Detecting Building Changes with a Certainty Index Using AHN and Rotterdam Point Cloud Dataset

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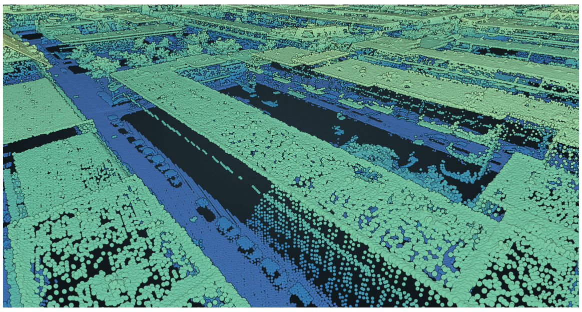
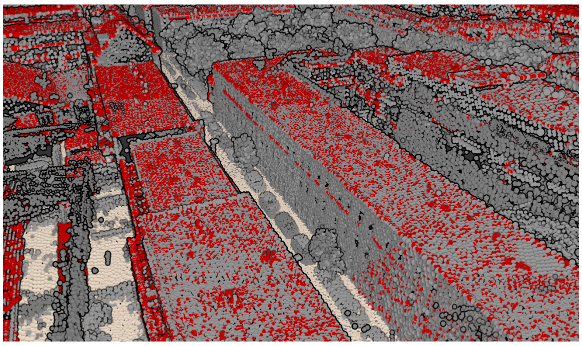
1 Introduction

The Netherlands is a highly organized country, where nearly every part of the land is carefully planned and used. However, there is a lot of pressure on the available space, as important challenges as housing, renewable energy production, and climate adaptation all require land (Evers et al., 2023). To manage this, 3D models of the world are very important for making better decisions.

One widely used 3D representation is the point cloud dataset. They can be used for generating a 3D city model, such as 3DBAG, which supports tasks like noise emission calculation, energy demand estimation and utility management (Biljecki et al., 2015). Alternatively, point clouds serve as raw data for direct measurements and analysis. In the Netherlands, the National Height Model of the Netherlands (AHN) is a source of point cloud data, collected using airborne laser scanning. The AHN is widely used for applications such as dike monitoring and sound map generation (Manders, 2024). Another source is the non-open Rotterdam point cloud dataset, updated yearly. These are utilized for municipality tasks, such as BAG-WOZ inspections, project development, and the maintenance of public spaces and heritage buildings (van Bochove, 2019). Figure 1 shows an example of these datasets for the same area.



(a) Screenshot urban part of AHN4 in Rotterdam. Color is based on height.



(b) Screenshot urban part of Rotterdam dataset 2023 in Rotterdam. Color is based on classification. Red is buildings.

Figure 1: Screenshort of same part in AHN and Rotterdam dataset.

Keeping these datasets up to date is critical, as detecting changes between different versions could make updates more efficient. While much of the current research on change detection focuses on 2D methods, these approaches have limitations. 2D data are more widely available and frequently updated (Qin et al., 2016, Kharroubi et al., 2022, Xiao et al., 2023), which makes it convenient, but it often lacks vertical height information (de Gélis et al., 2021b), is affected by seasonal changes, and suffers from perspective distortion (Kharroubi et al., 2022). In contrast, point clouds could retain the original 3D geometric information (Nofulla, 2023), can penetrate through tree canopies to reveal what lies beneath (Politz and Sester, 2022) and are robust to differences in lighting conditions (Kharroubi et al., 2022). These advantages make point clouds valuable for applications such as monitoring urban sprawl, assessing damage, and analyzing forest changes (Kharroubi et al., 2022).

This research focuses on detecting changes in buildings, as point clouds play a key role in developing smart cities (Lemmens, 2018) and managing urban spaces. Detecting building changes is also important for keeping resources such as the 3DBAG and the BAG. Additionally, focusing specifically on buildings allows the algorithm to be tailored and optimized for this purpose. However, detecting changes in point clouds comes with its own challenges. Point clouds from two different times cannot be directly compared, as the points from the second dataset will never match the exact positions of the points from the first dataset (Winiwarter et al., 2021). Moreover, the effectiveness of change detection methods depends on various factors, such as data acquisition techniques, dataset characteristics (especially point density), and analysis objectives. A major challenge is seperating real changes from pseudo-changes. To address these challenges, this study aims to develop a framework that includes a certainty index to ensure reliability. The goal of the algorithm is to classify each building point as either ”changed” or ”unchanged,” leaving the interpretation of the type of change to human analysis. A general overview is shown in Figure 2.

This research is conducted in collaboration with Geodelta, a company specializing in geo-information. Geodelta is known for its commitment to accuracy and precision. They support this thesis by providing data, sharing relevant information, and offering their expertise to help achieve the best possible results.

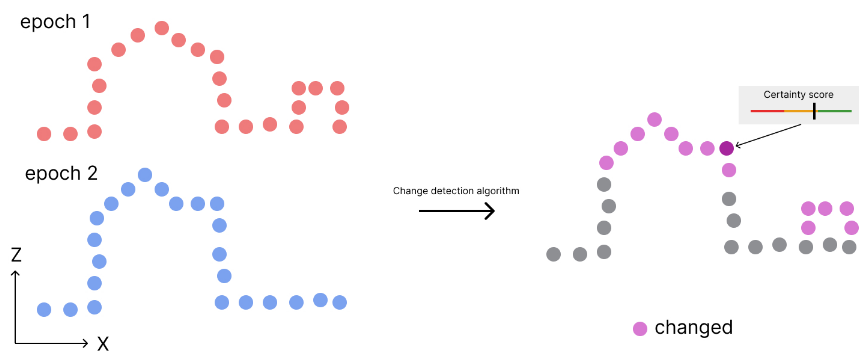


Figure 2: The goal of this thesis.

2 Related work

This section will review the relevant literature for this research. It will begin with a brief overview of point cloud data, followed by a discussion of methods for detecting changes in point clouds. Finally, the uncertainties and errors associated with point clouds will be explained.

2.1 Introduction to Point Cloud Data

A point cloud dataset consist of points in space having coordinates that represent objects or natural landscapes in 3D, usually represented with an x-, y- and z-coordinate per point (Dahle, 2020). Point-cloud datasets can be obtained using photogrammetry (including dense matching techniques) and LIDAR. This research will focus on the second method, light detection and ranging. A LIDAR scanner emits pulses to the surface and calculates the time between sending and receiving the pulse. Since the pulse travels with the speed of light, it is possible to calculate the distance from the scanner to the point (Scaioni et al., 2018). Next, the 3D coordinates of the point can be determined from the emitting angle and the location of the scanner (Liu, 2022). Mostly, topographic LIDAR systems are monochromatic systems, operating with single laser wavelength in the near infrared (Scaioni et al., 2018). In addition to capturing positional data, these systems can also measure the intensity of the backscattered laser signal (Scaioni et al., 2018). Furthermore, each point in the dataset can include additional attributes, such as color, the number of returns, or classification labels.

Point clouds have a wide range of applications, including monitoring, viewshed analysis, solar energy potential assessment, deformation studies, volume calculations, and vegetation or hydrology analysis (Oosterom, 2016). One key advantage of point clouds is their ability to represent environments realistically without significant data loss. However, the highly detailed nature of point clouds also results in very large datasets, making storage and processing challenging (Oosterom, 2016). These challenges will be further addressed in Subsection 2.5.

2.2 Point Cloud Change Detection Methods

A key challenge for any change detection method is distinguishing real-world changes from pseudo-changes. Pseudo-changes are errors in point clouds caused by factors like occlusions, inaccuracies in alignment (registration errors), or temporary variations such as seasonal vegetation changes or moving objects like cars. Various methods have been developed to detect urban changes in point clouds, see Qin et al. (2016), Kharroubi et al. (2022), Stilla and Xu (2023) and Xiao et al. (2023) for overviews. This subsection will review the most relevant literature for this research.

Commonly used techniques include Cloud-to-Cloud (C2C) and Cloud-to-Mesh (C2M) comparisons. Figure 3 provides an illustration of these methods. In C2C, the closest neighbor is found in the other epoch, and the distance between the two epochs is measured. Even tough C2C is simple, it is highly sensitive and is heavily based on dataset-specific thresholds (de Gélis et al., 2021b). In C2M, the change is measured as the distance between a selected point and the surface (mesh) created from the other dataset. For this method, the target point cloud needs to be converted into a mesh, but this can result in triangular surfaces that may include gaps or artifacts (Kharroubi et al., 2022). Both approaches face challenges when there are differences in the density of points within the same dataset or between two datasets, as well as when parts of the data are blocked from view (occlusion) (Kharroubi et al., 2022).

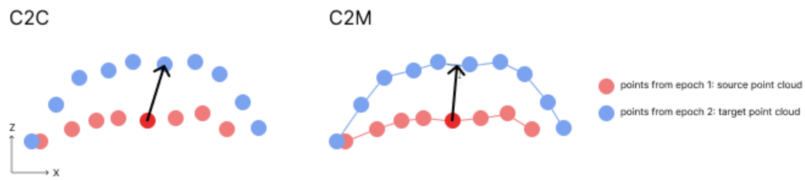


Figure 3: Illustration of how C2C (left) and C2M (right) methods work.

A popular alternative is to convert point clouds into DSMs for change detection (Xiao et al., 2023). Figure 4 shows an example of the differences in DSM. The area is divided into grids, and in each grid, at most one point is selected (e.g., the lowest point). These points are then connected using triangulation, assigning one height value per grid. To calculate changes, the grids are subtracted from each other. Kharroubi et al. (2022), Stilla and Xu (2023), de Gélis et al. (2021b) state that this method is efficient, but introduces information loss due to interpolation and only accounts for differences in a predefined direction. It also struggles to accurately capture precise building boundaries.

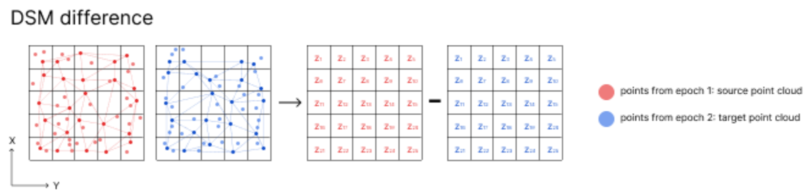


Figure 4: Illustration of how DSM difference is calculated.

The use of machine learning and deep learning in change detection is increasing. Figure 5 shows the general workflow of a learning-based algorithm. For each point or patch of points, the features are calculated. These features are based on information from one or both epochs. Then, a classifier (either machine learning or deep learning) is trained using a labeled dataset. Based on the labels, the algorithm identifies the changes and the type of change (e.g., added or removed building). The random forest algorithm, for example, has shown promising results (De Gélis et al., 2021, de Gélis et al., 2021b, Kharroubi et al., 2022, Nofulla, 2023). However, its performance is sensitive to the quality of the features (Nofulla, 2023) and decreases as the data becomes more heterogeneous (de Gélis et al., 2021b). Another interesting approach involves combining Siamese architectures with deep learning, which has shown strong performance (Kharroubi et al., 2022, De Gélis et al., 2021). Kharroubi et al., 2022 states the good performance of learning-based methods, but also states their limitation of a class-imbalanced problem and the probability of failing in minority classes. de Gélis et al. (2021a) claim to be the first to use deep learning directly on raw point clouds for change detection and characterization, and claims that it outperforms machine learning algorithms.

De Gélis et al. (2021) and Kharroubi et al. (2022) suggest the development of more spatially-aware deep neural networks for urban change detection, as these models can better understand the structured nature of objects on a global scale. Kharroubi et al. (2022) suggest to do more research on the use of graph neural networks for change detection, integrating the progress made in 3D segmentation, and to explore finer levels of structural detail to ensure scalability with large datasets. Stilla and Xu (2023) also highlight the importance of integrating semantic information and addressing measurement uncertainties in future methods.

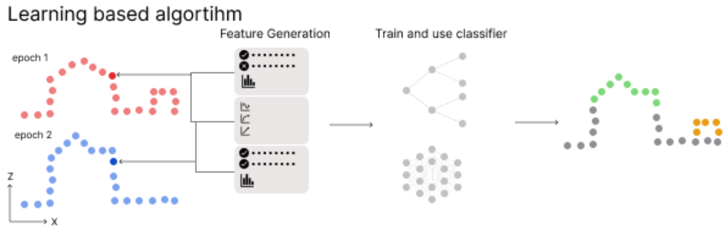


Figure 5: Illustration of how a learning based algorithm works, in general.

Many change detection methods struggle to detect small changes. Kharroubi et al. (2022) and Xu et al. (2015) highlight this by setting a filter for registration errors or false changes, like parked cars, which can also unintentionally exclude real changes, such as the addition of a dormer on a roof. Another reason they are mentioning is the low density of points representing small features or other limitations in the dataset.

Since this research will dive into change detection for AHN and the Rotterdam dataset, it is good to compare the methods, but that is difficult because of two reasons. (1) The nature of the objects being studied plays a significant role in determining the appropriate change detection method. For example, methods will differ depending on whether the goal is to monitor soil deformation, analyze forests, or study urban environments. (2) The quality of the results of change detection methods varies across datasets and produces diverse results. This variability complicates direct comparisons between methods, as each study uses different datasets, real or synthetic, with unique characteristics. A significant challenge is the lack of a well-labeled standardized dataset, which has been identified as a priority by de Gélis et al. (2021a) and Kharroubi et al. (2022).

2.3 Random Forest Classifier

This subsection explains the Random Forest (RF) classifier, which is planned to use in this research. Random Forest has been shown to perform well in 3D change detection, as demonstrated by Tran et al. (2018). It offers the following advantages. (1) It is resistance to overfitting. (2) Runs fast and efficiently for large datasets. (3) RF does not require a very large training data set, unlike convolutional neural networks. Other advantages of random forest are that it handles noisy data well and its results are easily interpretable (Belgiu and Drăguţ, 2016). There are also some limitations with the random forest classifier. de Gélis et al. (2021a) note that RF struggles when the data is highly diverse. Similarly, Nofulla (2023) points out that RF is sensitive to the quality of features and does not account for spatial relationships within the data.

Biau and Scornet (2016) explain that a random forest classifier is made up of a group of M regression trees that are randomized and work together to make predictions. These separated trees are trained on different dataset samples and all vote for a specific outcome, the final decision is made by a majority vote. Next to this end conclusion, probabilities per possible class are also able to generate. These probabilities are derived from the fraction of samples in each leaf that belong to that specific class and are aggregated throughout the forest.

Random forests are widely used and also in change detection in point clouds they are used. Tran et al. (2018) use both single-point features and multi-temporal features. For single points, they calculated normal and surface metrics like linearity, planarity, and omnivariance. They also considered neighborhood-based features such as EchoRatio, ZRank, and ZRange. Additional features included the height above the digital terrain model (DTM) and information from other echoes of the point. For features across different time periods (epochs), they measured the number of points from another epoch within a search radius, a stability metric (explained further in 2.5), and height differences.

2.4 Dataset Characteristics that Influence Change Detection in Point Clouds

Some challenges for change detection methods have already been discussed in the previous section. But there are also other difficulties. Differences in dataset characteristics significantly affect the results of change detection. Stilla and Xu (2023) note that the method of data acquisition plays a crucial role in determining the techniques used to identify changes. The key challenges related to this are outlined below.

- **Point density and distribution**. Differences in density or distribution of points impact the alignment and analysis of point clouds (Stilla and Xu, 2023). Inconsistent densities make comparison also challenging, while evenly distributed point clouds are considered in most cases free from sampling issues (Stilla and Xu, 2023). de Gélis et al., 2021b tested datasets with varying resolutions and noise levels, concluding that resolution has a greater impact on change detection than noise.

- **Information per point**. Semantic labels are critical for object-level analysis, as noted by Stilla and Xu (2023). While raw point clouds only provide geometric data, semantic annotations allow the identification of attribute-based changes.

- **Sensor type**. Another key difference lies in how the data is captured, such as photogrammetry or LiDAR. Within LIDAR, there are distinct platforms: Airborne Laser Scanning (ALS), Mobile Laser Scanning (MLS), and Terrestrial Laser Scanning (TLS). Xiao et al. (2023) state ALS is commonly used for detecting changes in buildings and trees, MLS is often applied to street and tree changes, and TLS is primarily used for trees and construction sites. Each sensor type has its own unique accuracy and characteristics.

- **Other scan properties**. Kharroubi et al. (2022) also highlight that scan timing, sensor location, weather conditions, sensor specifications, sensing range, and background variations produce variations for intra- and inter-class changes.

2.5 Uncertainties, Errors and Size of Point Clouds

Errors in point clouds make it complicated for change detection. de Gélis et al. (2021b) show that noise complicates the detection of change boundaries, making accurate identification more difficult. Winiwarter et al. (2021) describe several types of uncertainties that contribute to these challenges. First, they explained that every polar coordinate of a point (distance, azimuth, and polar angle) has its own uncertainties. Additionally, laser beams illuminate an area rather than a single point, meaning the detected signal could originate from any location within the illuminated region. Angular measurements are also recorded in discrete steps, introducing small errors when the actual position lies between these steps. Lastly, ranging uncertainties depend on factors such as distance, material reflectivity, and atmospheric conditions. Longer ranges create larger footprints, which increase uncertainty and reduce accuracy.

Errors can also occur from the properties of the scanned objects. Areas with non-diffuse reflection properties, such as water or windows, often cause noise in the data. These surfaces may not return enough energy for a proper distance measurement, leading to false positives where one scan detects a signal and the other does not (Kharroubi et al., 2022).

Another challenge is the storage requirements for large point cloud datasets like AHN. van Oosterom et al. (2022) emphasize the importance of proper spatio-temporal data organization. Many large point cloud datasets with great potential remain underutilized due to poor data management, limited access, and inadequate software.

2.6 Strategies to Mitigate Dataset Limitations

This subsection will highlight strategies that might work to help the challenges in the previous subsections.

Xu et al. (2015) solve the problem of occlusion without using occupancy grids. Related points in two epochs with a greater distance of 1 meter that lack any nearby points in one of the epochs within a horizontal plane are labeled as unknown. For walls, they label points as unknown if the neighboring roof has no change. They state this will also exclude lack of data due to pulse absorption by the surface material, e.g. water. But this method has some limitations, balconies and sun shades are far away from the roof and could be detected as changed and not as unknown.

Hebel et al. (2013) propose a method that uses a voxel structure to have a fast search operation on the fly while processing the ALS data. The reference data, dataset captured earlier in another epoch, is organized in that grid structure with wide cells (five times the average point-to-point distance) to reduce memory space, while maintaining efficient spatial indexing for queering. Two types of grid cells are then created, one representing the positions of the point cloud and another tracking the paths of laser beams traversing through each cell. For the last type, they applied Bresenham's 3D algorithm to calculate a raster line of that beam, identifying all the cells it traverses. Each cell in both grid cells can have none, one or multiple indices. With this information and the understanding of a point being a spatial extent rather than being a precise point (due to the laser's footprint, measurement uncertainty, and point density), they modeled a gradual transition between empty, occupied and unknown cells. Each cell is assigned belief masses of these states, following the Dempster–Shafer theory of evidence. Xiao et al. (2013) applied this to MLS and states it is an accurate method which distinguishes occlusion from real changes.

Tran et al. (2018) introduce the concept of a stability feature for each point in a LiDAR dataset. This feature is calculated as the ratio of the number of neighboring points within a sphere in the other epoch to the total number of points within a vertical cylinder also in the other epoch. They recommended using a search radius that is twice the average point spacing. Their findings showed that changed buildings and ground typically have a very low stability value, close to 0%, while unchanged buildings have a value of 100%. However, because vegetation is partially transparent to LiDAR, its stability values tend to vary and are less likely to be near 0% or 100%. de Gélis et al. (2021b) also use this stability factor as a feature for the random forest classifier which gave more precise results.

There are many factors that can affect the quality of a LiDAR dataset. These include positional uncertainties, density, the precise alignment of the laser beam, errors from the laser device itself, the curvature of the local surface, and the geometry of the scanning process (Mayr et al., 2020). Lague et al. (2013) introduce the concept of the Level of Detection (LoD), which is the smallest detectable change in the data. LoD is a spatially varying value that considers for every region in both epochs the variances, point counts and registration uncertainty (Winiwarter et al., 2021). Winiwarter et al. (2021) propose an improved version of LoD. Unlike the original method, which assumes a constant registration error, their approach incorporates measurement and alignment uncertainties by using error propagation. Measurement uncertainties are derived from the laser scanner's angular and range measurements, while alignment uncertainties are calculated using an Iterative Closest Point (ICP) algorithm in OPALS, which also generates a covariance matrix to represent these uncertainties.

Scaioni et al. (2018) describe the LiDAR intensity behaving as a measure of quality for point clouds. The experiments show a correlation between intensity and range noise.

To be able to handle the large size of point clouds, Diaz et al. (2024) develop a fast, space-filling curve-based method to calculate distances in epochs. They utilize a Morton curve to efficiently query neighboring points in the other epoch.

Another interesting finding about handling large datasets. Kharroubi et al. (2022) explain the concept of level of detail (LOD) as a way to manage large datasets. LOD involves using different levels of detail depending on the need. When more detail is required, the LOD is reduced, which works best for smaller areas. On the other hand, higher LODs involve processing fewer points, making them more suitable for larger areas. However, the impact of LOD on the results has not been fully studied yet. LOD has already been applied in visualization tasks. van Oosterom et al. (2022) expand on this by introducing continuous Level of Detail (cLoD). They decide whether a point should be displayed in a view based on its distance from the camera and its cLoD value. The cLoD is also used to organize and index the point cloud. Liu (2022) reinterpret the cLoD value as a measure of importance, where the value indicates how important one point is compared to another.

Since dataset characteristics influence the results of change detection methods (see Subsection 2.4), metrics to measure these characteristics can be useful. Manders (2024) investigated the characteristics of the AHN3 and AHN4 datasets, focusing on point density and point spacing, both of which affect computer algorithms. By "computer algorithms," the author refers to the computer's ability to interpret and understand the structure of 3D objects. To assess point spacing, the author uses a Delaunay triangulation for all buildings in a specific area. Triangles larger than a certain threshold were considered gaps.

3 Research objectives

The main research question for this thesis is:
To what extent can a building change detection method for aligned point clouds be developed to maximize reliability using a certainty index, incorporating dataset characteristics, using the AHN and Rotterdam datasets?

The goal of this research is to develop a reliable algorithm that detects changes to buildings in the AHN4, AHN5 and two epochs of Rotterdam datasets. To accomplish this, it can be defined in steps with questions per step that needs to be answered:

1. Type of changes and dataset analysis
   - What types of changes in buildings are there in AHN, Rotterdam and literature?
   - What are the characteristics of AHN and Rotterdam to make sure the synthetic dataset correspond to these datasets?
2. Simulating point cloud datasets
   - How can ALS point clouds be simulated to reflect all relevant building changes identified in the dataset analysis?
   - How can different dataset characteristics (e.g., density, noise, and semantics) be incorporated into the simulation to train the algorithm and to generate a certainty index?
3. Generating change detection method
   - How should the architecture of the change detection method look?
   - How can occlusion in point clouds be addressed during change detection?
   - How can a Certainty Index be generated to account for point cloud inaccuracies and other influencing dataset properties?
   - Based on this Certainty index, what are the effects of dataset characteristics on detecting changes?
4. Test the algorithm on AHN4-5 and Rotterdam
   - How can building areas be extracted from the point cloud datasets for testing?
   - How does the change detection method perform on the real datasets AHN and Rotterdam?
   - How does the performance of the developed algorithm compare to existing change detection methods?

3.1 Scope of the Research

Below you can find the requirements ordered in the MoSCoW method.

M
Must have

- make a simulated point cloud data set with possible changes to buildings.
- define a point cloud architecture for detecting changes to buildings.
- find occluded areas in point clouds.
- combine different data point cloud characteristics of the simulated dataset and show the result of the change detection method.
- find the points that represent the buildings in a test area of AHN4-5 and a test area of the Rotterdam datasets.
- apply the change detection method to the AHN4-5 and Rotterdam datasets separately.
- do visual validation of the results of the change detection method in the AHN4-5 and Rotterdam datasets.
- incorporate a certainty index in the change detection method that accounts for the characteristics of the data set.

S
Should have

- compare the change detection method with other change detection methods.
- optimize the change detection method for having two different datasets as input (AHN4 and Rotterdam dataset)
- optimize the change detection method to be able to deal with large datasets.

C
Could have

- make a labeled ground truth of epochs in AHN and Rotterdam datasets.
- compare the result of the change detection method with the outcome of the change detection with images or with voxels.

W
Will not have

- look into vegetation differences.
- look into AHN123.
- look at changes in infrastructure.
- focus on aligning of point cloud datasets.

Figure 6: MoSCoW prioritization.

4 Methodology

In this chapter the methodology will be outlined of this research. Figure 7 shows the workflow.

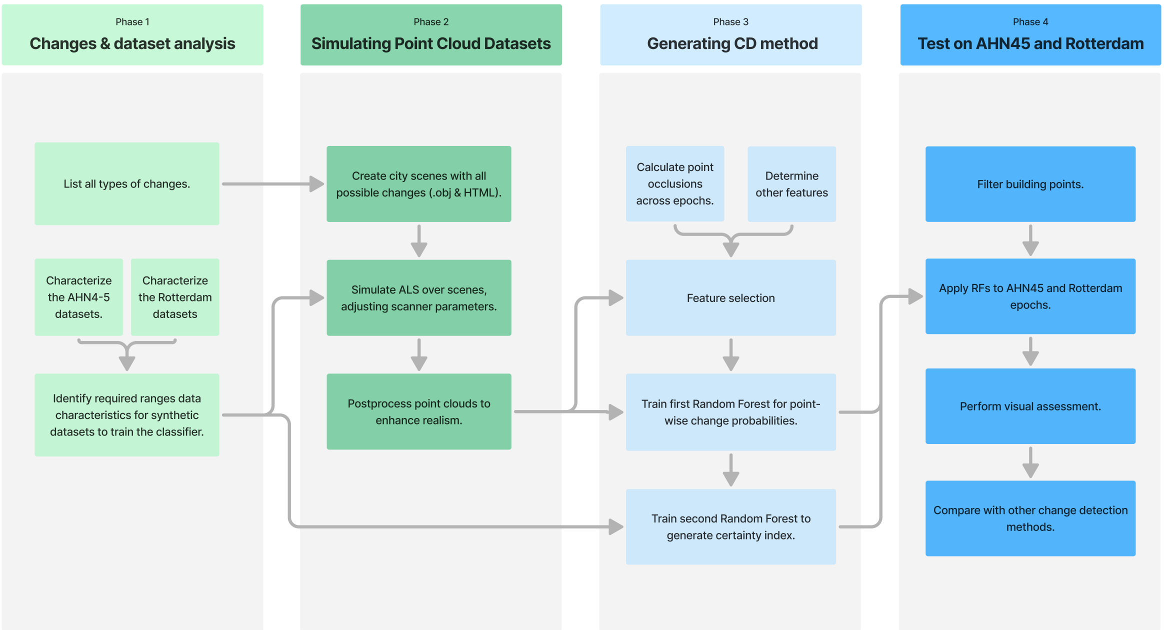


Figure 7: Workflow of methodology.

The following subsections will discuss every phase separately. This chapter will end with a risk analysis of the research.

4.1 Phase 1: Type of Changes and Dataset Analysis

The goal of this phase is to identify possible real and false changes. ANd to analyse which dataset characteristics could influence change detection algorithms.

Detecting small changes in buildings can be challenging for change detection methods, so these changes should be specifically defined before generating the simulated dataset. Additionally, this step will include identifying incorrect changes, such as temporary or seasonal variations. To achieve this, relevant literature will be reviewed, and a standard method will be applied to parts of the AHN and Rotterdam datasets. The fast SFC-based nearest neighbor algorithm developed by Diaz et al. (2024) will be used to identify both real and pseudo changes. The hypothesis is that this method will reveal all changes, including false positives, ensuring a complete understanding of potential variations.

The characteristics of the AHN and Rotterdam datasets will also be analyzed and documented. These include key attributes such as point spacing, as calculated by Manders (2024), dataset accuracy, point density, information per point, scan timing, sensing range, and the average distance between the sensor and the points. Other significant differences, as noted in Subsection 2.4, will also be recorded. This phase will conclude by identifying which data characteristics and their ranges should be incorporated for the next steps. These findings will provide the foundation for creating a simulated dataset in the following phase.

4.2 Phase 2: Simulating point cloud datasets

For this step, Helios++ will be used. Helios++ allows for the adjustment of scanner properties to simulate an ALS (Airborne Laser Scanning) dataset. The input for Helios++ consists of .obj files (representing the buildings, in this case) and a .html file that structures the scene. All potential building changes identified in the previous phase will be incorporated into these files. The 3D building models will be sourced from 3DBAG, with a variety of buildings included in the simulation.

Afterward, Helios++ will simulate an ALS flight over the scene. Scanner properties defined in the previous phase will be used to generate different datasets. Once the simulation is complete, a postprocessing step will make the point clouds as realistic as possible. This includes adding Gaussian noise, as also applied in De Gélis et al. (2021), and performing other adjustments to match the point spacing and dataset characteristics outlined in the previous phase.

These simulated datasets will serve two purposes: to train the algorithm and to make predictions about the certainty index based on the characteristics of the dataset. Multiple datasets will be generated for training, validation, and testing purposes.

4.3 Phase 3: Generating and Training Change Detection Method

From the literature described in Subsection 2.2, the following aspects are important to consider when developing a change detection method:

1. Avoid converting point clouds into rasters or voxels to prevent information loss.
2. Integrate both global and local spatial relationships into the model, potentially using graph-based or spatially-aware deep neural networks.
3. Learning-based methods show promising results in prior studies.
4. Make sure it is adaptable to different input datasets.

While deep learning methods are effective, they are not used in this research due to their lack of transparency, limited control, and high computational cost for large datasets like AHN. Instead, two Random Forest classifiers are employed to follow the above principles. The first focuses on classifying specific types of changes, while the second outputs a binary decision: change or no change.

Step 1: Random Forest for point-wise change probabilities
The first Random Forest classifier calculates the probability of each point belonging to a specific change detection class (e.g., "added dormer," "removed floor") or "no change." The following features will be considered:

- **x, y, z**. Position of the point.
- **Normal vector**.
- **Intensity**. LiDAR intensity.
- **RGB**. Color information of the point, if available.
- **Classification**. Classification or label information about the point.
- **Visible**.A boolean value indicating whether the point is visible in the other epoch. This will be done based on the method described by Hebel et al. (2013) to calculate occlusion.

- **Spatial Relationship**. Taking spatial relationship into account. Features inspired by Tran et al. (2018), such as planarity or the number of points around the target point.
- **Height difference**. Height difference between the point and the nearest point in the other epoch.
- **Density**. The number of points in a sphere around the target point's coordinates in the other epoch, normalized by the dataset's density.

A preprocessing step, such as grid search, will select the most relevant features based on a small test area. The output of this classifier will be a probability score for each point, indicating its likelihood of belonging to a specific change class. If change classes like "adding a dormer" or "removing a floor" prove too specific, broader categories such as "added building," "changed building," or "removed building" will be used.

Step 2: Random Forest for generating a certainty index
The second Random Forest classifier refines predictions by incorporating additional factors and generates a certainty index for each decision. Features for this classifier include::

- **Measurement inaccuracies**. Parameters such as scanner distance and laser angle, as noted in Winiwarter et al. (2021).
- **Alignment accuracies**. Alignment uncertainties calculated using covariance matrices with opalsICP.
- **Probability changes neighbours**. Sum of probabilities for points in the same change detection class within a sphere around the target point.
- **Dataset specific attributes**. Characteristics like density and acquisition parameters.

Similar to Step 1, a preprocessing step will identify the most relevant features. This classifier will output: (1) A binary decision (change or no change) (2) A certainty index, reflecting the algorithm's confidence in its prediction.

To ensure the algorithm works well with large datasets, a more global overview can be provided by selecting specific points based on their level of importance. The change detection algorithm will then be applied to these selected points. When zoomed out, fewer points will be analyzed, which may result in more errors. However, as you zoom in, more points will be included, allowing for greater accuracy and finer detail.

4.4 Phase 4: Test the algorithm on AHN and Rotterdam

This phase evaluates the algorithm using the AHN dataset and two or more epochs of the Rotterdam dataset. Since the focus is on detecting changes to buildings, it is essential to isolate building-related points in the datasets. For the AHN dataset, a buffer will be created around points classified as buildings in the x and y plane, and any points outside this buffer will be excluded from the analysis. A similar process will be applied to the Rotterdam dataset.

Next, the algorithm will be tested on selected portions of the AHN dataset as well as on parts or the entirety of the Rotterdam dataset. Its quality will be evaluated visually to assess how accurately it detects changes. In addition to accuracy, the processing time will be measured, as this is critical when working with large datasets. To further evaluate its robustness, the algorithm will also be applied to one dataset from AHN and another from Rotterdam to see how it performs across different datasets.

Finally, the results will be compared with other change detection methods. Current alternatives being considered for comparison include the SiamConv method, as described by de Gélis et al. (2023), and a DSM-based change detection method.

4.5 Risk Analysis

This project plan addresses many risks and limitations, but some uncertainties remain: (1) The algorithm will be trained using a synthetic dataset, which may not fully capture the complexity of real-world data. As a result, there is a risk that the model's quality may not meet expectations when applied to real-world datasets such as AHN4-5 and Rotterdam. (2) The accuracy of filtering building points relies heavily on the quality of semantic classification within the datasets. In the Rotterdam dataset, for instance, classification errors could lead to misidentification. Initial observations have already revealed that a crane was misclassified as a building. Such inaccuracies could affect the algorithm's ability to detect changes reliably.

5 Time planning

The first supervisor for this research is Ir. Edward Verbree. The second supervisor is Prof.dr.ir. Peter van Oosterom. The supervisor from Geodelta is Ir. Annemieke Verbraeck. Meetings with Edward and Annemieke will be held every two weeks, while Peter will join the meetings once a month.

On the next page, a Gantt chart illustrates the timeline for this research.

Phase	Task	Start	End	Duration
Phase 1: Changes & Dataset Analysis				
	List all types of changes	20-01-2025	02-02-2025	
	Characterize AHN4-5 datasets	10-02-2025	16-02-2025	
	Characterize Rotterdam datasets	10-02-2025	16-02-2025	
	Identify required data ranges	10-02-2025	23-02-2025	
Phase 2: Simulating Point Cloud Datasets				
	Create city scenes with changes	17-02-2025	02-03-2025	
	Simulate ALS over scenes	24-02-2025	09-03-2025	
	Postprocess point clouds	03-03-2025	16-03-2025	
Phase 3: Generating CD Method				
	Determine features & selection	17-03-2025	13-04-2025	
	Calculate point occlusions	24-03-2025	06-04-2025	
	Train Random Forests	14-04-2025	20-04-2025	
Phase 4: Test on AHN45 & Rotterdam				
	Filter building points	21-04-2025	27-04-2025	
	Apply RFs & visual assessment	28-04-2025	18-05-2025	
	Compare with other methods	19-05-2025	01-06-2025	
Other tasks				
	P2	22-02-2025		
	Prepare for P3	3-03-2025	07-04-2025	
	P3	07-04-2025	13-04-2025	
	Writing report	13-04-2025	15-06-2025	
	Prepare for P4	28-04-2025	11-05-2025	
	P4	12-05-2025	18-05-2025	
	Prepare for P5	02-06-2025	15-06-2025	
	P5	16-06-2025	22-06-2025	

Table 1: Rotated Gantt Chart Schedule

6 Tools and datasets used

6.1 Tools

Tools	Description
Helios++	For simulating ALS datasets.
Cloudcompare	For visualisation of point clouds. Also to do some rough calculations.
QGIS	For visualisation of point clouds.
Python	Programming language used for some rough calculations and within Helios++ used. Packages as Scikitlearn and PCL.
C#	Programming language used for the final implementation of the change detection method.
Latex	Software system that is used for documentation.
Potree	For visualisation of point clouds.
LAStools	Software to process LiDAR.
opalsICP	An ICP algorithm that will be used to measure alignment inaccuracies.
SiamConv	Might be used to compare to own algorithm.

Table 2: Tools to be used in this thesis.

6.2 Datasets

In this research two point cloud datasets will be used, AHN and non-open Rotterdam datasets. Below they will be explained.

AHN

The AHN displays height data of the whole of the Netherlands. It consists of classified point cloud data. The AHN is created through a cooperation between water authorities, provinces and Rijkswaterstaat. It provides a dense point cloud dataset obtained via airborne laser scanning (ALS). There are five datasets captured at different years. In this research only AHN4 and AHN5 are used. AHN4 and AHN5 have a systematic error of 5 cm and a stochastic error of 5 cm. AHN4 has a density of 10-14 points/ m^2 and a higher density around Schiphol of 20 - 24 points/ m^2. For AHN5 the minimum requirement is 10 points/m^2. The position is in (RD, NAP)-system. In addition to the point data, flight line information is also available. Furthermore, Geotiles includes RGB values for each point in the AHN datasets. However, as Nofulla (2023) highlighted, these RGB values can contain significant inaccuracies due to differences in the timing of data capture, as the images were acquired at a different time than the point cloud data. But as stated in AHN's update, the goal is to collect simultaneous images when capturing AHN. Calibration of the datasets is achieved by aligning the gable roofs.

Rotterdam Dataset

The Rotterdam datasets contain the whole Rotterdam municipality and are a non-open dataset that can be acquired through Geodelta. There is an ALS dataset for Rotterdam from the years 2021, 2022, 2023, and 2024. The density is 30 points per m^2 or more except for water areas. The position is in (RD, NAP)-system. The standard deviation in height is 5 cm in height or better, for planimetry it is 8 cm. The systematic deviation of the height is max 5 centimeters, for planimetry it is 8 cm. In total 0.1% of errors are allowed. All datasets include semantic information. The 2022 and 2023 datasets have detailed classifications like buildings, water, ground, wires and 'kunstwerk'. However, the 2021 and 2024 datasets only include broader categories such as ground, not ground, or unclassified.

6.3 Collaboration with Geodelta

Collaborating with Geodelta for this research brings several benefits. Their advanced algorithms can handle tasks beyond the scope of this study, eliminating the need to address them separately. Additionally, they provide access to the Rotterdam datasets, which are crucial for this research. Geodelta's extensive experience in geodata, particularly with point cloud data like AHN and Rotterdam, adds significant value. Their expertise includes verifying that AHN meets the required specifications, ensuring data quality. This collaboration also offers me the opportunity to seek advice and receive valuable feedback throughout the research process.

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