Urban-Trained, Forest-Ready

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

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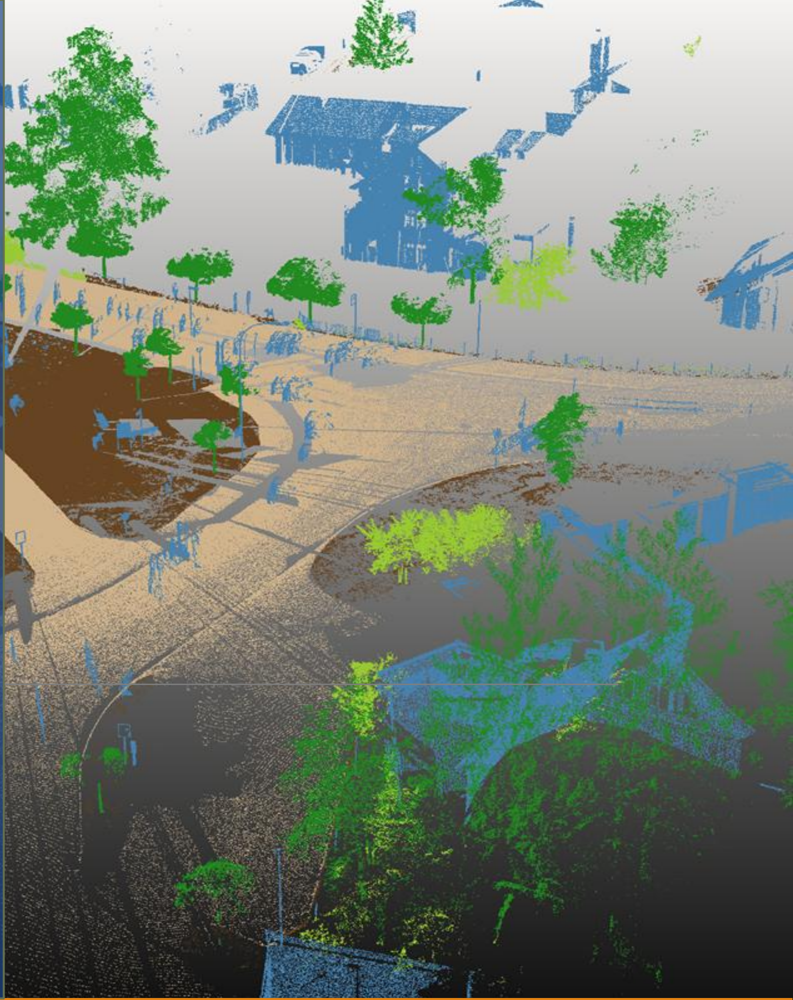
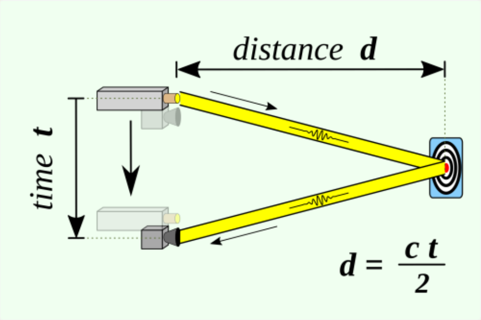
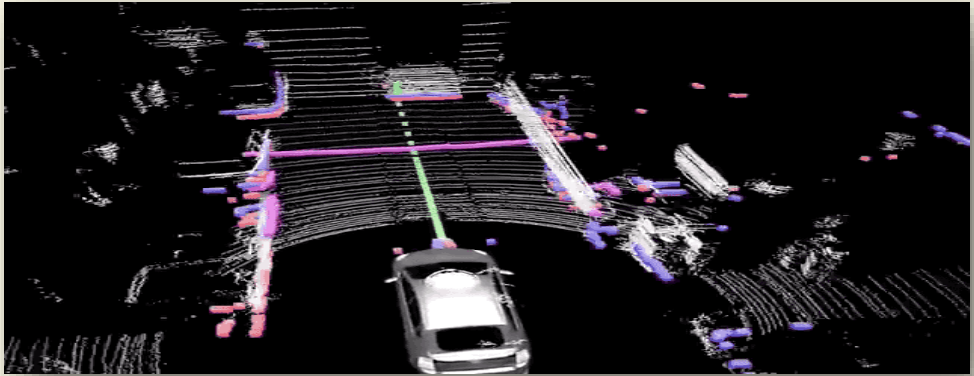
AGU 2025

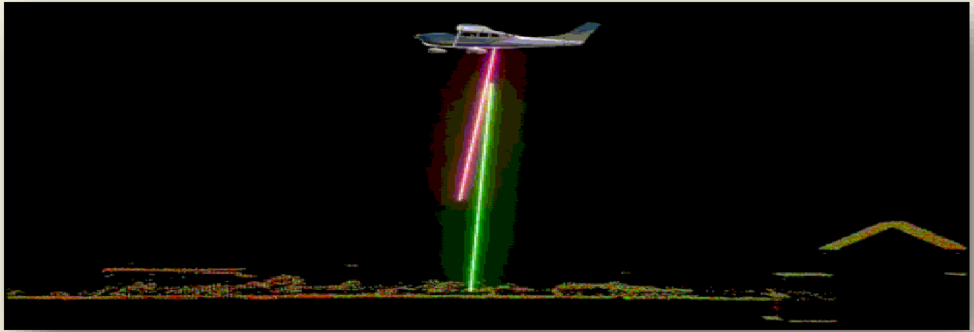


LiDAR Point Cloud





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.

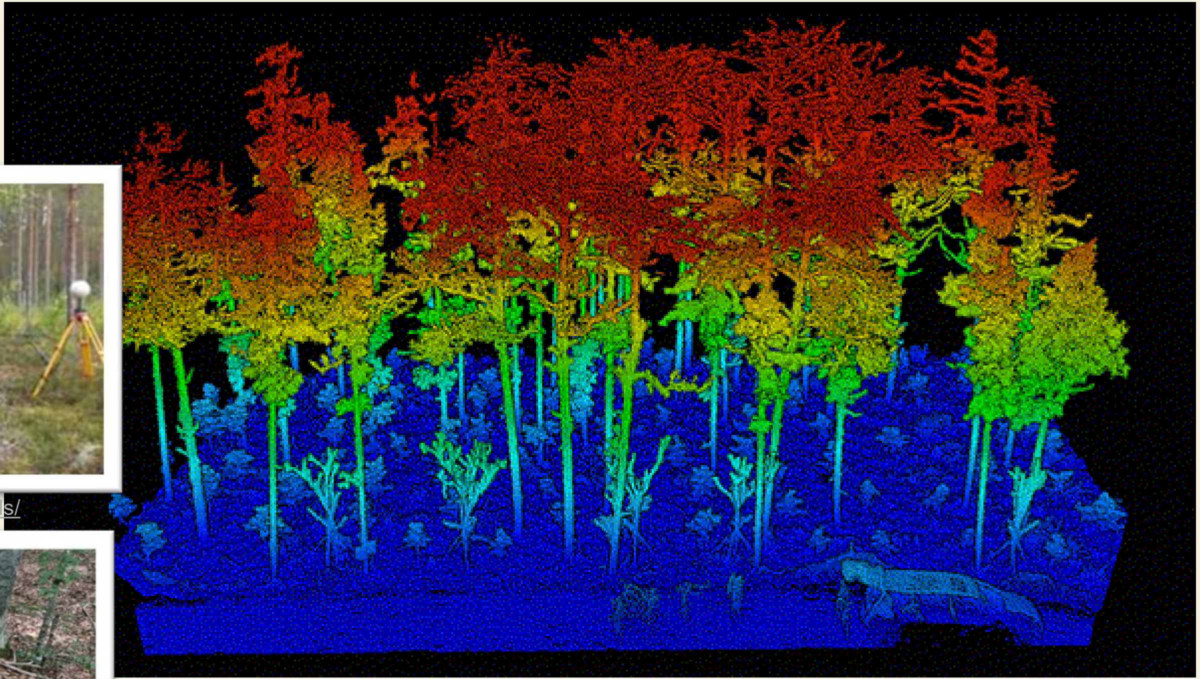
LiDAR Point Cloud for Forests

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/

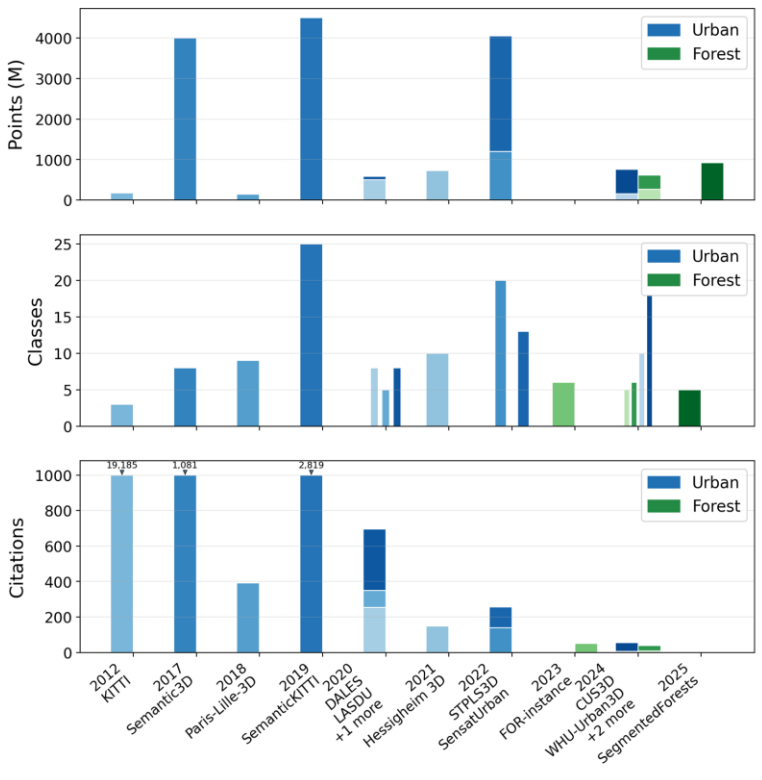


https://candrone.com/blogs/news/lidar360-v8-0-smarter-point-cloud-processing-10?srsltid=AfmBOooYBeqJTRtHtih0EPavLFx9f4-S9brSqhEbrZpTj2dSyvGos-7w

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

Cross-domain learning: Can models trained on urban LiDAR generalize to forests?

The Domain Shift

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

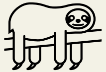
Urban Domain

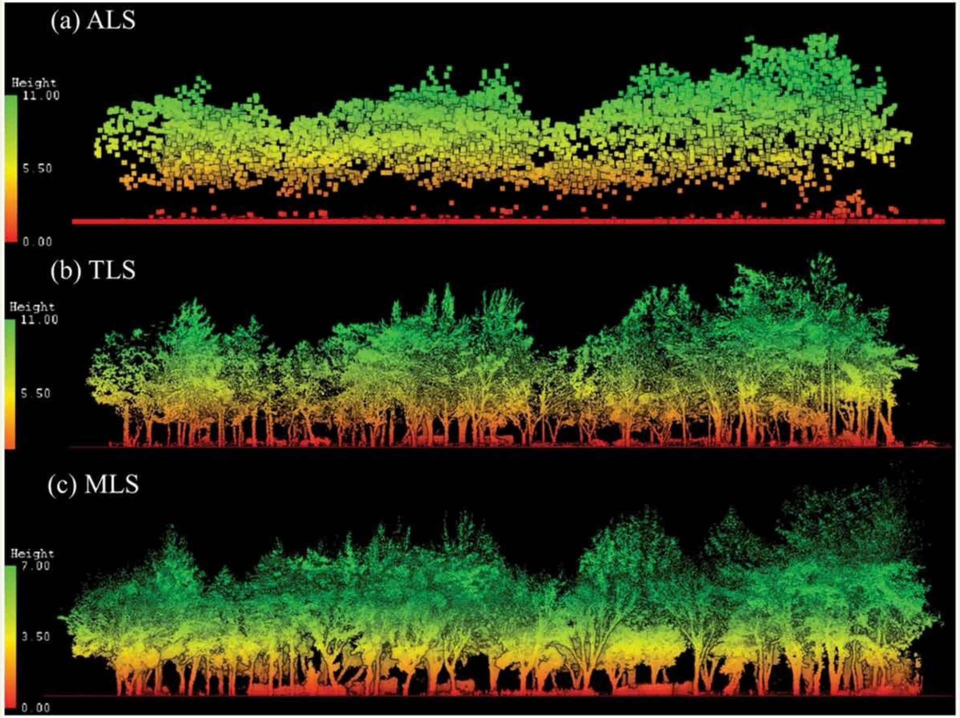
Class distribution shift!

Forest Domain

The Domain Shift

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



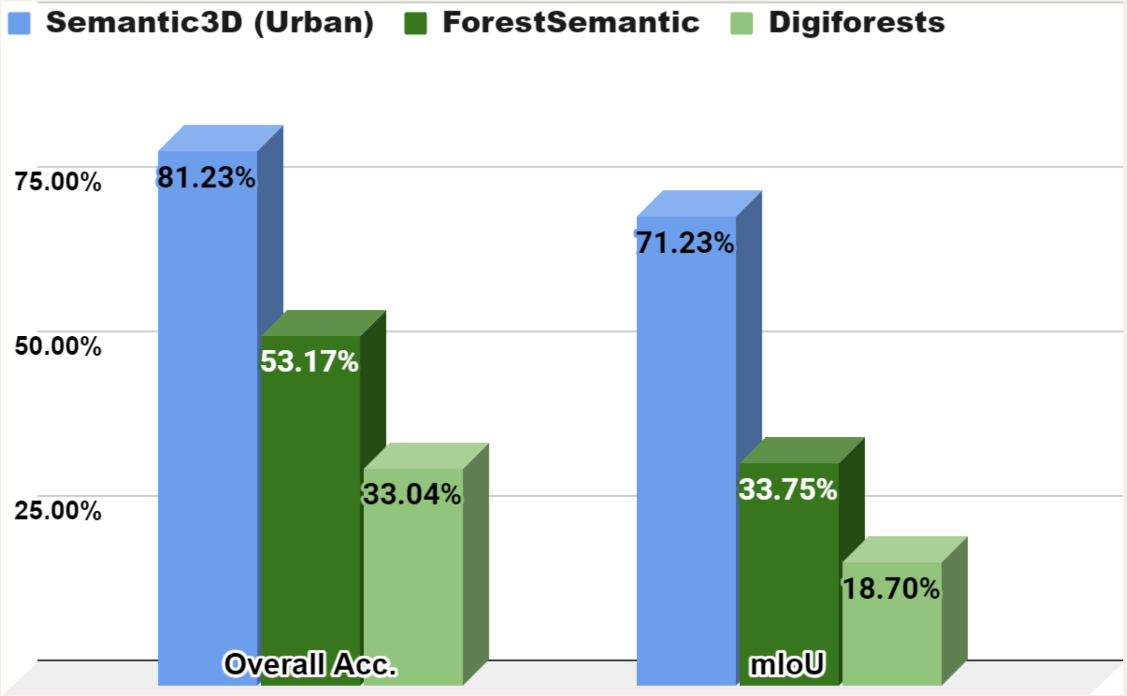


Choi, H., & Song, Y. (2022)

Sensor and platform heterogeneity!

The Domain Shift

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



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

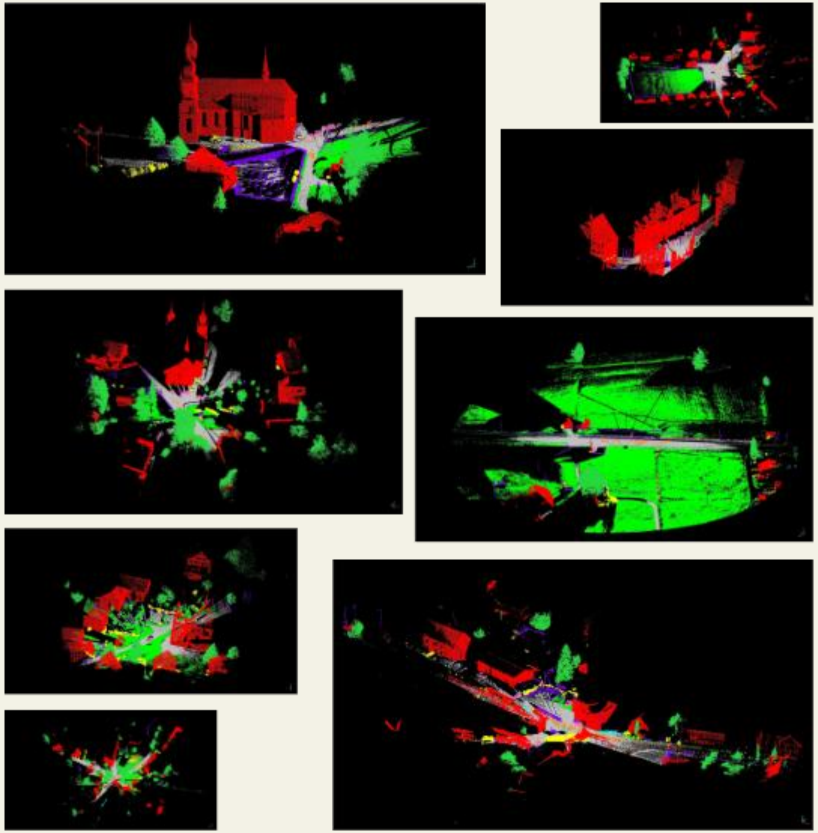
Further train the network to align features from both domains, ensuring the model focuses on invariant structural properties.

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

Hackel, Timo, et al. (2017)

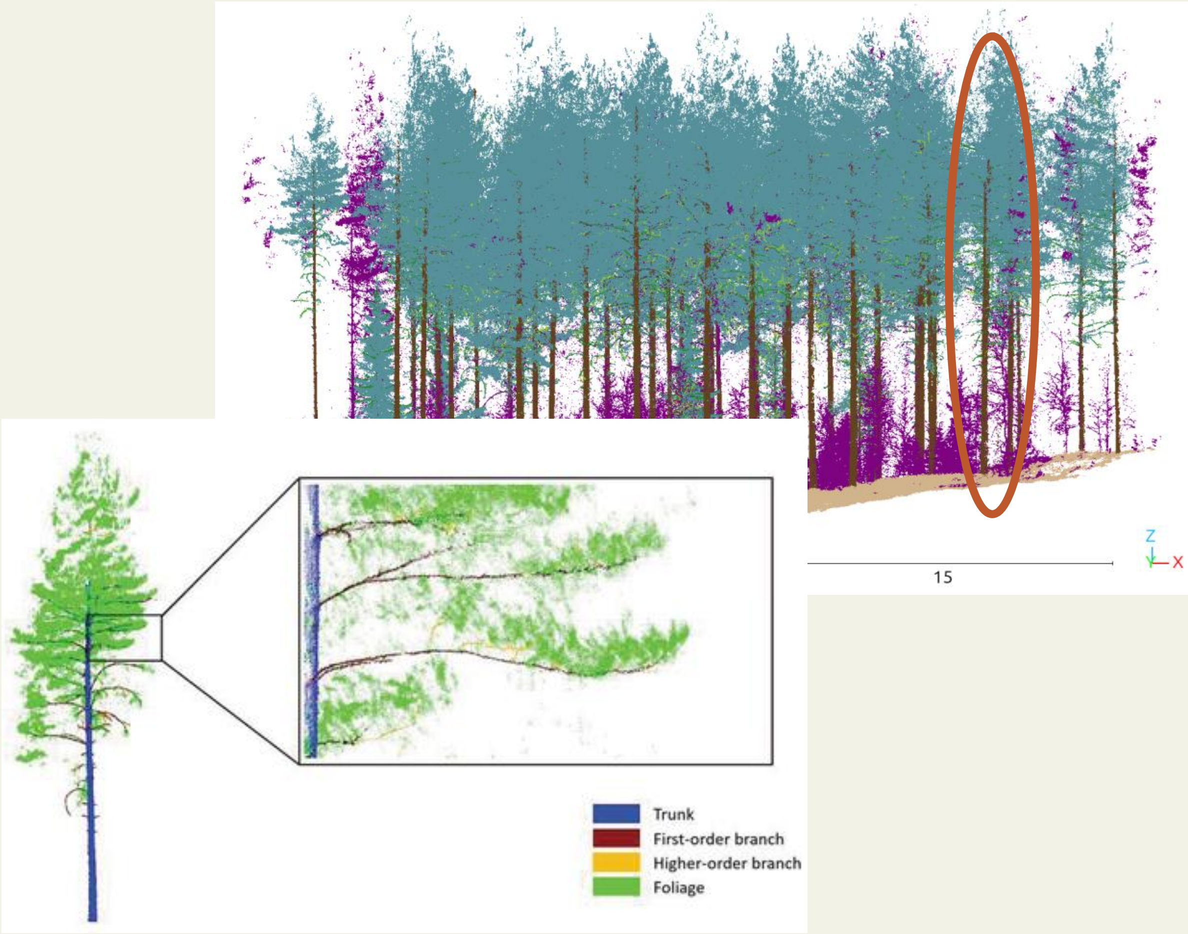


Forest Dataset A

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

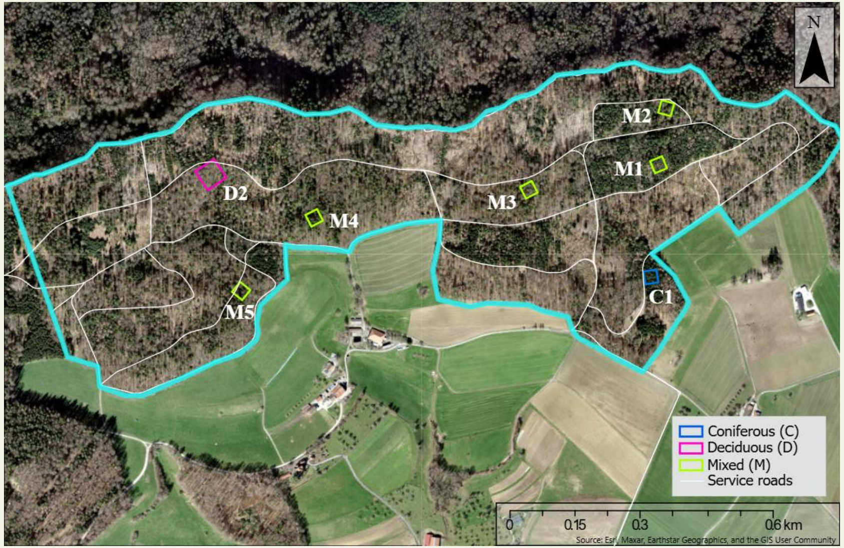
Liang, Xinlian, et al. (2023)



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



Meher V.R. Malladi, et al. (2025)

RandLANet – a SOTA Neural Network Model

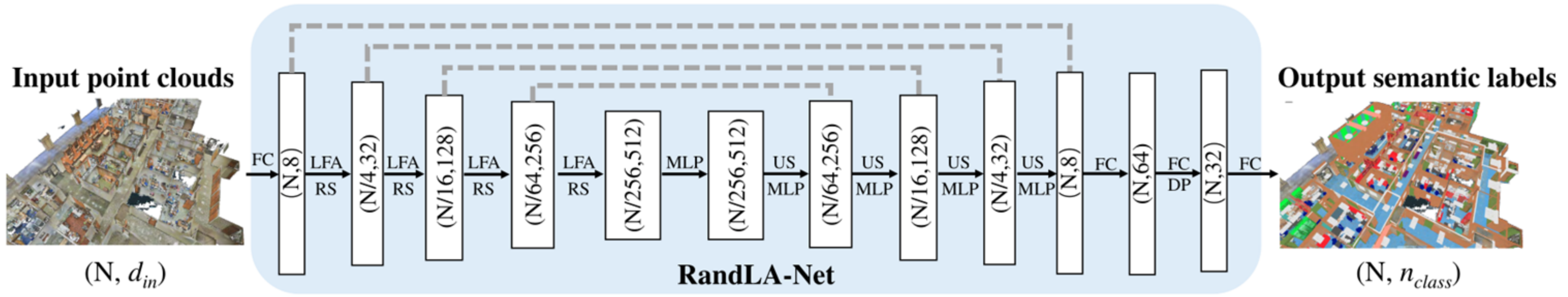
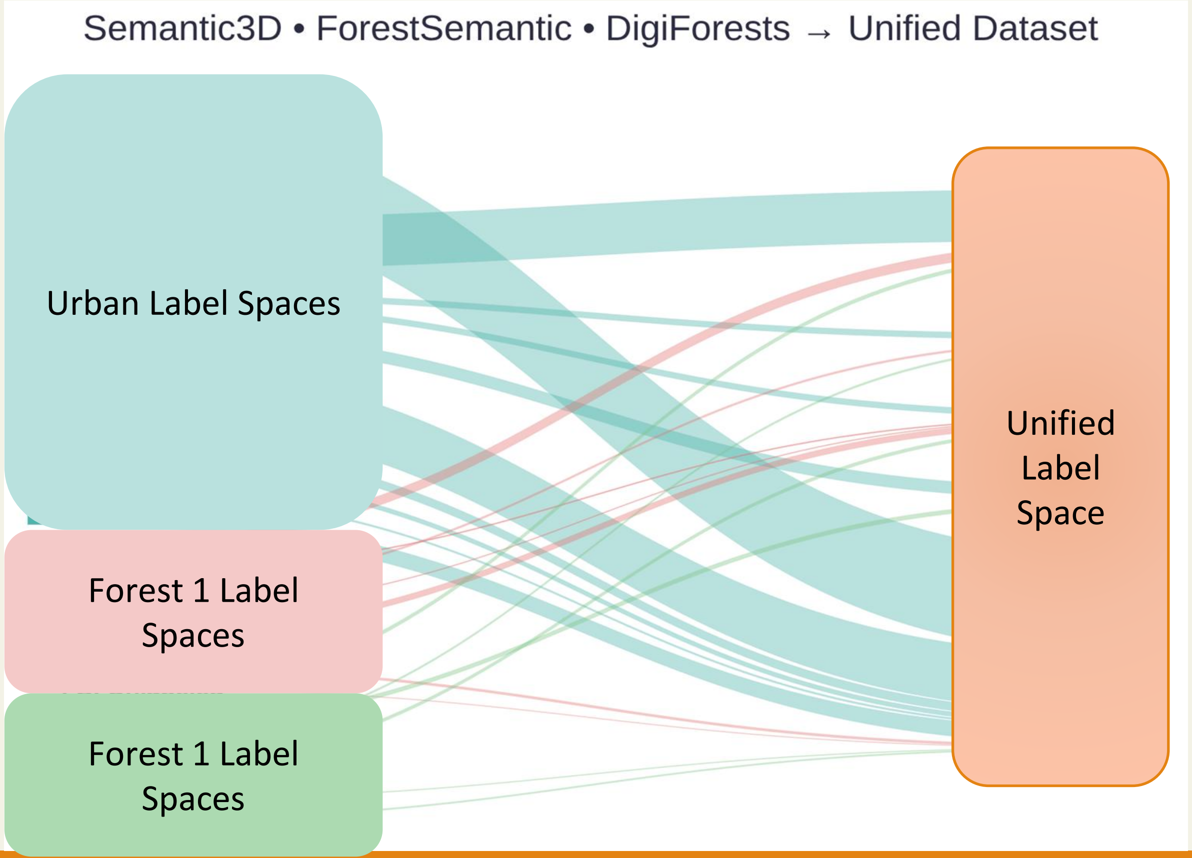


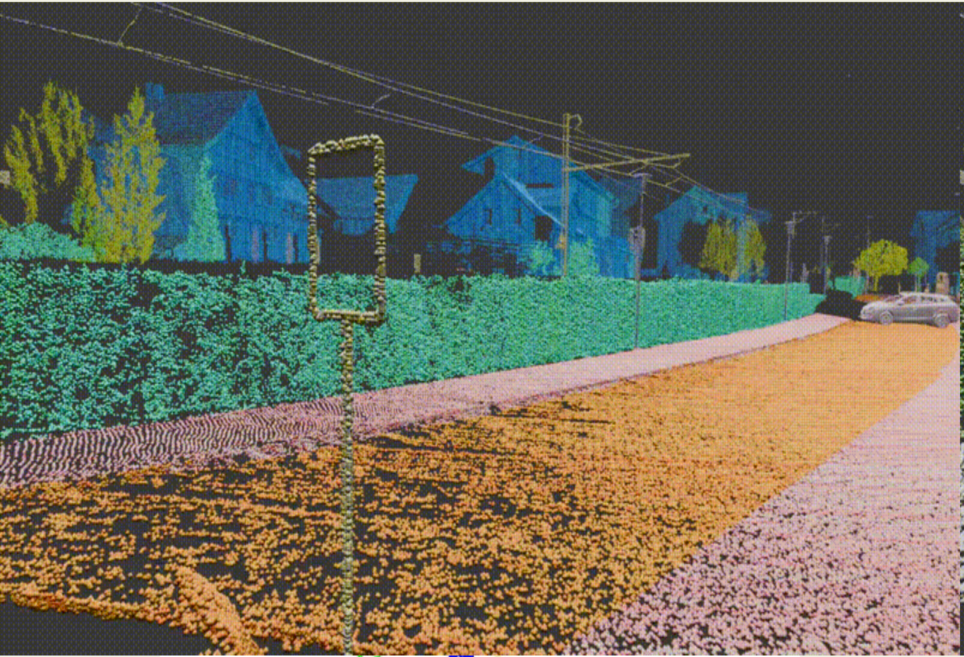
Figure 7. The detailed architecture of our RandLA-Net. (N, D) represents the number of points and feature dimension respectively. FC: Fully Connected layer, LFA: Local Feature Aggregation, RS: Random Sampling, MLP: shared Multi-Layer Perceptron, US: Up-sampling, DP: Dropout.

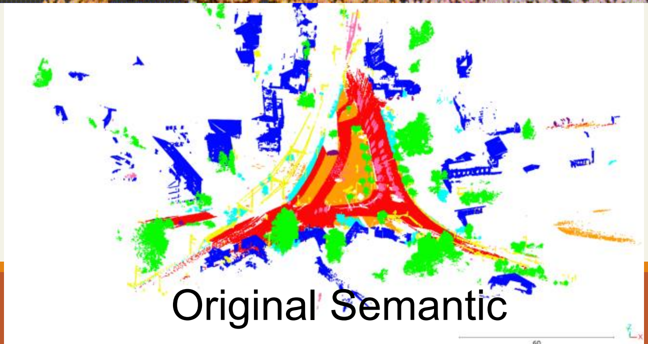
Hu, Qingyong, et al. "Randla-net: Efficient semantic segmentation of large-scale point clouds." *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*. 2020.

Stage 1: Dataset Curation & Label Remap

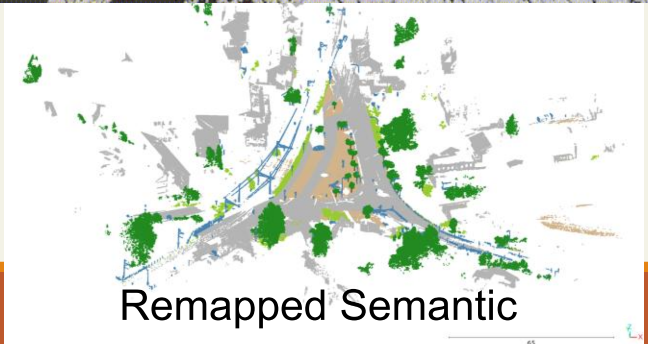


Semantic3D - scan# s27-station5



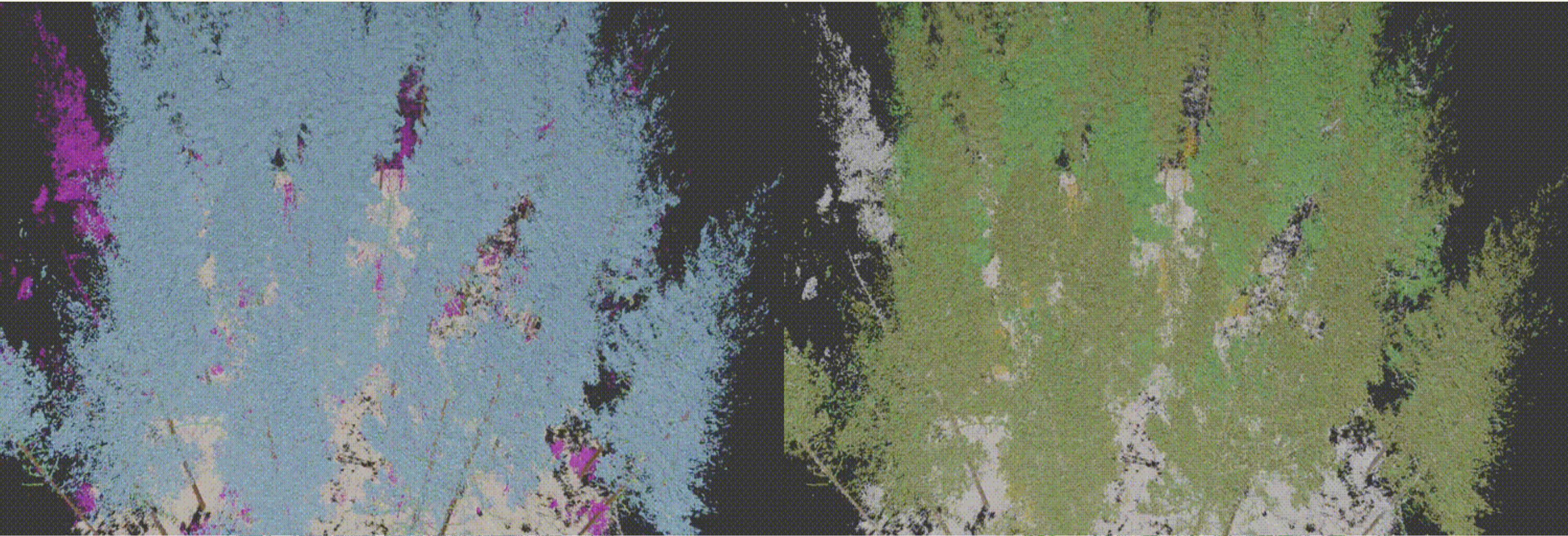


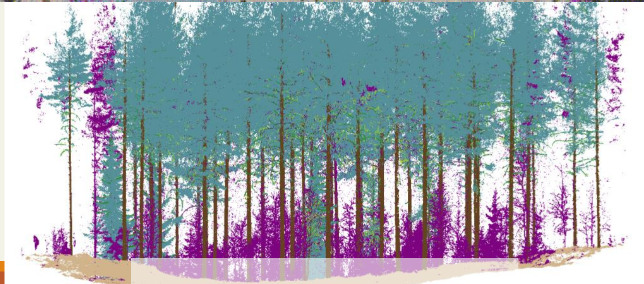
Original Semantic



Remapped Semantic

ForestSemantic - Plot #1

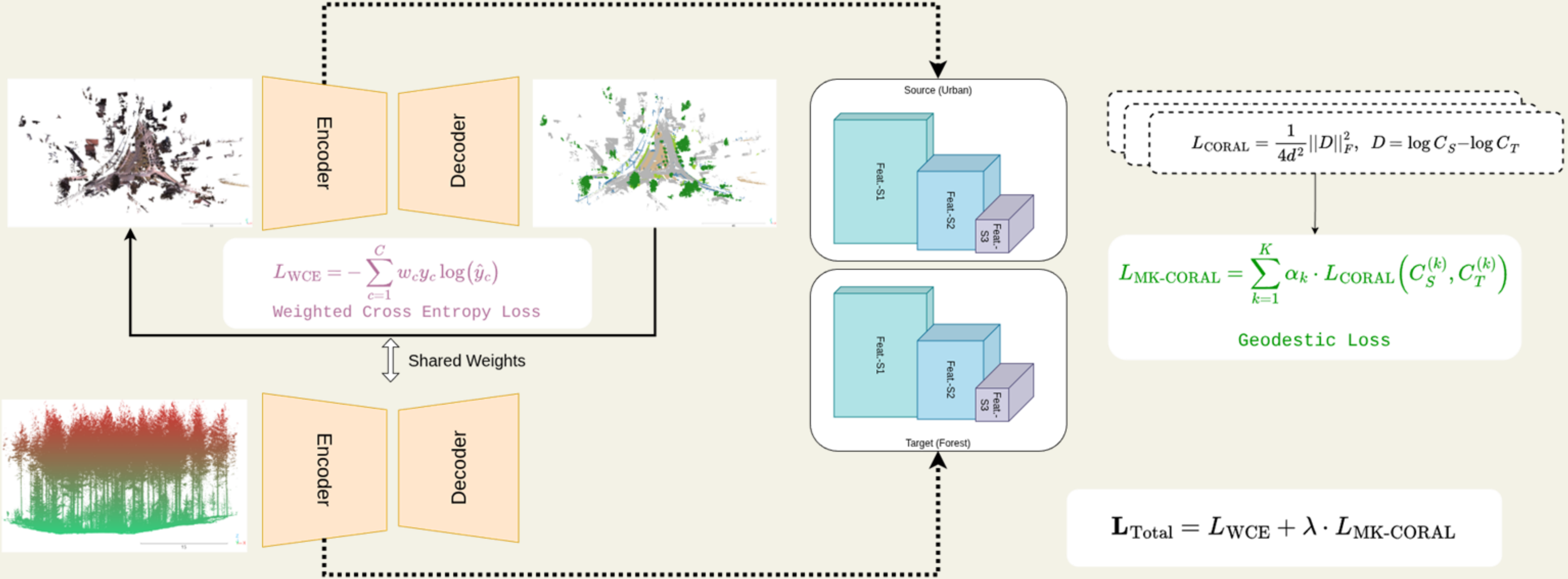




Original Semantic

Remapped Semantic

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**.

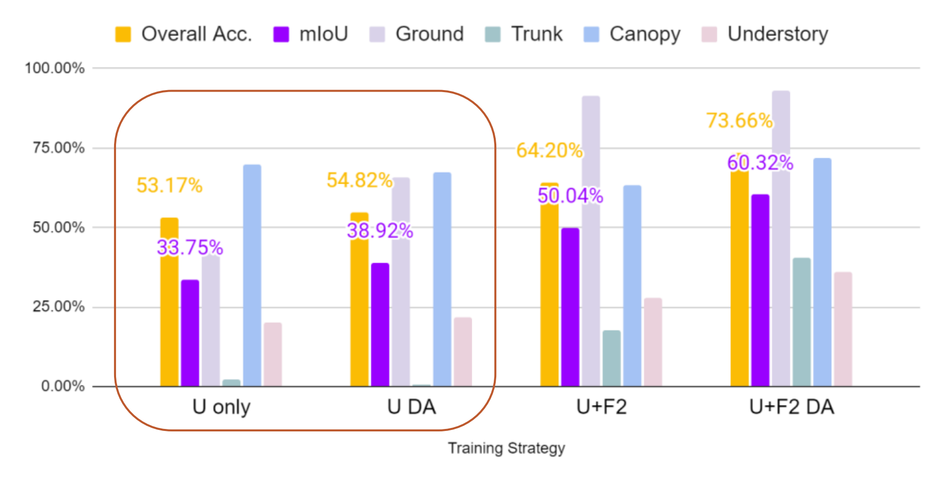
Domain Adaptation (Feature Alignment)
Pretrain on the **source domain**, followed by **feature-alignment training** using both **source and target data**.

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

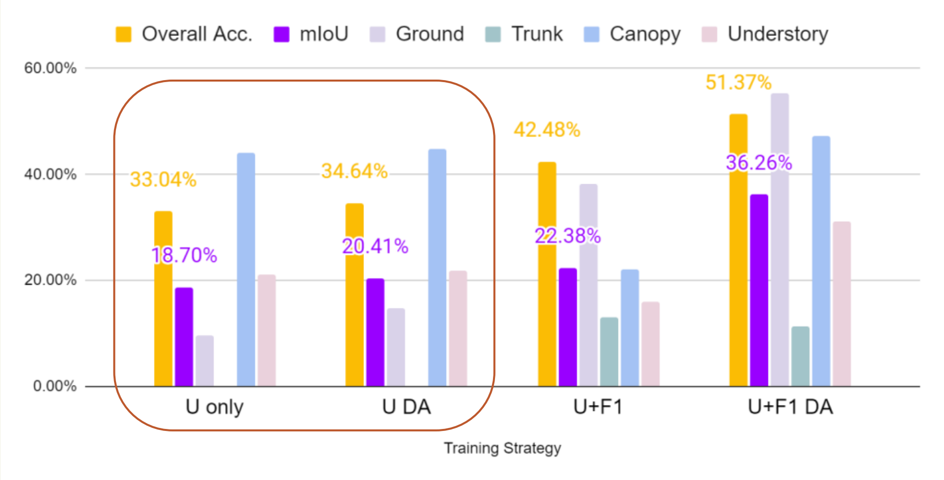
Urban → Forest (F1, F2)	**Urban + F1 → F2**	**Urban + F2 → F1**

Results

Segmentation Performance

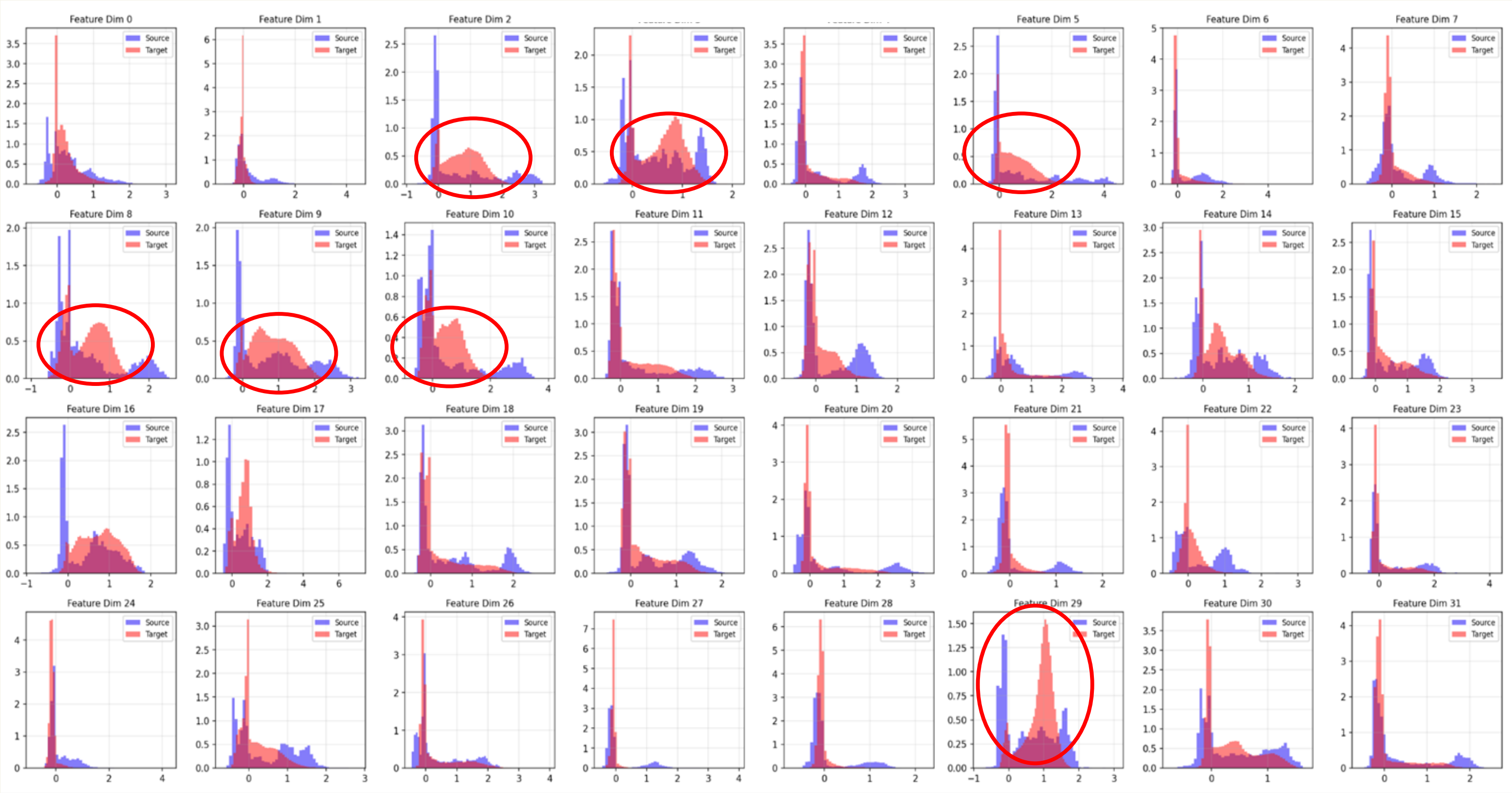


Evaluation on ForestSemantic

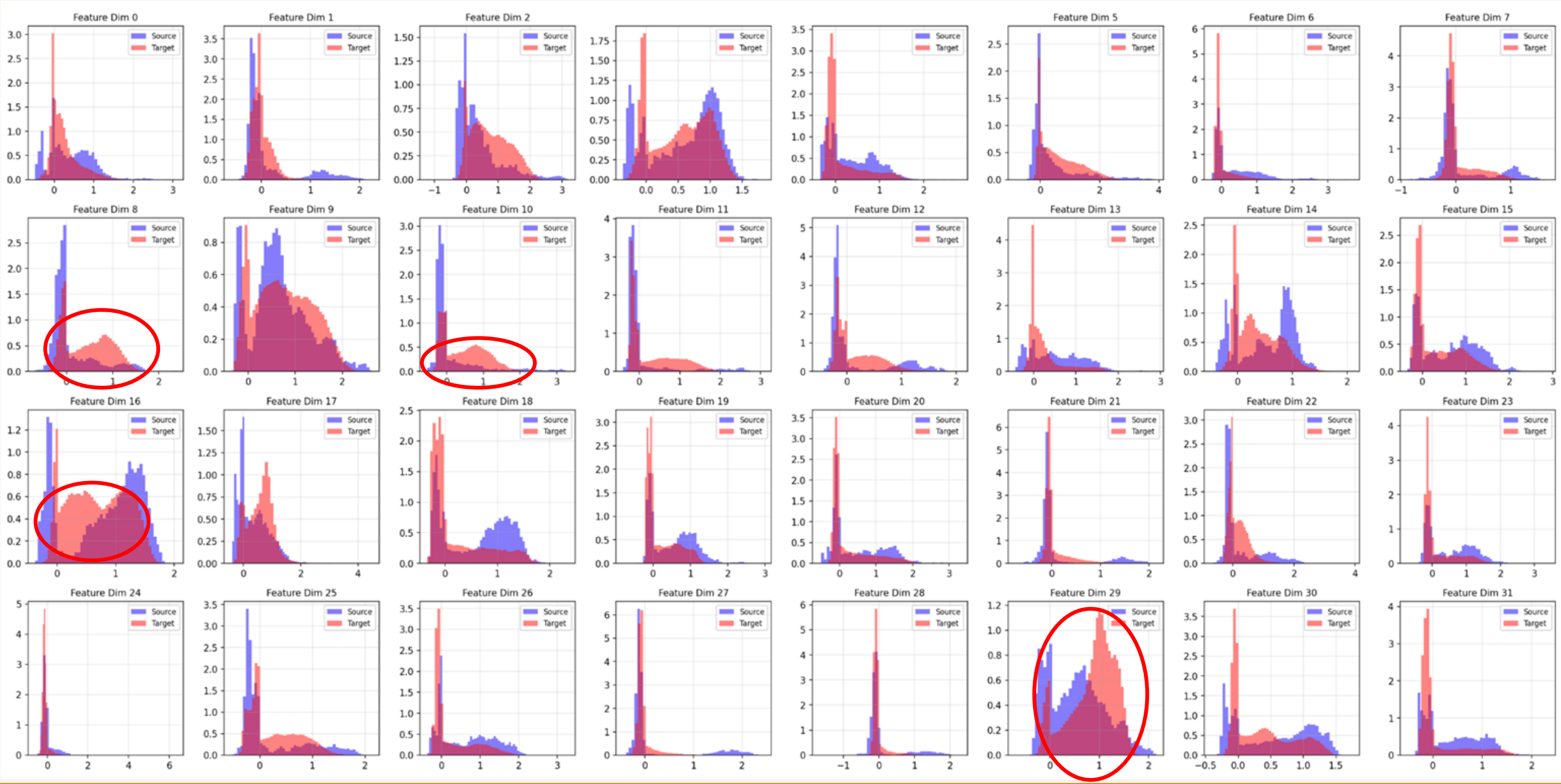


Evaluation on Digiforests

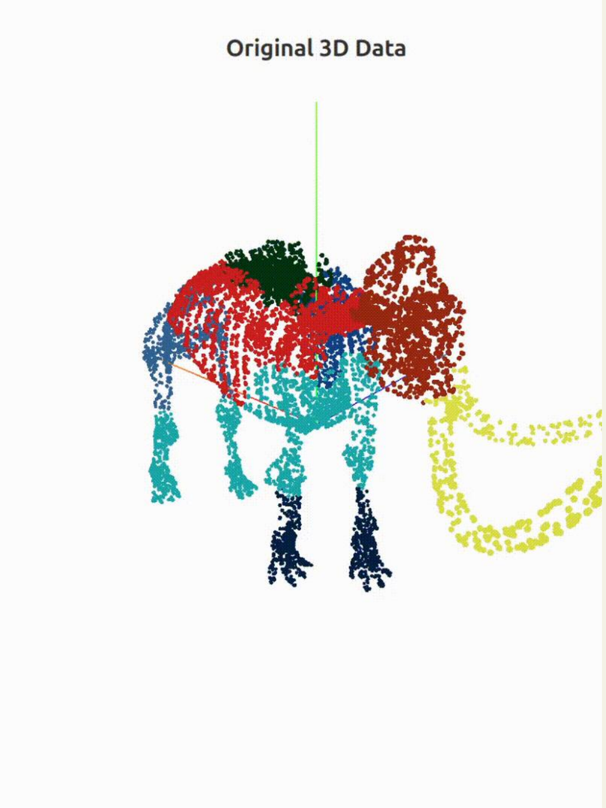
digiforest – before DA – decoder features

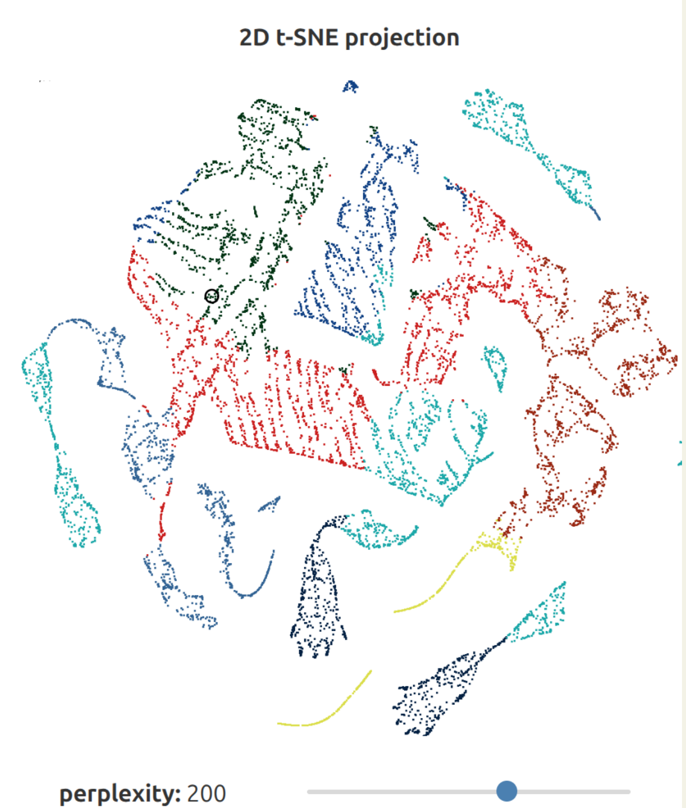


digiforest – after DA – decoder features



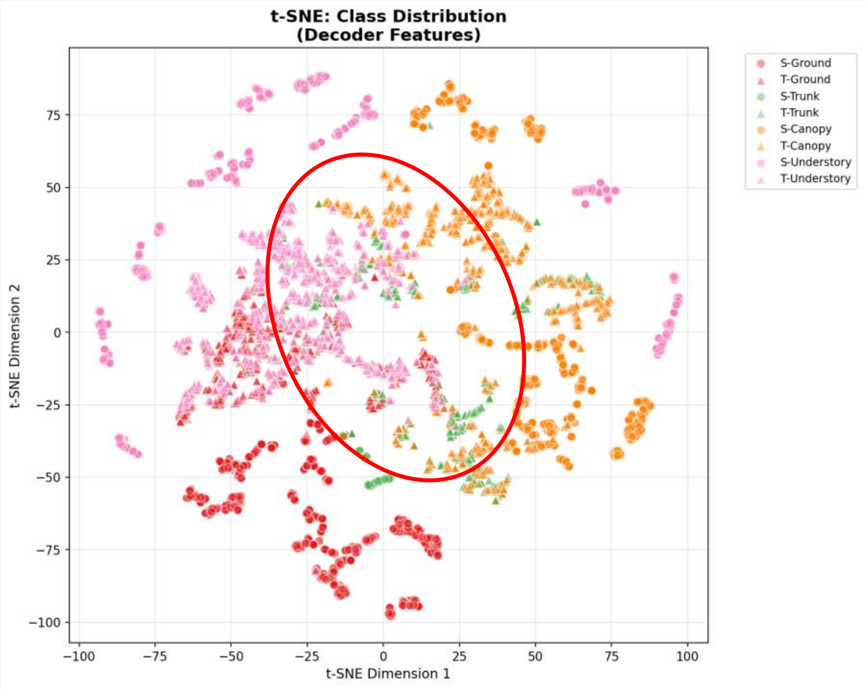
t-SNE

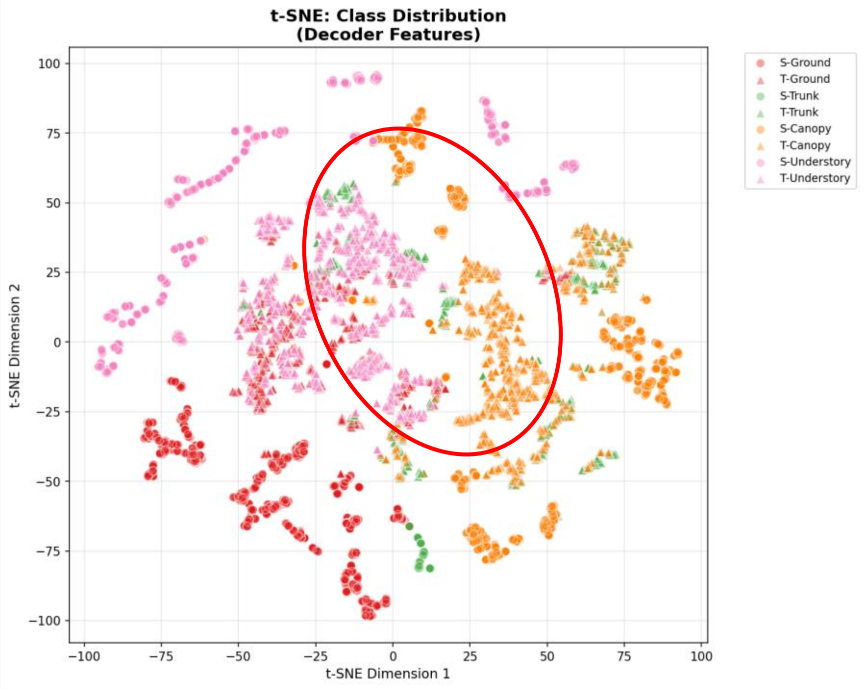




ref: https://pair-code.github.io/understanding-umap/

t-SNE - digiforest – DA before and after





Lessons Learned

If something is irrelevant, make it irrelevant to the model (stage 1).

All datasets and classes matter—but not equally (stage 1&2).

Start from what is accessible, while keeping the big picture in mind (dataset curation).

Key Findings

1. **Urban-only data can initialize the model up to ~50% overall accuracy in forest data**, 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.**

[Stay tuned] The pipeline will be applied to custom datasets in Harvard Forest, Massachusetts.

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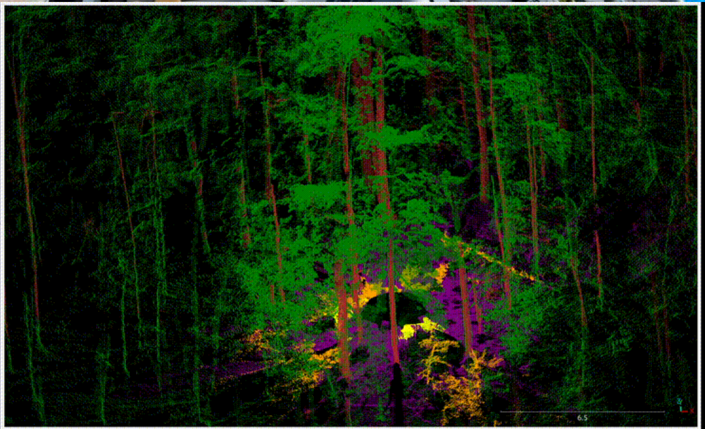


Harvard Forest

Questions?

THANK YOU FOR YOUR ATTENTION.

fzhcis@rit.edu

Scan for more details

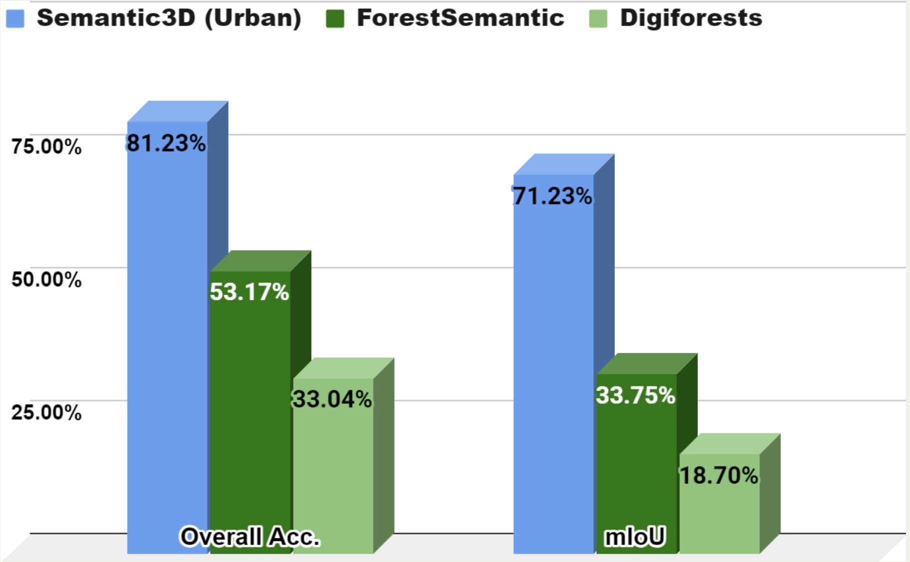
Backup Slides

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%

Stage 1: Dataset Curation & Label Remap

Extract vegetation points from the Urban data.