Estimating building heights from footprints and coarse-scale height data

Brandon Knutson[1], Clinton Stipek[2], Taylor Hauser[2], Robert Stewart[2]
[1]Colorado School of Mines, Golden, CO, [2]Oak Ridge National Laboratory, Oak Ridge, TN

COLORADO SCHOOL OF MINES

OAK RIDGE National Laboratory

OAK RIDGE INSTITUTE FOR SCIENCE AND EDUCATION
Shaping the Future of Science

INTRODUCTION

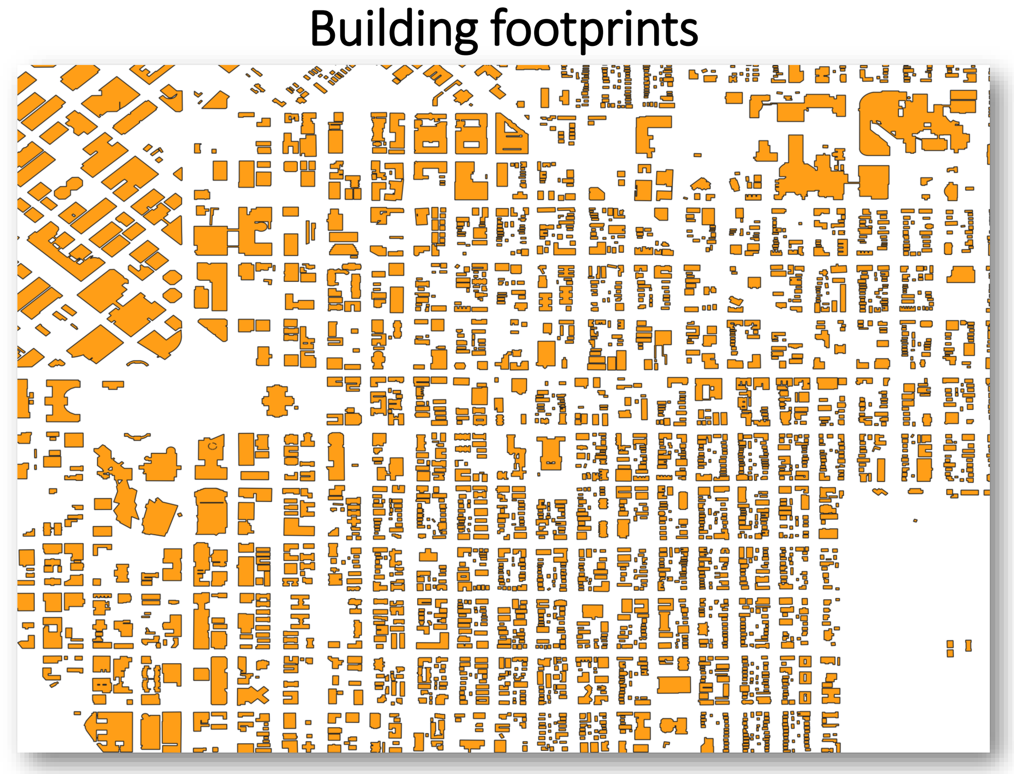
- **Building height estimates are valuable** inputs to a variety of important scientific models including fine-scale maps of population, measures of stability in earthquakes, and climate change risks such as flooding.
- **Building footprints are highly predictive of height** [1]. LiDAR directly measures both footprints and height but is expensive. Satellite imagery is cheaper and globally available. Footprints extracted from imagery allow footprint feature calculation (area, perimeter, etc.), providing a means to estimate individual building height at scale.
- **Objective:** Can coarse-scale measures of height further improve prediction over planar footprint features alone? We build a ML workflow to test impact of adding coarser-than building level 100m resolution height data to planar footprint features. We test the workflow and assess the results for buildings in Colorado.
- **Impact**: Accurate building heights enable scaling efficacy and increase realism in built environment models.

DATA

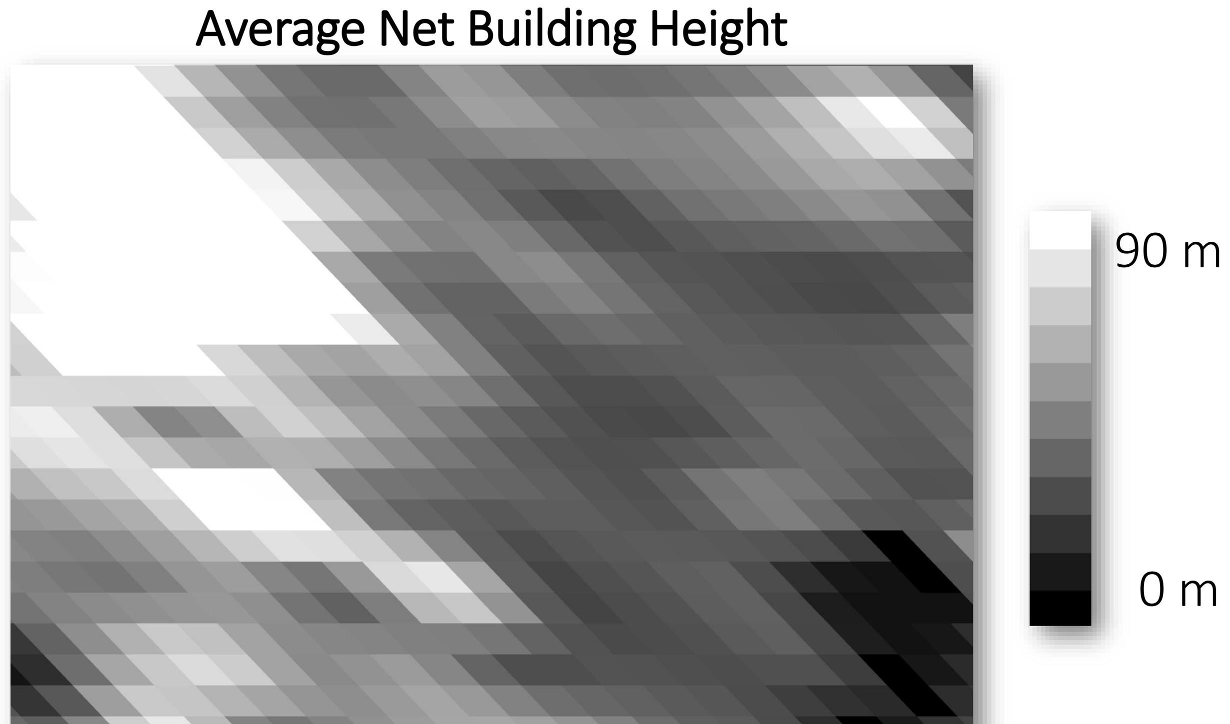
- **LiDAR:** LiDAR data from 133 U.S. cities was used to identify building footprints and heights, which then served as model training data
- **GAUNTLET:** ORNL's GAUNTLET tool computed 65 features from the LiDAR-based footprints for more than 31.7M buildings (figure below)
- **GHSL:** 100-meter Average Net Building Height (ANBH) from the GHSL project [2] provided local average height

Satellite imagery

Building footprints



Average Net Building Height



GAUNTLET features

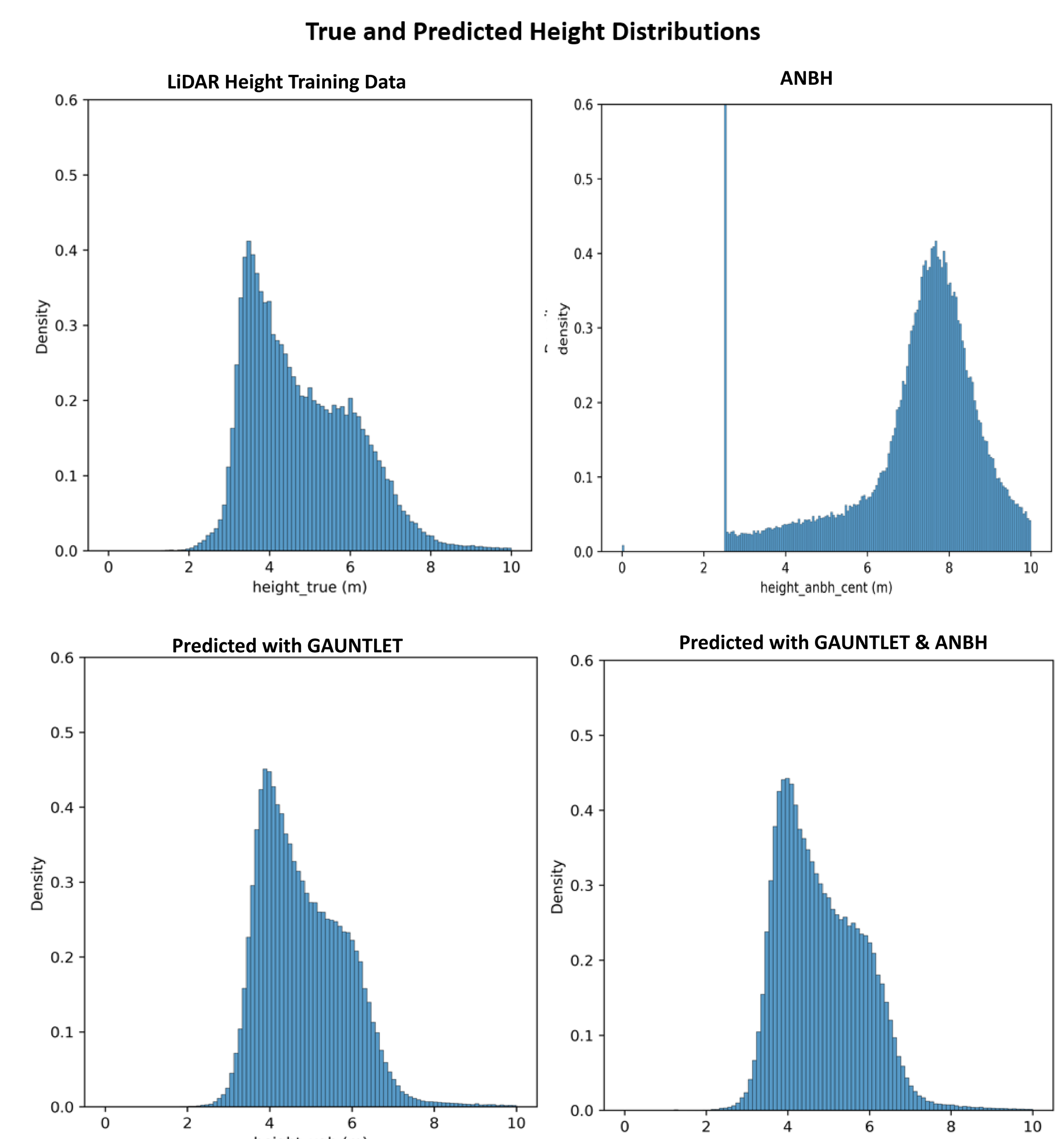
footprint area
footprint perimeter
of vertices
vertices per area
of buildings within 50 meters
of buildings within 250 meters
of buildings within 1,000 meters
nearest neighbor index within 50 meters
nearest neighbor index within 250 meters
nearest neighbor index within 1,000 meters
… (55 other features)

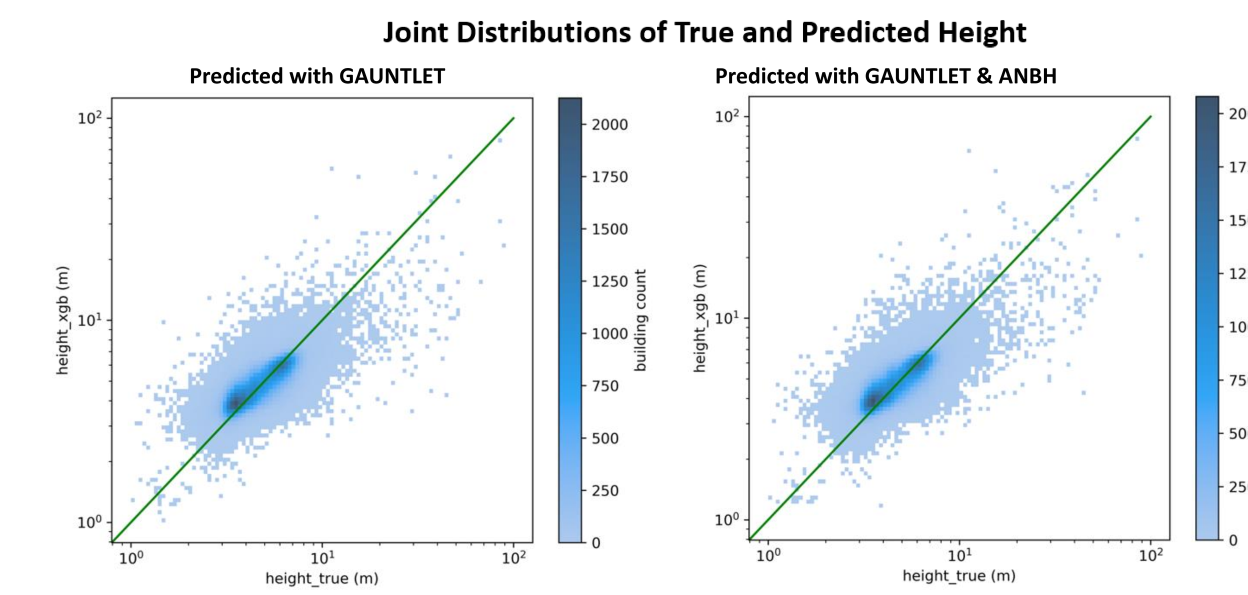
Building height predictions

METHOD

- XGBoost [3] was used to predict building heights in Colorado with and without the addition of ANBH data. Colorado is a good choice for a case study because it has a diverse building population, spanning rural to suburban to urban environments.
- The training (80%) and testing (20%) dataset consisted of 898k buildings with LiDAR-based footprints and building heights. First, we trained a model with footprint-based features as the inputs: area, perimeter, building density, and so on. Second, we trained the same model but with ANBH as an input as well to see if accuracy would increase.
- Note that our approach was restricted to regions where highly accurate LiDAR-data exists so that pristine footprints and true heights are available. This allowed a proof of concept under ideal conditions, but future work will examine how estimates may be diminished by less accurate satellite-derived footprints.

RESULTS





	GAUNTLET	GAUNTLET & ANBH
MAE (m)	0.698	0.695
RMSE (m)	1.134	1.128
R^2	0.528	0.533

CONCLUSION

- Adding ANBH as an input resulted in a negligible increase in performance according to all three metrics: MAE, RMSE, and R^2. **We conclude that the ANBH average height does not significantly improve building height prediction accuracy, even for tall buildings.** This means that there is unlikely to be height information present in the coarse-scale ANBH data that is unattainable from the fine-scale footprint-based features identified in [1].
- Interestingly, XGBoost feature importance for ANBH was 4th highest, after minimum building height within 100 meters (1st), complexity ratio (2nd), and footprint area (3rd). This means ANBH contains more height information than most footprint-base features but does not have significant height information beyond top performing planar features. Future work could include other predictive features visible in satellite imagery, such as road networks [1], or use a neural network instead of XGBoost.

ACKNOWLEDGEMENTS

This research was supported in part by an appointment to the Oak Ridge National Laboratory Graduate Research Student Internship, sponsored by the U.S. Department of Energy and administered by the Oak Ridge Institute for Science and Education. Special thanks to Justin Epting.

REFERENCES

[1] N. Milojevic-Dupont *et al.*, "Learning from urban form to predict building heights," *PLoS ONE*, vol. 15, no. 12, p. e0242010, Dec. 2020, doi:10.1371/journal.pone.0242010.
[2] M. Pesaresi, C. Corbane, C. Ren, and N. Edward, "Generalized Vertical Components of built-up areas from global Digital Elevation Models by multi-scale linear regression modelling," PLoS ONE, vol. 16, no. 2, p. e0244478, Feb. 2021, doi: 10.1371/journal.pone.0244478.
[3] T. Chen and C. Guestrin, "XGBoost: A Scalable Tree Boosting System," in Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, San Francisco California USA: ACM, Aug. 2016, pp. 785–794. doi: 10.1145/2939672.2939785.