




Mapping potential productivity in the PNW for climate change and other economic projections

Greg Latta, Research Assistant Professor of Forest Economics

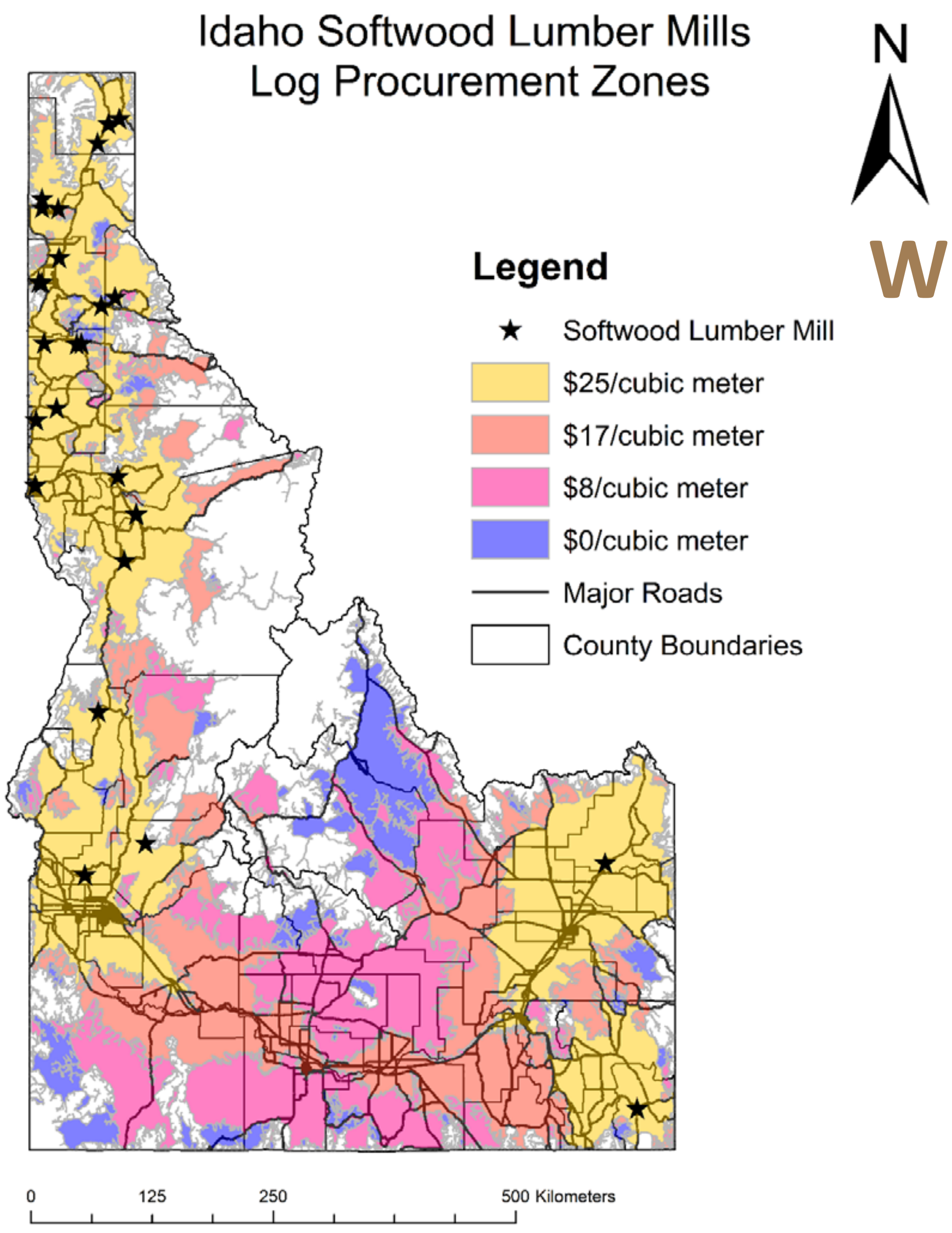
Intermountain Forestry Cooperative Technical Meeting
Tuesday, March 27, 2018

University of Idaho
College of Natural Resources

Outline

University of Idaho
College of Natural Resources

- **Punch line first: I am looking for site index data to generate a Site Index map for Idaho**
  - Why?
- **What I have done in the past**
  - Localized Regression Techniques *(which you all are familiar with)*
  - Mapping PNW Potential Site Productivity
- **Back to the punch line**

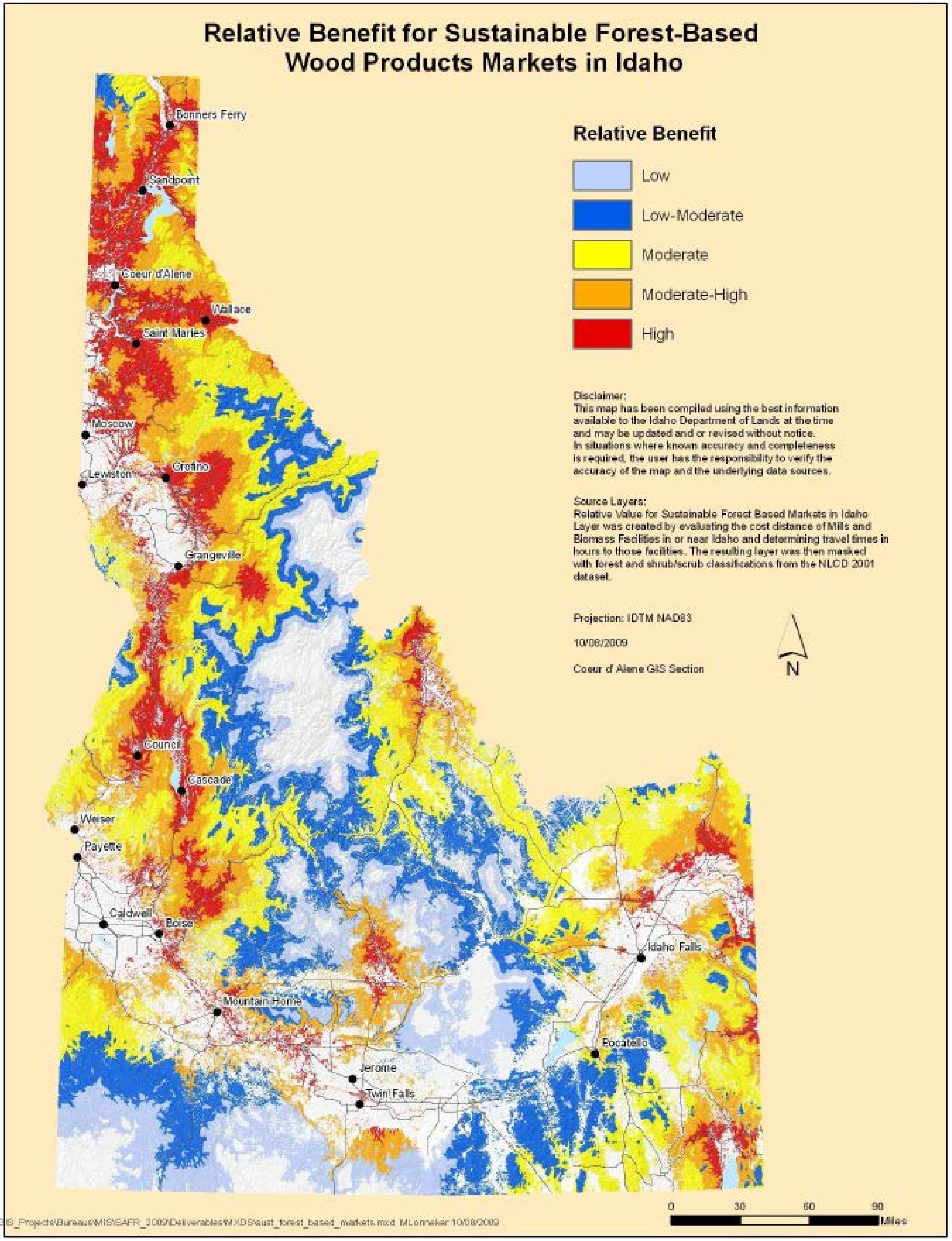


University of Idaho
College of Natural Resources

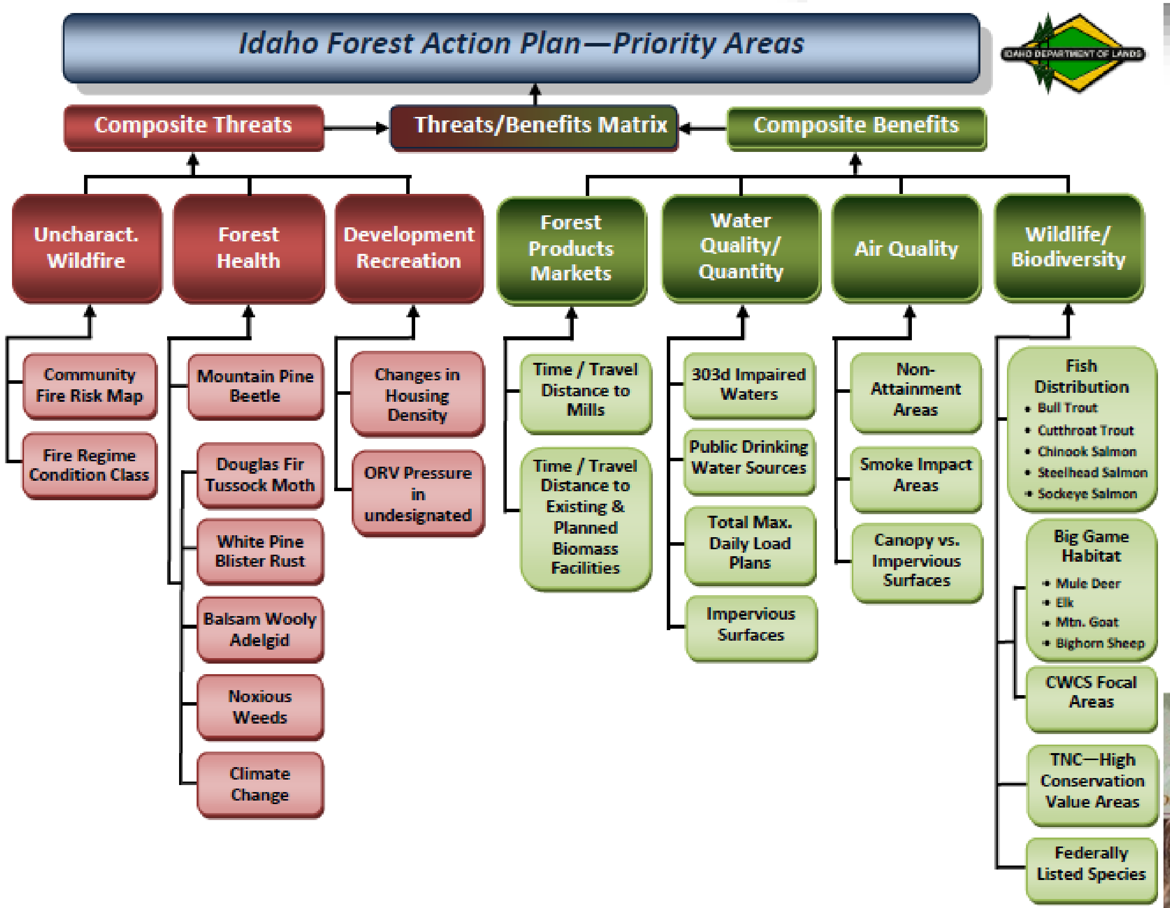
Why am I looking for a site index map?

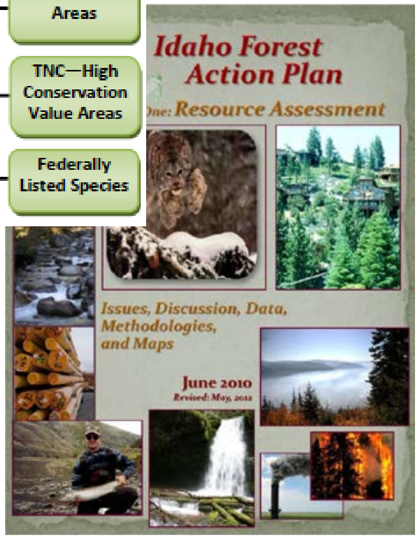
We have been evaluating log procurement zones for Idaho

Potential Stumpage $/m3	Procurement Area hectares
25	6,315,400
17	+ 4,165,900
8	+ 3,768,600
0	+ 1,538,000



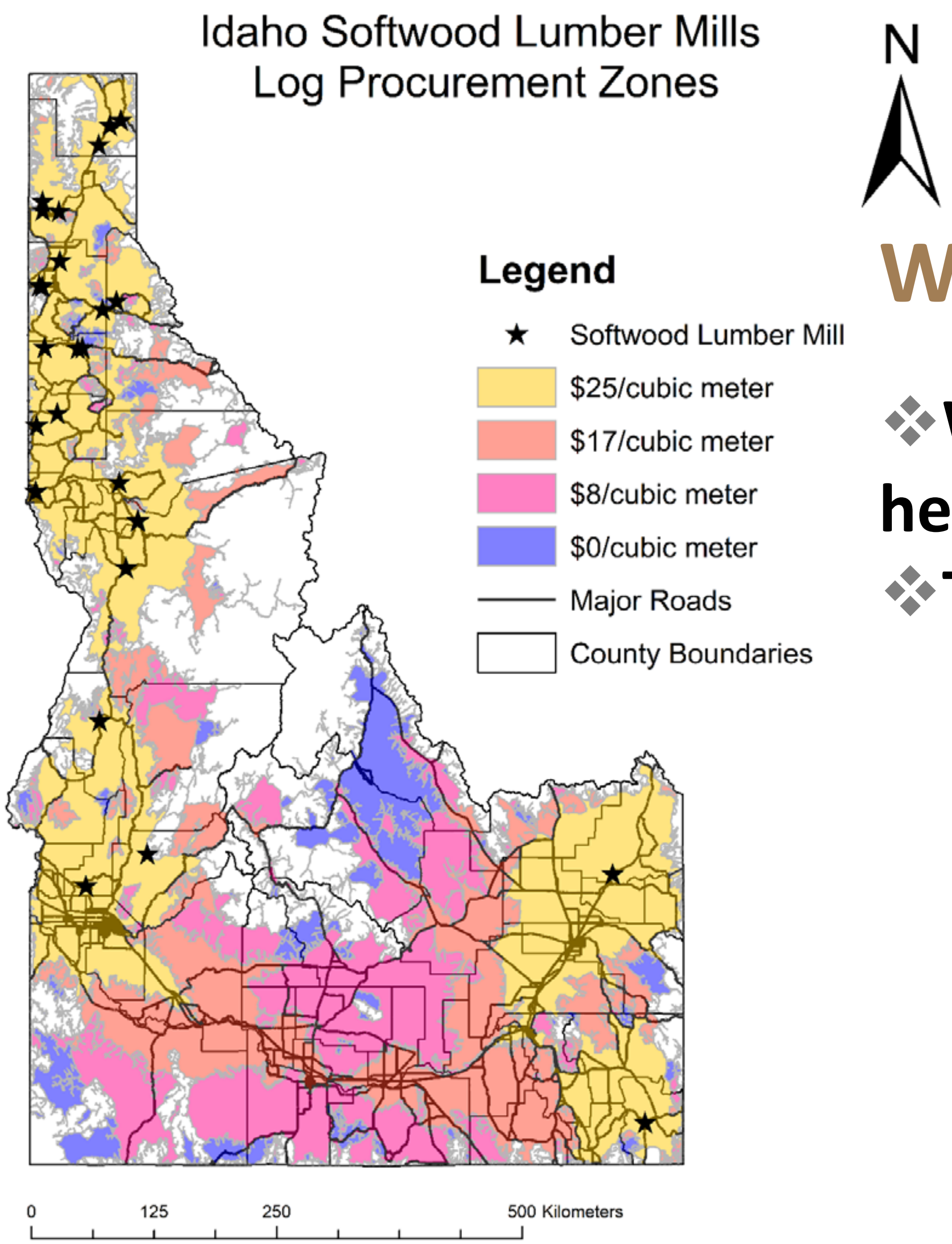
Why am I looking for a site index map?





Idaho Forest Action Plan (FAP) Resource Assessment

GIS-based analysis to assist in guiding resources to priority areas



University of Idaho
College of Natural Resources

Why am I looking for a site index map?

- **We: UI and the Policy Analysis Group want to help IDL with the market GIS assessment**
- **To do this we would add**
  - More information - *such as*
    - Ownership
    - Diversity in log use *(sawmill and pulpmill >sawmill>biomass)*
    - Socioeconomic parameters *(unemployment rate, etc)*
    - ***Forest productivity***
      - ***This is where the IFC wealth of experience (and data) comes in handy***

What have I done in the past?

I was involved in a site productivity imputation project

- We compared methods to generate productivity maps from climate parameters
  - We also used that model and climate projections to evaluate how future climate regimes could change productivity across the PNW (OR and WA *– I was at OSU at the time, so Idaho didn't exist to me*)
    - FYI - I'm not looking to do that (*the climate change thing*) here

Latta, G., Temesgen, H., and T. Barrett. 2009. Mapping and imputing potential productivity of Pacific Northwest Forests using climate variables. *Canadian Journal of Forest Research* 39(6): 1197-1207.

Latta, G., H. Temesgen, D. Adams and T. Barrett. 2010. Analysis of potential impacts of climate change on forests of the United States Pacific Northwest. *Forest Ecology and Management* 259(4): 720-729.

Localized Regression Techniques

Challenge some of the basic regression assumptions spatially

Spatial Autoregressive Model (SAR)

Challenges the assumption that e_i is the same across the map

$$y_i = \sum_{j=1}^{m} \beta_{j} x_{ij} + e_i$$

For *i* observations and *j* regressors

Geographically Weighted Regression (GWR)

Challenges the assumption that B_j is the same across the map

PNW Site Productivity Imputation Study

University of Idaho
College of Natural Resources

Examine and identify the best practical method using climatic parameters to estimating site productivity and assigning productivity to timberland on PNW-FIA plots that are missing site index trees.

The 4 methods evaluated

- Most Similar Neighbor - MSN
- Multiple linear regression model - OLS
- Thin plate spline functions (ANUSPLIN, Hutchison 1995)
- Simultaneous Autoregressive Model - SAR

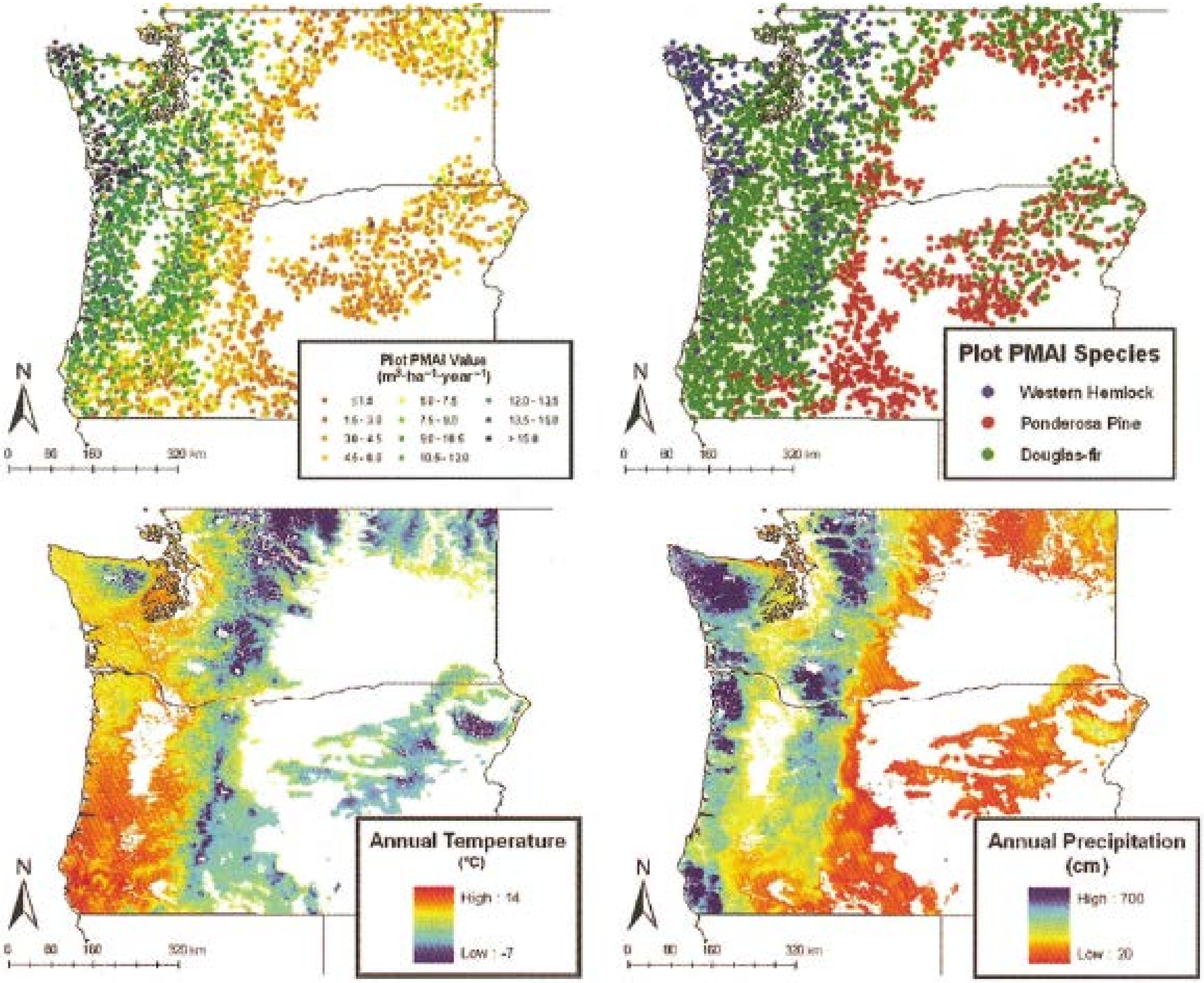
Data – Descriptive Statistics

University of Idaho
College of Natural Resources

- Potential mean annual increment and geographic attributes were obtained for 3356 measurement plots in Oregon and Washington.
- Monthly temperature and precipitation normal data for the period 1971-2000 was produced by the Parameter-elevation Regressions on Independent Slopes Model (PRISM).
- Short wave incoming solar radiation was calculated based on Coops et al. (2000) utilizing latitude, longitude, slope, aspect, elevation and the PRISM monthly maximum and minimum temperatures.

Variable	Units	Mean	Median	Maximum	Minimum	Std. Dev.
PMAI	$Meter^3$/Hectare/Year	7.4	6.8	23.8	0.2	4.08
Geographic Variables						
Latitude	Degrees	45.4	45.3	49.0	42.0	1.98
Longitude	Degrees	-121.6	-122.1	-116.5	-124.7	2.02
Elevation	Meters	808.2	777.4	2171.4	4.9	503.97
Climatic Variables						
Temperature	Degrees Celsius	8.4	8.5	13.7	0.8	2.16
Precipitation	Centimeters	143.7	127.0	593.9	25.7	90.62
CMI	Millimeters	-30.3	-34.2	83.8	-80.0	19.61

Data - Maps


Plot PMAI Value
Plot PMAI Species
Western Hemlock
Ponderosa Pine
Douglas-fir
Annual Temperature
(°C)
High : 14
Low : -7
Annual Precipitation
(cm)
High : 700
Low : 20
N
0
80
160
320 km


STIHL

Data - Maps

University of Idaho
College of Natural Resources

The Climate Moisture Index in this study is the millimeters of precipitation per year in excess of evaporation and plant transpiration given a location solar radiation and temperature

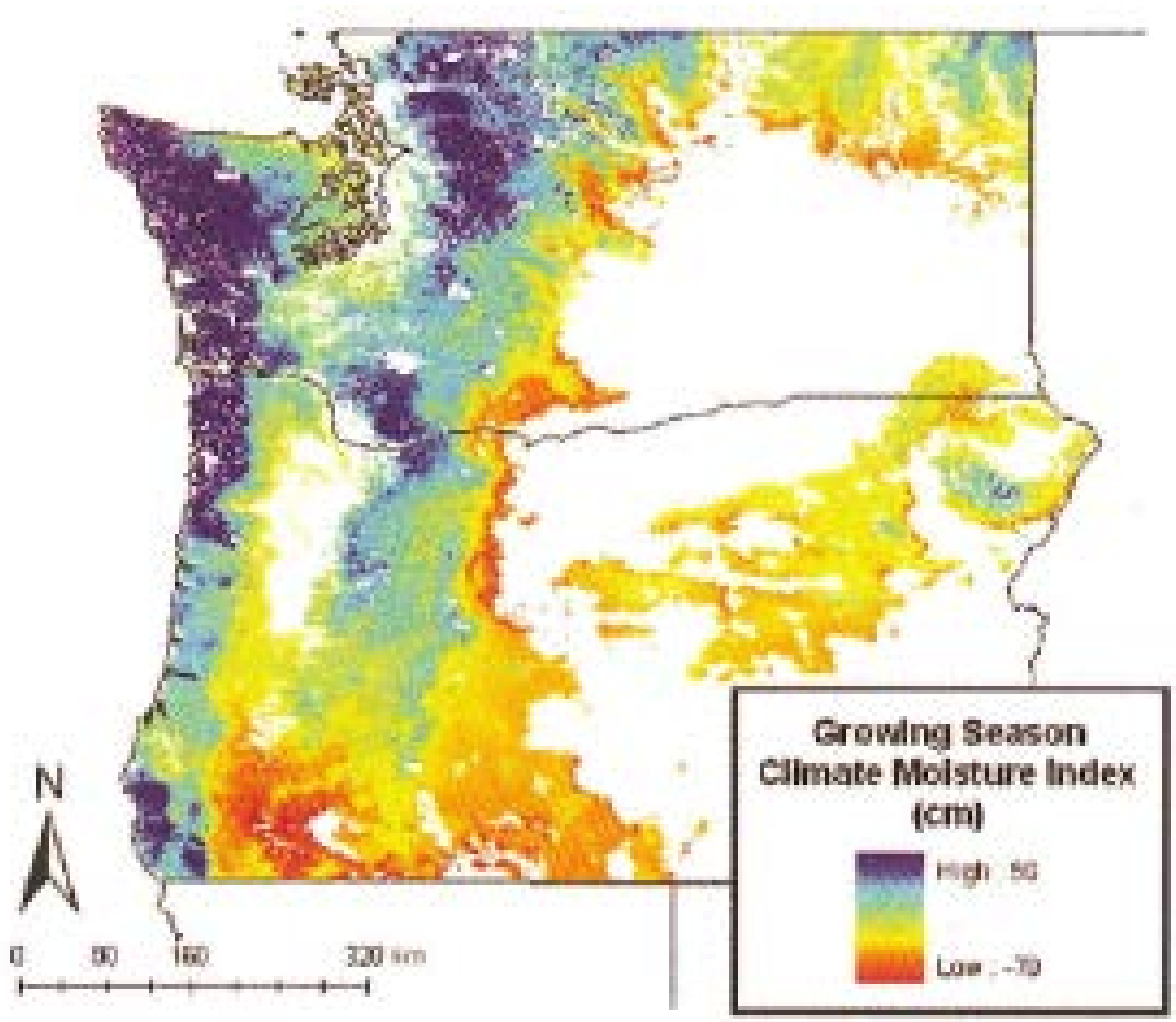
$$CMI = \sum_{months} \Pr ecipitation - (days_{Month} * Evapotranspiration / 10)$$

Where Evapotranspiration is calculated using a variant of the Hargreaves Model which given mean temperatures in ° Celsius and solar radiation in mega joules per square meter per day

$$Evapotranspiration = 0.0135 * (Temperature + 17.78) * Solar\_Radiation * \left(\frac{238.8}{595.5 - 0.55 * Temperature} \right)$$

Monthly precipitation, temperature values came from PRISM (www.prism.oregonstate.edu) and are averages over the 1971-2000 period and solar radiation was calculated utilizing latitude, longitude, slope, aspect, elevation and the PRISM monthly maximum and minimum temperatures.

Data - Maps


Growing Season
Climate Moisture Index
(cm)
High
Low
N
0 80 160 320 km


STIHL

PMAI Nearest Neighbor (NN) Map

University of Idaho
College of Natural Resources

Imputation of PMAI from another similar plot

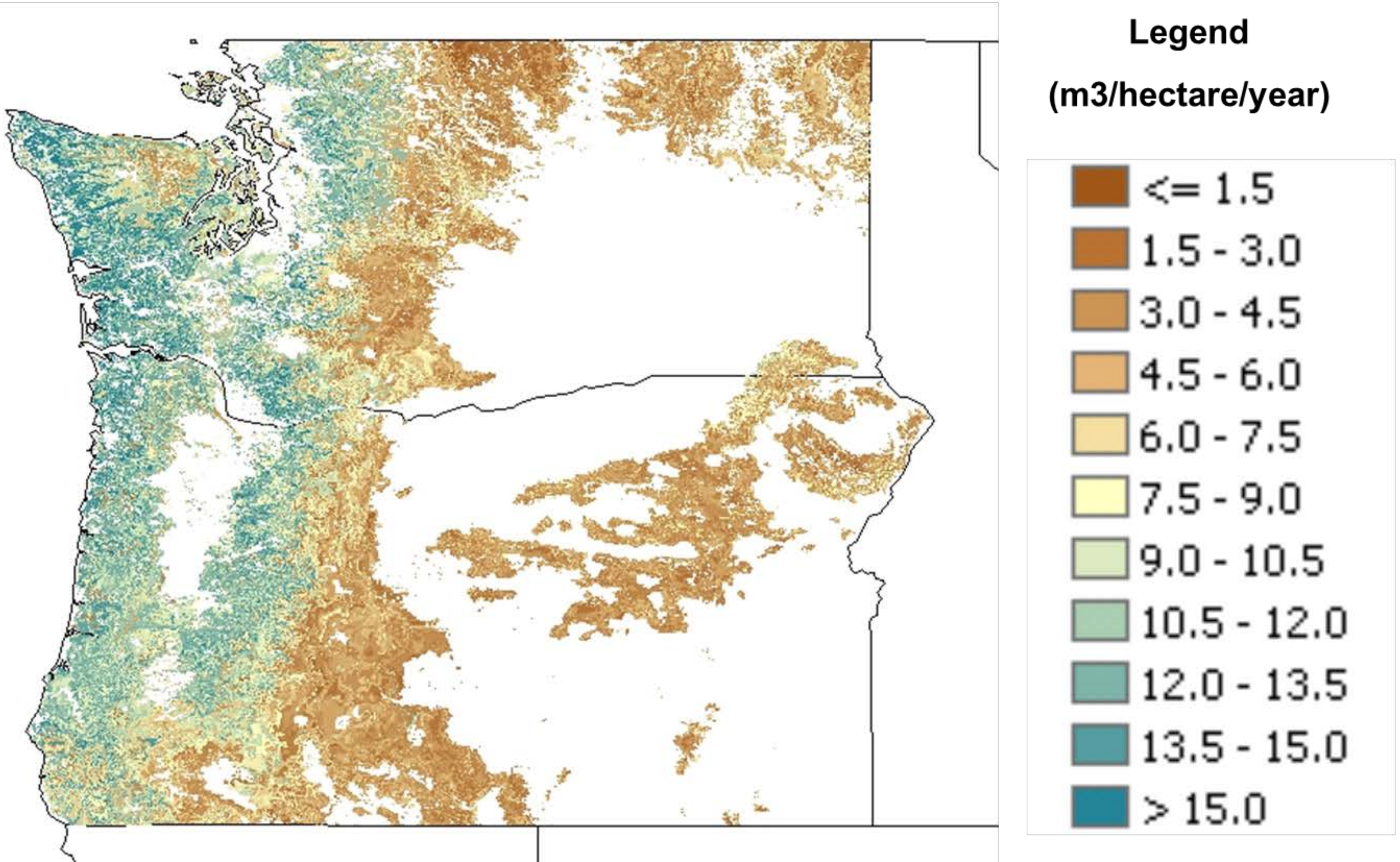
$$PMAI_j = Min_i\left(\sum_{i=1}^{n}\left(\left(\frac{1}{C^2_{(X,PMAI)}}*\left(\frac{X_i - X_j}{\bar{X}}\right)\right)^2\right)\right)$$ For each j

Where: I is the plots with known PMAI values

j is the plots missing PMAI values

X is the plot attributes used to define the neighborhood (Here they are Temperature (T), Growing Season Climate Moisture Index (CMI), Temperature*Precipitation (P), Temperature², Precipitation², and Shade Tolerance (ST)

C(X,PMAI) is the correlation between the X attribute and PMAI

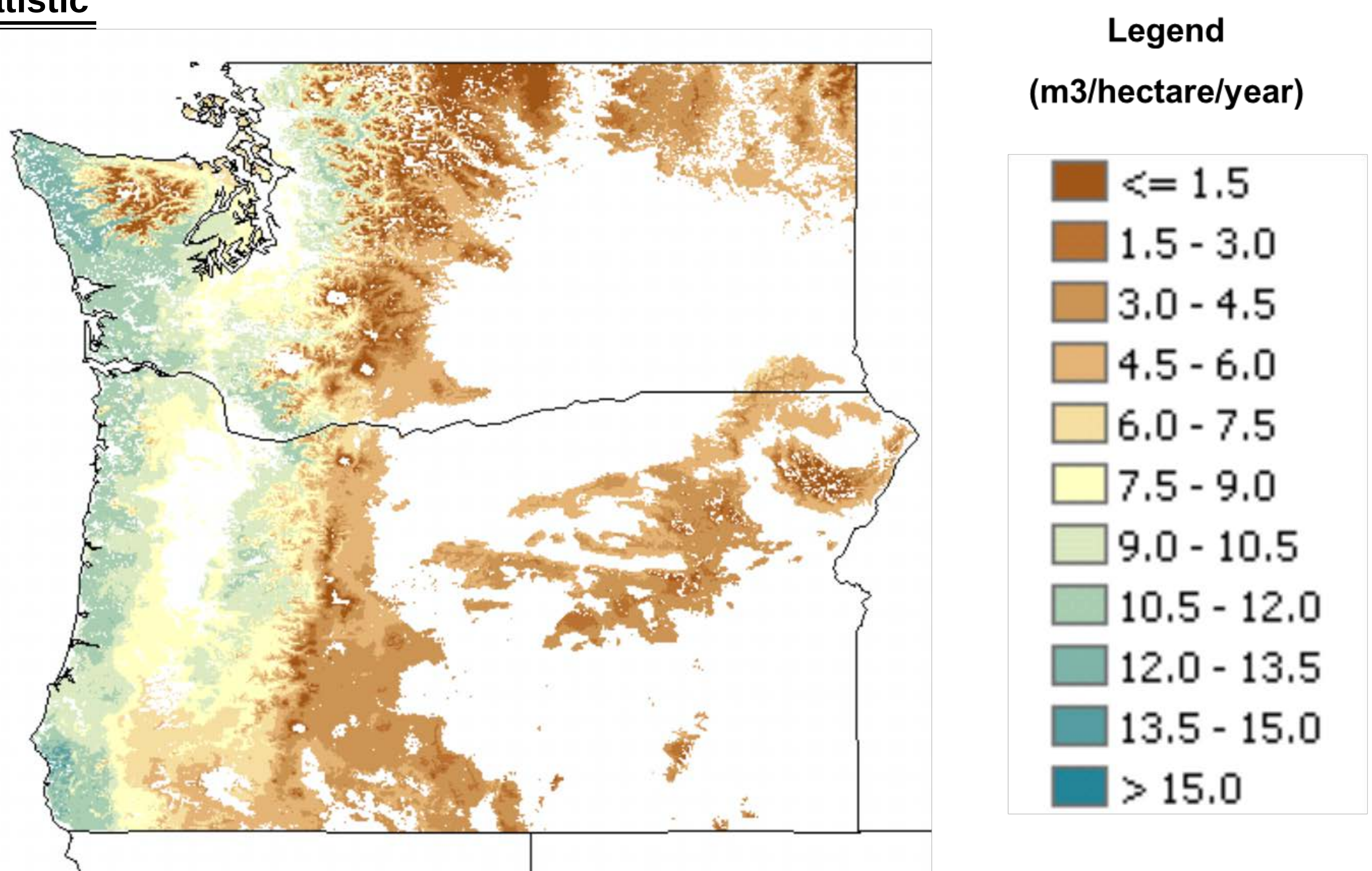


PMAI Multiple Linear Regression (MLR) Map

$$PMAI_i = \beta_1 + \beta_2 T_i + \beta_3 CMI_i + \beta_4 T_i * P_i + \beta_5 T_i^2 + \beta_6 P_i^2 + \beta_7 ST_i + e_i$$

Variable	Coefficient	Std. Error	t-Statistic
β_1	-0.903	0.232	
β_2	0.809	0.058	
β_3	0.027	0.002	
β_4	0.001	0.000	
β_5	-0.043	0.004	
β_6	0.000	0.000	
β_7	1.711	0.068	

Regression Statistics	
Adj R-Squared	0.64
Standard Error	2.45



PMAI Thin-plated Splines (TSP) Map

We used ANUSPLIN

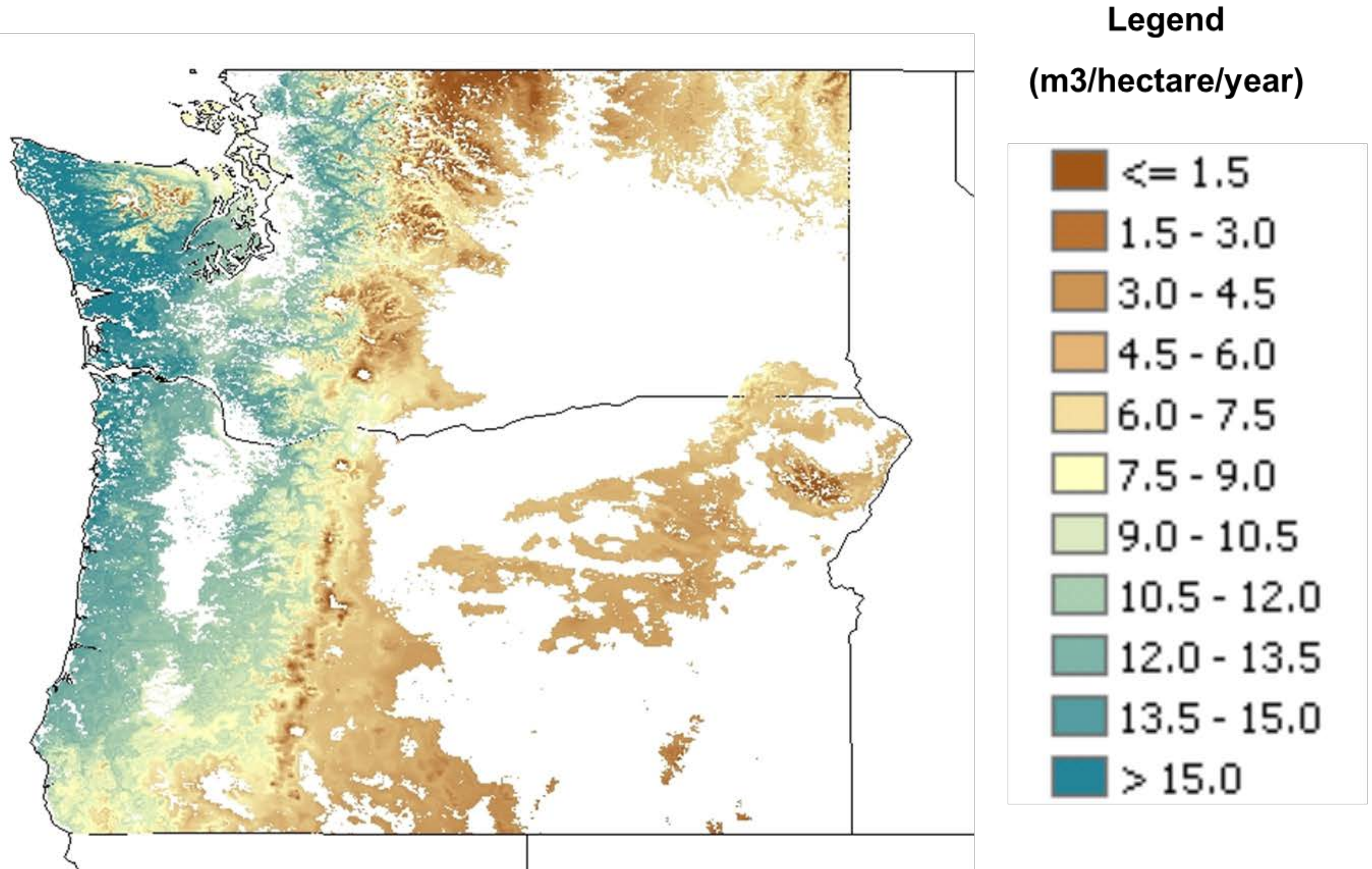
Thin plate splines are defined by minimizing the roughness of the interpolated surface, subject to having a prescribed residual from data.

Independent Spline Variables

- *Latitude*
- *Longitude*
- *Temperature*
- *Growing Season Climate M*
- *Precipitation*

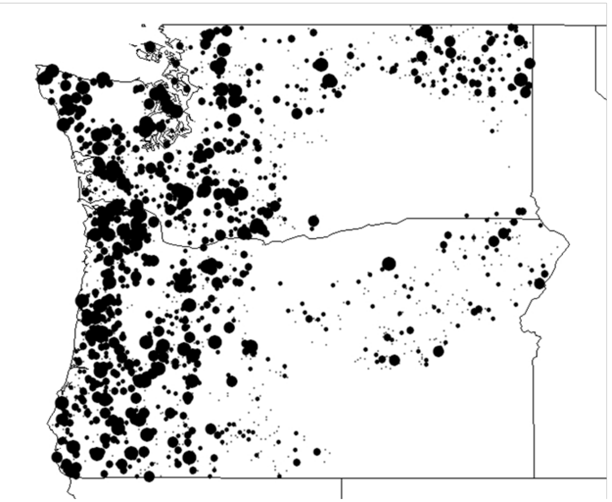
Used to create a third order spline over on surface

Thin plate splines do NOT rely upon spatial dependence within the data, while krigir dependence. [Interpolation vs. De-trending]

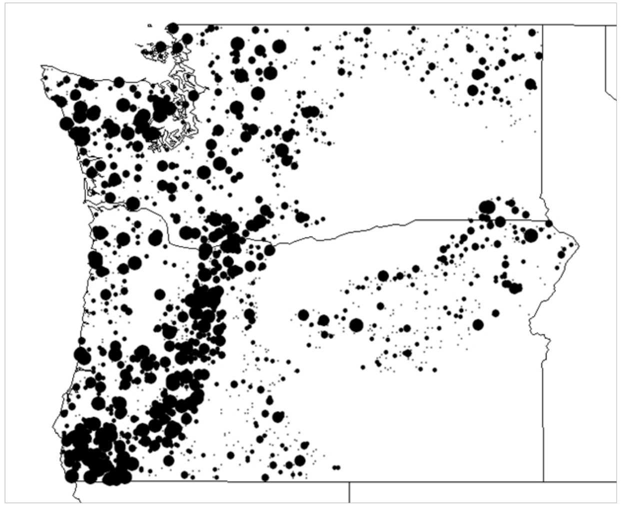


Data – Error Maps

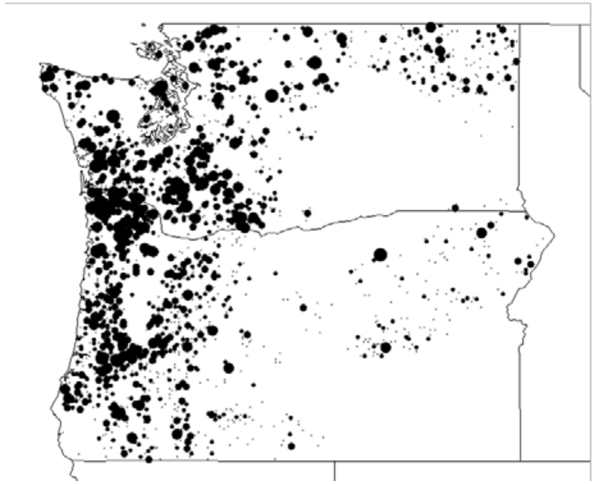
NN Underestimation



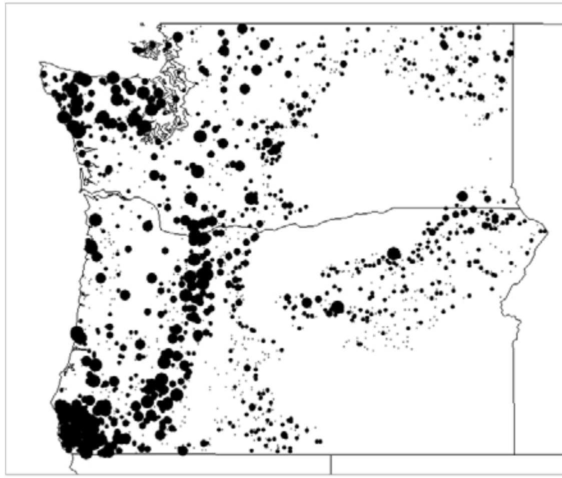
NN Overestimation



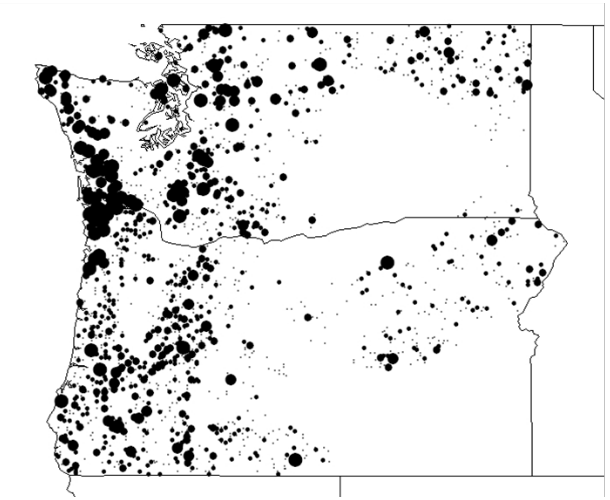
MLR Underestimation



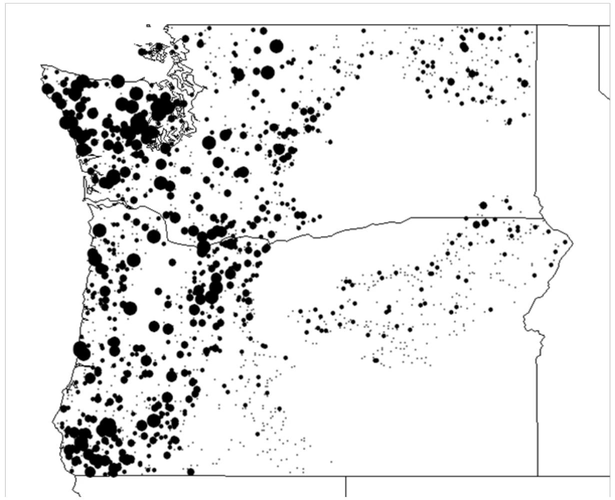
MLR Overestimation



TPS Underestimation



TPS Overestimation



0 – 1.4 · 1.4 – 2.8 · 2.8 – 4.2 · 4.2 – 5.6 · > 5.6 cubic meters per hectare per year

PMAI Nearest Neighbor Map

Imputation of PMAI from another similar plot

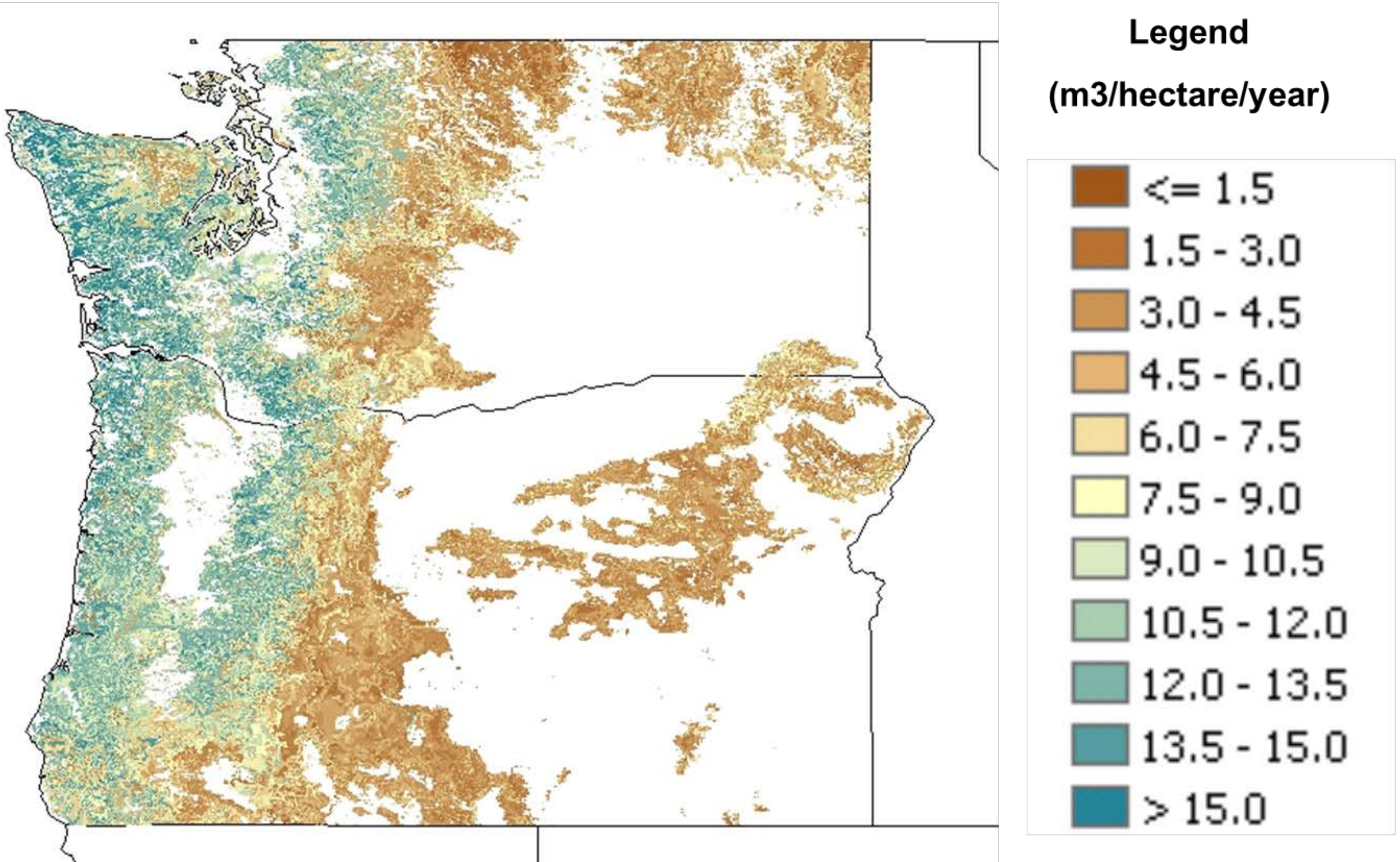
$$PMAI_j = Min_i\left(\sum_{i=1}^{n}\left(\frac{1}{C^2_{(X,PMAI)}} * \left(\frac{X_i - X_j}{\overline{X}}\right)\right)^2\right) \quad \text{For each j}$$

Where: I is the plots with known PMAI values

j is the plots missing PMAI values

X is the plot attributes used to define the neighborhood (Here they are Temperature (T), Growing Season Climate Moisture Index (CMI), Temperature*Precipitation (P), Temperature^2, Precipitation^2, and Shade Tolerance (ST)

C(X,PMAI) is the correlation between the X attribute and PMAI



Testing for Spatial Autocorrelation

University *of* Idaho
College *of* Natural Resources

Moran's I was used to test for spatial autocorrelation

Moran's I is a statistic that can be utilized to detect correlation among spatial data. It can take values between 1 and -1 with positive values indicating clumping or clustering and negative values indicating dispersion

$$I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\left(E_i - \bar{E}\right)\left(E_j - \bar{E}\right)}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\sum_{i}^{n}\left(E_i - \bar{E}\right)^2}$$

Where: n is the number of observations

W_{ij} are the weights for the ith and jth observation

E are the error data to be tested

The standard error is calculated as given below (SE(I)) and can be used along with the expected I (E(I)-1/(1-n)) to calculate what is called a Z score which is used similar to a t stat.

$$SE(I) = \sqrt{\frac{\frac{n^2}{2}\sum_{i=1}^{n}\sum_{j=1}^{n} 2w_{ij}^{2} - n\sum_{i=1}^{n} 2\left(\sum_{j=1}^{n} w_{ij}\right)^2 + 3\left(\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\right)^2}{\left(\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\right)^2 \left(n^2 - 1\right)}}$$

$$Z = \frac{\left(I - E(I)\right)}{SE(I)}$$

Testing for Spatial Autocorrelation

Average spatial autocorrelation statistics for thirty replications of four approaches outlined above randomly dividing data into 2237 reference plots and 1119 target plots

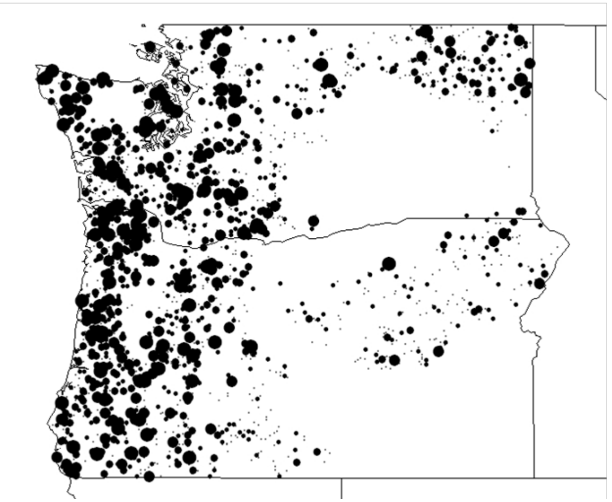
	Reference Dataset		Target Dataset	
Model	Moran's I	Z Score	Moran's I	Z Score
NN	0.049	11.0	0.049	10.6
MLR	0.227	51.1	0.225	49.1
TSP	0.096	21.6	0.091	19.8

Positive indicates clumping, Negative indicates dispersal

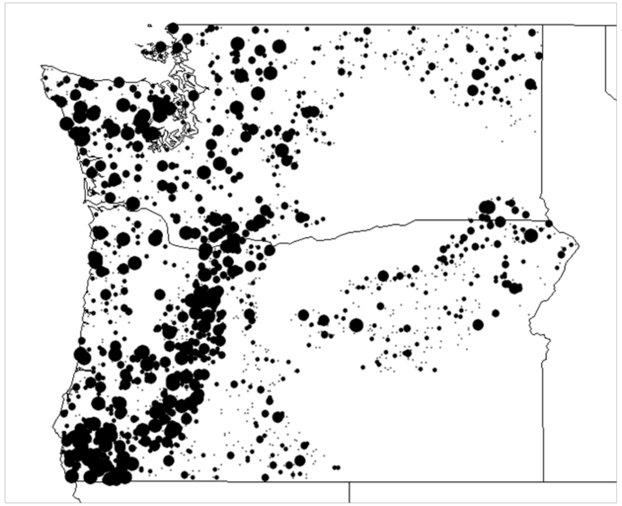
University of Idaho
College of Natural Resources

Data – Error Maps

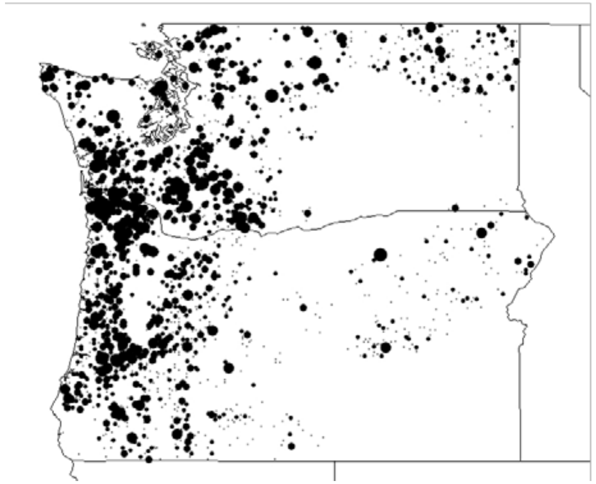
NN Underestimation



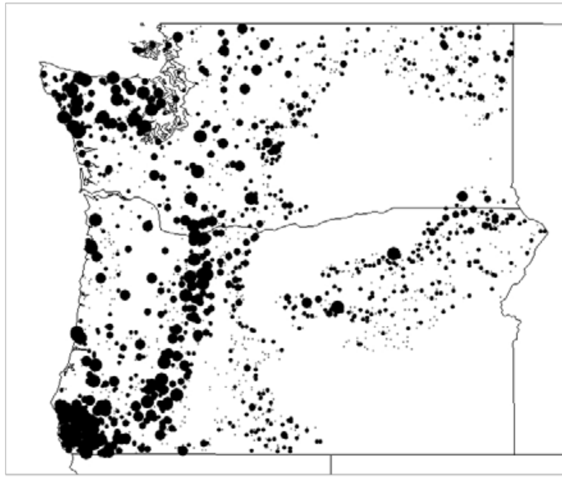
NN Overestimation



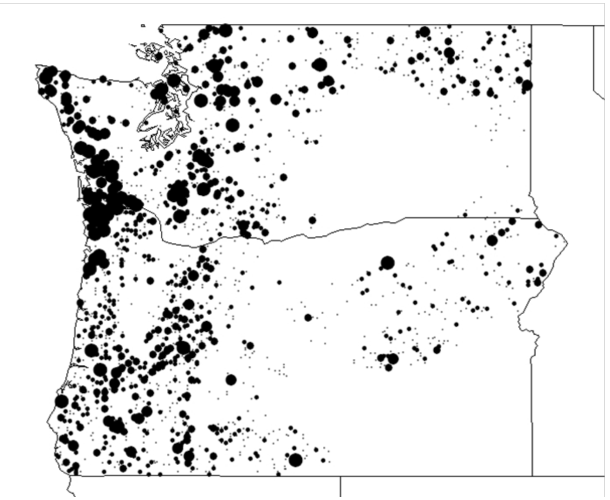
MLR Underestimation



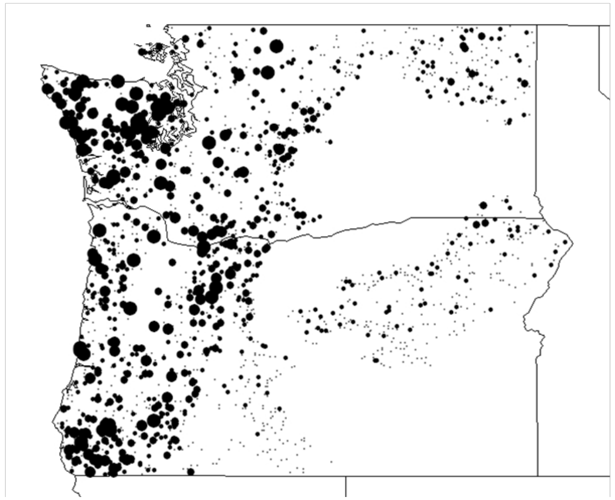
MLR Overestimation



TPS Underestimation



TPS Overestimation



	Reference Dataset		Target Dataset	
Model	**Moran's I**	**Z Score**	**Moran's I**	**Z Score**
NN	0.049	11.0	0.049	10.6
MLR	0.227	51.1	0.225	49.1
TSP	0.096	21.6	0.091	19.8

Positive indicates clumping, Negative indicates dispersal

· 0 – 1.4 • 1.4 – 2.8 • 2.8 – 4.2 ● 4.2 – 5.6 ● > 5.6 cubic meters per hectare per year

PMAI Simultaneous Autoregressive Model (SAR) Map

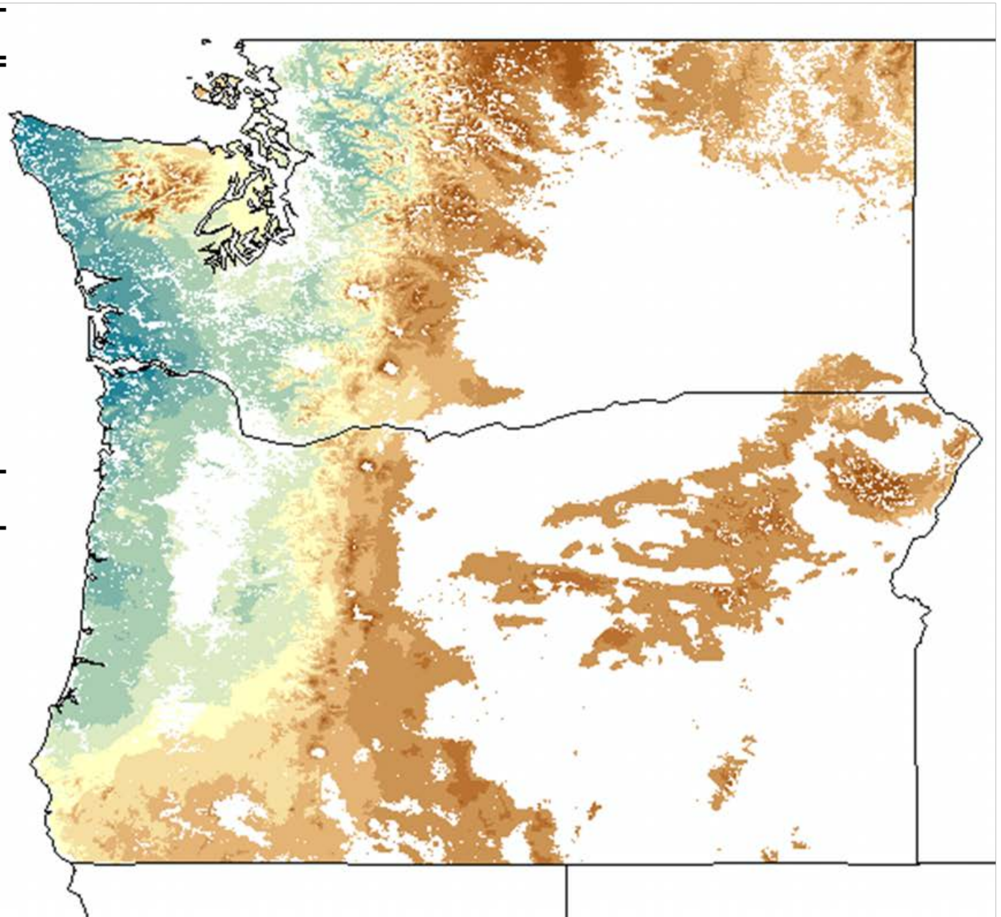
$$PMAI_i = \beta_1 + \beta_2 T_i + \beta_3 CMI_i + \beta_4 T * P_i + \beta_5 T_i^2 + \beta_6 P_i^2 + \beta_7 ST_i + \rho U_N + e_i$$

where:

$$U_N = PMAI_N - \left(\beta_1 + \beta_2 T_N + \beta_3 CMI_N + \beta_4 T_N * P_N + \beta_5 T_N^2 + \beta_6 P_N^2 + \beta_7 ST_N\right)$$

Variable	Coefficient	Std. Error	t-Statistic
β_1	-1.326	1.032	-1.28
β_2	0.416	0.064	6.55
β_3	0.007	0.002	3.58
β_4	0.001	0.000	8.68
β_5	-0.023	0.004	-5.90
β_6	0.000	0.000	-10.82
β_7	1.415	0.064	22.25
ρ	1.041	0.019	56.17

Regression Statistics	
Adj R-Squared	0.73
Standard Error	2.09



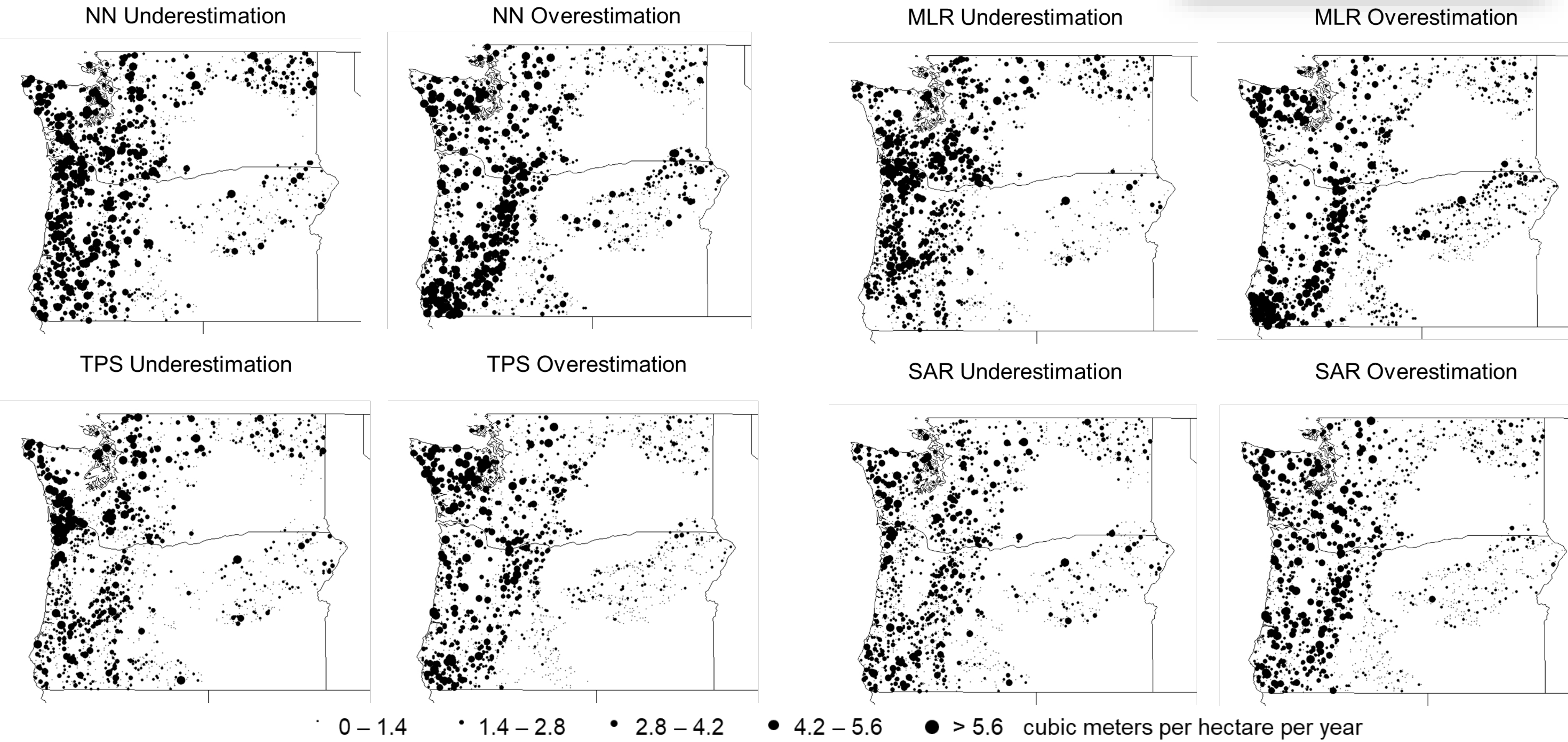
Legend

(m3/hectare/year)

- <= 1.5
- 1.5 - 3.0
- 3.0 - 4.5
- 4.5 - 6.0
- 6.0 - 7.5
- 7.5 - 9.0
- 9.0 - 10.5
- 10.5 - 12.0
- 12.0 - 13.5
- 13.5 - 15.0
- > 15.0

Data – Error Maps

University of Idaho
College of Natural Resources



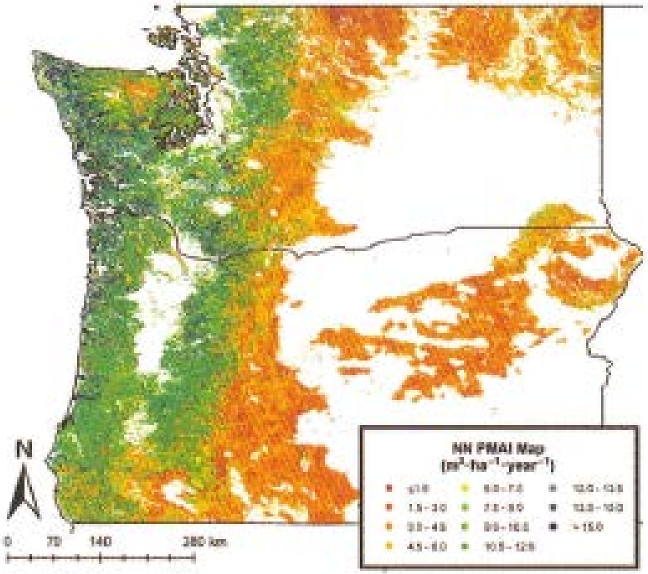
Testing for Spatial Autocorrelation

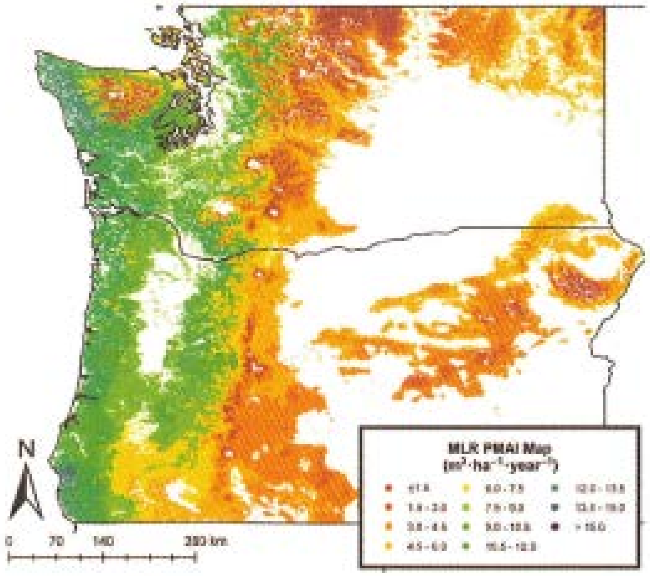
Average spatial autocorrelation statistics for thirty replications of four approaches outlined above randomly dividing data into 2237 reference plots and 1119 target plots

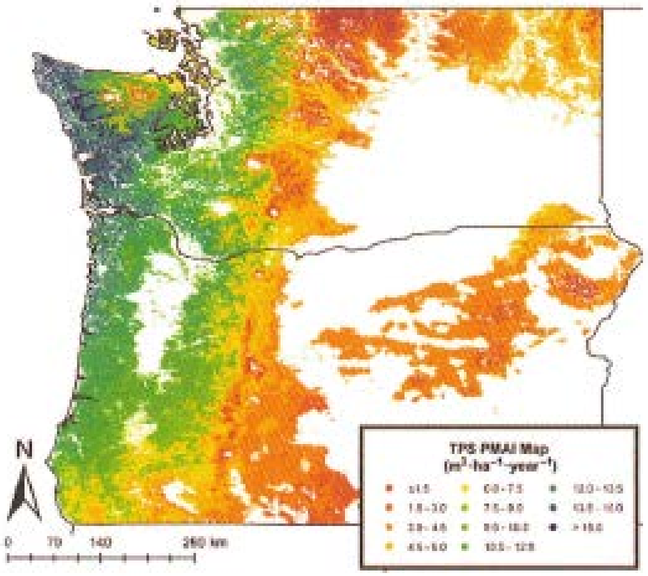
	Reference Dataset		Target Dataset	
Model	**Moran's I**	**Z Score**	**Moran's I**	**Z Score**
NN	0.049	11.0	0.049	10.6
MLR	0.227	51.1	0.225	49.1
TSP	0.096	21.6	0.091	19.8
SAR	-0.010	-2.3	-0.009	-2.2

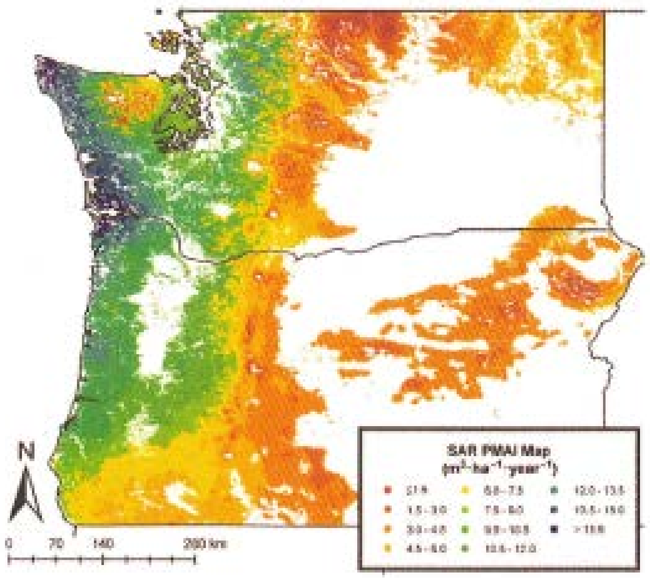
Positive indicates clumping, Negative indicates dispersal

Final PMAI Maps









Final PMAI Imputation Model Statistics

University of Idaho
College of Natural Resources

Average spatial autocorrelation statistics for thirty replications of four approaches outlined above randomly dividing data into 2237 reference plots and 1119 target plots

Imputation approach	Reference data set				Target data set			
	Average	Minimum	Maximum	SD	Average	Minimum	Maximum	SD
r^2								
NN	0.50	0.47	0.52	0.017	0.49	0.45	0.54	0.021
MLR	0.64	0.62	0.66	0.008	0.64	0.61	0.67	0.016
TPS	0.71	0.69	0.72	0.008	0.69	0.65	0.72	0.015
SAR	0.74	0.72	0.75	0.007	0.73	0.70	0.77	0.013
RMSE								
NN	3.14	3.03	3.26	0.062	3.15	2.99	3.29	0.083
MLR	2.45	2.36	2.50	0.026	2.46	2.35	2.62	0.052
TPS	2.21	2.15	2.29	0.030	2.28	2.11	2.43	0.066
SAR	2.09	2.04	2.14	0.024	2.11	2.01	2.22	0.049
Bias								
NN	−0.005	−0.090	0.058	0.036	0.004	−0.206	0.252	0.107
MLR	0.000	0.000	0.000	0.000	0.009	−0.176	0.129	0.073
TPS	−0.008	−0.049	0.044	0.023	0.015	−0.089	0.098	0.046
SAR	0.000	0.000	0.001	0.000	0.017	−0.132	0.109	0.067

Note: NN, nearest neighbour; MLR, multiple linear regression; TPS, thin plate splines; SAR, simultaneous autoregressive model.

Back to the punch line

Is this possible for all of Idaho (wall-to-wall map) ?

- What Localized Regression Technique to use (SAR vs GWR)

Localized Regression Techniques

Challenge some of the basic regression assumptions spatially

Spatial Autoregressive Model (SAR)

Challenges the assumption that e_i is the same across the map

$$y_i = \sum_{j=1}^{m} \beta_{jx_{ij}} + e_i$$

For *i* observations and *j* regressors

Geographically Weighted Regression (GWR)

Challenges the assumption that B_j is the same across the map



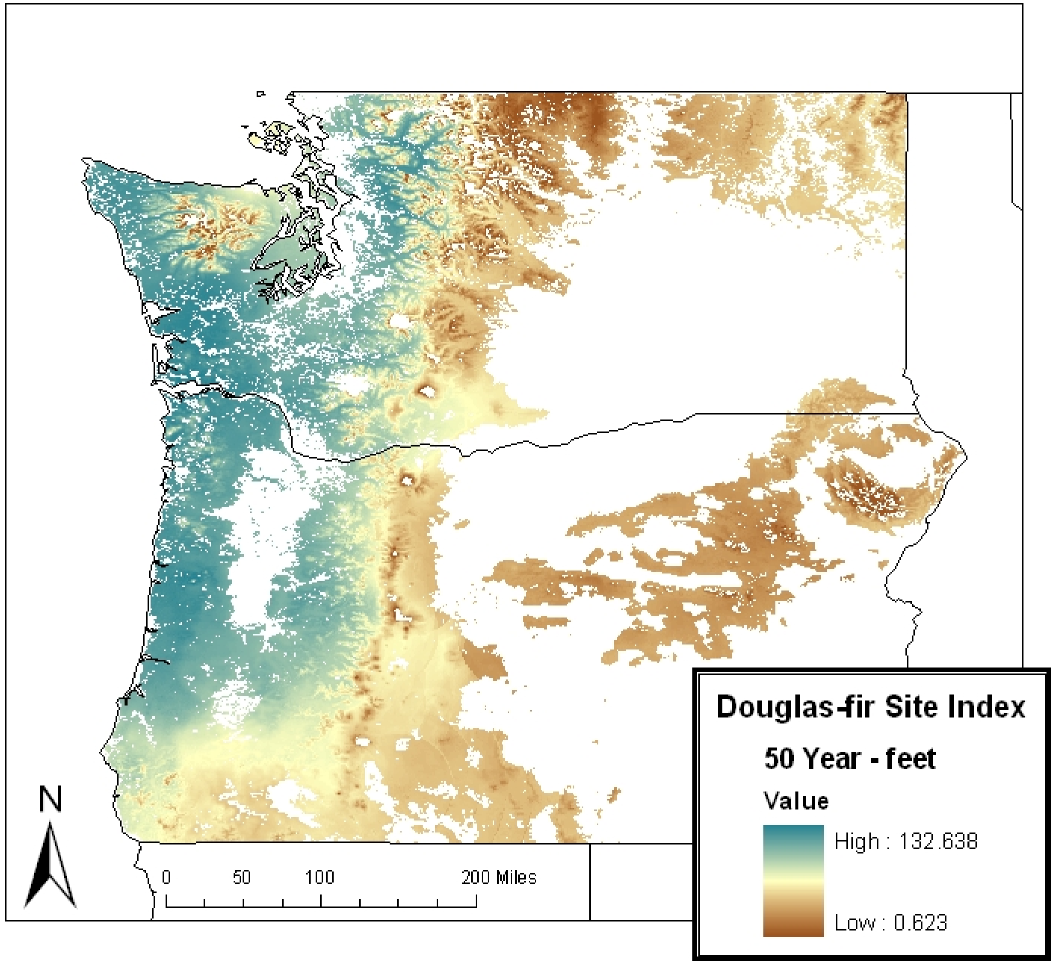





Final Thoughts and Bonus Slides

But Greg, who cares about PMAI?

- True, but to get PMAI you need site index.



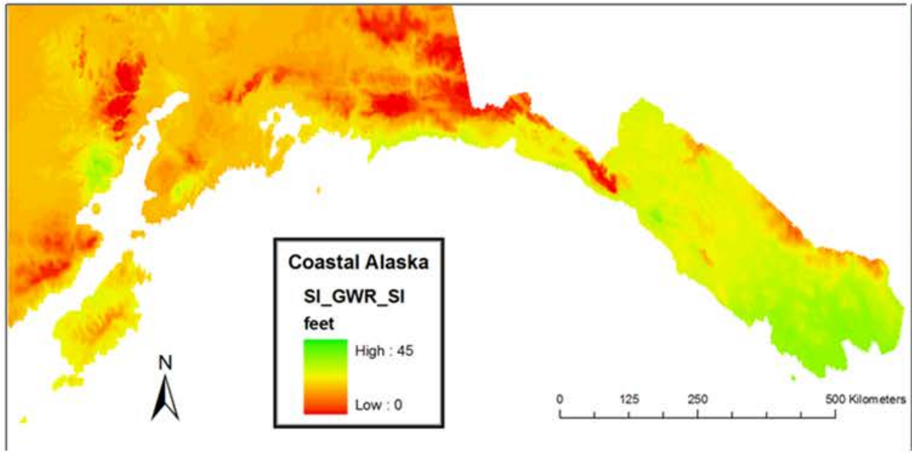
Bruce on the Westside,
Cochran on the Eastside

Final Thoughts and Bonus Slides

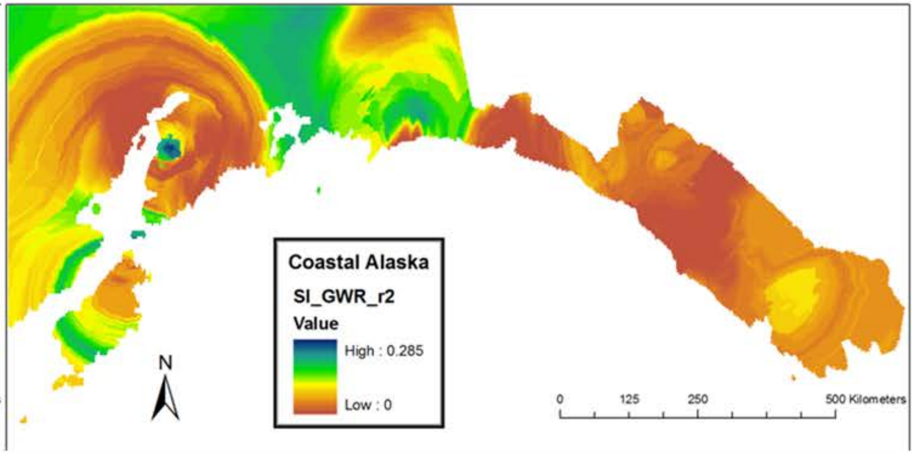
University of Idaho
College of Natural Resources

Cool aspect of GWR – mapping your model

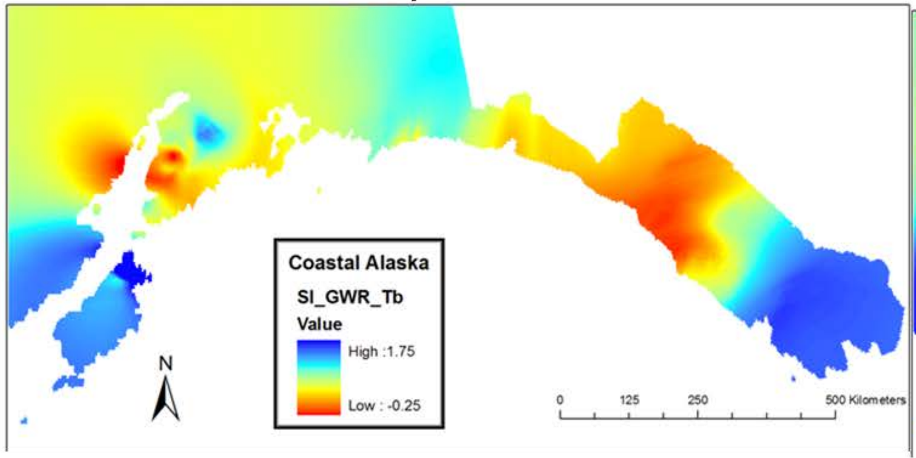
Site Index



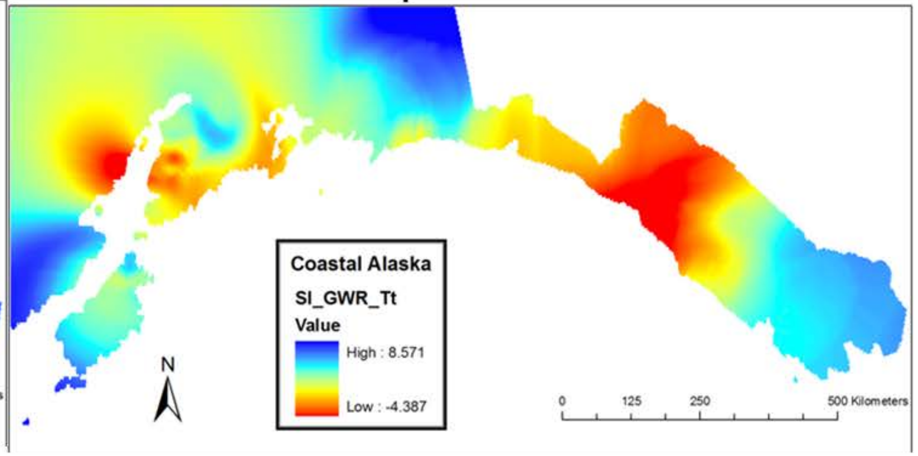
r2



Temperature B

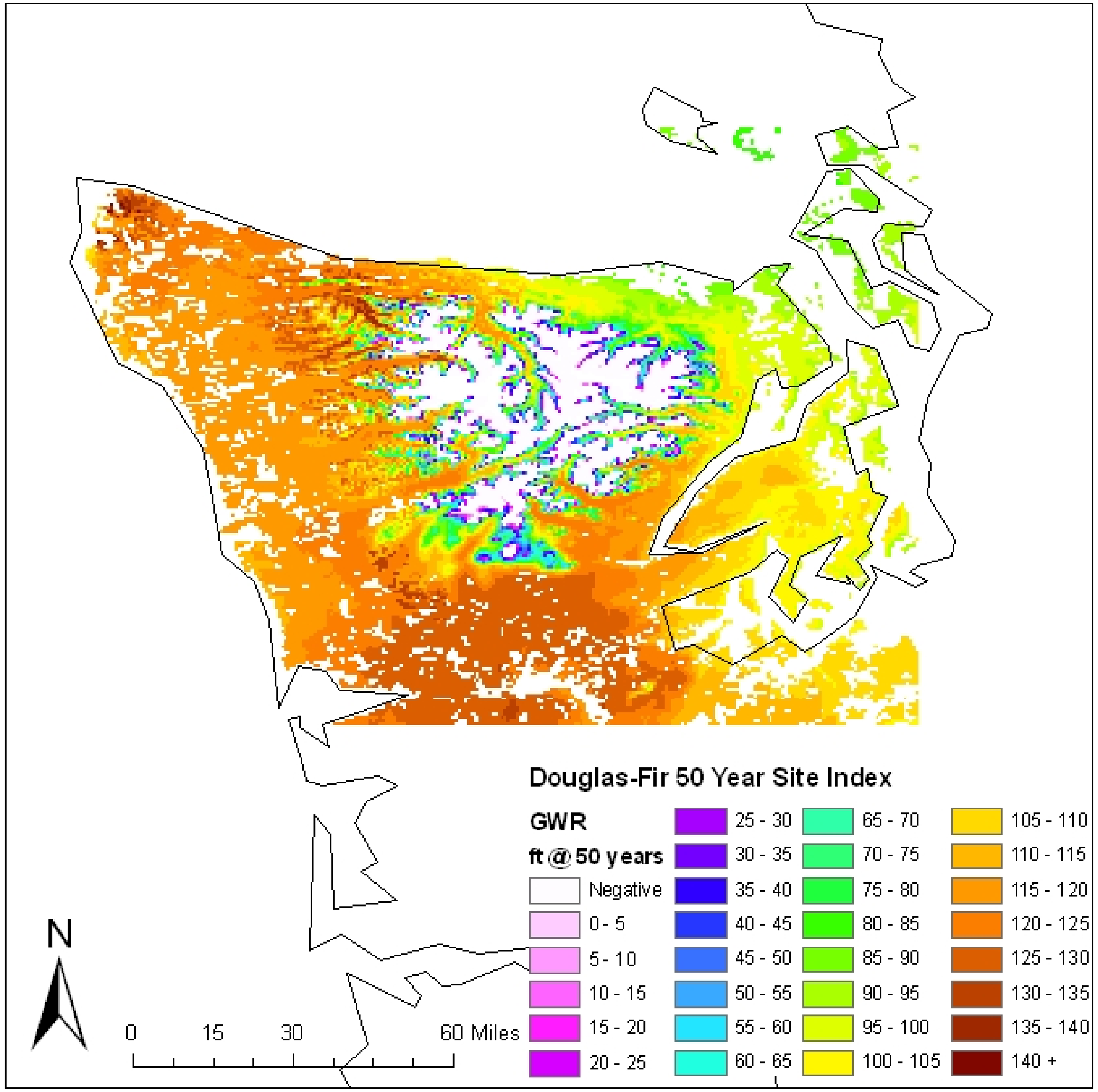


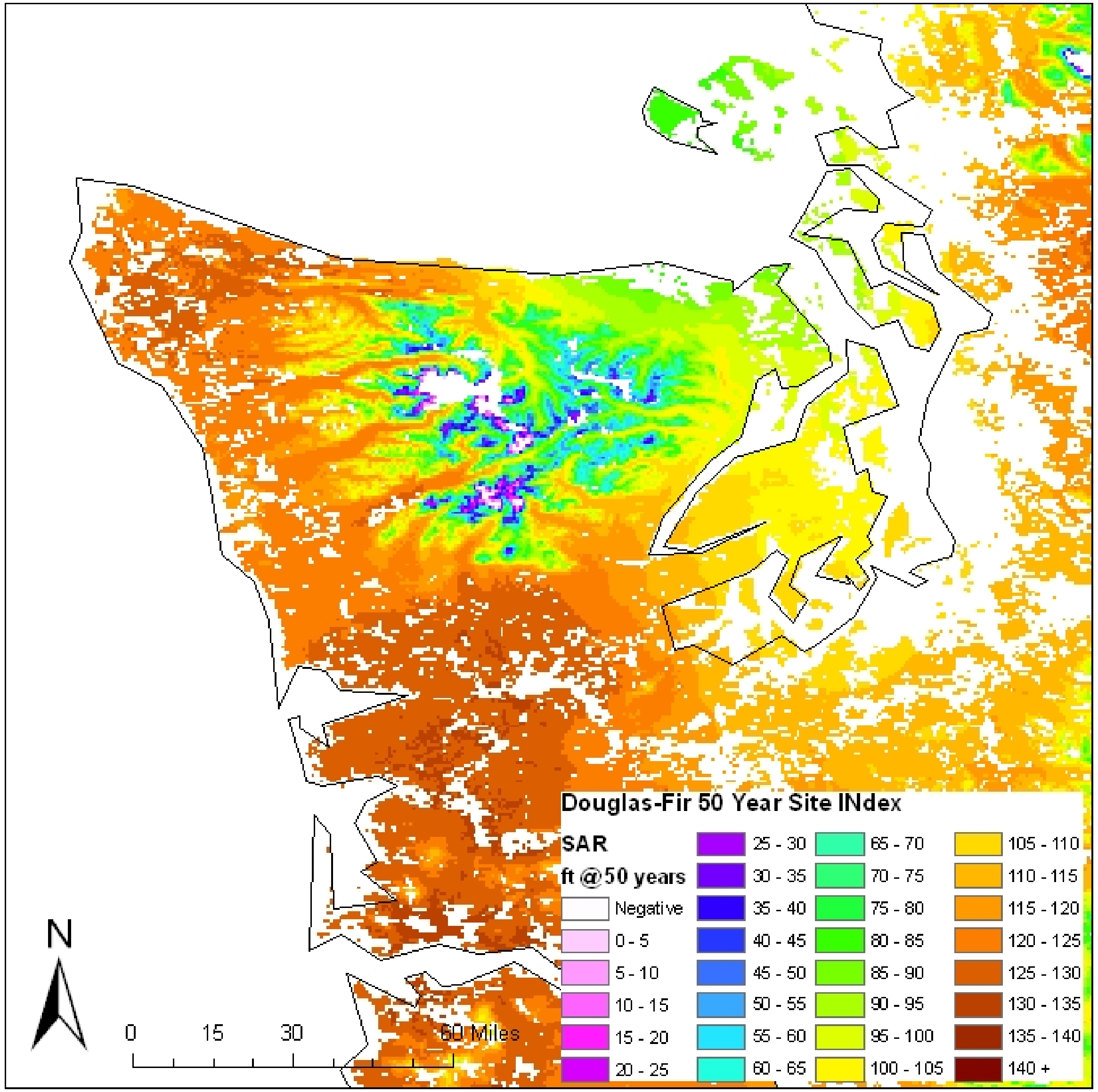
Temperature t-stat



Final Thoughts and Bonus Slides

University of Idaho
College of Natural Resources





Final Thoughts and Bonus Slides

University of Idaho
College of Natural Resources

Like you guys with GWR – weighting SAR models has been a challenge

u_i is the expected error term

u_i can be defined by a neighborhood

u_i is usually weighted (1/distance) is common

$$u_i = \frac{\sum_{j \neq i} w_{ij} y_j}{\sum_{j \neq i} w_{ij}} - \beta_k \frac{\sum_{j \neq i} w_{ij} x_{jk}}{\sum_{j \neq i} w_{ij}}$$

But what about w_{ij} ?

$$w_{ij} = e^{\left(-0.5\left(\frac{\alpha_0 dist_{ij}}{d25_i}\right)^{\alpha_1}\right)}$$

Felixible by adjusting α_0 and α_1

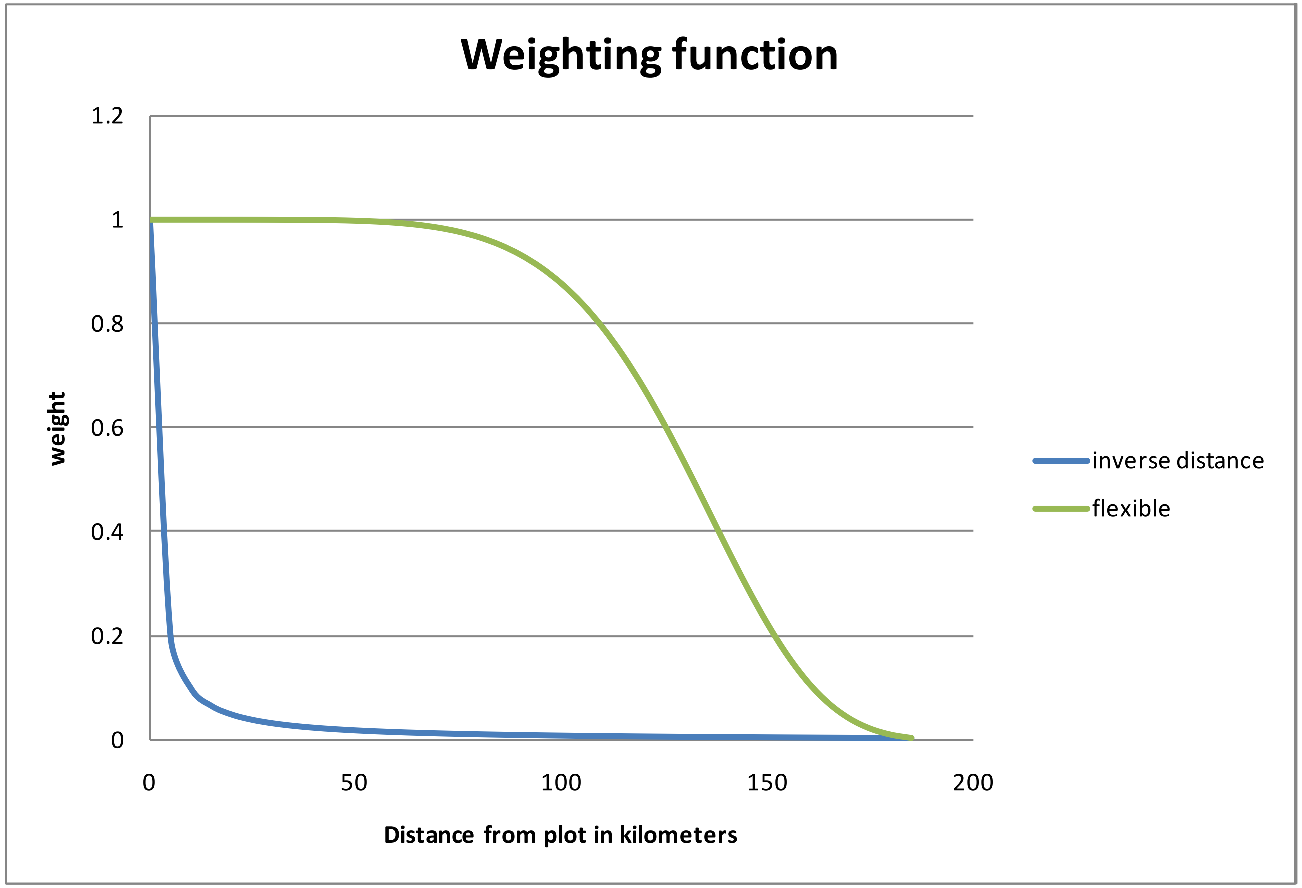
adjusts to plot density through $d25_i$ which is the distance of the 25th closest plot

Final Thoughts and Bonus Slides

Weighting Function

$$w_{ij} = e^{\left(-0.5\left(\frac{\alpha_0 dist_{ij}}{d25_i}\right)^{\alpha_1}\right)}$$

$\alpha_0 = 4$
$\alpha_1 = 6$
$d25_i = 125$



Greg Latta
Research Assistant Professor of Forest Economics
Natural Resources & Society
University of Idaho
glatta@uidaho.edu; 541.619.9212

Research Webpage: http://www.uidaho.edu/cnr/pag

University of Idaho
College of Natural Resources