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Potential of Point Cloud Upsampling for Environmental Protection: Enhancing Airborne LiDAR Data for Sustainable Resource Management

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High-resolution, dynamic geospatial data support sustainable infrastructure, optimize urban services, and improve the quality of life of residents. Airborne Laser Scanning is an increasingly popular remote sensing technology that can be used to collect very large datasets of 3D point clouds over extensive areas, including forests, river basins, coastal wetlands, and mountainous regions. These datasets facilitate the analysis of vegetation structure, biomass estimation, hydrological modeling, and land cover detection or change monitoring. However, Airborne Laser Scanning-derived point clouds are typically limited to low density and spatial resolution, which preclude meaningful analysis for fine-scale ecological and environmental modeling.
Point cloud upsampling is a permissible way to augment the spatial robustness of Airborne Laser Scanning point cloud data, and does so without adding a logistical burden of the data acquisition in the field, or the need to resurvey at high costs and time. Upsampling is synthetic in nature, achieving increased data point count, but maintaining dimensional integrity for continuity of surfaces and geometric fidelity, which is essential in methodologies that intervene for derived products such as digital terrain models, canopy height models, and vegetation metrics. This manuscript examines using point cloud upsampling as part of environmental monitoring. It reviews the upsampling algorithms that have been developed to date, synthesizes existing methods, and considers their relevance to the state of practice in forestry, watershed management, and conservation planning. The work considers and focuses on methodological bases for robustness and dimensionality, and although considerably nuanced, the methodological efficacy is subtended and suggests how enhanced points improve outcomes for ecological models and the information provided supports resource management decisions related to resource and sustainability decisions.. Ultimately and conclusively, the work establishes the understanding of point cloud enhancement for its visualization, but also its potential as an emergent action that contributes to construction and promotes a sustainability intention in environmental science and policy.
This article appears as a mini-review. This writing aims to synthesise existing knowledge and conceptual strategies, rather than a novel outcome of an experiment. It is written to give an overview of existing methods and structured conceptual frameworks for employing point cloud upsampling techniques in the environmental monitoring and sustainability context. The review reiterates the conceptual soundness of point cloud upsampling in the workflow of environmental monitoring. The proposed framework reinforces the benefits of greater data richness and decision-making based on sustainability, without assuming new costs for data generation.

1. Introduction

The monitoring, management, and conservation of natural environments are becoming an increasingly serious issue due to global climate change, rapid loss of biodiversity, and added anthropogenic pressures to ecosystem processes. In light of these pressures, the world will need high-quality spatial data that is timely, accurate, and

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high-resolution to support the development of reasonable decision-making, effective policy design, and sustainable resource management decisions. According to Skidmore et al. (2015), it is essential to have biodiversity metrics to help consistently track biodiversity from space, and Venter et al. (2016) demonstrate the ways in which long-term changes in the global human footprint can impact the priority for biodiversity and resource management. Fine-scale observations are essential for monitoring ecosystem processes, planning conservation strategies or ecosystem management planning. In contrast to earlier reviews, which focused solely on geometric or algorithmic efficiency, this article frames point cloud upsampling within environmental sustainability and monitoring. Airborne Laser Scanning (ALS) is an example of remote sensing technologies and is a valuable tool for collecting three-dimensional data over a large area in environments that are often too difficult to access or understudied, such as forests, mountains, and coastal environments. For example, Hollaus et al. (2007) showed the potential of ALS for detailed structural characterizations of forests in rugged mountainous environments, and White et al. (2016) showed the potential for ALS to inform extensive forest inventories and resource management.

Most ALS systems used today use near-infrared wavelengths. They are mounted on airplane platforms (helicopters, drones, balloons, etc.) flying at altitudes of several hundred m, up to above 1,000 m, depending on mission design parameters and regulations. Contemporary ALS sensors can produce point cloud (PC) densities of 5–30 points per square metres (pts m^2), with typical mean densities between 10 and 15 pts m^2 for forest inventory applications. Current vertical location accuracies are usually about ±5–10 cm, while horizontal (planimetric) accuracies are usually within 0.2 m. With regular acquisition and processing conditions, the root mean square error (RMSE) of interpolated surface models of the ground is generally between 0.10 m and 0.30 m, with variability based on terrain morphology, vegetation structure, and the interpolation used.

In related fields, more robust classical registration schemes such as the variant of the Iterative Closest Point (ICP) have been suggested, which can improve the robustness and the geometric fidelity of PC data types (Sha et al., 2016). If this PC data is sparse, digital terrain models (DTMs), Canopy height models (CHMs), vegetation metrics, etc., are limited in their accuracy and ultimately limit the rigor of relevant models/assessments that are based on such data. Specifically, deep learning (DL) based methods have the potential to synthetically augment PCs by increasing the point density of the PC area but maintaining the basic geometric forms and surface continuity. Traditional interpolation techniques, especially large area ones, tend to create artifacts or oversmooth features, whereas a DL based upsampling method can capture complex patterns and fine-scale variability apparent in natural settings. DL proposed methods for upsampling can increase density in a paranormal way while still retaining surface geometric fidelity and continuity. Accordingly, environmental modeling and feature extraction can be enhanced in a manner that involves no additional fieldwork or expensive resurveys (Zhang and Filin, 2022). This is particularly advantageous in the case of operational approaches to forest inventory, watershed hydrology modelling, monitoring coastal erosion, or conserving habitats, where the quality of spatial resolution and richness of data absolutely affect the effectiveness of management actions. The primary aim of the research was to investigate point cloud upsampling (PU) and its function in improving sustainable management through environmental monitoring. In this paper, we provide a comprehensive overview of existing PU algorithms, which mainly include classic and DL approaches. This paper is presented as a mini-review and conceptual study. Instead of offering new experimental results, the structure summarises the research landscape PU for ALS data and offers a conceptual structure to help guide future use in environmental monitoring and sustainability analysis.

2. Background and related work

Managing the environment sustainably and responsibly requires access to accurate and fine-scale spatial data that can adequately reflect the complexity of ecological processes. Bakó et al. (2021) demonstrated that high-resolution remote sensing will be significantly helpful in regard to monitoring natural habitats and conserving natural resources. Maurya and Kumar (2024) also demonstrated how geospatial data could play an important role in making rational long-term decisions based on sustainable development. Given accelerating climate change, biodiversity loss, and intensifying anthropogenic pressures, spatial data have become critical for monitoring environmental trends, evaluating the condition of our natural resources, and evaluating the impacts of conservation and restoration actions. ALS has taken the limelight as an increasingly important remote sensing technology for collecting large-scale three-dimensional datasets across a variety of terrestrial landscape types such as forests, wetlands, river systems, coastal zones, and mountainous regions. ALS PCs are particularly relevant for environmental applications because they provide accurate terrain models and object-level information essential for topographic analysis and feature separation (Kraus and Pfeifer, 1998). In addition, they enable detailed assessment of vegetation structure, height, spatial distribution, and canopy morphology, which are critical for ecological monitoring and habitat characterization (Roussel et al., 2020). It is generally acknowledged that ALS offers a superior method for collecting environmental data at the large scale compared with traditional ground-based surveys, as ALS is easier, less invasive, and spatially continuous, and aligns with sustainability-oriented initiatives that measure environmental impacts with the least disturbance to the ecosystem, with volumetric sustainability with minimal resources (Figure 1). In spite of these strengths, PC are not without their limitations. The spatial resolution and point density of ALS surveys are often limited by sensor specifications, flight design, budget, and environmental conditions. Higher density PCs are not sufficiently spatially rich to meet detailed modelling purposes, especially in heterogeneous areas with dense vegetation. Derivative products of ALS data (e.g., digital terrain models, canopy height models, vegetation indices) are important data inputs for ecological assessments, hydrological modelling, and land management purposes, but the relative lack of point density often creates barriers to the ability to produce these products. Moreover, it is often infeasible to get around these limitations through further data capture because of high operational costs and environmental effects of additional flight acquisition (Salvoni et al., 2021). PU provides a computational means of enhancing the spatial richness of ALS data without requiring further data capture. PU can result in synthetic densifications of PCs that maintain geometric fidelity and topological consistency of the original PC. By upsampling existing ALS datasets, we can enhance their applicability. This method creates opportunities for data reuse and enrichment, develops work efficiencies, and decreases repeated interaction with the environment, which is a sustainable way of working. DL-based workflows and methods will help in this area because they can capture fine-scale spatial patterns while preserving surface characteristics in complex terrain, which is now increasingly available and applied in Global Navigation Satellite System (GNSS) spatial techniques. Informed implications for downstream model development are made from enriched datasets, which can help downstream models better predict vegetation structure, provide improved assessments and resource allocations, assess change over time, and respond and implement mitigating strategies. Zhang et al. (2022) state that most of the existing methods for PU have been designed and evaluated on synthetically or object-based datasets, typically generated from either indoor scans or computer-aided design (CAD) models, where variability in the environments was limited. Kwon et al. (2023) also note that there remains limited research on applying these techniques to ALS datasets and to data in practical scenarios, when faced with the issues of sensor noise, complex structures, and variability in the environment. Further, little is known about the potential for PU to support sustainability goals that include long-term monitoring of forest conditions, watershed management, and planning for conservation. This study attempts to fill this void through research that combines the PU with actual environmental spatial workflows and places a value on providing enhanced geospatial information for sustainable environmental resource management. The work is not only intended to advance our technical development of PU methods, but also to promote a more general discussion regarding how computational technologies can extend the lifetime and utility of remotely sensed data for the purposes of environmental stewardship.

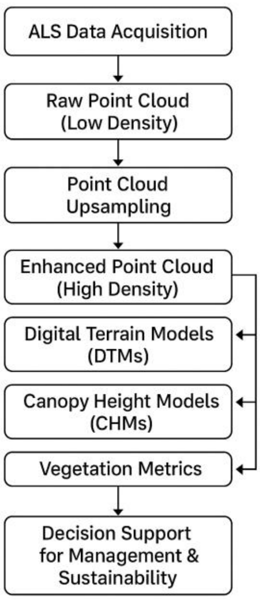

Figure 1: Conceptual workflow of ALS point cloud upsampling from data acquisition to derived products and decision support (Source: own creation)

3. Approach to airborne LiDAR upsampling

The proposed methodological framework for PU aims to mitigate the shortcomings of low-density Light Detection and Ranging (LiDAR) acquisitions by creating enriched datasets that enhance the capabilities for environmental monitoring, resource management, and planning for sustainability over time. This framework utilizes a modular design that permits the inclusion of various data types, methods of algorithms, and methods of computation, while maintaining a logical and reproducible order, which is beneficial for the integrity of the workflow. This modular design will allow for the adaptation of the framework to a multitude of applications, geographic locations, and technical limitations, while allowing continued processing and re-use of sampling whenever appropriate, presenting both adaptability and scalability.

The ALS data collection process begins with the acquisition of the PCs, which are typically collected through a national mapping agency, an airborne survey focused on research purposes, or publicly available from various governmental and scientific institutions. The data is most often stored as LAS or LAZ files because of the compatibility with numerous LiDAR processing tools, although PLY and similar 3D formats are also available, particularly for research purposes. The point density of the PCs is also variable depending on flight altitude, pulse repetition frequency, scanning angle, and other limitations due to ambient conditions like vegetation cover or atmospheric conditions. In a lot of cases, the native resolution may be suitable for large-scale mapping but not for detailed assessments that need to have fine-scale representations of terrain morphology, canopy architecture, or human-used features.

Processing is a key step for ensuring that the subsequent PU methods are based on clean and consistent input data. Processing generally involves identifying and eliminating noise and statistical outliers due to sensor error, atmospheric effects, or incorrect classifications in the initial ground filtering. Elevation normalization is applied to convert raw height into a consistent vertical reference system, typically using geoid or ellipsoid corrections to ensure consistency when integrating data from multiple sources. Ancillary properties - such as return intensity, classifications (land use, ground cover, etc.), and RGB colour values - should also be preserved and, where applicable, normalized or resampled so that they can be propagated through the same PU process, undistorted or misaligned. Proportionately preparing ancillary properties will also allow access to more advanced modelling procedures and frameworks, which might use both geometry and radiometric information.

The PU process is the central focus of the framework, and it can be executed in many different methodological families. Traditional methods such as triangulated irregular network-based (TIN), inverse distance weighting (IDW), and kriging methods are user-friendly and computationally inexpensive. However, they are subject to oversmoothing and degradation of detailed structural information. Optimization-based methods attempt to enhance spatial uniformity, stabilize structural elements, or both by exploring the problem through the lens of energy minimization. In recent years, DL-based approaches to PU have presented a fruitful direction by employing deep neural architectures to learn the geometry structure and fine details. The first end-to-end framework to learn multi-scale point features directly into densely sampled point sets from sparse inputs is PU-Net (Yu et al., 2018). They model a point-wise neural network architecture with a focus on multi-scale features to create uniform point distributions. MPU (Yifan et al., 2019) next conceptualizes a patch-based progressive upsampling framework that will learn to reconstruct fine-grained geometric structure through progressive levels of detail. Subsequently, PU-GAN (Li et al., 2019) conceptualizes an adversarial framework that improves point distributions to uniformity and surface proximity regardless of the input density or perturbation. Lastly, PUGeo-Net (Qian et al., 2020) uses a neural network to integrate discrete differential geometry with the upsampling process by jointly learning point coordinates and normals and learning to represent intrinsic surface properties. These methods for ALS data require minor adjustments to the DL method and parameters to appropriately address the irregular point density in the affine density in the vegetated areas, the partial penetration of laser pulses through canopy layers, and the differences in scale between open areas and heavily forested areas.

The post-processing stage is where the output from the upsampling stage is improved to confirm that the enriched dataset is an accurate portrayal (in terms of location) and is of sufficient quality for its intended purpose. This involves a second round of outlier removal to eliminate artefacts caused by the densification process, implementation of uniform spacing of points to manage clustering, and the merging of deltas with the original dataset such that both datasets remain intact. It is possible that this step involves reclassification of points based on their location in relation to a terrain model or canopy model, creating thematic consistency across the dataset.

The advantage of these enhanced PCs is the generation of higher-quality environmental products. DTMs can be rebuilt with better representation of small-scale topographic features, i.e., micro channels, embankments, or small-scale erosion features. CHMs will have increased sampling of upper and lower canopy layers, allowing for more accurate estimation of vegetation structure and biomass. From these outputs (DTM, CHM, vegetation indices, and improved land cover classifications), hydrologic parameters will be more robust for watershed analysis as well. Finally, these products will be the inputs to downstream applications ranging from biodiversity assessments to risk analysis of infrastructure.

It is important to incorporate validation and quality evaluation to ensure the credibility of upsampled products. For example, geometric accuracy can be measured by RMSE, Chamfer distance, and Hausdorff distance, while thematic accuracy may be evaluated by the comparison of derived DTMs, CHMs, or classification maps to trusted reference data. The validation is designed to be hierarchical, where high-density airborne or Unmanned Aerial Vehicle (UAV)-borne lidar, terrestrial laser scanning, or terrestrial surveys provide points of reference and are used quantitatively and statistically to provide estimates of performance both spatially and statistically. The assessment of performance through validation and quality evaluations can help identify systematic bias, localized errors, or conditions where some PU methods failed to perform adequately.

The framework is intended to serve as part of an operational workflow that can support forestry management, watershed modelling, protection of coastlines, and planning for conservation. By embedding cloud-based processing solutions, enabling batch processing, and eventually nearly real-time processing, the costs and environmental footprint associated with aerial surveys can be reduced by facilitating the use of purpose-built aerial surveys. More importantly, we provide a concrete and flexible framework for upsized PCs as resolution and needs for environmental science and policy continue to evolve.

4. Challenges and limitations

Though PU clearly has advantages for improving ALS datasets, several limitations remain. It is not clear how models will transfer between different landscapes, as a given model trained on one biome does not appropriately generalize to other biomes that differ significantly in terms of canopy structure or the morphologies of the ground and canopy. Additionally, ALS acquisitions are notoriously heterogeneous (i.e., flight altitude, scan angle, and sensor specifications), which will lead to differences in how PU workflows are standardized. Moreover, the computation cost of prominent DL methods is notable, and if large-scale or near-real-time monitoring tasks are to be conducted without the use of extensive hardware resources, these methods remain challenging to implement. Another important limitation is the type of artefacts/biases that arise during the PU process: while the PC is being densified, there is also the potential to generate artificial structural patterns that can misrepresent true surface properties - this is especially true for vegetated surfaces where the effects of occlusion predominate. As such, it is important to consider model selection, benchmarking against independent reference datasets, and possibly hybrid methods that utilize deep learning with physics-based or statistical models to improve generalisability and or reproducibility.

5. Conclusion and future directions

Further model generalization is necessary, reducing computational requirements, and ensuring that enriched PCs retain geometric and attribute information. Future development work will likely see, but not be limited to, DL models that preserve attributes, multi-sensor inputs including UAV-based LiDAR and multispectral imagery, and cloud-based processing pipelines enabling near-real-time environmental condition monitoring. Additional work in any of these areas can transition PU from research projects into operational activity as part of sustainable environmental management. In practical usage, the conceptual framework outlined here demonstrates how PU is applied to enhance existing environmental monitoring programs. For the forestry sector, denser PCs provide more accurate estimates of tree- and stand-level biomass estimates, as well as contribute to more accurate large-scale forest inventory programs. For watershed hydrology, denser PCs enable the modelling of river networks, floodplains, and slopes susceptible to erosion at a finer resolution, enhancing hydrological assessments. Greater spatial detail in coastal environments is beneficial in monitoring shoreline change and sediment processes to support erosion controls and climate adaptation. Similarly, denser PCs enhance conservation planning by allowing for enhanced detection, monitoring, and tracking of habitat structure, species niche space functionality, and biodiversity indicators, which may enhance stewardship and management.

While this synthesis does not present empirical results, it highlights the potential to utilize workflows for PU and to reduce expensive re-surveys of the same area, as well as increasing confidence in the downstream ecological models. This conceptual study demonstrates that the upsampling of PC data increases spatial detail while incurring potential cost savings for the sustainability of monitoring environmental conditions. An important contribution of the research presented above is to show evidence of a shift to an operational workflow for resource management that relies on data and incorporates a more resilient approach.

Moving forward, work to calculate and validate PU workloads and to test different methods for different dataset needs must continue, especially to determine which methods can improve the precision and accuracy of different ecological indicators. The development of practices for the standardization of PU methods for clear long-term monitoring and sustainability planning should also be a consideration for future work. In this way, PU will evolve from a new and promising concept to a routine, valuable method for addressing the environmental and societal dilemmas facing our coupled societies in the next few decades.

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