University of Idaho
College of Natural Resources

FOREST MANAGEMENT WITH AI AND MACHINE LEARNING

IFC REGIONAL AND NATIONAL SDImax MODELING

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GMUG
Growth Model User's Group

APRIL 16, 2025

Intermountain Forestry Cooperative

RESEARCH SUPPORT

PRIVATE-PUBLIC PARTNERSHIP

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SETTING THE CONVERSATION

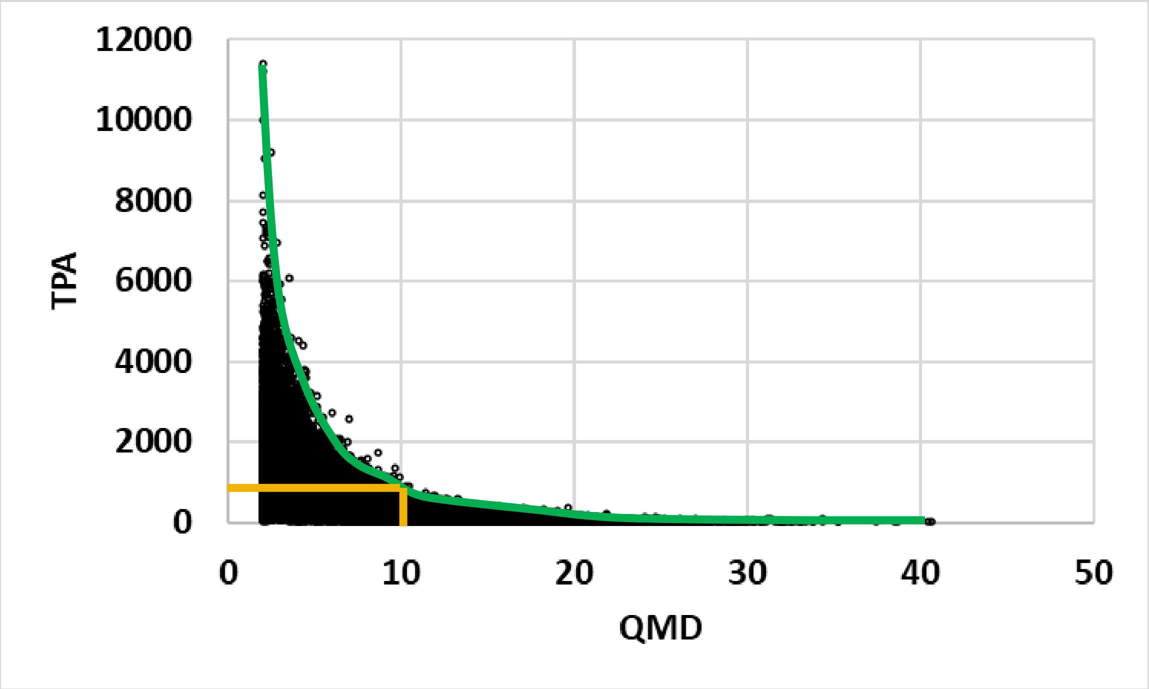
HOW DOES SDIMAX MODELS INFORM MANAGEMENT DECISIONS?

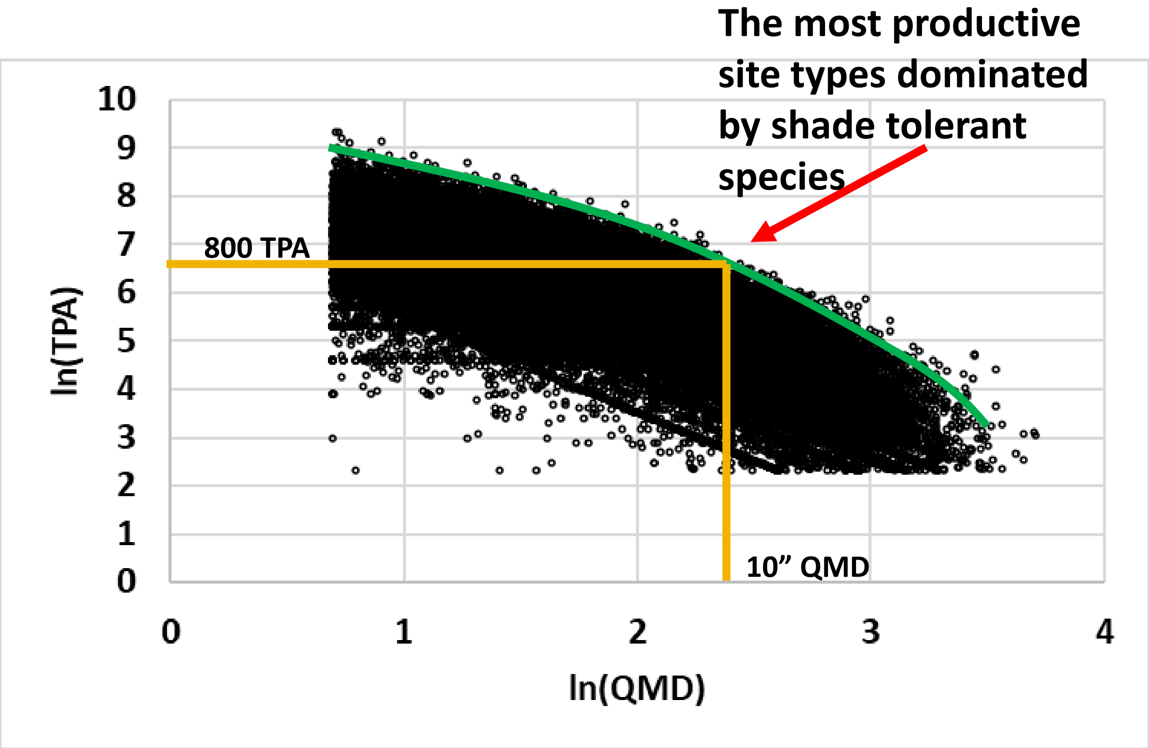
- *We need tools that spatially quantify expert knowledge that can address questions like:*
  - *How many trees are too many?*
  - *How is "too many" related to stand development stage, species composition, site type (climate, soil, geology, topography)?*
  - *How can we optimize #trees/acre to meet management objectives through initial planting density, PCT or CT, site-species relationships, while minimizing density induced growth reduction/mortality*
  - *Does projected climate patterns suggest modifying current management strategies?*

LET'S VISUALLY DEFINE SDI$_{MAX}$

STAND DENSITY INDEX (SDI) = ƒ(QUADRATIC MEAN DIAMETER, TREES PER ACRE)

$$SDI = TPA \times (QMD/10)^{1.605}$$

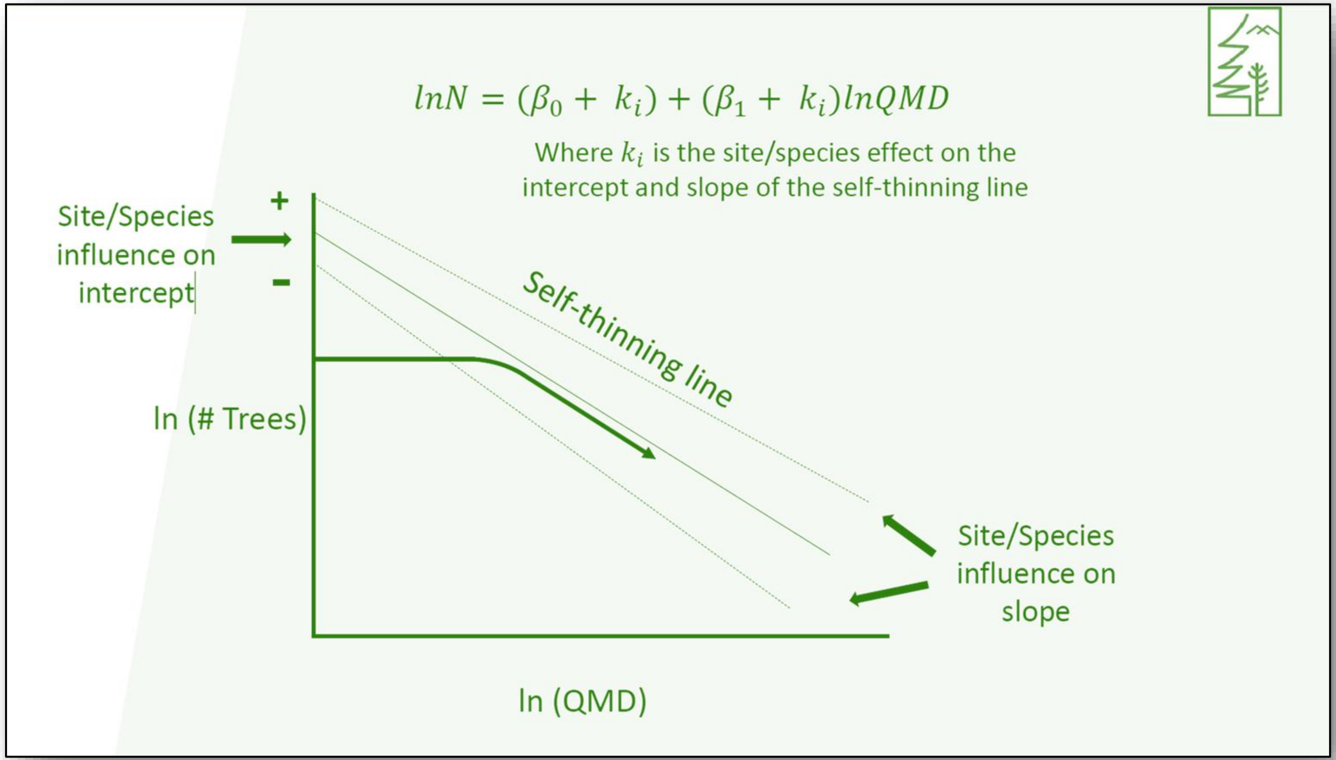




Maximum SDI referenced to a stand with a QMD of 10 inches = ~800 TPA

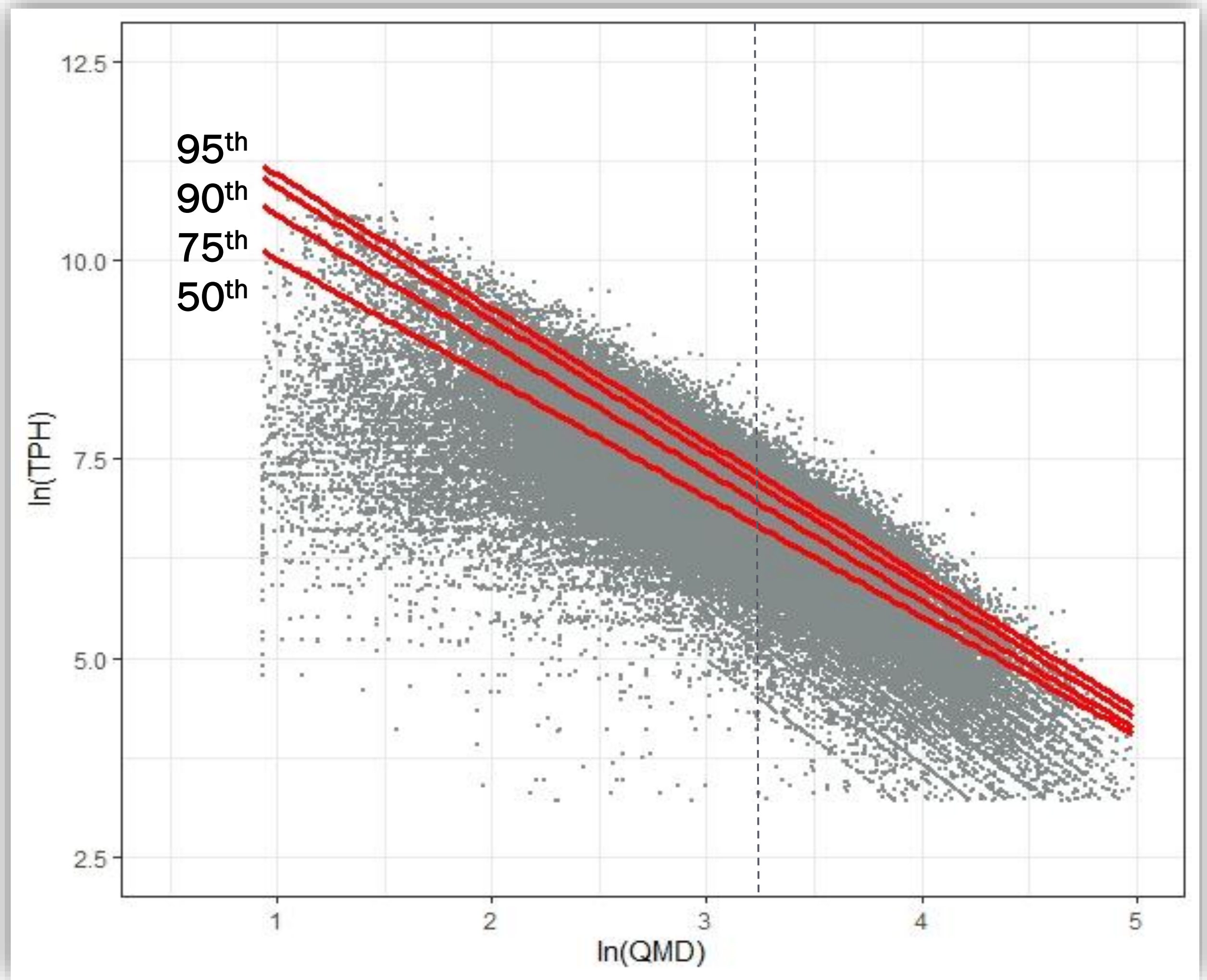
SDImax Modeling - Model Versions

- ❑ Reineke (1933) first described the self-thinning line utilizing log-log paper and visually fit a reference curve to the outer boundary.
- ❑ Ordinary least squares
- ❑ Linear mixed models
- ❑ Quantile regression
- ❑ Linear quantile mixed models
- ❑ **Frontier analysis**



HOW DOES SITE QUALITY IMPACT SDI?

WHERE IS SDIMAX IN THIS CLOUD OF DATA POINTS?



- ***SDI – a function of QMD & TPA***
- How can we pull out site?
  - For example, if you plot a stand's QMDxTPA and if falls within the 75th percentile of all plots, is it nearing a maximum density for its suite of site-stand features,
  - or is it simply a point along its size-density stand development continuum?

Looking Back: IFC's Work on SDImax

Contents lists available at ScienceDirect

Forest Ecology and Management

journal homepage: www.elsevier.com/locate/foreco

ELSEVIER

Site sensitive maximum stand density index models for mixed conifer stands across the Inland Northwest, USA

doi.org/10.1016/j.foreco.2018.11.013

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Canadian Science Publishing

ARTICLE

A species-specific, site-sensitive maximum stand density index model for Pacific Northwest conifer forests[1]

Ryan R. Heiderman and Mark J. Kimsey, Jr.

https://doi.org/10.1139/cjfr-2020-0426

Received: 2 March 2023 | Accepted: 19 June 2023

https://doi.org/10.1111/nrm.12381

DOI: 10.1111/nrm.12381

Natural Resource Modeling WILEY

Pacific Northwest conifer forest stand carrying capacity under future climate scenarios

Ryan R. Heiderman | Mark J. Kimsey Jr.

Development Drivers:
Forest Carrying Capacity Calculator v2.0

- **Regional Discrepancies**:
  Feedback reveals: V1.0 overpredicting in South Central Oregon, East Slopes of Cascades, underpredicting in North Central Idaho.

- **Methodological Constraints**:
  Current V1.0 model relies on Stochastic Frontier Analysis (SFA), which poses limitations due to specific form assumptions and linearity in input-output relationships.

- **Species Coverage Gap:**
  V1.0 model: Few species, unclear mix impact on carrying capacity (is mix of shade tolerants, or drought tolerants?)

Why Machine Learning? A Path Forward

Limitations of Current Approach

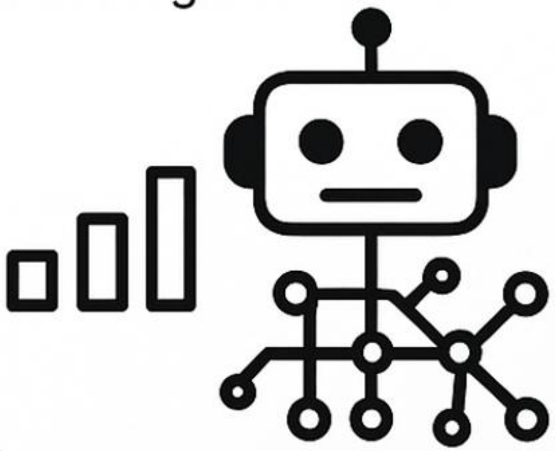
- SFA and traditional regression assume fixed model forms and relationships,
- Difficulty handling:
  - Non-linearity
  - High-dimensional interactions
  - Regional and species-specific variations

Enter Machine Learning (ML)

- **Definition: ML** models *learn* patterns from data without assuming specific forms.
- **Flexibility:** Captures complex, non-linear, and interactive effects
- **Adaptability:** Can be trained separately for different regions, species, or ecoregions

ML for Carrying Capacity Modeling

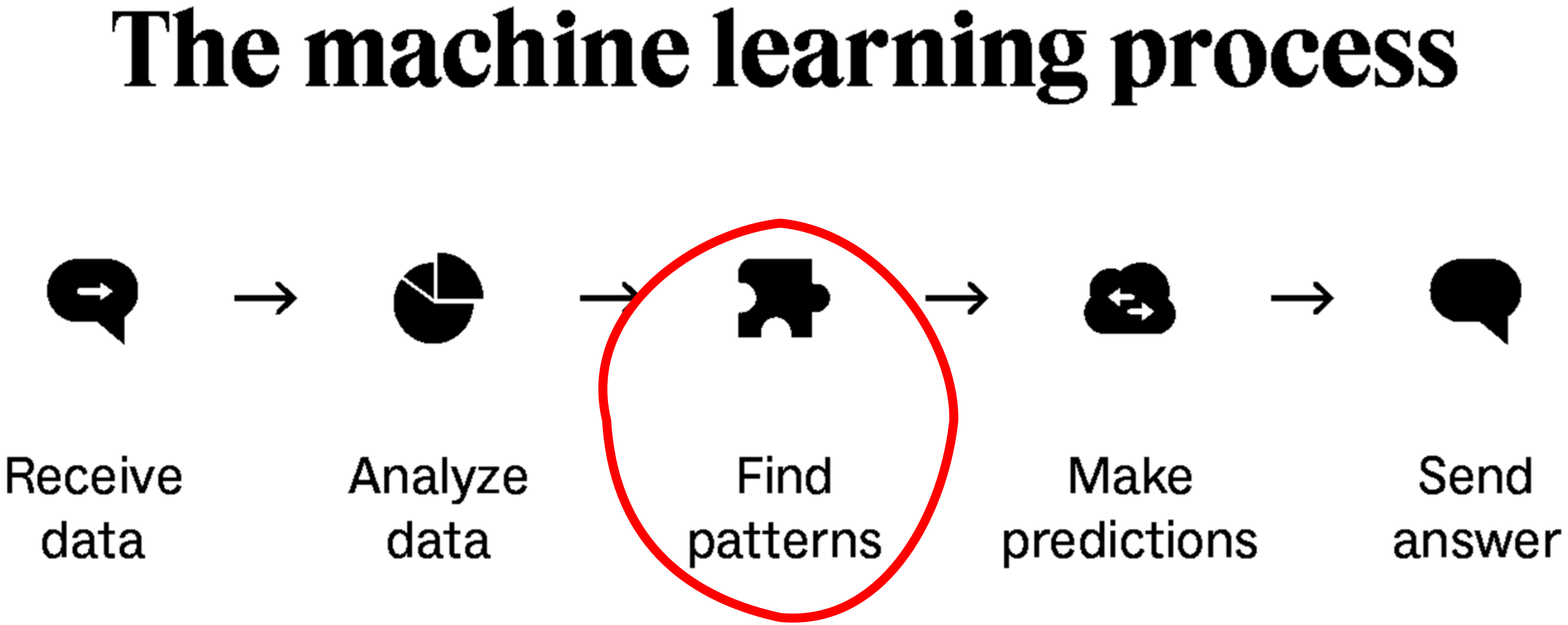
- Integrates species composition, site productivity, and climatic interactions
- Handles **imbalanced datasets** (e.g. more data from some regions/species)
- Enables **uncertainty quantification** and error **tracking**

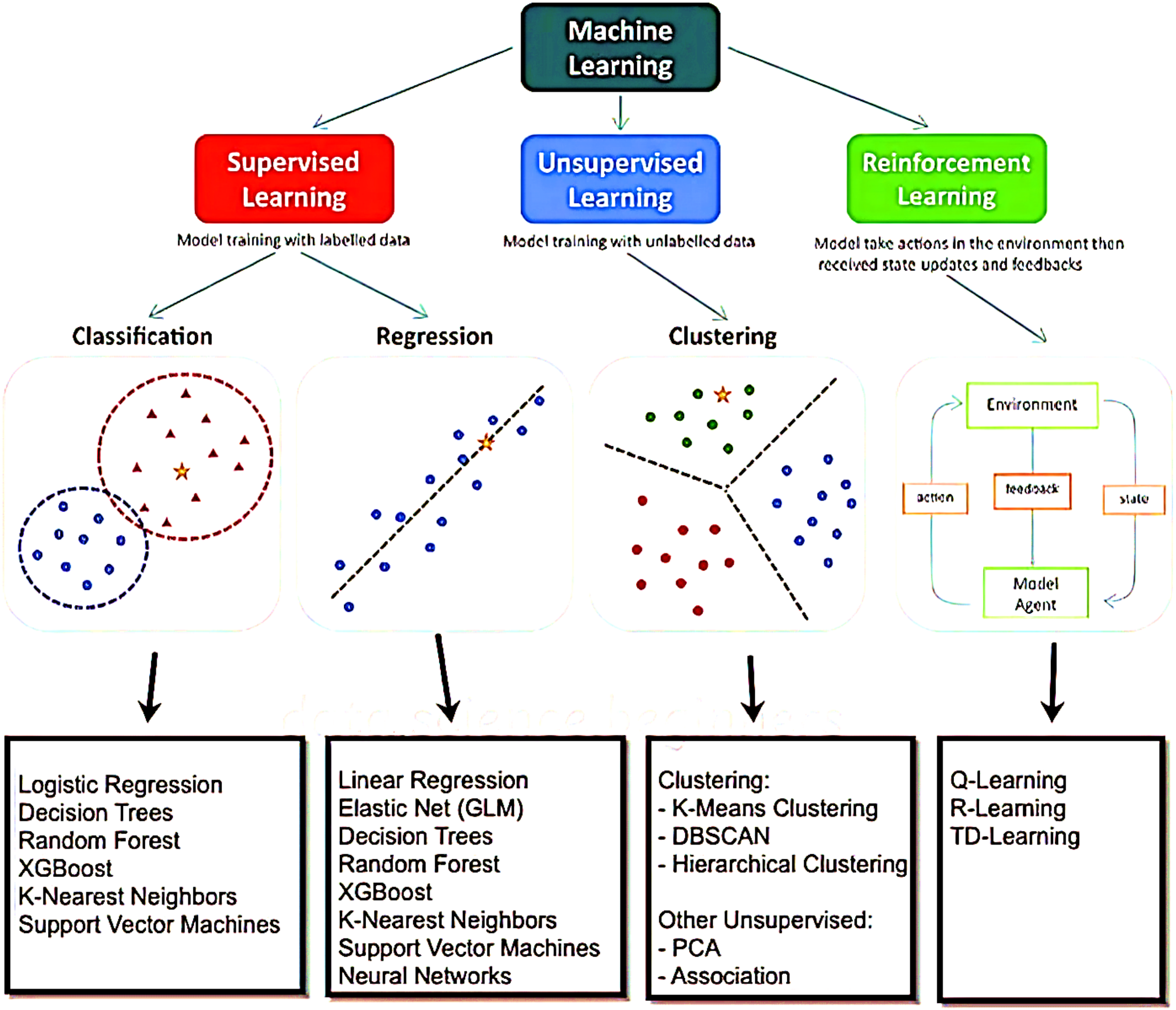


What is machine learning?

- Machine Learning is the art of turning data into decisions using algorithms and optimization
- ML is an automated hypothesis testing framework at scale — powered by data, driven by loss, refined by iterations.
- Machine Learning is how we teach machines to learn like humans — by experience, from examples, and through correction.
- Machine Learning Is Not Magic: It’s All About Math, Stats, Data, and Programming

What is machine learning?





Choosing the Best Supervised ML Model

Why Data Scientists Test Multiple Models

No One-Size-Fits-All

- No Free Lunch Theorem"

  Every algorithm performs differently on different data. Data-specific characteristics drive model performance

Bias-Variance Trade-Off

Model	Bias	Variance
Logistic Regression	High	Low
Random Forest	Medium	Medium
XGBoost/LightGBM	Low	High

Find the sweet spot by experimenting

Practical Strategy

- Cross-validation is your best friend
- Test on actual data, not just assumptions

AutoML for Speed

- Auto-sklearn
- H2O.ai
- Google AutoML

Then Optimize

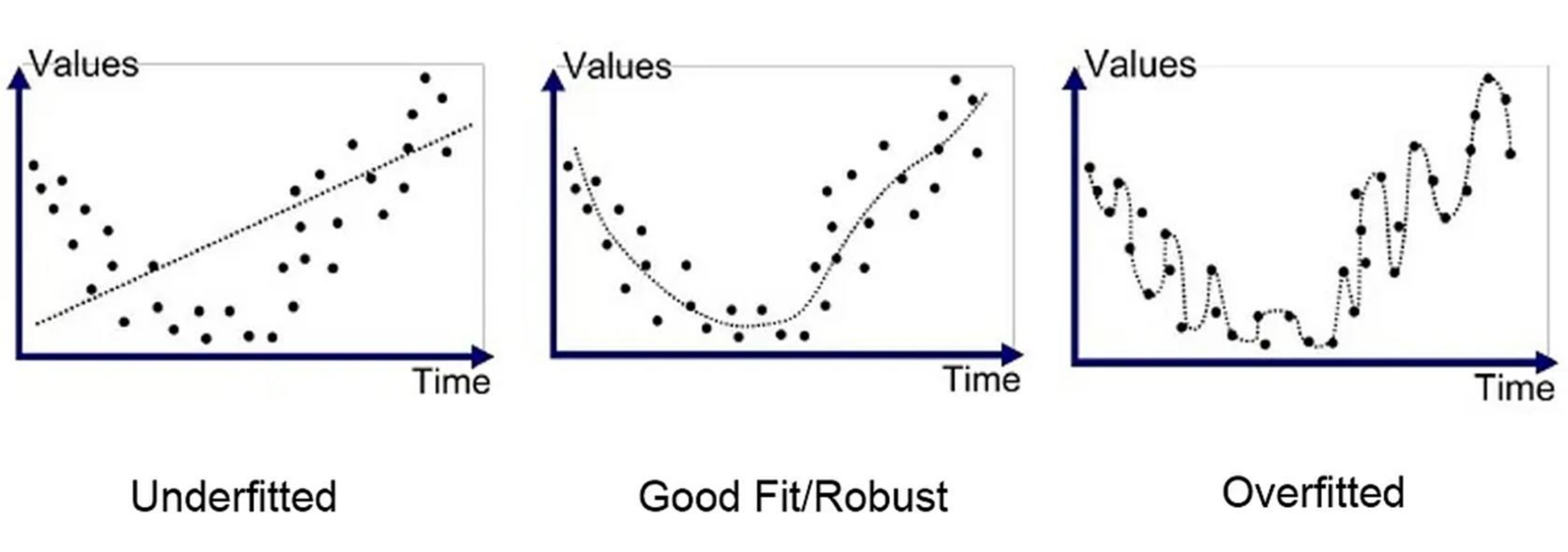
- Tune hyperparameters
- Compare performance metrics

Model choice should be data-driven, not guesswork. Experiment. Evaluate. Evolve.

Preventing Overfitting in Machine Learning

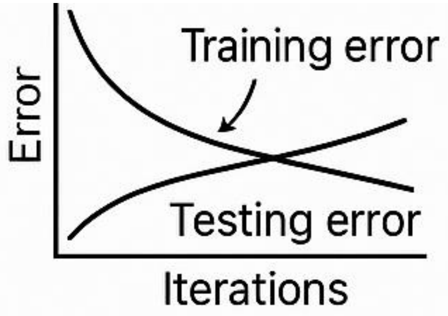
Understanding Overfitting

Bias-Variance Tredeoff



- If performance is much better on the training data than on testing data, overfitting is likely

- Train with More Data
- Cross-Validation
- Early Stopping
- Regularization
- Ensembling



Beyond Accuracy: The Case for Explainability

Great accuracy ≠ Great model

Model explainability (or interpretability) refers to our ability to understand and trust the predictions made by a machine learning model. It's about opening up the "black box."

Technique	Description	Best for
Feature Importance	Shows which features contributed most to a prediction	Tree models like Random Forest, XGBoost
SHAP (SHapley Additive exPlanations)	Provides a unified measure of feature impact across models	Any model (very popular)
LIME (Local Interpretable Model-Agnostic Explanations)	Explains individual predictions by approximating the model locally	Any model
Partial Dependence Plots (PDP)	Shows the relationship between features and predictions	Tabular data models

Inland Northwest Data

- 145,041 plots/stands info post pre-processing and EDA.

I.e., TPA, QMD, Species BA proportions

- Weighted Shade Tolerance & Drought Tolerance

(Niinemets and Valladares (2006))

- Species diversity indices

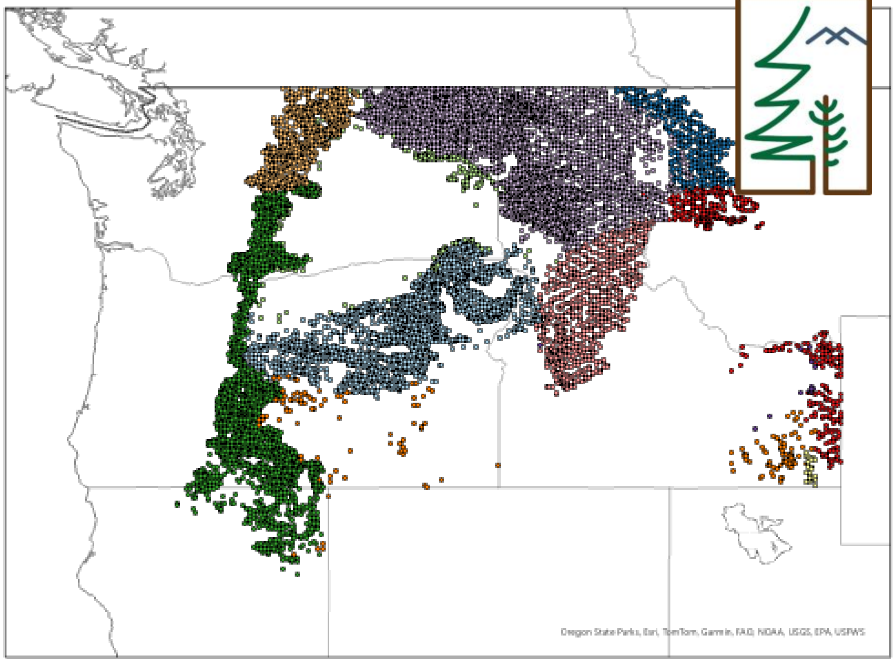
(e.g., Shannon Diversity Index, Species Richness, Pielou evenness, Berger Parker Index)

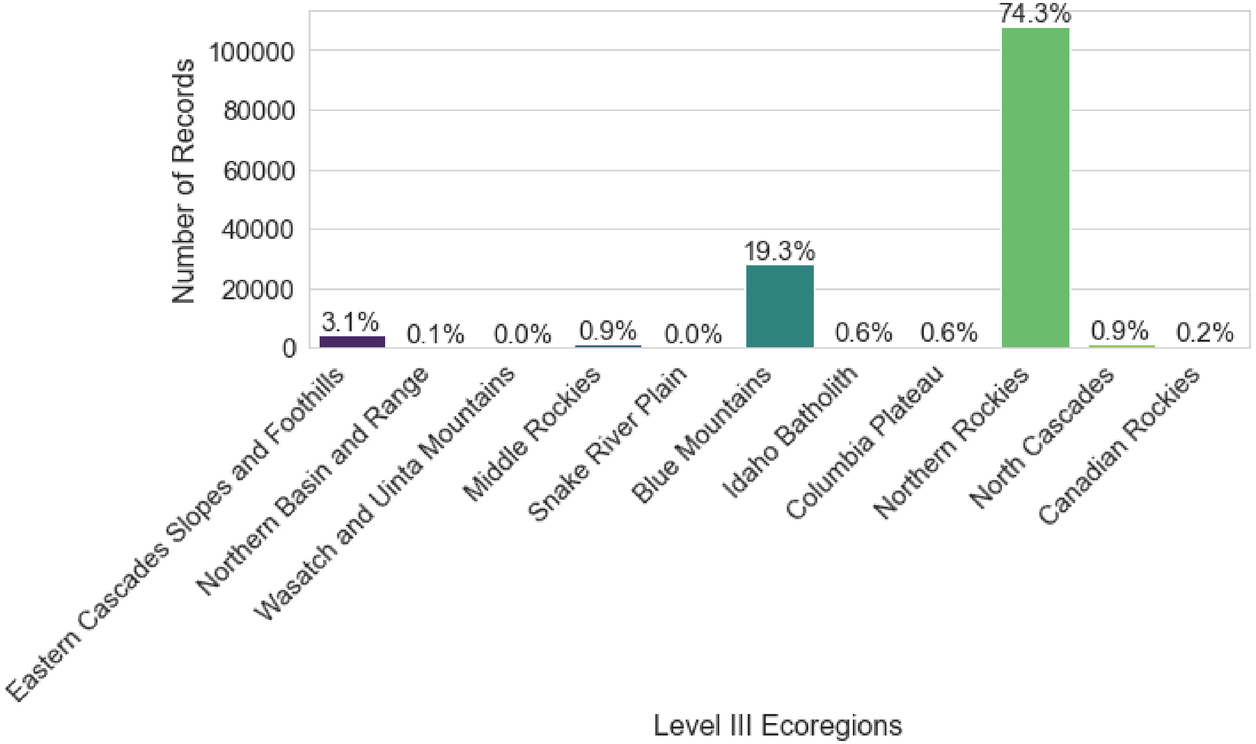
- Topography extraction from 30m DEM

(e.g., Slope, Aspect, Topographic wetness index, Solar radiation)

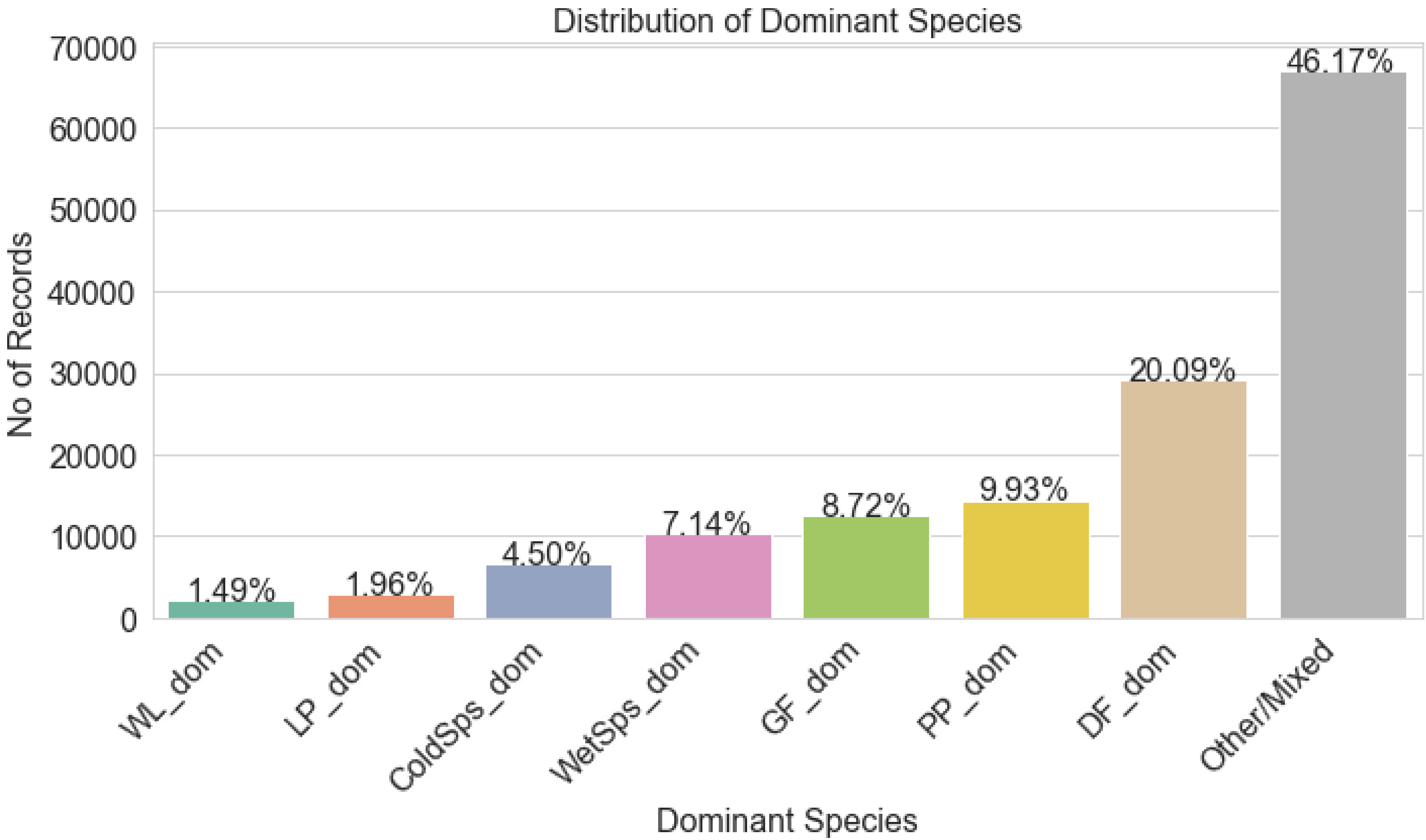
- ClimateNA – (Annual, Month, Season)

- Geology and Soil layer - (SGMC & gSSURGO geodatabase





Insights into the Data



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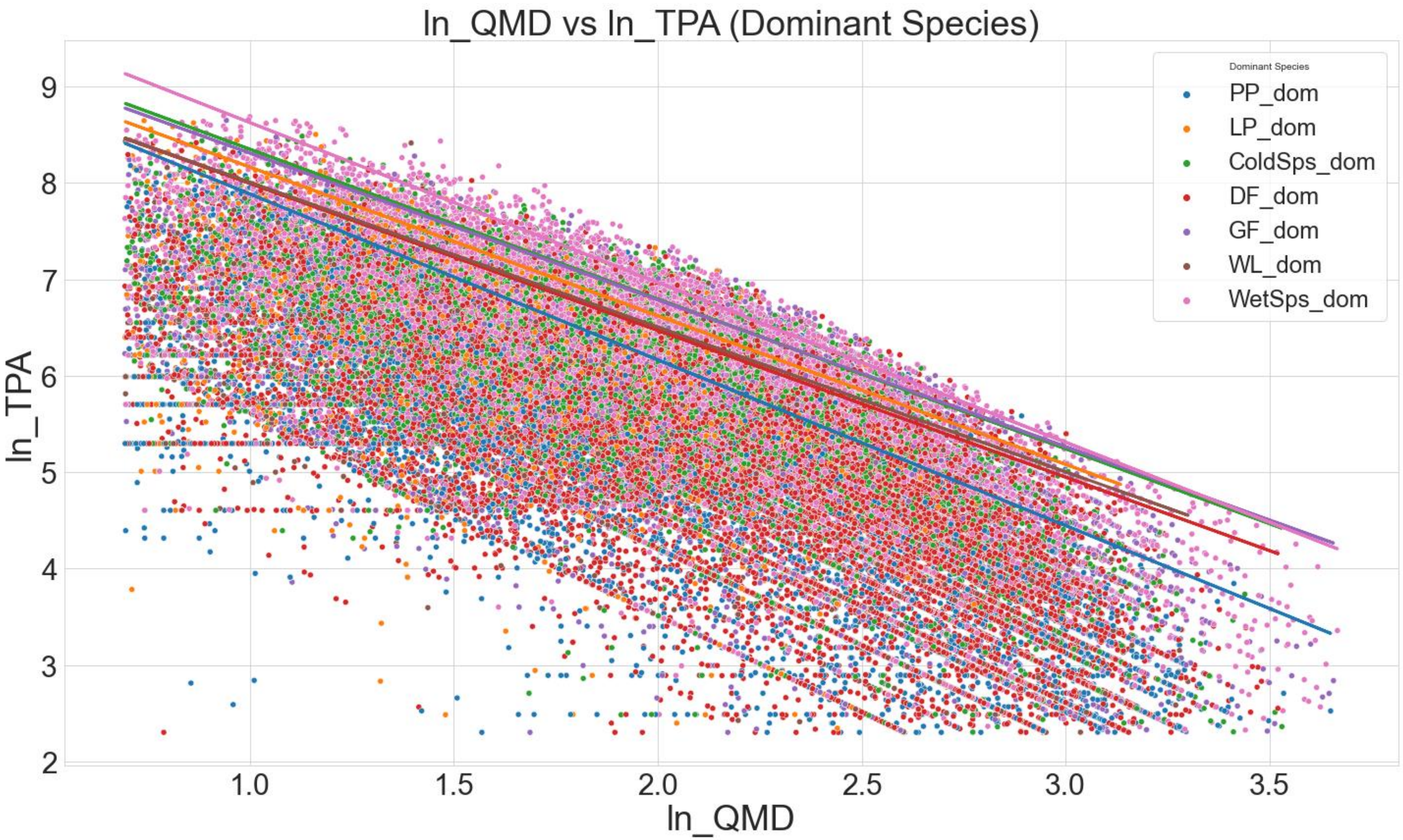

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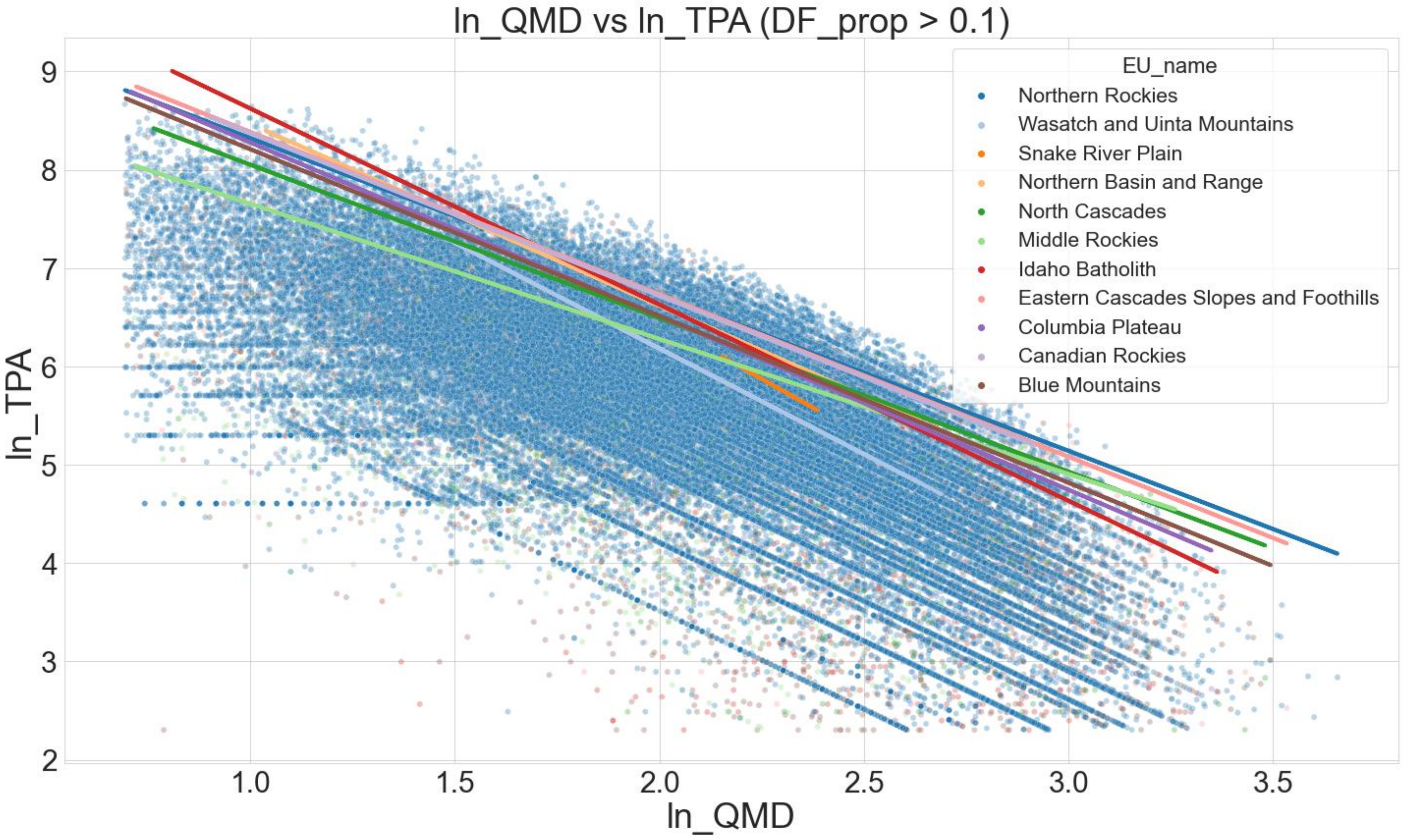
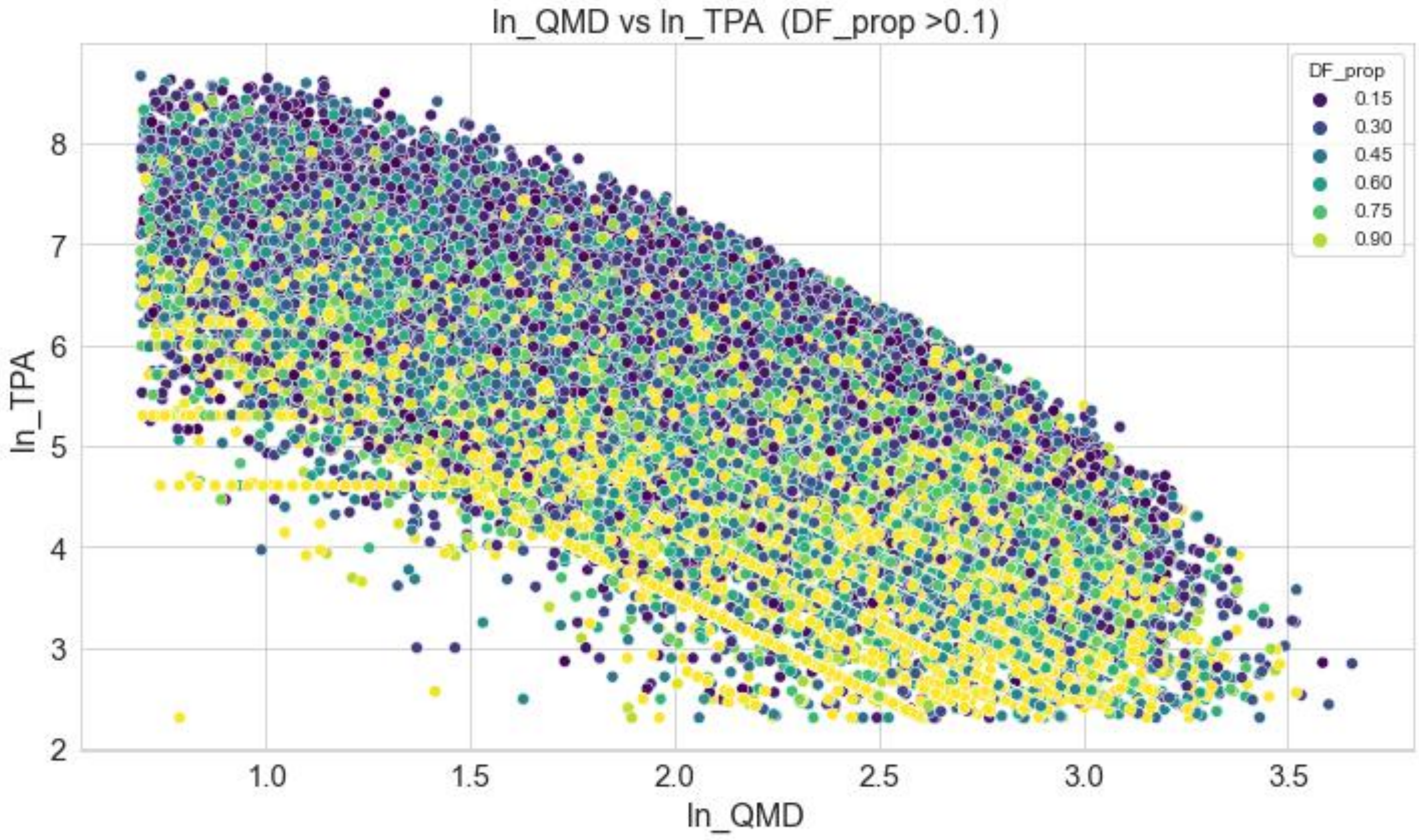


Insights into the Data



Modeling Approach

Data Cleaning:

Missing expansion factors, at least 10 TPA, QMD at least 2-inch, questionable & missing data

Feature Selection: Correlation + Mutual Information Score (MIS)

Step 1: Find Highly Correlated Pairs

- Compute Pearson Correlation between all feature pairs
- Select pairs with |correlation| > 0.7

Step 2: Calculate MIS

- Compute Mutual Information Score between each feature and the target
- MIS is non-parametric → supports all data type

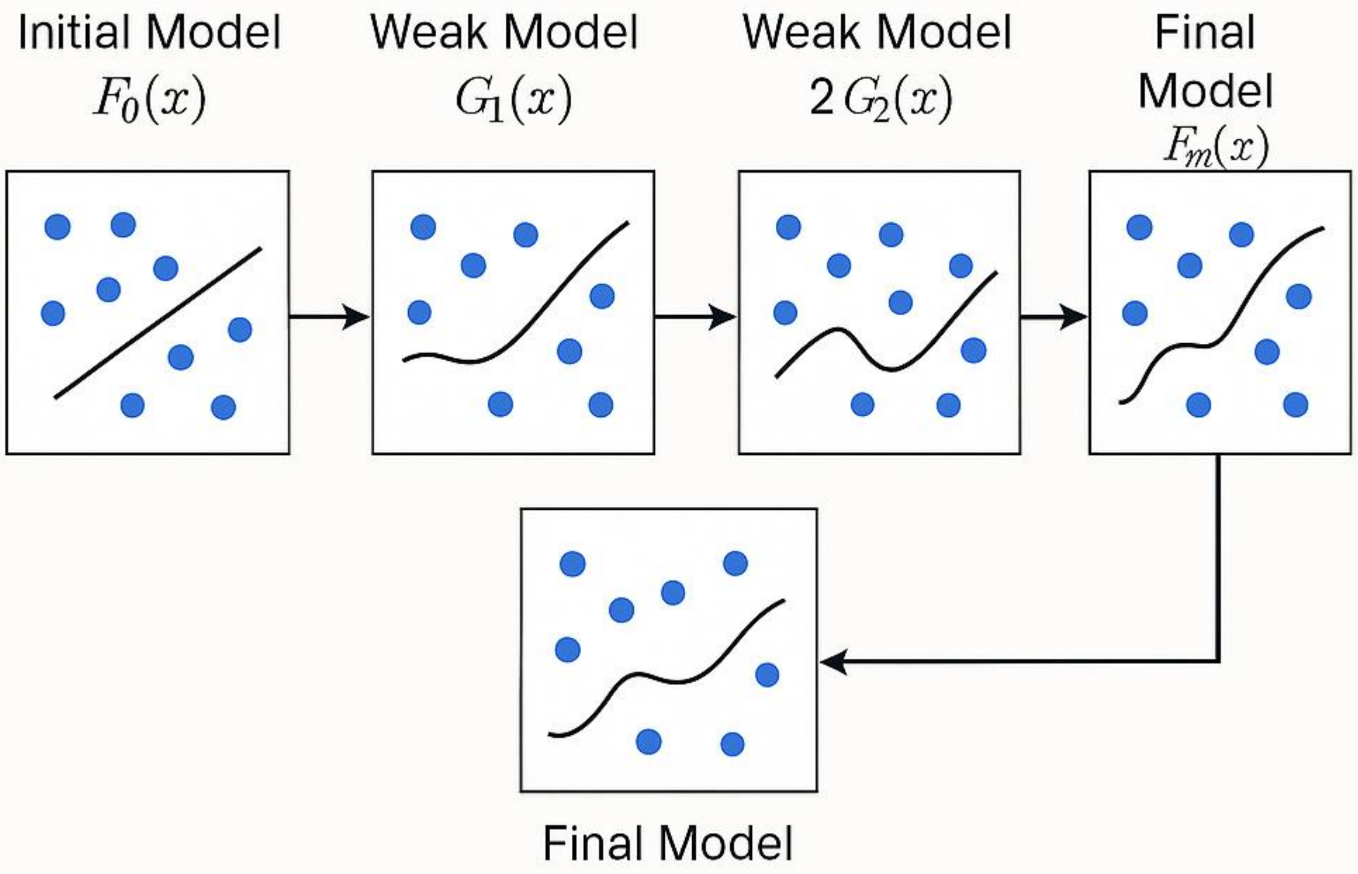
Step 3: Eliminate Redundant Features

- For each correlated pair:
  - Compare their MIS values
  - Remove the one with lower MIS
- Repeat until no correlated pairs remain

Final Result:

- High relevance to target (via MIS)
- Low redundancy between features (via correlation

Gradient Boosting



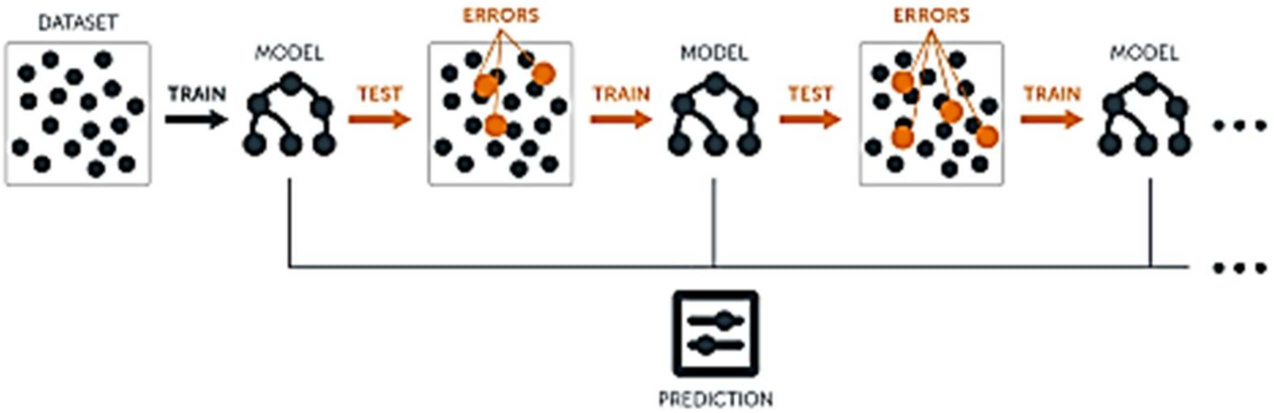
Final Model $= F_0(x) + \gamma_1 G_1(x) + \gamma_2 G_2(x) + \gamma_3 G_3(x)$

- ❑ GBM is an ensemble learning method that builds models sequentially, where each new model corrects the errors of the previous one.
- ❑ Workflow: Start with a base model (like a decision tree).
- ❑ Train new models on the residuals (errors) of the previous model.
- ❑ Combine models to minimize the loss function using gradient descent.

Addressing Challenges: The Analytical Approach

Quantile Gradient Boosting Machine

Quantile GBM predicts upper quantiles of size-density or carrying capacity distributions, targeting extreme values and high-density scenarios, providing insights into the self-thinning relationship.



Flexibility

Accommodating complex relationships and interactions in stand density data.

Accuracy

Capturing non-linearities and handling high-dimensional predictor spaces effectively

Robustness

Robust to model misspecification, ensuring reliable estimation of maximum stand density even in the presence of outliers and complex data patterns.

Model Summary:

Quantile regression loss function can predict a specified percentile

Quantile

$$f = \begin{cases} w \times QuantileAlpha \times (y - f) & \text{for } y > f \\ w \times (1 - QuantileAlpha) \times (f - y) & \text{for } y \leq f \end{cases}$$

Where:

- y is a true response
- f is a predicted response
- w is weight

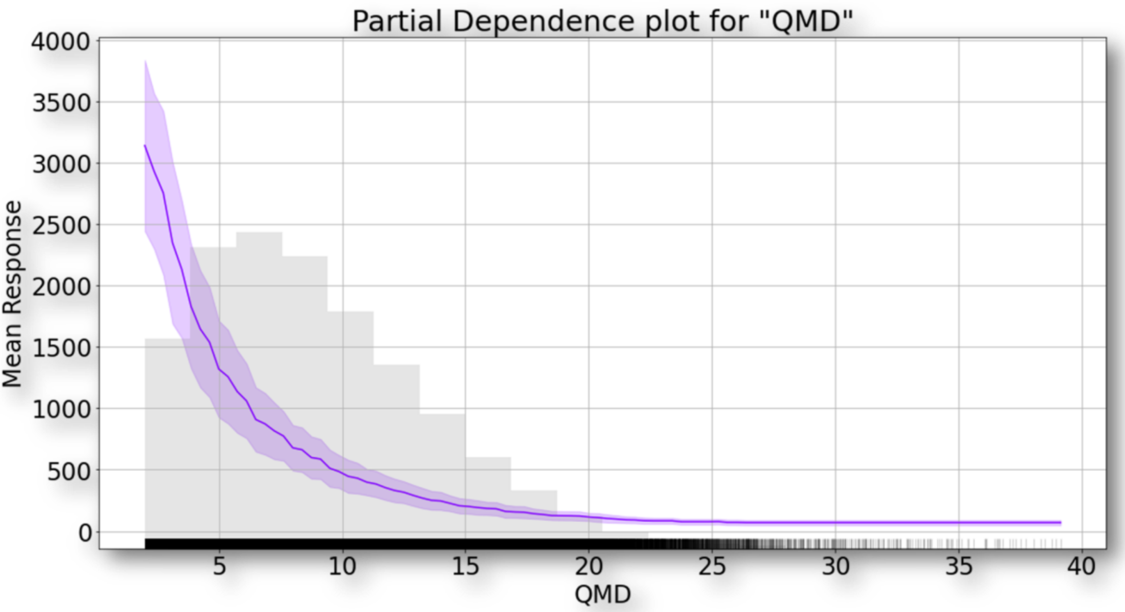
distribution = "quantile", quantile_alpha =.95

number_of_trees	number_of_internal_trees	model_size_in_bytes	min_depth	max_depth	mean_depth	min_leaves	max_leaves	mean_leaves
75	75	32206	5	5	5	19	32	29.493334

Consistent pinball loss (~32) in training and cross-validation signifies robust quantile estimation.

KEY PREDICTORS OF SDIMAX

QMD	RC_prop	TD	Cons_LITH
W_ShadeTol	WH_prop	PRATIO	soc0_20
W_DroughtTol	GF_prop	MAPMCMT	DEP2RES
	LP_prop	Rad_sm	aws0_100
	WL_prop	HeatLoad	Slope
	DF_prop		
	PP_prop		



TD - Temperature difference between mean warmest month temperature and mean coldest month temperature

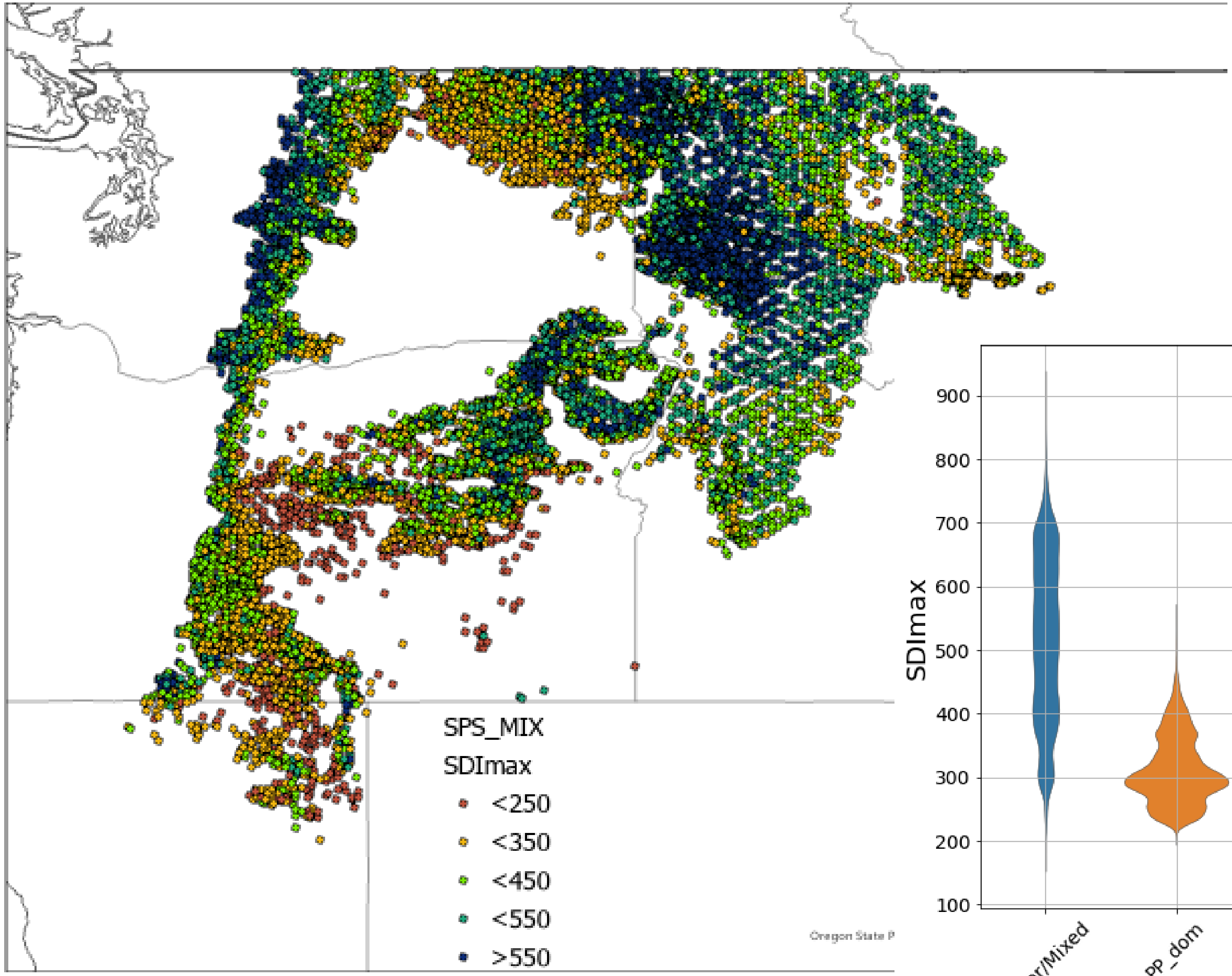
PRATIO - Ratio of growing season precipitation to total precipitation

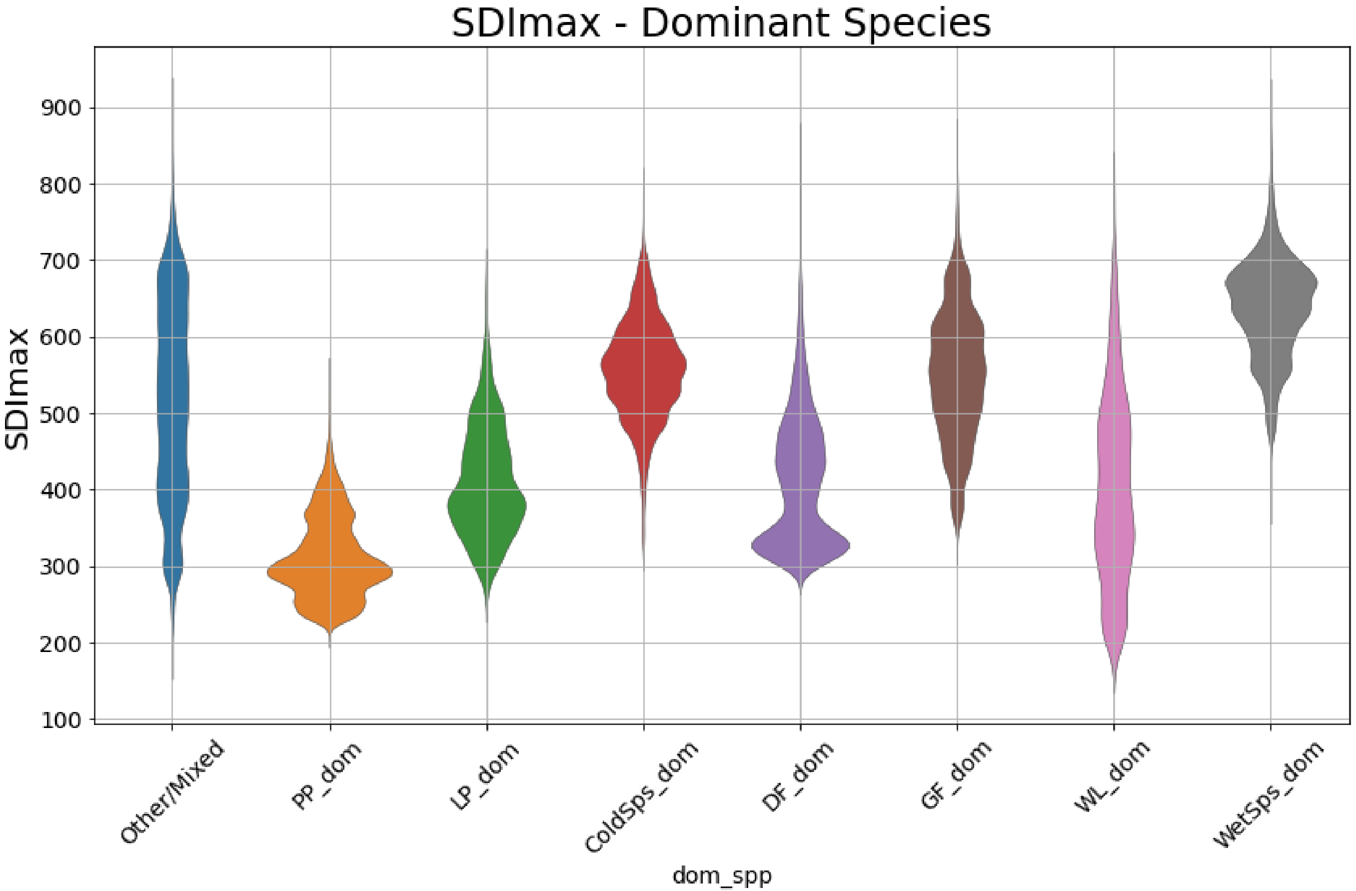
MAPMCMT - Interaction between mean annual precipitation and mean coldest month temperature

RAD_sm - Summer solar radiation

Heatload - Interaction between Annual Solar Radiation and Degree Days between 10 and 40 degrees Celsius

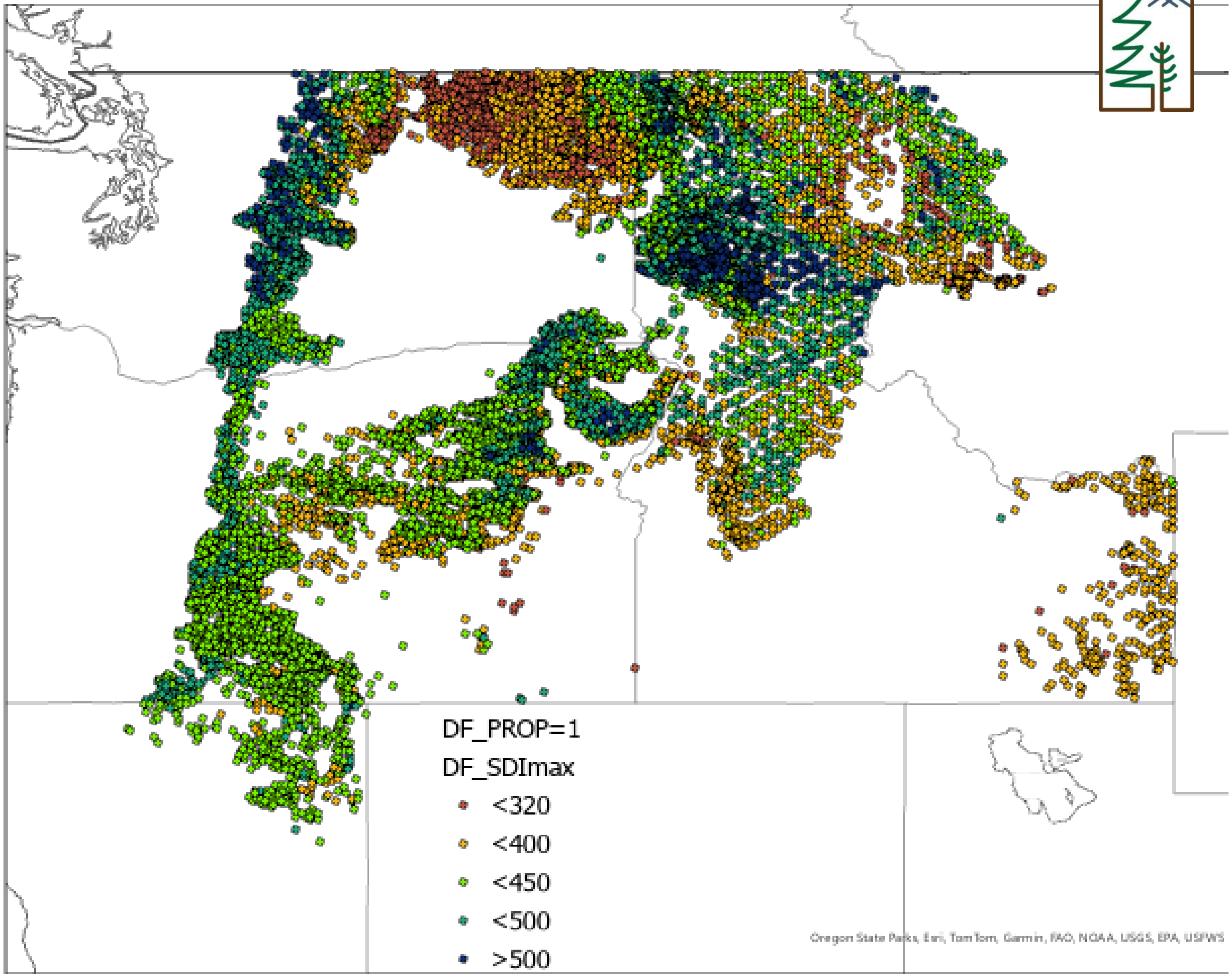
SDImax estimates with Species info



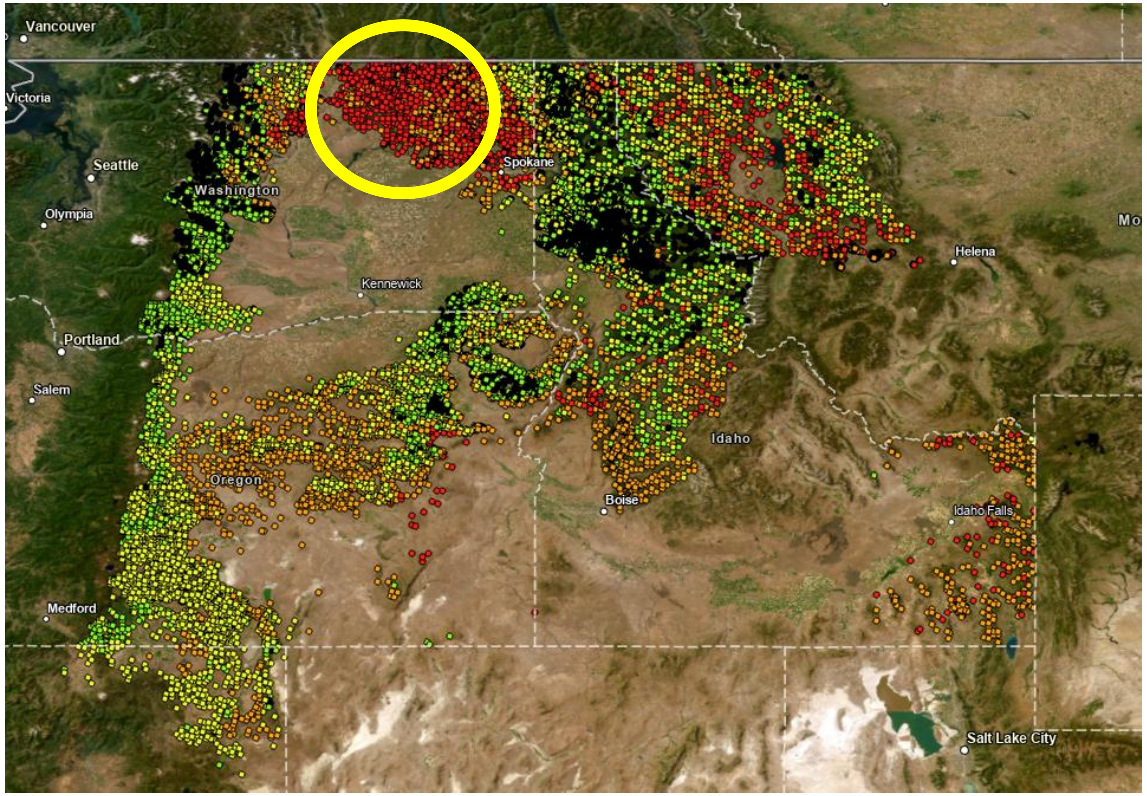


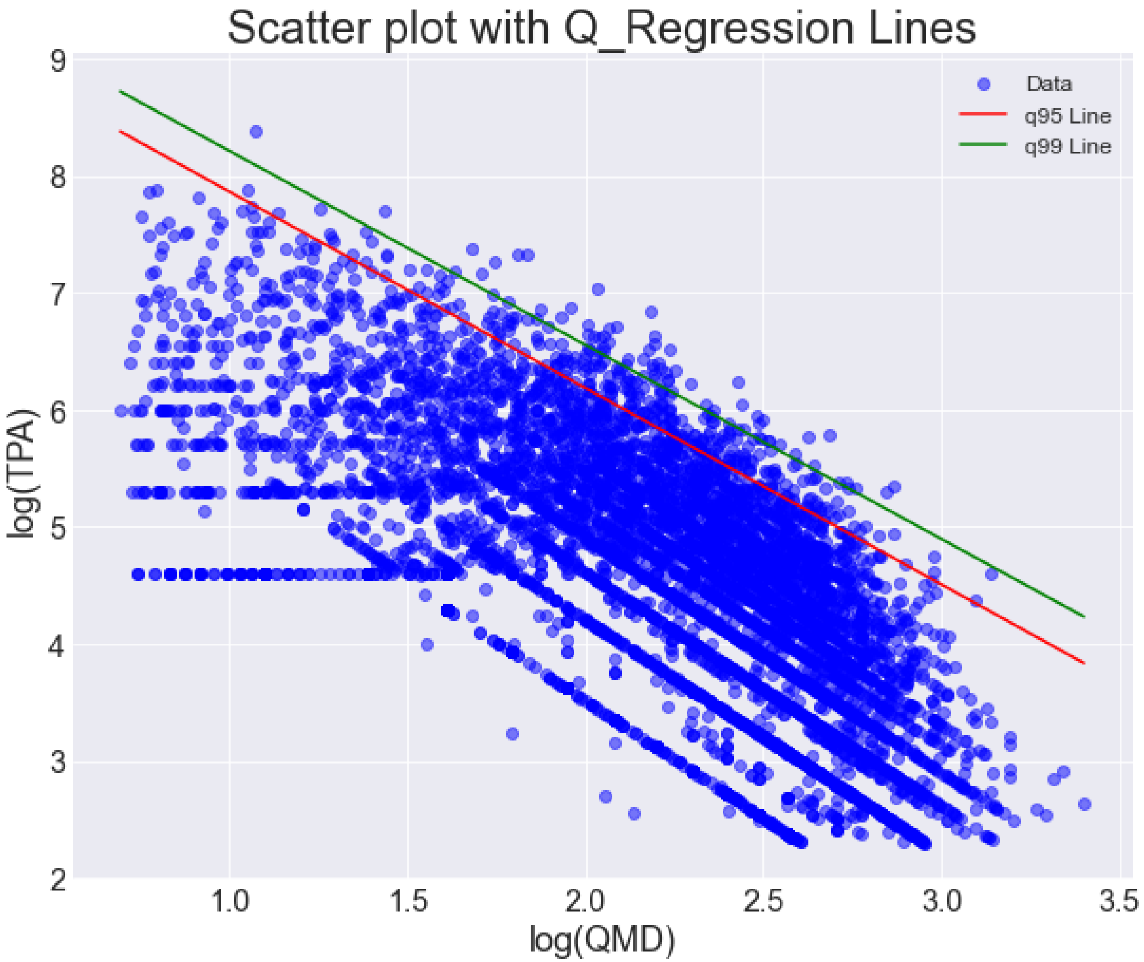
SDImax estimates for 100% Douglas-fir

min	290
25%	348
mean	423
50%	434
75%	476
95%	527
99%	548
max	668

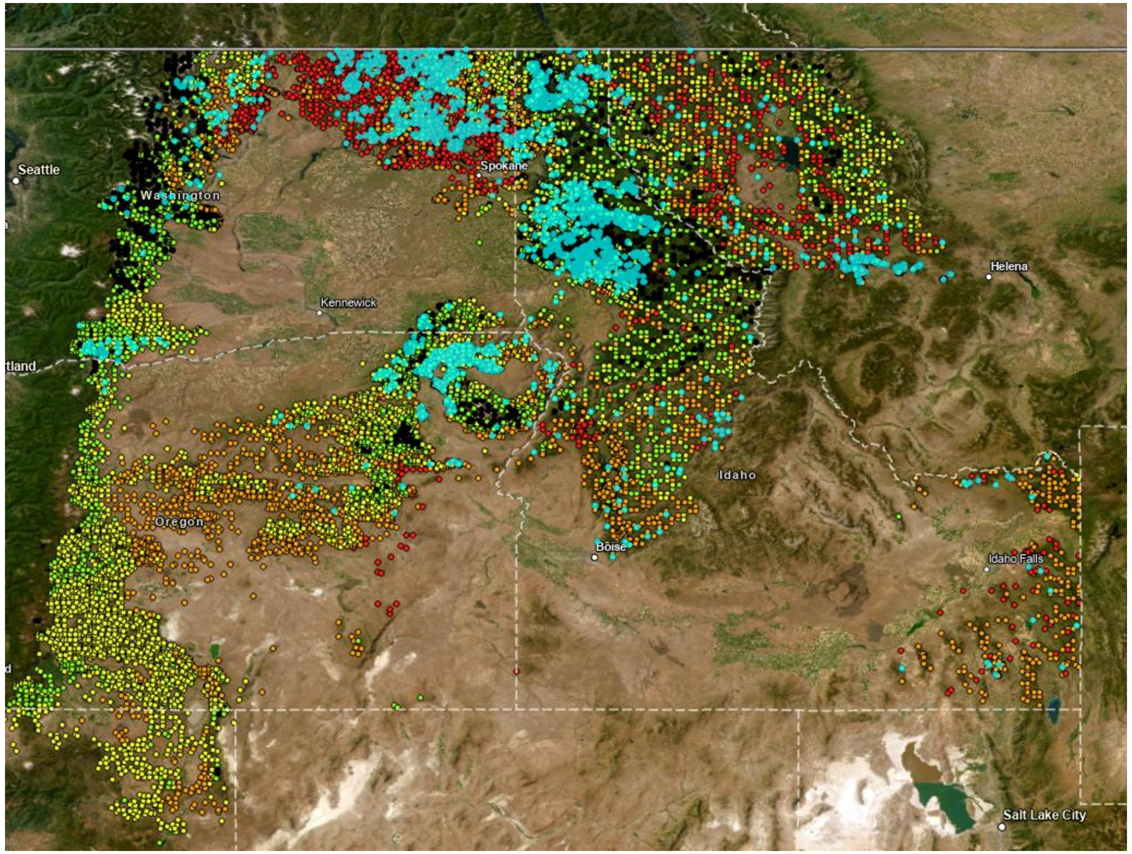


6747 pure stands of Douglas-fir (20% of total)

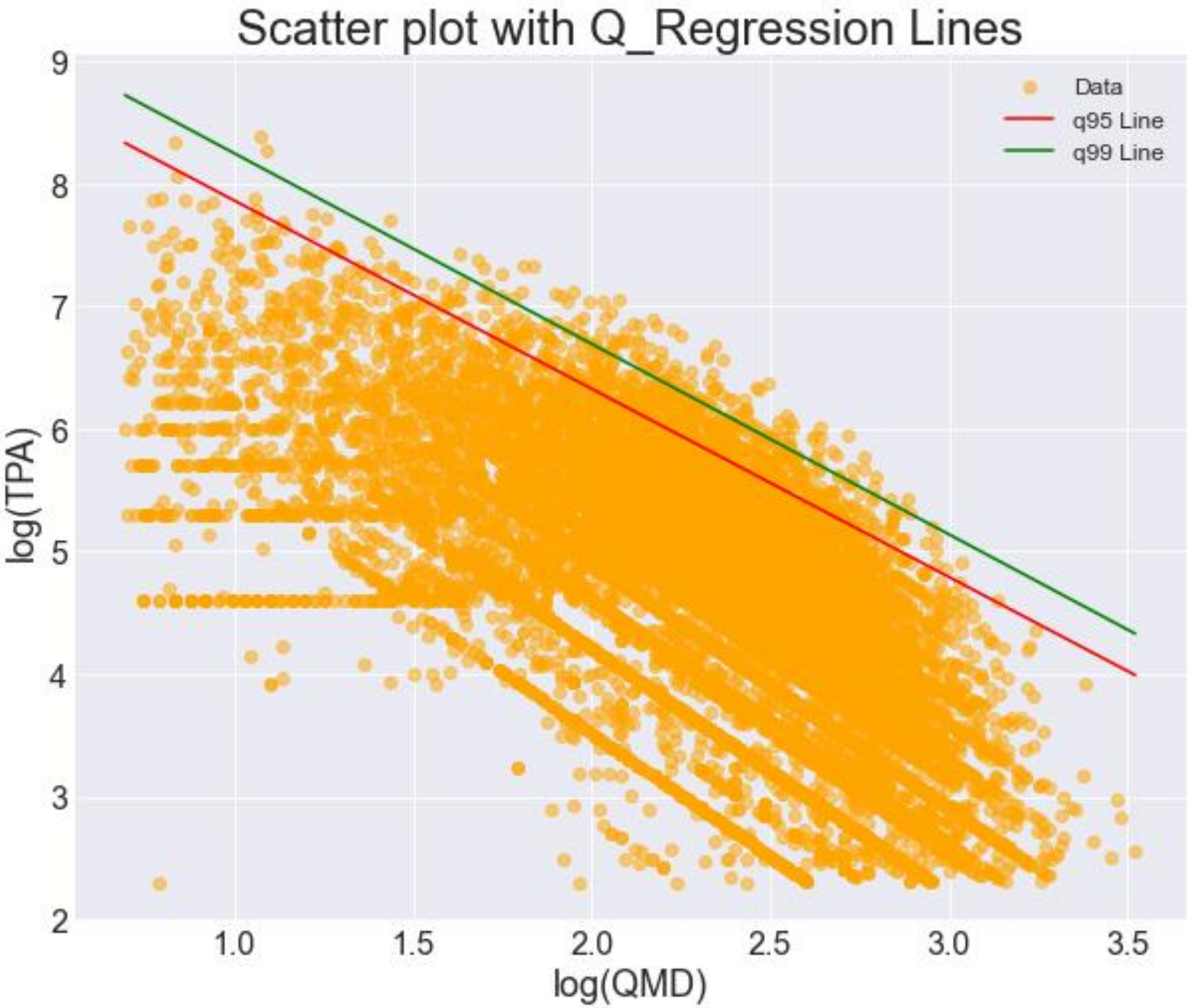




@QMD 10-inch Q95 of TPA = 292 and Q99 of TPA =405

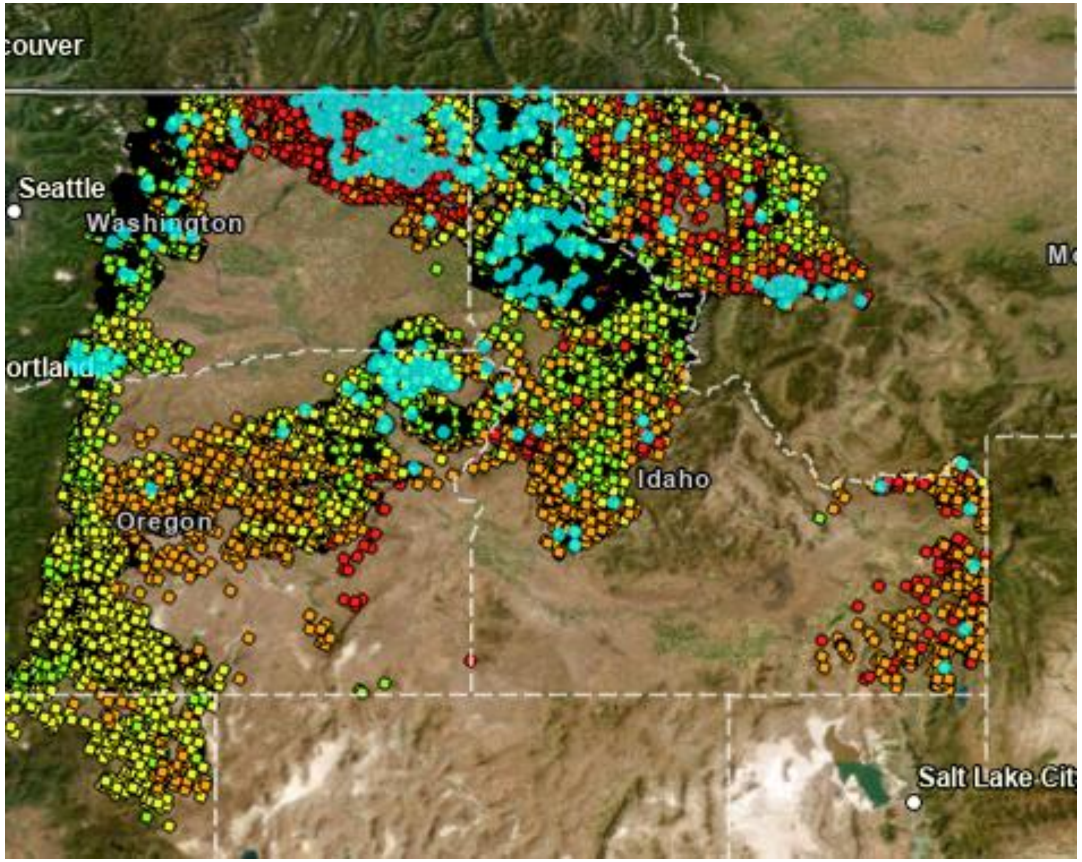


13622 pure stands of Douglas-fir (10% of total records)



@QMD 10-inch Q95 of TPA = 350 and Q99 of TPA =504

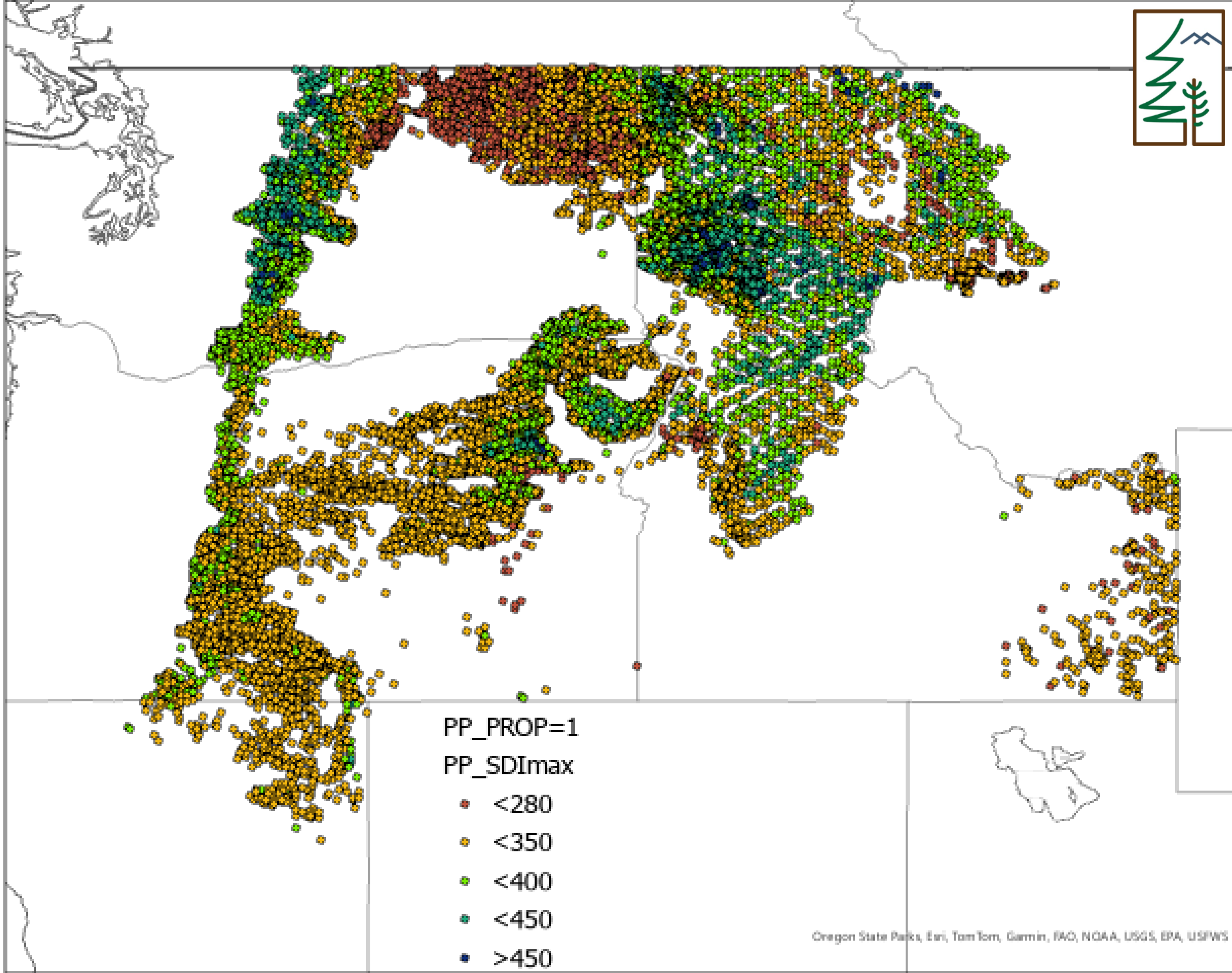
824 stands of Douglas-fir with 90%BA



@QMD 10-inch Q95 of TPA = 469 and Q99 of TPA = 670

SDImax estimates for 100% Ponderosa Pine

min	250
25%	300
mean	350
50%	343
75%	400
95%	439
99%	458
max	561

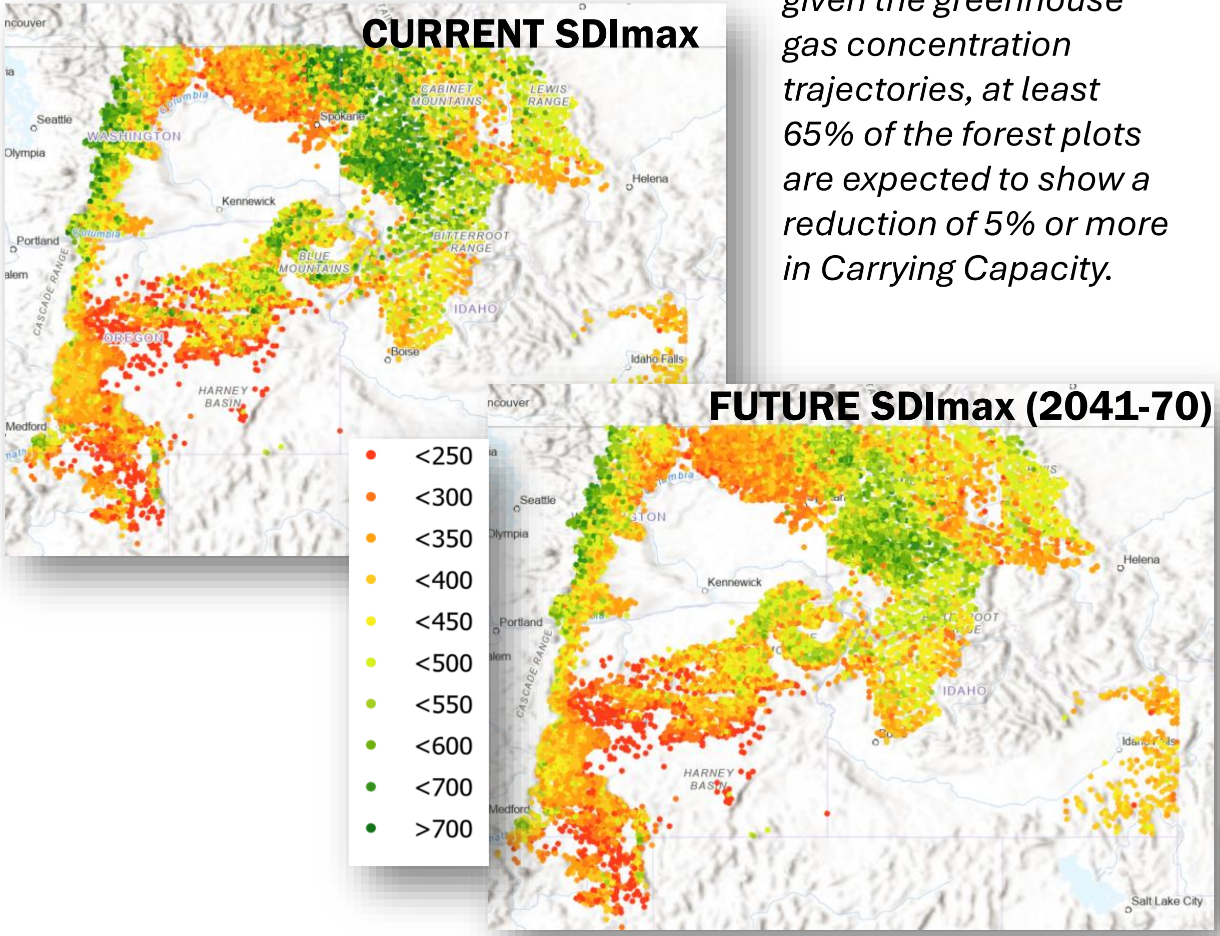


Model showed significant increases in maximum SDI when shifting from pure stands of Douglas-fir or Ponderosa pine to mixed stands (Other Species BA prop >10%)

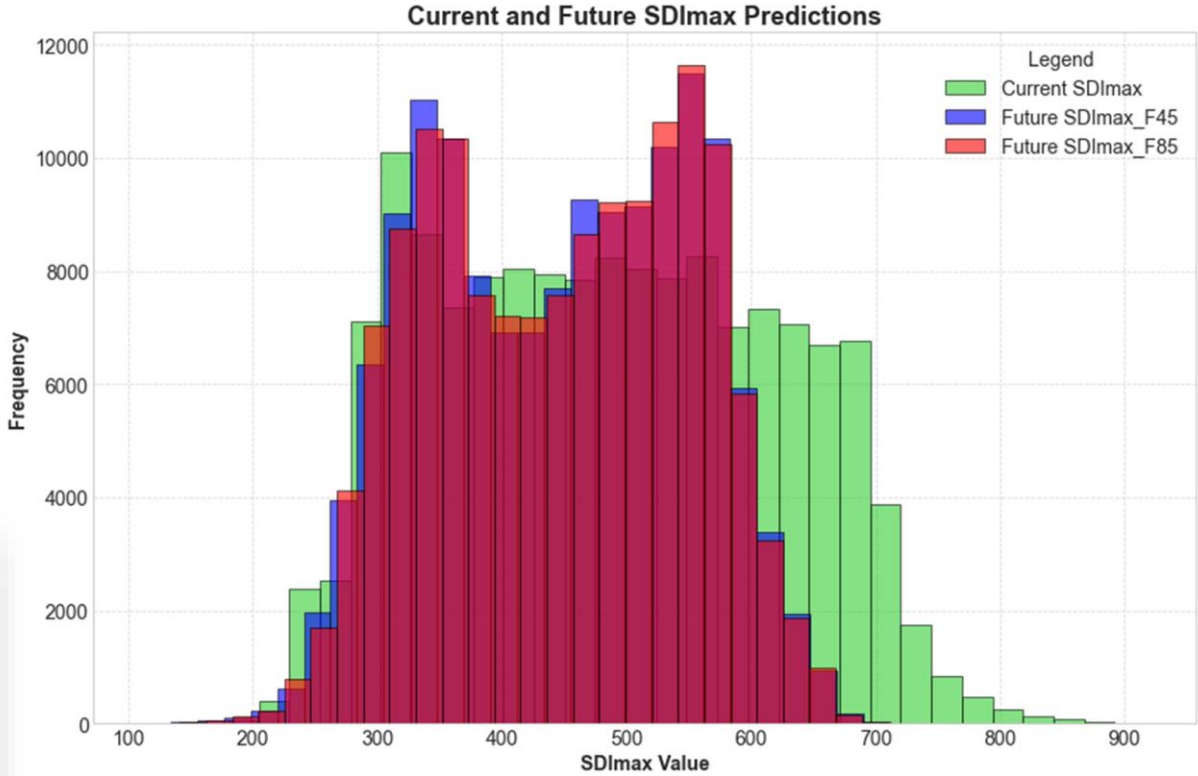
- This increase is due to a mixing of more shade tolerant species as shown throughout the literature
- Models reflective of habitat/forest type based SDImax thresholds
  - Powell's Green Book

Climate projections – impact on FCC

INLAND EVALUATION



This study revealed that, given the greenhouse gas concentration trajectories, at least 65% of the forest plots are expected to show a reduction of 5% or more in Carrying Capacity.



RCP4.5

WCRP CMIP5 World Climate Research Programme

SDI IN A ML ENVIRONMENT

SOLUTION NEEDED

Reineke based SDI Equation

$$SDI = TPA \times \left(\frac{QMD}{10}\right)^{\mathbf{1.605}}$$

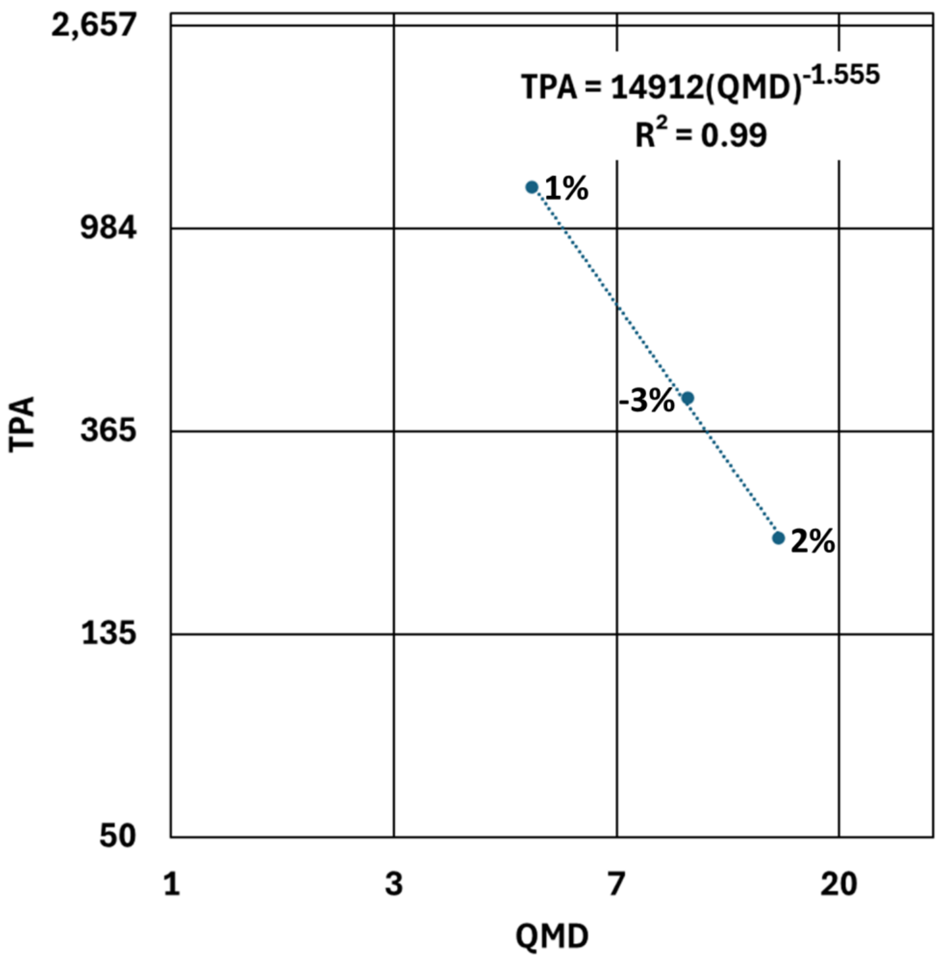
$$RD = {SDI}/{SDImax}$$

- 1.605 exponent a legacy of Reineke's MaxSDI modeling and subsequent species, linear based modeling efforts
- IFC V1.0 models created using Stochastic Frontier Regression (linear models) created a revised species model exponent that could be substituted for **1.605** to compute Relative Density (RD)
- New Machine Learning approach to SDImax modeling is not linear, exponent is unique to each user input – *f*(stand, site conditions)
- Exponent critical to compute Relative Density as a function of predicted IFC SDImax after inventory updates

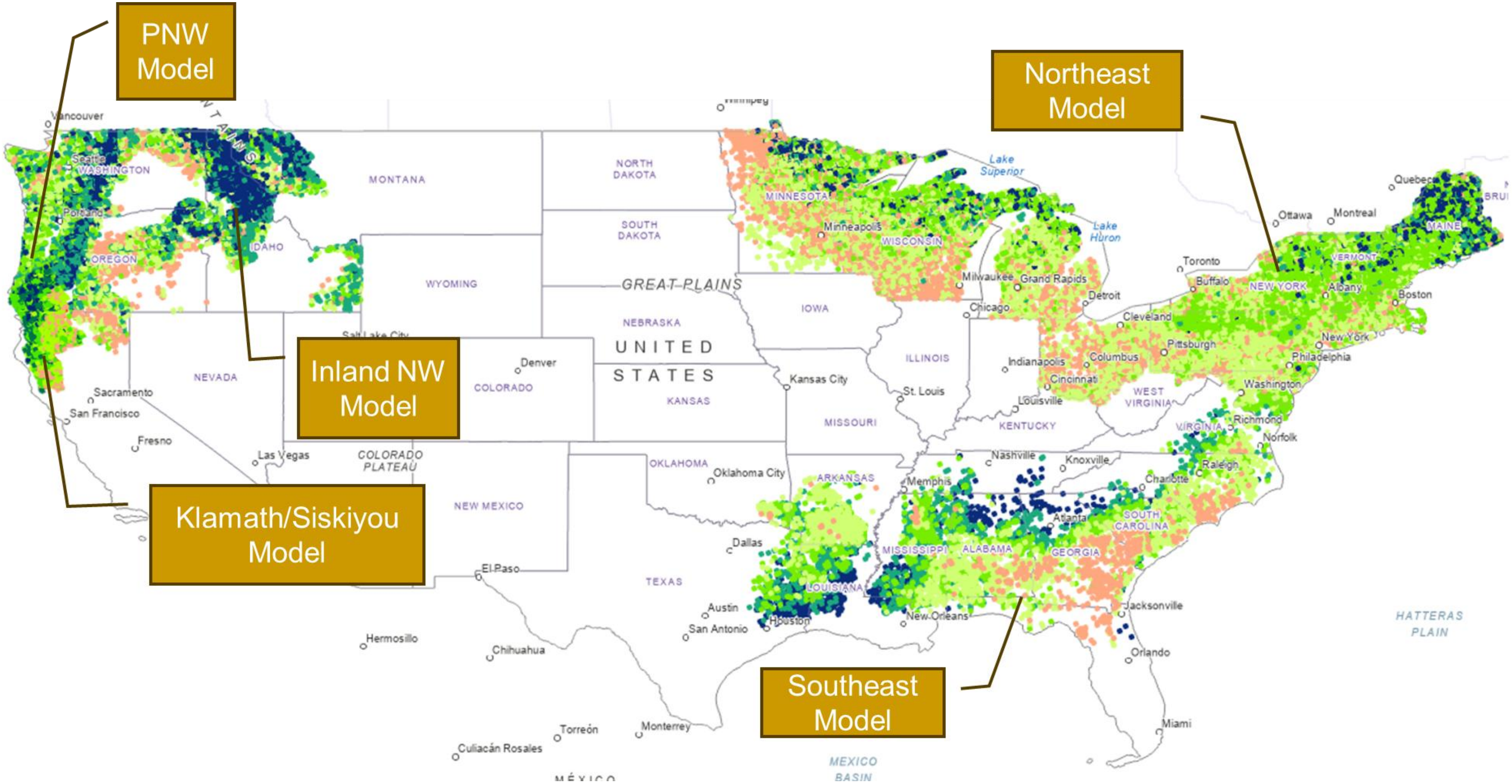
INTRODUCING IFC SDI FORMULATION

CUSTOM EXPONENT COMPUTATION

- One time computation of SDI max for a range of QMDs and User Inputs (initial stand metrics, location)
- Fit power functions to the X-Y pairs of predicted max TPA and associated QMD
- Power function exponent is the slope required to compute SDI
- Integrate slope coefficients into User database for future RD computation after inventory updates
  - No need to re-run SDImax model to update RD



SDI$_{MAX}$ MODELS AVAILABLE



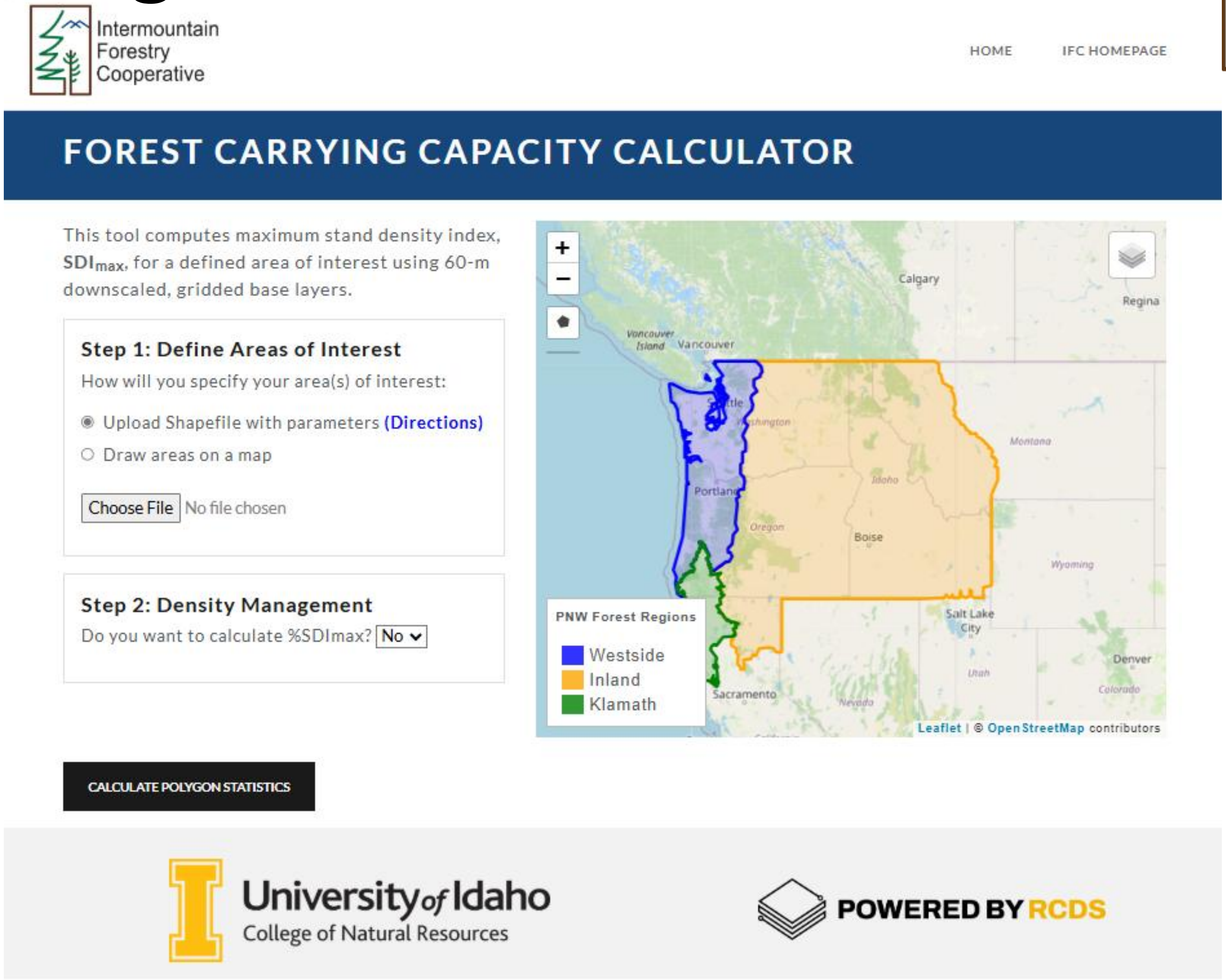
Toolsets for managers

IFC WEB APP

V2.0 INLAND,

V1.0 K-S,

V1.0 PACIFIC



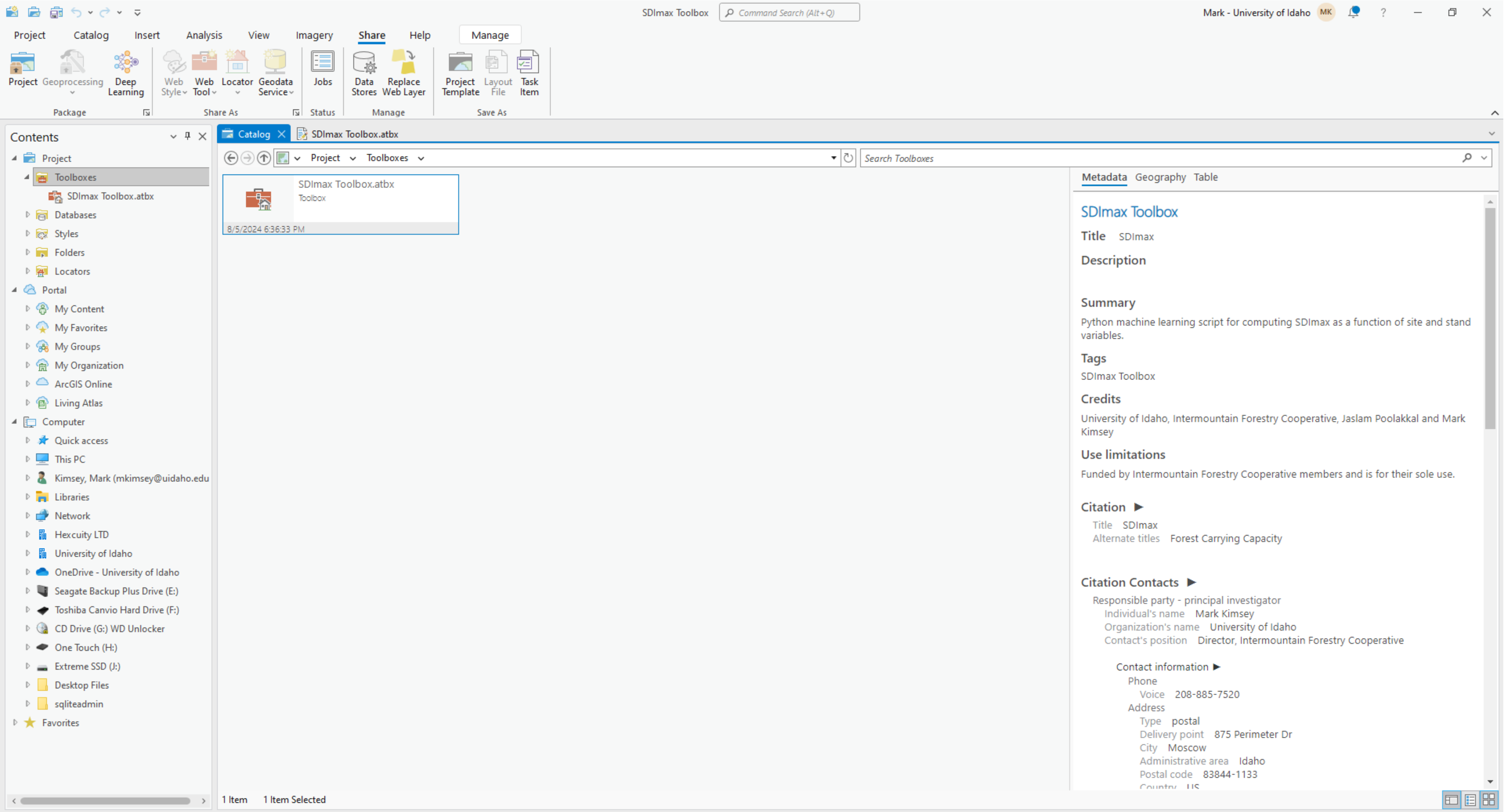
TOOLSETS FOR MANAGERS

JUPYTER NOTEBOOK

TOOLSETS FOR MANAGERS

Available Summer 2025

ARC TOOLBOX



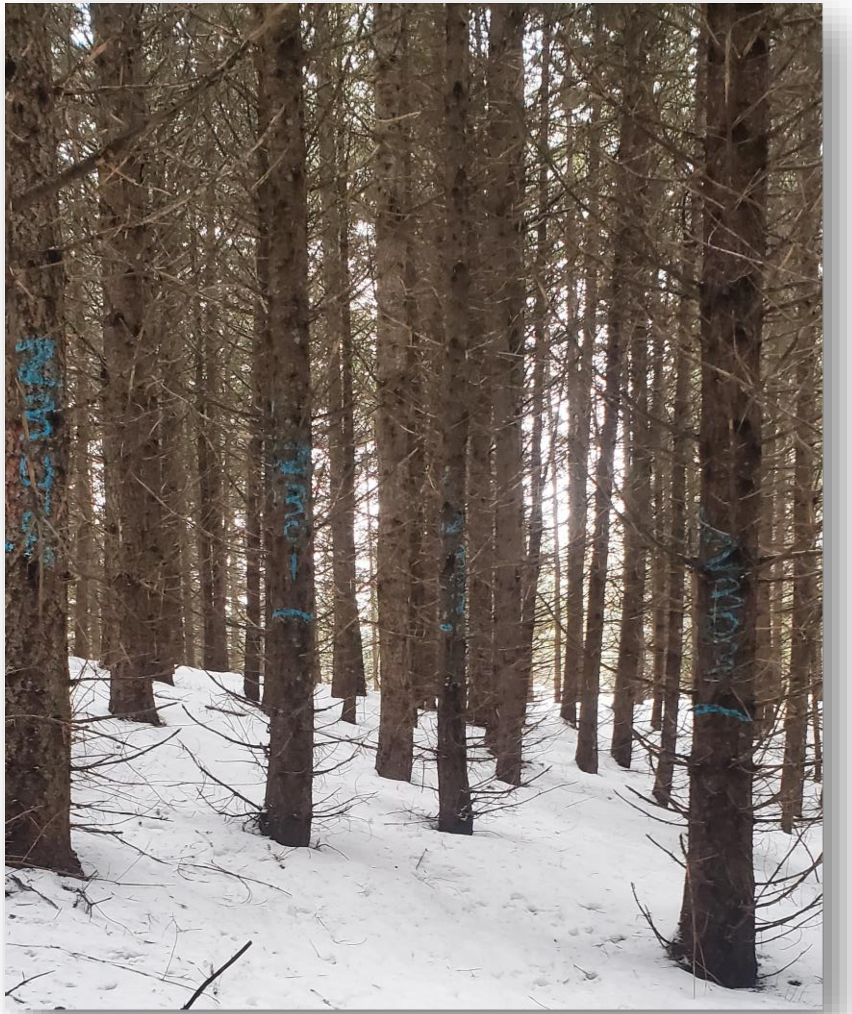
Take home points

CUSTOM SOLUTIONS FOR DENSITY MANAGEMENT

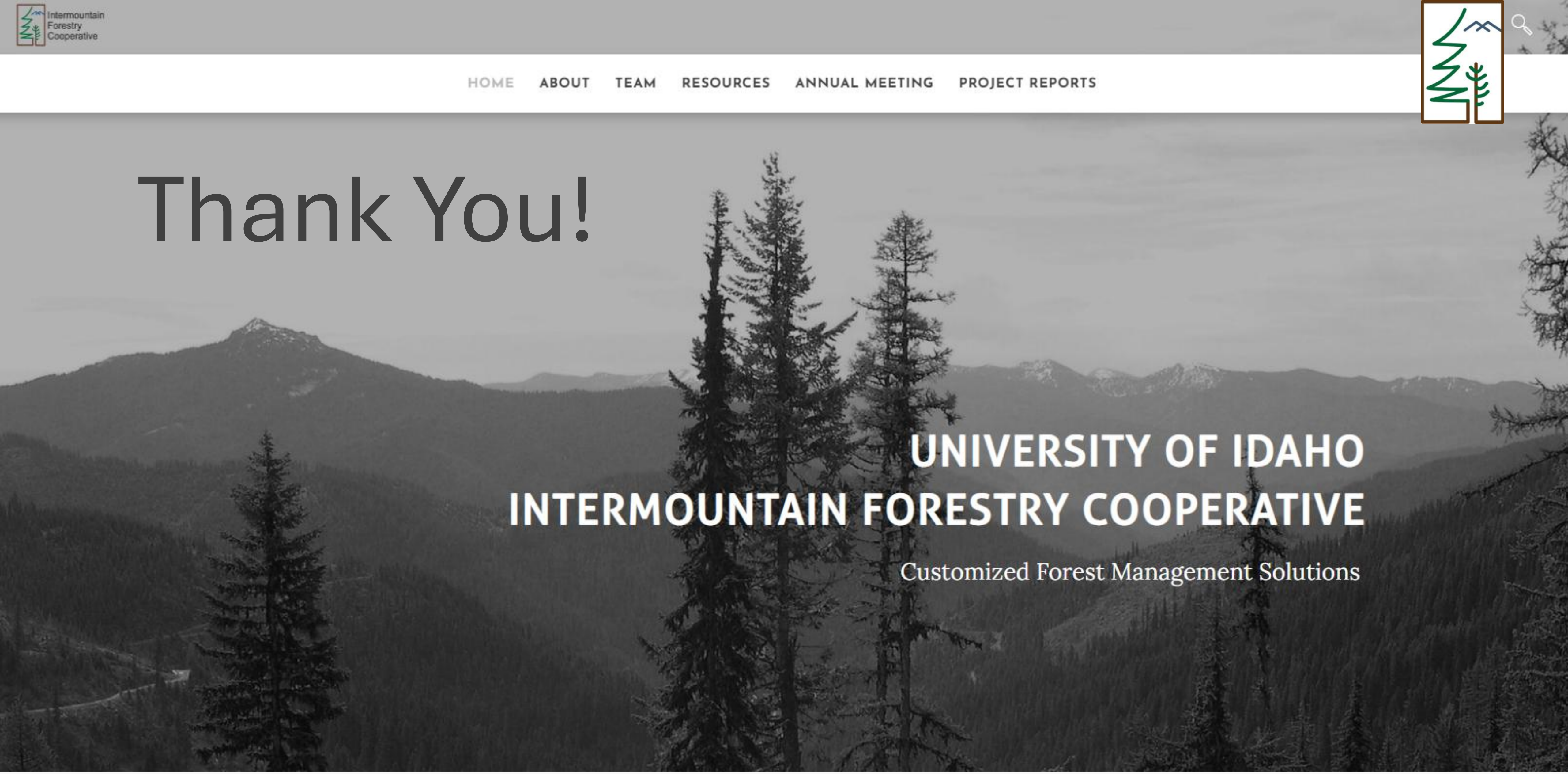
- SDImax predictions customized to your ownership, and stand inventory – leveraging the power of machine learning

- Climate projections for both the broader Pacific Northwest indicate a range of 5-20% reduction in carrying capacity on average (RCP 4.5 models) – summary report to be provided

- Customized SDI exponent solution incoming for computing Relative Density as a function of SDImax models



Thank You!



SPECIALIZING IN APPLIED SILVICULTURE RESEARCH

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