

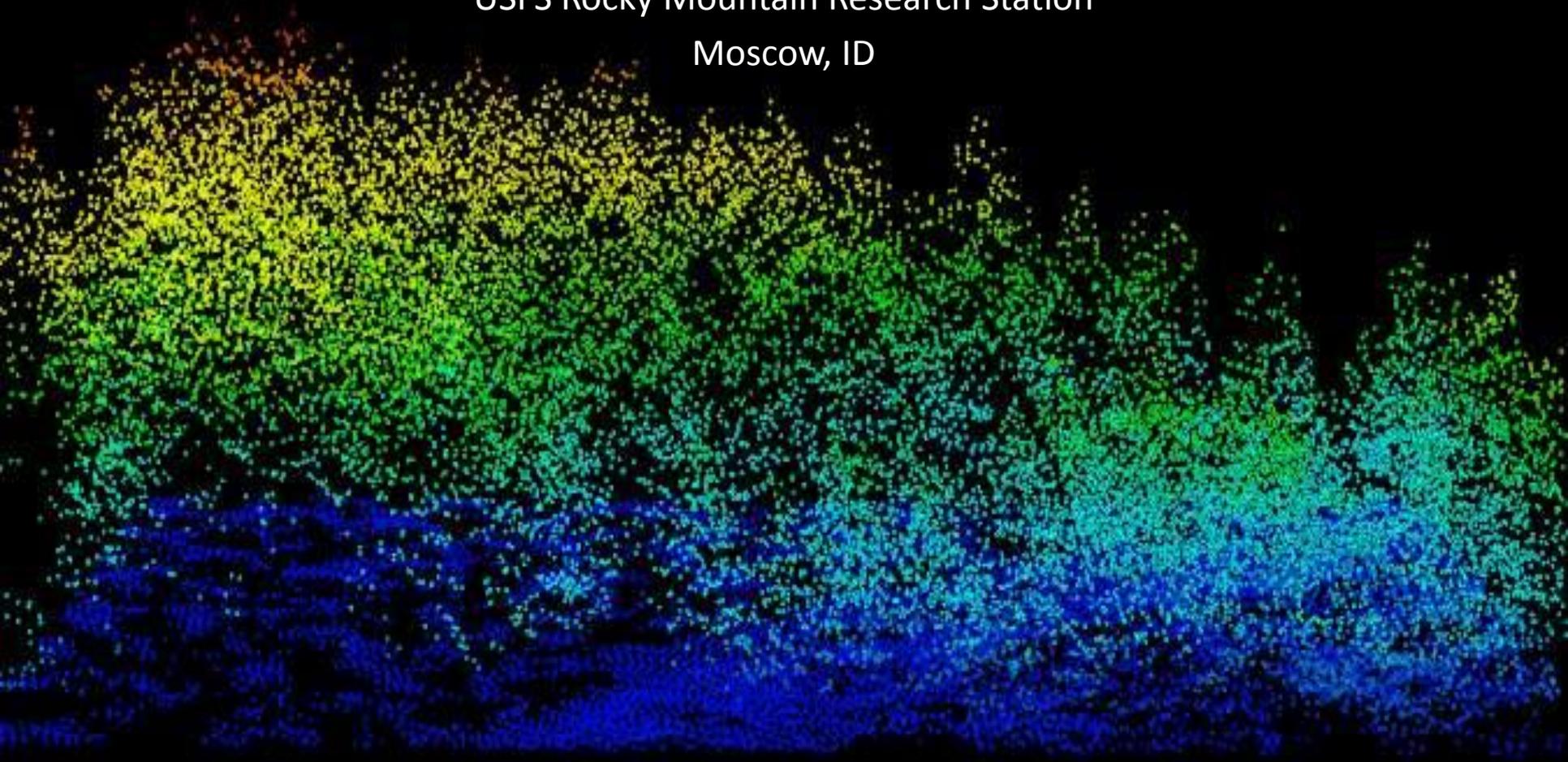
Modeling and mapping stand structure attributes operationally from LiDAR-based inventories

Andrew T. Hudak

Research Forester

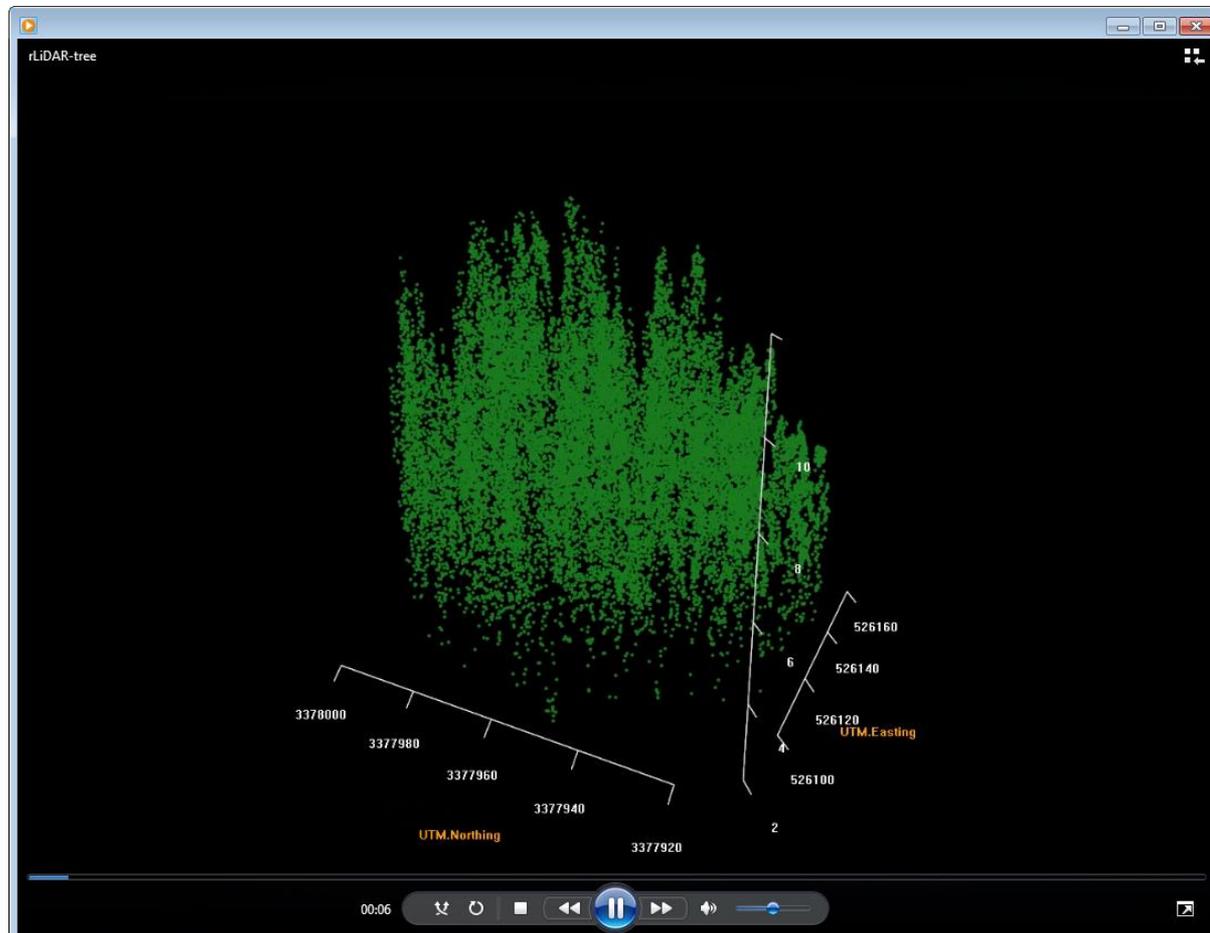
USFS Rocky Mountain Research Station

Moscow, ID



Outline

- Light Detection and Ranging (LiDAR) Data and Processing
- Small Area Based Modeling
- Local Study
 - Imputation
 - Results
 - Conclusions
- Regional Study
 - Regression
 - Results
 - Conclusions



Airborne Laser Scanning

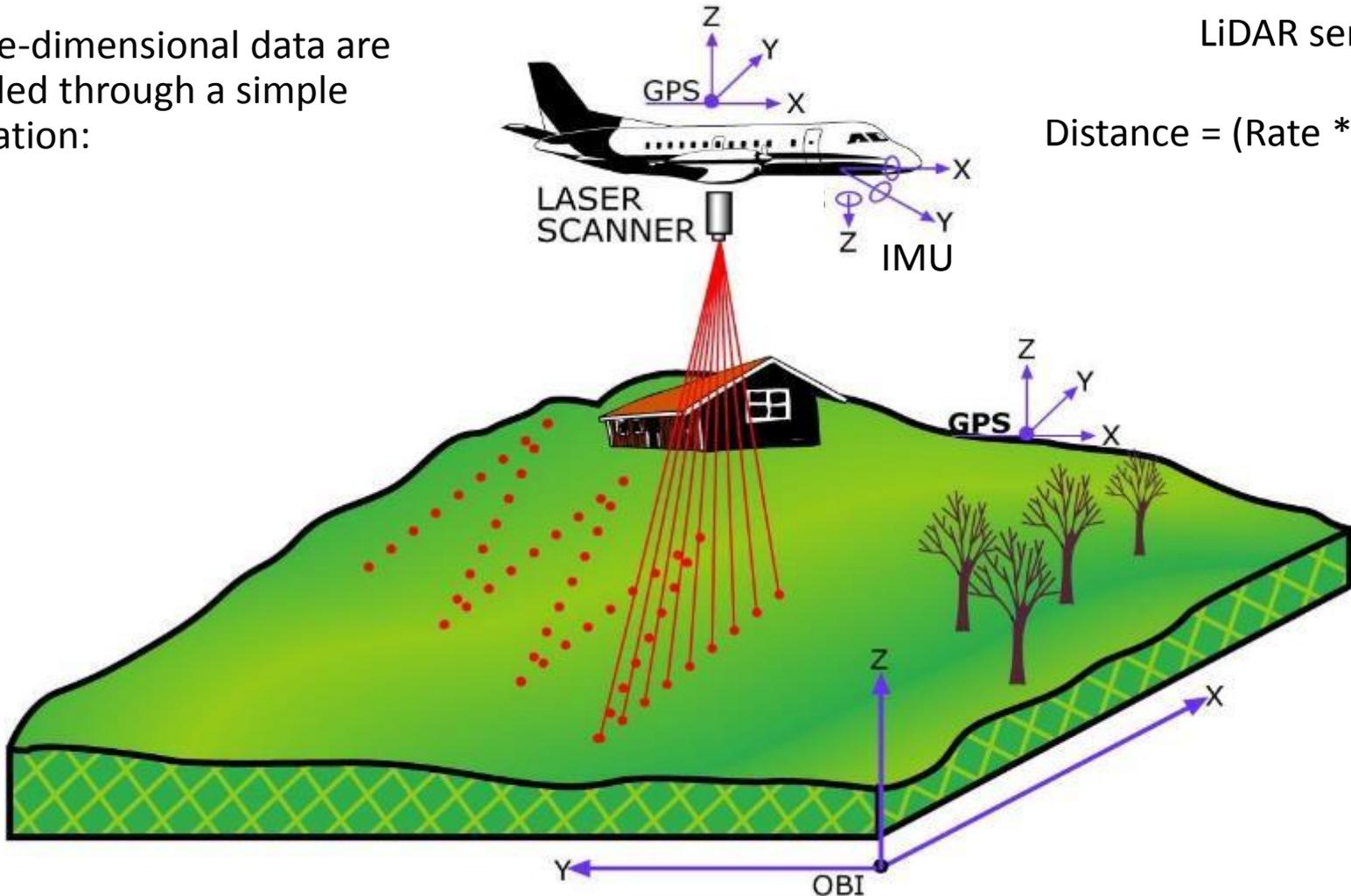
- LiDAR instrument actively emits laser pulses
- Three-dimensional data are recorded through a simple calculation:

$$\text{Distance} = \text{Rate} * \text{Time}$$

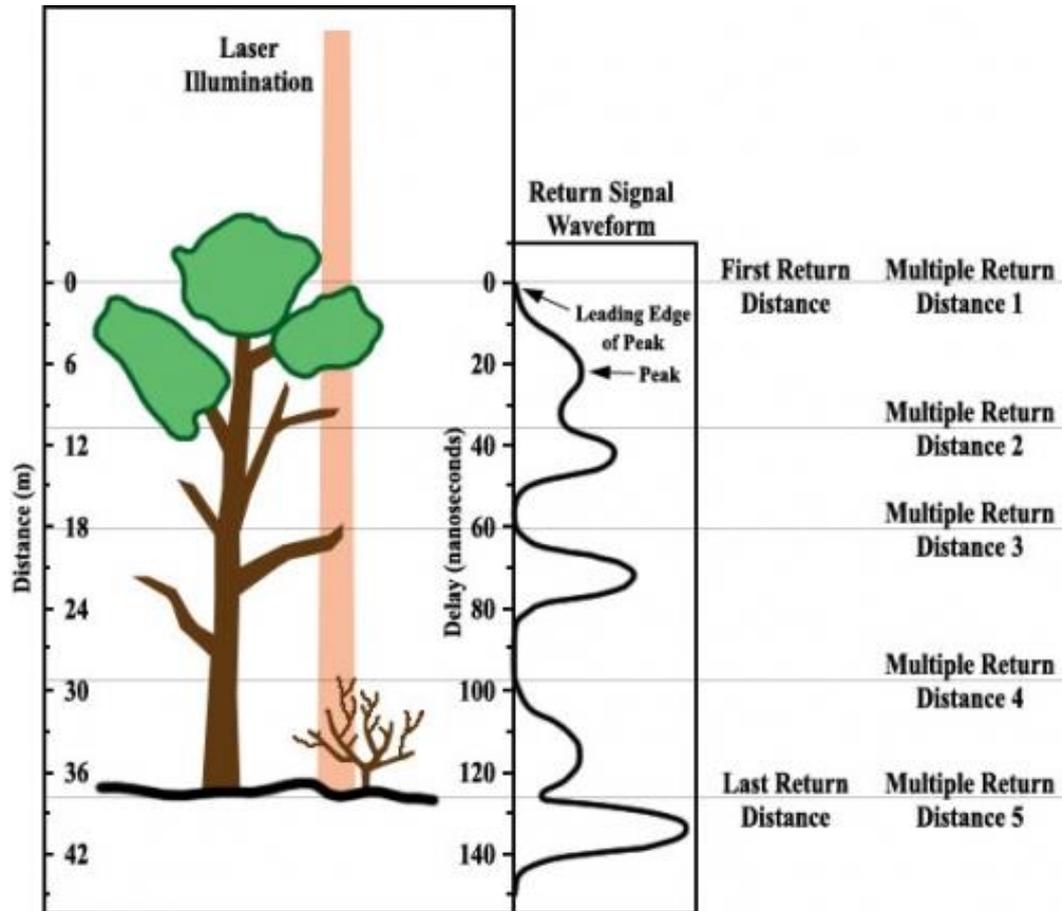
$$\text{Rate} = \text{speed of light} \\ (299,792,458 \text{ m/s})$$

Time -> measured by the
LiDAR sensor

$$\text{Distance} = (\text{Rate} * \text{Time}) / 2$$

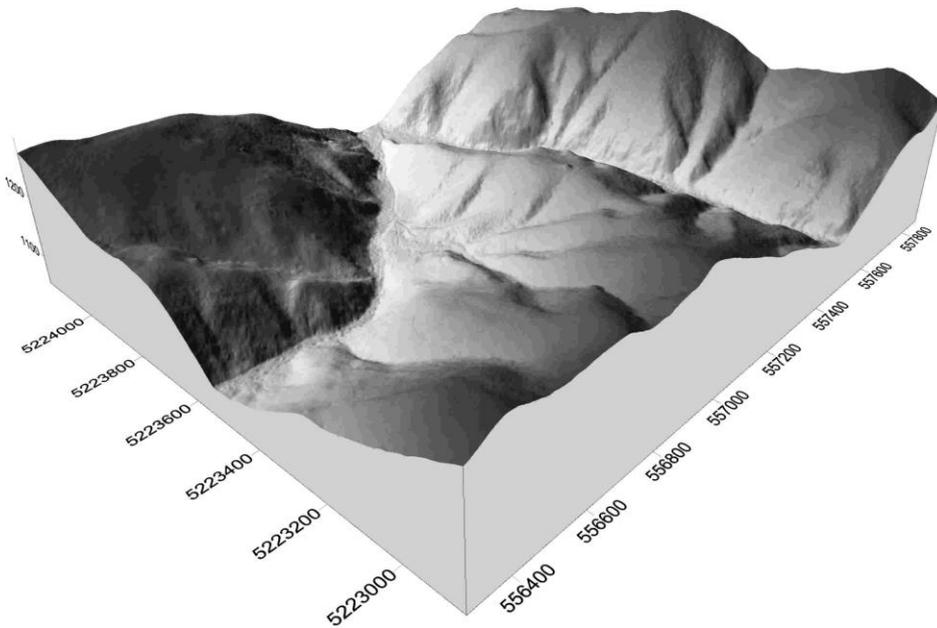


LiDAR Pulse Hits an Object



Topographic Metrics from Digital Terrain Model

Topography



ELEV – Elevation (m)

SLP – Slope (degrees)

SPS – Slope position

SCOSA – Slope * $\cos(\text{Aspect})$

SSINA – Slope * $\sin(\text{Aspect})$

INSOL – Solar Insolation

TRASP – Transformed Aspect

TRI – Topographic Ruggedness Index

TRMI – Topographic Relative
Moisture Index

HLI – Hierarchical Landscape Index

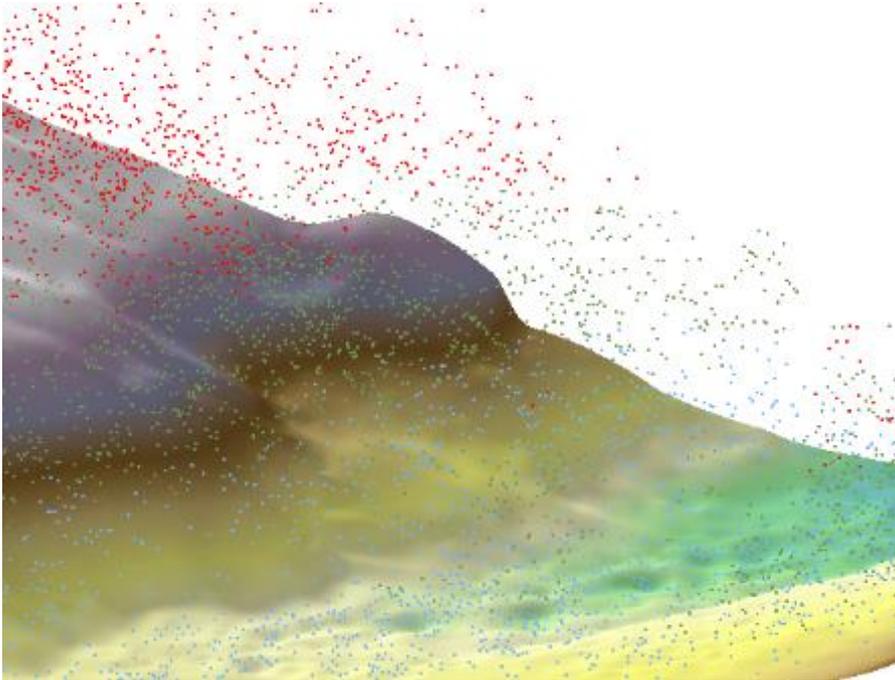
HSP – Hierarchical slope position

CTI – Compound Topographic Index

DIS – Dissection Coefficient

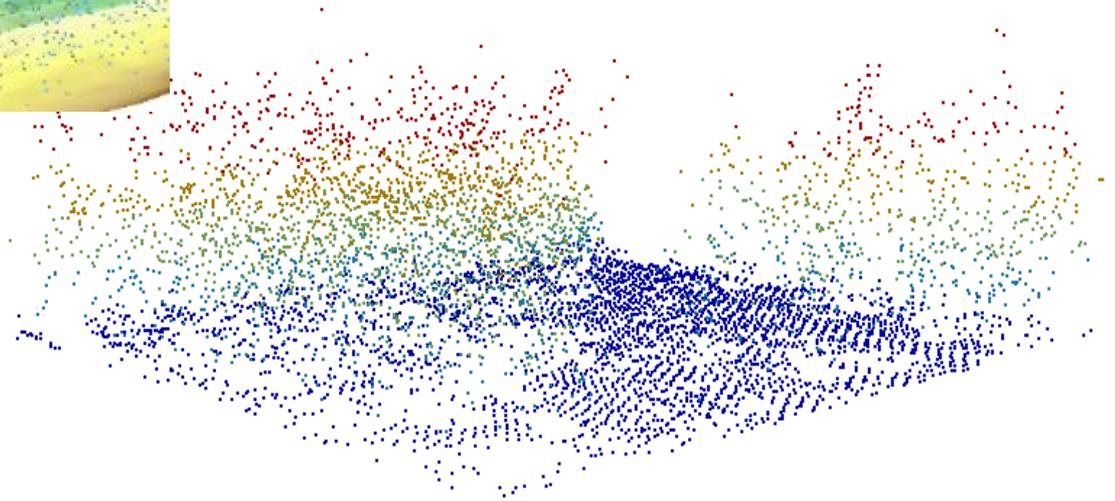
ERR – Elevation Relief Ratio

Calculating Canopy Height

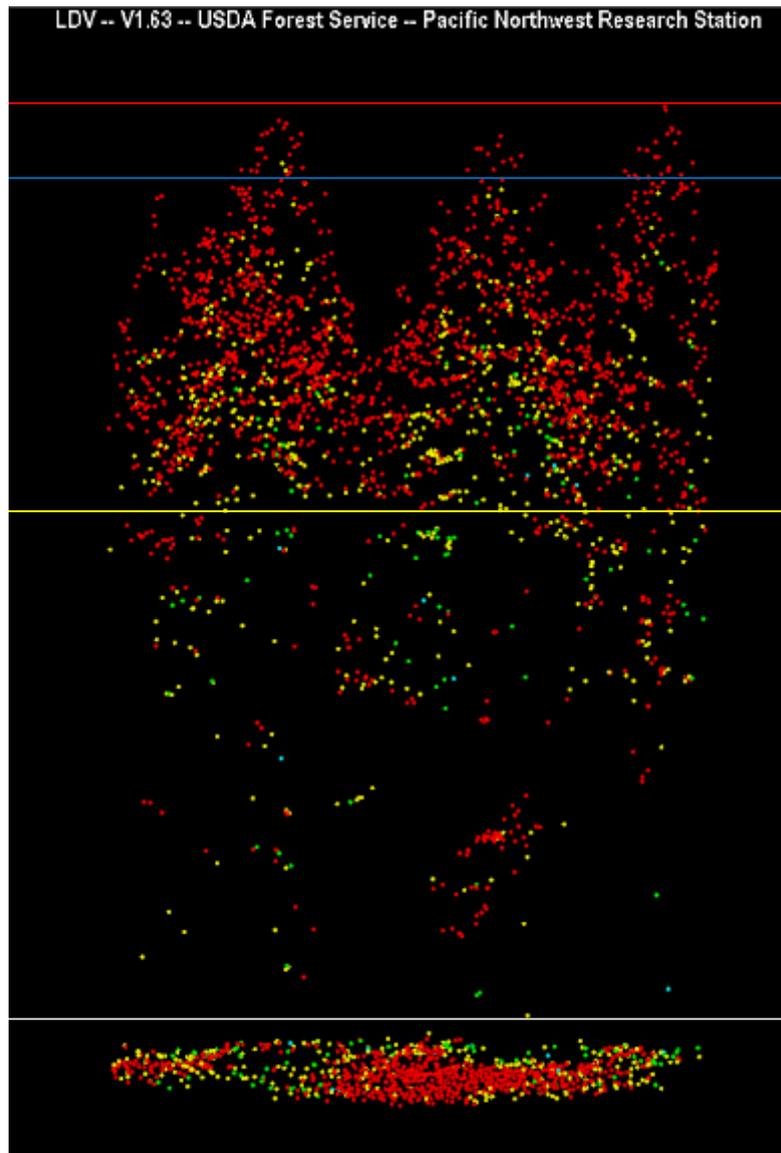
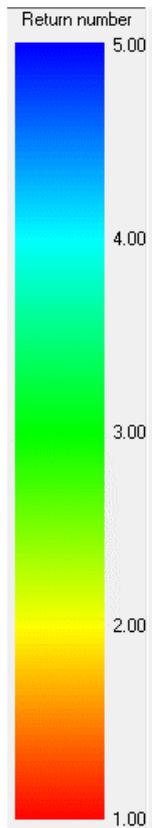


Subtract DEM ground surface from the elevation of LiDAR returns to normalize Z values for canopy height

- Removes the effect of topography



Lidar Height Metrics

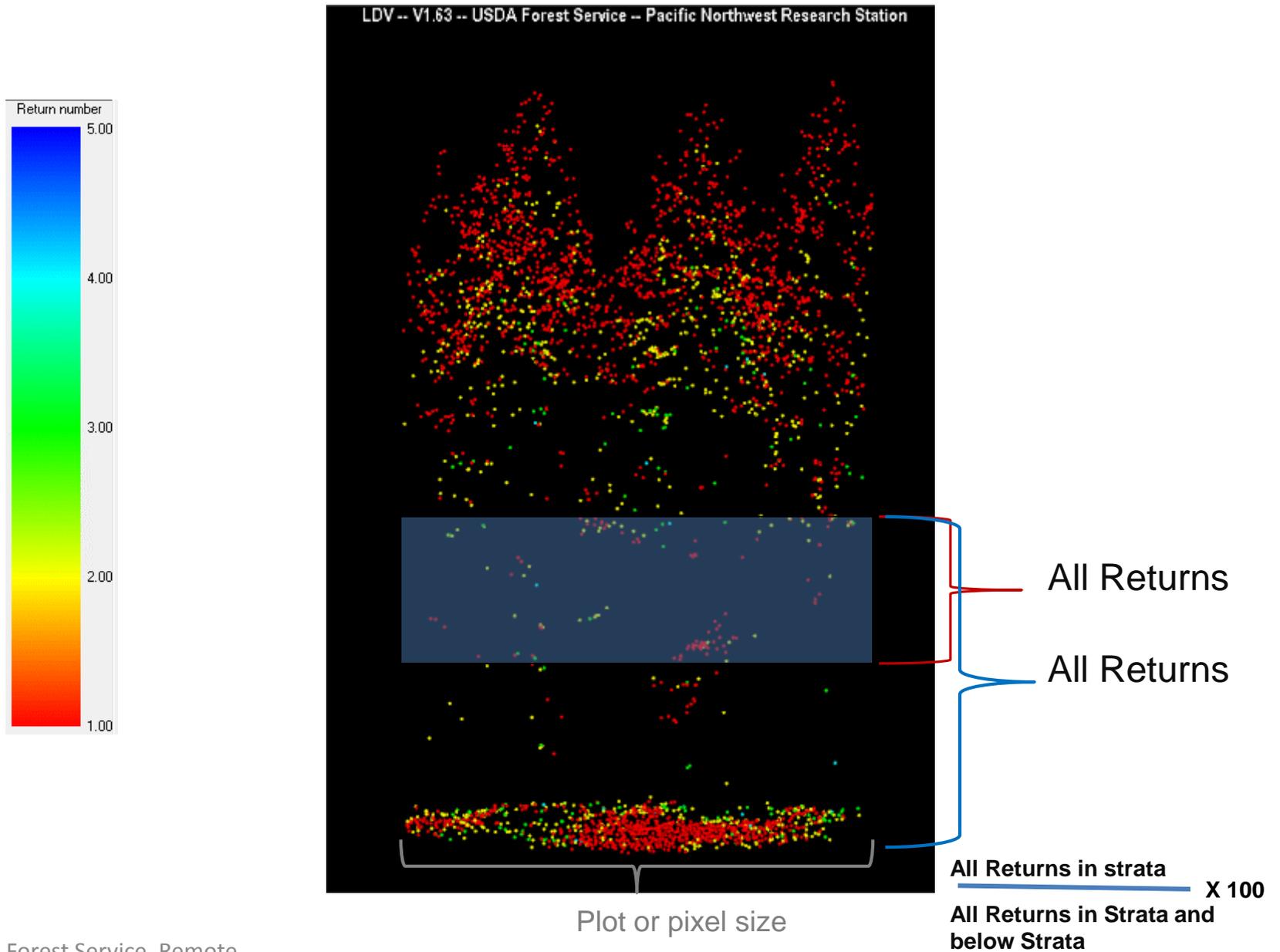


Maximum Canopy Height
95th percentile

Mean Canopy Height

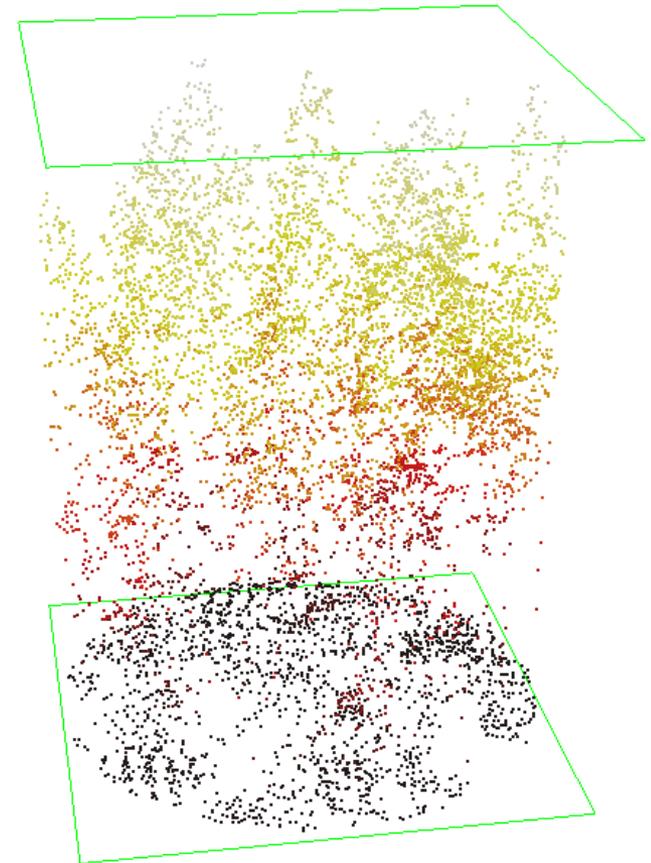
Height Cutoff (1.37 m)

Lidar Mid-story Density Metrics



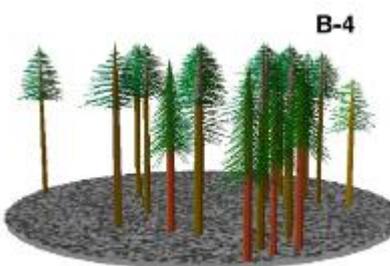
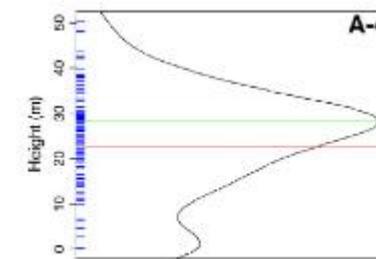
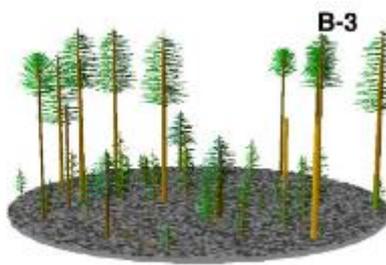
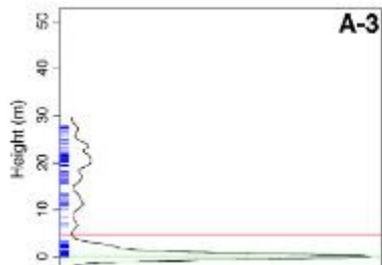
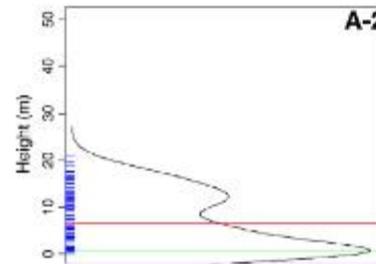
Predictor (x) and Response (y) Variables

- Predictor Variables (from lidar measures):
 - LiDAR metrics
 - Topographic metrics
- Response variables (from tree measures):
 - Above ground biomass (AGB)
 - Basal area (BA)
 - Crown competition factor(CCF)
 - Quadratic mean diameter (QMD)
 - Stand density index (SDI)
 - Average top height (TopHt)
 - Tree density (Tpa)
 - Volume – merch (MCuFt)
 - Volume – total (TCuFt)



Example point cloud in a 0.1 acre plot

Build a Database of Reference Plots

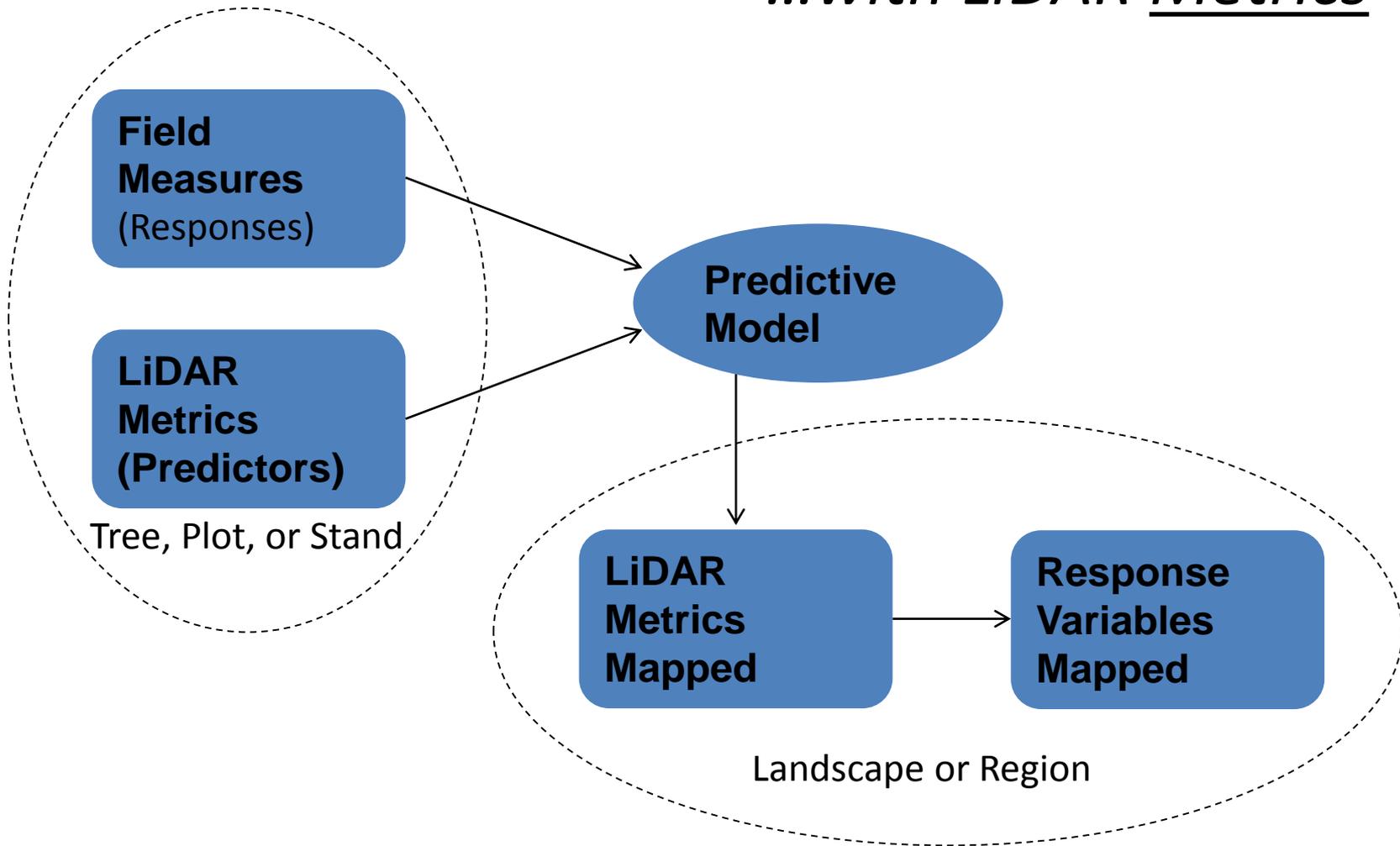


Important ABCs for LiDAR-based forest inventory:

- A. Stratify landscape of interest and apply a stratified random design to place field plots for efficient, unbiased sampling
- B. Use fixed-radius, not variable-radius plots
- C. Accurately geolocate plot centers using resource-grade (or better) GPS with differential correction capability

Model and Map Vegetation Attributes

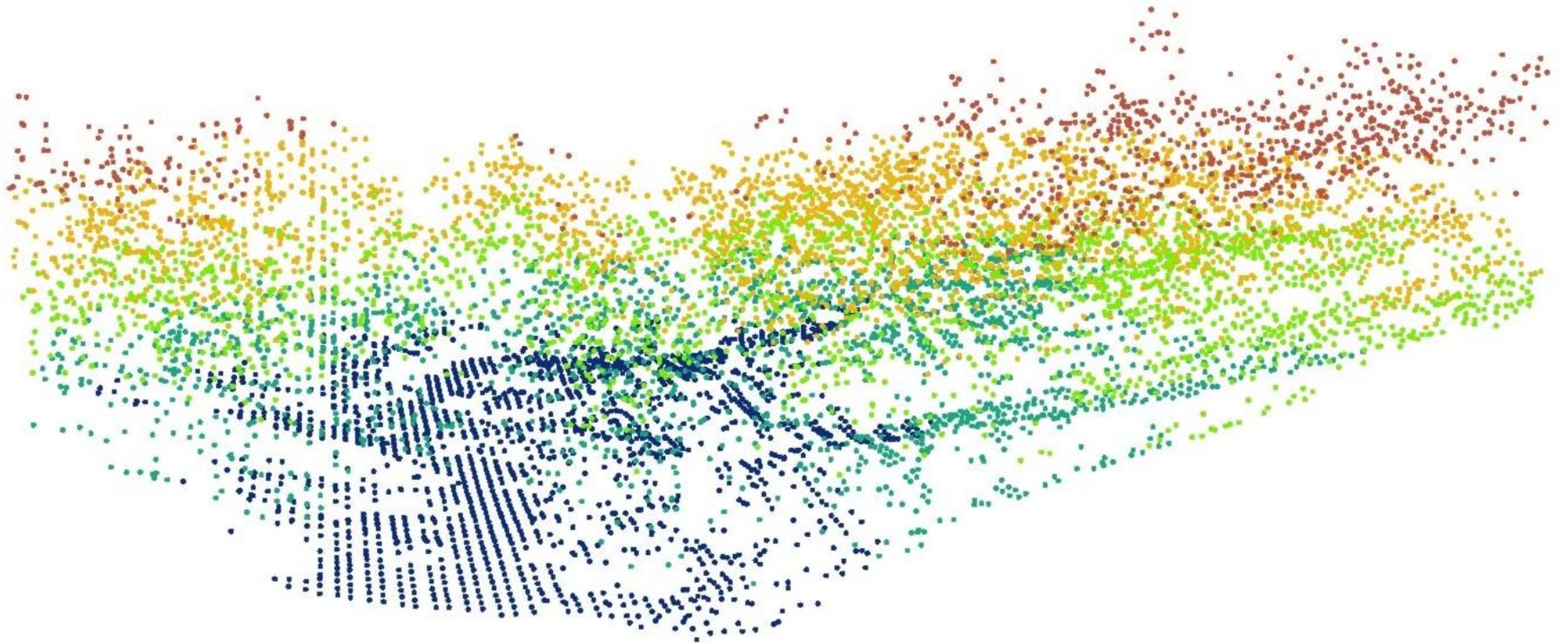
...with LiDAR Metrics



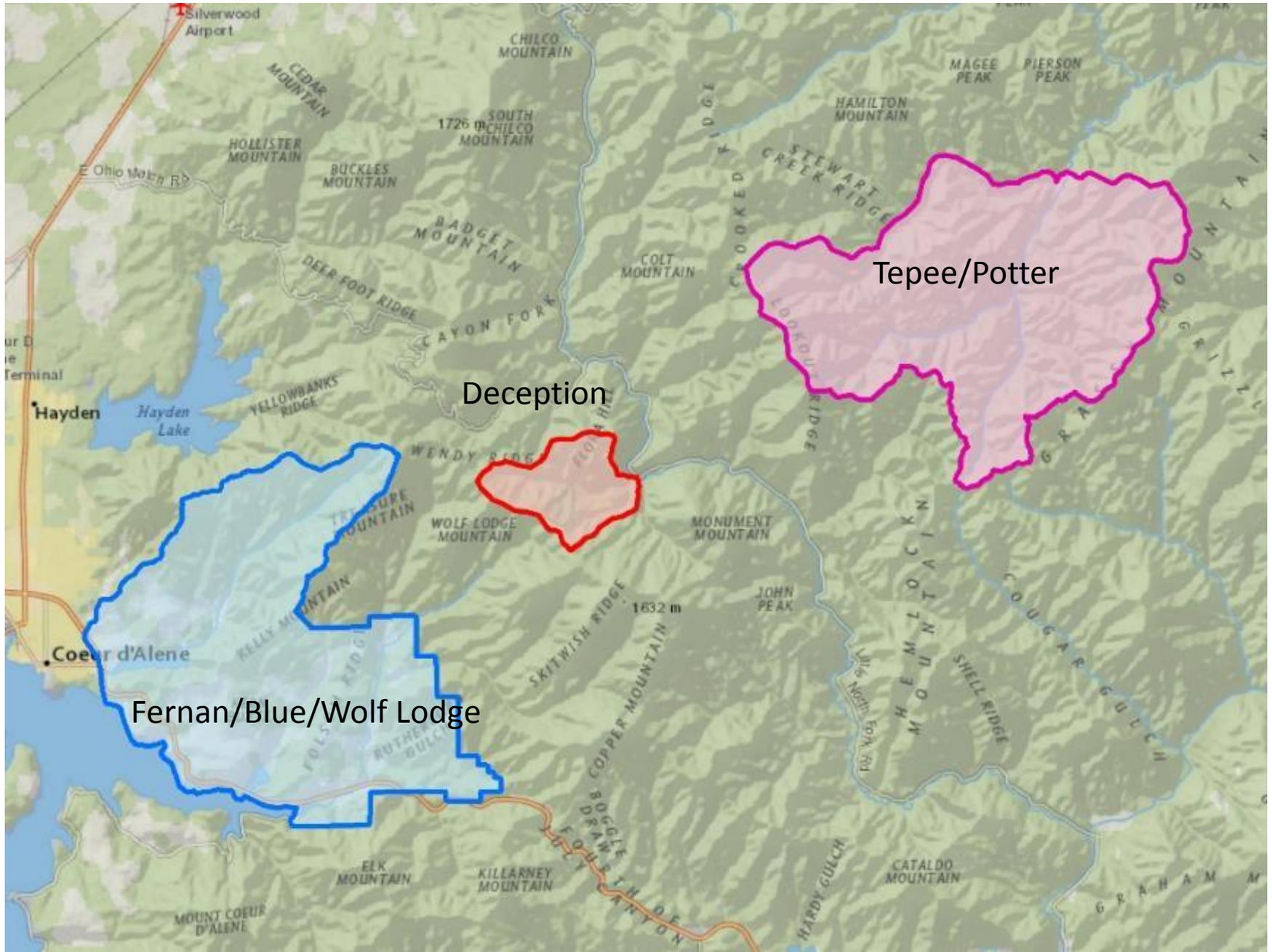
Predictive modeling approaches include:

multiple linear regression, generalized linear models, machine learning algorithms (e.g., Random Forests), neural networks, imputation, etc.

Local Study



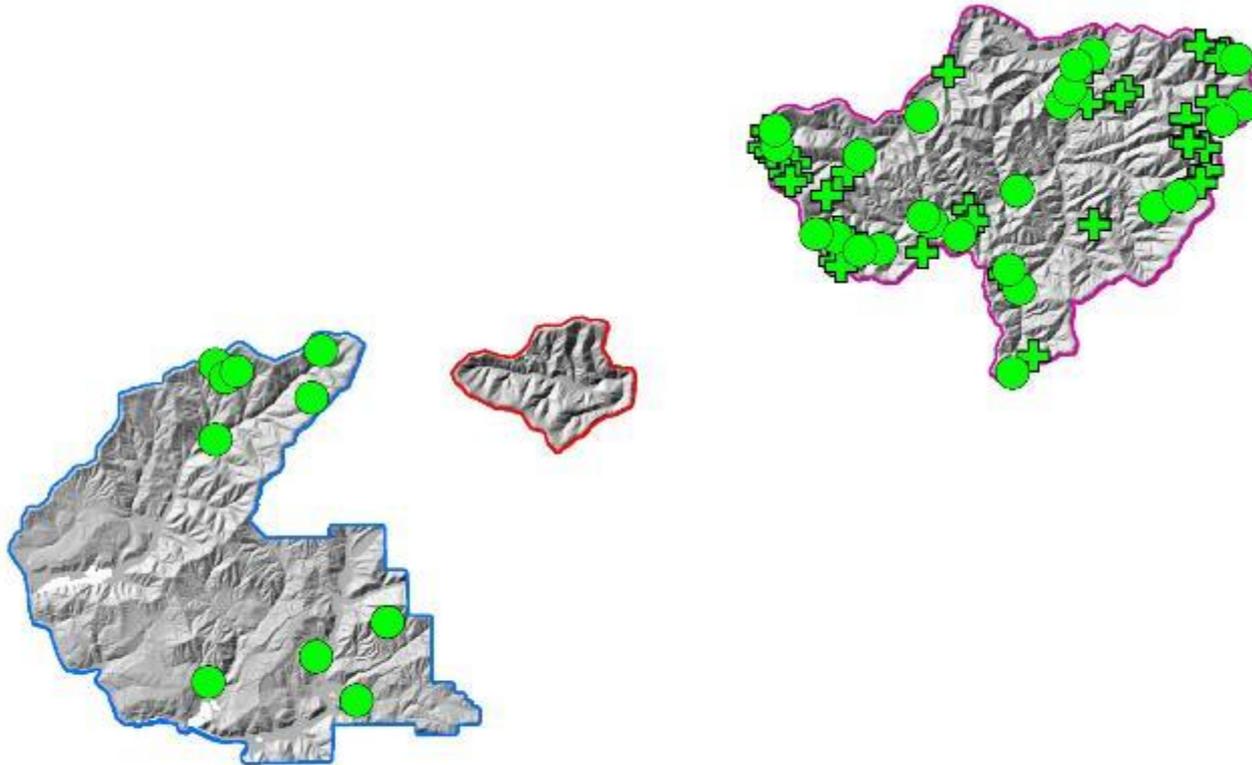
Local Study LiDAR collections



Local Study Data Description

- Data
 - Fernan, Blue, and Wolf Lodge Creeks:
 - LiDAR flown winter 2014-2015 (leaf-off)
 - 10 plots, 1/10 acre, characterized 2015
 - Tepee and Potter Creeks:
 - LiDAR flown spring (24-29 May) 2015 (leaf-on)
 - 24 plots, 1/10 acre, characterized 2015
 - 39 USFS plots , 1/10 acre, characterized 2014

Field Plots Placed Per Stratified Random Sampling Designs



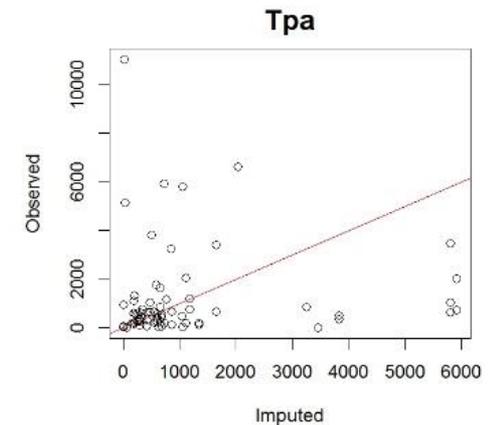
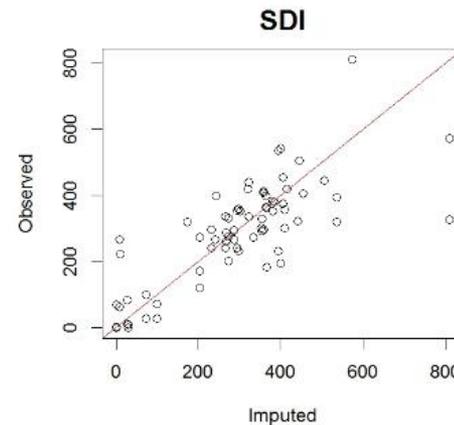
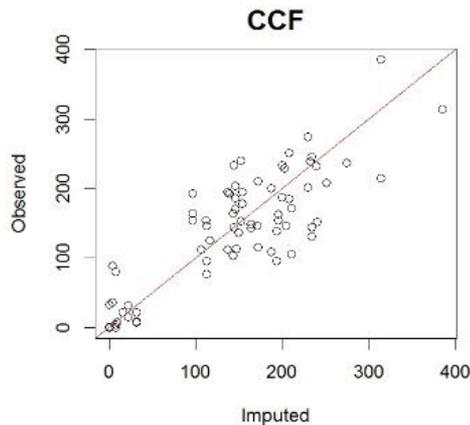
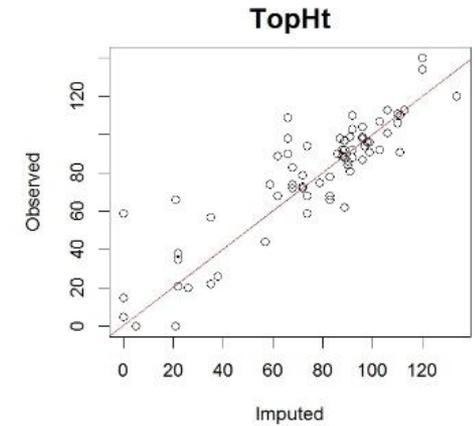
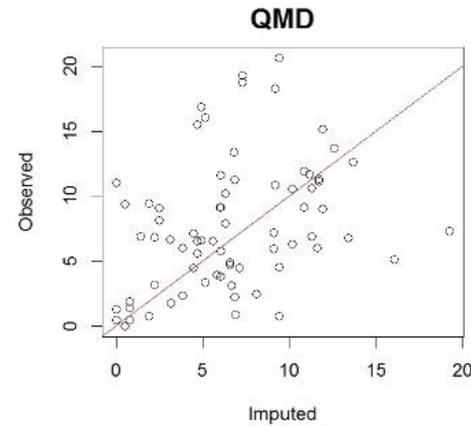
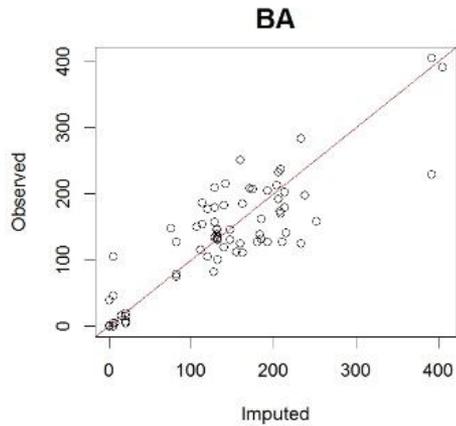
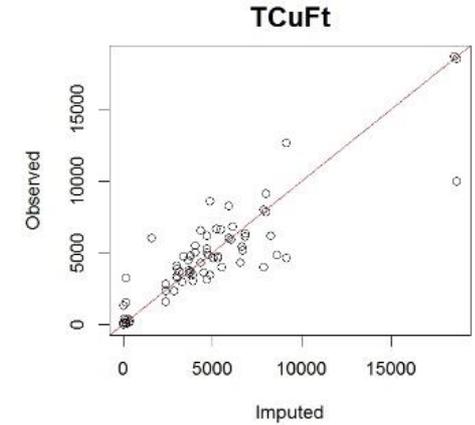
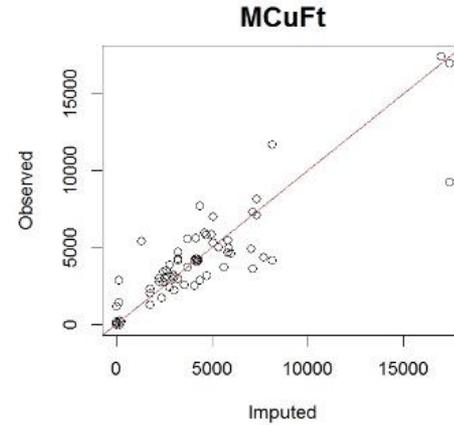
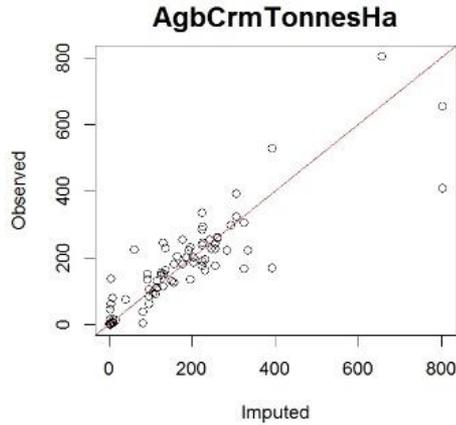
Imputation

- Imputation is 1 of numerous modeling techniques
- Multiple response variables can be predicted simultaneously
- Imputation is weighted by the relationship between multiple response variables and multiple predictors
- The model matches unknown response variables with the 'nearest neighbor' set of known response variables, based on 'most similar' set of known predictor variables

Model Results

Strong correlations when imputing AGB & BA

Poor correlations when imputing QMD and tree density (Tpa)



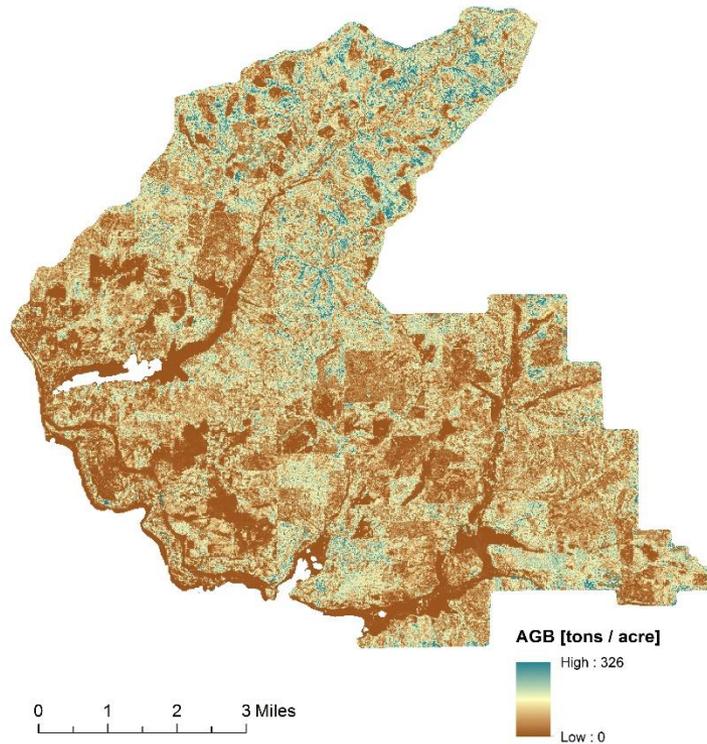
Imputation model fit statistics

RMSD – Root Mean Square Difference

RMSD			
Response Variable	Units	RMSD	%
AGB	tons / ac	49	66
BA	sq-ft / ac	62	46
CCF		67	47
QMD	in	5.7	75
SDI		131	46
Average top height	ft	17	21
Tpa	trees / ac	2163	191
Volume - merch	cubic ft / ac	2834	73
Volume - total	cubic ft / ac	3049	68

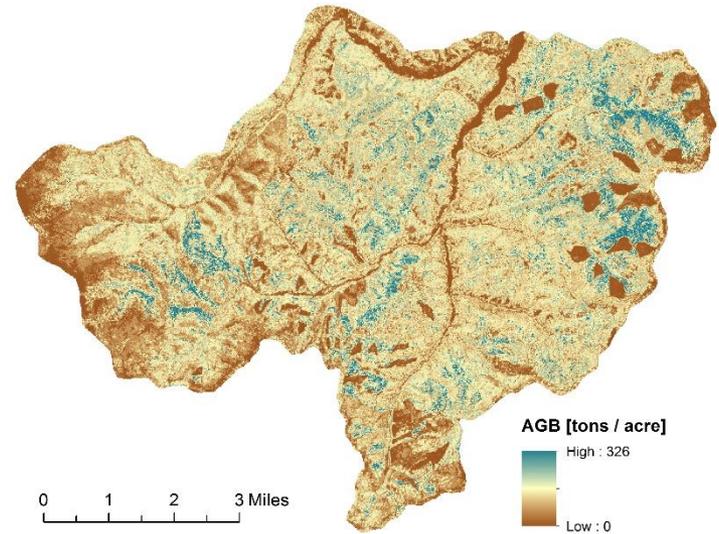
Biomass Estimates Under Different Management Regimes

Fernan



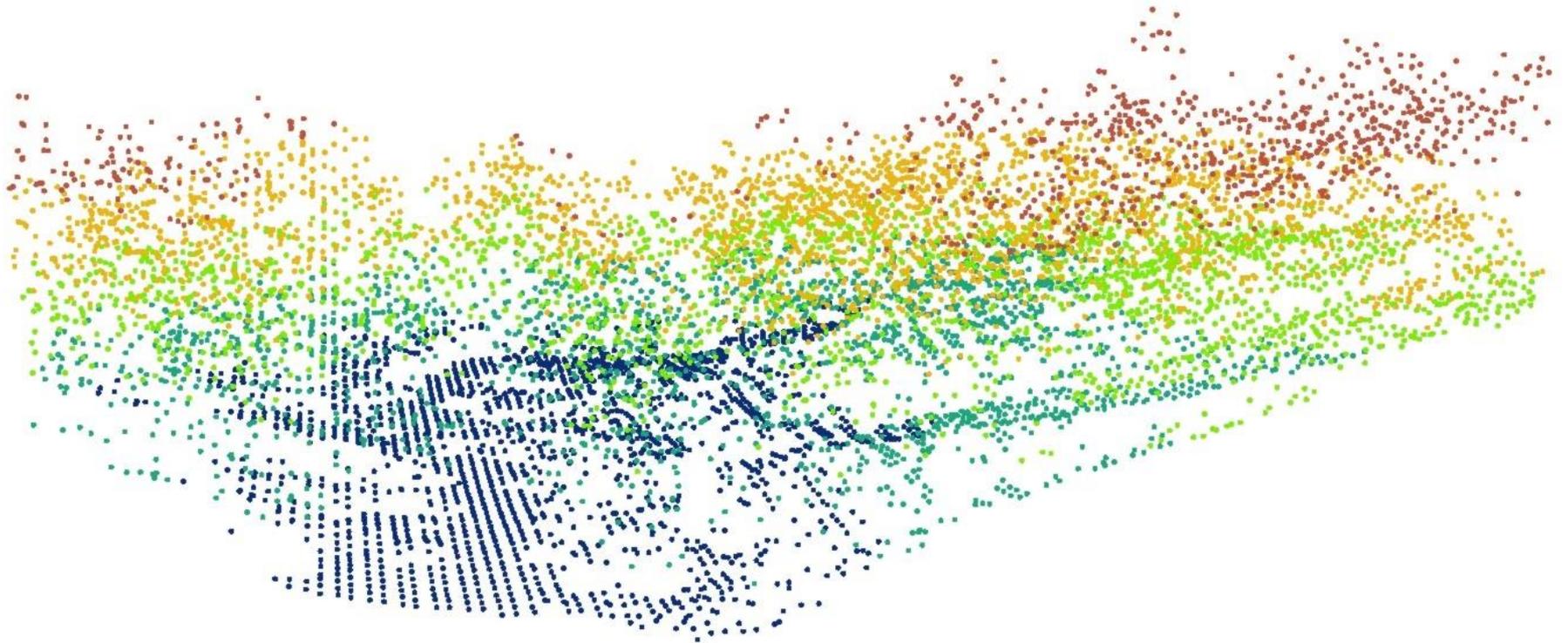
Private land: harvests follow property boundaries
USFS: harvests have 'soft' edges

Tepee Creek



USFS: less harvesting;
effects of topography on biomass

Regional Study



Fekety, P.A., M.J. Falkowski, A.T. Hudak, T.B. Jain and J.S. Evans. (2018) Transferability of lidar-derived basal area and stem density models within a northern Idaho ecoregion. *Canadian Journal of Remote Sensing* 44(2): 131-143.

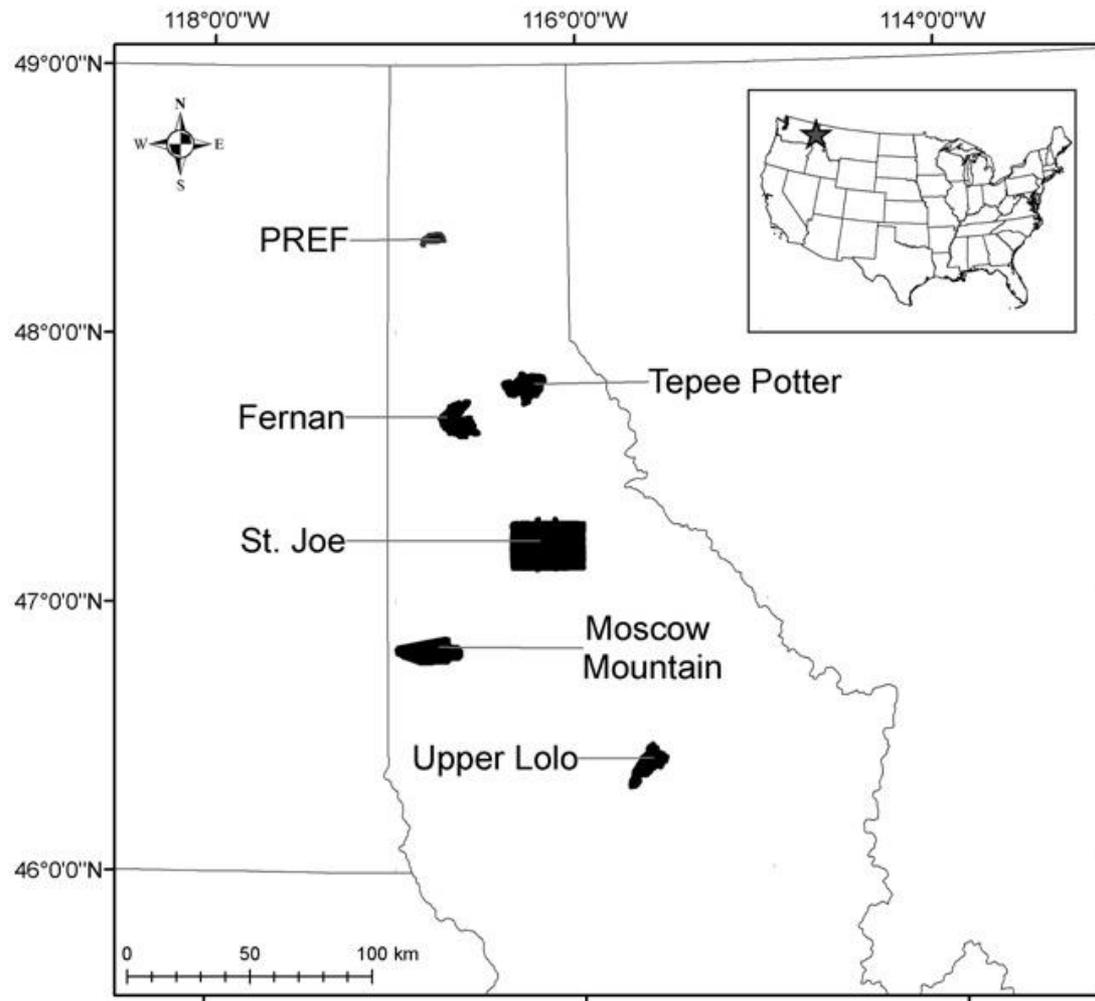


Table 1. Field data collection parameters.

Field dataset	<i>n</i>	Year	Lidar unit	Plot Area (m ²)	Plot design	Sampling design
CdA-East	24	2015	Tepee Potter	400	Fixed radius	Stratified by elevation, transformed aspect, and wetness
CdA-West	10	2015	Fernan	400	Fixed radius	Stratified by elevation, transformed aspect, and wetness
Moscow Mtn.	85	2009	Moscow Mtn.	400	Fixed radius	Stratified by elevation, solar insolation, and NDVIc
PREF	96	2011	PREF	400	Fixed radius	Stratified by forest type and canopy cover
St. Joe	79	2003-2004	St. Joe	400	Fixed radius	Stratified by elevation and solar insolation
Tepee Potter	39	2014	Tepee Potter	400	Fixed radius	Stratified by elevation, solar insolation, and NDVI
Upper Lolo	27	2007	Upper Lolo Creek	400	Fixed radius	Stratified by elevation, transformed aspect, and NDVIc

Note: CDA-East and CDA-West were part of the same data collection exercise. Both Tepee Potter and Fernan lidar units were combined for the stratification.

Imputation vs Regression Models

- Regression generates unique predictions based on the best model fit to a single response variable
- Imputation is weighted by the relationship between multiple response variables and multiple predictors.
- Imputations are the values observed at the reference plots assigned to unsampled locations.
- Regression predictions have a better fit to observations than imputations
- An advantage of imputation is the ability to predict ancillary variables.

Table 4. Potential explanatory variables.

Description of explanatory variables	Data source	
H05Pct: Height 5th percentile	FUSION	Height
H25Pct: Height 25th percentile	FUSION	
H50Pct: Height 50th percentile	FUSION	
H75Pct: Height 75th percentile	FUSION	
H95Pct: Height 95th percentile	FUSION	
Hmean: Height mean	FUSION	
Hstdv: Height standard deviation	FUSION	
Hskew: Height skewness	FUSION	
Hkurt: Height kurtosis	FUSION	
CRR: Canopy relief ratio (McGaughey 2016)	FUSION	
Stratum 0: Percentage lidar returns <0.15 m	FUSION	Density
Stratum 1: Percentage lidar returns >0.15 m and <1.37 m	FUSION	
Stratum 2: Percentage lidar returns >1.37 m and <5.0 m	FUSION	
Stratum 3: Percentage lidar returns >5 m and <10 m	FUSION	
Stratum 4: Percentage lidar returns >10 m and <20 m	FUSION	
Stratum 5: Percentage lidar of returns >20 m and ≤0 m	FUSION	
Stratum 6: Percentage lidar of returns >30 m	FUSION	
Pct1Rtn_1.37: Percentage lidar first returns above 1.37 m	FUSION	
Pct1Rtn_mean: Percentage lidar first returns above height mean	FUSION	
Elev: DTM elevation at 20 m resolution	FUSION	
Slope: Percent slope at 20 m resolution	FUSION	
TrAsp: Transformed aspect at 20 m resolution	Calculated in R	
SCOSA: Slope cosine aspect transformation	Calculated in R	
SSINA: Slope sine aspect transformation	Calculated in R	
GlobRadEquinox: Radiance estimate on 23 Sept	GRASS	
accumulation: Hydrologic flow accumulation	GRASS	
tci: Topographic convergence index	GRASS	
twi: Topographic wetness index	GRASS	

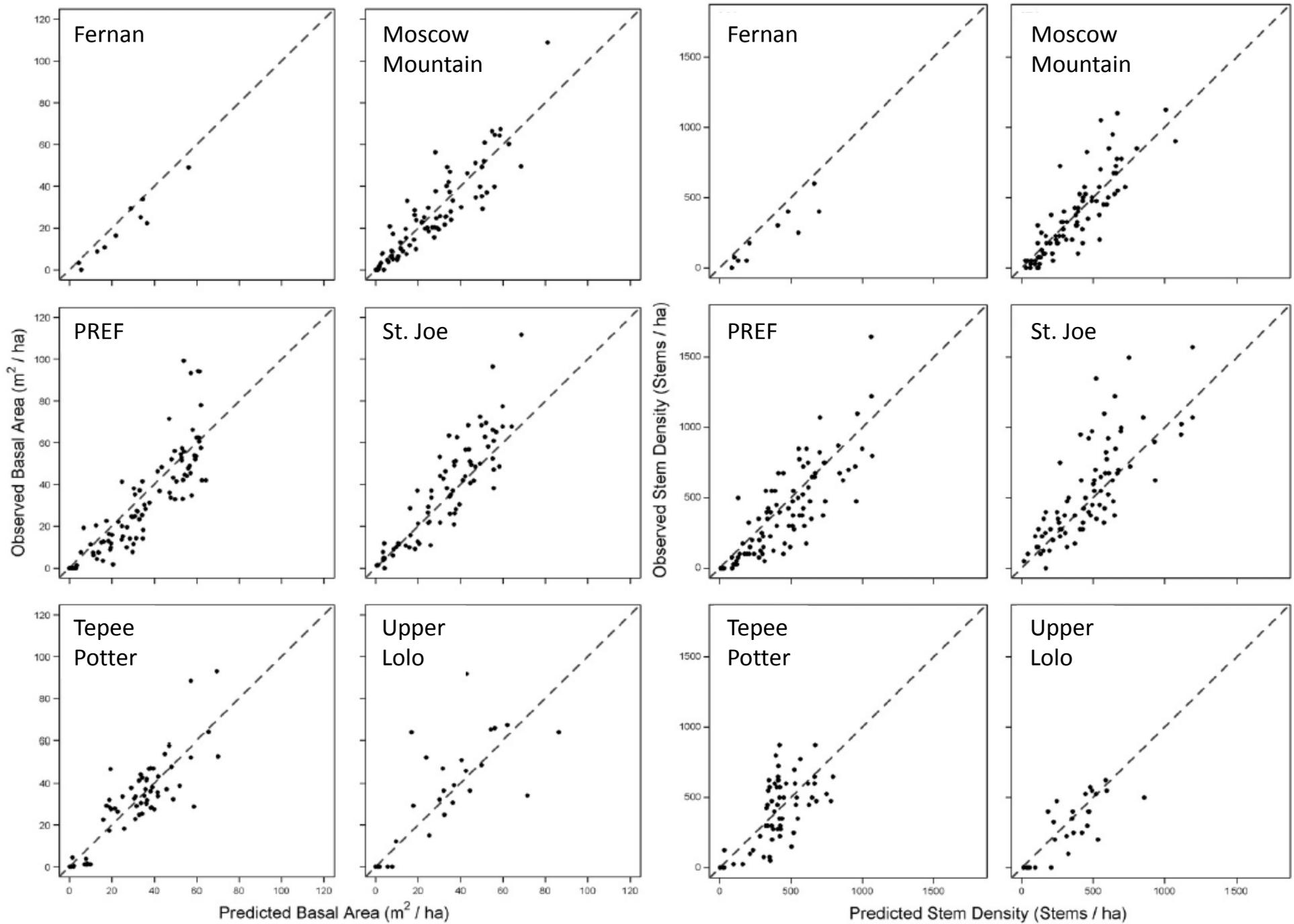
Table 5. Explanatory variables used in basal area and stem density random forests models.^a

Explanatory Variable	Basal Area							Stem Density						
	Fernan	Moscow Mtn.	PREF	St. Joe	Tepee Potter	Upper Lolo	Fernan	Moscow Mtn.	PREF	St. Joe	Tepee Potter	Upper Lolo		
H05Pct	X		X	X	X	X	X	X	X	X	X	X		
H95Pct	X		X	X	X	X								
Hmean		X												
Pct1Rtn_mean	X	X	X	X	X	X	X	X	X	X	X	X		
Stratum 0								X			X			
Stratum 1	X			X	X		X	X	X	X		X		
Stratum 2			X											
Stratum 3									X					
Stratum 4	X	X	X	X	X		X	X	X	X		X		
Stratum 5	X	X	X	X	X	X	X	X	X		X	X		
Stratum 6		X												

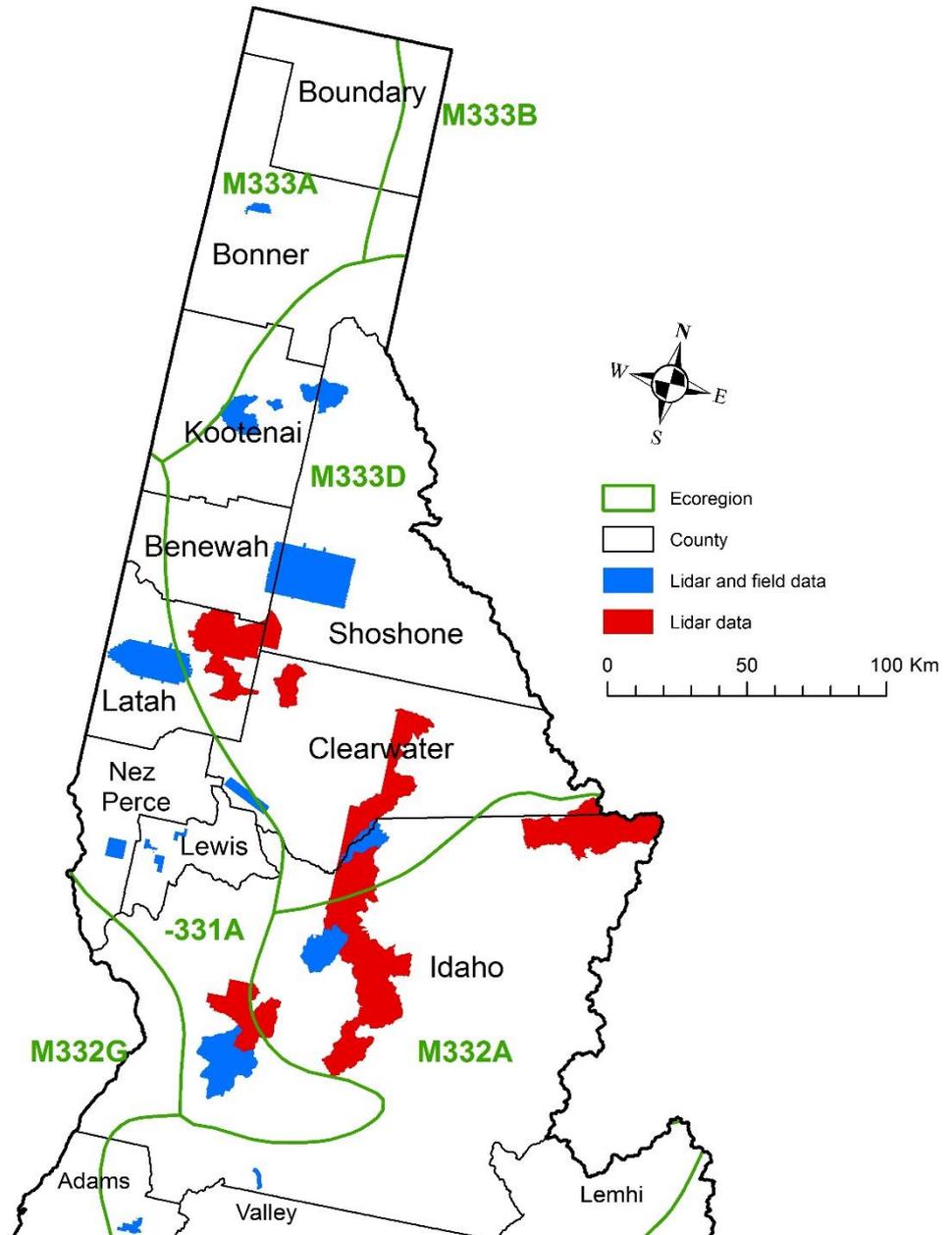
Note: X: selected variable. ^aSee Table 4 for description of explanatory variables.

Table 6. Median cross-validated model fit statistics (and standard deviation) for basal area and stem-density models.

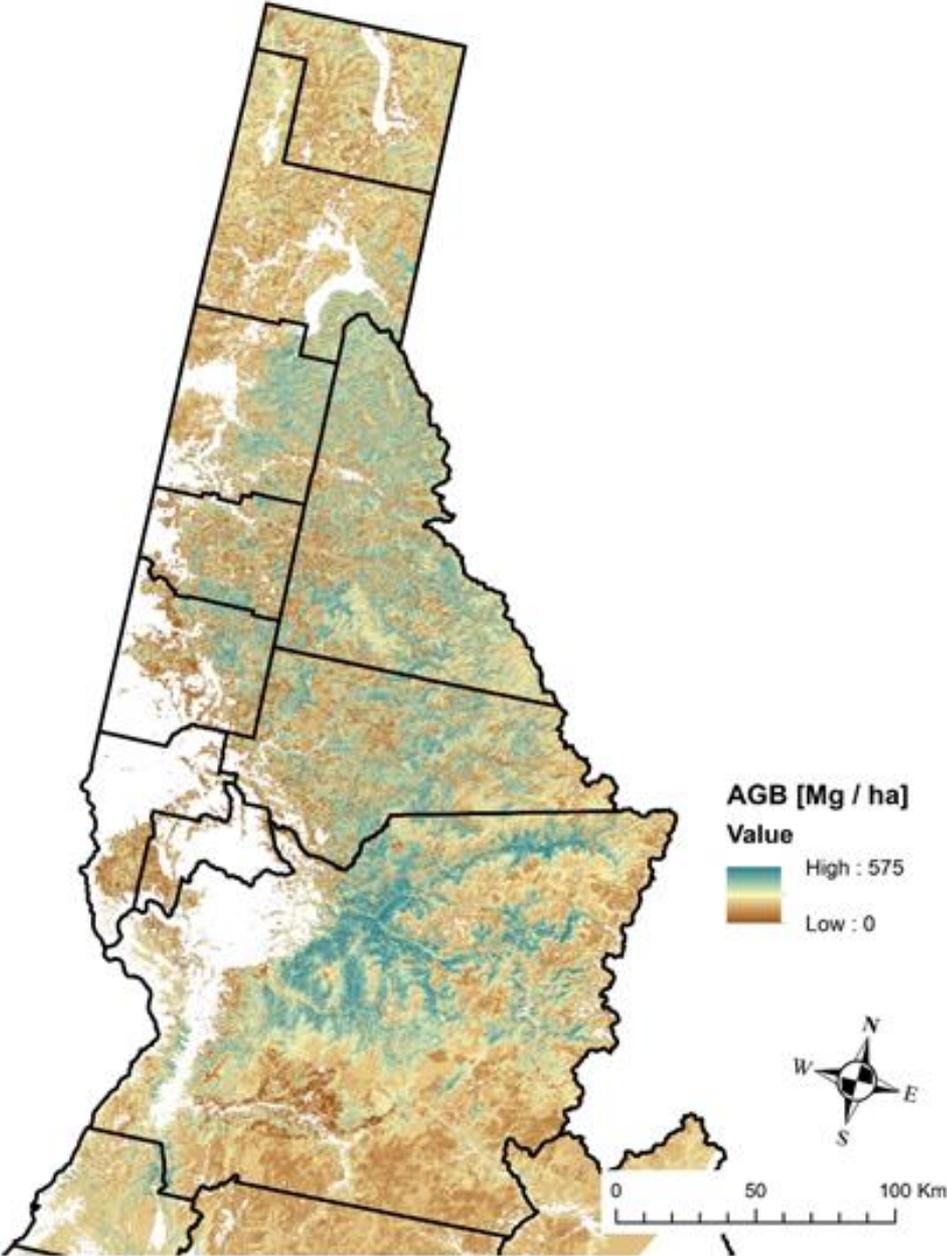
Response	Model	Variance Explained (%)	SD (%)	RMSE% (%)	SD (%)
Basal area	Fernan	76.9	(1.0)	35.2	(5.6)
	Moscow Mountain	73.3	(1.1)	34.9	(6.8)
	PREF	76.7	(0.9)	32.0	(6.7)
	St. Joe	76.8	(1.2)	35.2	(6.9)
	Tepee Potter	76.7	(1.0)	36.9	(6.4)
	Upper Lolo	79.1	(0.8)	32.5	(5.0)
Stem density	Fernan	65.6	(1.3)	42.5	(5.5)
	Moscow Mountain	64.4	(1.4)	43.7	(7.1)
	PREF	61.8	(1.5)	44.7	(6.9)
	St. Joe	65.5	(1.0)	43.8	(8.4)
	Tepee Potter	69.1	(1.1)	42.4	(7.7)
	Upper Lolo	65.6	(1.3)	43.9	(6.6)



Expanding LiDAR Coverages



Regional Forestry Study



Current Work

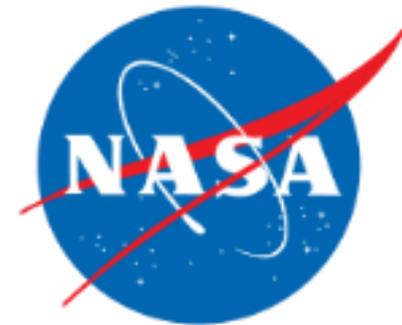
- Predicting AGB across large spatial extents from annual Landsat image time series
 - Use LiDAR-mapped 30m AGB pixels as reference data
 - Use 30m Landsat pixels without lidar as target data
- Instead of topographic predictors, using climate predictors
 - To capture regional environmental gradients that drive productivity across the Inland and Pacific Northwest
 - To allow for future AGB projections under climate change scenarios

FUSION

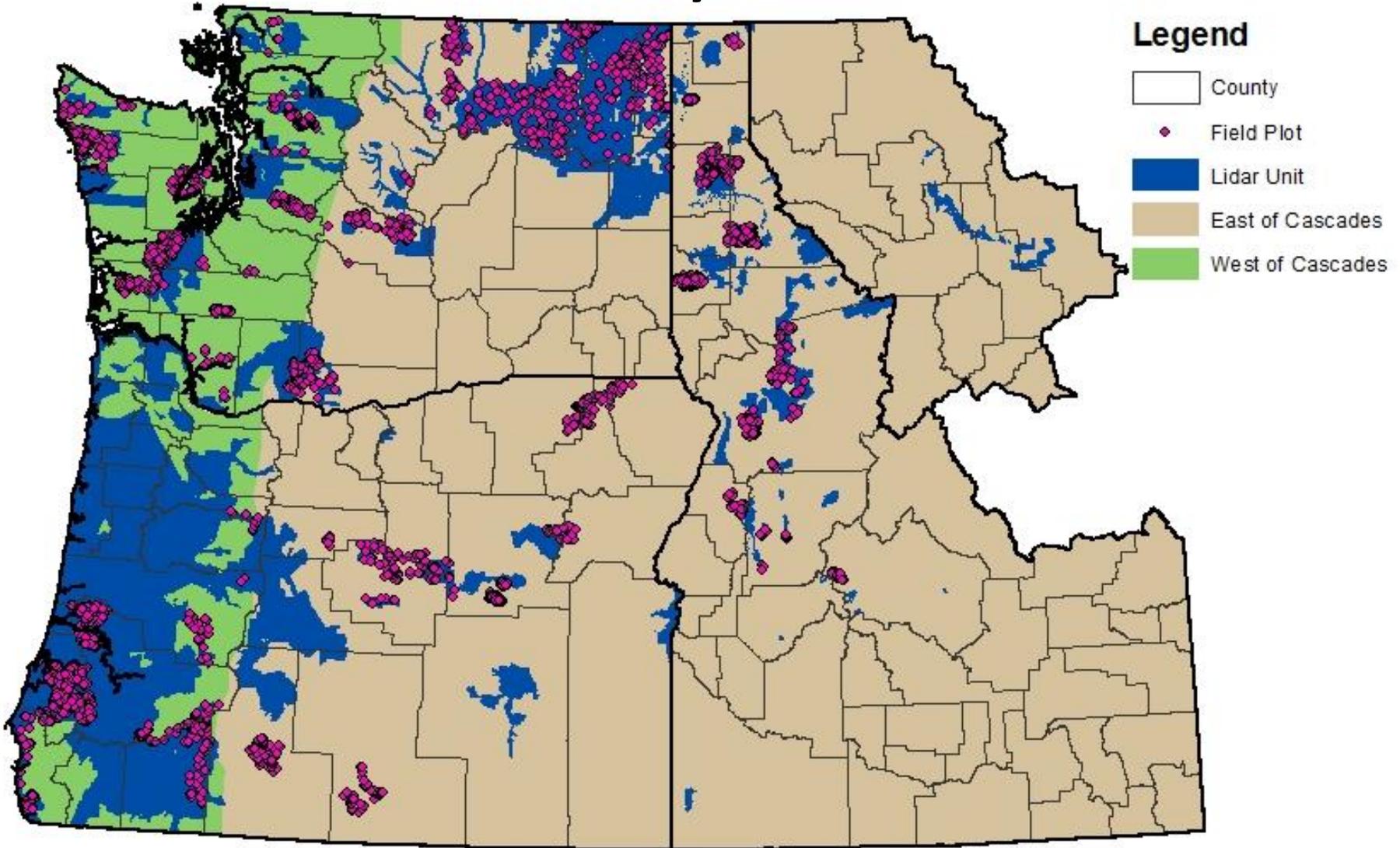
*Providing fast,
efficient, and flexible
access to LIDAR, IFSAR
and terrain datasets*



*Robert J. McGaughey
Pacific Northwest Research Station*

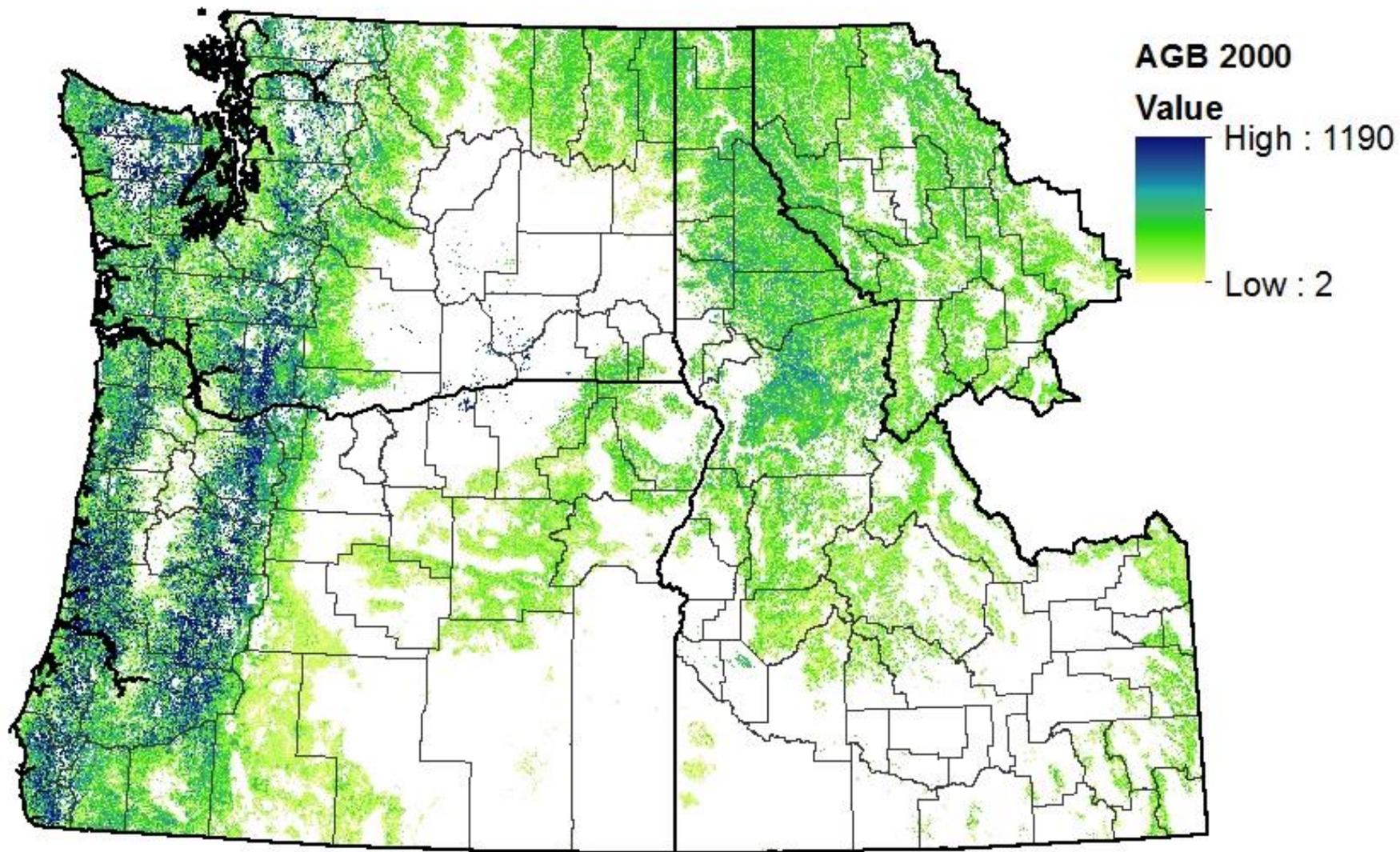


Study Area

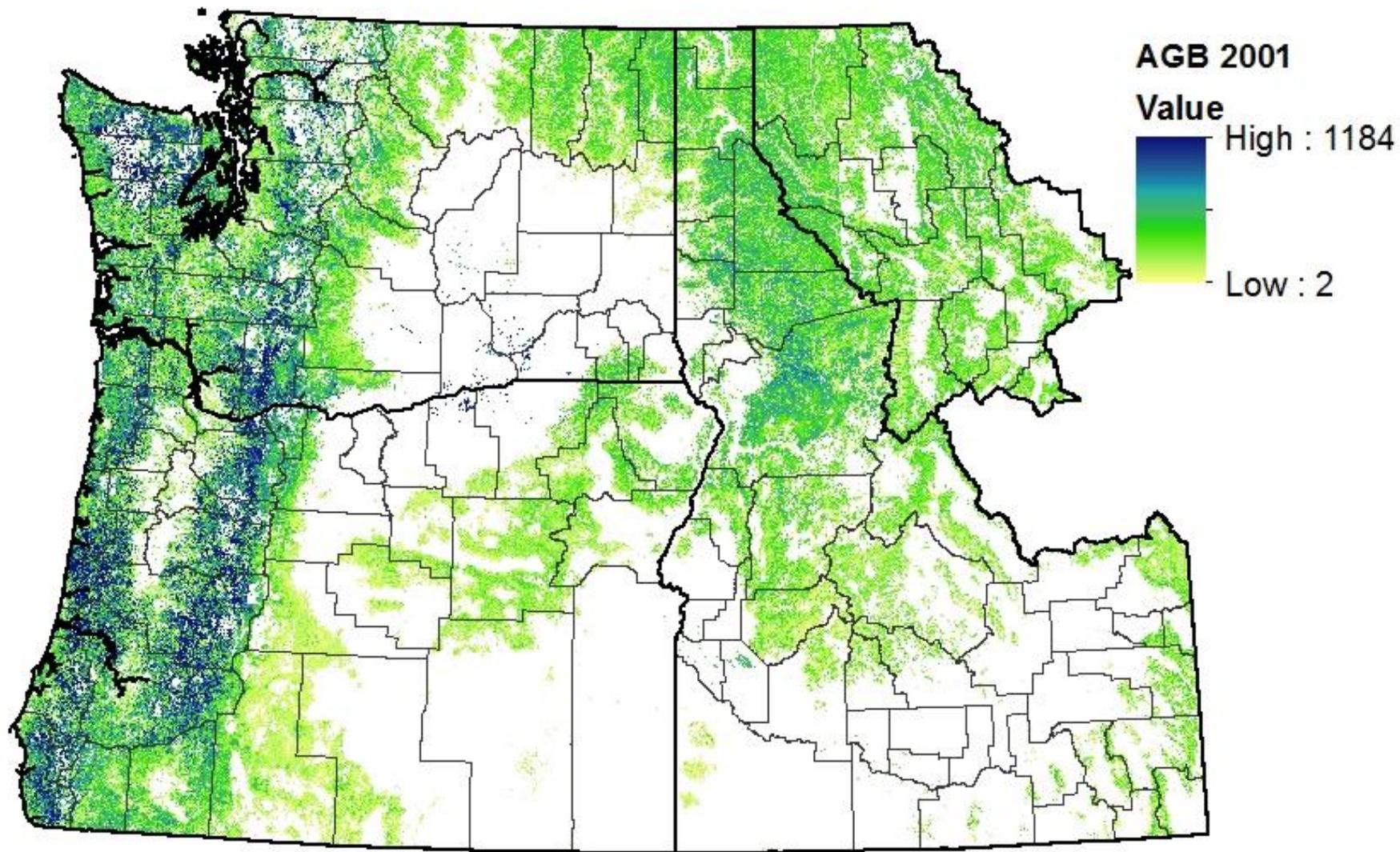


0 100 200 300 400 km

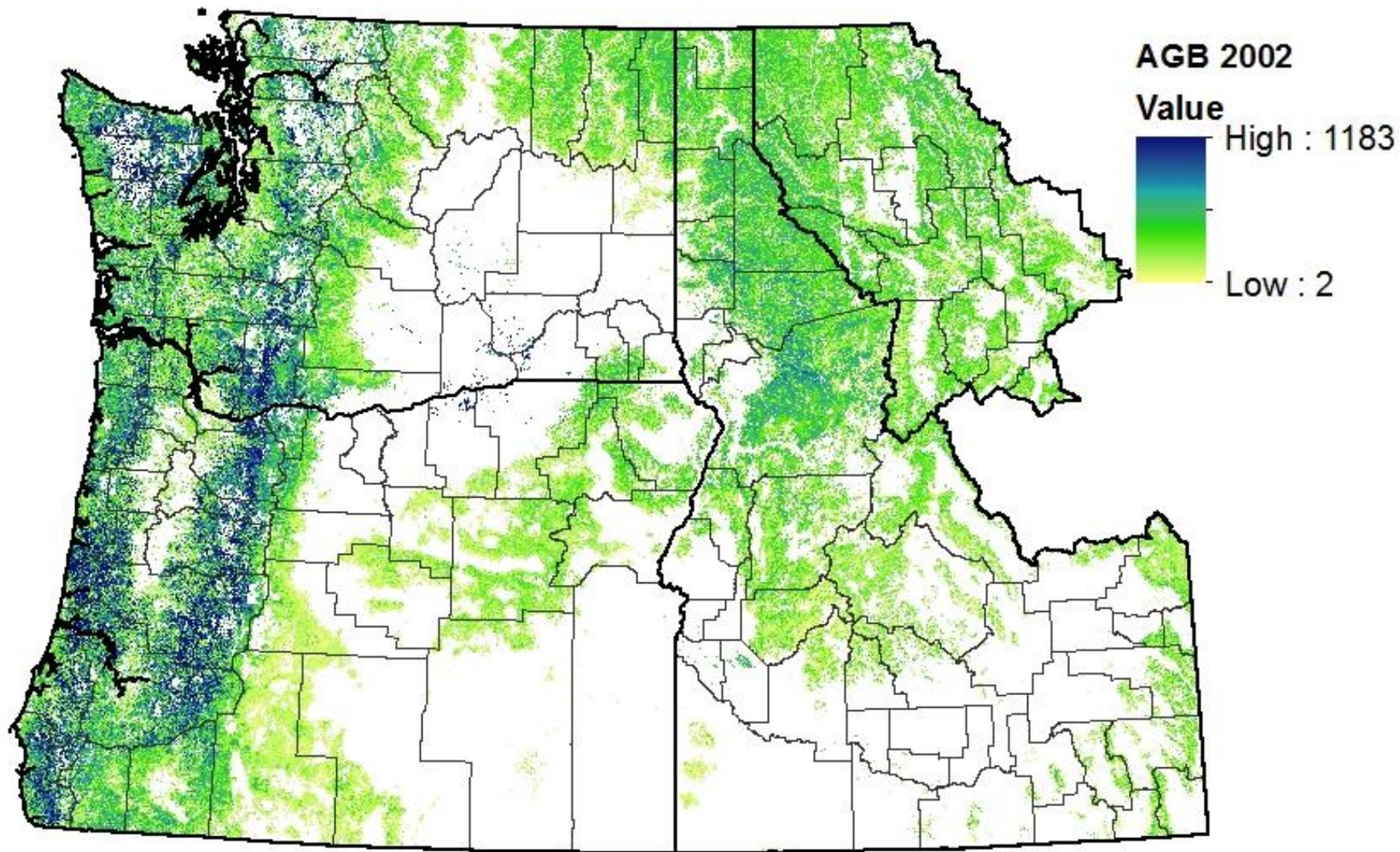
3,672 project-level field plots
~3M ha airborne LiDAR



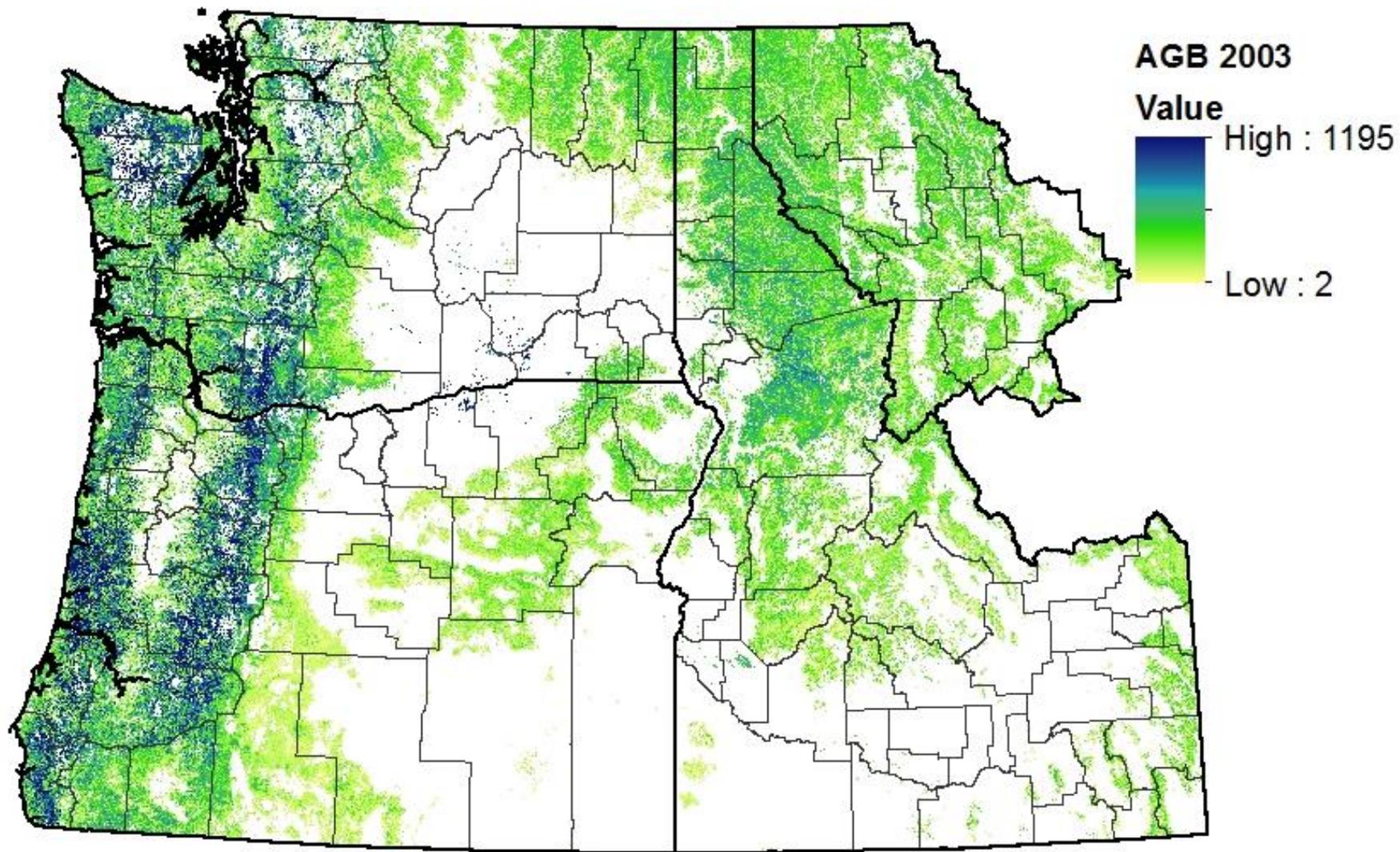
0 100 200 300 400 km



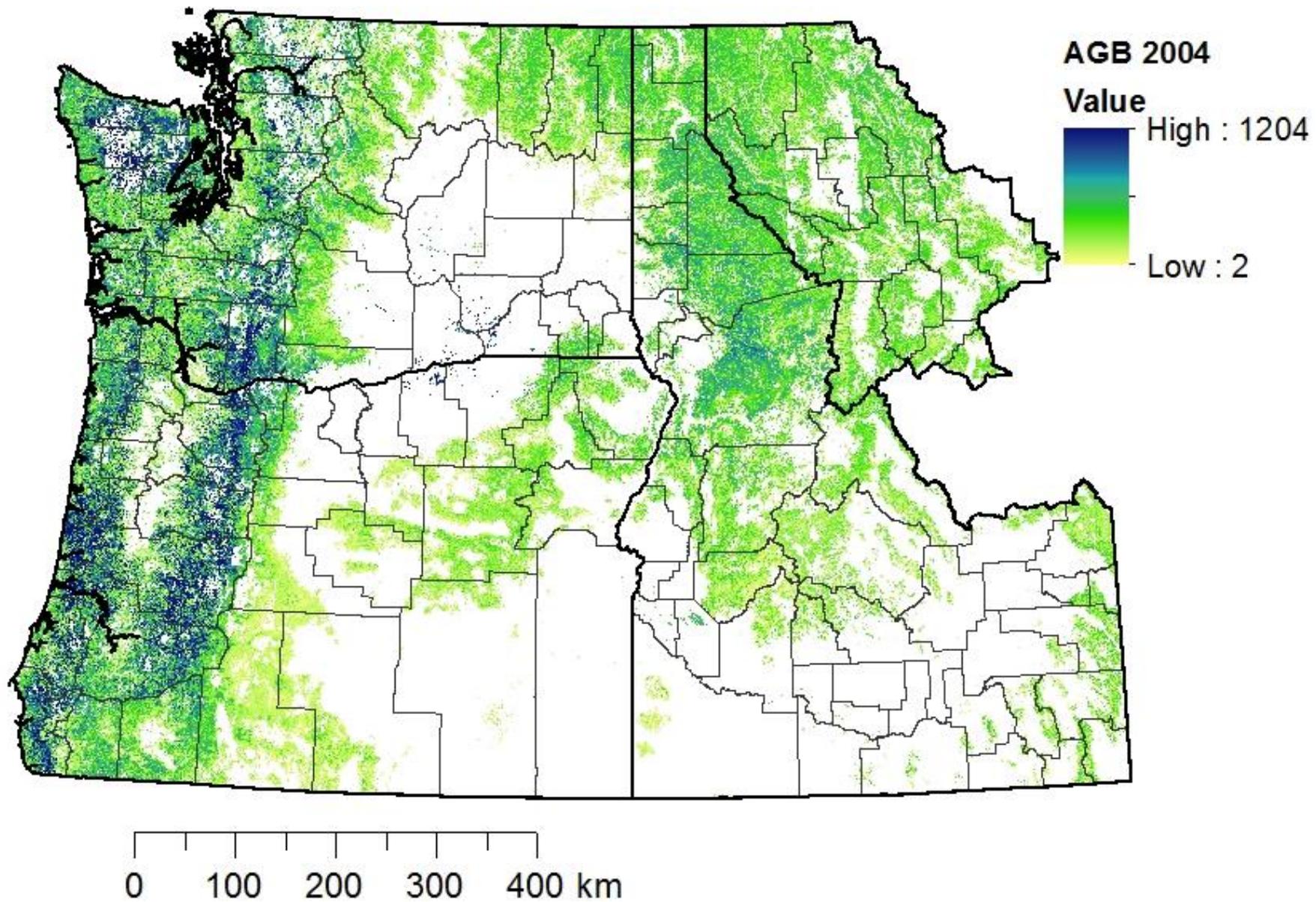
0 100 200 300 400 km

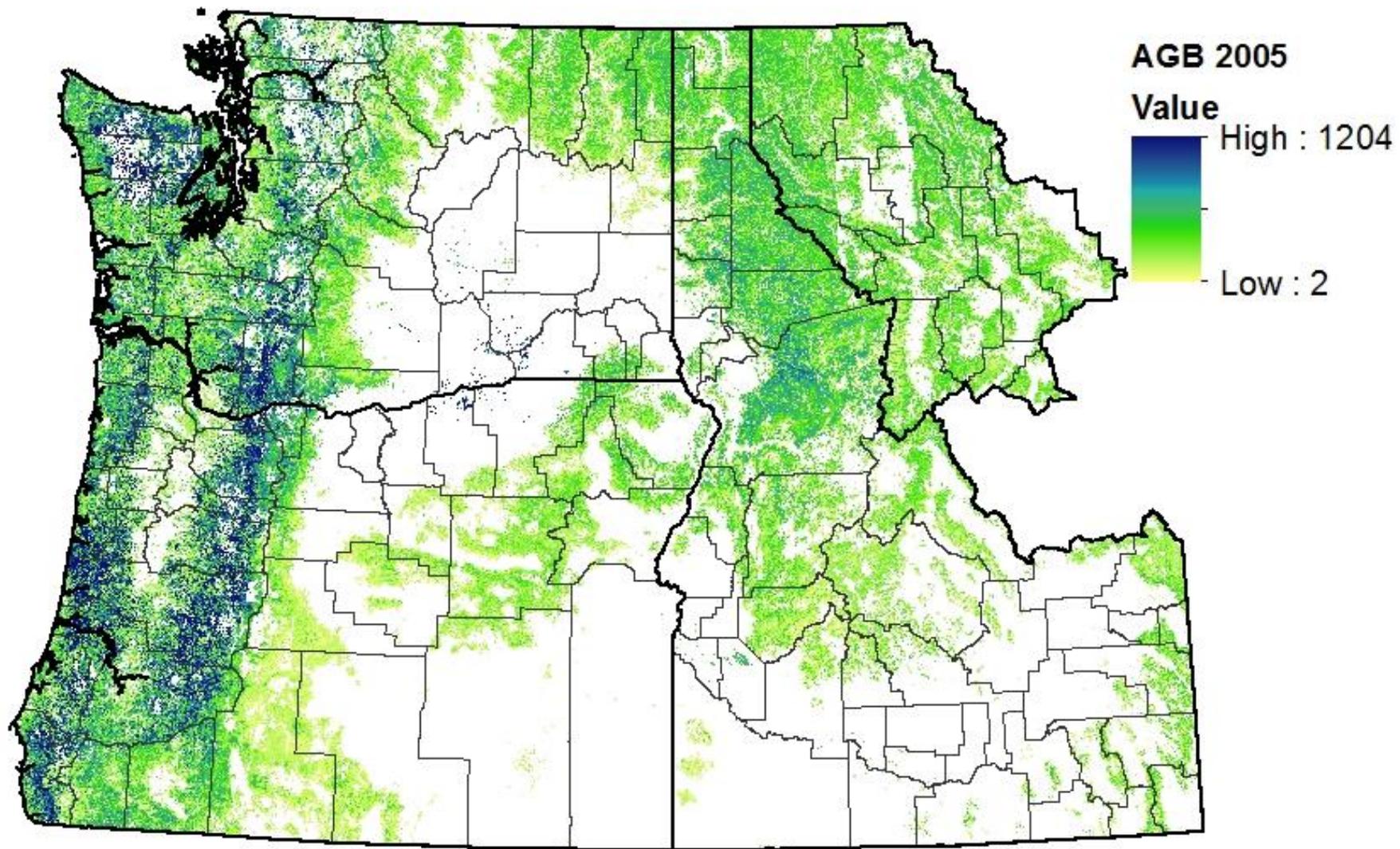


0 100 200 300 400 km

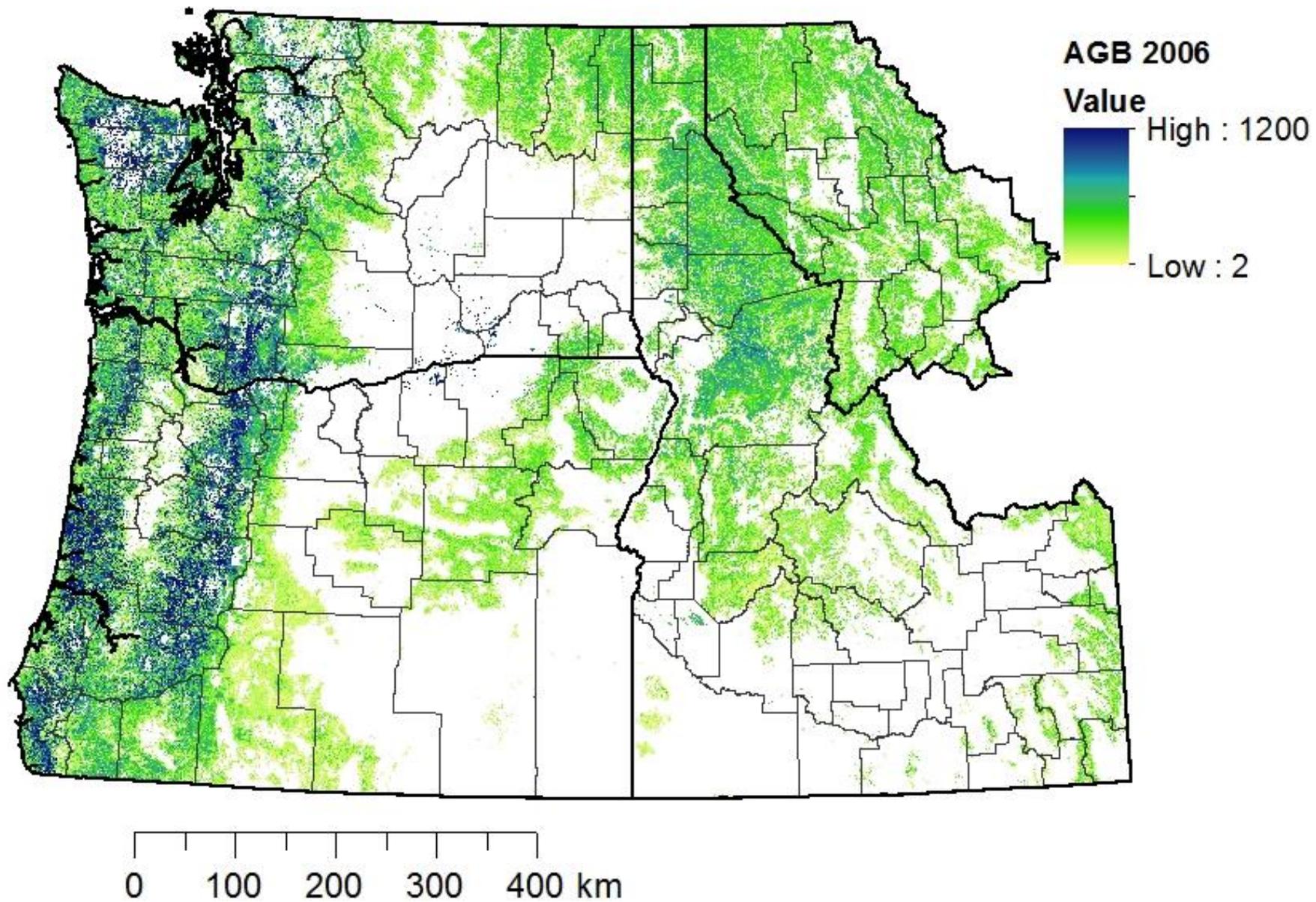


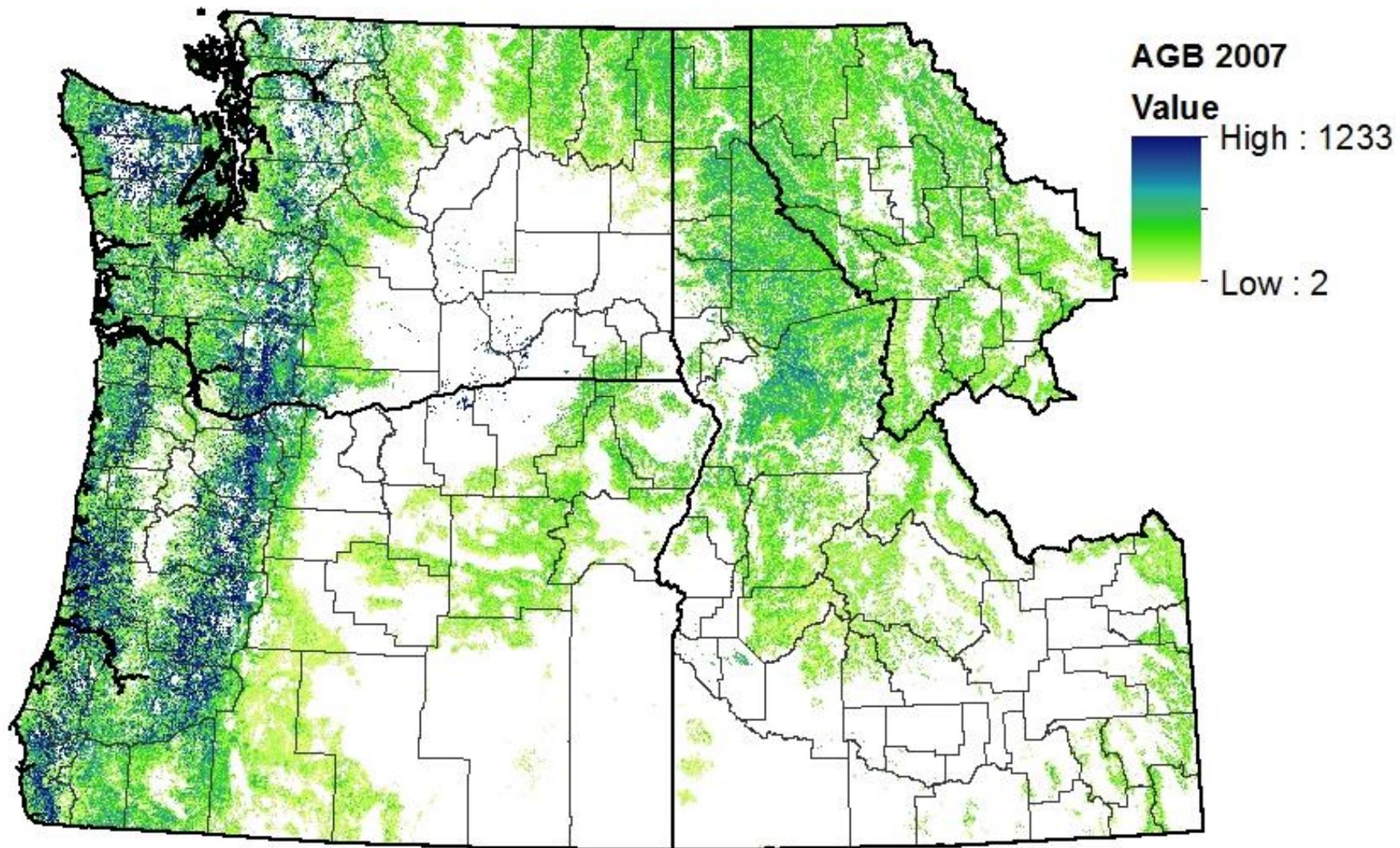
0 100 200 300 400 km



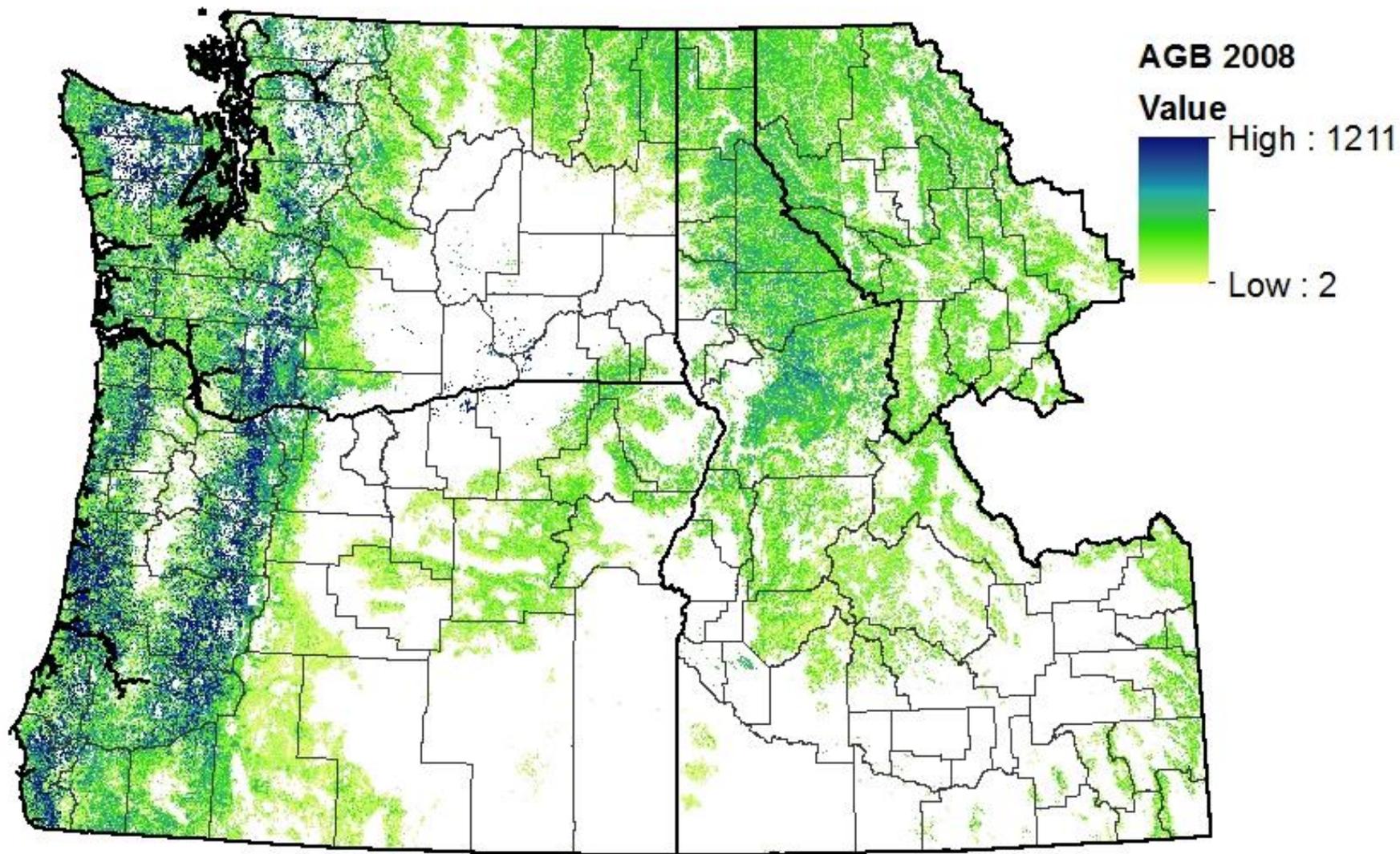


0 100 200 300 400 km

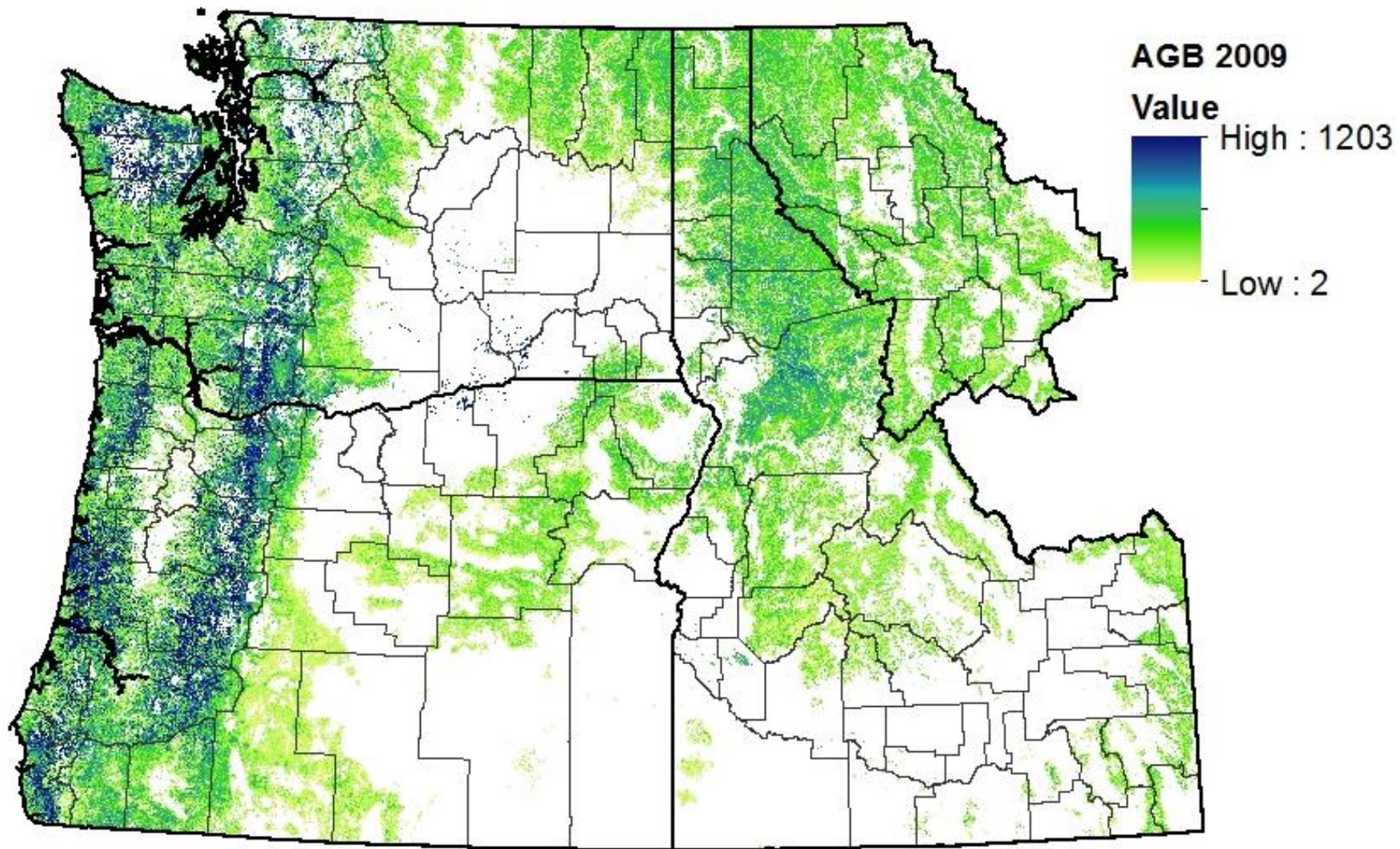




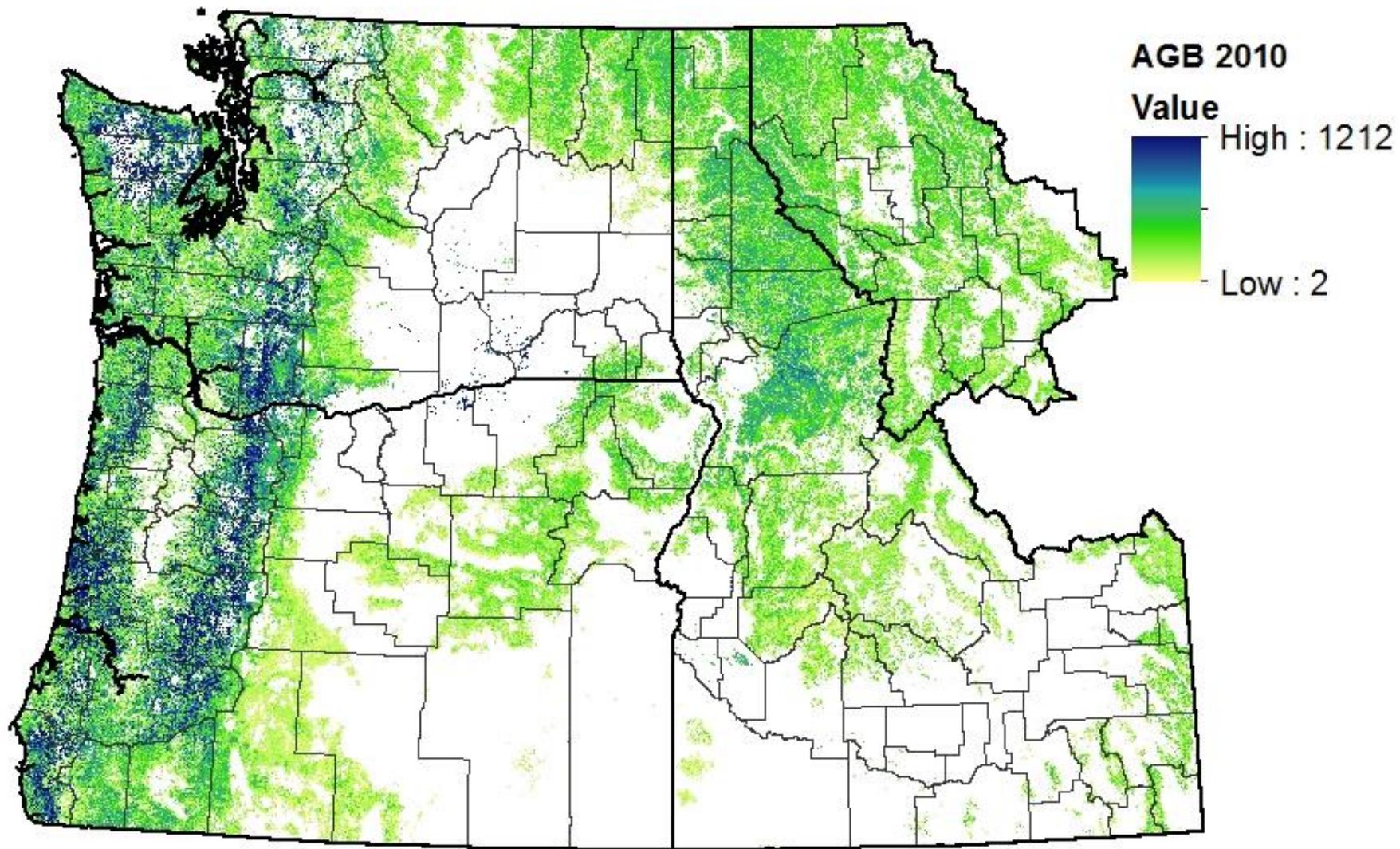
0 100 200 300 400 km



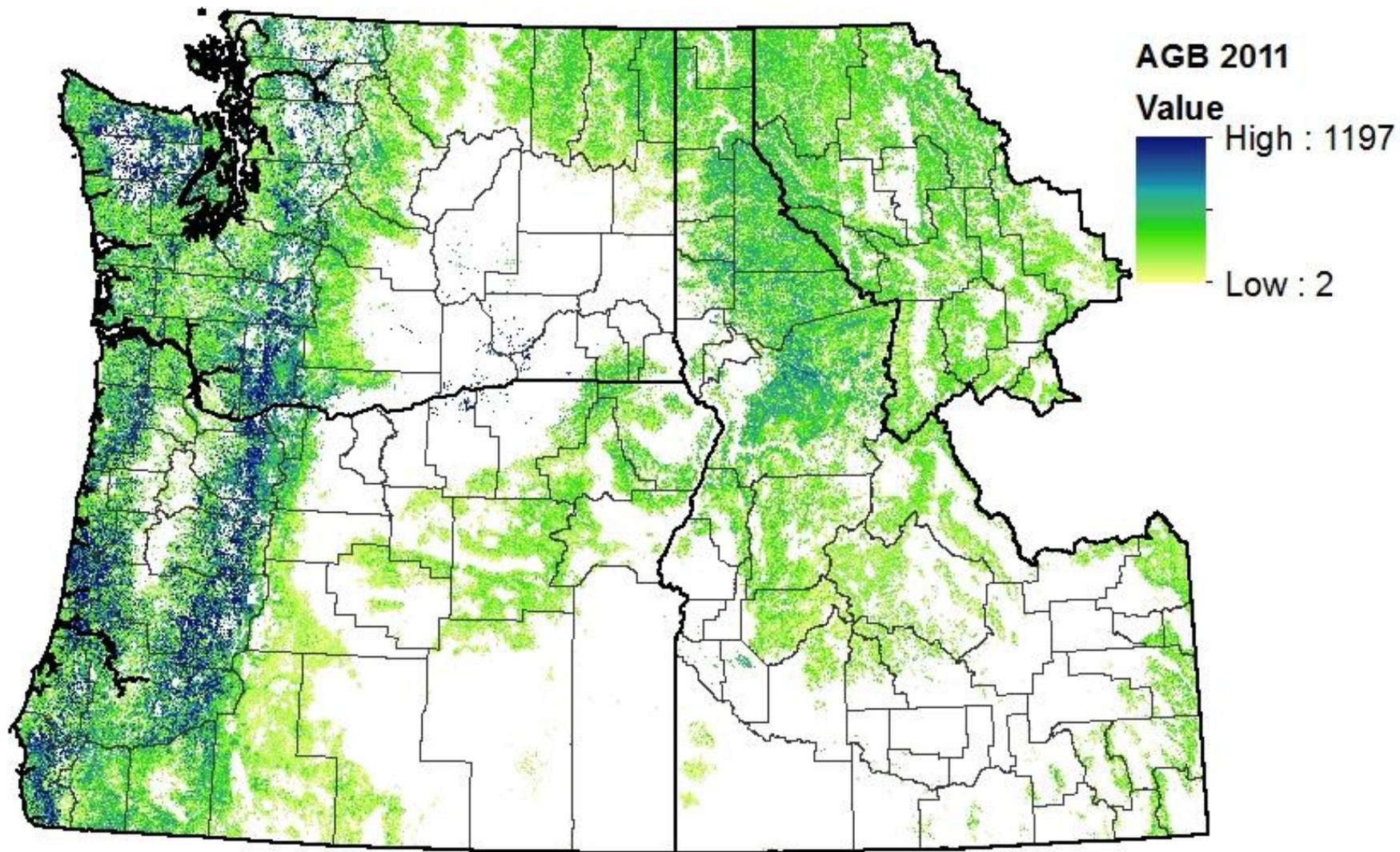
0 100 200 300 400 km



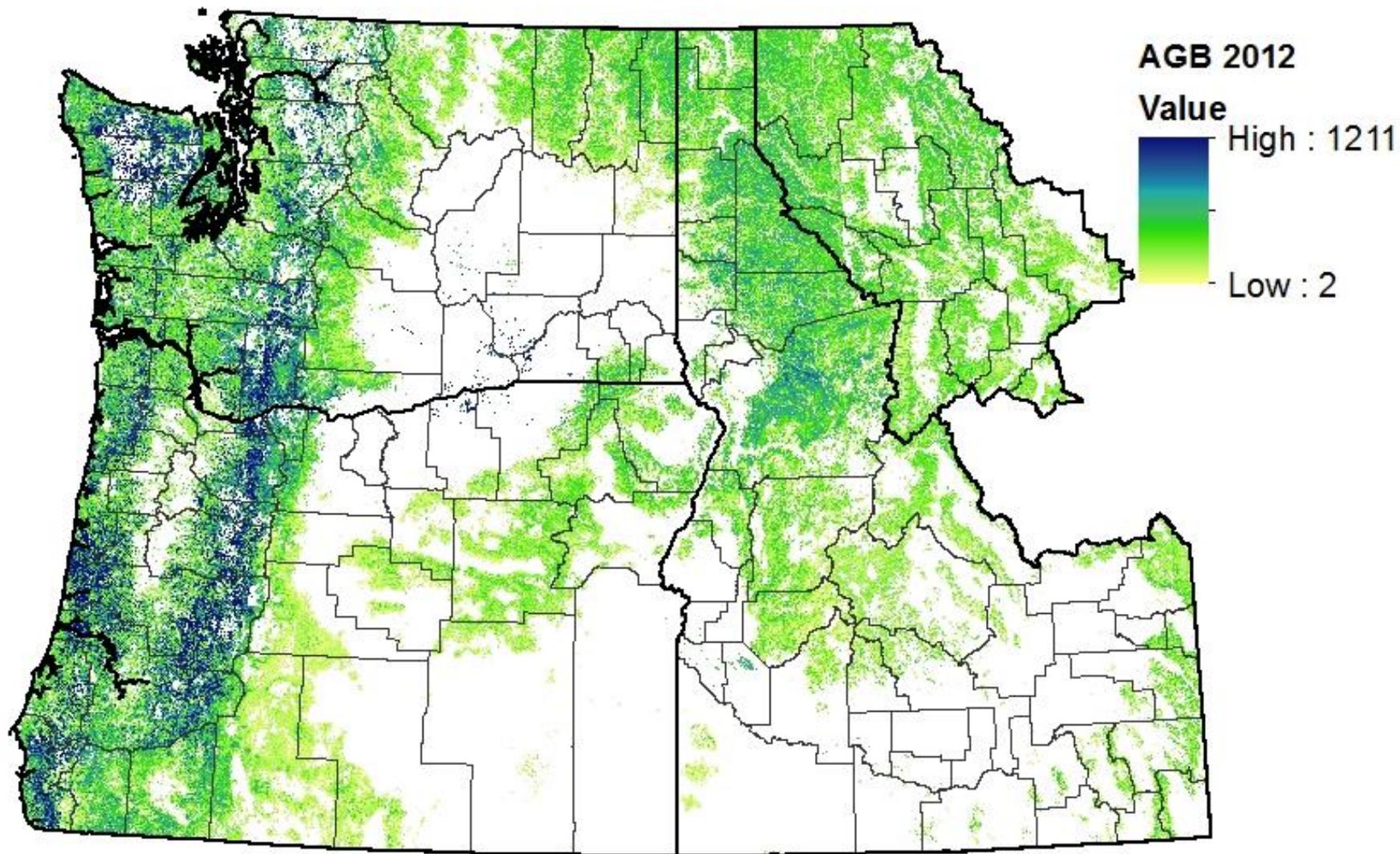
0 100 200 300 400 km



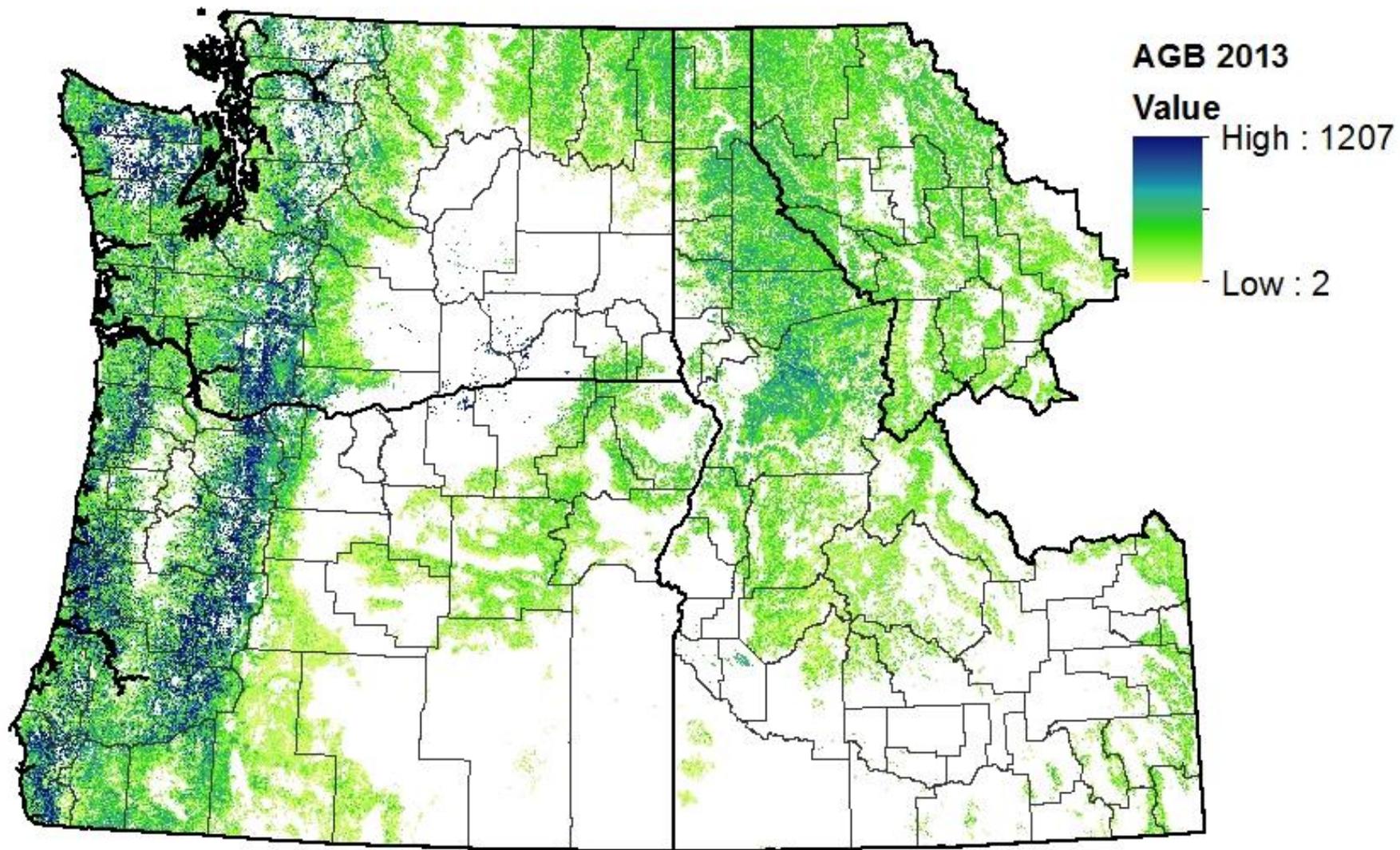
0 100 200 300 400 km



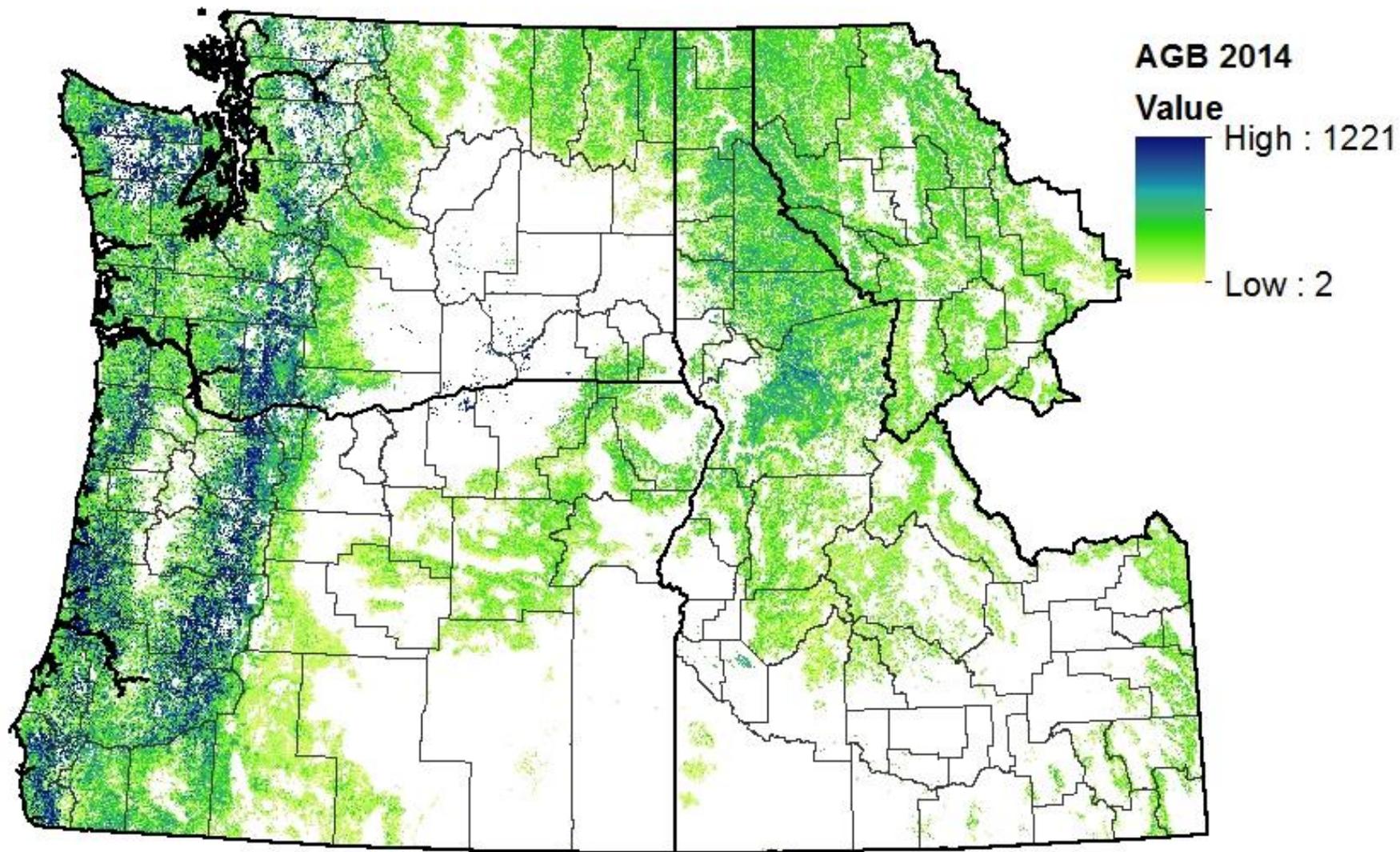
0 100 200 300 400 km



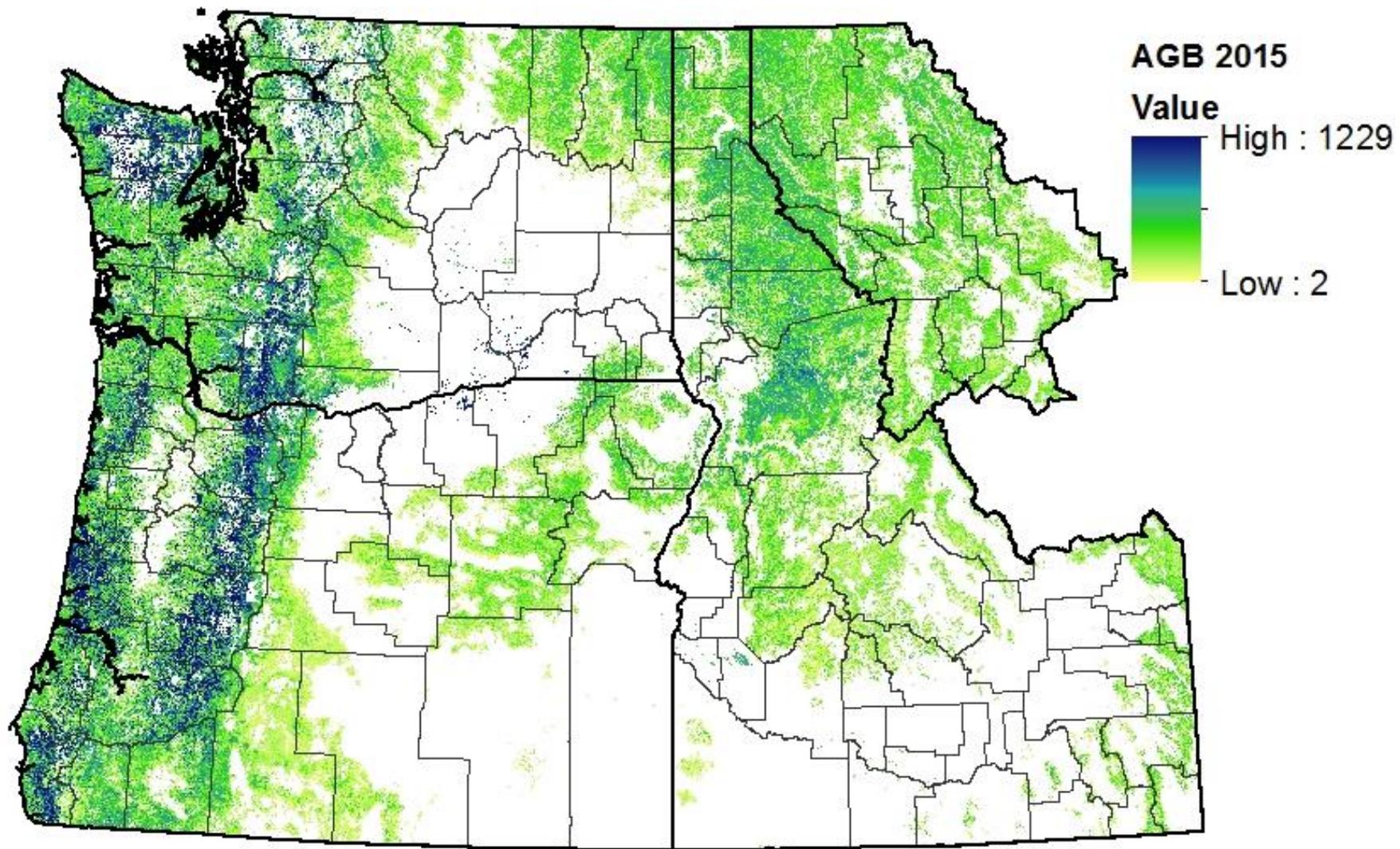
0 100 200 300 400 km



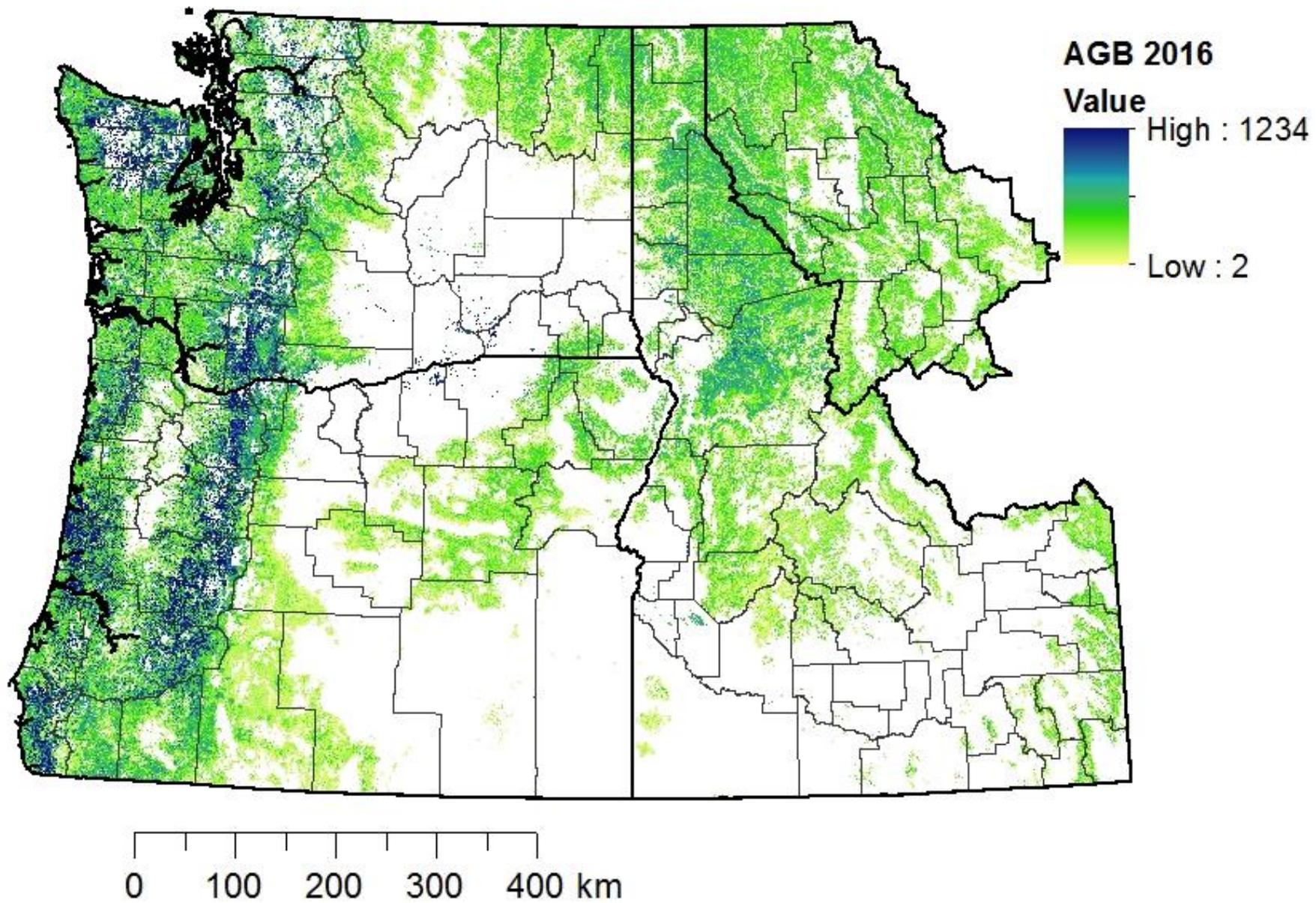
0 100 200 300 400 km



0 100 200 300 400 km



0 100 200 300 400 km



Acknowledgements

- Patrick Fekety, Mike Falkowski – CSU
- Jason Jerman – USFS Idaho Panhandle National Forest
- University of Idaho, Private Landowners
- Funding – NASA, USFS, University of Idaho, IDL



Questions?

