619698: A Generalizable Strategy for Riparian Vegetation Assessment Using LiDAR

Sky Jones[1], Dr. Racha El Kadiri[2], Dr. Henrique Momm[3]

American Geophysical Union Fall Meeting 2019

[1]Undergraduate Student, Middle Tennessee State University Department of Geosciences; [2]Assistant Professor, Middle Tennessee State University Department of Geosciences; [3]Associate Professor, Middle Tennessee State University Department of Geosciences

Study Areas

HUC12	Name	Location	Type	Size (sq km)	Trained Area (sq km)	Training Fraction
180500020905	Lobos Creek-Frontal San Francisco Bay Estuaries	San Francisco, CA	Very Urban w/ Parks	25.3		0.0
070801050901	Walnut Creek	Kelley, IA	Flat cropland	50.7		0.0
130202090102	Ox Spring Canyon	Near Alamo, NM	Desert, Forest	66.1		0.0
080102040304	North Fork Forked Deer River Middle	Western TN	Cropland	161.1		0.0
010500021301	Branch Lake	Penobscot, ME	Rugged forested coastal	80.0		0.0
030902040303	Middle Fakahatchee Strand State Preserve	Naples, FL	Flat coastal	74.7		0.0
140801040103	Mineral Creek	Central CO	Mountainous	136.8		0.0
TOTAL				**594.7**	**0.0**	**0.0**

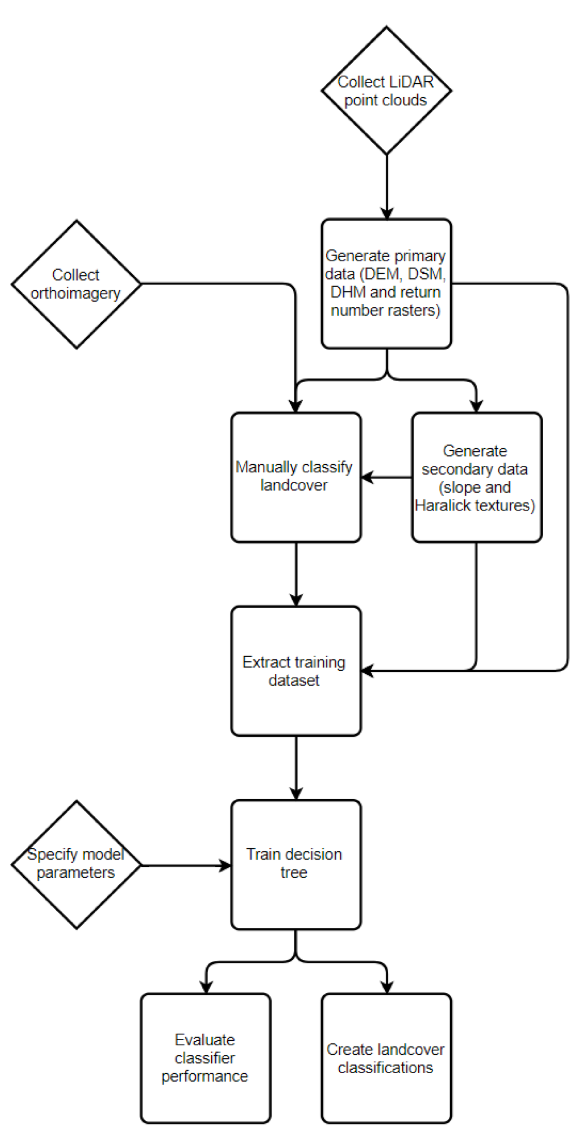
Training Data

Ordinal	Product Name	Explanation
Primary	Digital Elevation Model (DEM)	The elevation of the last LiDAR return
	Digital Surface Model (DSM)	The elevation of the first LiDAR return
	Digital Height Model (DHM)	The average number of of LiDAR returns per pulse
	Return Number (RN)	The difference between the DSM and DEM (also called the canopy height model)
Secondary	Slope	The slope, in degrees, of a given raster
	Roughness	The absolute value of the maximum difference between a cell and the 8 adjacent cells
	Haralick Textures	Any of the textural features described by *Haralick, Shanmugam & Dinstein*

Landcover was manually classified for each watershed using LiDAR-derived data products and temporally concurrent aerial orthoimagery as a reference. These landcover classifications and data products were used to train the decision tree classifier.

Secondary data products were created by applying a given procedure to each of the primary data products. LiDAR intensity values were not used because there is no set standard for normalization of intensity, meaning values from different LiDAR missions cannot be compared.

Simplified Workflow



Abstract

Hydrologists, watershed planners, stream restorationists and other investigators have long used LiDAR derived-data to classify riparian landcover, but the classification models that have been developed are limited in scope, requiring reinvestigation and retraining for each new study area. We have generalized this LiDAR-based approach to landcover classification by showing that a single model can perform accurate 3-class landcover classification in 7 watersheds across the United States with dissimilar ecological and geomorphological characteristics. Multiple models were investigated that use various combinations of LiDAR-derived datasets that account for inconsistencies in data preparation and collection between different LiDAR data vendors. The landcover classification scheme used was “trees”, “herbaceous vegetation” and “other”, which is sufficient for many remote-sensed watershed investigations.

Model Performance

	Precision	Recall	F1-Score	Support
Trees	0.98	0.96	0.97	930218
Natural Vegetation	0.59	0.79	0.67	404300
Other	0.95	0.88	0.92	1628525
Accuracy		0.89		
Macro Average	0.84	0.88	0.85	2963043
Weighted Average	0.91	0.89	0.90	2963043

This is just a sample; will want to include the above table as well as a comparison of F1 scores for each watershed

Discussion

Discussion of success and shortcomings (as of now, can’t discern impervious surfaces which is a big problem, but less so if we consider the model is intended to classify riparian corridors, and also textural analysis has not yet been implemented)

Sample Output

(2-3 orthophoto views along with predicted landcover. Decision tree probably too big to place legibly)

Future Work

The model will be refined further by adding additional dissimilar study areas, in particular watersheds dominated by open prairies or suburban development. In the near future it may be possible to incorporate LiDAR intensity values into the model as vendors begin to standardize this parameter, allowing accurate comparison of intensity values collected during different missions. Performance may be improved by adjusting decision tree boundaries with an optimization heuristic such as a genetic algorithm or simulated annealing.

Acknowledgements

Thank you to my advisors Dr. Racha El Kadiri and Dr. Henrique Momm for their guidance and support during this project, and to the National Resources Conservation Service for funding. Additional thanks to Conner Reed for his assistance with creating the training landcover classifications.

References

Haralick, R. M., Shanmugam, K., & Dinstein, I. (1973). Textural Features for Image Classification. *IEEE Transactions on Systems, Man, and Cybernetics*, *SMC-3*(6), 610–621. doi: 10.1109/tsmc.1973.4309314

Kashani, A., Olsen, M., Parrish, C., & Wilson, N. (2015). A Review of LIDAR Radiometric Processing: From Ad Hoc Intensity Correction to Rigorous Radiometric Calibration. *Sensors*, *15*(11), 28099–28128. doi: 10.3390/s151128099

Momm, H., Easson, G., & Kuszmaul, J. (2009). Evaluation of the use of spectral and textural information by an evolutionary algorithm for multi-spectral imagery classification. *Computers, Environment and Urban Systems*, *33*(6), 463–471. doi: 10.1016/j.compenvurbsys.2009.07.007

Natural Resources Conservation Service

MIDDLE TENNESSEE STATE UNIVERSITY