# BUILDING ROOFTOP ANALYSIS FOR SOLAR PANEL INSTALLATION THROUGH POINT CLOUD CLASSIFICATION - A CASE STUDY OF NATIONAL TAIWAN UNIVERSITY

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***ABSTRACT:*** *As climate change intensifies, we must embrace renewable solutions like solar energy to combat greenhouse gas emissions. Harnessing the sun's power, solar energy provides a limitless and eco-friendly source of electricity, reducing our reliance on fossil fuels. Rooftops offer prime real estate for solar panel installation, optimizing sun exposure, and maximizing clean energy generation at the point of use. For installing solar panels, inspecting the suitability of building rooftops is essential because faulty roof structures or obstructions can cause a significant reduction in power generation. Computer vision-based methods proved helpful in such inspections in large urban areas. However, previous studies mainly focused on image-based checking, which limits their usability in 3D applications such as roof slope inspection and building height determination required for proper solar panel installation. This study proposes a GIS-integrated urban point cloud segmentation method to overcome these challenges. Specifically, given a point cloud of a metropolitan area, first, it is localized in the GIS map. Then a deep-learning-based point cloud classification model is trained to detect buildings and rooftops. Finally, a rule-based checking determines the building height, roof slopes, and their appropriateness for solar panel installation. While testing at the National Taiwan University campus, the proposed method demonstrates its efficacy in assessing urban rooftops for solar panel installation.*

***KEYWORDS:*** *Sustainable campus, renewable energy, point cloud segmentation, deep learning*

## 1. INTRODUCTION

One of the most critical and urgent challenges we face in this century is climate change, resulting mainly from human mass consumption of fossil fuels. Thus, replacing fossil fuels-based energy with renewable energy is a key solution to this problem (IPCC, 2022). Increasing the supply and usage of renewable energy relies on not only efforts by power producers and public sectors but also energy-heavy industries and private sectors. Hence, in recent years, many major corporations worldwide have announced their targets for decreasing carbon emissions and increasing renewable energy usage to fulfill their corporate social responsibility (CSR), and higher education institutions are no exception. Many universities worldwide have also announced their climate targets and planned to increase the usage and supply of renewable energy for their university's social responsibility (USR) (THE, 2022). National Taiwan University (NTU) also announced its carbon-neutral target and pathway in Nov 2021. To achieve this goal, the decrease in building energy usage and the increase in renewable energy are two key strategies. For the latter, how to install more solar panels and smart energy systems on campus is a key question to be explored.

To increase renewable energy supply, using spare spaces on building rooftops for solar panel installation is common in cities worldwide. Various factors affect the effectiveness of solar panel installation on the rooftops, including roof angles, shades created by nearby buildings or penthouses, and obstacles on the rooftops (Lin et al., 2022). To evaluate the potential of solar panel installation effectively, the collection and creation of digital data and models of study objects become critical (Sierra et al., 2022, Chen et al., 2023). Airborne laser scanning is a common practice to capture the basic outline of study objects (Wang et al., 2018). After segmenting the collected point cloud data via deep learning models, large-scale building reconstruction and automated extraction of building instances can be easily achieved (Huang et al. 2022, Feng et al. 2022).

This paper aims to analyze buildings' rooftops for solar panel installation through point cloud segmentation, taking National Taiwan University (NTU) in Taipei, Taiwan, as a study case. As the first university established in Taiwan, more than 100 buildings are on the main campus, built between the 1920s and the present. Large-scale building

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point cloud is collected using airborne LiDAR, and a commercial GIS tool, ArcGIS Pro, is used for further analysis. The analysis process and results are presented in sections 2 and 3, along with the challenges encountered. The research outcome can be a good reference for other university campuses which aims to use similar dataset for similar analysis. The main contribution of the paper is as follows:

- It proposes an end-to-end workflow for building rooftop analysis using point cloud data.
- It also proposes a simple and fast methodology for point cloud segmentation using commercial software tools such as ArcGIS Pro.

## 2. RELATED STUDIES

### 2.1 Point Cloud Classification for Building Rooftop Analysis

The application of point cloud data obtained from advanced technologies such as LiDAR has significantly transformed geospatial analysis (Dawood et al., 2017). This innovative approach has garnered the attention of researchers tapping into these datasets to extract valuable insights about urban landscapes and, more specifically, to evaluate the feasibility of deploying solar panels on building rooftops (Stack & Narine, 2022). A focal point of this effort lies in utilizing point cloud classification techniques, which can discern various objects and surfaces within the three-dimensional environment. By harnessing these techniques, researchers can effectively identify the detailed contours of building structures, ascertain the orientation of roof planes, and anticipate potential obstructive elements (Sun et al., 2016). This approach starkly contrasts traditional two-dimensional methodologies, allowing for a much more exhaustive and nuanced assessment of the diverse attributes associated with rooftops. Consequently, this three-dimensional perspective empowers researchers and planners to make informed decisions regarding optimizing solar panel placements and leveraging rooftops for sustainable energy generation (Stack & Narine, 2022). The fusion of GIS and point cloud data has opened new avenues for geospatial analysis, enabling researchers to analyze urban environments in three-dimensional detail. However, previous studies hardly integrated point clouds and GIS to check the rooftop suitability for solar panel installation.

### 2.2 Deep Learning and Machine Learning Approaches

The amalgamation of deep learning and machine learning techniques has marked a substantial leap forward in enhancing the precision and effectiveness of point cloud classification (Pal & Hsieh, 2021). Prominent among these methodologies are convolutional neural networks (CNNs) and other sophisticated deep-learning architectures that have showcased exceptional prowess in deciphering intricate roof structures and discerning the diverse array of rooftop attributes (Yang et al., 2023). These methodologies have emerged as dynamic tools capable of automatically extracting valuable information from point cloud data. This encompassing capability spans identifying building footprints, precisely measuring roof areas, and detecting possible shading elements (Pohle-Fröhlich. et al., 2019). The cumulative result of these advancements is a substantially elevated accuracy and depth in evaluating rooftops' suitability for solar panel deployment (Tan et al., 2019). As these methods continue to mature and evolve, their application within the domain of point cloud classification holds tremendous promise for facilitating increasingly refined and reliable analyses, thus paving the way for more informed and effective decision-making processes related to solar energy integration.

## 3. METHODOLOGY

The methodology adopted in this study is divided into four steps: data acquisition, preprocessing, classification and analysis, and data aggregation. Figure 1 shows a graphical representation of the proposed methodology. This study uses ArcGIS Pro software for GIS-integrated point cloud classification and analysis. Details of each step of the method are explained in the following paragraphs.

### 3.1 Data acquisition

A UAV-mounted Light Detection and Ranging (LiDAR) device collects the point cloud data. This process begins with mission planning, outlining flight paths and parameters to ensure comprehensive coverage. Laser pulses are emitted toward the ground, and the LiDAR system calculates the return time to determine distances. The collected data generates a point cloud containing detailed 3D coordinates of terrain, buildings, vegetation, and other features. Georeferencing is achieved through GPS and INS for accurate positioning. Collected point clouds are stored in multiple LAS files of manageable sizes. LAS format is an industry-standard file format developed and managed by the American Society for Photogrammetry and Remote Sensing (ASPRS). It is a widely accepted and published standard for exchanging LiDAR data.

## 3.2 Preprocessing

In the preprocessing step, the point cloud data is in LAS format imported into ArcGIS Pro software, where the "Create LAS Dataset" tool is employed to establish a structured dataset for subsequent analysis. To accurately register the point cloud data with the GIS map, the map data frame should be in the same coordinate system as the LiDAR point cloud tile. The preprocessing involves aligning the coordinate system, performing initial classification, differentiating ground points, and applying quality checks. The dataset is then clipped to focus on the specific study area, and optional filtering and compression steps are used to enhance data quality and efficiency. This processed dataset is the foundation for various geospatial analyses within the ArcGIS Pro environment, including classification, feature extraction, and terrain modeling.

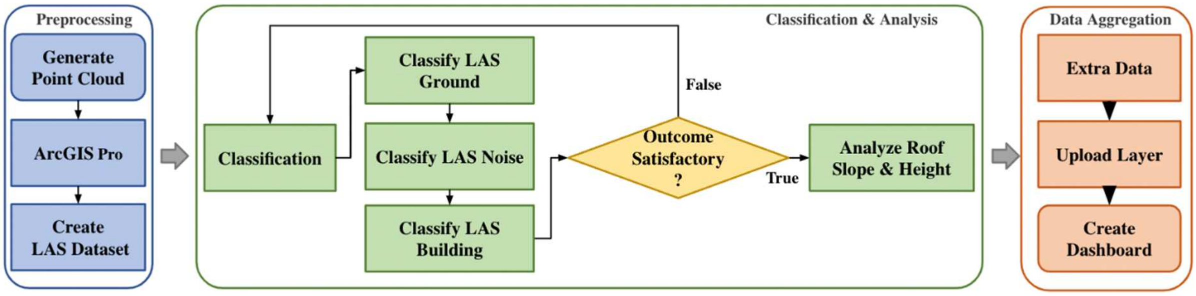


Fig. 1: Overview of the proposed methodology

## 3.3 Classification and analysis

Once the preprocessing is done, point cloud classification, roof slope analysis, and building height analysis are the next steps. Details of these steps are described below.

### 3.3.1 Point cloud classification

The point cloud classification is conducted in three steps: (1) using the built-in LAS classification functions such as Classify LAS Ground and Classify LAS Building. (2) 2D shapefile-based classification such as Set LAS Class Codes Using Features, and (3) Classifying a point cloud with deep learning.

First Classify LAS Ground tool is used for the identification of ground points. Ground point assignment is reserved exclusively for LAS points with 0, 1, or 2 class code values. If LAS files employ distinct class code values for unclassified or ground measurements, the Change LAS Class Codes tool can reassign them correspondingly. Next, Classify LAS Building tool is used to classify building rooftops with class code values 0, 1, and 6. Before rooftop classification, LAS data must have classified ground points. This method may not classify points representing walls, vertical facades, and small rooftop features like chimneys. Before building classification, point cloud noises are filtered using Classify LAS Noise function.

The 2D shapefile of buildings is used to enhance the classification quality further. LAS points intersecting the 2D positions of the input polygons are reclassified as buildings. Built-in function Set LAS Class Codes Using Features is used for this purpose. The ArcGIS software uses the American Society for Photogrammetry and Remote Sensing (ASPRS) defined LAS classification scheme. Although this step improves the classification, wall and façade classification is still challenging.

In the final step, a pre-trained deep-learning model, PointCNN, for building classification is used to improve the classification results further. The deep-learning model is inputted as a Deep Learning Package (*.dlpk) in the ArcGIS software. Using the Existing Class Code Handling parameter control over modifications in the target LAS point cloud was achieved. Points already correctly classified (such as grounds) are kept unchanged.

### 3.3.2 Roof slope and building height analysis

A raster file is created using elevation values stored in the LiDAR points referenced by the LAS dataset for roof slope and building height analysis. Subsequently, a digital elevation model (DEM) of the buildings is created. Next Spatial Analyst function for Slope calculation is used to identify the slope from each cell of the raster file. The Slope tool uses a three-by-three moving window of cells to compute the slope value. The extent of values in the output depends on the measurement units employed. When utilizing degrees, the range of slope values spans from 0 to 90. The analysis can be accelerated using GPU.

Building heights are estimated by comparing the digital surface model (DSM) and the DEM created earlier. The Zonal Statistics tool is used for this purpose. A zone encompasses all regions within the input that share an identical value. The input for defining zones can comprise both raster and feature data types. This tool helps in arithmetic statistics calculations such as Mean, Majority, Maximum, Median, Minimum, Minority, Percentile, Range, Standard deviation, Sum, and Difference. A zonal statistics raster is generated. In this study, the zonal statistics raster represents the building height. Finally, the suitability of the building for rooftop solar panel installation is determined by rule-based checking.

### 3.4 Data aggregation

During the data aggregation phase, the analysis outcomes, encompassing critical metrics like building heights, mean roof slopes, and evaluations of building suitability, are initially compiled into a structured comma-separated value (.csv) file. This file format aids in organizing the data for seamless processing and interpretation. Subsequently, this collected analytical information is integrated into the university campus's existing Geographic Information System (GIS) shapefile. This incorporation ensures that the analysis outcomes are appropriately aligned with the geographic context of the campus and can be readily accessed for further exploration. Additionally, an additional map layer is generated to enhance the visual representation of these analysis outcomes and promote efficient decision-making. This newly created layer is specifically tailored to present the aggregated results coherently and visually engagingly. The GIS-integrated dashboard within the ArcGIS software serves as a versatile tool for visualizing and interacting with the outcomes, facilitating comprehensive insights and informed actions based on the analysis conducted.

## 4. RESULTS

The proposed methodology was tested on the expansive 115-hectare main campus of National Taiwan University (NTU) in the Da'an District of Taipei. This sprawling campus hosts a multitude of academic and administrative buildings, exceeding a count of 100. The core objective of this study is to evaluate these buildings' viability for installing rooftop solar panels. To collect the crucial data, an unmanned aerial vehicle (UAV)-mounted LiDAR device was employed, effectively capturing the intricate point cloud representation of the campus. This extensive point cloud dataset was systematically stored in 13 distinct parts, all adhering to the standardized LAS format. Commercial software ArcGIS Pro was used for hosting, processing, and analyzing the point cloud and integrated GIS data. A computer with Intel i7-1370P central processing unit (CPU), 64-gigabyte (GB) random access memory, and 32 GB Intel®Iris®Xe Graphics graphics processing unit (GPU) is used to run the software tool.

In conjunction with this voluminous point cloud dataset, a Geographic Information System (GIS) map showcasing the 2D polygonal representation of campus buildings was prepared. Figure 2 visually depicts the campus's point cloud model and the 2D GIS map. A comprehensive LAS dataset was constructed by amalgamating all 13 LAS files within the ArcGIS Pro software. This amalgamation was executed in accordance with the preprocessing phase described within the methodology. The subsequent phase encompassed applying a three-step classification technique to the compiled LAS dataset, enabling the precise segmentation of building-related point cloud data. The initial stage involved the classification of ground points utilizing the LAS code, following which the 2D GIS polygons facilitated the segmentation of the building point cloud. Eventually, implementing a deep learning model proved instrumental in impeccably classifying and segmenting the points that accurately represented buildings. The outcomes of this segmentation are depicted in Figure 3, which showcases the successful classification outcomes for ground and building points.

Fig. 2: Point cloud (left) and 2D GIS map (right) of NTU main campus

Following the successful classification of building points, a customized DEM raster specific to the campus building was generated. Subsequently, the slope analysis tool was employed to accurately estimate the slope on building rooftops. In this study, the slope measurement unit was defined in degrees, resulting in values spanning the spectrum from 0 to 90 degrees. The ensuing outcome, depicted on the left-hand side of Figure 4, showcases the slope analysis raster. Significantly, the color coding scheme holds informative value: shades of green signify shallower slopes denoting suitability for solar panel installation, while shades of red signify steeper slopes indicating unsuitability. Notably, buildings characterized by substantial rooftop obstructions are prominently indicated in red hues. Furthermore, the color transition observed at building edges is attributed to shifts in slope characteristics, rendering rooftop edges prominently delineated in a striking red color.

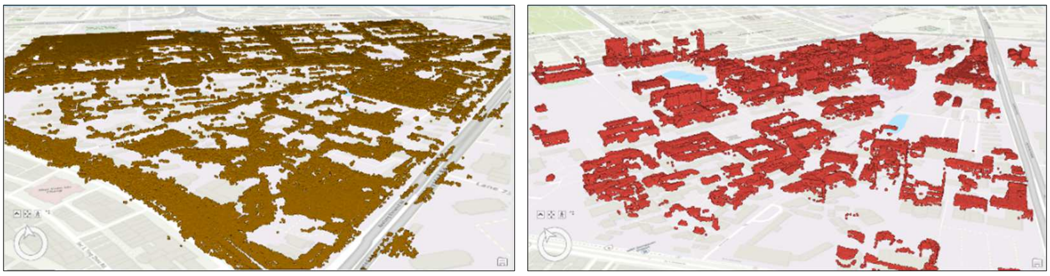

Fig. 3: Point cloud classification results: ground classification (left) and building classification (right)

Building heights were estimated through a comparison between the DSM and DEM rasters, utilizing the Zonal Statistics tool. The outcome of this building height estimation is rendered as a raster, distinguished by color codes corresponding to different heights. This representation is exhibited in the diagram on the right-hand side of Figure 4. Observations indicate that the tool proficiently determined building heights in the majority of cases. However, a few instances (depicted in red) disclosed significant inaccuracies in estimations. Subsequent in-depth analysis established that factors such as noise within the point cloud data, substantial tree obstruction, and inherent point cloud incompleteness substantially influenced the tool's performance.

Finally, the roof slope analysis and building height estimation results were exported into a .csv file, and the existing GIS shapefile was updated. The NTU's GIS dashboard is used to display the analysis results. It can help university administrators to make decisions in a more interactive way. An example of data integration for five buildings is shown in Table 1. The check column of the table shows the suitability of the building for rooftop solar panel installation. The checking result was incomplete for the civil engineering building because of the point cloud incompleteness. The GIS representations of these buildings are shown in Figure 5.

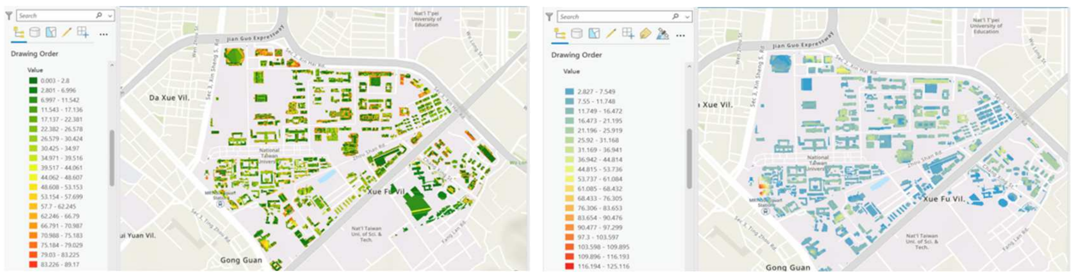


Fig. 4: Results of roof slope analysis (left) and building height estimation (right)

Concluding the process, the roof slope analysis and building height estimation outcomes were transferred into a .csv file, and the pre-existing GIS shapefile was updated concurrently. The integrated results are seamlessly displayed through NTU's GIS dashboard, enhancing the capacity of university administrators to make decisions in an interactive and informed manner. This holistic approach facilitates a more dynamic decision-making process. Exemplifying the integration, Table 1 demonstrates data amalgamation for five specific buildings. Notably, the "Check" column within the table signifies the suitability of each building for rooftop solar panel installation. However, it's essential to underscore that the checking process remained incomplete for the civil engineering building due to inherent point cloud incompleteness. The visual GIS representations of these buildings are depicted in Figure 5. This comprehensive integration emphasizes the analytical and visual richness of the approach.

## 5. DISCUSSIONS

Although the methodology successfully analyzed building rooftops for solar panel installation, its performance is affected by several factors: point cloud completeness, obstacles from tree leaves, noise in the point cloud data, etc. This method faces a challenge in rooftop analysis of the shorter buildings at the NTU campus because the rooftops of such facilities are often obstruction by tree leaves. Also, the state of these leaves is inherently unstable, subject to growth, pruning, and even shedding, introducing an element of uncertainty into the ongoing analysis. A potential solution could involve implementing filtering criteria during the initial point cloud scanning phase. This strategic approach would enable the retention of essential data points, subsequently alleviating the workload and refining the data for subsequent analysis. Also, the accuracy of the classification methods is subject to several factors, such as the completeness of the existing 2D GIS map data, proper alignment of the map and point cloud data, and the efficiency of the deep-learning model. The incompleteness of the map data and slight discrepancies between map data and point cloud data often leads to manual adjustments.

Table 1: Integration of analysis results in campus GIS map

| Building Name | Area. | Mean slope ( ° ) | Height (m) | Check |
|---|---|---|---|---|
| NCREE | 13135.83 | 15.96 | 21.93 | Great |
| College of Liberal Arts | 5980.44 | 33.23 | 11.96 | Ok |
| Dept. of Chemistry | 11460.91 | 37.71 | 27.19 | Ok |
| Floricultural Hall | 1381.30 | 41.26 | 13.04 | Ok |
| Dept. of Civil Engineering | 9686.44 | 60.05 | 21.75 | Insufficient Data |

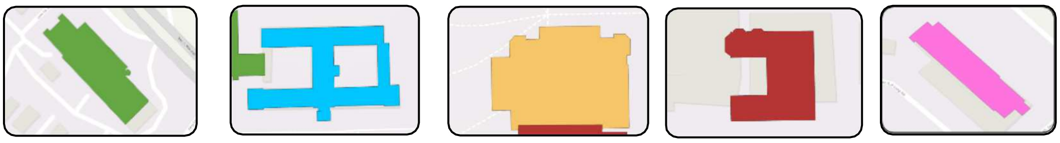

Fig. 5: Building displayed in GIS dashboard. From left: NCREE, College of Liberal Arts, Dept. of Chemistry, Floricultural Hall, Dept. of Civil Engineering

## 6. CONCLUSION & FUTURE WORK

In conclusion, this study presents a holistic approach to evaluating the suitability of building rooftops for solar panel installation, contributing to the overarching goal of mitigating climate change through renewable energy solutions. The pressing need to curtail greenhouse gas emissions highlights the imperative to transition away from fossil fuels. Integrating renewable sources, particularly solar energy, is pivotal in this attempt. Rooftops provide an underutilized space for solar panel deployment, offering decentralized clean energy generation. However, the effectiveness of such installations hinges on accurate assessments of rooftop attributes. This research introduces a sophisticated methodology amalgamating Geographic Information System (GIS) techniques with advanced point cloud segmentation methodologies. By harnessing airborne LiDAR technology and leveraging deep learning models, the proposed approach deftly addresses challenges such as rooftop slope analysis and building height determination, ensuring the accuracy and applicability of solar panel placement assessments. The study's application on the National Taiwan University campus confirms the practical viability of the methodology.

As universities and organizations worldwide set ambitious carbon neutrality goals, the methods outlined herein provide valuable tools for optimizing renewable energy integration. Moreover, the interdisciplinary nature of this research, encompassing spatial analysis and environmental considerations, exemplifies the multi-faceted approach required to address complex challenges like climate change. We can advance our understanding of sustainable energy practices through such interdisciplinary endeavors and work towards a greener and more resilient future.

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