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Urban 3D Change Detection Using LiDAR Sensor for HD Map Maintenance and Smart Mobility

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ABSTRACT High-definition 3D city maps underpin smart transportation, digital twins, and autonomous driving, where object level change detection across bi temporal LiDAR enables HD map maintenance, construction monitoring, and reliable localization. Classical DSM differencing and image based methods are sensitive to small vertical bias, ground slope, and viewpoint mismatch and yield cellwise outputs without object identity. Point based neural models and voxel encodings demand large memory, assume near perfect pre alignment, degrade thin structures, and seldom enforce class consistent association, which leaves split or merge cases unresolved and ignores uncertainty. We propose an object centric, uncertainty aware pipeline for city scale LiDAR that aligns epochs with multi resolution NDT followed by point to plane ICP, normalizes height, and derives a per location level of detection from registration covariance and surface roughness to calibrate decisions and suppress spurious changes. Geometry only proxies seed cross epoch associations that are refined by semantic and instance segmentation and a class constrained bipartite assignment with augmented dummies to handle splits and merges while preserving per class counts. Tiled processing bounds memory without eroding narrow ground changes, and instance level decisions combine 3D overlap, normal direction displacement, and height and volume differences with a histogram distance, all gated by the local level of detection to remain stable under partial overlap and sampling variation. On 15 representative Subiaco blocks the method attains 95.2% accuracy, 90.4% mF1, and 82.6% mIoU, exceeding Triplet KPConv by 0.2 percentage points in accuracy, 0.2 in mF1, and 0.8 in mIoU, with the largest gain on Decreased where IoU reaches 74.8% and improves by 7.6 points. The Subiaco 2025 HD LiDAR dataset and annotations are released at [IEEE DataPort](#), and the implementation is available at [GitHub](#).

INDEX TERMS 3D change detection, LiDAR, point clouds, urban mapping, uncertainty-aware registration

I. INTRODUCTION

Western Australia is advancing smart transportation, digital-twin, and autonomous driving deployments that depend on high-definition 3D city maps maintained at operational cadence [1], [2]. Within this context, change detection denotes the object-level identification of additions, removals, and volumetric increases or decreases across bi-temporal LiDAR maps, enabling HD-map maintenance, construction and asset

monitoring, and timely updates for localization and planning in autonomy stacks [3]–[7]. LiDAR sensing further supports this task by providing dense geometry that separates long-term structural changes from transient dynamics such as vehicles and pedestrians [8]–[10]. Subiaco lies immediately west of Perth’s CBD and functions as a key transport hub with two arterial roads linking the areas and substantial daily commuting, which makes it a representative and consequen-

tial testbed [11], [12]. Addressing city-scale change detection in Subiaco is therefore directly aligned with Western Australia's smart-city and autonomy objectives and motivates the problem tackled in this work [13].

Existing approaches to urban 3D change detection fall into height or digital surface model differencing, 2D image based change detection, and point based deep models [14], [15]. Height differencing requires sub decimeter co registration and uniform sampling [16], [17]. In dense street scenes small vertical biases and ground slope introduce systematic errors, curb lines and façade parallax generate false positives, and the output remains cell wise without object identity [16], [18]. Image based change detection cannot resolve vertical geometry and suffers from viewpoint mismatch with ground LiDAR [19], [20]. Point wise Siamese or triplet networks such as KPConv variants operate on cropped tiles with millions of points [21]–[23]. Runtime and memory grow with area, training assumes balanced labels, and predictions are per point rather than per object, which weakens Added and Removed reasoning when overlap is partial or occlusion changes sampling [24], [25]. Voxel or bird's eye encodings reduce memory but erode thin structures and narrow ground changes, which forces a trade off between coverage and fidelity [26], [27]. Public benchmarks for 3D change detection cover limited extents or rely on aerial campaigns, and object level annotations across epochs are rare [28], [29]. For Subiaco, publicly accessible LiDAR captures are single epoch and not paired at consistent specification, and no object level multi epoch ground truth exists [28]. Many pipelines also assume perfect pre alignment and do not propagate registration uncertainty into decision thresholds, which leads to spurious changes near loop junctions or under canopy [30]–[34]. Methods seldom enforce class consistent association between epochs, so split and merge cases remain unresolved and per class counts drift at city scale [29], [35], [36]. These constraints limit transfer to operational HD map maintenance over a dense transport hub and expose the need for a city scale, object centric and uncertainty aware formulation.

Our changing detection method is object centric and uncertainty aware, and it operates at city scale on bi-temporal LiDAR maps. An overview of the acquisition, mapping, and change-analysis stages is shown in Fig. 1. It begins with global alignment of the two epochs using multi-resolution NDT followed by point-to-plane ICP, after which both maps are height normalized and a per-location level-of-detection is derived from registration covariance and surface roughness. This step replaces the usual perfect pre-alignment assumption and supplies calibrated thresholds that suppress spurious changes along loop junctions and under canopy. We then generate geometry-only proxies to seed cross-epoch associations and perform semantic and instance segmentation for ground, building, vegetation, and mobile classes on single-epoch geometry. Class-constrained bipartite matching refines correspondences while handling split and merge cases through an augmented assignment with dummies, which prevents drift in per-class counts and enforces label consistency

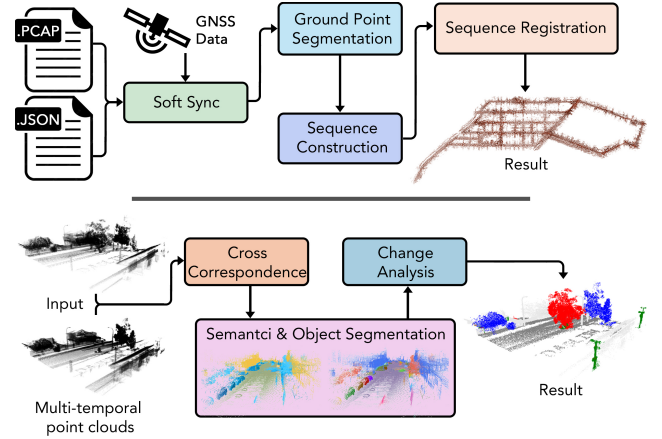


FIGURE 1: Overview of the Subiaco city-scale 3D change-detection pipeline. Top: acquisition/mapping (soft GNSS sync, ground segmentation, sequence construction, NDT $\rightarrow$ ICP). Bottom: analysis (cross-epoch association, semantic/object segmentation, and uncertainty-gated instance labels).

across time. The city is partitioned into overlapping tiles of fixed size so memory and runtime remain bounded, which enables processing of dense streets without the erosion of thin structures that accompanies coarse voxel encodings. Change decisions are computed per object using 3D occupancy overlap, normal-direction displacement, height and volume differences, and a histogram distance in the intersected volume, and every statistic is gated by the local level-of-detection. This object-level formulation directly resolves Added and Removed when overlap is partial, avoids cell-wise artifacts from slope and curb geometry, and reduces false positives that arise from viewpoint or sampling change. The output is a per-instance change table and tiled maps with the five labels Added, Removed, Increased, Decreased, and Unchanged together with confidence, which are aggregated over the full extent to support HD-map maintenance and autonomous driving use cases.

We validate the approach on bi-temporal city-scale maps of Subiaco by constructing a new 2025 high-definition LiDAR map and comparing it with the 2023 counterpart [37] under object-level annotations. Aggregated over 15 representative blocks, the method attains 95.2% ACC, 90.4% mF1, and 82.6% mIoU. Compared with the strongest baseline, Triplet KPConv, these results correspond to absolute gains of 0.2 percentage points in accuracy, 0.2 percentage points in mF1, and 0.8 percentage points in mIoU. The largest classwise improvement appears on Decreased, where the IoU reaches 74.8%, exceeding the SOTA baseline by 7.6 percentage points.

Our contributions are summarized below:

- 1) **Dataset.** A city-scale HD LiDAR dataset for Subiaco **2025** with a globally referenced .ply map, per-instance semantics for {ground, building, vegetation, mobile}, and object-level change labels obtained by registering the public 2023 map to the 2025 frame. Released on [IEEE DataPort](#).

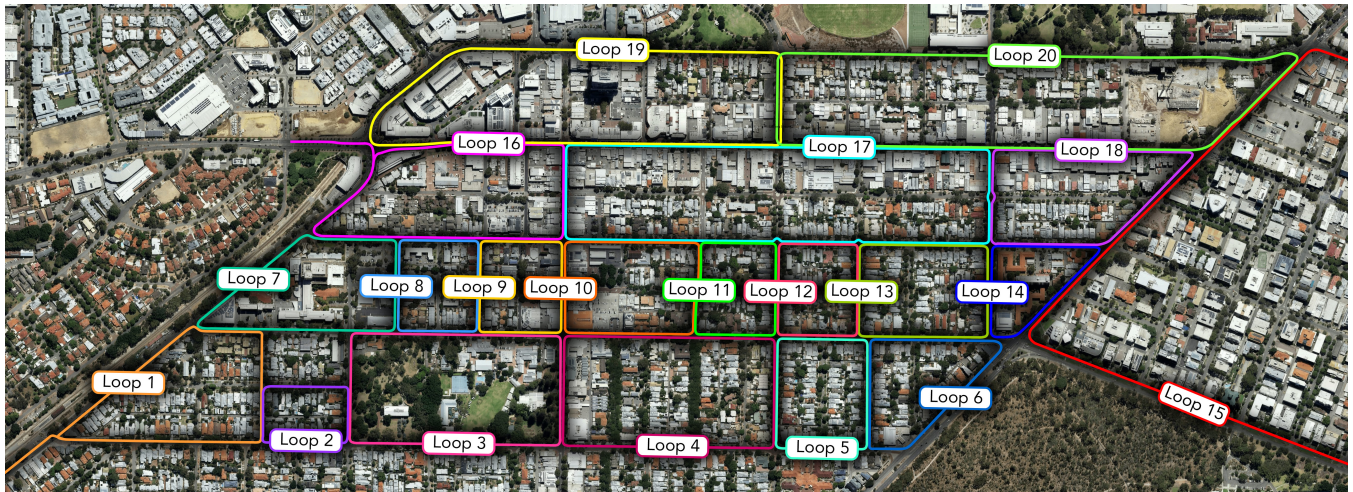


FIGURE 2: Subiaco driving loops for the 2025 campaign. Colored polylines denote twenty overlapping loops that provide repeated viewpoints across arterials, residential blocks, and intersections.



FIGURE 3: Sensor rig and installation. The system comprises an Ouster OS1-128 LiDAR, a dual-antenna RTK GNSS with MEMS IMU, and a logging unit mounted on a reinforced roof plate with a measured antenna baseline.

- 2) **Method.** An object-centric, uncertainty-aware 3D change detector that combines city-scale registration, local level-of-detection gating, class-consistent association, and instance-wise decisions on overlap, displacement, height, and volume. On 15 representative blocks it achieves 95.2% accuracy, 90.4% mF1, and 82.6% mIoU.
- 3) **Pipeline.** A reproducible end-to-end workflow for urban change mapping that spans acquisition, map construction, semantic and instance segmentation, association, and change analysis with bounded-memory tiling. Code and configurations are available at [GitHub](#).

II. SUBIACO 2025 3D LIDAR MAP CONSTRUCTION

This section specifies the acquisition and mapping workflow that yields the 2025 Subiaco reference used throughout. It

covers survey design and sensor configuration, logging and georeferencing, packet deskewing and density standardization, intra and inter sequence alignment with loop closures and GNSS priors, and the final fusion and height normalization that produce a single globally referenced point cloud at uniform resolution. The goal is to make explicit the data fidelity and coordinate frame assumptions required by the downstream registration, segmentation, and change analysis stages.

A. SURVEY PLAN AND SENSOR SETUP

The survey covered Subiaco with overlapping road loops that span arterial corridors, residential blocks, and major intersections to force repeated viewpoints for loop closure and cross-street alignment. Figure 2 illustrates the twenty loops used in 2025. Data were collected from a roof-mounted rig at 10 to 30 km/h during low-traffic windows. The primary sensor is an Ouster OS1-128 operated at 10 Hz in dual-return mode with a 45° vertical field of view, 0.35° angular resolution, and approximately 2.62 M points per second. Geodetic reference and motion state come from a dual-antenna RTK GNSS with a MEMS IMU. GNSS fixes are logged at 5 Hz and IMU at 73 Hz. Sensors are rigidly co-located on a reinforced roof plate with a measured antenna baseline to improve yaw observability, as shown in Figure 3. Hardware time is synchronized with GNSS PPS. The LiDAR accepts the PPS and stamps packets with synchronized timestamps. All streams are recorded on an Ubuntu host using GigE for LiDAR and USB or serial for GNSS and IMU. Factory extrinsics are refined by a short constrained-motion routine and verified by reprojection residuals on planar façades. Raw LiDAR packets (.pcap) are converted to per-scan .ply with dual returns and per-point timestamps, and GNSS or IMU logs are exported as .csv with UTC time, quality flags, and orientation.

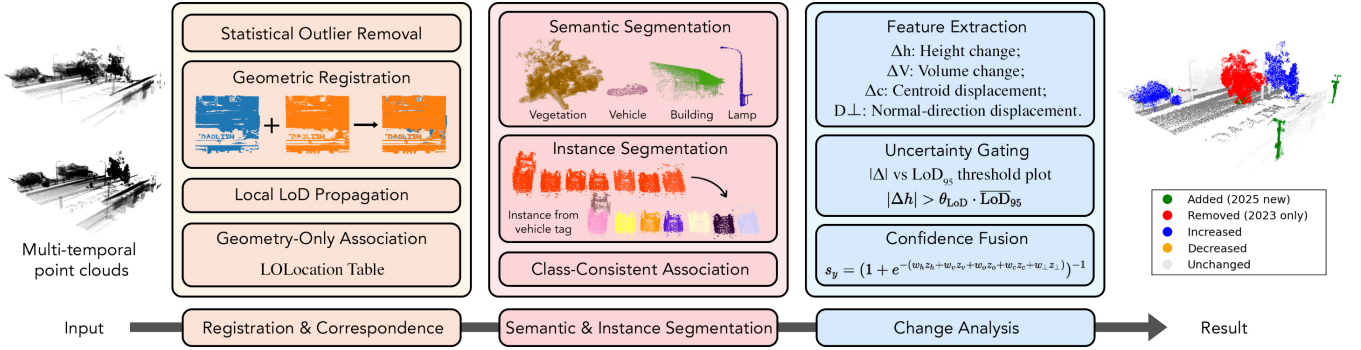


FIGURE 4: Object-centric, uncertainty-aware pipeline. Left-to-right: registration and correspondence, semantic/instance segmentation with class-consistent association, change analysis with LoD gating and confidence fusion, and the instance-level result.

B. ACQUISITION SUMMARY

Each route is logged as an independent sequence with continuous 10 Hz LiDAR frames, 5 Hz GNSS fixes (RTK state recorded), and 73 Hz IMU samples. LiDAR frames contain 260k–280k points per scan with intensity and ring index. We retain both Strongest and Last returns; mapping uses Strongest by default while both are archived for analysis. Sequences were recorded under dry daylight conditions to minimize rain and multipath artifacts; segments with RTK loss or packet drop exceeding pre-set thresholds are flagged in a YAML manifest. All trajectories and maps are georeferenced to GDA2020 / MGA Zone 50 and stored as globally referenced `.ply` maps together with per-sequence odometry in KITTI format.

C. MAP GENERATION

LiDAR packets are deskewed using per-pixel timestamps and the closest IMU segment. Statistical outlier removal and a voxel pyramid (1.0/0.5/0.25 m) standardize density. Within each sequence, multi-resolution NDT provides stable coarse alignment; point-to-plane ICP refines at each level. Loop closures are proposed by 360° LiDAR descriptors and verified by geometric consistency; a pose graph solves for globally consistent per-sequence poses. GNSS is used as a soft spatial prior: pose graph nodes that coincide with high-quality GNSS fixes (based on RTK status and dilution of precision) are anchored with adaptive weights, while GNSS-denied segments are down-weighted. Adjacent sequences are merged by aligning overlapping submaps with feature-initialized ICP and then fused. After global fusion, ground tiles are fit by robust plane models to define the vertical axis and zero height per tile; both epochs are rotated to align the vertical to e_z and are height-normalized to suppress long-wavelength bias. The final deliverable is a single globally referenced city-scale `.ply` map for 2025 at 0.25 m leaf size with per-point coordinates, intensity, and normals, which is the input to registration/LoD estimation and the semantic layer.

III. METHODOLOGY

This section formalizes the object centric change detection pipeline on paired LiDAR maps. It introduces calibrated registration with a local level of detection to quantify uncertainty, derives geometry based correspondences, and constructs semantic and instance abstractions for ground, building, vegetation, and mobile classes. Class consistent association is then enforced and per object evidence from overlap, displacement, height, volume, and histogram cues is combined under uncertainty gating to produce five change labels with confidence. The design targets stability at city scale and supports reproducible evaluation and deployment. The end-to-end workflow and data flow are summarized in Fig. 4.

A. GEOMETRIC REGISTRATION AND OBJECT-LEVEL CORRESPONDENCE

Let $\mathcal{P}^{23}$ and $\mathcal{P}^{25}$ denote the city-scale LiDAR maps of Subiaco acquired in 2023 and 2025, respectively, each stored as a globally georeferenced `.ply`. This layer estimates a single rigid transform $T_{23 \rightarrow 25} \in \text{SE}(3)$ to align $\mathcal{P}^{23}$ onto $\mathcal{P}^{25}$, propagates registration uncertainty to a local level-of-detection (LoD), and derives object-level correspondences (LOLocation) that will be refined by the semantic layer.

We first apply statistical outlier removal and build a voxel pyramid with leaf sizes $\{1.0, 0.50, 0.25\}$ m to equalize density and reduce computation. Surface normals are estimated per level using a fixed-radius neighborhood ($r_n = 0.8$ m). Coarse alignment T_0 is obtained, when external priors are insufficient, by feature-based registration on the 1.0 m level: ISS keypoints, FPFH descriptors, and RANSAC with salient/support radii $\{1.5, 2.0\}$ m and an inlier threshold of 0.6 m (20k iterations).

Fine alignment proceeds from coarse to fine with Normal Distributions Transform (NDT) followed by point-to-plane ICP. NDT supplies a stable pose update at each level; ICP then reduces the residual geometric error using target normals. Given correspondences $\{(p_i, q_i, n_i)\}$, we minimize

$$\min_{R \in \text{SO}(3), t \in \mathbb{R}^3} \sum_i w_i \rho_\tau(n_i^\top (R p_i + t - q_i)), \quad (1)$$

where w_i down-weights long-range pairs via a Huber kernel on Euclidean distance and $\rho_\tau(\cdot)$ is Tukey's biweight with

$\tau = 0.3$ m. We solve (1) by Gauss–Newton with analytic Jacobians and reject ill-conditioned updates via a normal-direction Fisher-information test. To stabilize long, low-curvature structures, a plane-to-plane penalty is added at the finest level after RANSAC plane extraction on façades and ground:

$$\mathcal{L}_{\text{pl2pl}}(R) = \lambda \sum_k \|R \bar{n}_k^{(23)} - \bar{n}_k^{(25)}\|_2^2, \quad \lambda = 0.1, \quad (2)$$

and the total objective is $\mathcal{L} = (1) + \mathcal{L}_{\text{pl2pl}}$. The final estimate is $T_{23 \rightarrow 25}$ at 0.25 m. We report point-to-plane RMSE, inlier ratio, and the covariance-derived pose standard deviations.

After refinement, we enforce a consistent frame by robust ground-plane fitting on a 20×20 m grid. The median ground normal defines the vertical axis; both epochs are rotated such that this axis aligns with $\mathbf{e}_z$. Heights are re-zeroed by subtracting the median ground elevation per tile to suppress long-wavelength vertical bias.

Registration uncertainty is propagated to a per-location LoD that will gate change claims in the analysis layer. For each evaluation site, the 95% LoD along the local normal is

$$\text{LoD}_{95} = 1.96 \sqrt{\frac{\sigma_{n,23}^2}{N_{23}} + \frac{\sigma_{n,25}^2}{N_{25}} + \sigma_{\text{reg}}^2}, \quad (3)$$

where $\sigma_{n,\cdot}$ denotes normal-direction roughness estimated in a cylindrical neighborhood (radius 1 m), $N_\cdot$ is the local sample size, and σ_{reg} is the global registration standard deviation from the final ICP Hessian. Equation (3) is evaluated on a 5 m grid and bilinearly interpolated to points.

To initialize object-level associations prior to semantics, we extract geometry-only proxies. Ground cells are removed, and connected components are computed on a 0.5 m occupancy grid with morphological closing. For each component o we compute a centroid $c(o)$, an oriented bounding box $\text{OBB}(o)$ from PCA, the 95th height quantile $h_{95}(o)$, and covariance eigen-features (linearity, planarity, sphericity). Cross-epoch association uses gated nearest neighbors with a shape-consistency cost

$$\begin{aligned} \text{cost}(o_i^{23}, o_j^{25}) &= \alpha \|c_i - c_j\|_2^2 \\ &+ \beta (1 - \text{IoU}(\text{OBB}_i, \text{OBB}_j)) \\ &+ \gamma D_{\chi^2}(H_i, H_j). \end{aligned} \quad (4)$$

where H is a 10-bin height histogram. We set $(\alpha, \beta, \gamma) = (1, 2, 0.5)$ and accept a pair if $\|c_i - c_j\|_2 < 2$ m, $\text{IoU} > 0.1$, and $\text{cost} < 3.5$. Unmatched components are forwarded as Added/Removed candidates. Matched pairs form the LOLocation table $\pi : \mathcal{O}^{23} \rightarrow \mathcal{O}^{25}$ with attributes $(c, \text{OBB}, h_{95}, \dots)$. The semantic/instance segmentation module subsequently refines identities and resolves split/merge cases while preserving these geometric correspondences.

B. SEMANTIC AND INSTANCE SEGMENTATION

This layer assigns semantic classes (ground, building, vegetation, mobile) to points and produces instance-consistent objects per class. The design is unsupervised with geometry- and topology-based criteria; the annotated Subiaco maps are reserved for evaluation only. All decisions are made on

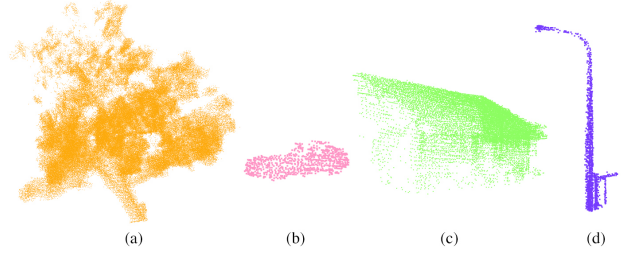


FIGURE 5: Examples of the four semantic categories: (a) vegetation, (b) mobile object, (c) building, and (d) other object (e.g., pole or ground fragment).

single-epoch geometry and are later reconciled with cross-epoch correspondences before the change analysis.

We first compute per-point features on the finest voxel level (leaf 0.25 m): eigenvalues $(\lambda_1 \geq \lambda_2 \geq \lambda_3)$ of the local covariance (radius 0.6 m), normal $\mathbf{n}$, roughness σ_n along $\mathbf{n}$, height above ground z_g measured against the frame in Sec. III-A, and local density ρ . From $(\lambda_1, \lambda_2, \lambda_3)$ we derive linearity $L = (\lambda_1 - \lambda_2)/\lambda_1$, planarity $P = (\lambda_2 - \lambda_3)/\lambda_1$, and sphericity $S = \lambda_3/\lambda_1$. Points are grouped into superpoints by cut-pursuit on a k -NN graph ($k=20$) using an energy with a piecewise-constant data term on $(L, P, S, \|\mathbf{n} \cdot \mathbf{e}_z\|, z_g)$ and a Potts boundary term weighted by feature contrast. Let $\mathcal{V}$ be the node set (initial points) and $\mathcal{E}$ the edge set; the superpoint partition $\mathcal{U}$ minimizes

$$\begin{aligned} \min_{\mathcal{U}} \sum_{u \in \mathcal{U}} \sum_{i \in u} \|\mathbf{f}_i - \boldsymbol{\mu}_u\|_1 + \eta \sum_{(i,j) \in \mathcal{E}} \omega_{ij} \mathbb{1}[\mathcal{U}(i) \neq \mathcal{U}(j)] \\ \omega_{ij} = \exp\left(-\frac{\|\mathbf{f}_i - \mathbf{f}_j\|_2^2}{\sigma_f^2}\right). \end{aligned} \quad (5)$$

where $\mathbf{f}_i = [L, P, S, \|\mathbf{n}_i \cdot \mathbf{e}_z\|, z_{g,i}]^\top$, $\boldsymbol{\mu}_u$ is the median feature of segment u , η is the boundary weight, and σ_f is set by median feature distance.

Semantic labeling is assigned to superpoints and then propagated to points. Ground is detected by robust plane support and slope: a superpoint is ground if its median distance to the local ground model is below 0.10 m and $\arccos(\|\mathbf{n} \cdot \mathbf{e}_z\|) > 85^\circ$ on at least 80% of its points; road markings and curbs adhere to ground via morphological closing in 2D tiles (5×5 m). Building is assigned to superpoints that satisfy $P > \tau_P$ with $\tau_P=0.6$, verticality $\|\mathbf{n} \cdot \mathbf{e}_z\| < 0.25$, residual-to-plane < 0.08 m, and minimum planar area $> 6 \text{ m}^2$ after merging coplanar neighbors by normal deviation $< 10^\circ$. Vegetation is assigned to superpoints with $S > \tau_S$ where $\tau_S=0.35$, median $z_g > 0.5$ m, and high normal variance within the segment (95th–5th percentile of $\mathbf{n}$ azimuth difference $> 30^\circ$). Remaining non-ground segments with compact size, moderate height, and weak planarity are set as mobile candidates if their oriented bounding box (OBB) satisfies: longest side < 5 m, height < 3 m, and volume $< 60 \text{ m}^3$; segments with persistent strong planarity are reassigned to building. Class conflicts are resolved by a priority rule $\text{ground} \rightarrow \text{building} \rightarrow \text{vegetation} \rightarrow \text{mobile}$ applied only when thresholds are within 5% of each other; otherwise the original assignment is kept.

Figure 5 illustrates typical outputs for the four semantic categories used in this work. Instances are produced per

class by class-specific connectivity and geometry constraints. Ground instances are not required and remain a single support layer for later height and footprint queries. Building instances are formed by agglomerating coplanar façade patches through shared boundary length > 1.0 m and inter-patch normal deviation $< 12^\circ$, then merging façade sets with overlapping horizontal OBB footprints (IoU > 0.3) to form a building volume; small roof patches attached to the same footprint are merged if their normals are within 25° of horizontal. Vegetation instances are extracted by Euclidean clustering with a distance threshold $d_c = \max(0.8 \text{ m}, 1.8/\sqrt[3]{\rho})$ and a minimum of 200 points; touching crowns are separated by a marker-based opening in height slices of 1 m. Mobile instances are obtained with DBSCAN in (x, y) with $\varepsilon = 0.7$ m and $\text{minPts} = 30$, refined by removing attachments to the ground boundary via a 0.15 m erosion on the ground mask.

The LOLocation table from Sec. III-A is then made class-consistent by constraining correspondences to identical semantic labels and re-solving the assignment on each class-induced bipartite graph. Let $\mathcal{O}_c^{23}$ and $\mathcal{O}_c^{25}$ be the instance sets of class c at the two epochs, and let $\delta(o_i, o_j)$ denote the geometric cost in Eq. (4). The class-constrained association solves

$$\min_{\mathbf{x} \in \{0,1\}^{|\mathcal{O}_c^{23}| \times |\mathcal{O}_c^{25}|}} \sum_{i \in \mathcal{O}_c^{23}} \sum_{j \in \mathcal{O}_c^{25}} (\delta(o_i, o_j) + \kappa \phi(o_i, o_j)) X_{ij} + \lambda \sum_{i \in \mathcal{O}_c^{23}} (1 - \sum_j X_{ij}) + \lambda \sum_{j \in \mathcal{O}_c^{25}} (1 - \sum_i X_{ij}). \quad (6)$$

where ϕ penalizes LoD-unsafe overlaps by $\phi(o_i, o_j) = \max(0, \text{LoD}_{95}(o_i, o_j) - d_\perp(o_i, o_j))$ with $d_\perp$ the median normal-direction separation over the OBB intersection, $\kappa=2.0$, and λ the split/merge slack (set to 1.0). Problem (6) is solved by a Hungarian solver on an augmented cost matrix with dummies; accepted pairs satisfy in addition OBB IoU > 0.05 and centroid distance < 2 m. This step preserves the geometric matches while enforcing semantic consistency and prepares per-instance, per-class correspondences required by the change analysis. For Subiaco, parameters are fixed as follows: $(\eta, \sigma_f) = (0.8, \text{median} \|\mathbf{f}_i - \mathbf{f}_j\|_2)$ in (5); ground residual 0.10 m, building plane residual 0.08 m and area 6 m^2 ; vegetation thresholds $\tau_S = 0.35$ and crown split slice 1 m; DBSCAN $(\varepsilon, \text{minPts}) = (0.7 \text{ m}, 30)$; assignment $(\kappa, \lambda) = (2.0, 1.0)$ with LoD gating from Eq. (3).

C. CHANGE ANALYSIS

For each class $c \in \{\text{ground}, \text{building}, \text{vegetation}, \text{mobile}\}$ and each associated pair (o_i^{23}, o_j^{25}) , we compute overlap, displacement, height, volume, and shape statistics at a fixed voxel size of 0.5 m and derive one of five labels $\{\text{Added}, \text{Removed}, \text{Increased}, \text{Decreased}, \text{Unchanged}\}$. All measurements are gated by the local level-of-detection LoD_{95} from Eq. (3) to suppress pseudo-changes.

For overlapping geometry, we approximate the normal-direction displacement by sampling the intersection of the two oriented bounding boxes and projecting the local inter-epoch offset onto the average normal. Let $\Omega(o_i, o_j)$ be the set of voxel centers in the OBB intersection, $p_{23}(x)$ and

$p_{25}(x)$ the nearest points to x in $\mathcal{P}^{23}$ and $\mathcal{P}^{25}$, and $\bar{n}(x)$ the unit average of their estimated normals. The signed normal displacement is

$$D_\perp(o_i, o_j) = \text{median}_{x \in \Omega(o_i, o_j)} \bar{n}(x)^\top (p_{25}(x) - p_{23}(x)), \quad (7)$$

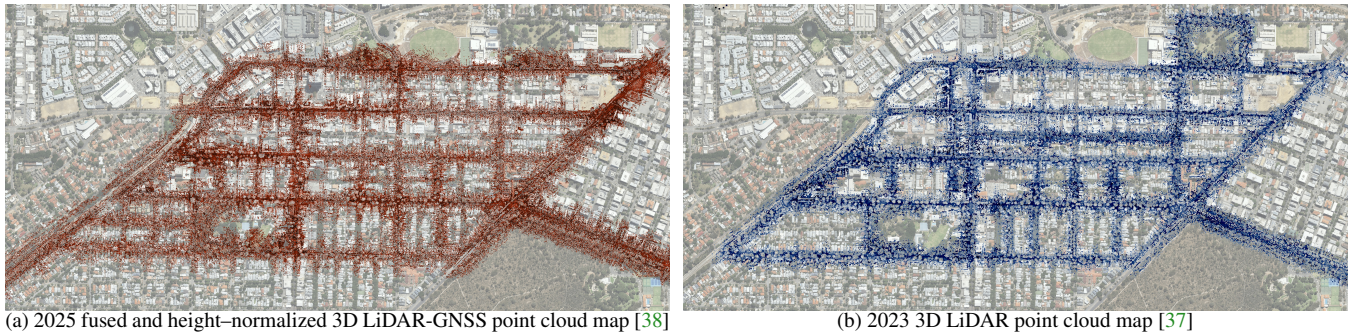
and we declare it informative only if $|D_\perp(o_i, o_j)| > \theta_{\text{LoD}} \cdot \overline{\text{LoD}}_{95}(o_i, o_j)$ with $\theta_{\text{LoD}} = 1.2$ and $\overline{\text{LoD}}_{95}$ the median LoD_{95} over $\Omega(o_i, o_j)$. We compute 3D occupancy IoU on the union OBB at 0.5 m, centroid shift $\Delta c = c_j - c_i$, height change $\Delta h = h_{95}^{25} - h_{95}^{23}$, volume change $\Delta V = V^{25} - V^{23}$ where V is the occupied-voxel volume, and a chi-square distance between height histograms in the intersection OBB. All scalars are reported together with the per-class decision.

Decisions are class-specific and use fixed thresholds for Subiaco. For building, a pair is labeled Increased if $\text{IoU}_{3D} > 0.10$ and either $|\Delta h| > 0.50$ m with $\Delta h > 0$ and $|\Delta h| > \theta_{\text{LoD}} \cdot \overline{\text{LoD}}_{95}$, or $\Delta V/V^{23} > 0.10$; it is labeled Decreased if $\text{IoU}_{3D} > 0.10$ and $\Delta V/V^{23} < -0.10$ or $\Delta h < -0.50$ m with the same LoD gate. A pair is Unchanged if $\text{IoU}_{3D} > 0.20$, $\|\Delta c\| < 1.5$ m, $|\Delta h| \leq 0.50$ m, and $|\Delta V|/V^{23} \leq 0.10$, or if all informative statistics remain below their LoD. If $\text{IoU}_{3D} \leq 0.10$ but a building instance exists only at 2025, it is Added; if it exists only at 2023, it is Removed. For vegetation, we keep the same logic with ($\text{IoU}_{3D} > 0.08$, $\|\Delta c\| < 2.0$ m) and thresholds ($|\Delta h| > 0.30$ m, $|\Delta V|/V^{23} > 0.15$); the histogram distance is used to break ties in favor of Increased when vertical mass shifts upward. For ground, changes are evaluated on a 2 m raster: a tile is Increased if the median ground elevation difference exceeds $+0.15$ m over a contiguous area $> 25 \text{ m}^2$; it is Decreased if the difference is below -0.15 m with the same area constraint; otherwise Unchanged. Ground Added/Removed does not apply. For mobile, instances unmatched across epochs are labeled Added/Removed; matched instances are Unchanged if $\text{IoU}_{3D} > 0.20$ and $\|\Delta c\| < 2.0$ m, otherwise they are discarded from city-scale reporting since persistent mobiles are rare in multi-year intervals.

To aggregate heterogeneous evidence into a confidence score attached to each decision, we standardize the informative statistics by their uncertainty and combine them through a logistic map. Let $z_h = \frac{|\Delta h|}{\sqrt{\text{LoD}_{95}^2 + \sigma_h^2}}$, $z_v = \frac{|\Delta V|}{\sqrt{(V^{23} \cdot \sigma_v)^2 + \epsilon}}$, $z_o = 1 - \text{IoU}_{3D}$, and $z_c = \frac{\max(0, \|\Delta c\| - \tau_c)}{\tau_c}$ with $(\tau_c^{\text{bld}}, \tau_c^{\text{veg}}) = (1.5 \text{ m}, 2.0 \text{ m})$. The confidence for the selected label y on pair (o_i, o_j) is

$$s_y(o_i, o_j) = (1 + \exp[-(w_h z_h + w_v z_v + w_o z_o + w_c z_c + w_\perp \frac{|D_\perp(o_i, o_j)|}{\overline{\text{LoD}}_{95}})])^{-1}. \quad (8)$$

with class-dependent weights fixed for Subiaco as $(w_h, w_v, w_o, w_c, w_\perp) = (0.35, 0.30, 0.20, 0.10, 0.05)$ for buildings and $(0.30, 0.35, 0.15, 0.10, 0.10)$ for vegetation; for ground we use $(w_h, w_v, w_o, w_c, w_\perp) = (0.50, 0.00, 0.25, 0.00, 0.25)$ with Δh interpreted as median elevation difference on the tile. The score s_y is reported jointly with the label.



(a) 2025 fused and height-normalized 3D LiDAR-GNSS point cloud map [38]

(b) 2023 3D LiDAR point cloud map [37]

FIGURE 6: City-scale reconstructions over Subiaco. The side-by-side layout avoids vertical overflows while keeping both panels within the page margins.

The final outputs are a per-instance change table containing the instance identifiers, class, label, Δh , ΔV , Δc , IoU_{3D} , $D_{\perp}$, and s_y , and tiled maps for ground with per-tile elevation change and confidence. Instances that fail the LoD gate for all statistics are set to Unchanged.

IV. EXPERIMENTS

This section evaluates the approach on the Subiaco map pair under a consistent protocol. Qualitative results on representative blocks illustrate typical urban patterns, and quantitative results report accuracy, macro F1, and macro IoU together with per class IoU. Comparisons with classical and point based baselines assess effectiveness across object categories and ground works, using fixed parameters and tiled processing to reflect the intended operational setting.

A. SUBIACO 2025 3D MAP CONSTRUCTION RESULT

The 2025 Subiaco map was fused into a single globally referenced point cloud at 0.25 m voxel leaf size with per-point normals and intensity. LiDAR packets were deskewed using per-pixel timestamps and IMU. Outliers were removed and a 1.0/0.5/0.25 m voxel pyramid standardized density. Each sequence was aligned by multi-resolution NDT followed by point-to-plane ICP. Loop closures from 360° LiDAR descriptors formed a pose graph. GNSS fixes with quality flags anchored the graph with adaptive weights. Overlapping submaps were aligned with feature-initialized ICP and fused. Ground tiles were fit by robust planes to define the vertical axis and to zero local heights, which eliminated long-wavelength vertical bias.

Figure 6 compares the 2025 reconstruction with the 2023 map after registration into the 2025 frame. The 2025 map shows continuous curb lines, coherent façades across contiguous blocks and closed intersections with consistent approach geometry. Roof ridges and small roof appendages are preserved. Under canopy the ground surface remains connected and tree crowns form complete outer envelopes. The 2023 overlay presents local shear near loop junctions, duplicated façade strips from drift and lateral offsets at intersections. The 2025 reconstruction is used as the geometric reference in all subsequent analyses.

B. QUALITATIVE CHANGE DETECTION ON REPRESENTATIVE BLOCKS

To enable city-scale processing and visualization, both epochs are partitioned into 52 square blocks of 80×80 m with a 10 m overlap to avoid boundary artifacts during association and to keep each tile under memory limits at 0.25 m voxels. All tiles are registered into the 2025 frame, and change labels are produced per object with the LoD gate and the class rules defined in the methodology. Results are visualized with five panels per block: raw projection, height map, semantic labels, instance labels, and the change map that encodes Added in green, Removed in red, Increased in blue, Decreased in orange, and Unchanged in gray. Blocks 6, 7, and 8 are reported because they cover the typical patterns observed in Subiaco, namely building redevelopment around courtyards and street corners, vegetation growth and pruning under canopy, and roadway resurfacing at multi-lane intersections with parking bays. They also include strong occlusion, long façades, and tree rows, which are failure modes for point-wise differencing but are handled by object-level reasoning.

Figure 7 shows qualitative outcomes for the three blocks. In Block 6 the method flags a large vegetation cluster as Removed at the center, multiple crowns along the verges as Increased, and narrow ground strips along the carriageway as Decreased consistent with resurfacing, while building volumes remain Unchanged. In Block 7 new built volumes inside the inner lot are labeled Added with height Increased at the northern frontage, and several shrubs along the southern footpath are Removed; ground in the adjacent parking area is Decreased and the surrounding façades keep high overlap. In Block 8 tree rows along a boulevard produce alternating Added and Removed crowns, a central median is reprofiled with contiguous Increased ground, and two small structures at the edge are Removed. Across the three tiles thin façade duplicates and boundary splits are suppressed by the overlap and by class-consistent assignment, and small ephemeral objects are ignored by the instance size and LoD thresholds. These examples illustrate the intended operating regime before the quantitative evaluation.

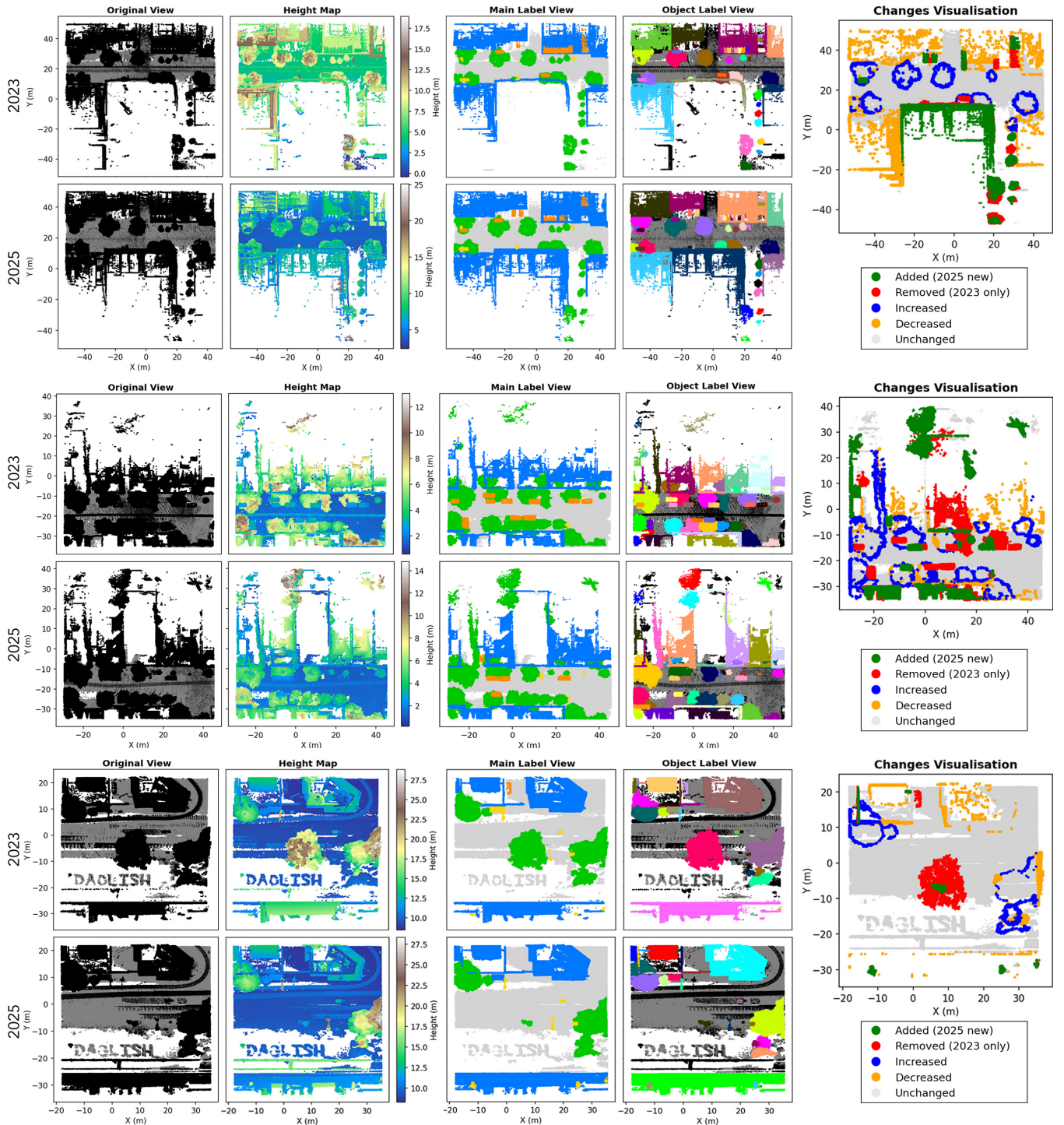


FIGURE 7: Qualitative change detection on three representative Subiaco blocks. Each image presents the 2023 and 2025 projections, height maps, semantic and instance views, and the object-level change map with the legend embedded. From top to bottom: Blocks 6, 7, and 8.

C. QUANTITATIVE EVALUATION ON CITY BLOCKS AND METHOD COMPARISON

We evaluate object-level change prediction on the Subiaco map pair using the five labels {Added, Removed, Increased, Decreased, Unchanged}. Three metrics are used consistently: accuracy is the micro overall accuracy, mF1 is the macro-averaged F1 across the five labels, and mIoU is the

macro-averaged Intersection over Union. Per-class IoU is reported to expose failure modes. Fifteen representative blocks are selected from the 52 tiled blocks to cover redevelopments, vegetation dynamics and ground works while keeping the class distribution comparable to the full set. Across the 15 blocks in Table 2, accuracy ranges from 94.1% to 96.0%, mF1 from 88.6% to 91.6%, and mIoU from 79.6% to 84.8%.

TABLE 1: Comparison with representative methods on the Subiaco dataset using identical metrics. Accuracy is micro accuracy, mF1 is macro F1 across the five change labels, and mIoU is macro IoU. Right-hand columns report per-class IoU.

Method	Source	ACC	mF1	mIoU	Per-Class IoU (%)				
					Added	Removed	Increased	Decreased	Unchanged
RF [39]	ML'01	90.7	71.6	55.8	61.3	52.4	31.8	43.8	89.7
DSM-Siamese [20]	ICIP'18	92.1	73.9	58.3	69.4	54.2	29.7	46.1	92.1
DSM-FC-EF [40]	TGRS'19	92.2	72.7	57.2	68.7	52.3	27.9	43.5	93.6
Siamese KPConv [21]	ICCV'19	94.6	89.0	80.1	85.9	78.4	72.8	68.1	95.5
Triplet KPConv [41]	ISPRS'21	95.0	90.2	81.8	88.4	82.1	75.6	67.2	95.9
DC3DCD EFSKPConv [42]	ISPRS'25	92.0	74.1	58.9	69.1	53.2	31.0	47.2	93.9
Object-based (ours)	—	95.2	90.4	82.6	86.9	80.8	76.6	74.8	93.8

TABLE 2: Performance on 15 representative Subiaco blocks (out of 52). Metrics are accuracy (micro accuracy), mF1 (macro F1 across five change labels), and mIoU (macro IoU). Right-hand columns report per-class IoU. All values are percentages. The last row aggregates all instances across the 15 blocks.

Block	ACC	mF1	mIoU	Per Class IoU (%)				
				Added	Removed	Increased	Decreased	Unchanged
B06	95.1	90.3	82.4	88.4	81.8	75.3	74.0	92.5
B07	95.4	90.7	83.1	87.6	81.9	74.5	77.7	93.8
B08	94.8	89.9	81.6	86.7	81.8	74.0	70.2	95.3
B09	95.7	91.3	84.0	85.9	82.7	78.5	78.2	94.9
B10	94.1	88.6	79.6	87.2	82.7	75.9	60.3	92.1
B11	96.0	91.6	84.8	85.1	79.1	76.2	90.0	93.7
B12	94.5	89.4	80.7	85.9	79.1	76.3	69.2	92.9
B13	95.6	91.0	83.5	88.4	80.8	77.2	79.1	92.1
B14	95.2	90.8	83.0	88.4	78.6	75.7	76.3	96.0
B15	94.3	88.9	80.4	88.7	80.1	78.2	60.0	94.8
B16	94.9	90.1	81.9	87.4	82.4	78.2	68.5	93.2
B17	95.8	91.5	84.6	85.1	79.2	78.0	86.5	94.4
B18	95.3	90.7	82.9	87.2	81.5	77.4	75.7	92.7
B19	94.7	89.7	81.2	87.0	81.9	76.6	66.9	93.8
B20	95.9	91.4	84.8	85.1	78.2	77.5	89.4	94.0
all	95.2	90.4	82.6	86.9	80.8	76.6	74.8	93.8

IoU for Unchanged is above 92% on all blocks, indicating stable assignment of non-events. The lowest per-class scores appear on Decreased where ground reprofiling is narrow and partially overlaps with curbs. The last row aggregates all instances across the 15 blocks and gives the overall performance of our pipeline: 95.2% accuracy, 90.4% mF1 and 82.6% mIoU with per-class IoUs of 86.9% for Added, 80.8% for Removed, 76.6% for Increased, 74.8% for Decreased, and 93.8% for Unchanged.

We compare the pipeline with representative baselines and point-based models under a unified protocol. Table 1 shows that classical DSM and RF variants remain below 60% mIoU. KPConv variants raise mIoU to the low 80s but are sensitive to thin ground changes. Using the aggregated metrics from Table 2, our object-based method achieves 95.2% accuracy, 90.4% mF1, and 82.6% mIoU, surpassing all compared methods on all three summary metrics. Relative to Triplet KPConv, the improvements are 0.2 percentage points in accuracy, 0.2 percentage points in mF1, and 0.8 percentage points in mIoU. The largest classwise gain is observed for Decreased, where the IoU reaches 74.8%, exceeding the baseline by 7.6 percentage points and reducing false positives on narrow resurfaced strips while preserving competitive performance on the remaining classes.

V. CONCLUSION

We addressed urban 3D change detection in Subiaco using an object level, uncertainty aware framework on bi temporal LiDAR at city scale. The approach replaces perfect pre alignment assumptions with calibrated registration and a local level of detection, enforces class consistent instance association to resolve split and merge cases, and applies tiled processing with per object overlap, displacement, height, and volume cues to bound memory while preserving narrow ground changes. On 15 representative blocks the method reached 95.2% accuracy, 90.4% mF1, and 82.6% mIoU, improving over the strongest baseline by 0.2, 0.2, and 0.8 points, with a 7.6 point IoU gain on *Decreased*. The released Subiaco 2025 dataset and implementation enable reproducible evaluation and support HD map maintenance and smart mobility operations. Future work will extend to multi epoch sequences for trend analysis, fuse aerial and ground sensing, and learn thresholds that incorporate spatially varying uncertainty for online map updates.

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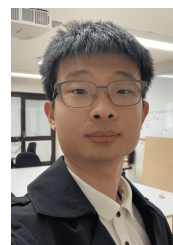
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