the above framework is different steps to make them useful: this can occur through integrating these features into spatial decision support systems. For example, by embedding enriched PCs and measures into municipal GIS or smart city dashboards, linking urban greenery and green space to visualisations of the real-time status of urban greens (Orozco Carpio et al., 2024). In these settings, action can include scenario evaluation, interactivity, and alerts where measurable thresholds have reached precursors to degradation (e.g., canopy loss exceeds a percentage). As an illustration, the system could help prioritise areas that are good candidates for tree planting based on low shading coverage, or it could also help identify parks that may require maintenance due to shading loss and thinning of the canopy. The framework provides the potential for strategic planning and future-proofing through generative and iterative processes, allowing for the establishment of digital urban twins that represent the trees and green infrastructure in detail. From these digital twins, development plans for future urban development can be simulated with regard to green space availability, new green corridors can be tested for their expected benefits, and the potential cooling benefit of expanded canopy cover can be evaluated due to climate change. The framework forms a foundational element for cities wanting to incorporate nature-based approaches to planning and climate adaptation. Beyond technical improvements, the framework supports a shift in how cities think about and manage urban nature. By thinking of green infrastructure in the context of not just a passive background element, but as a living system that requires planning, monitoring, maintenance and management as an ongoing process, they are supported towards a more systematic approach to urban sustainability, relatively, they acknowledge the multiple nature-based values of green spaces, systems, or infrastructure and integrate these factors into as many aspects of urban planning as possible, such as mobility, housing, public health or energy efficiency.

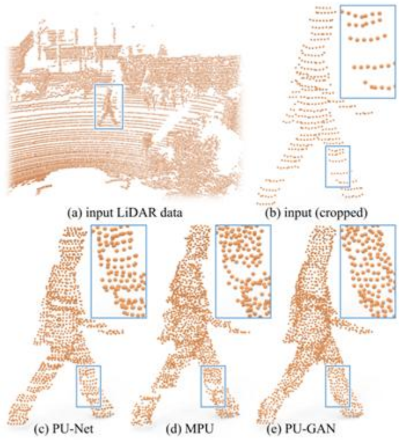

Figure 2: Comparison of point cloud upsampling methods (PU-Net, MPU, PU-GAN). Adapted from Li et al. (2019)

5. Discussion

This study highlights significant developments regarding high-quality 3-D datasets emerging as an important foundational resource in sustainable urban management and green infrastructure monitoring. Improving the opportunity for LiDAR-based PCs to assess the problems associated with natural irregular 3-D data is an important step forward with respect to AI-driven PU of raw, say, digital elevation models. They present an imaginable means to discover a level of 3-D detail that is potentially more reliable data than 2D representations in regard to structural emotion, upon which demands in the proven analytics of urban planning, with respect to greater ecological values, can be leveraged for better environmental assessments, targeting interventions, and forward-thinking sustainable resilience.

PU can serve as a reference layer across multiple varied and disparate municipal functions, ranging from resident environmental surveillance, biodiversity protection and natural asset management, public health monitoring for adaptation or resistance response assessment, to routine site-marshalling, urban climate adaptation planning. Enabling a greater level of accuracy and completeness in urban models of green urban natural assets provides municipalities with the possibility of assessing long-term trends and emerging challenges, developing a legislative framework to allocate resources in a way that is evidence-based, value-driven, sustainable and traceable.

At the same time, by accepting DL-based PU methods, the perspective can shift from seeing point cloud datasets as just static datasets to dynamic, evolving elements of a living digital twin. This shift allows us to interrogate an integrated perspective of urban systems in which technological abilities, environmental aspirations, and societal needs are inextricably linked. As computing resources and algorithms continue to improve, these methods become more accessible, scalable, and appropriate to become near real-time in decision-support systems (Hu et al., 2024). The potential exists for the DL-based UP processes to be a building block of smart city geospatial architecture. The potential of creating site-specific data, not just fulfilling the gaps in data or improving geospatial 3D models, represents a more informed, responsive, and prospective opportunity in our pursuit of urban sustainability. Ongoing research and development will be needed to leverage this potential, and better equip future cities with the intelligence, tools and information to make resilient and sustainable decisions in the management of our natural assets.

6. Conclusion

The inherent constraint with ALS data is the output's low-point density, where often the obtainable spatial fidelity will inhibit the successful delivery of reliable DTMs, CHMs, and other vegetation structure metrics. The results showed that by synthetically elevating the point density, while retaining the geometric accuracy of the ALS output, PU has the opportunity to advance the value of geospatial analytical products and reduce uncertainty with downstream environmental models. Quantifiable performance metrics cited in current literature illustrate this increased performance: PU-Net produced a ~ 6.1 % reduction in voxel-to-surface variance and a ~ 30.5 % improvement in spatial variance when compared with raw datasets. Conversely, frequency-selective geometry PU produced point-to-point variances up to 4.4× lower compared with PU-Net using the same PU factors. Such performance improvements have the potential to significantly alleviate uncertainties surrounding downstream ecological proxy indicators of canopy cover, shading potential, and stormwater retention potential.

DL workflows are clearly preferable in heterogeneous urban landscapes that are dominated by vegetation, buildings, and complex surfaces. Distinguishing spatial and physical consistency and reconstructing local geometric forms make DL-based PU ideal for urban green infrastructure monitoring applications. Amplified PC data will then support the development of virtual twins, support nature-based solutions, and contribute to urban resilience.

Future studies should consider prioritising the combination of PU workflows with multi-source datasets, retaining non-geometric attributes, and methodological adjustments leading to decreased computing time to improve real-time capabilities. This indicates PU evolve into an intrinsic enabling technology for smart city design and sustainable environmental management. These advancements have real-world applications. Denser PCs will result in more robust monitoring of green infrastructure and improve digital twins for smart city and climate adaptation decisions.

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