Urban building extraction and change detection from multi-temporal LiDAR using a deep learning and rule-based method

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Introduction and Questions

Background

Urbanization is happening at an unprecedented pace during the past several decades

Urban changes occurs in complex 3D patterns and optical remote sensing data can hardly capture them

Mapping 3D features of individual buildings in urban environment is difficult

Multi-temporal LiDAR provides an ideal way for delineating individual buildings and capturing 3D patterns of urban change

Questions

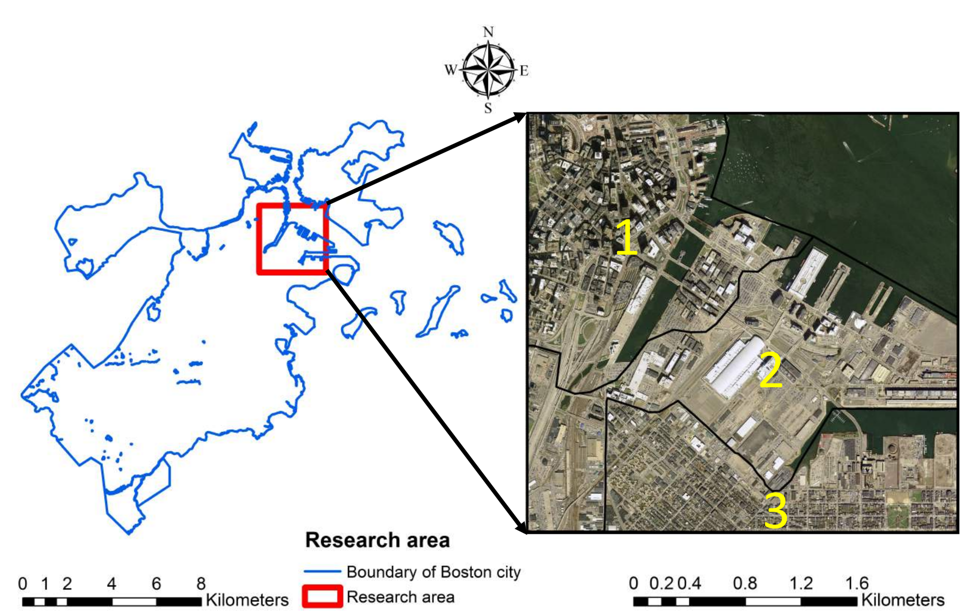
Can we extract individual buildings in 3D using deep learning from multitemporal LiDAR data?

Can we accurately estimate building volumes and overcome the missing of facet points while creating 3D models of individual buildings?

Is it possible to recognize different types of building changes and quantify the changes?

How is the detection accuracy among commercial, residential, and industrial buildings?

Study Site and LiDAR Data



Study area (1: commercial area; 2: industrial area; 3: residential area)

Our study area locates at central east Boston downtown and part of southern Boston

This area has an active records of urban changes from 2002 to 2014

The 2002 LiDAR dataset used in this research was collected by 3Di Technologies, Inc. (Now Spectrum Mapping LLC) and provided by Massachusetts Executive Office of Technology Services and Security.

The 2014 LiDAR dataset used in this research was collected by the New England CMGP Lidar Processing project for the United States Geological Survey (USGS) and provided by NOAA

Both of the datasets in 2002 and 2014 are small footprint, discrete return LiDAR

The average point density of both 2002 and 2014 datasets is 3 pts/m²

Methods

A point-based deep learning framework is developed and used for the classification of building and non-building points by integrating PointSIFT algorithm and a patch-based voting strategy

Point-based features including surface normal, curvature, and coefficient variance are estimated for each individual point within its neighborhood

A 3D Euclidean clustering method is used for delineating individual buildings and generating building footprints

Facet points of building are vertically compensated in order to overcome the shadow issues from LiDAR

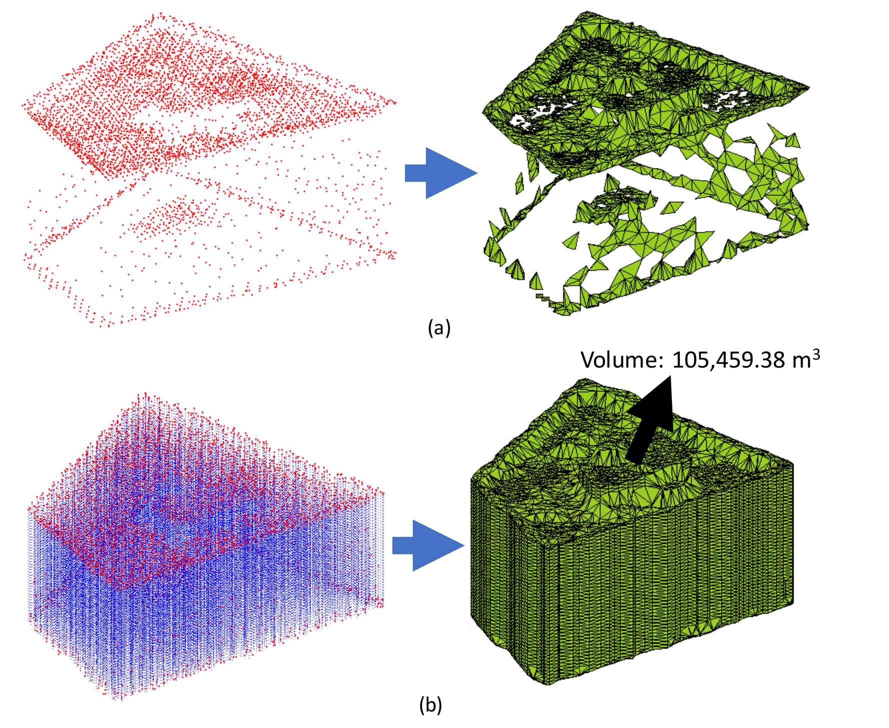
A 3D Alpha shape (concave hulls) is estimated for each individual building and the building volume is estimated based on it

Four types of changes (building demolition, new construction, reduction, and expansion) are identified by comparing volume and footprint changes for each individual building from 2002 to 2014

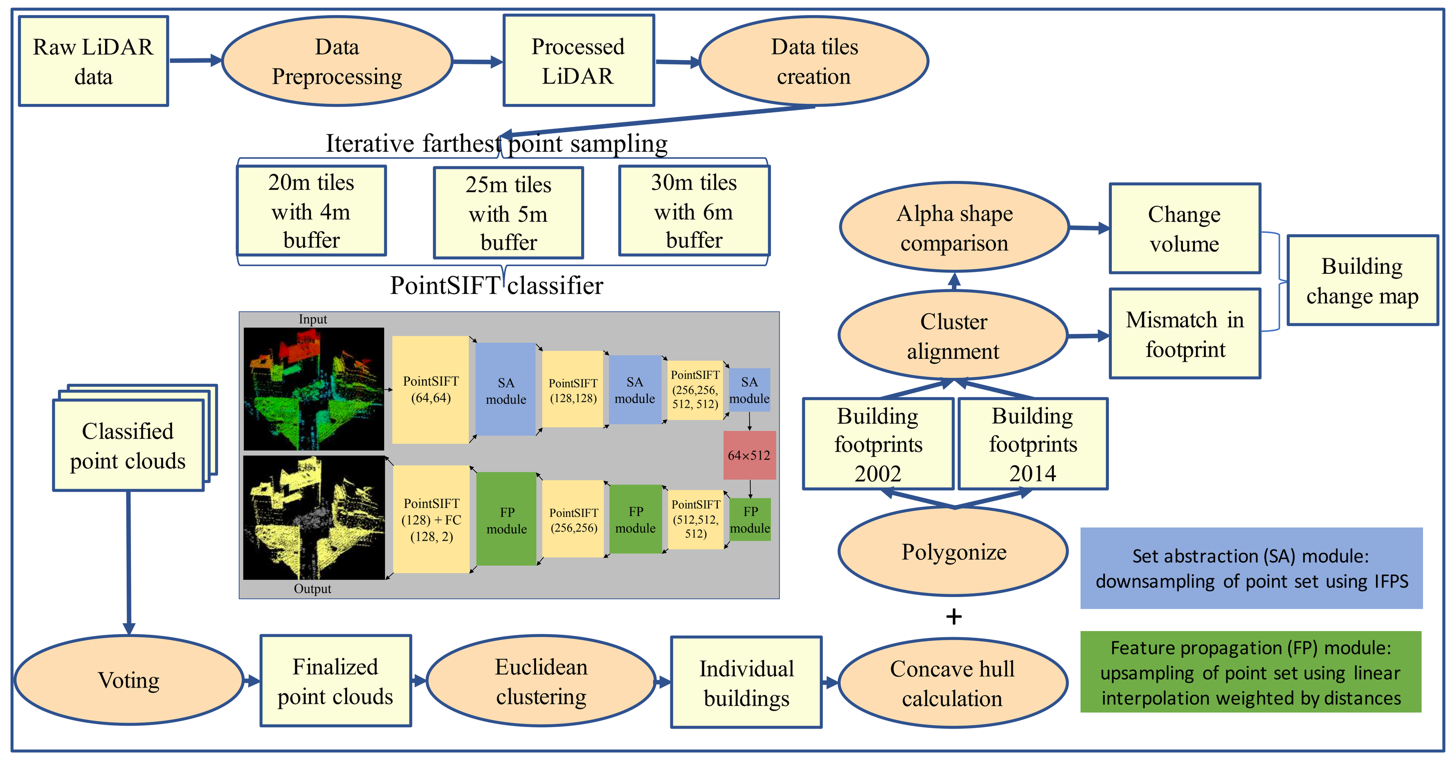
$$Covariance = \frac{1}{n}\sum_{i=1}^{n} \cdot (P_i - \overline{P}) \cdot (P_i - \overline{P})^T, \; C \cdot \overline{V_j} = \lambda_j \cdot \overline{V_j}, \; j \in \{0,1,2\}$$

$$Curvature = \frac{\lambda_0}{\lambda_0 + \lambda_1 + \lambda_2}$$

where *n* is the number of point neighbors considered in the neighborhood of Pi, P represents the 3D centroid of the nearest neighbors, jis the j-th eigenvalue of the covariance matrix, and Vj is the j-th eigenvector. 0,1,2 are the three eigenvalues of the covariance matrix.

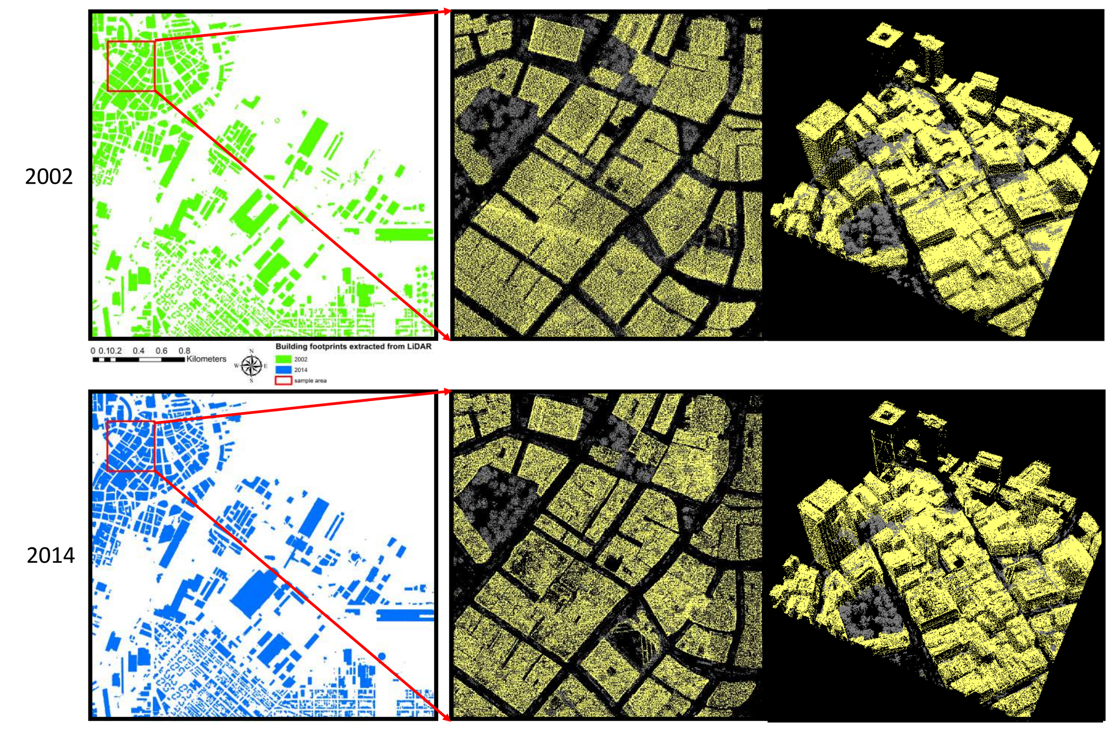


The generation of 3D alpha shape of a building (a: the model generated from original points; b: the model generated from vertically compensated points)

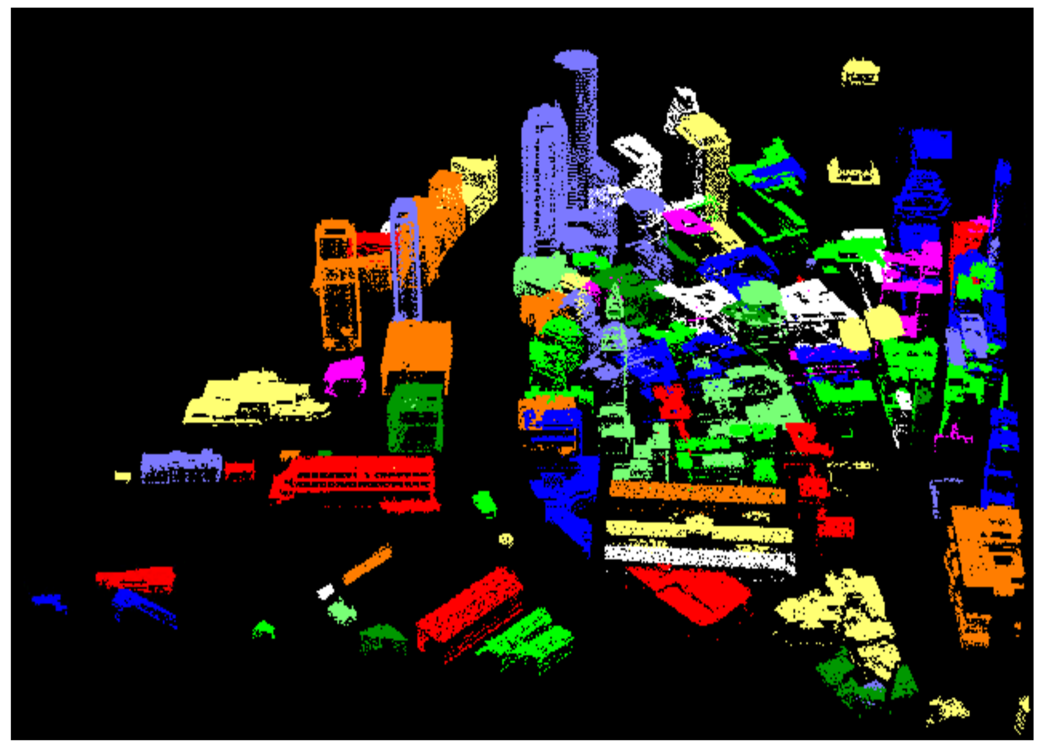


Flowchart of the proposed method for individual building classification and change detection

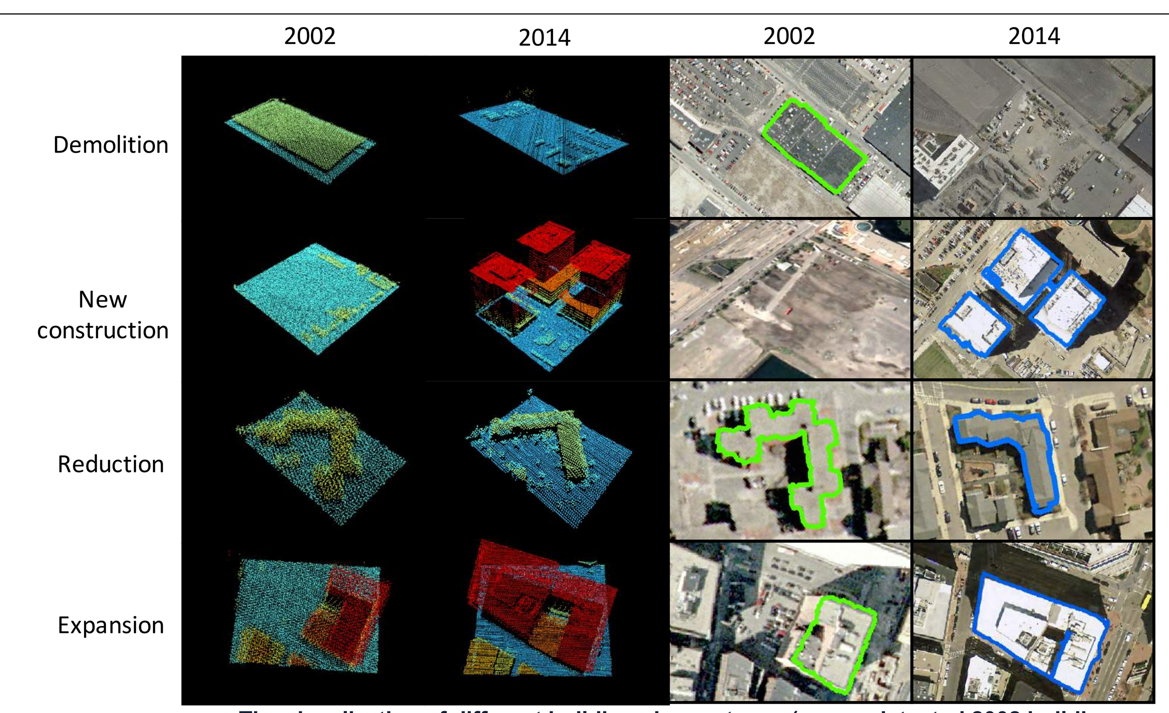
Results



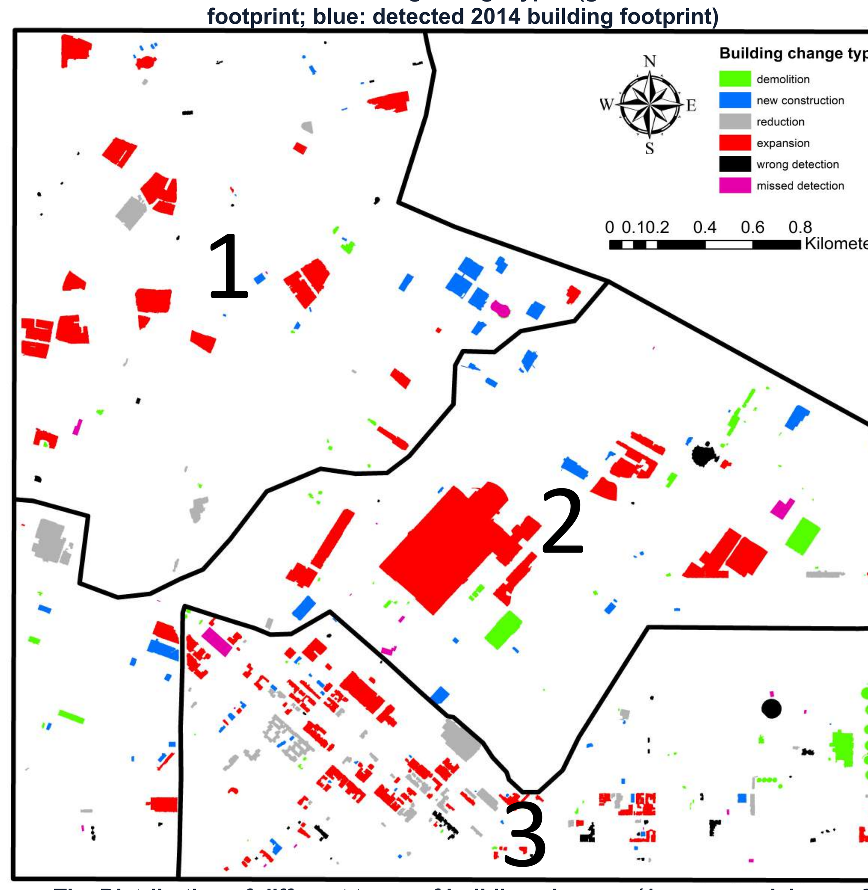
The Extracted building points using patch-based PointSIFT method



A 3D Visualization of extracted individual building points



The visualization of different building change types (green: detected 2002 building footprint; blue: detected 2014 building footprint)



The Distribution of different types of building changes (1: commercial area; 2: industrial area; 3: residential area)

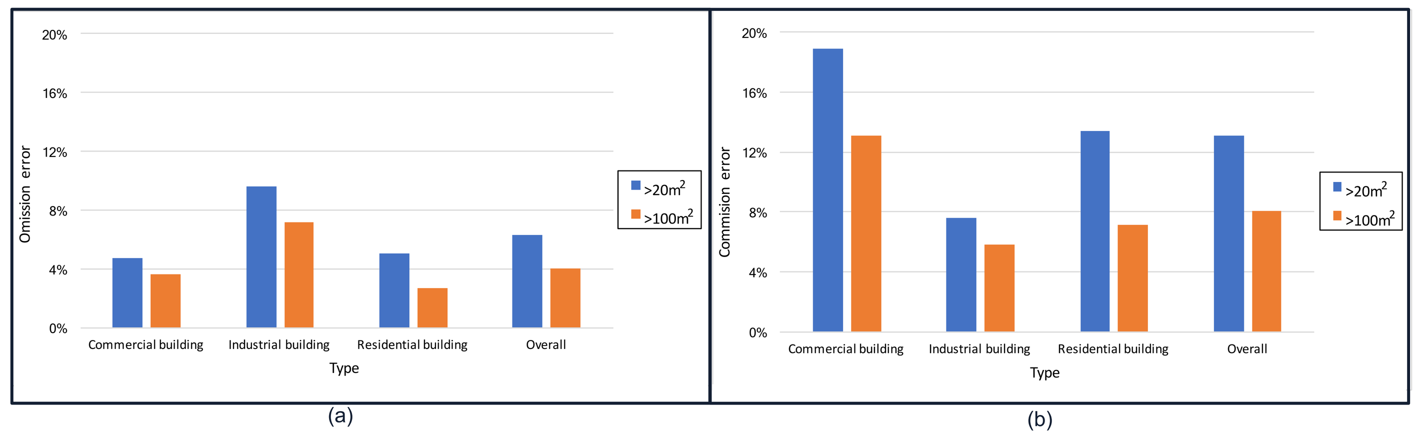
Accuracy assessment

Year	Type	Commercial building	Industrial building	Residential building	Overall accuracy
2002	Precision	98.01%	100.00%	98.52%	98.64%
	Recall	96.47%	90.86%	89.81%	91.79%
	F1 Score	97.23%	95.21%	93.96%	95.09%
2014	Precision	0.9921875	0.99382716	0.994475138	0.993756504
	Recall	0.954887218	0.899441341	0.955752212	0.945544554
	F1 Score	0.973180077	0.944281525	0.974729242	0.969051243

Note:
>20m²: buildings with footprint larger than 20m²
>100m²: buildings with footprint larger than 100m²

Footprint Area (m2)	Type	Commercial building	Industrial building	Residential building	Overall
>20m2	Precision	81.08%	92.39%	86.60%	86.94%
	Recall	95.24%	90.43%	94.92%	93.71%
	F1 score	87.59%	91.40%	90.57%	90.20%
>100m2	Precision	86.89%	94.20%	92.90%	91.93%
	Recall	96.36%	92.86%	97.30%	95.97%
	F1 score	91.38%	93.53%	95.05%	93.91%

Accuracy assessment of building change detection



Omission and commission errors of detected changes with different building types: (a) omission error; (b) commission error

The algorithm performs well in individual building extraction with an average F1 score 0f ~95% between the two time periods

Buildings with larger footprints tends to have a higher change detection accuracy (+3.71% in F1 score) compared to buildings with smaller footprints

The industrial building has the largest omission error and most of the errors are from small fabricated houses at construction sites

The commercial building has the largest commission error and most of the error cases are small and irregularly shaped buildings in the downtown area

Conclusions

The proposed deep learning method performs well in extracting individual buildings and capturing different types of building changes in urban environment

The proposed model is fully automatic which eliminates the computationally intensive point registration process in previous methods

The training data needs to be further refined to include more types of small buildings in both downtown and industrial area

The model needs to be tested at other locations and is expected to be more effective on LiDAR data with higher point density

Acknowledgments

Data provider:

Massachusetts Executive Office of Technology Services and Security

National Oceanic and Atmospheric Administration

Funding provider:

National Science Foundation (OAC-1443080 and OAC-1743184)

US Geological Survey (CESU Grant #G14AC00244)

Reference

Jiang, Mingyang, Yiran Wu, and Cewu Lu. "PointSIFT: A SIFT-like Network Module for 3D Point Cloud Semantic Segmentation." arXiv preprint arXiv:1807.00652 (2018).

Xu, Zewei, et al. "A 3D convolutional neural network method for land cover classification using LiDAR and multi-temporal Landsat imagery." *ISPRS journal of photogrammetry and remote sensing* 144 (2018): 423-434.