Hybrid Geometric Data Integration for Building Block Energy Modeling

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Abstract

This research explores a novel hybrid method for building block geometric modeling that combines diverse data sources, including LIDAR (light detection and ranging), DEM (digital elevation model), DTM (digital terrain model), nDSM (normalized digital surface model), DSM (digital surface model) and drone imagery. By amalgamating these data sources and enhancing them with machine learning approaches, the study can offer insights into the built environment's three-dimensional structure by complementing the datasets, providing visual context, and upgrading the overall accuracy. The results of the present work indicate promising accuracy, with approximately 71% of the models exhibiting a root mean square error below 1.75 m for the level of detail (LoD) 2 models. Future work includes refining the methodology for complex roof shapes and validating drone data integration to develop LoD 3 models. The research approach aims to create a comprehensive strategy to achieve LoD 3 quality for BEM usage with additional usage in urban planning and disaster management.

1. Introduction

In modern-day architecture, Canada is more pioneering than most of the other countries in the building science sector. However, in 2020, Canada was the fourth-largest consumer of electricity on a per capita (per person) basis. Since then, recent research and policy efforts have focused on building energy efficiency standards in Canada. Various geography-based factors influence the energy consumption of buildings, such as weather, shading effects, building characteristics, etc. Implementing energy-efficient building practices and retrofitting existing buildings have been identified as key strategies to reduce energy usage and improve the built environment. Building energy modeling (BEM) is essential for assessing the energy performance of existing buildings. It enables clear opportunities to analyze potential energy-saving strategies, understand the efficiency of the buildings and make informed decisions regarding retrofitting or improvement measures.

Modeling three-dimensional (3D) building geometry is a time-consuming task in the building energy modeling (BEM) process. However, automated processes have been developed to tackle this issue. A few methods involve creating a proprietary 3D thermal model of a building and initially having it as semantic and then converting it into standard BEM formats (Adán et al., 2023). Additionally, a system for automated geometric modeling has been proposed to reduce the dependence on manual modeling and promote BIM implementation (Yang et al., 2023). The scan-to-BIM process, which uses scanning devices and deep learning techniques, can also automate the creation of accurate digital representations of physical elements (Won Ma et al., 2022). Furthermore, a semi-automated approach using visual programming language and boundary representation methods has been developed to reconstruct architectural elements from 3D surveying data (Roman et al., 2023).

With the growing rate of different techniques, the quality of automatic 3D geometry modeling in urban building energy modeling can be compromised when there is a focus on quantity and time constraints. The complexity of urban geometries, especially in dense areas with multiple building structures, can lead to errors such as gaps and non-manifold edges in the generated geometry (Pađen et al., 2022). Additionally, the use of non-calibrated physics-based computational methods can result in overly large errors in the models (Oraiopoulos & Howard, 2022). The availability and quality of input data also pose challenges, as there may be data gaps and heterogeneity in the development of the city over time (Sharma et al., 2020). Furthermore, integrating the workflow with data sources of different formats for urban building energy modeling tools is not fully utilized, which can affect the accuracy of the models (Abolhassani et al., 2022). Overall, the trade-off between quantity and time in automatic 3D geometry modeling can impact the quality and accuracy of urban building energy models.

In another research work, (Peters et al., 2021) integrated aerial LiDAR point cloud data with 2D GIS (geographic information system) data to develop an automated algorithm for reconstructing buildings at varying levels of detail (LoD

1.2 and LoD 2.2). LoD 1.2 offers a slightly higher-level detail within the LoD 1 category, might incorporate additional attributes such as basic surface textures, however, still lacks finer details. Whereas LoD 2.2 offers precise representation of building geometric elements, like, façade, and defined textures. Their research focused on the Netherlands, where they successfully reconstructed approximately 10 million buildings. Their method yielded valid geometries for around 98% of the reconstructed structures, as per the standards outlined in ISO 19107. The research by (Nys et al., 2020) introduced a reconstruction method that is automated by utilizing two input datasets (CityJSON and CityGML). In this work, a region-growing algorithm is used for segmenting roof surfaces from airborne LiDAR point cloud, leading to the creation of LoD 2 buildings. It has improved geometric complexities than LoD 1. However, it is worth noting that while the authors have developed this workflow, its real-world applicability remains untested due to the unavailability of both reconstructed geometries and code for public access. In this rapidly developing research area, the need to produce LoD 3 building models are increasingly growing. LoD 3 buildings have high accurate building envelope and gives access into the glazing and opening aspect of the buildings. In (Usta & Zengin, 2022), the importance of glazing effects and its impact on energy consumption is analyzed through building energy simulation. This study is inspired by all this previous work, to create a workflow to generate LoD 3 building model on a neighbourhood scale. To use this model for various needs, pertinently for building energy modeling.

In the present research work, extracting building footprints from LiDAR data and generating LoD 2 quality 3D building models by integrating elevation details acquired from DTM, DSM and nDSM begins with data preprocessing, where Point Cloud data is acquired and checked for appropriate elevation values and classification accuracy. Adjusting point spacing ensures optimal feature extraction quality. Subsequently, building footprints are extracted using ArcGIS Pro tools, with the option for manual classification if necessary. Following this, initial footprints are refined, addressing any gaps or imperfections and accounting for variations in building heights and roof types. Segmentation algorithms are then applied to detect elevation differences within footprints, enhancing model accuracy and detail. Leveraging surface model attributes, such as building height, the 3D building generation process automates model creation, incorporating procedural rules for realism. Result analysis involves reviewing the generated models for accuracy and completeness, ensuring fidelity to the original LiDAR data. By including various data sources to create LoD 2 quality 3D model and implementing strategies to extract the model for cross-functional uses by making it versatile, this methodology provides a systematic approach to urban environment representation, offering applications in diverse fields such as urban building energy modeling, urban planning and disaster management. Future research will focus on refining workflow accuracy through advanced processing techniques and machine learning algorithms. Especially, exploring the potential ways to achieve high level LoD 3 output through point cloud extraction from drone imagery.

2. Living Lab: Data Collection and Processing

For this research, Georgetown is selected as a case study, a community in Three Rivers County in Prince Edward Island, Canada. The case study location is being developed as a living lab where net-zero assessment research is undergone in collaboration with various stakeholders such as government, municipality, community, and institution seeking co-creation for transition. To contribute to global sustainability efforts, a net-zero assessment study is being conducted in Georgetown by implementing a comprehensive rapid neighborhood energy modeling approach. For this purpose, the airborne LiDAR data is accessed through the Government of Prince Edward Island. The projection coordinate used for point cloud geotagging is NAD 1983 CSRS Prince Edward Island.

Figure 1: LAS Dataset of the sample block of Georgetown

In this work, a sample block presented in Figure 1 from Georgetown is selected and developed as 3D model. In the previous discussion, the limitations of using only the LiDAR data to generate 3D neighbourhood model are identified. The LiDAR data is further supplemented through drone imagery data to upgrade the quality of the 3D model generated and to increase it cross-functionality across various domains. The drone data is collected by the research team through implementing strategies for rapid data collection and accuracy. The drone used for this research is a DJI mini 4 pro. It has a battery life of 25-30 minutes. The images were captured in a 1080p x 720p resolution. The flight path is automated for the sample block covering all the whole building from all directions (a representative image is presented in Figure 2).

Figure 2: Illustrative image of drone data collection

3. Method

The process of extracting elevation surfaces from classified LiDAR points involves several sequential steps using ArcGIS. Initially, the raw LiDAR data is subjected to preprocessing procedures, including quality control measures to eliminate noise and classification algorithms to categorize points into different classes (Figure 3) such as ground, vegetation and buildings. Subsequently, ground filtering techniques are applied to separate ground points from non-ground points, crucial for isolating terrain features. Following this, interpolation methods are employed to estimate elevation values for the ground points, forming the basis of the elevation surface. Additional surface smoothing algorithms may be utilized to reduce noise and irregularities.

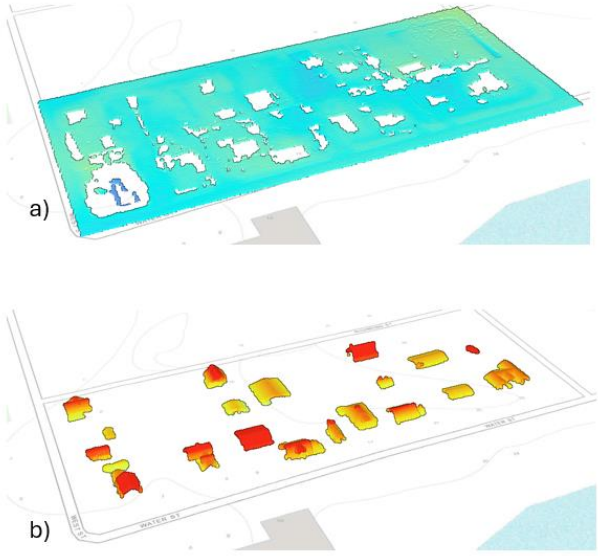


Figure 3: LAS data classification a) as ground points and b) as building points

The process begins with the extraction of elevation surfaces from LiDAR data. This involves acquiring a LiDAR dataset and processing it to generate digital surface models (DSM), digital terrain models (DTM) and normalized digital surface models (nDSM). From Figure 4, it is identified that digital surface model (DSM) encompasses all surface features and objects above ground level on the earth's terrain. In contrast, the digital terrain model (DTM) specifically represents the earth's bare surface without any above-ground structures. The normalized DSM (nDSM) is obtained by calculating the disparity between the DSM and DTM, effectively isolating and emphasizing features like buildings and vegetation that extend above the bare ground surface.

In the expansive realm of geospatial data and mapping, it's crucial to grasp the differences between DEMs, DSMs and DTMs, as they serve as essential tools for accurately representing and analyzing terrain. As exploring the complexities of elevation data, unique attributes that distinguish each dataset are identified.

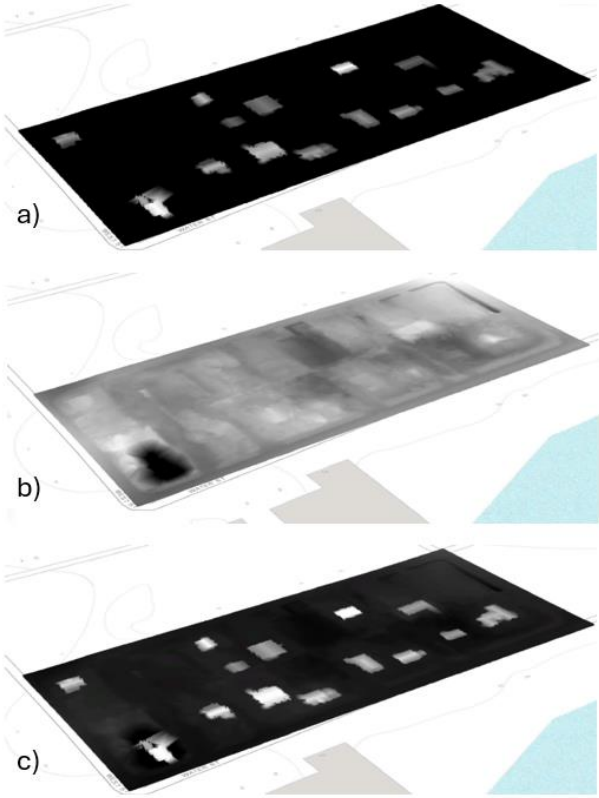


Figure 4: Building block representation as a) n-DSM, b) DTM, and c) DSM

DEMs provide fundamental elevation values, DSMs depict both terrain and structures and DTMs offer precise terrain-focused information. Each dataset contributes uniquely to shaping spatial understanding and insights. Following elevation surface extraction, a step is included to modify the ground elevation around building footprints. This adjustment ensures that buildings sit accurately within the terrain, avoiding discrepancies between building heights and ground elevation. By modifying the elevation surface to accommodate buildings, a more realistic representation of the landscape is achieved.

The next step focuses on extracting building footprints from the LiDAR data. This process involves analyzing LiDAR point cloud classifications to identify and isolate points corresponding to buildings. Additionally, the point spacing of the LiDAR data is considered, with smaller point spacings leading to more accurate feature extraction. Building footprints are delineated using algorithms that detect clusters of points indicatives of building structures. Once building footprints are extracted, preprocessing steps may be applied to enhance their accuracy. This could include splitting building footprints along property boundaries or segmenting footprints based on elevation differences. Splitting building footprints along property boundaries ensures that each building is represented accurately, considering variations in building heights and configurations.

Another preprocessing step involves segmenting building footprints based on elevation differences within each structure. By identifying variations in elevation, such as changes in roof height or slope, building footprints can be divided into more precise segments. This segmentation improves the definition of building features and facilitates the subsequent generation of 3D building models.

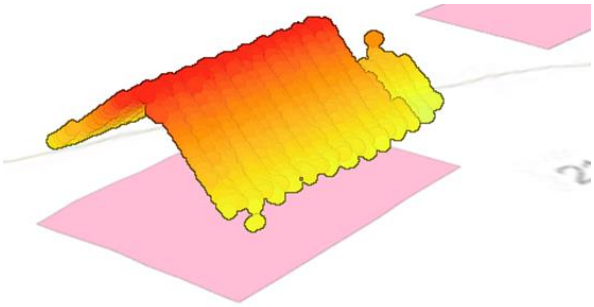


Figure 5: LAS building points and extracted building footprint

With accurately extracted building footprints and building roof points as mentioned in Figure 6, the next step involves generating 3D building models. This process utilizes the extracted footprints as input, along with additional data such as elevation attributes and roof types. Procedural rules, often derived from software tools like CityEngine, are applied to automatically generate detailed 3D geometry for each building. Parameters such as building height, roof shape and architectural style may be specified to ensure realism in the resulting models. Finally, the extracted features and generated 3D models undergo thorough review and refinement. This step involves assessing the accuracy and completeness of the data and models, identifying any discrepancies or errors and making necessary adjustments. Parameters may be fine-tuned, preprocessing steps revisited, or procedural rules modified to improve the quality of the final output.

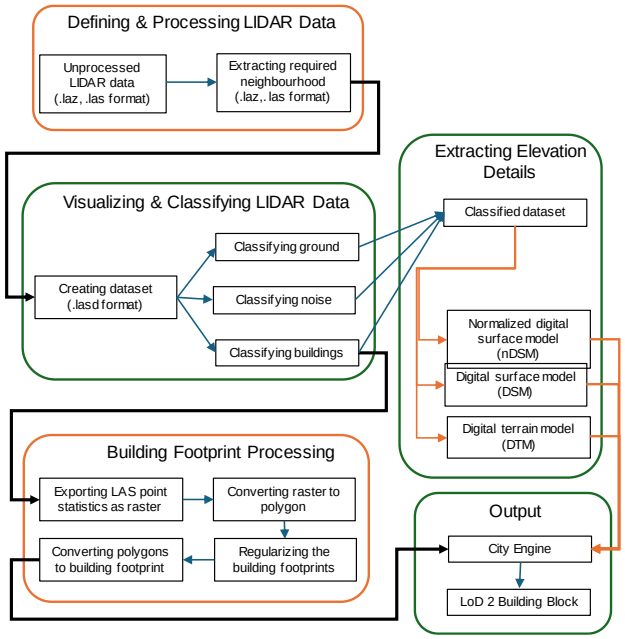


Figure 6: Flow chart representation of LoD 2 Building block extraction process

Manual inspection is then conducted to identify areas requiring refinement. Utilizing the "Modify Buildings" tool, manual segmentation is performed to adjust roof shapes and correct inaccuracies in the extraction. Manual adjustments are made based on visual inspection and comparison with the original LiDAR data. Attributes such as building height are modified to improve alignment with the actual structures. These adjustments are facilitated by procedural rules, ensuring instant updates in the 3D scene based on attribute changes. Once manual refinement is completed, the next step involves converting the refined building footprints into proper 3D objects. This process, termed "Fuse Buildings," consolidates segmented portions of the buildings to create cohesive 3D representations. Texture mapping can then be applied to enhance visual realism, either by utilizing existing textures from libraries or by generating custom textures. Upon finalization, the refined 3D buildings can be published for further analysis or visualization purposes. This methodology enables the iterative refinement of automatic extraction results, ensuring the accuracy and fidelity of 3D building models derived from LiDAR data.

This research work is part of an ongoing project, where the overarching goal is to generate accurate LoD 3 models of building blocks representing building envelope features such as windows and doors. For this purpose, advanced machine learning (ML) techniques such as convolutional neural network (CNN) and region-based CNN (or R-CNN) models are trained using drone images data to identify building details, including windows, doors and garages. The training process involves multiple iterations, with validation

conducted to assess network performance. Precision values are evaluated for object detection, focusing on windows and doors due to their prevalence in the dataset. Trained CNN and R-CNN models are employed to detect building details from drone images data, considering factors such as object overlap and classification errors. Post-processing techniques are applied to address misclassifications, such as screen doors being identified as windows. The accuracy of CNN models in identifying building details is assessed through precision and recall metrics. Qualitative analysis of errors, such as challenges with shaded building faces and dark windows, informs model refinement. Iterative adjustments to training parameters and data augmentation techniques enhance model performance.

Figure 6: Training ML algorithm to identify windows and doors for point cloud conversion

This research integrates DTM, DSM and nDSM with building footprint acquired form LiDAR data, as an approach to achieve the LoD 2 model and ML-based classification of drone data to generate LoD 3 building block models. Terrain elevation data is combined with 3D building models to create realistic urban landscapes. Validation against ground truth data ensures accuracy, with refinements made as necessary to enhance completeness and fidelity. The presented methodology offers a systematic approach to creating LoD 2 and LoD 3 models, leveraging terrain modeling techniques and object detection from drone image data. By following these detailed steps, researchers and practitioners can generate accurate and detailed 3D representations of urban environments, facilitating various applications in energy modeling, urban planning, environmental analysis, digital twins, and virtual simulations. Integration of LiDAR and drone data (workflow is developed) is currently under progress, hence in this work results for LoD 2 building block modeling are presented.

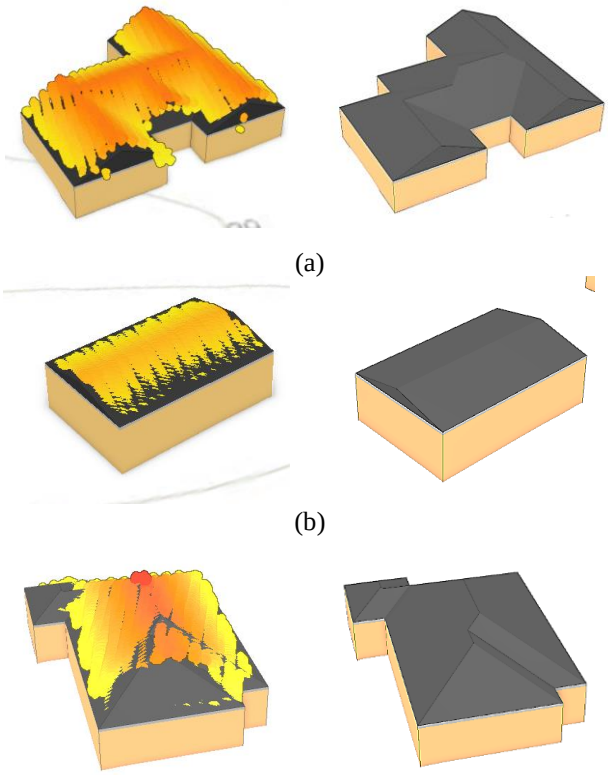
4. Results and Discussion

As sample results, four buildings from a residential block of 14 buildings from Georgetown PEI are presented in Figure 7. Further, in Table 1, geometric attributes related to these four buildings are presented. In the preliminary results it is found that the sample models have yielded to have an RMSE (root mean square error) of less that 2.0 m. RMSE would identify and calculate the distance between the original point geo spacing and the 3D model spacing, giving sufficient accuracy information for the generated roof forms. The RMSE used as a confidence measure is calculated by,

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}\left(\hat{z}(s_i) - z(s_i)\right)^2}{n}}$$

Where, n is the number of roof points of one building block, $z(s_i)$ is the actual point location and $z(s_i)$ is the predicted model location placement.

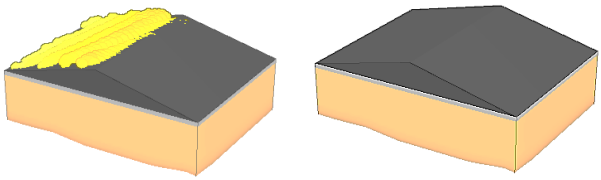
Building perimeter, area and building height are found compatible with the actual buildings. Additionally, different roof types like gable and hip are also extracted depending on point cloud layer. On a large-scale dataset to analyze the difference in closed-spaced blocks and populating them accordingly is the way forward in urban-scale 3D building modelling. These generated models are versatile in their cross-functional usages; the pertinent focus is to incorporate these models into BEM usage.



(a)

(b)

(c)



(d)

Figure 7: Resulting Output of LoD 2 model extracted in comparison with LiDAR points.

Table 1:3D model attributes and values

Building	Perimeter (m)	Area (m^2)	Building height (m)	Roof form	RMSE (m)
1	74.38	238.5	5.47	Gable	0.94
2	40.16	96.90	4.83	Gable	1.77
3	61.09	186.31	6.09	Hip	1.53
4	35.07	75.59	10.37	Gable	1.06

A confidence measure value is calculated to evaluate the extraction process's effectiveness. This measure assesses the accuracy of building footprint extraction, particularly focusing on complex structures. By visualizing the building footprints with color-coded confidence levels, discrepancies between the extracted footprints and actual structures become apparent.

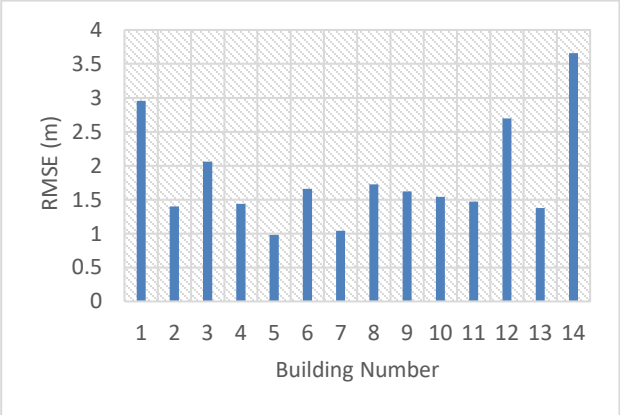
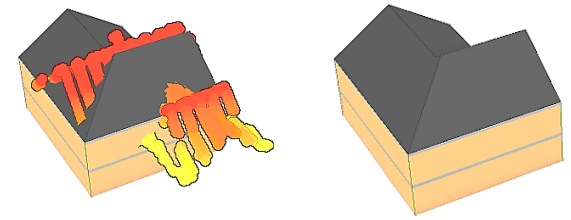


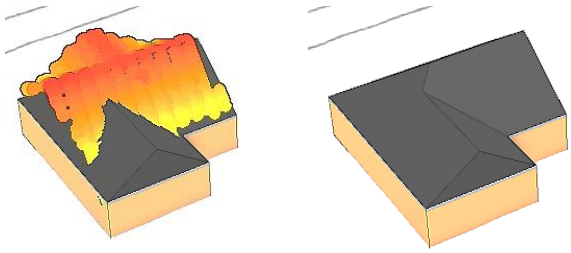
Figure 9: RSME value comparison of the generated buildings in the sample block

The assessment involves analyzing the disparity between the rebuilt model and the initial data points, pinpointing the peak deviation between the reconstructed mesh and the point clouds, and flagging any discrepancies detected. For the LoD2 building models, approximately 14% exhibit an RMSE of under 1 m, while about 71% display an RMSE below 1.75 m. These findings, outlined in Figure 7, signify ongoing efforts to enhance our workflow by scrutinizing quality parameters. Further evaluation endeavors are currently underway to refine the methodology.

There have been a few other buildings in the extracted LoD 2 model with visually noticeable discrepancies. These buildings, outlined in Figure 8, each having an RMSE of 1.65 m and 2.69 m, give the research further insights into potential errors that need to be rectified. Through the initial findings, it is observed that the models with complex roof structure, when not corresponded with building footprint complimented with inaccuracies in the elevation information stored in the DSM while integrating tends to generate models with visually noticeable errors. The research has implemented strategies to reduce the level of error.



(a)



(b)

Figure 8: LoD 2 model with complex roof shape extracted with error in comparison with LiDAR points.

4.2. Future work

The future work will further integrate the drone data to develop neighborhood-scale 3D geometry LoD 3 model. The resulting 3D building blocks can be exported as shapefiles (.sph format) that can further be converted into virtual reality modeling language (VRML or .wrl format) which is compatible with many building energy modeling software such as Rhino Grasshopper. The discussion further explores the potential synergies and benefits of integrating GIS and BEM and outlines the key considerations for successful implementation. Data integration and visualization facilitate the seamless integration of diverse datasets, including geographical, environmental, and

building-related data. This integration enables researchers to visualize complex spatial relationships, such as the impact of building orientation, shading, and surrounding land use on energy performance. Visualizing energy-related data within a geographic context enhances understanding and decision-making as well as spatiotemporal modeling of energy demand and supply, enhancing resilience planning in urban environments. By considering spatial variations in energy demand, renewable energy potential, and infrastructure vulnerabilities, stakeholders can develop more resilient and adaptive energy systems.

5. Conclusion

In this work, a neighborhood block is considered in the case study location of living lab Georgetown, PEI. A block containing 14 buildings has been selected for the process of extracting elevation surfaces and generating detailed 3D building models from LiDAR data involving a systematic and comprehensive approach that integrates various techniques and data sources including LiDAR, DTM, nDSM, DSM, and drone imagery, to enhance the three-dimensional representation of the built environment. By amalgamating these data sources, the study aims to provide insights into building geometry and topography, thereby facilitating comprehensive energy modeling and analysis. Furthermore, the integration of drone imagery and machine learning techniques is proposed to enhance the extraction of building details such as windows and doors, contributing to the creation of more detailed level of detail (LoD) models. In this research, the outcome has been varying between a minimum of 0.94 m and a maximum RMSE of 3.6 m. This research furthermore explores methods to rectify the error in generated building geometries. In the considered building block, approximately 14% of the LoD2 building models exhibit a root mean square error (RMSE) of under 1 m, while about 71% display an RMSE below 1.75 m. However, the proposed workflow yielded less accuracy while generating complex roof shapes resulting in an RMSE of 3.6 m. This work is part of ongoing research and future research directions will focus on further improving the accuracy of workflow dealing with complex roof shapes and machine learning application form to generate LoD 3 models. The proposed methodology for extracting building footprints and generating 3D building models from LiDAR data offers a systematic approach to urban environment representation, with applications in energy modeling, urban planning, and disaster management.

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