Estimating biomass in the Panther Creek Watershed using LiDAR

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Presentation Overview

- Background
- Research question
- Study area
- Data
- Methods
- Results
- Discussion

Panther Creek study area vegetation plot

Background

Biomass is key to understanding carbon sequestration (Houghton, 2005).

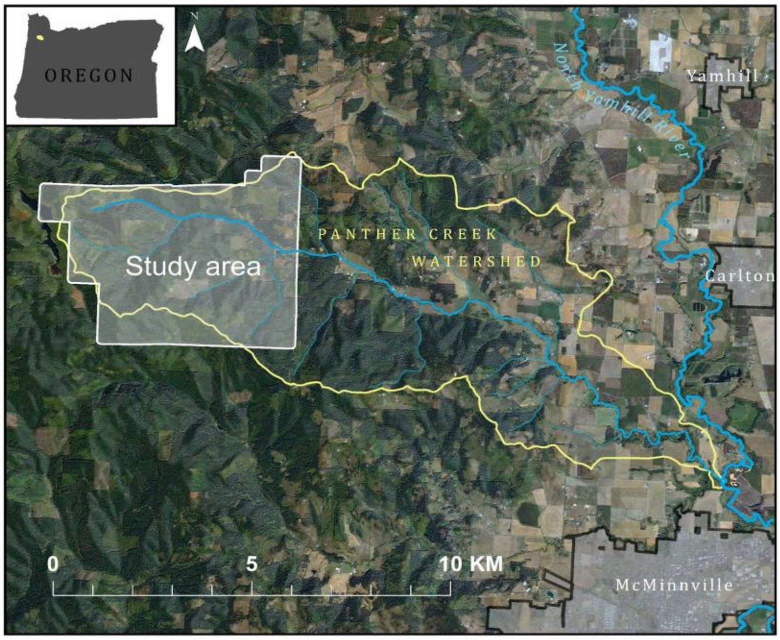
Estimating biomass involves costly field work and destructive sampling (Brown, 2002).

Increasingly, researchers are looking to estimate biomass with remotely sensed data.

Research question

How accurately can LiDAR-derived data predict biomass in the Panther Creek watershed?

What is the biomass above ground within the study area?



Data

Vegetation sample plot data:

- 78 circular plots of 100 ft. diameter, 2009
- Diameter at breast height (DBH)
- Tree height

LiDAR data:

- Discrete return data collected in leaf-off conditions, 2010
- Pulse density of ~ 8 pulses/m^2

GIS data:

- ESRI grids of bare earth LiDAR returns
- Study area

Workflow and Software Used

Calculate biomass for each plot (R)

Calculate LiDAR feature height statistics by plot (Fusion)

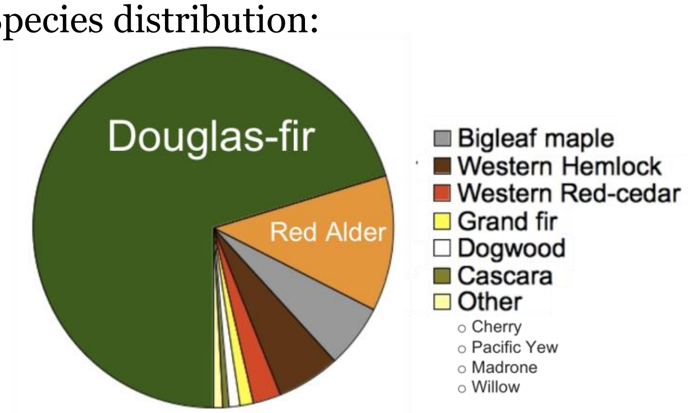
Variable selection, OLS regression (R)

Derive LiDAR surface of selected variable (Fusion)

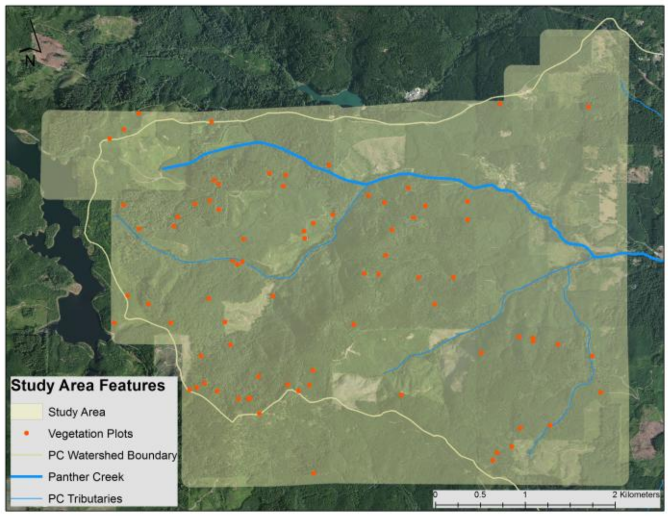
Estimate LiDAR-derived biomass (ArcGIS)

Calculating biomass

- Allometric equations for each tree by species.
- Variables: DBH, Height, wood density
- Species distribution:



78 vegetation sample plots



Biomass

Bole biomass

+

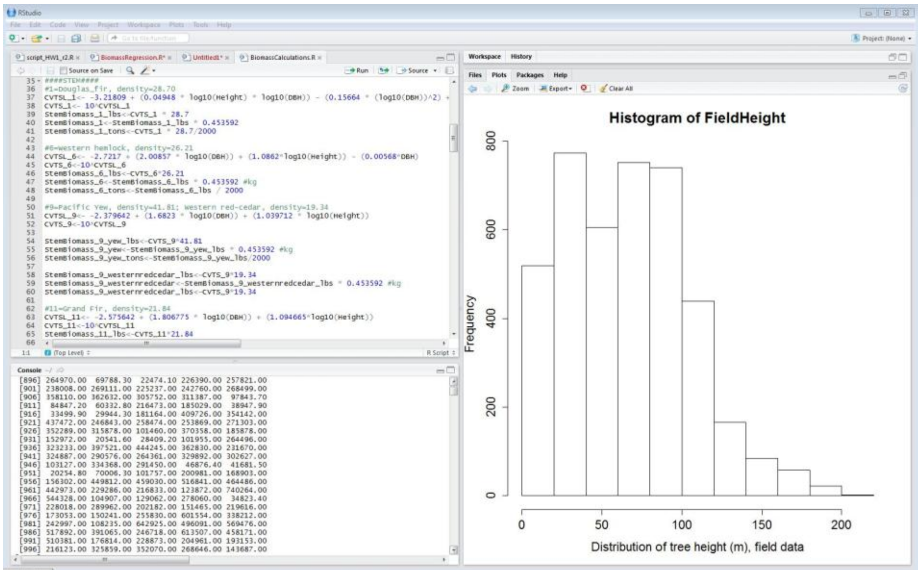
Bark biomass

+

Branch biomass

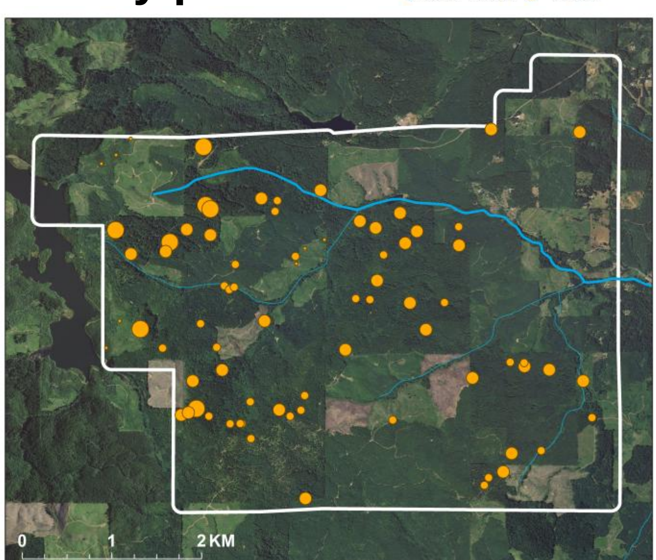
= Tree biomass

Calculating plot biomass in R

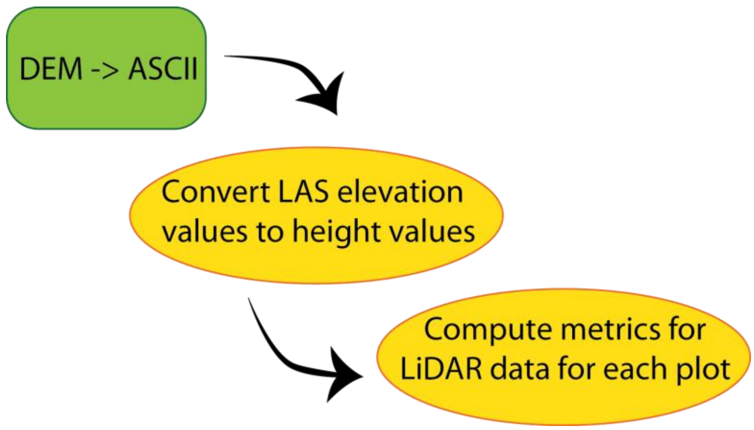


Biomass by plot

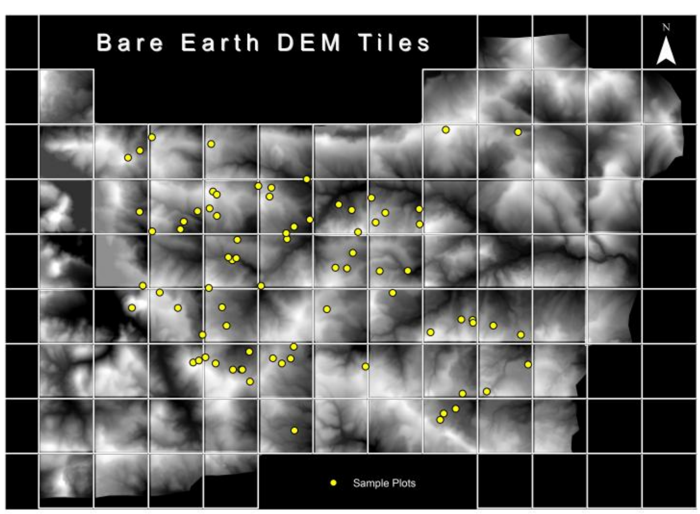
Above-ground biomass (kilograms)
< 5000
25,001 - 50,000
5000 - 25,000
> 50,000



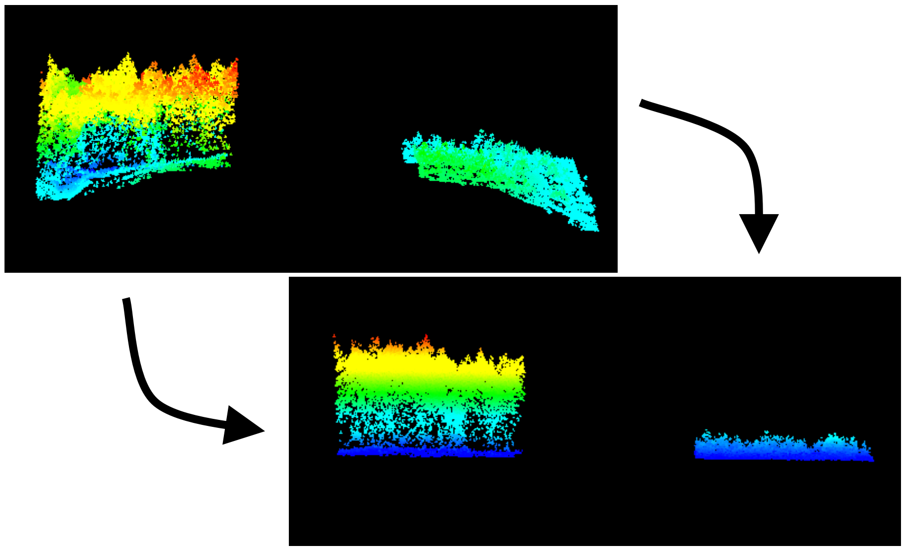
LiDAR data processing



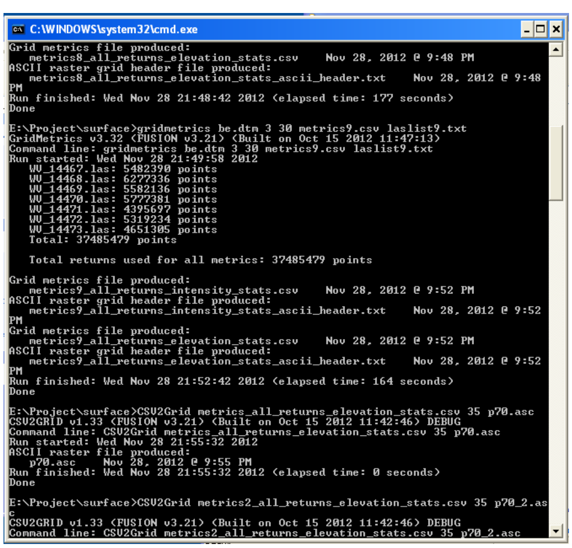
DEM to ASCII



LAS elevation to height values



Compute metrics



- Cloudmetrics
- Run through DOS Command Prompt

Statistical variables for each plot

DataFile	Total return co	Return 1 coun	Return 2 coun	Return 3 coun	Return 4 coun	Elev maximum	Elev mean	Elev mode	Elev stddev	Elev variance	Elev CV
H100401.las	12498	11802	686	10	0	14.22	4.621556	0	2.754607	7.587859	0.596034
H100402.las	11608	10234	1245	128	1	30.35	3.612764	0	5.182526	26.858576	1.434504
H100405.las	13353	12338	1011	4	0	11.84	2.942742	0	2.299572	5.288031	0.781439
H102401.las	23140	14964	6640	1448	88	49.380001	24.481475	3.135238	13.947134	194.522553	0.569702
H103202.las	29692	19014	8542	2121	15	29.77	11.305664	0	9.268144	85.8985	0.819779
H103901.las	11358	9374	1765	217	2	37.91	15.625375	0	11.714203	137.222562	0.749691
H103902.las	15433	11691	3303	438	1	40.560001	11.683235	0	12.940384	167.453535	1.107603
H104801.las	19799	16581	2845	369	4	27.219999	16.303926	0	6.695693	44.832306	0.41068
H107701.las	14895	11554	2891	442	8	48.849998	28.511079	0	11.919617	142.077266	0.41807
H107801.las	8813	5506	2608	680	19	58.450001	26.687281	0	18.944219	358.883419	0.709859
H108201.las	25777	23762	1967	48	0	14.03	4.410234	0.222698	3.295509	10.860383	0.747241
H108501.las	12657	11864	786	7	0	10.38	1.864876	0	2.170986	4.713179	1.164145
H108601.las	15719	11530	3537	648	4	32.220001	12.480986	0	8.212272	67.441411	0.657983
H109101.las	15556	9359	4968	1178	51	47.27	19.066554	0	13.003967	169.103167	0.68203
H109102.las	13815	9922	3349	539	5	44.349998	21.346581	0	13.062587	170.63117	0.611929
H109103.las	18103	10061	6206	1773	63	48.080002	17.812784	0	12.256123	150.212556	0.688052
H109301.las	14524	9725	4020	769	10	42.040001	15.775109	0	10.528293	110.844951	0.667399
H109302.las	19041	11192	6305	1485	59	45.060001	18.808387	0	11.258744	126.759313	0.598602
H109303.las	26140	18068	6586	1463	23	49.73	26.213469	0	15.184596	230.571966	0.579267
H109602.las	9931	8940	793	192	6	36.919998	3.286358	0	6.985553	48.797945	2.125621
H109604.las	7787	7787	0	0	0	5.87	0.640198	0	1.006261	1.012561	1.571797
H109605.las	19259	19182	77	0	0	7.42	1.151948	0	1.412467	1.995063	1.226155
H109701.las	10395	9550	790	55	0	23.950001	15.996281	17.867461	4.865639	23.674442	0.304173
H109804.las	35088	21581	10750	2718	39	68.68	19.339932	0	19.261677	371.012197	0.995954
H110101.las	14986	10678	3723	581	4	31.719999	10.455238	0	7.77496	60.450007	0.743643
H110102.las	16819	13353	3073	392	1	30.73	15.031928	0	8.074056	65.190376	0.537127
H110104.las	16388	12872	3161	353	2	29.68	13.418677	0	8.335566	69.481664	0.621191
H110201.las	22444	12581	7630	2223	10	35.369999	13.100495	0	10.182679	103.686951	0.777274
H110301.las	19642	11100	6689	1779	74	42.040001	15.683661	0	12.08761	146.110308	0.770714
H110302.las	18861	11216	6074	1558	13	29.469999	8.884988	0	8.265337	68.315794	0.930259
H110401.las	14835	12008	2544	283	0	33.099998	7.478881	0	9.835777	96.742514	1.31514
H110402.las	16518	11466	4229	812	11	43.07	17.325582	0	11.761741	138.338559	0.678866
H110403.las	21596	11705	7368	2440	83	40.77	15.943275	0	10.711176	114.729281	0.67183
H111001.las	24453	19618	4181	648	6	34.580002	20.226679	0	8.545543	73.026311	0.422489
H111002.las	18184	14066	3597	510	11	36.709999	20.821136	23.307936	7.070995	49.998968	0.339607
H111003.las	12241	8396	3143	700	2	35.919998	19.431229	0	11.428963	130.621197	0.588175
H112701.las	17896	15730	2030	136	0	21.129999	11.297735	0	4.680392	21.90607	0.414277
H112702.las	16657	11513	4318	823	3	23.370001	10.39226	0	6.933397	48.071987	0.667169
H112705.las	14951	10659	3484	805	3	25.84	11.270925	0	6.465567	41.803552	0.57365
H114001.las	16818	11967	4161	678	12	56.560001	27.600132	0	17.812133	317.272065	0.645364
H114002.las	15722	9584	4775	1322	41	64.139999	27.843022	0	18.670952	348.60445	0.670579
H114005.las	17622	11365	5179	1040	38	59.689999	26.585131	0	19.57621	383.227981	0.736359
H200101.las	18609	12083	5497	973	56	63.060001	27.160127	0	20.124521	404.996363	0.740958
H200102.las	23961	17579	5467	887	28	58.09	32.56595	0	14.012871	196.360541	0.430292

Regression analysis

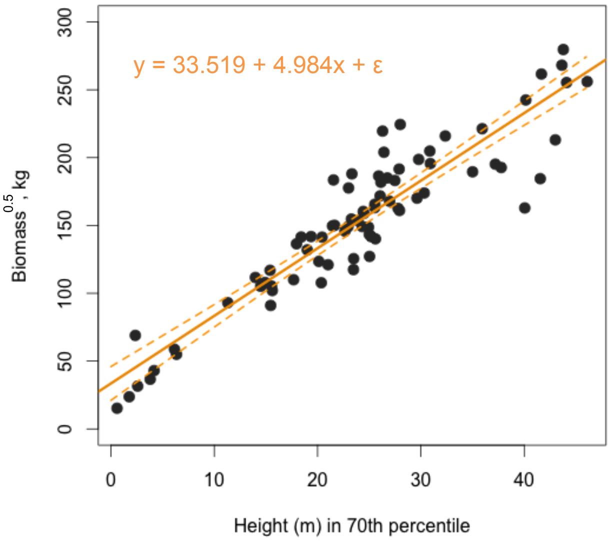
Best predictor = 70th percentile, LiDAR feature height

- Highly correlated with biomass (r = 0.8824)
- Straightforward interpretation

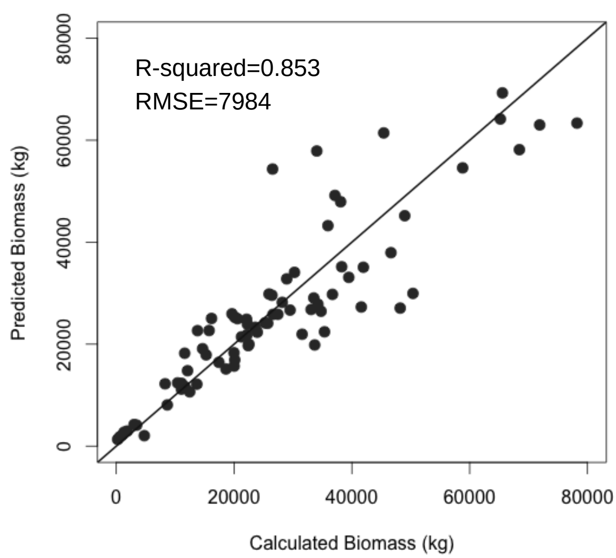
Ordinary least square regression

- Estimate slope (α) and intercept (β): $\mathbf{Y = \alpha + \beta X + \varepsilon}$
- Goodness-of-fit: **R^2, RMSE**

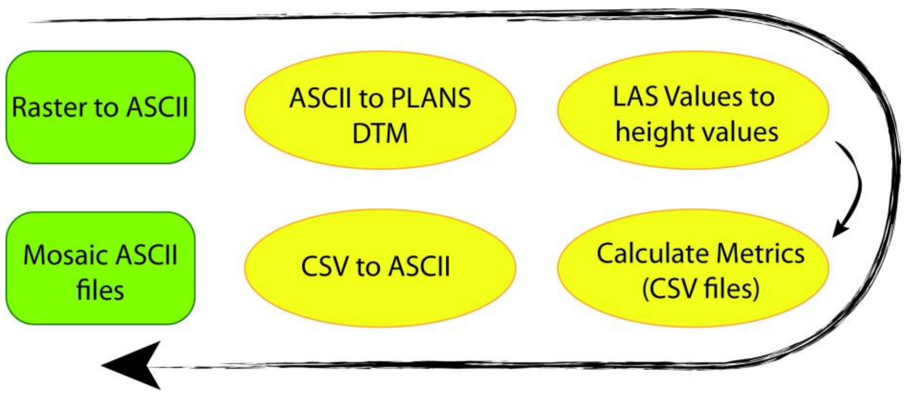
Regression equation



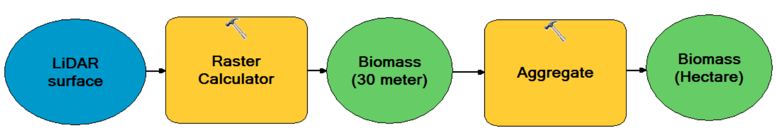
Predicting plot biomass from LiDAR

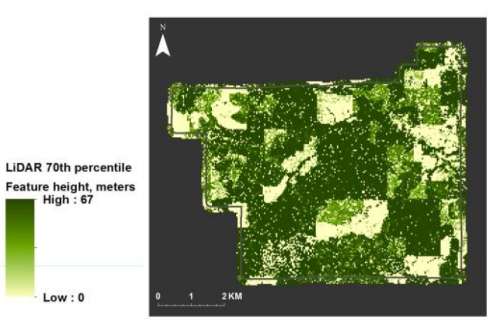


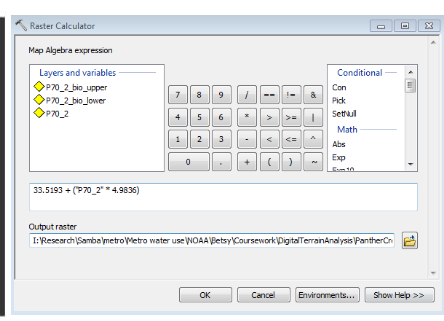
Derive surface from LiDAR returns



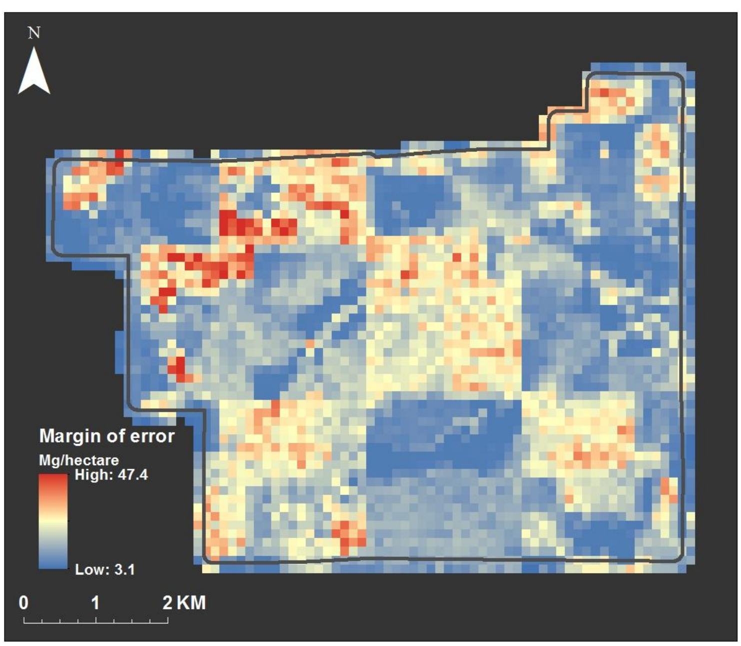
Estimating biomass across study area



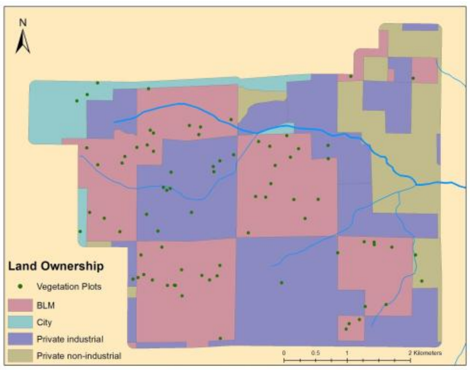


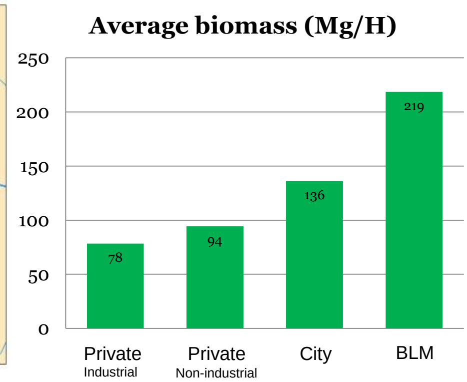



N
Biomass
Mg/hectare
High : 740.3
Low : 5.6
0 1 2 KM


N
Margin of error
Mg/hectare
High: 47.4
Low: 3.1
0 1 2 KM

Land Ownership in the Study Area





Discussion

Max height is not the best predictor. We found that the 70-90th percentile is better.

Very good correlation for plots with 70th percentile < 25 meters. Rsq=0.85 below, 0.51 above.

The accuracy of this method is contingent on the accuracy of the derived surface and elevation models as well as allometric equations for biomass.

Conclusion

Remotely-sensed data can be used to model biomass.

Forest biomass ranges from 5.6 Mg/h for deforested areas to 740.3 Mg/h on forested stands. Avg = 135.7 Mg/h throughout study area.

Acknowledgements

Demetrious Gatziolis, USFS

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References

Brown, Sandra. 2002. “Measuring carbon in forests: current status and future challenges.” *Environmental Pollution*, 116(3), 363-372.

Houghton, R. A. 2005. “Aboveground forest biomass and the global carbon balance.” *Global Change Biology*, 11(6), 945-958.