Urban-Trained, Forest-Ready

A Source-Mix Domain-Adaptation Pipeline for Large-Scale Forest Point Cloud Segmentation

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DIRS Digital Imaging and Remote Sensing Lab

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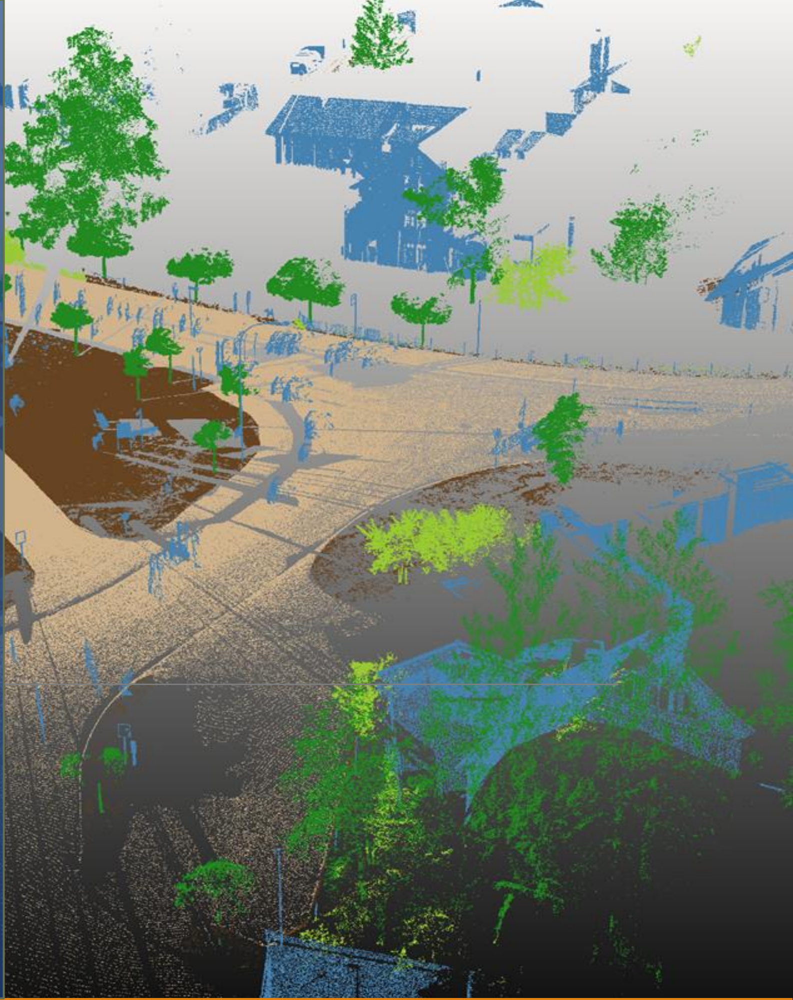
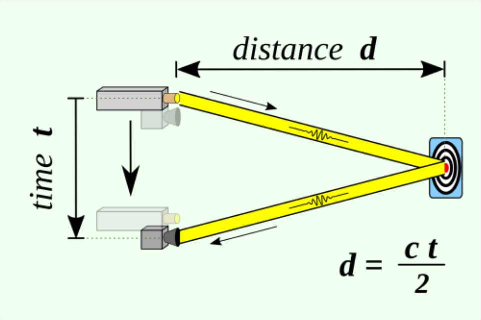
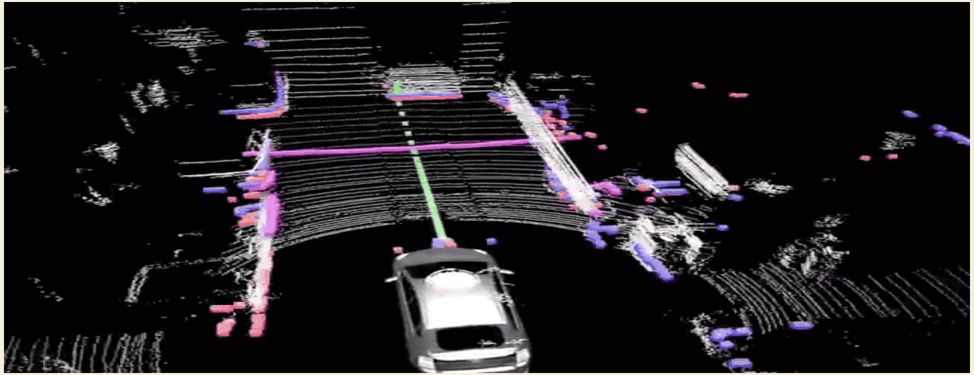
Pacific Islands Climate Adaptation Science Center

Forest Service U.S. Department of Agriculture

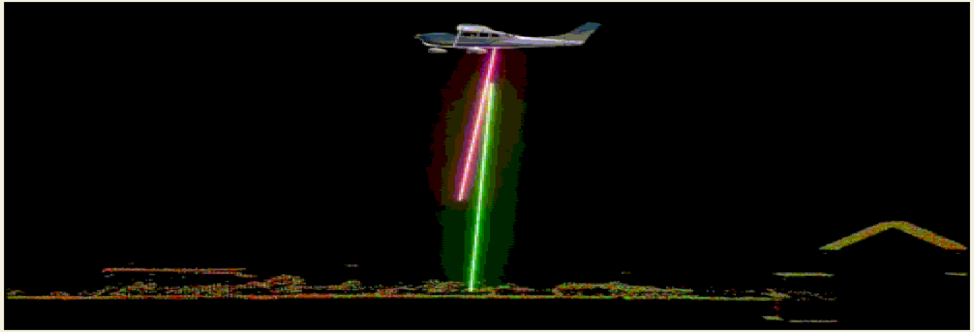


LiDAR Point Cloud





https://medium.com/@BabakShah/lidar-in-self-driving-cars-cee29db94af7



ref: https://www.geoilenergy.com/en/servicios/geoespaciales/eagle-mapping

Data structure:

- **Points:** A collection of millions of discrete measurements.
- **Geometry:** Each point p_i has coordinates $\{x, y, z\}$.
- **Attributes:** Intensity, return number.

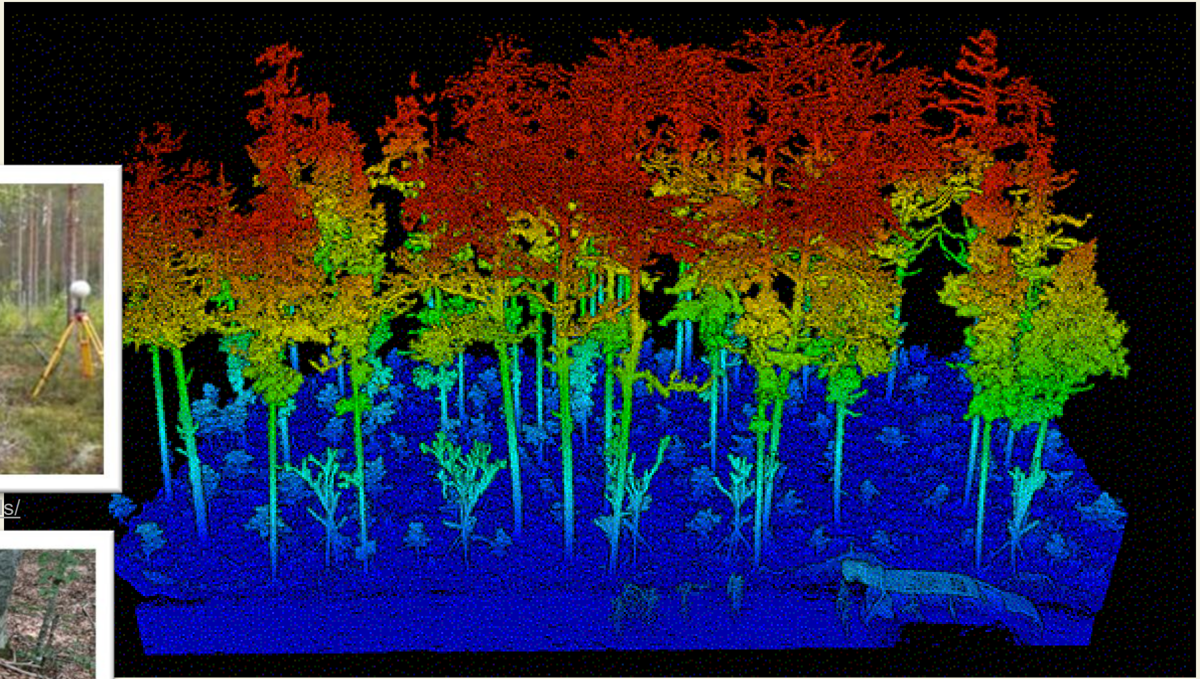
LiDAR Point Cloud for Forests

https://www.yellowscan

s://www.earthscope.org/what-is/tls/

https://htirc.org/backpack-system-for-high-resolution-forest-inventory/

https://geolabforest.com/spot-vallombrosa/

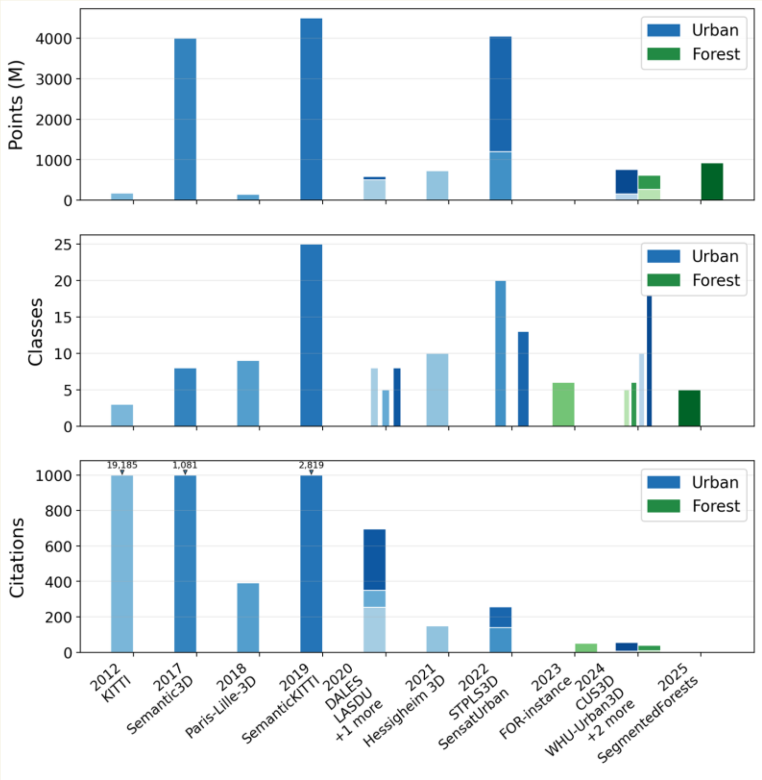


https://candrone.com/blogs/news/lidar360-v8-0-smarter-point-cloud-processing-10?srsltid=AfmBOooYBeqJTRtHtih0EPavLFx9f4-S9brSqhEbrZpTj2dSyvGos-7w

Urban Data Abundance vs Data Scarcity in Forest

Category	Name	# points (million)	# classes	Citations	References
Urban	**Semantic3D**	4000	8	1081	Hackel, Timo, et al. (2017)
	SemanticKITTI	4500	25	2819	Behley, Jens, et al. (2019)
	Toronto-3D	78.3	8	347	Tan, Weikai, et al. (2020)
	Paris-Lille-3D	143	9	391	Roynard, Xavier, et al. (2018)
	DALES	505	8	255	Varney, Nina, et al (2020)
	SensatUrban	2847	13	117	Hu, Qingyong, et al. (2022)
	KITTI	179	3	19185	Geiger, Andreas, et al. (2012)
	LASDU	3.12	5	94	Ye, Zhen, et al. (2020)
	STPLS3D	1200	20	139	Chen, Meida, et al. (2022)
	CUS3D	152	10	7	Gao, Lin, et al. (2024)
	Hessigheim 3D	730	10	150	Kölle, Michael, et al. (2021)
	WHU-Urban3D	606	18	48	Han, Xu, et al. (2024)
Forest	**SegmentedForests**	920	5	1	Laino, Diego, et al. (2025)
	FOR-instance	25	6	51	Stefano Puliti, et al. (2023)
	ForestSemantic	355	6	31	Liang, Xinlian, et al. (2023)
	DigiForest	265	5	8	Meher V.R. Malladi, et al. (2025)

Urban Data Abundance vs Data Scarcity in Forest



Urban v.s. Forest Point Cloud Datasets: Data Volume, Classes, and Scholarly Attention.

Urban

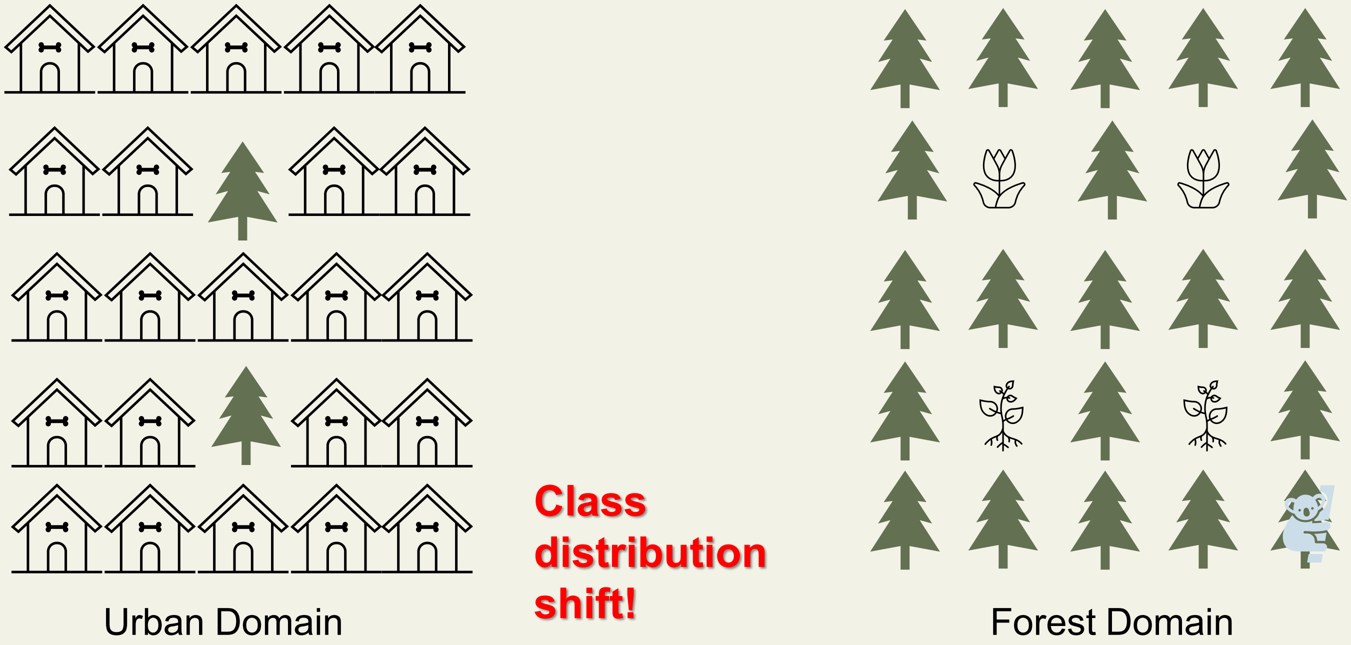
- Trillions of points, large area
- 10+ classes - diversity
- Widely used & tested

Forest Label Famine

- Traditional methods struggle with the complexity of unstructured terrain.
- Lack of labeled data hinders the deployment of deep learning models in forestry.
- Annotating 3D data is labor-intensive

The Domain Gap

Models trained solely on urban data fail to generalize to forest environments!



The Domain Gap

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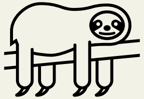

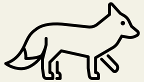

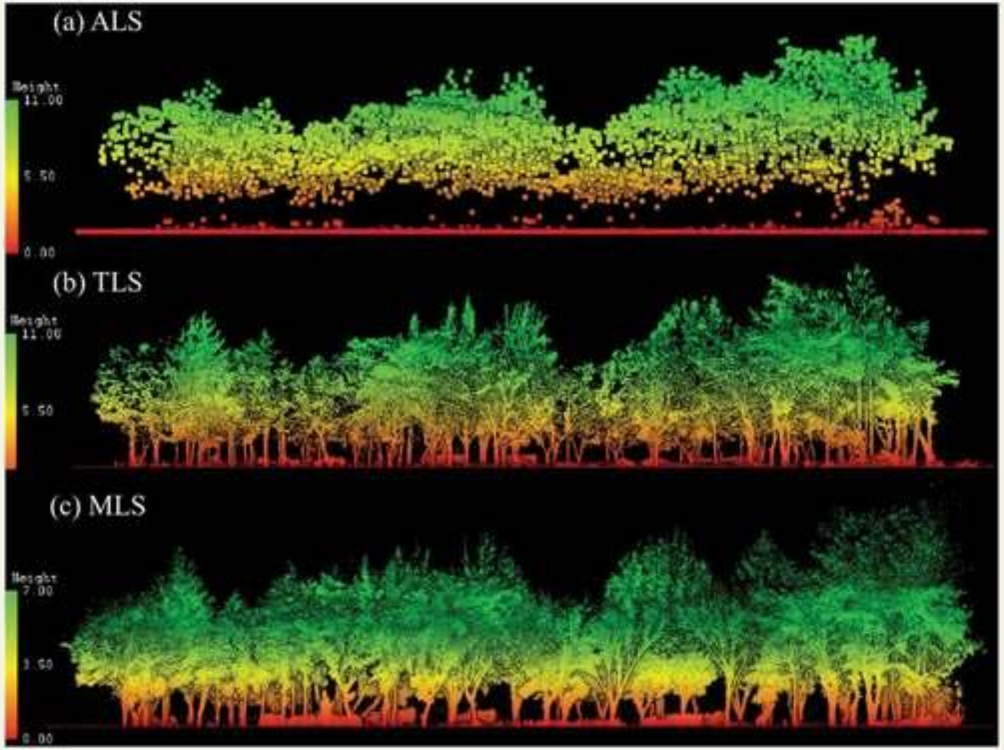

Sensor and platform heterogeneity!

Choi, H., & Song, Y. (2022)

The Domain Gap

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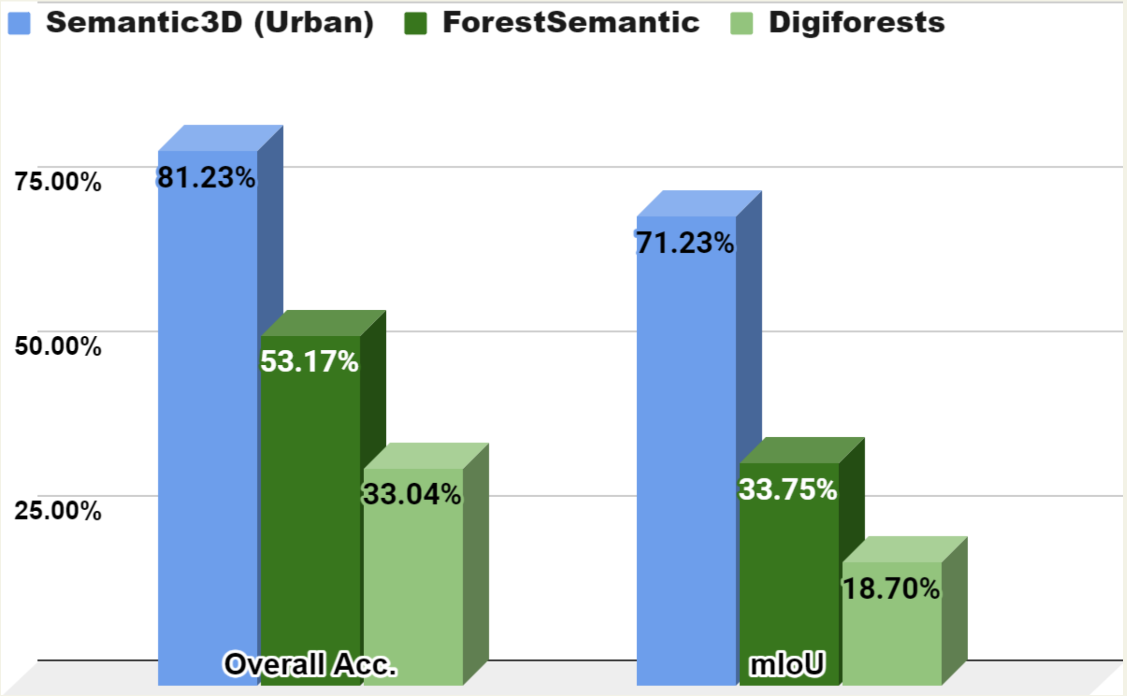


Source-Mix Domain Adaptation Pipeline

Stage 1: Dataset Curation & Label Remap

We remap urban and forest datasets into a unified label space.

Stage 2: Pretraining

A SOTA Deep Neural Network model is pretrained on remapped urban data

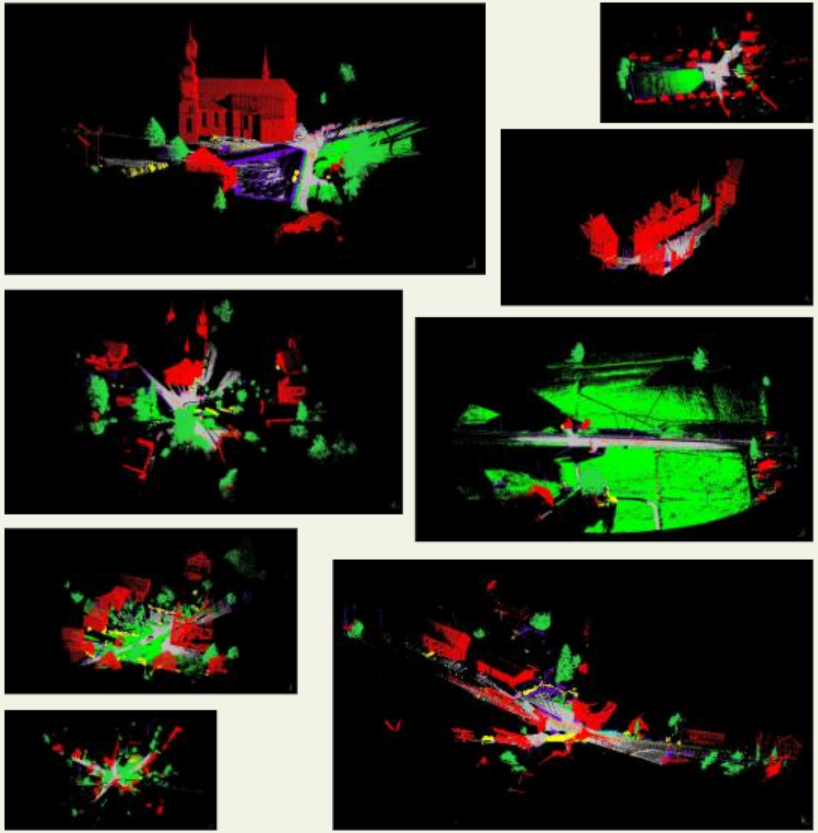
Stage 3: Feature-Alignment Training

Further train the network to align features from both domains, ensuring the model focuses on invariant structural properties.

Urban Dataset

Semantic3D

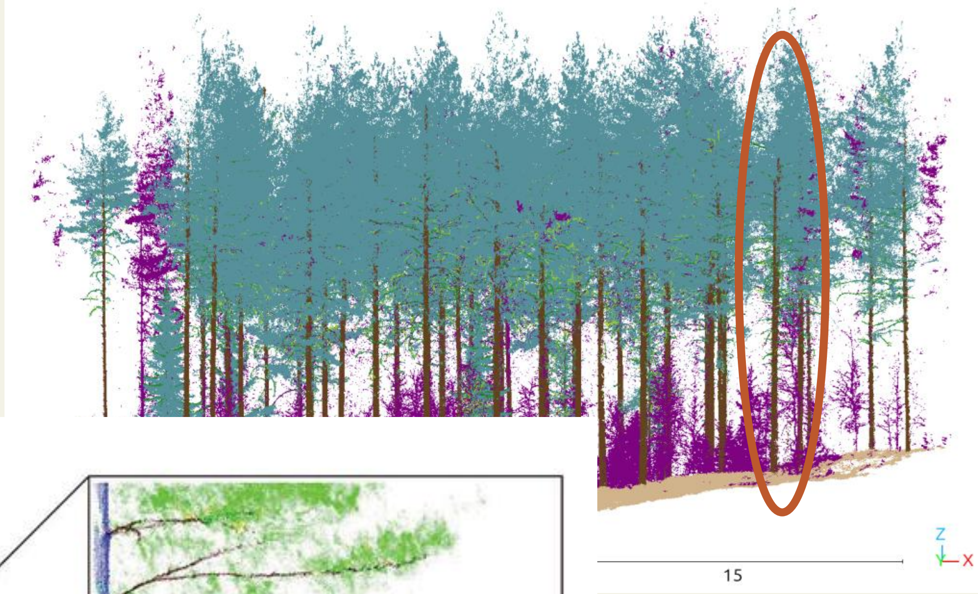
- over **4 billion points;**
- Terrestrial LiDAR
- 15 diverse urban scenes: churches, streets, railroad tracks, squares, villages, soccer fields, castles, etc.
- 8 (+1) classes
    - 0: Unlabeled
    - 1: man-made terrain
    - 2: natural terrain
    - 3: high vegetation
    - 4: low vegetation
    - 5: buildings
    - 6: hard scape
    - 7: scanning artefacts
    - 8: cars

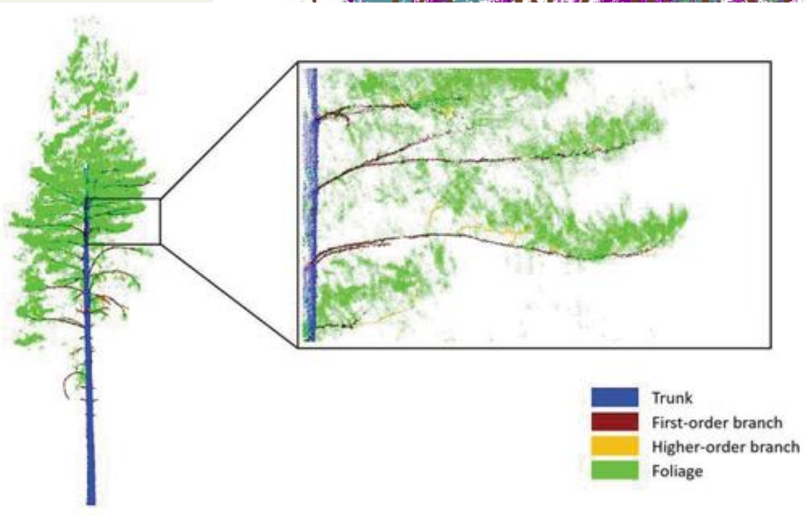


Forest Dataset A

ForestSemantic

- over **355 million points**
- Terrestrial LiDAR
- 3 forest plots
- 6 (+1) classes
    - 0: Unlabeled
    - 1: Ground
    - 2: Trunk
    - 3: First-order branch
    - 4: Higher-order branch
    - 5: Foliage
    - 6: Miscellany

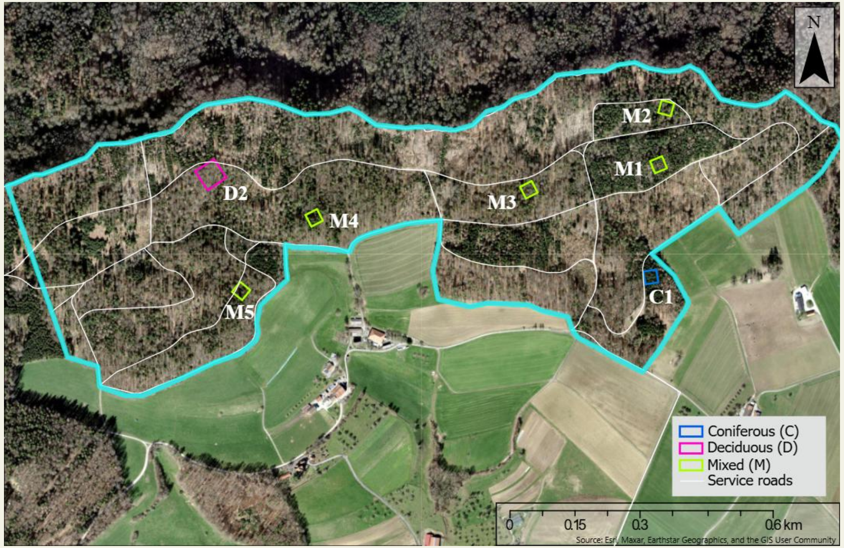




Forest Dataset B

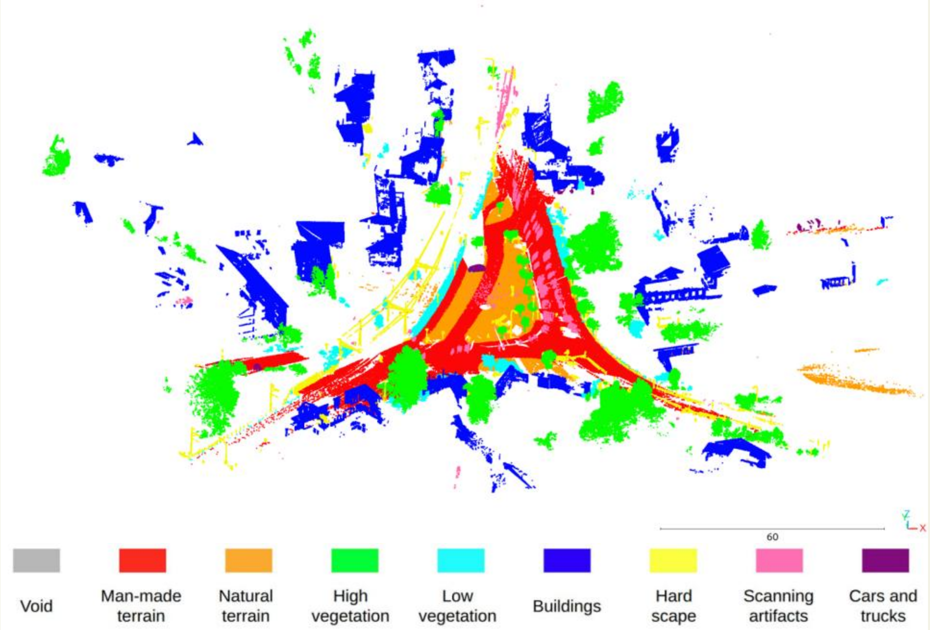
DigiForests

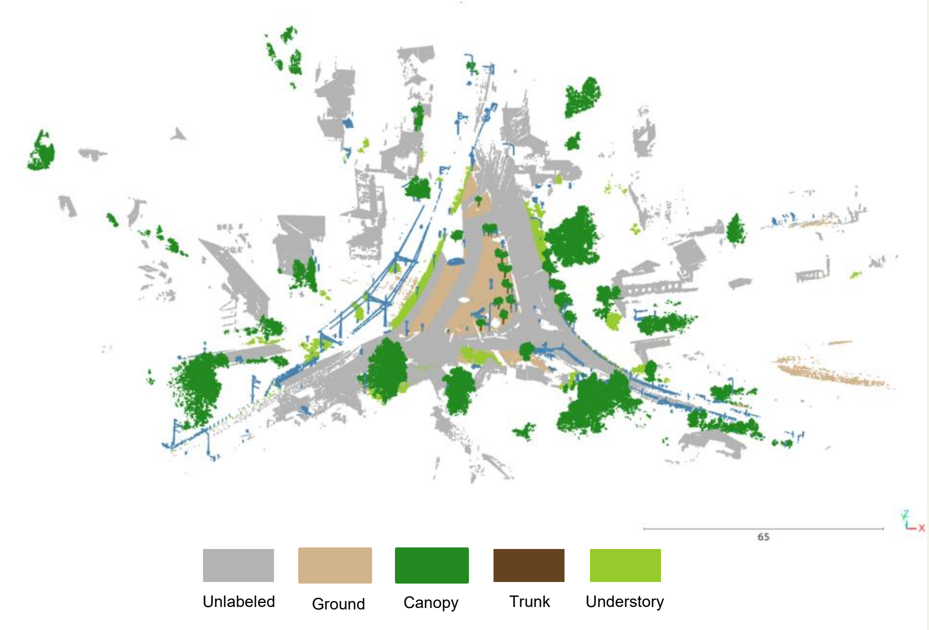
- over **265 million points**
- Mobile backpack + UAV LiDAR
- 10 forest plots
- 5 (+1) classes
    - 0: Unlabeled
    - 1: Ground
    - 2: Shrub
    - 3: Stem
    - 4: Canopy
    - 5: Miscellaneous



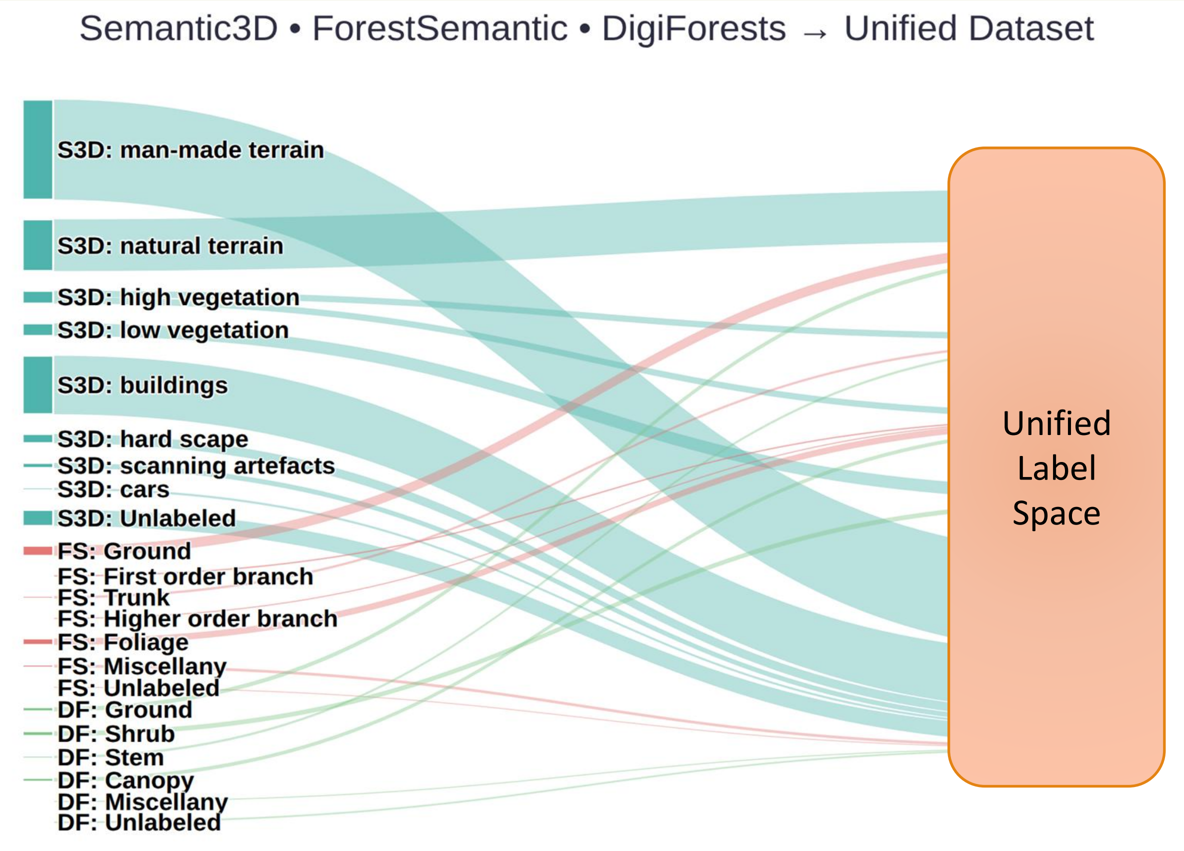
Stage 1: Dataset Curation & Label Remap

Extract vegetation points from the Urban data.

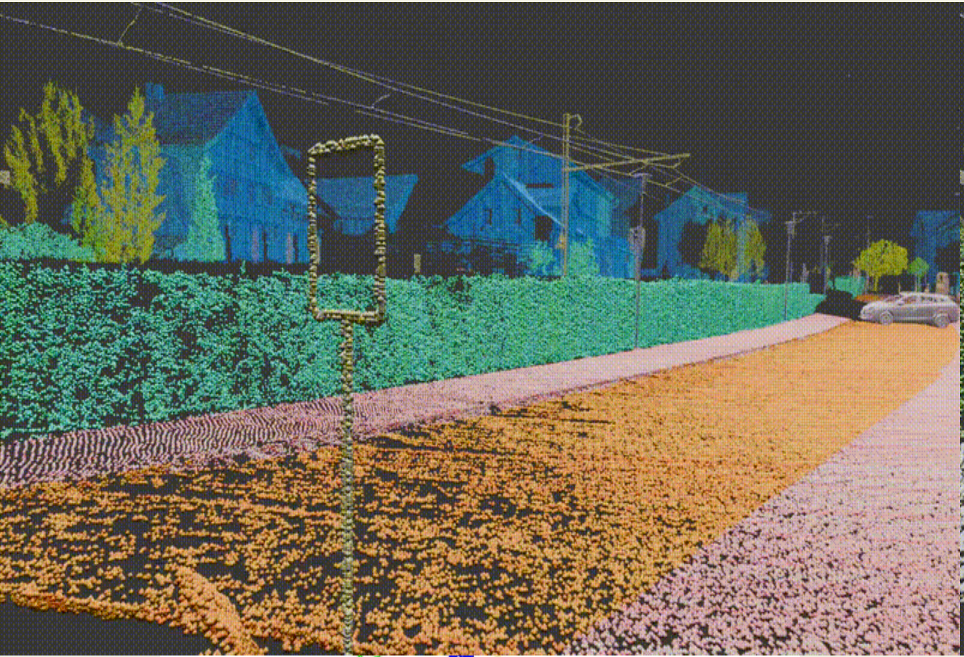


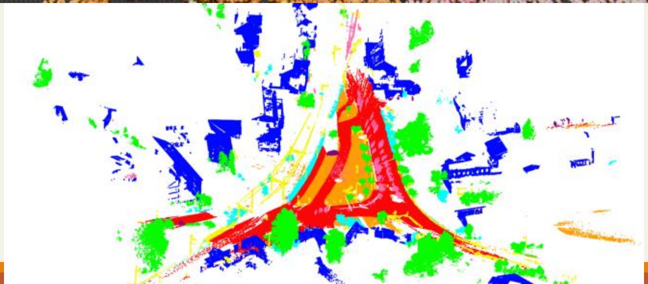


Stage 1: Dataset Curation & Label Remap

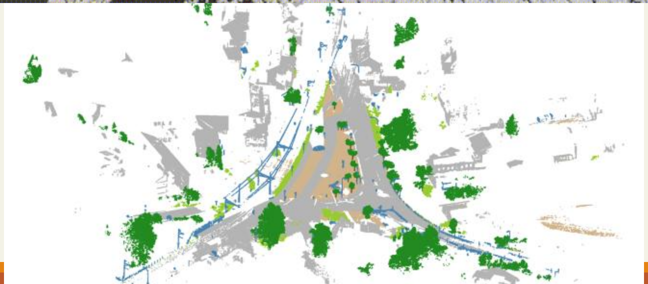


Semantic3D - scan# s27-station5



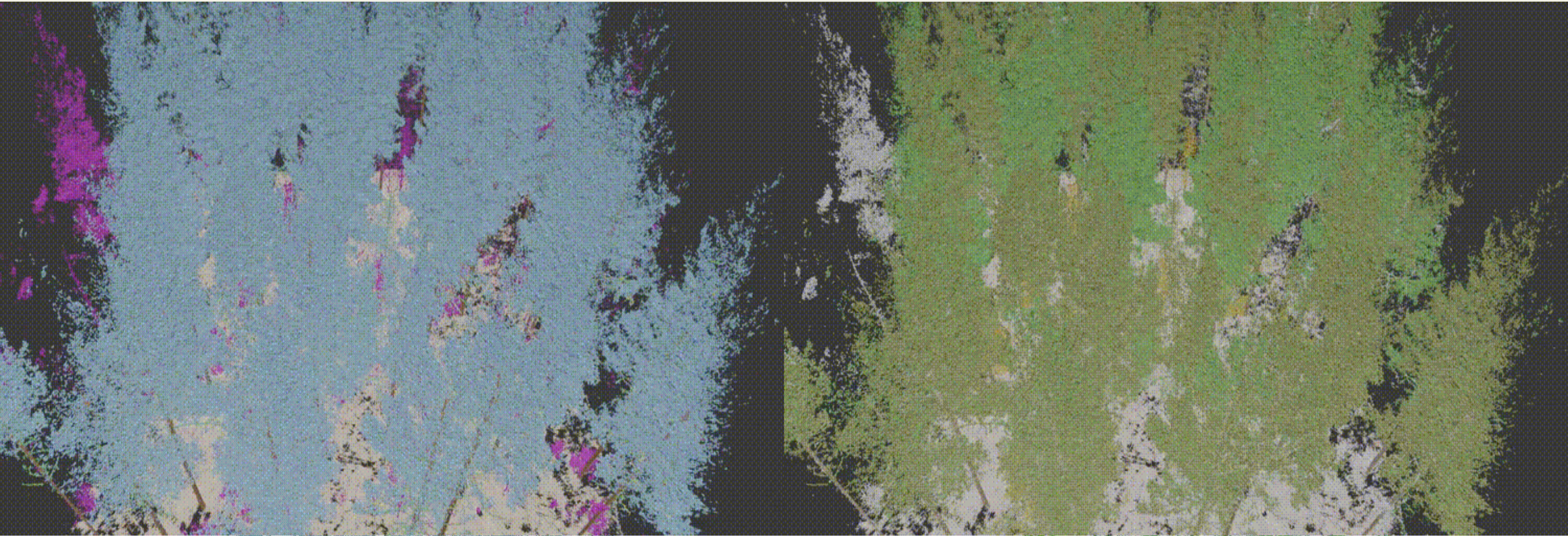


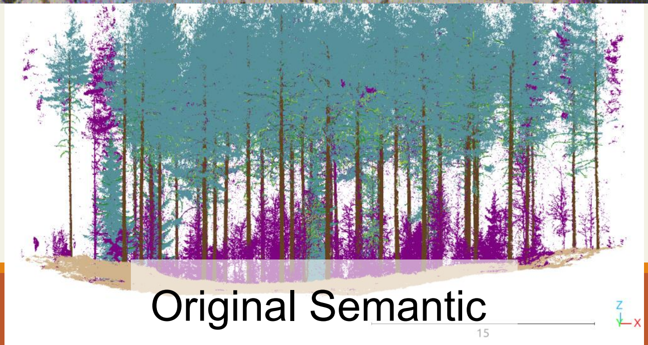
Original Semantic



Remapped Semantic

ForestSemantic - Plot #1





Original Semantic

Remapped Semantic

RandLANet – a SOTA Neural Network Model

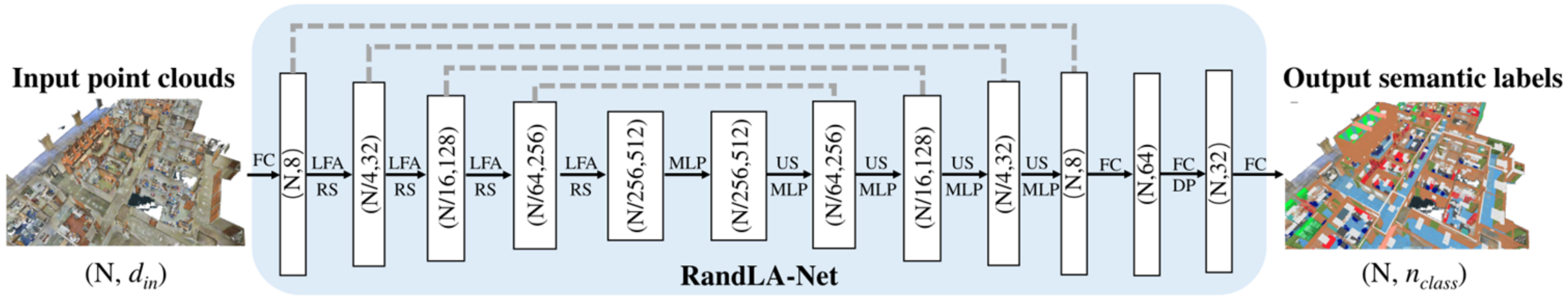
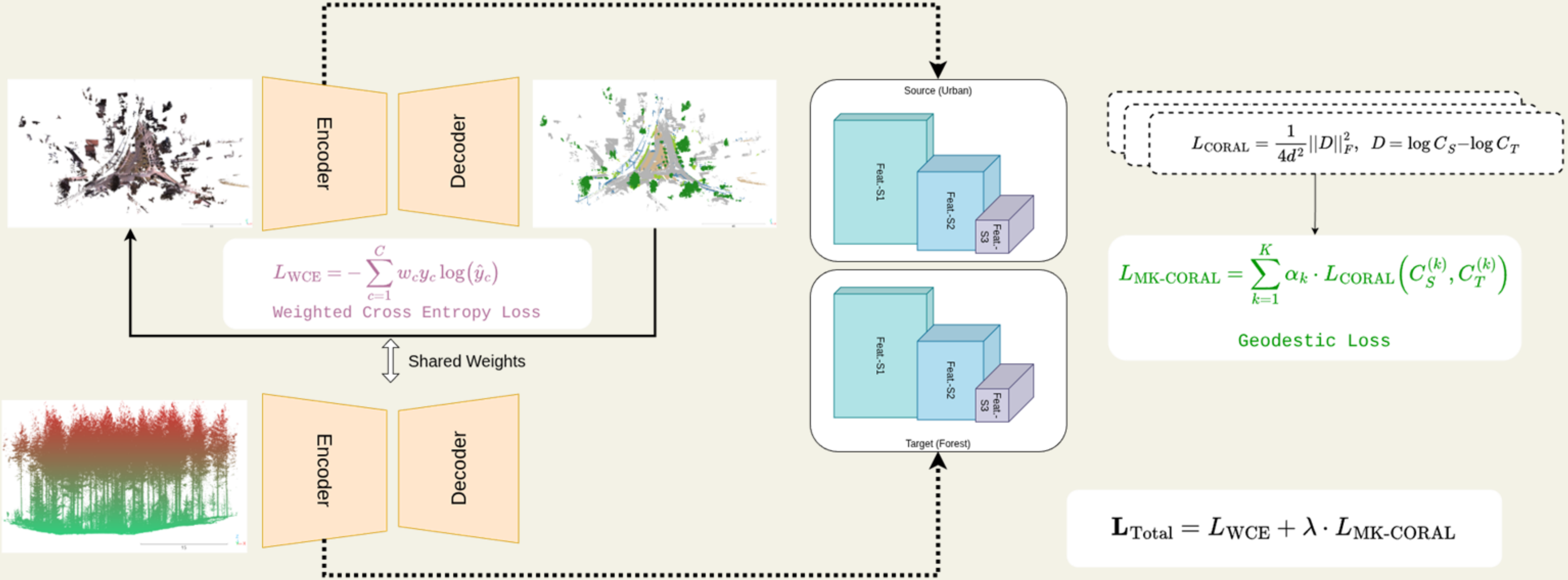


Figure 7. The detailed architecture of our RandLA-Net. (N, D) represents the number of points and feature dimension respectively. FC: Fully Connected layer, LFA: Local Feature Aggregation, RS: Random Sampling, MLP: shared Multi-Layer Perceptron, US: Up-sampling, DP: Dropout.

Hu, Qingyong, et al. "Randla-net: Efficient semantic segmentation of large-scale point clouds." *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*. 2020.

CORAL: Geometry-Aware Covariance Alignment



We align multi-scale feature covariances between urban and forest domains using a geometry-aware CORAL loss, enabling pseudo-labeling and unsupervised cross-domain LiDAR segmentation.

Experimental Design and Training Protocol

Baseline (No Domain Adaptation)
Train on the **source domain** and evaluate on both **source and target domains**.

↓

Domain Adaptation (Feature Alignment)
Pretrain on the **source domain**, followed by **feature-alignment training** using both **source and target data**.

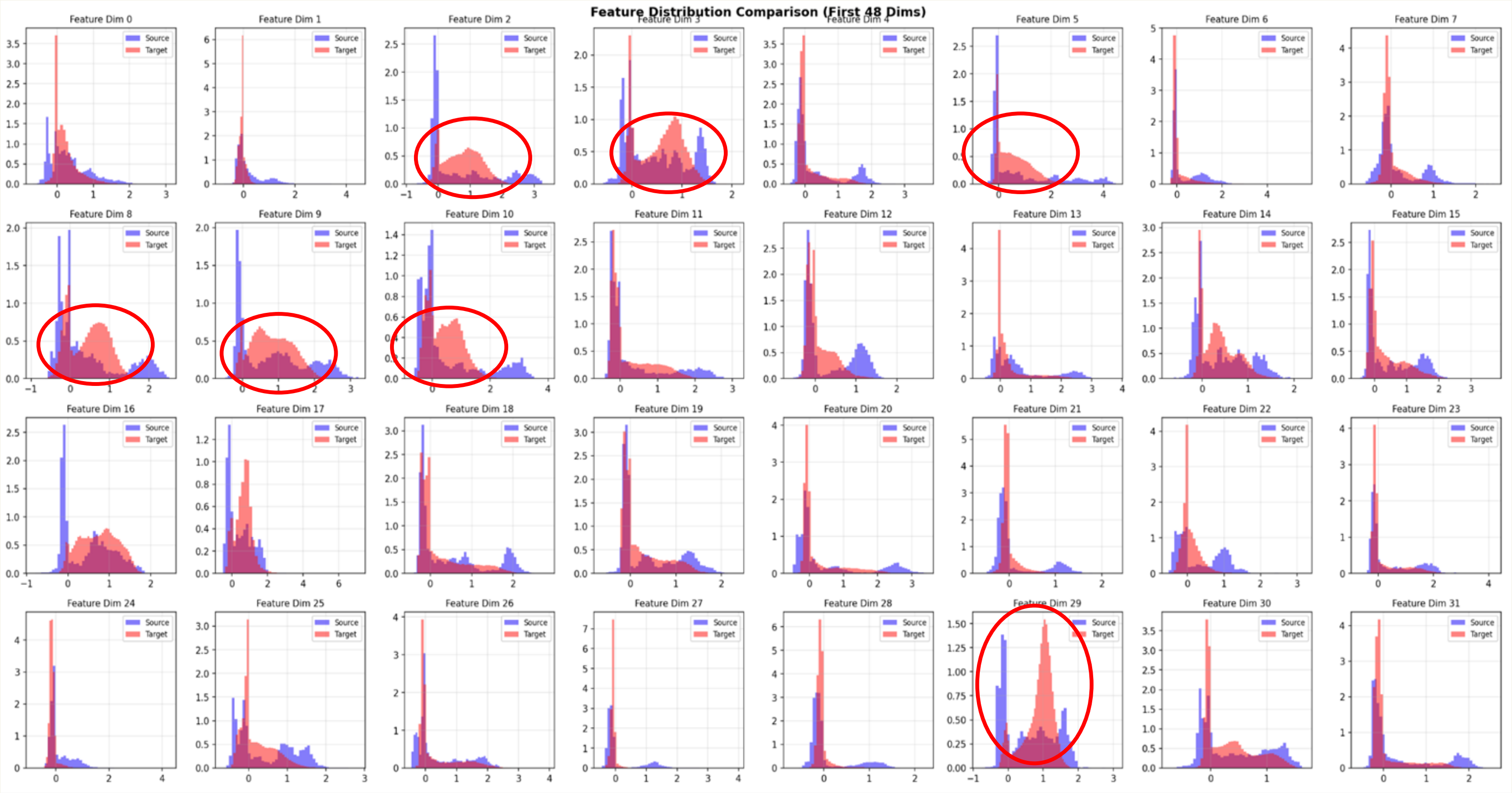
↓

Training–Target Configurations
Steps (1) and (2) are repeated under three source–target settings:

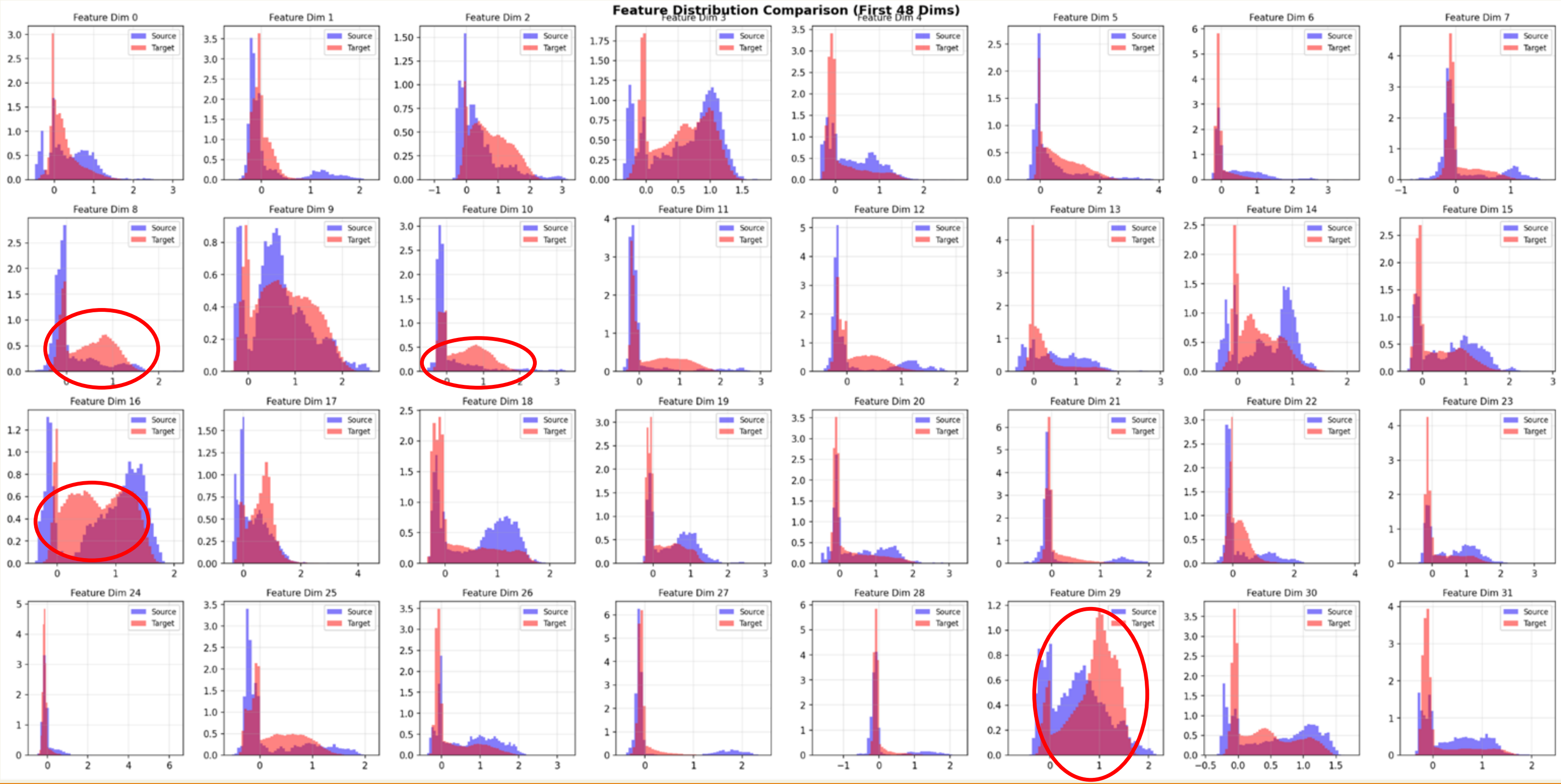
Urban → Forest (F1, F2)	**Urban + F1 → F2**	**Urban + F2 → F1**

Results

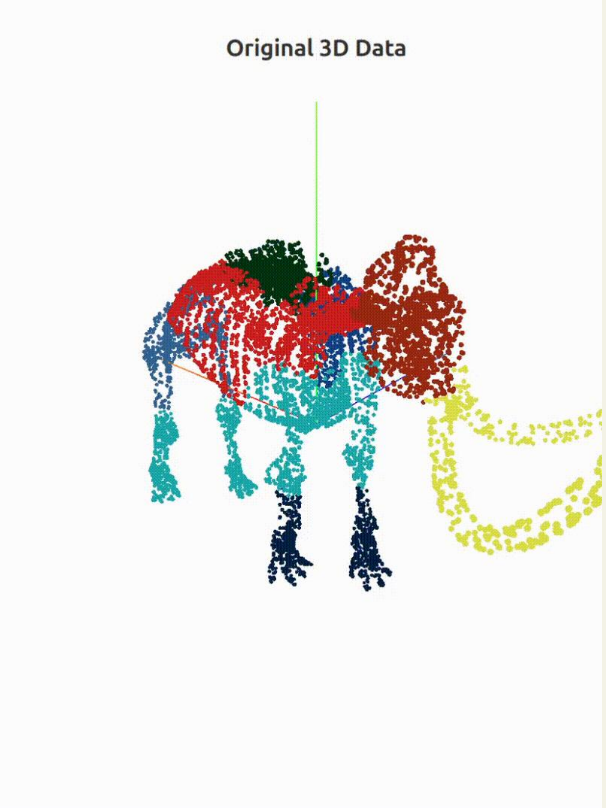
digiforest – before DA – decoder features

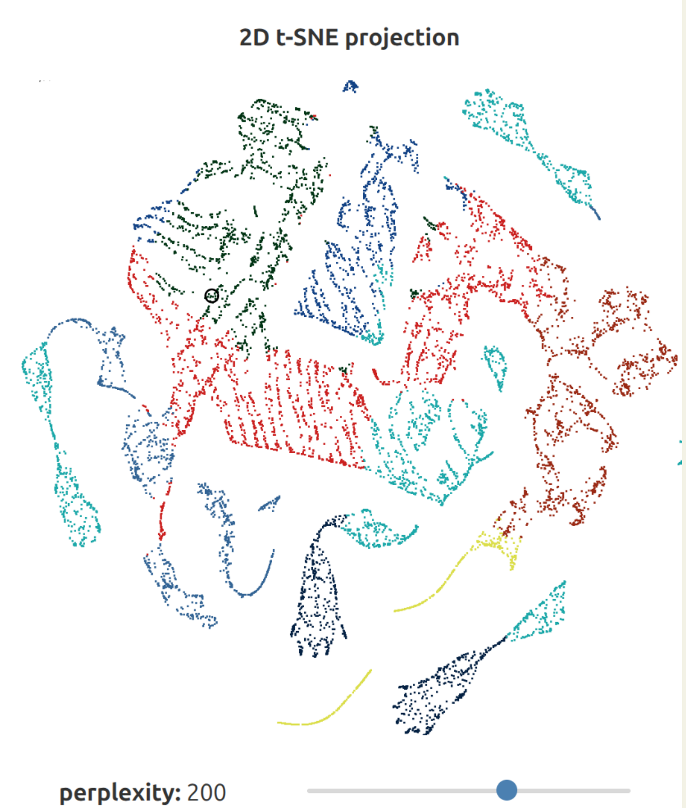


digiforest – after DA – decoder features



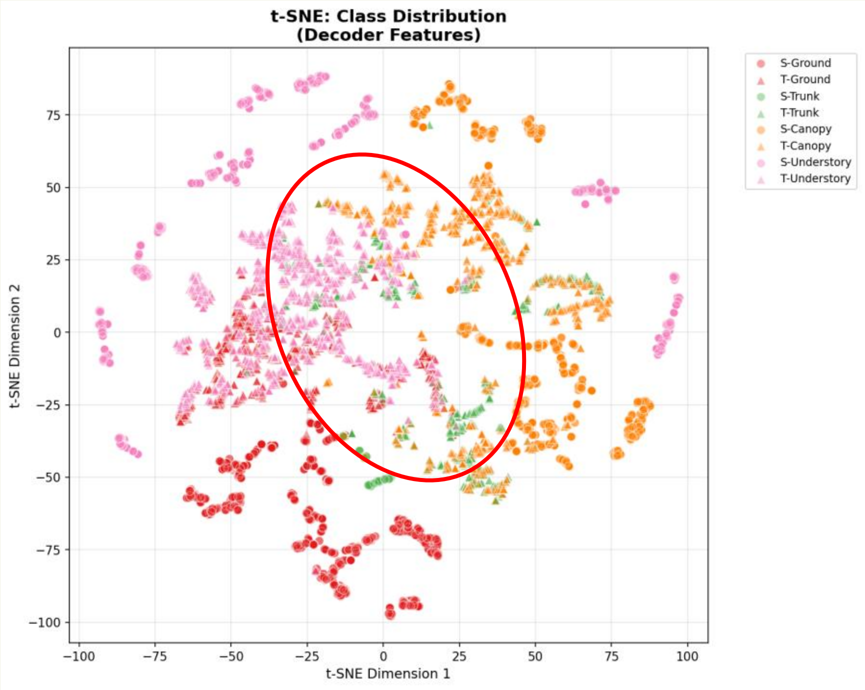
t-SNE

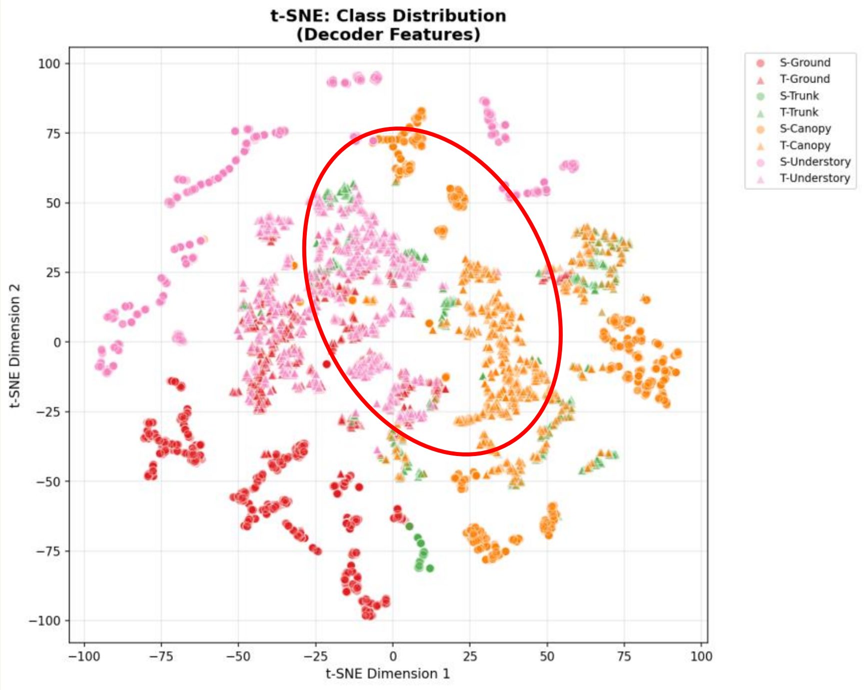




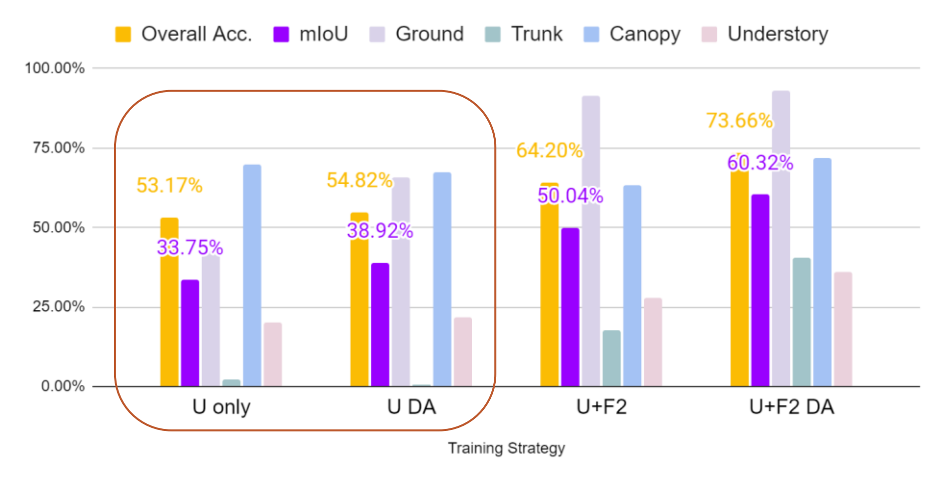
ref: https://pair-code.github.io/understanding-umap/

t-SNE - digiforest – DA before and after

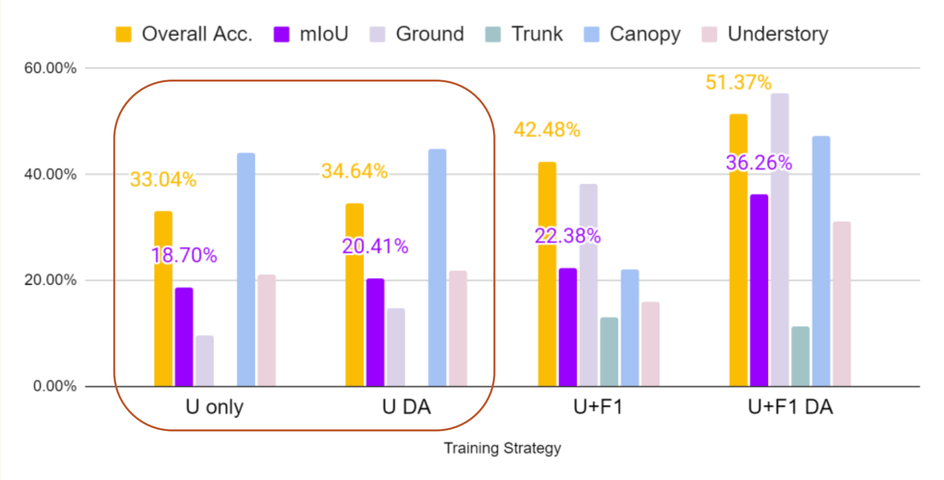




Segmentation Performance



Evaluation on ForestSemantic



Evaluation on Digiforests

Lessons Learned

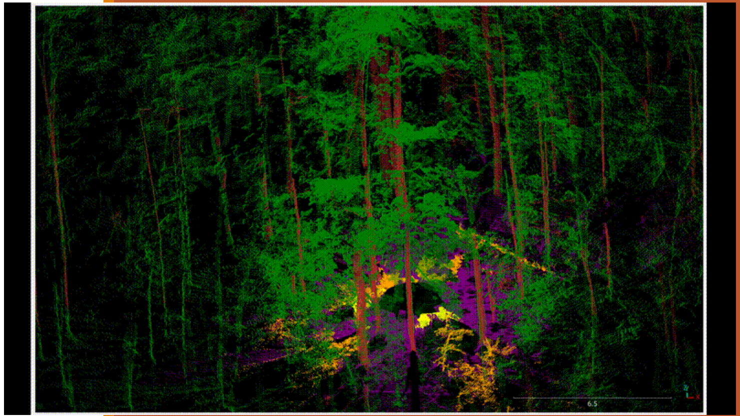
If something is irrelevant, make it irrelevant to the model
(explicitly encode what does *not* matter).

All datasets and classes matter—but not equally
(prioritization is essential).

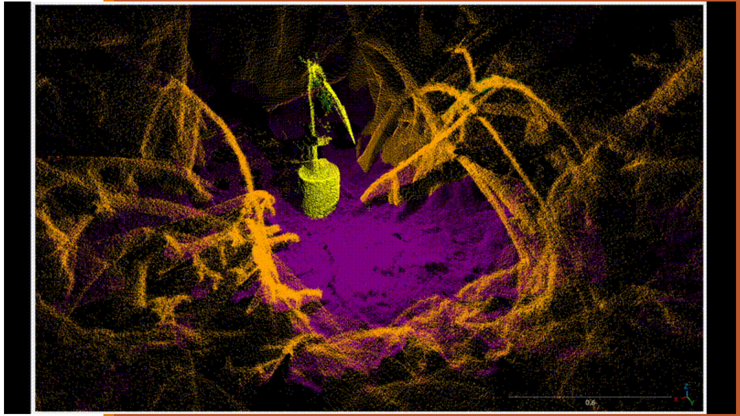
Start from what is accessible, while keeping the big picture in mind.

Key Findings

1. **Urban-only data can initialize the model to ~50% overall accuracy**, without any human annotation.
2. **CORAL-based domain adaptation improves mIoU by up to ~14% when pretrained on mixed-source datasets**.
3. **Downstream tasks can be framed as either pseudo-labeling or fully unsupervised semantic segmentation**.
4. **The pipeline is extensible to additional SOTA models and open-source datasets.**
5. **The pipeline will be applied to custom datasets from Harvard Forest and mangrove ecosystems.**



Harvard Forest



Mangroves in Palau

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· LiDAR · 3D Point Clouds · Machine Learning ·

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Questions?

THANK YOU FOR YOUR ATTENTION.

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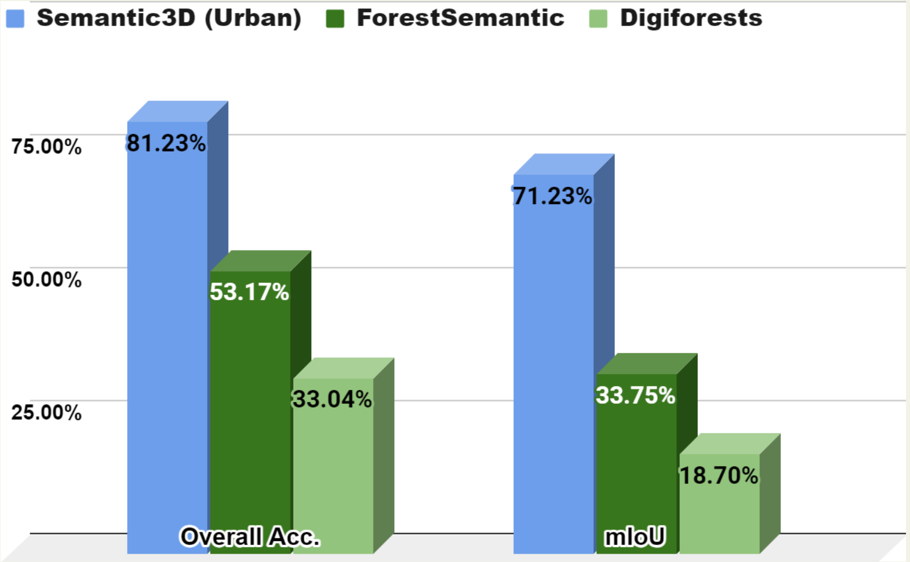
Backup Slides

The Domain Gap

Models trained solely on urban data fail to generalize to forest environments!

Structural Differences

- Different class distribution
  - Vegetation are a relatively small part in urban scenes.
  - Forest scenes are dominated by trees.
- Different sensors and platforms
  - Terrestrial LiDAR vs Mobile vs UAV



Segmentation Performance

	Datasets	Overall Acc.	mIoU	Ground	Trunk	Canopy	Understory
U only	ForestSemantic	53.17%	33.75%	42.72%	2.37%	69.87%	20.05%
	Digiforests	33.04%	18.70%	9.64%	0.00%	44.15%	21.01%
U DA	ForestSemantic	54.82%	38.92%	65.74%	0.61%	67.56%	21.76%
	Digiforests	34.64%	20.41%	14.83%	0.00%	44.88%	21.94%
U+F1	ForestSemantic	66.81%	57.27%	80.20%	60.54%	70.93%	17.42%
	Digiforests	42.48%	22.38%	38.33%	13.10%	22.15%	15.95%
U+F2	ForestSemantic	64.20%	50.04%	91.26%	17.85%	63.17%	27.87%
	Digiforests	75.72%	58.62%	70.72%	47.65%	68.73%	47.38%
U+F1 DA	ForestSemantic	72.71%	58.93%	73.60%	62.39%	73.05%	26.66%
	Digiforests	51.37%	36.26%	55.22%	11.24%	47.38%	31.20%
U+F2 DA	ForestSemantic	73.66%	60.32%	93.10%	40.54%	71.75%	35.88%
	Digiforests	79.91%	61.40%	70.99%	50.39%	71.74%	52.48%