Habitat Suitability Modeling with HEMI 2

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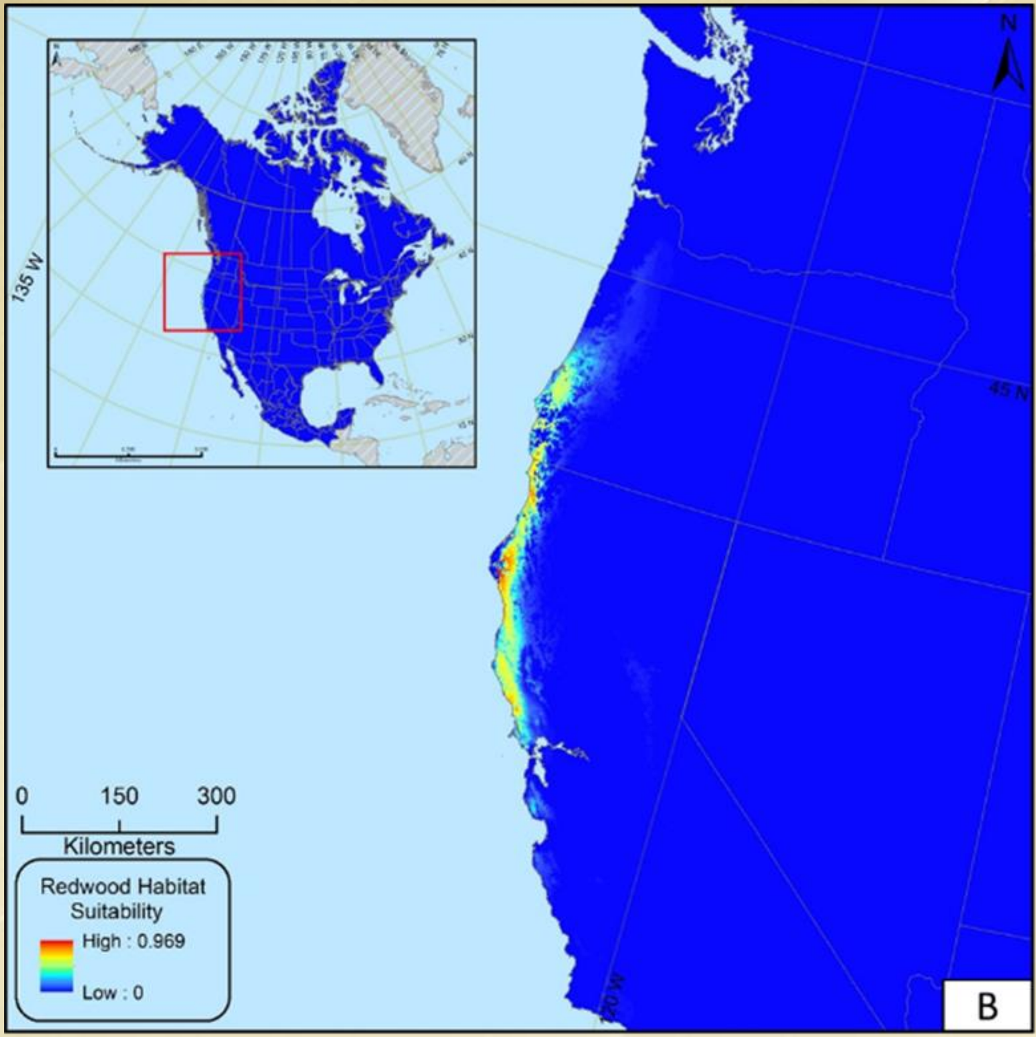
SCGIS

June 24th, 2016

Photo by Chris Muhl

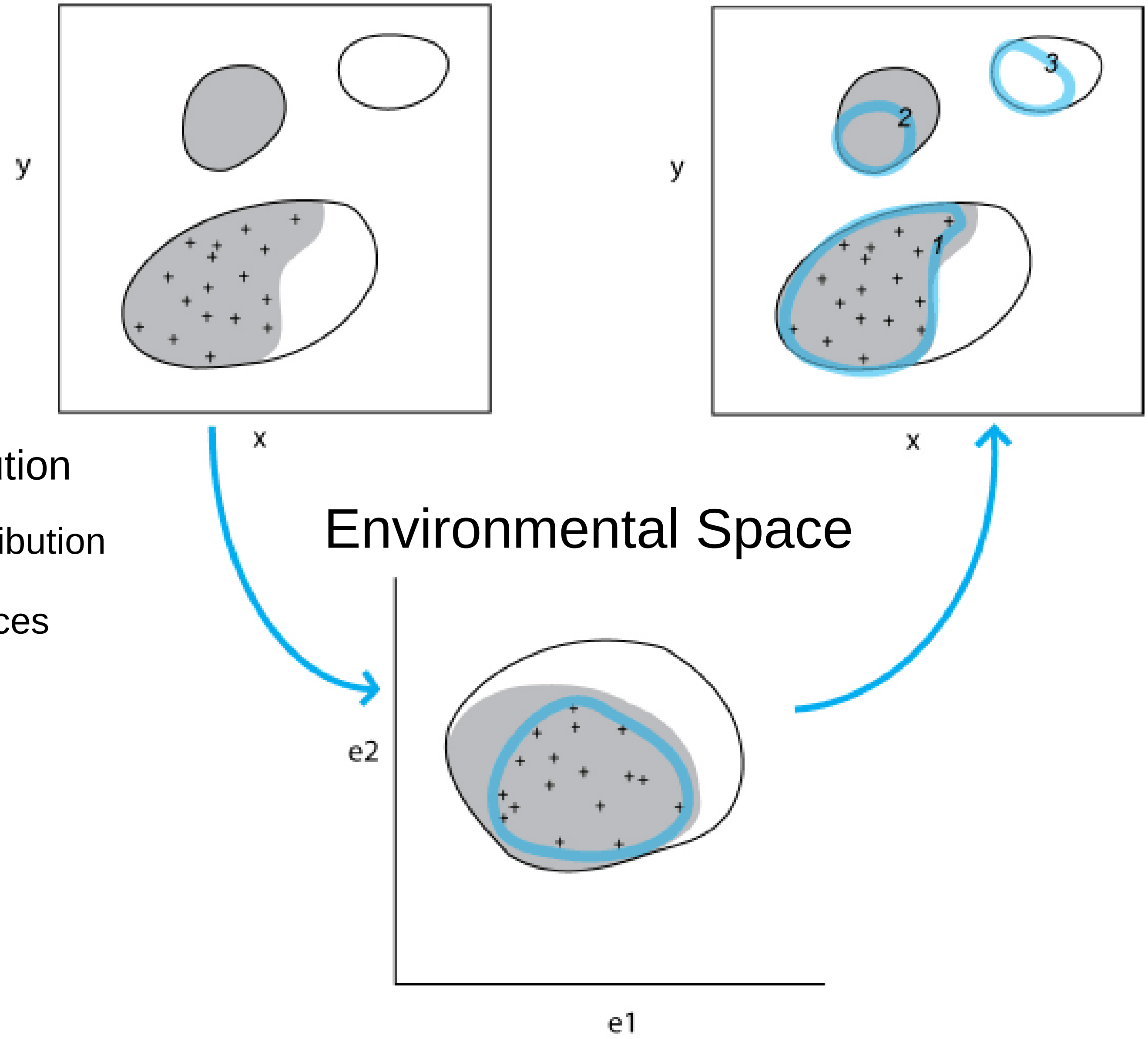
Habitat Suitability Modeling

- Predicts where a species could live, with some uncertainty
- Also known as,
  - Species Distribution Modeling
  - Ecological Niche Modeling


N
135 W
45 N
120 W
0
150
300
Kilometers
Redwood Habitat Suitability
High : 0.969
Low : 0
B

Kimble, 2016

Geographical Space



+ Observed Occurrences

● Realized Niche/Distribution

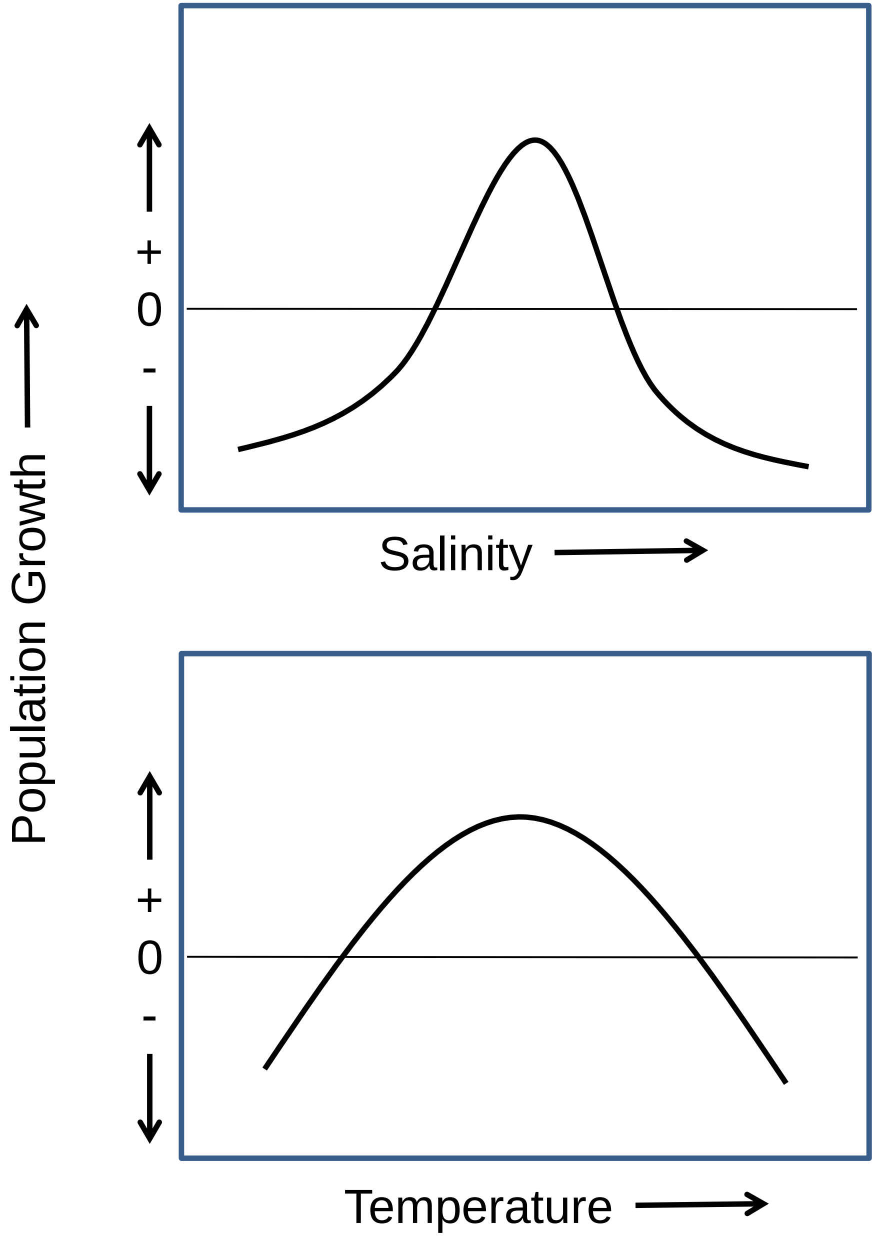
○ Fundamental Niche/Distribution

○ Model Fitted to Occurrences

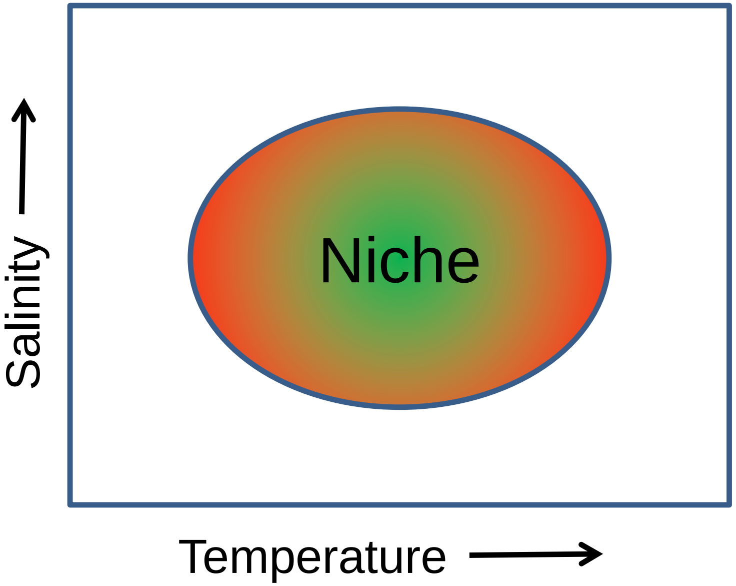
Environmental Space

Adapted from Richard Pearson, Center for Biodiversity and Conservation at the American Museum of Natural History

From the Theory of Biogeography

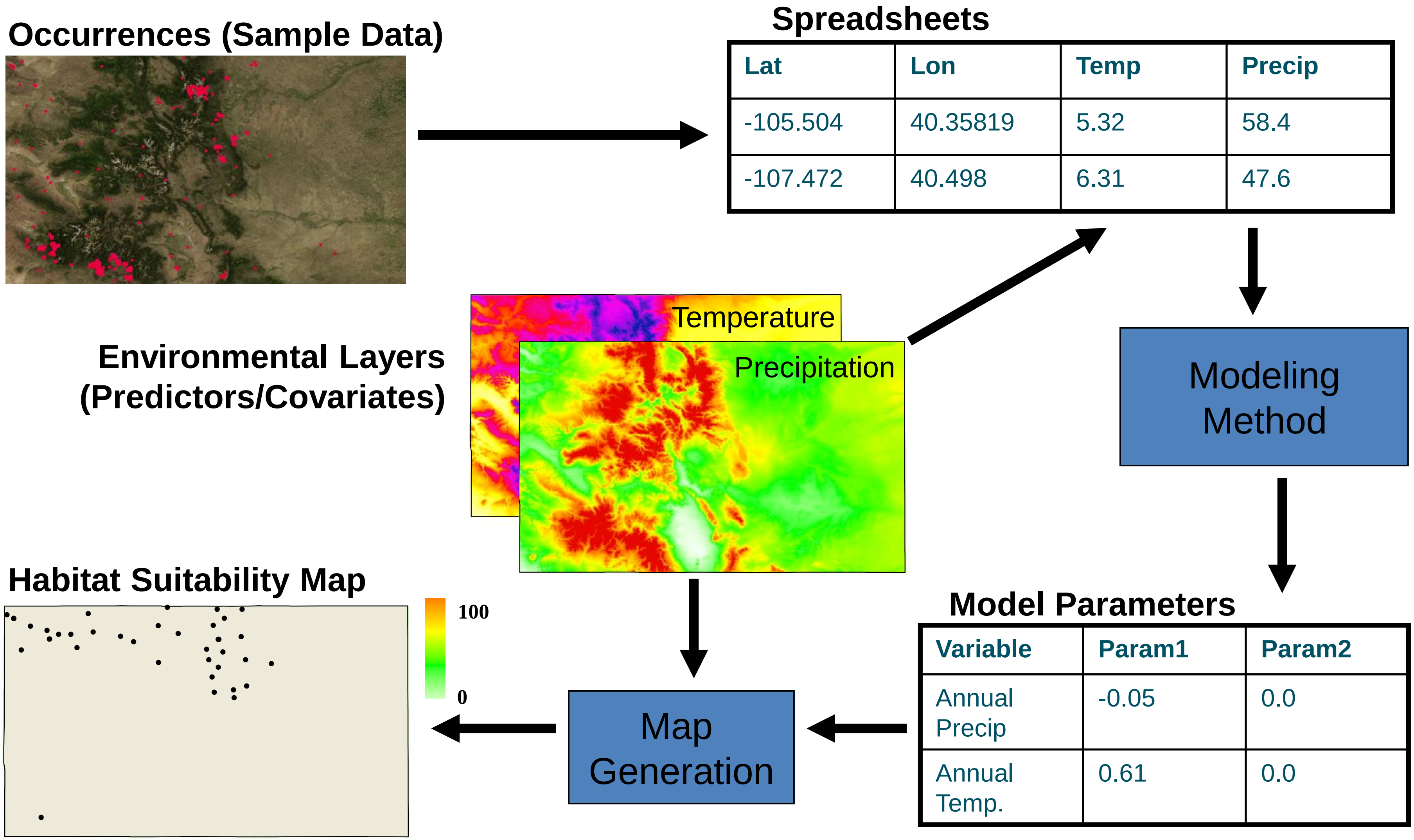


Environmental Space


Niche
Salinity
Temperature

Adapted from Brown, J.H., Lomolino, M.V. 1998, Biogeography: Second Edition. Sinauer Associates, Sinauer Massachusetts

HSM Process



Occurrences (Sample Data)

Spreadsheets

Lat	Lon	Temp	Precip
-105.504	40.35819	5.32	58.4
-107.472	40.498	6.31	47.6

Environmental Layers (Predictors/Covariates)

Modeling Method

Model Parameters

Variable	Param1	Param2
Annual Precip	-0.05	0.0
Annual Temp.	0.61	0.0

Map Generation

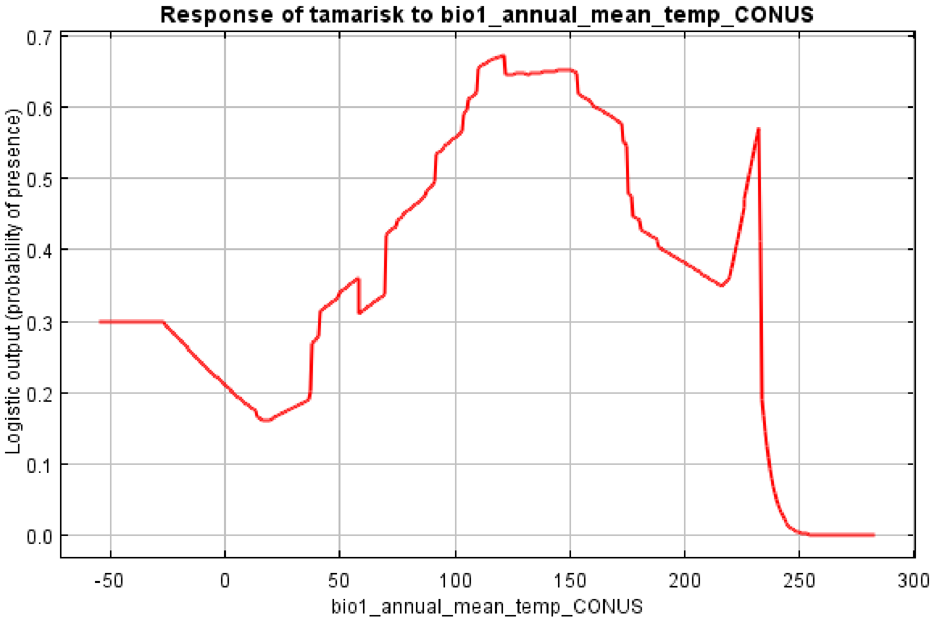
Habitat Suitability Map

Model of Purple Loosestrife in Colorado, Dr. Catherine Jarnevich

Spatial Modeling Concerns

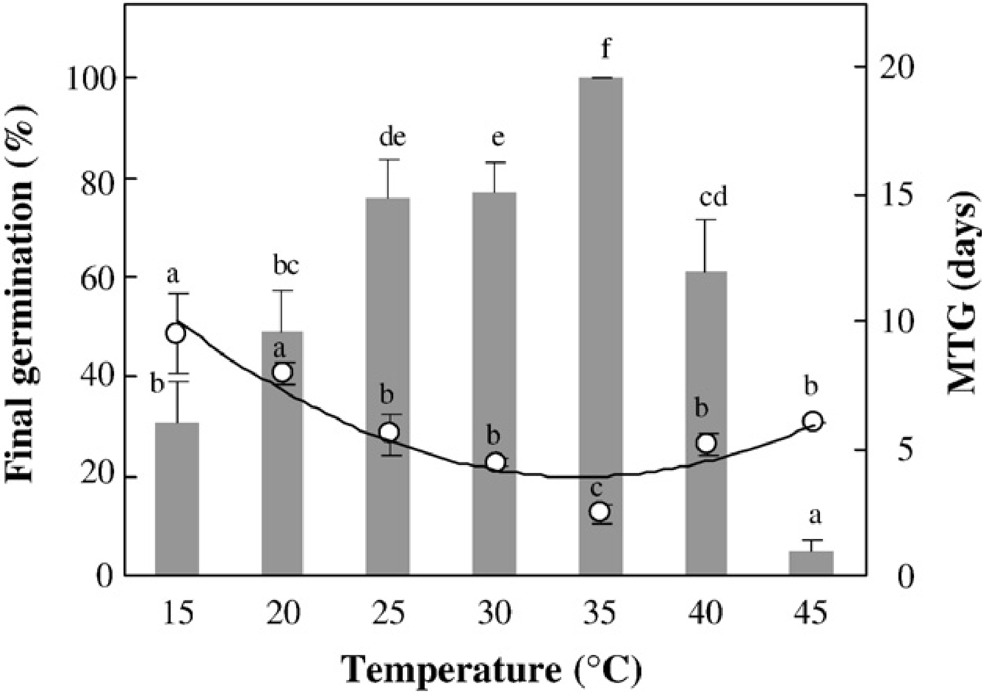
- Our data is a combination of:
  - True species habitat constraints
  - Natural history of the species (dispersal & survival)
  - Sampling method
  - Other sources of uncertainty (measurement error)
- What should the models look like?

Over-fitting The Data?



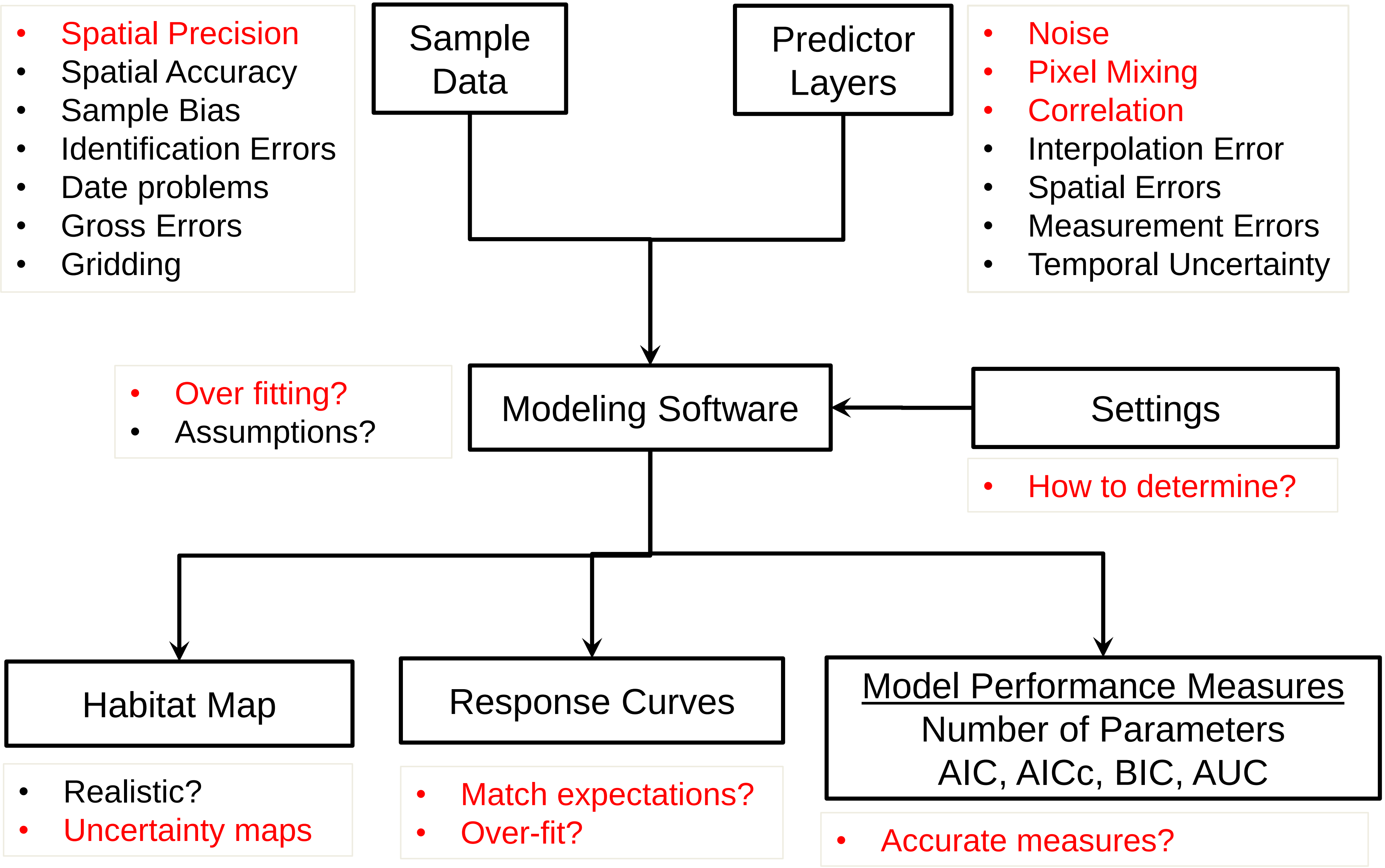
Maxent model for *Tamarix* in the continental US: response to temperature when modeled with temperature and precipitation

What should the model look like?



Maraghni, M., M. Gorai, and M. Neffati. 2010. Seed germination at different temperatures and water stress levels, and seedling emergence from different depths of Ziziphus lotus. South African Journal of Botany 76:453-459.

Road Map of Uncertainty



- Spatial Precision
- Spatial Accuracy
- Sample Bias
- Identification Errors
- Date problems
- Gross Errors
- Gridding

Sample Data

Predictor Layers

- Noise
- Pixel Mixing
- Correlation
- Interpolation Error
- Spatial Errors
- Measurement Errors
- Temporal Uncertainty

- Over fitting?
- Assumptions?

Modeling Software

Settings

- How to determine?

Habitat Map

- Realistic?
- Uncertainty maps

Response Curves

- Match expectations?
- Over-fit?

Model Performance Measures

Number of Parameters

AIC, AICc, BIC, AUC

- Accurate measures?

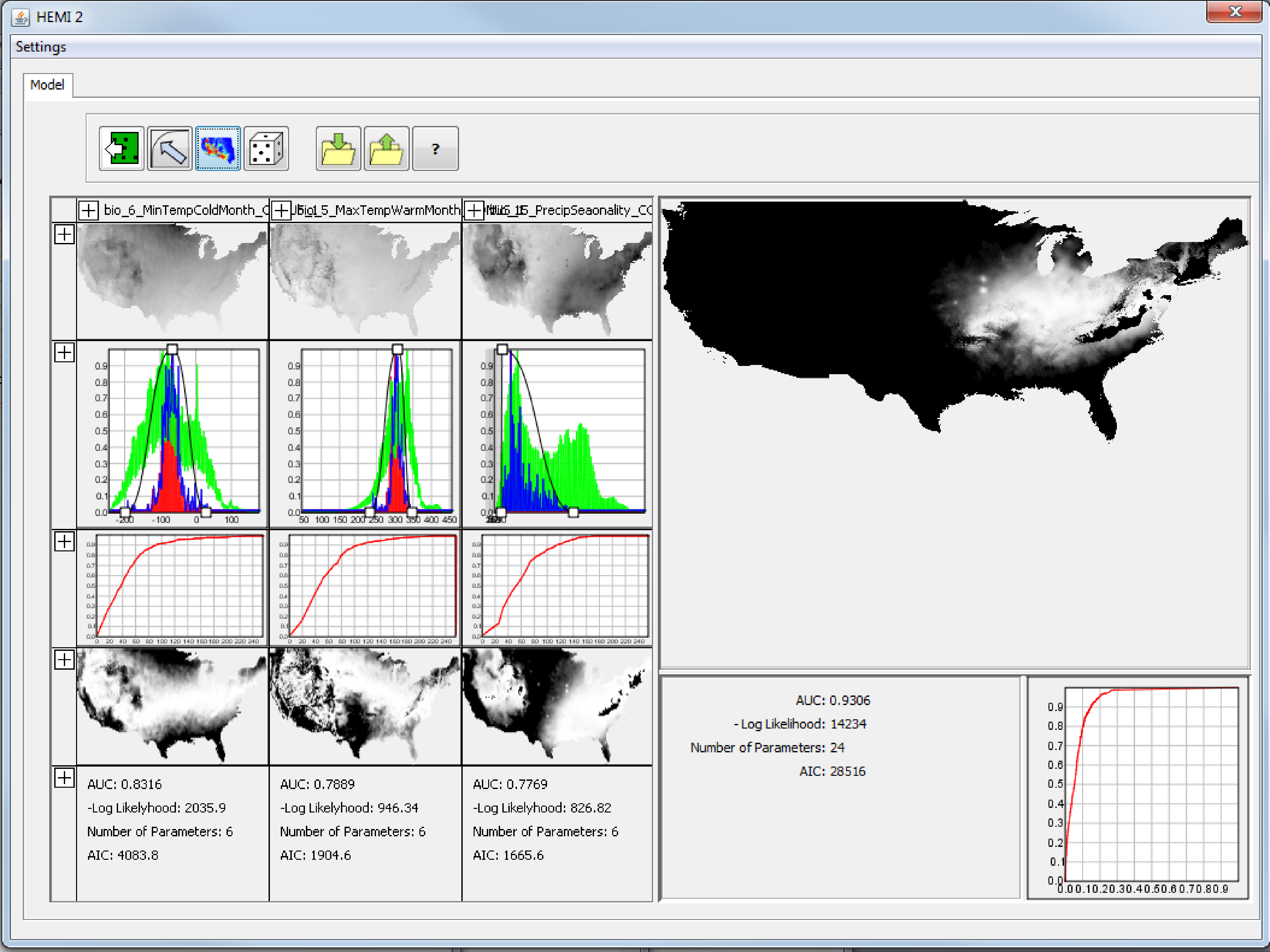
What is the best model?

Our data is the sum of “signals”

- Occurrences are the sum of three signals:
  - Habitat
  - Species dispersal
  - Sampling method
  - Habitat is the lowest “frequency” so we need to “smooth” our models (low-pass filter)
- Environmental Layers (covariate rasters)
  - Cannot represent the complexity on the earth
  - They will hide small, unique, habitats

HEMI 2

- Follow-on to HEMI 1
- Models each environmental variable with smooth Bezier curves
- Multiplies models together to create final HSM
- Includes Monte Carlo methods for: noise injection, cross-validation, sensitivity testing
- Implemented in BlueSpray from SchoonerTurtles.com


HEMI 2
Settings
Model
?
bio_6_MinTempColdMonth_C
bio_5_MaxTempWarmMonth
bio_15_PrecipSeasonality_CC
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
-200
-100
0
100
50 100 150 200 250 300 350 400 450
0 20 40 60 80 100 120 140 160 180 200 220 240
0.0 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9

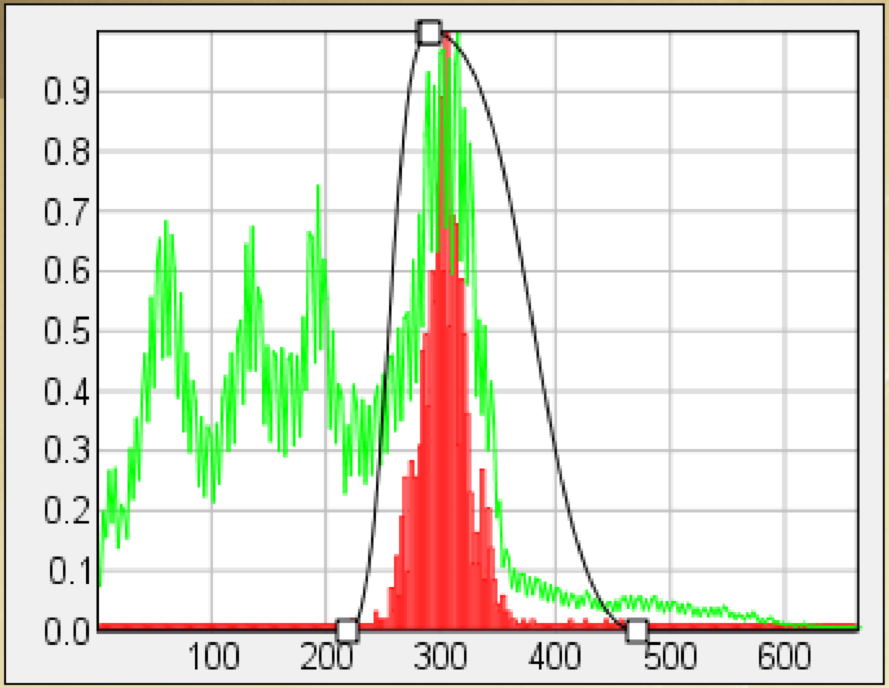
AUC: 0.8316
-Log Likelihood: 2035.9
Number of Parameters: 6
AIC: 4083.8

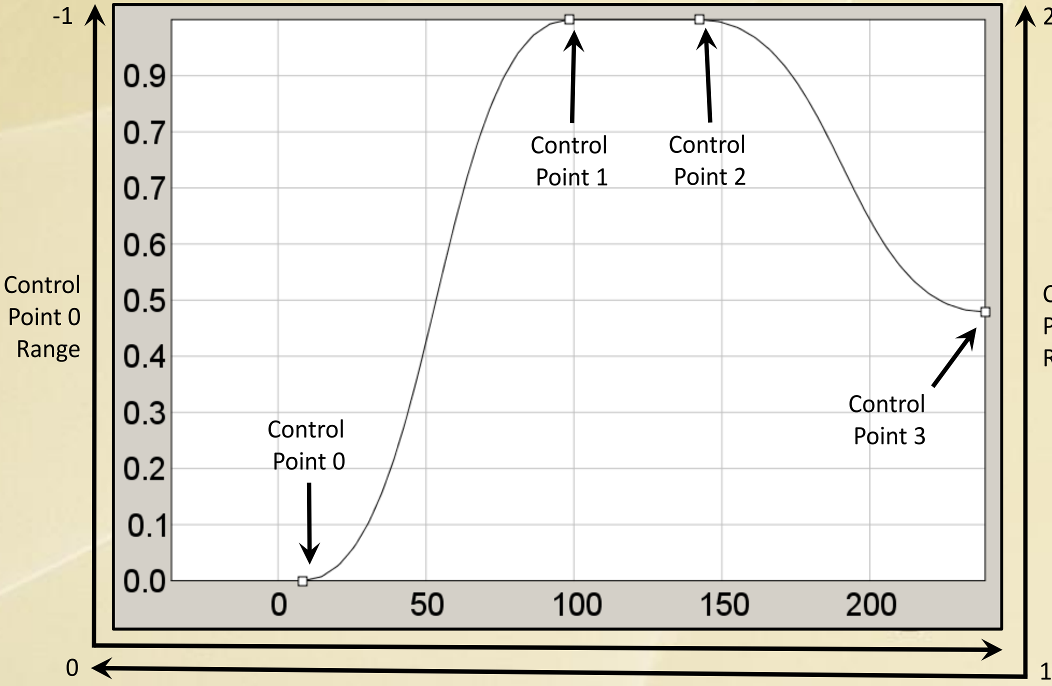
AUC: 0.7889
-Log Likelihood: 946.34
Number of Parameters: 6
AIC: 1904.6

AUC: 0.7769
-Log Likelihood: 826.82
Number of Parameters: 6
AIC: 1665.6

AUC: 0.9306
- Log Likelihood: 14234
Number of Parameters: 24
AIC: 28516

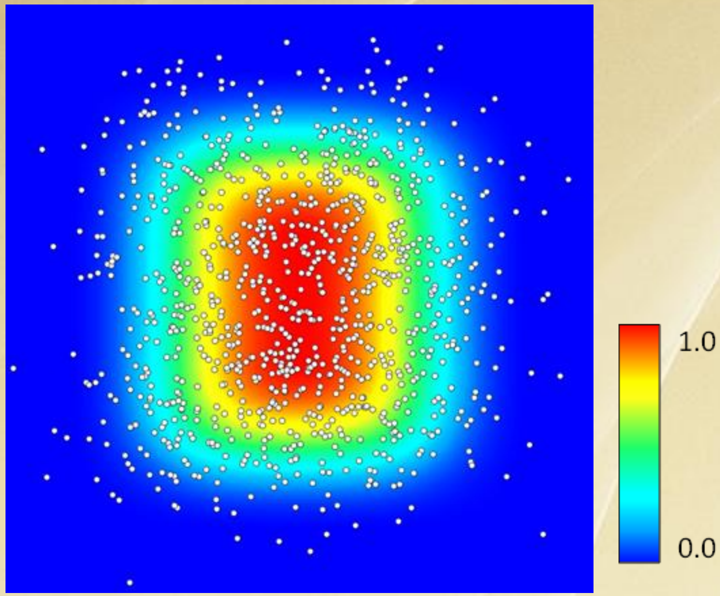
- Sample response curve for precipitation of wettest quarter for Ohio Buckeye
- Control points can be automatically place and manually edited
- AIC and AUC values provided in real time

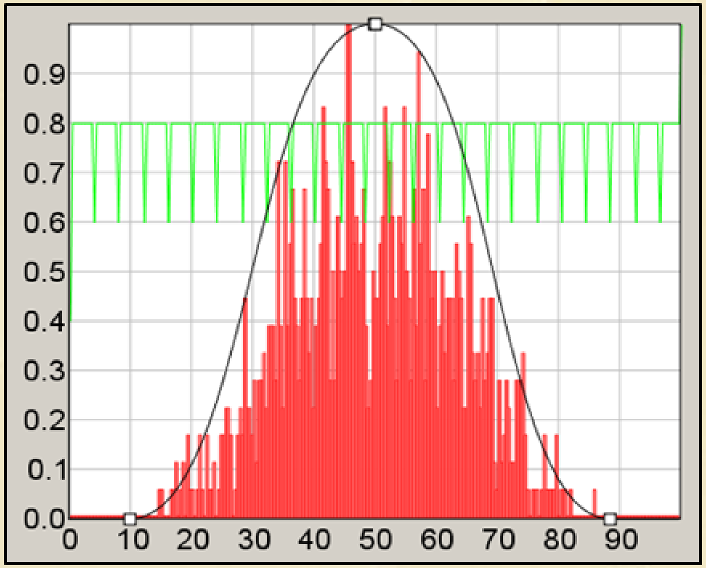




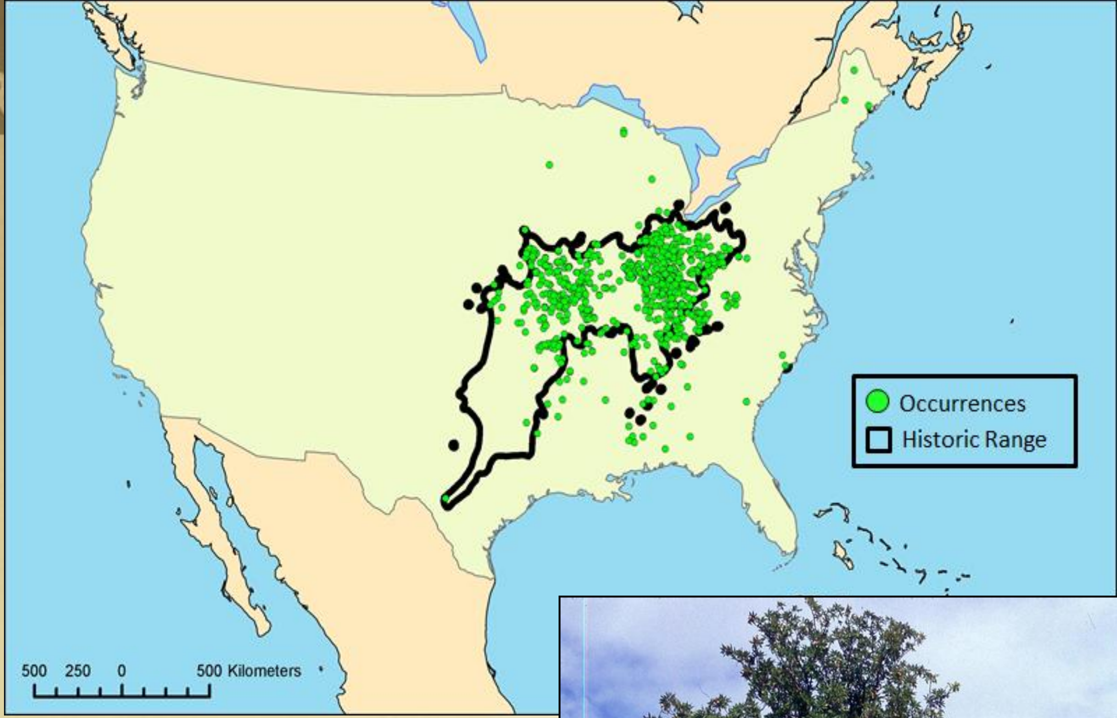
Evaluating HEMI 2

- Occurrences:
  - Synthetic Data
  - Forest Inventory Analysis (FIA) database
- Environmental Variables: BioClim/WorldClim

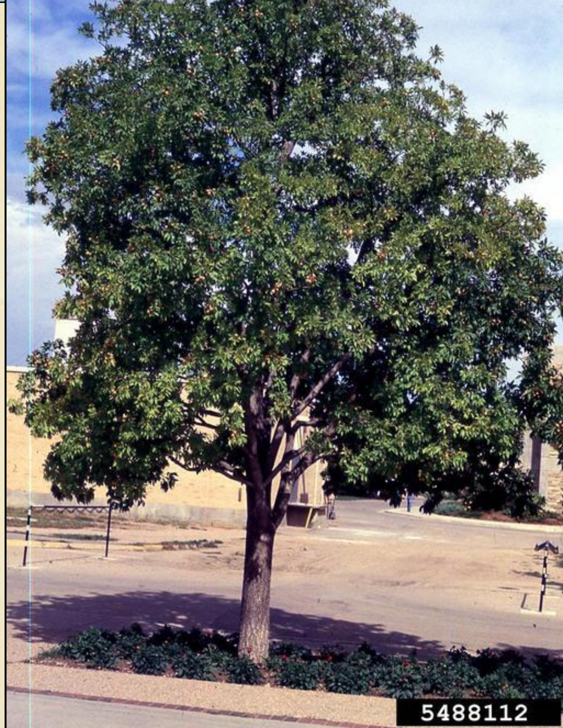




Ohio Buckeye


🟢 Occurrences
☐ Historic Range
500 250 0 500 Kilometers

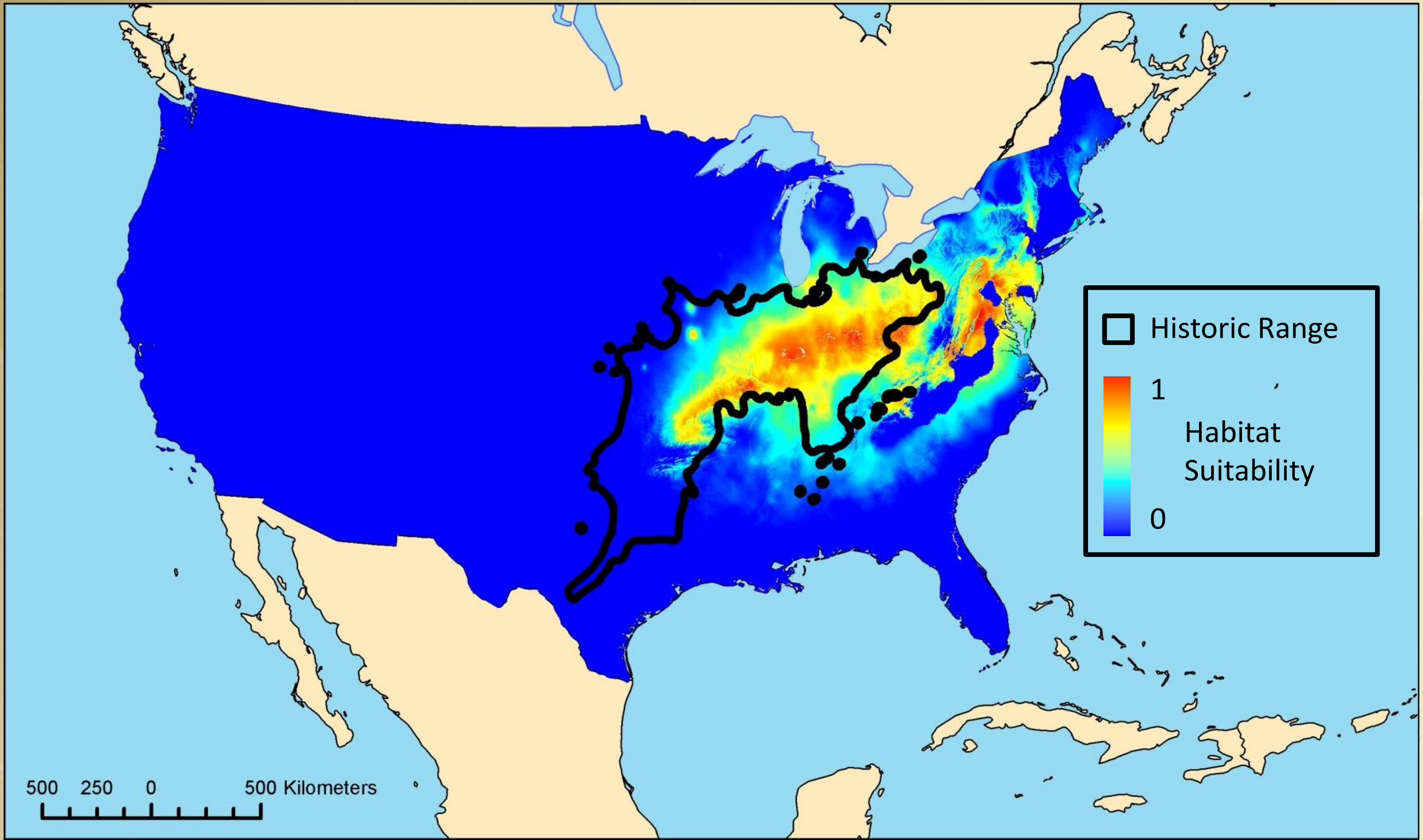
- Precipitation:
  - 30 to 60 inches
- Temperature :
  - Cold required
  - Min of 145 frost free days
  - Min temp. of -33 degrees F
- Soil:
  - pH ranged from 5.0 to 7.1
  - fine to medium textured soils



http://plants.usda.gov/charinfo.html

Invasives.org

Environmental variables	Mean AIC	Mean AUC
BIO5_MaxTemp, BOI6_MinTemp, BIO15_PrecipSeason, BIO18_PrecipWetQuarter	**28516**	0.930
BIO5_MaxTemp, BOI6_MinTemp, BIO17_PrecipDryQuarter, BIO18_PrecipWetQuarter	28637	0.927
BIO5_MaxTemp, BOI6_MinTemp, BIO15_PrecipSeason	28687	0.924
BIO5_MaxTemp, BOI6_MinTemp, BIO18_PrecipWetQuarter	28701	**0.933**

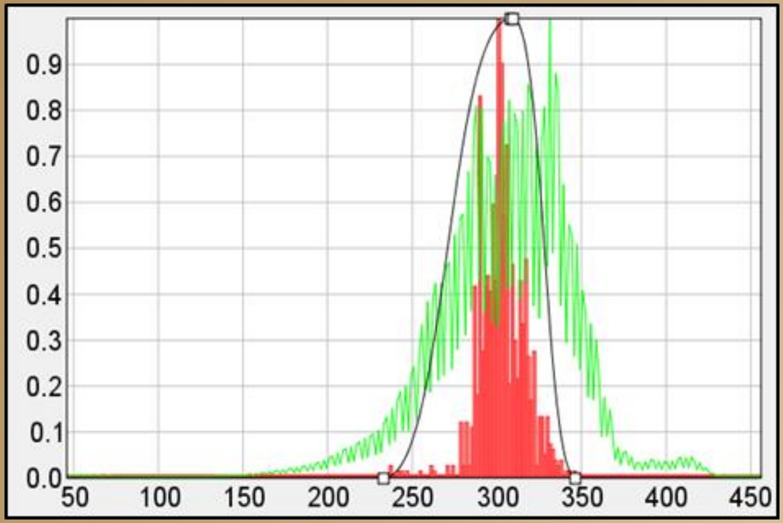

Historic Range
1
Habitat Suitability
0
500 250 0 500 Kilometers

Response Curves

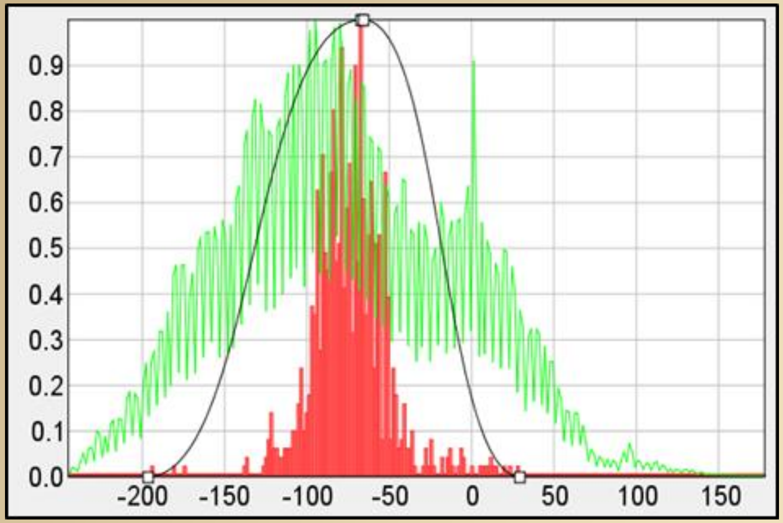
🟩 All Values

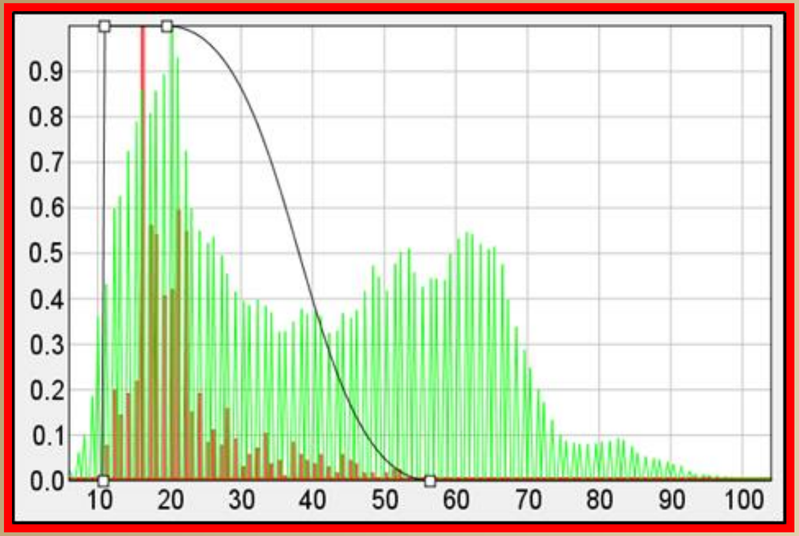
🟥 Occurrences

BIO5_MaxTemp

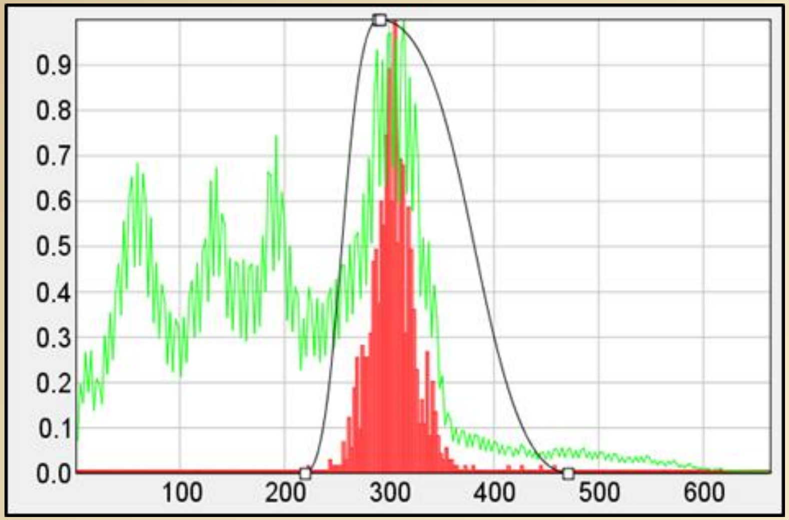


BOI6_MinTemp





BIO15_PrecipSeason

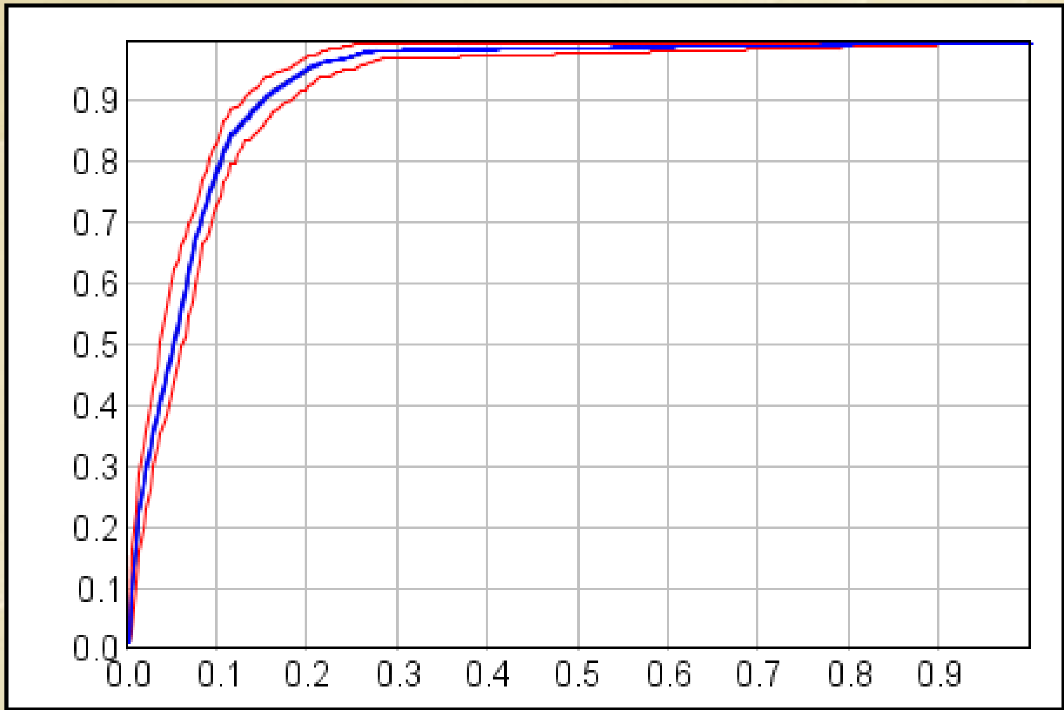


BIO18_PrecipWetQuarter

Cross-Validation

- 70% Training, 30% Test, 100 Times
- AIC: 11773 (not comparable)
  - std dev: 2069
- AUC: 0.93
  - std dev: 0.004

Receiver Operator Curve



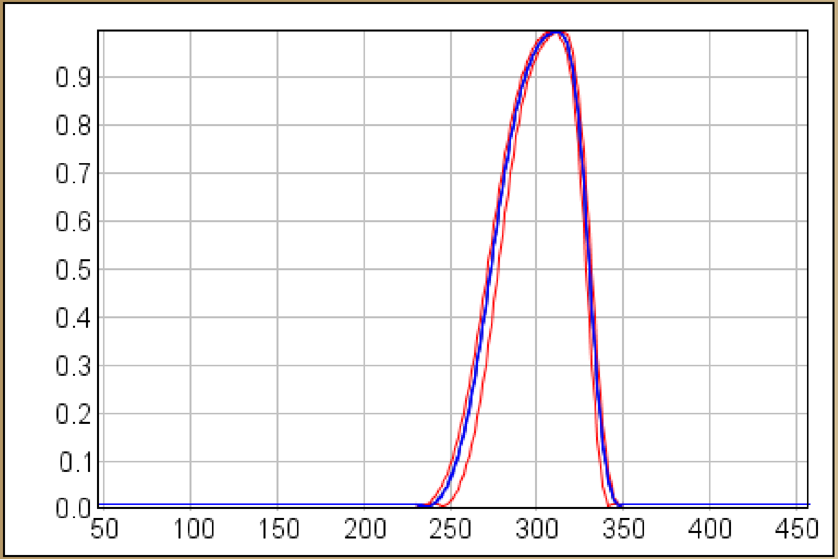
■ Mean

■ 95% Confidence Interval

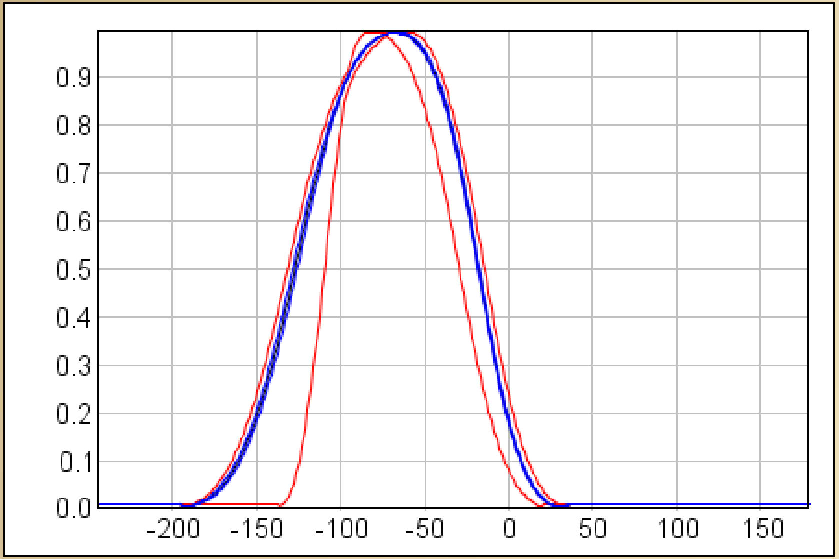
■ Minimum & Maximum

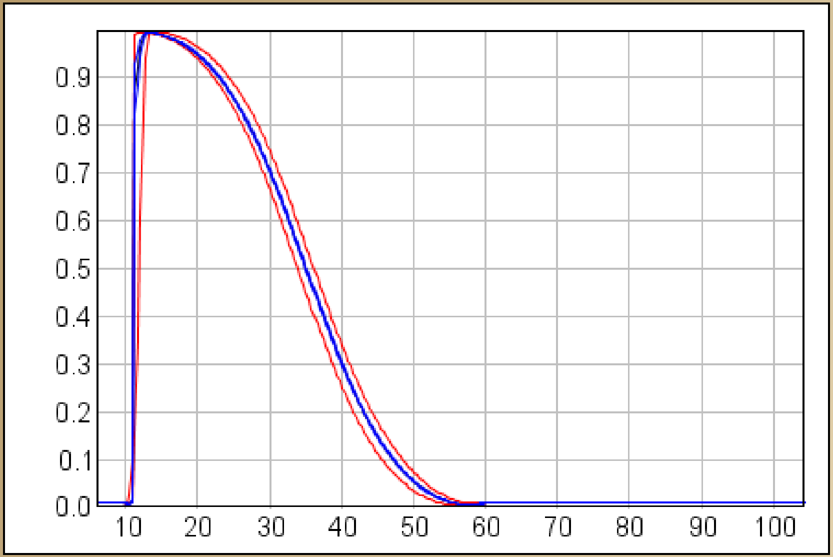
Cross-Validation

BIO5_MaxTemp

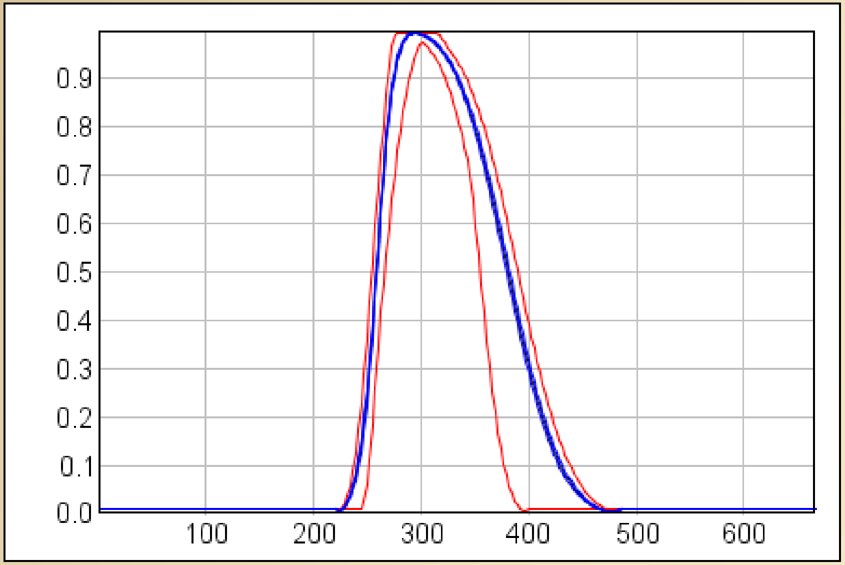


BOI6_MinTemp



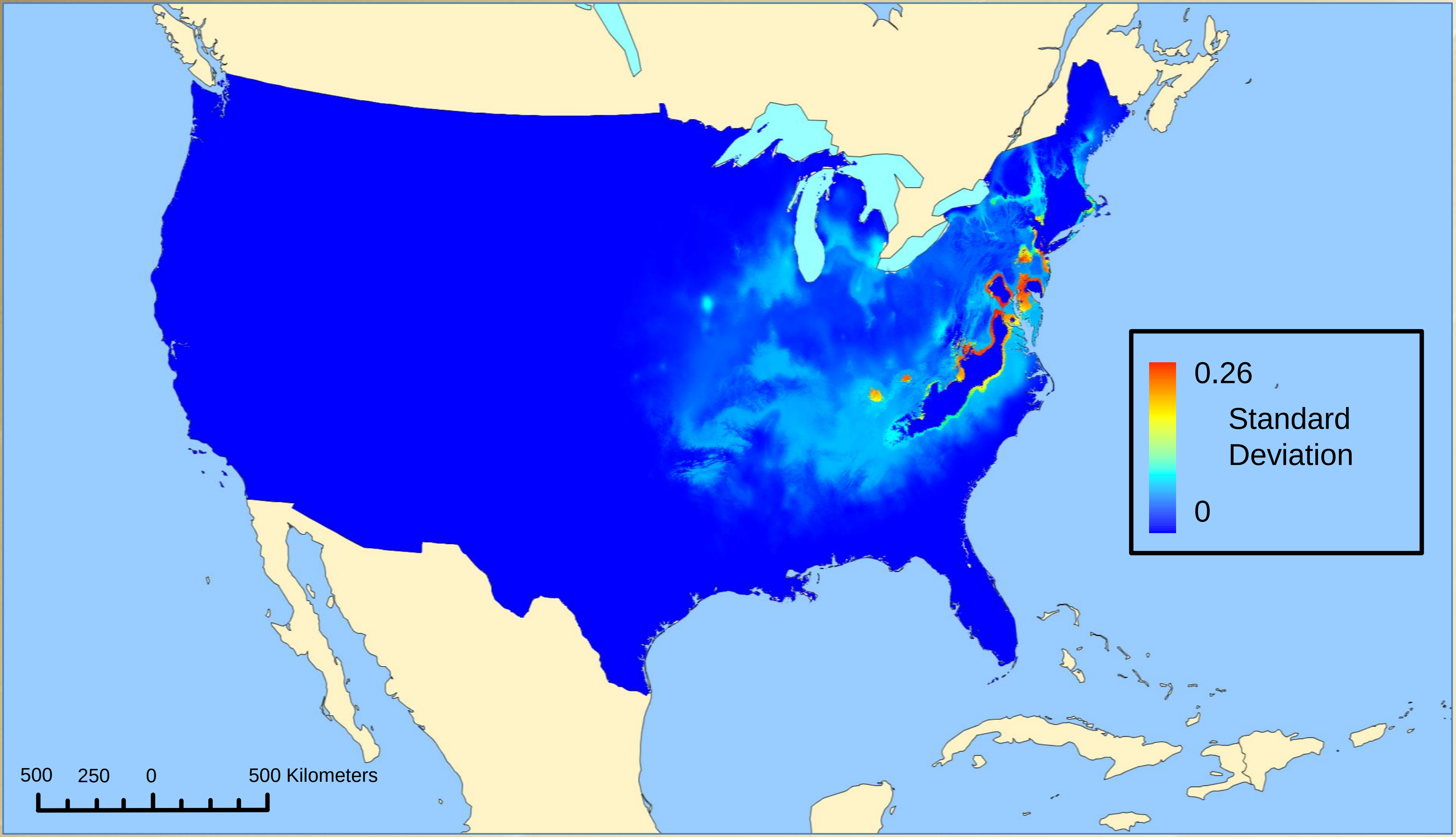


BIO15_PrecipSeason

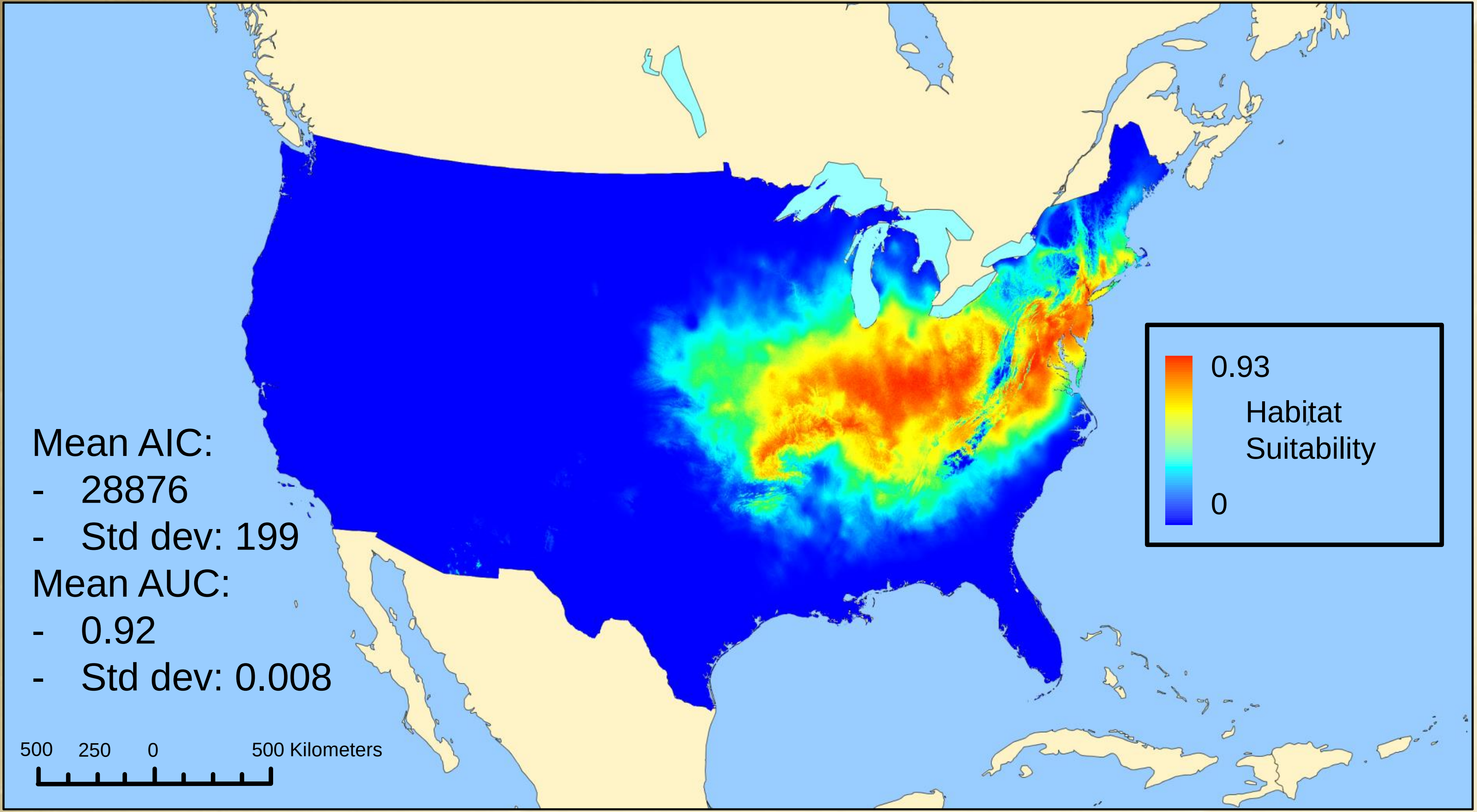


BIO18_PrecipWetQuarter

Cross-Validation: Standard Deviation


0.26
Standard Deviation
0
500 250 0 500 Kilometers

Environmental Noise Injection


0.93
Habitat Suitability
0
500 250 0 500 Kilometers

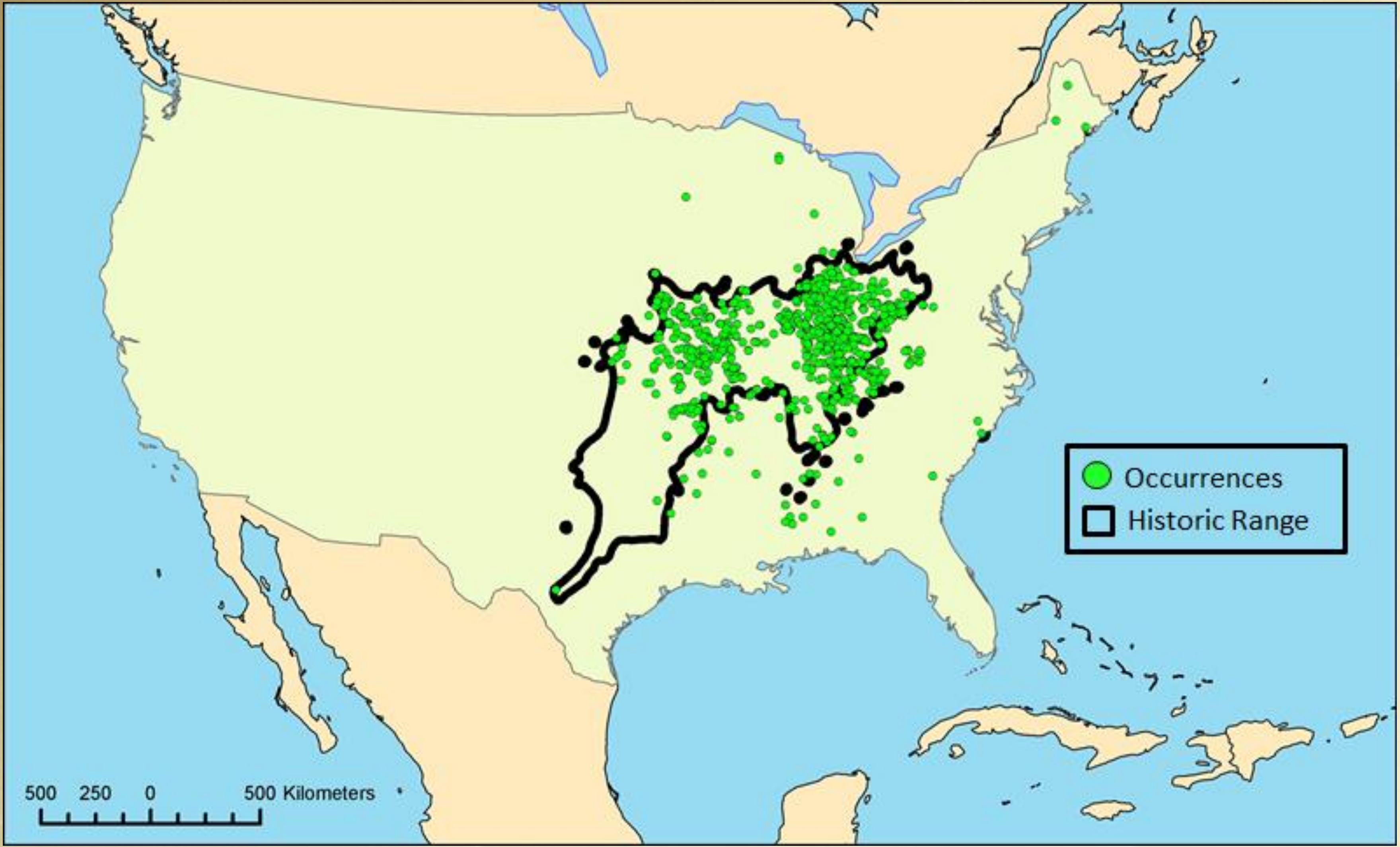
Mean AIC:

- 28876
- Std dev: 199

Mean AUC:

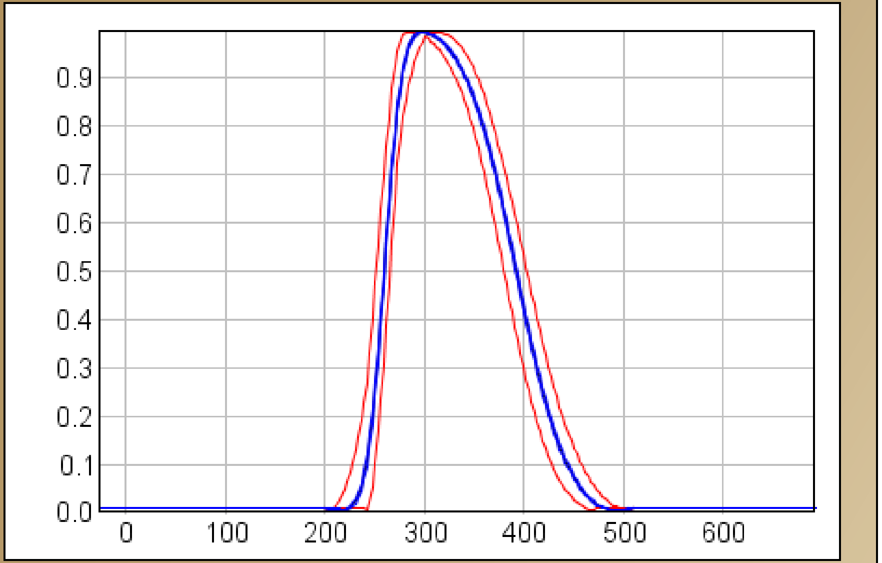
- 0.92
- Std dev: 0.008

Occurrences and Historical Range

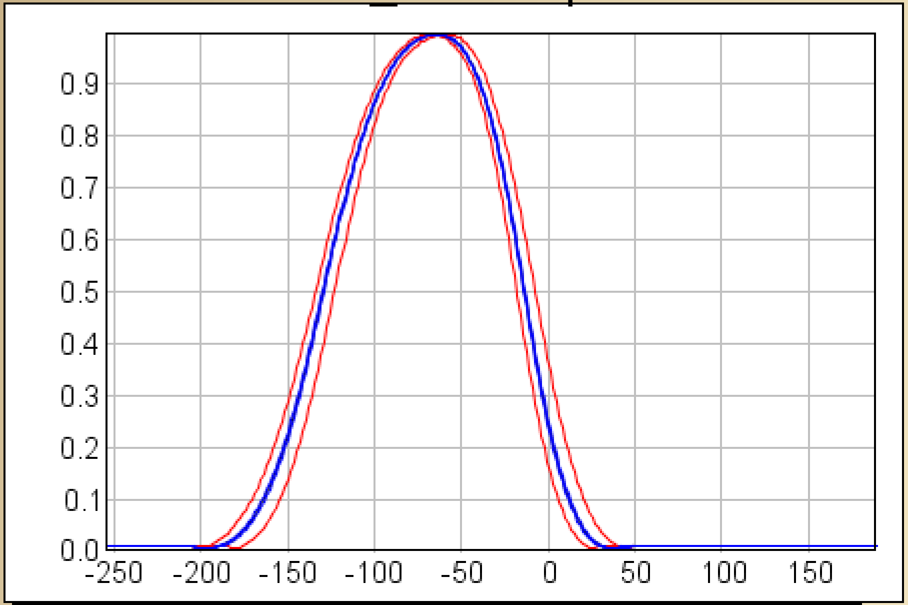

Occurrences
Historic Range
500 250 0 500 Kilometers

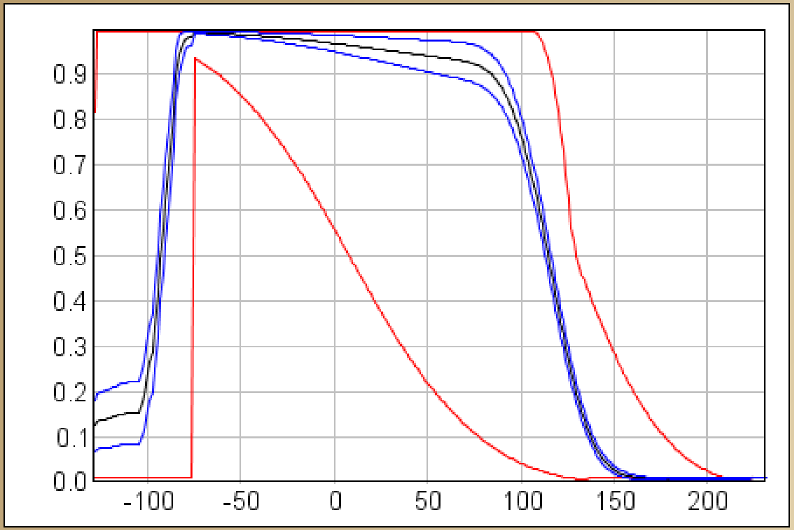
Environmental Noise Injection

BIO5_MaxTemp

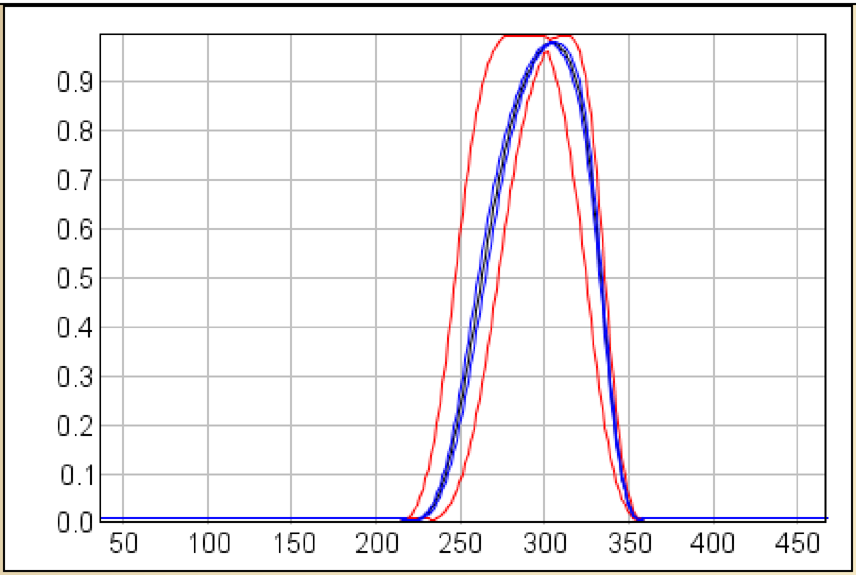


BOI6_MinTemp



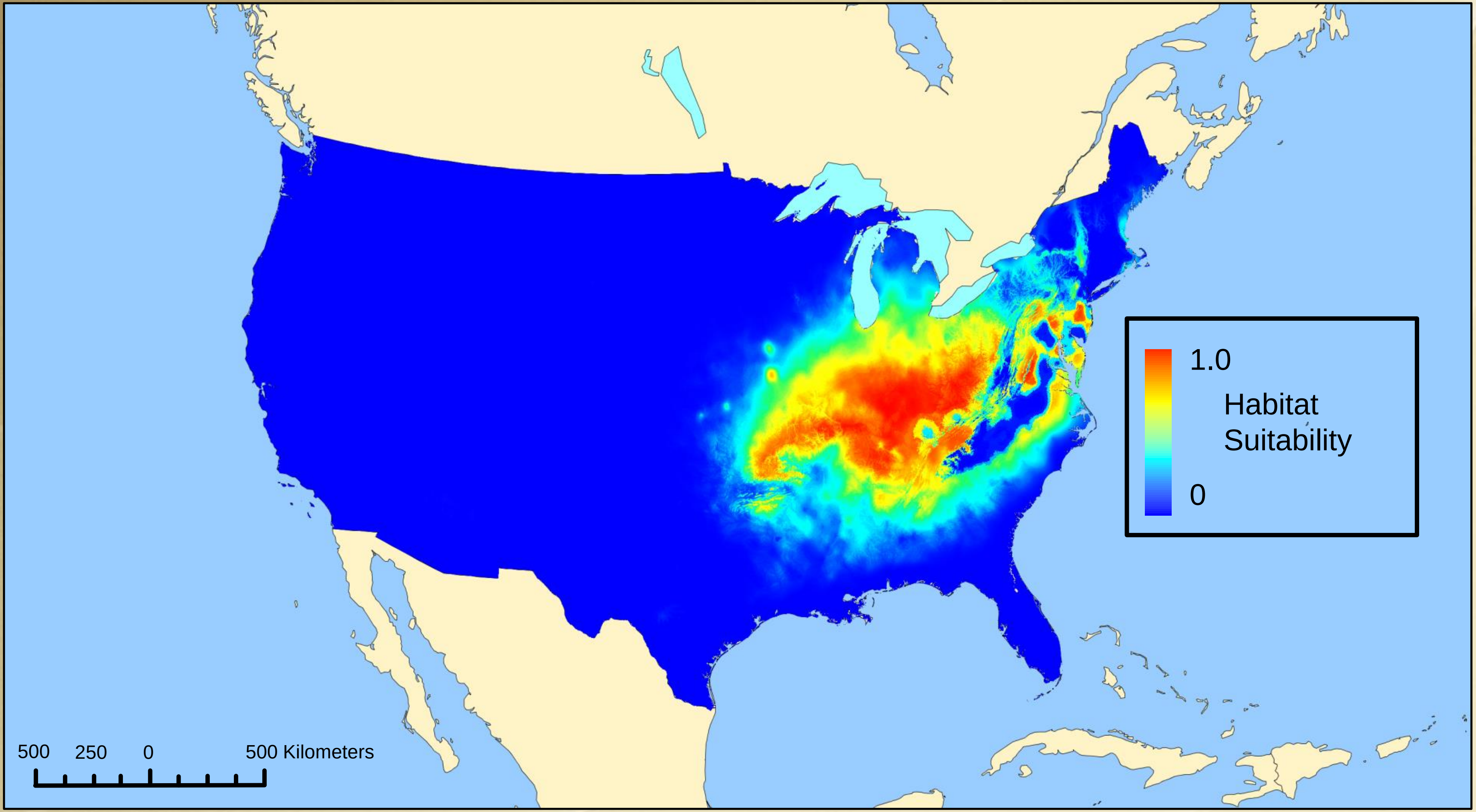


BIO15_PrecipSeason

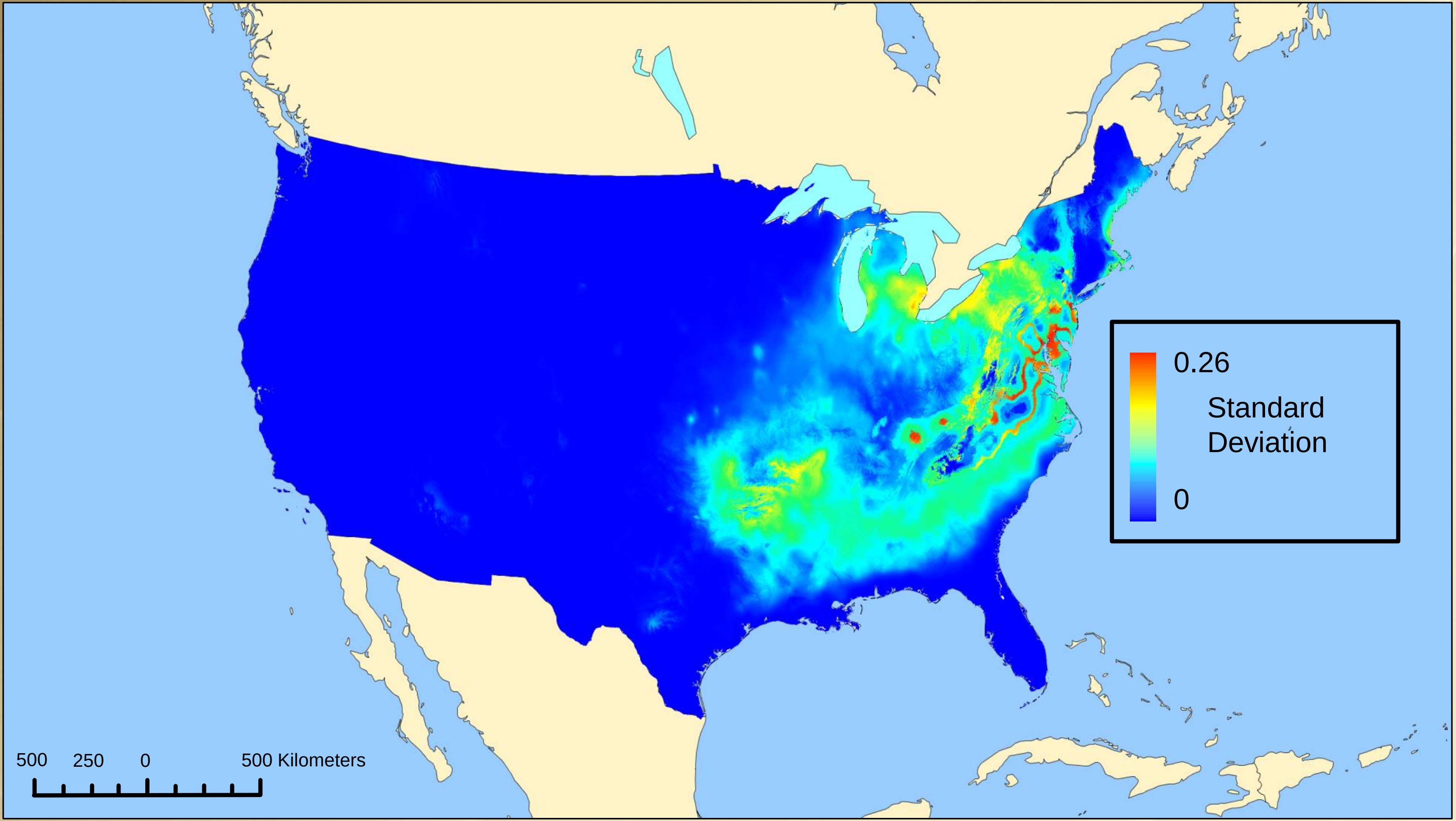


BIO18_PrecipWetQuarter

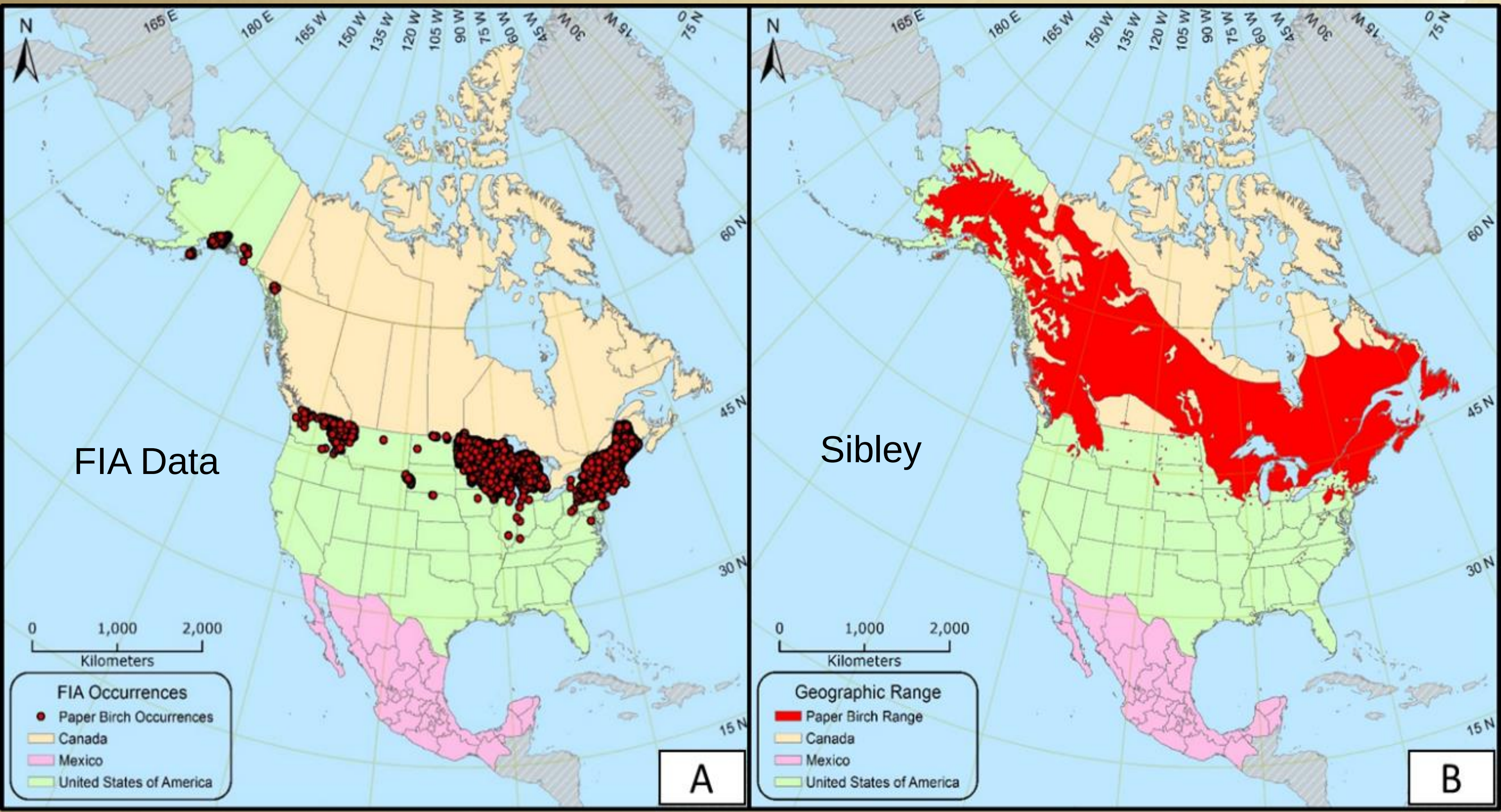
Occurrence Noise Injection

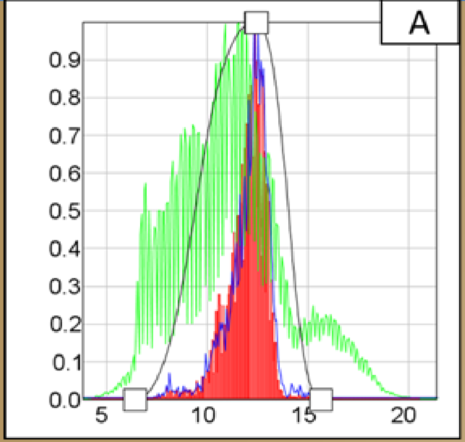

1.0
Habitat Suitability
0
500
250
0
500 Kilometers

Occurrence Noise Injection

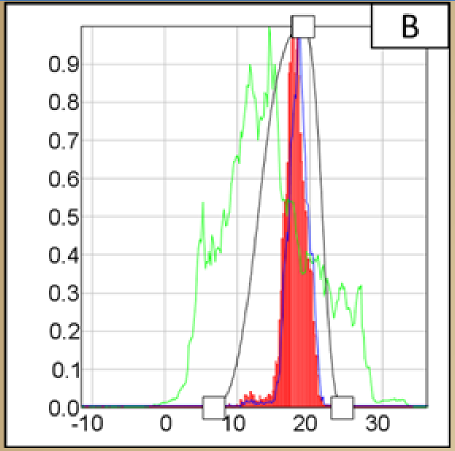

0.26
Standard Deviation
0
500
250
0
500 Kilometers

Paper Birch

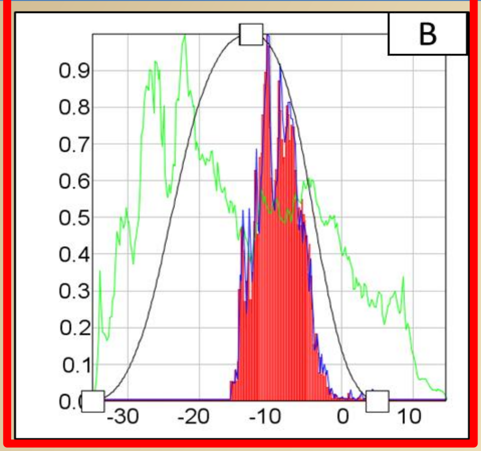

FIA Data
Sibley
N
165 E
180 E
165 W
150 W
135 W
120 W
105 W
90 W
75 W
60 W
45 W
30 W
15 W
0
75 N
60 N
45 N
30 N
15 N
0
1,000
2,000
Kilometers
FIA Occurrences
● Paper Birch Occurrences
Canada
Mexico
United States of America
A
Geographic Range
Paper Birch Range
Canada
Mexico
United States of America
B



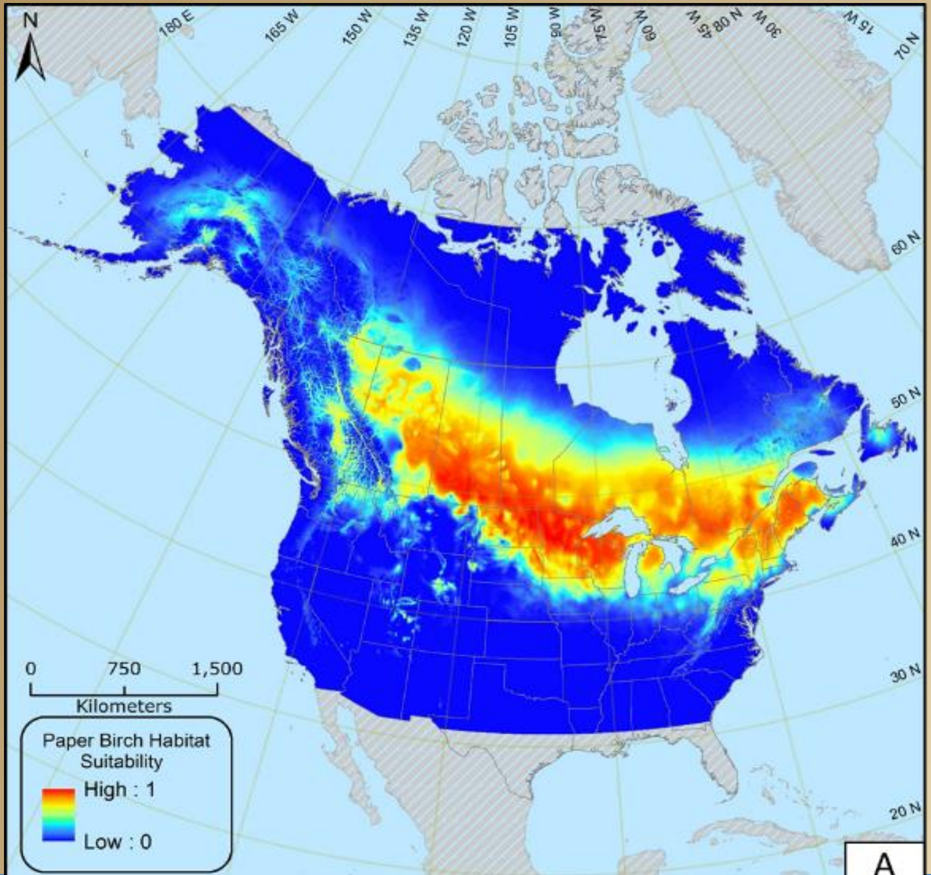
Mean Diurnal Range (C)

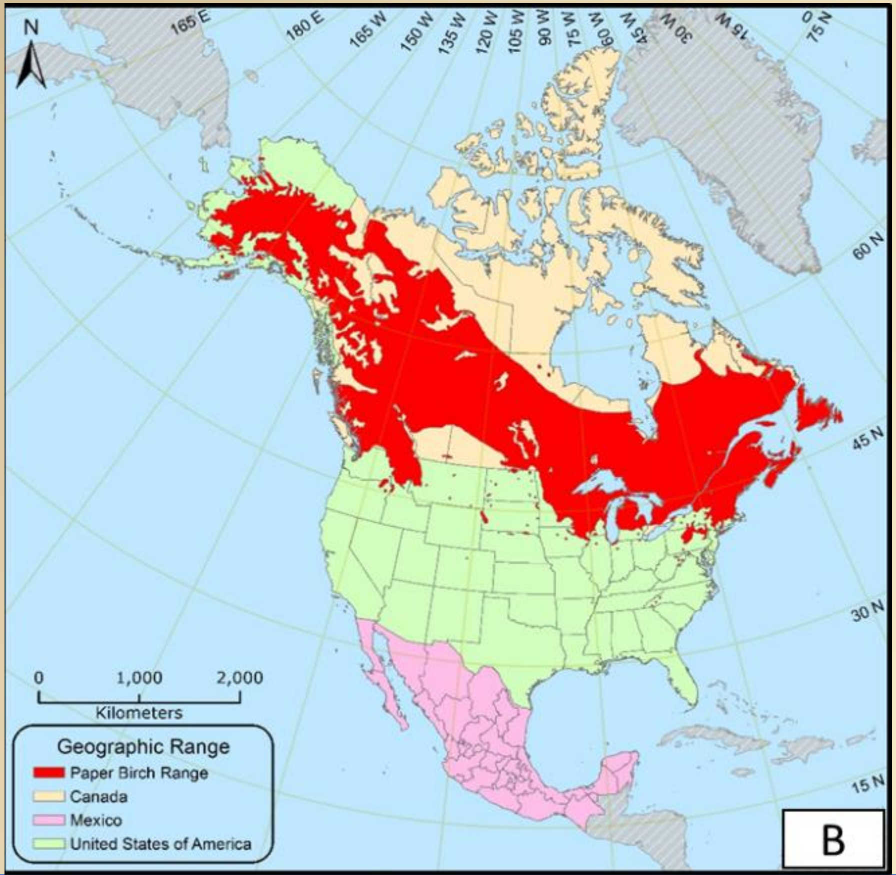


Temp. Warmest Quarter



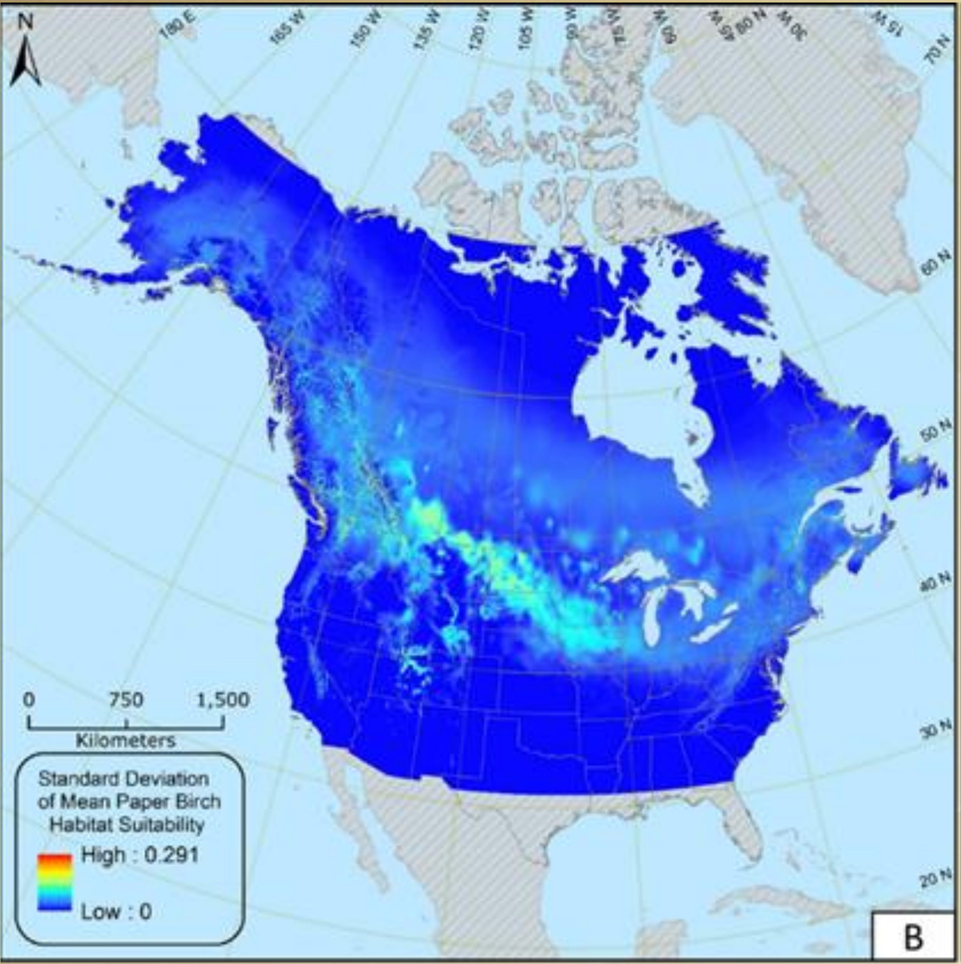
Temp. Coldest Quarter


N
180 E
165 W
150 W
135 W
120 W
105 W
90 W
75 W
60 W
45 W
30 W
15 W
70 N
60 N
50 N
40 N
30 N
20 N
0
750
1,500
Kilometers
Paper Birch Habitat Suitability
High : 1
Low : 0
A

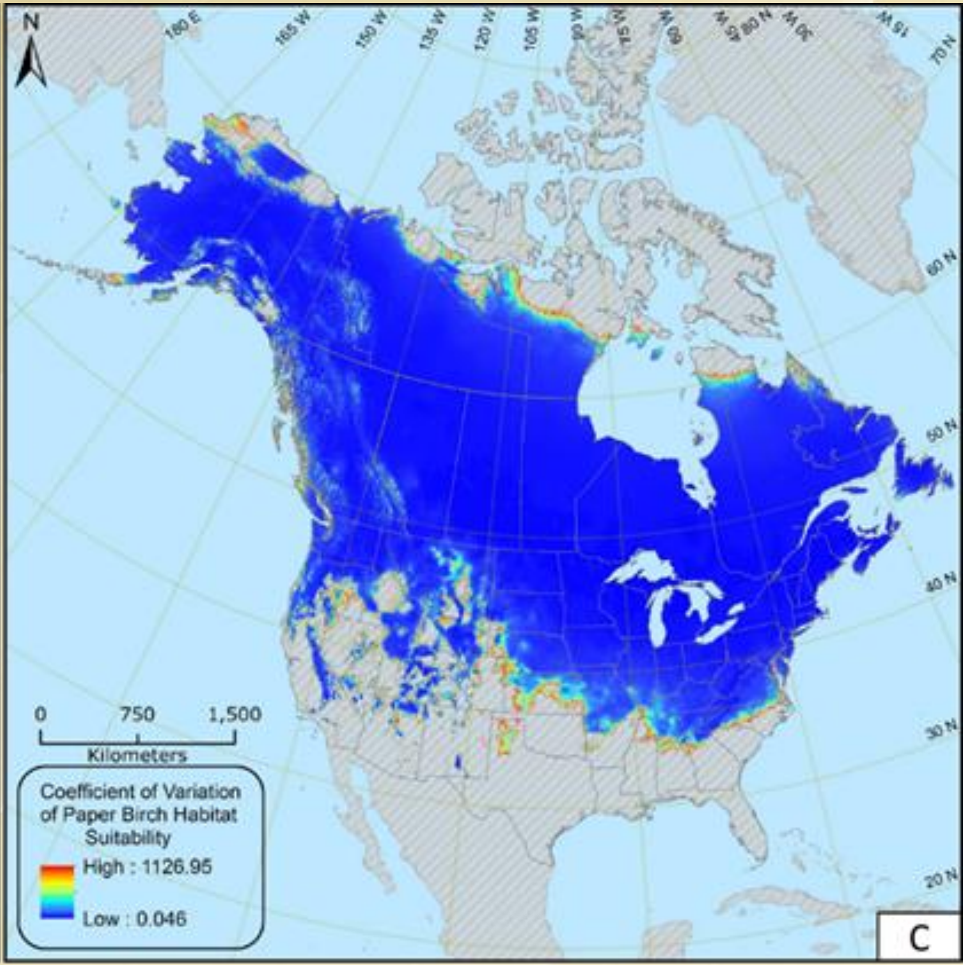

N
165 E
180 E
165 W
150 W
135 W
120 W
105 W
90 W
75 W
60 W
45 W
30 W
15 W
0
75 N
60 N
45 N
30 N
15 N
0
1,000
2,000
Kilometers
Geographic Range
🟥 Paper Birch Range
Canada
Mexico
United States of America
B

Paper Birch – Environmental Layer Noise Injection

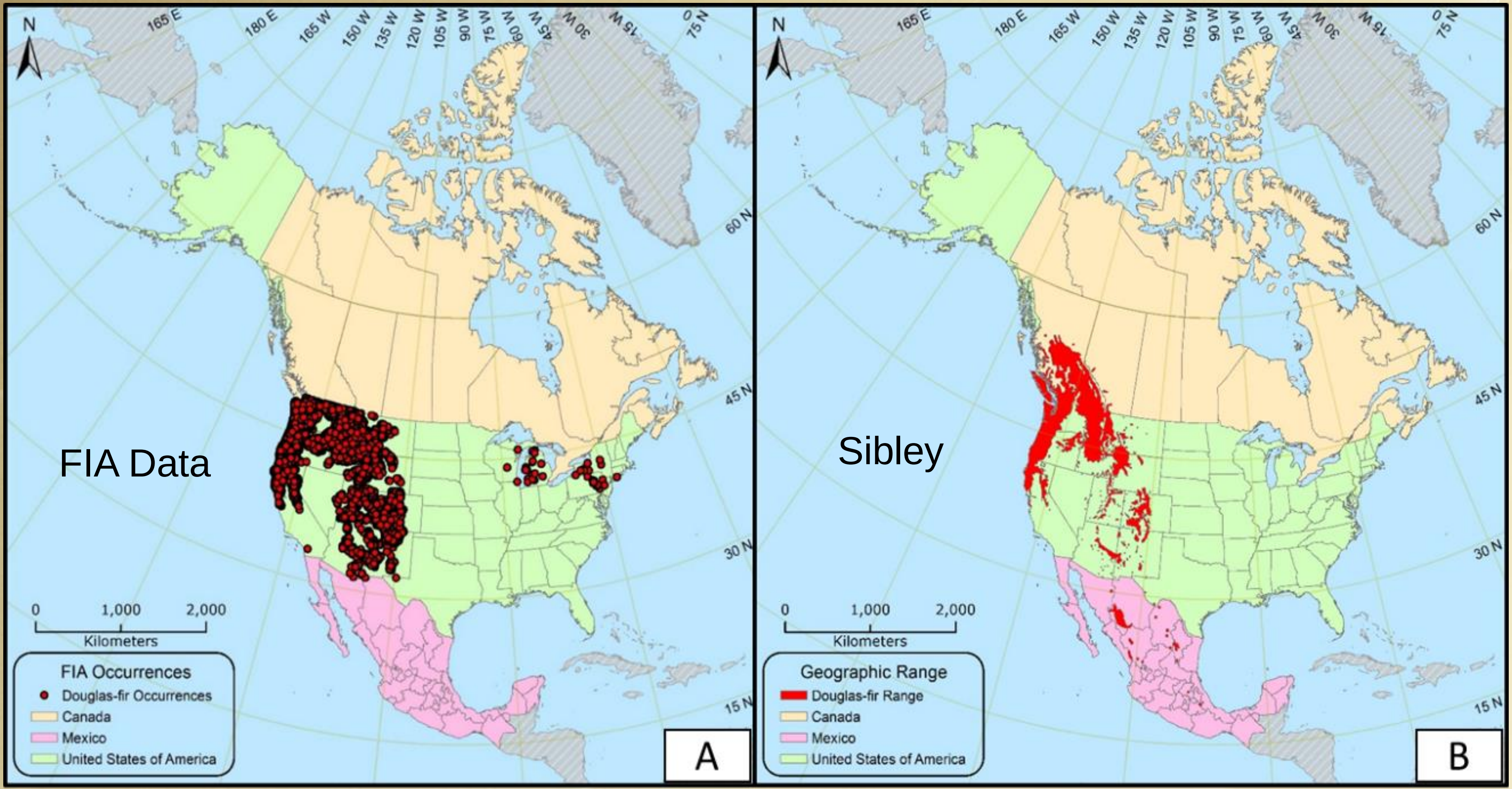
Standard of Deviation


N
0 750 1,500
Kilometers
Standard Deviation of Mean Paper Birch Habitat Suitability
High : 0.291
Low : 0
B

Coefficient of Variation

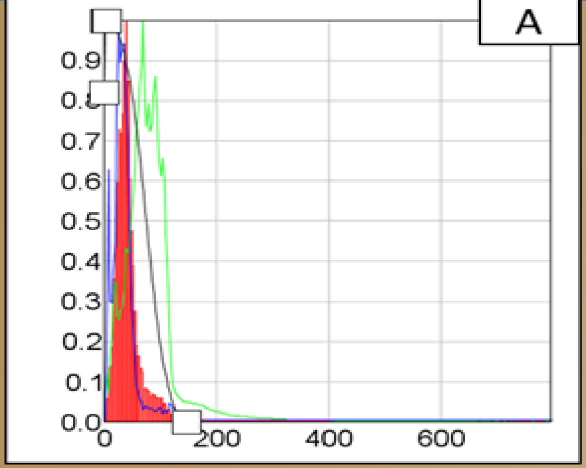

N
0 750 1,500
Kilometers
Coefficient of Variation of Paper Birch Habitat Suitability
High : 1126.95
Low : 0.046
C

Douglas Fir

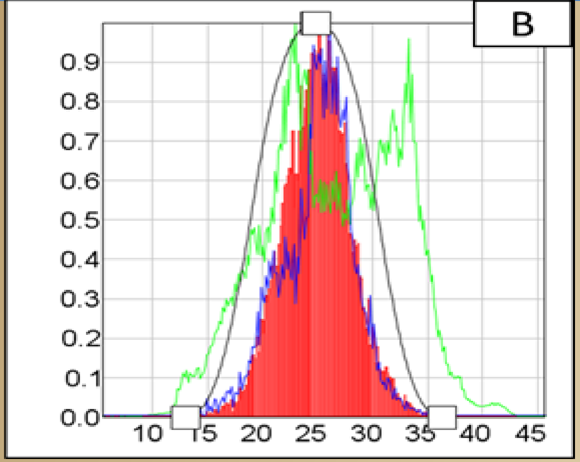

N
165 E
180 E
165 W
150 W
135 W
120 W
105 W
90 W
75 W
60 W
45 W
30 W
15 W
0
75 N
60 N
45 N
30 N
15 N
0
1,000
2,000
Kilometers
FIA Occurrences
● Douglas-fir Occurrences
Canada
Mexico
United States of America
A
Geographic Range
Douglas-fir Range
Canada
Mexico
United States of America
B

FIA Data

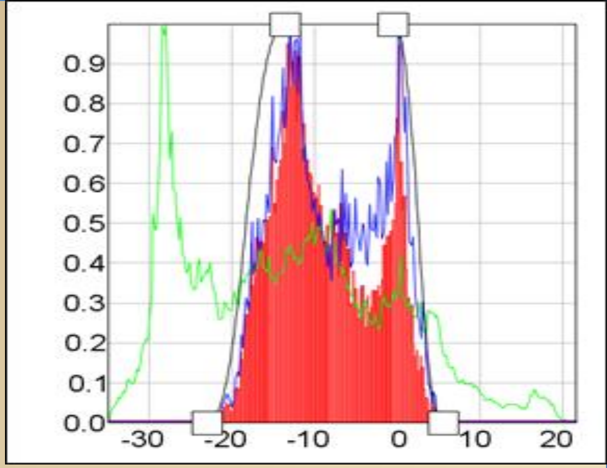
Sibley



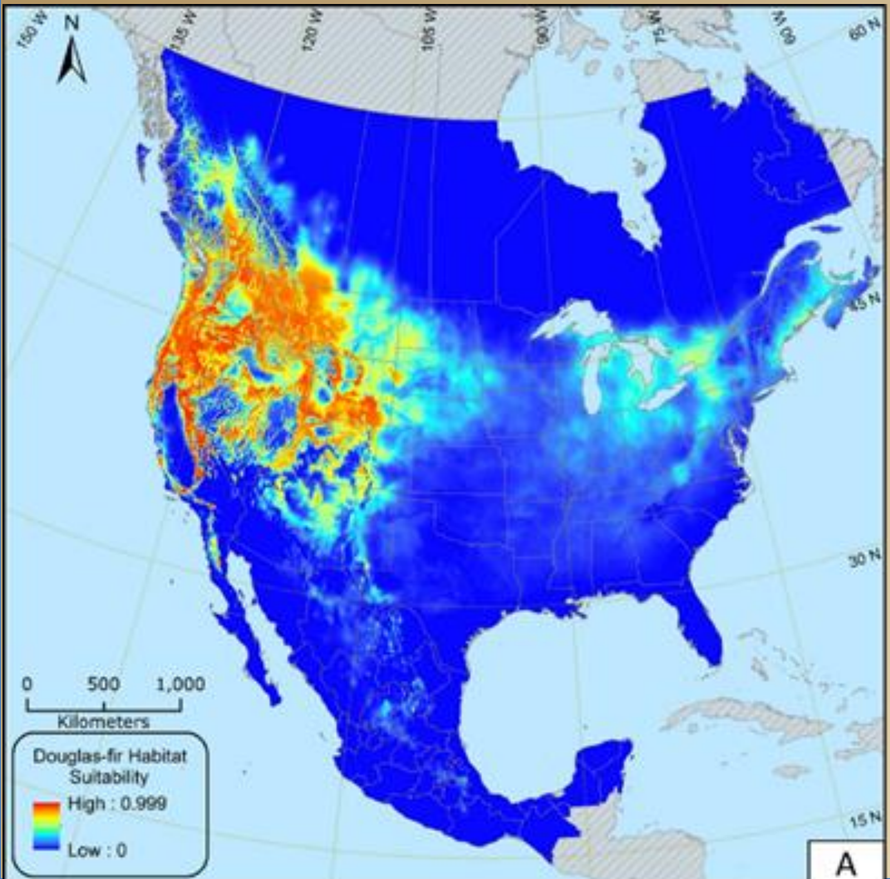
Precip. For August (mm)

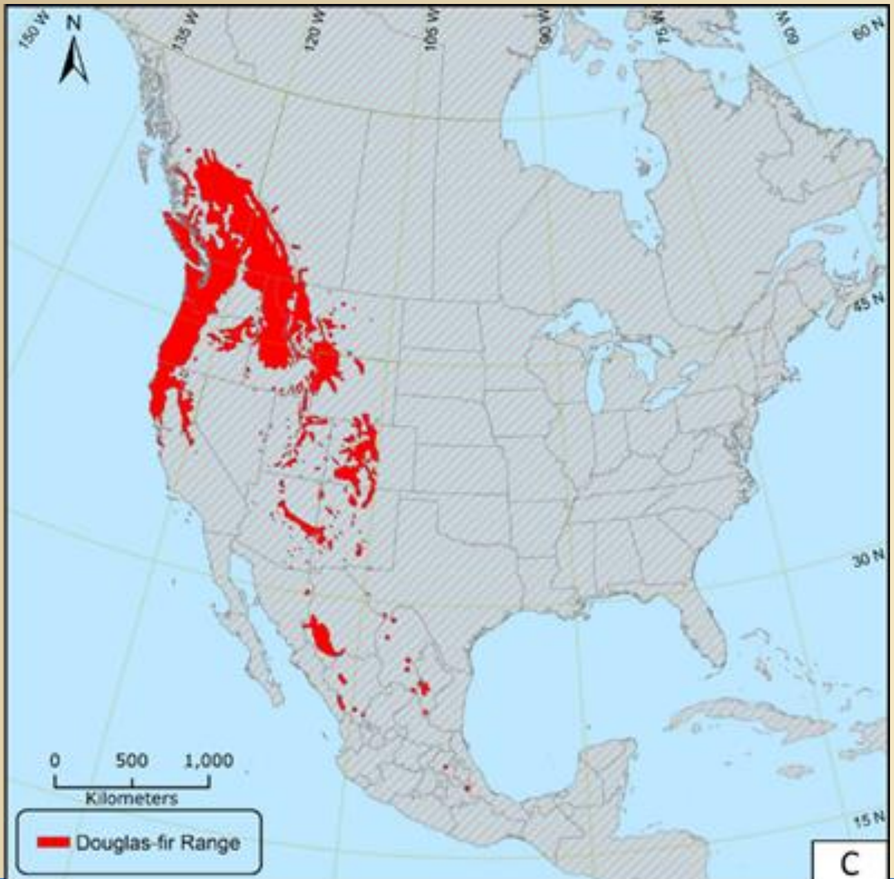


Max. Temp for July (C)

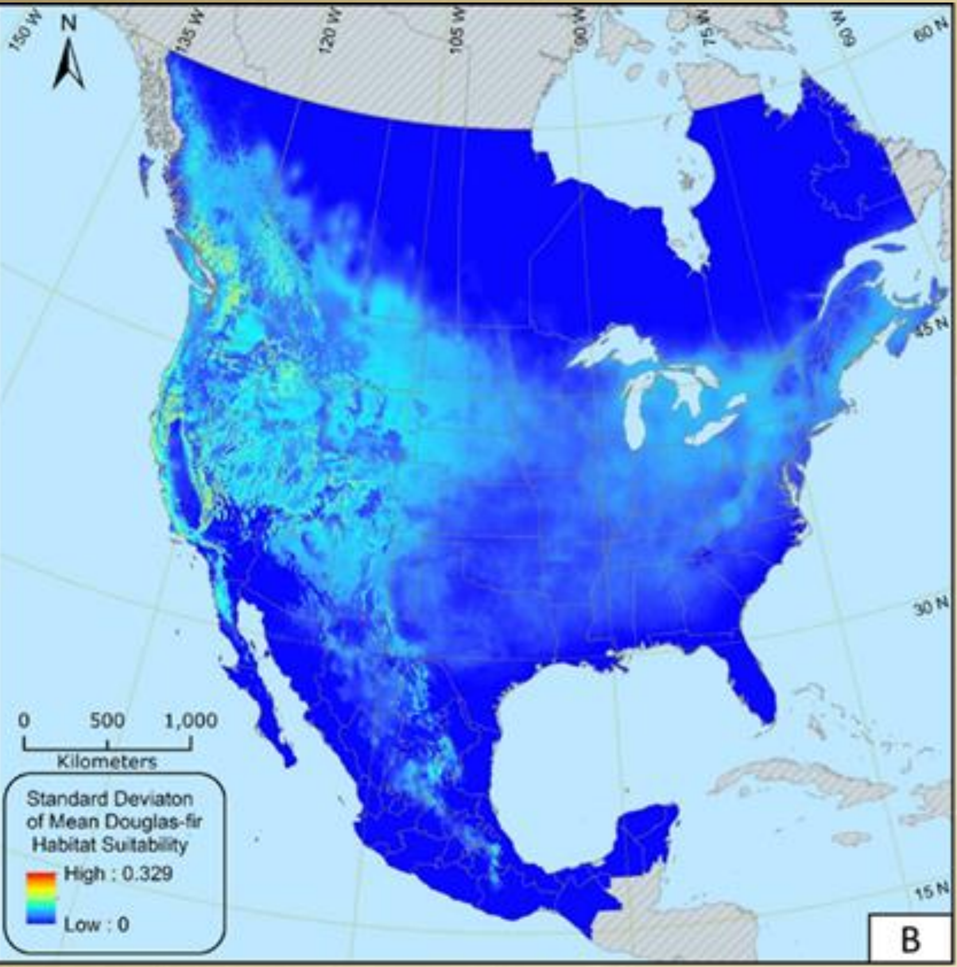


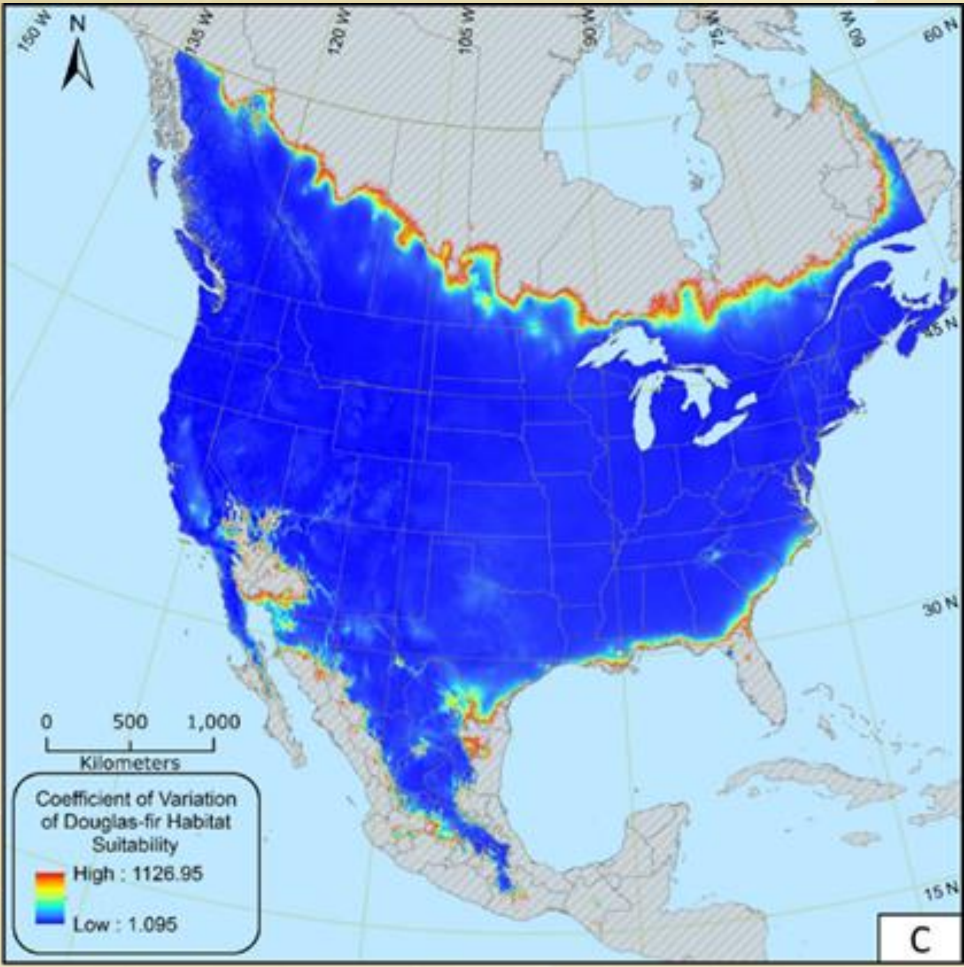
Minimum temp for January (C)


N
150 W
135 W
120 W
105 W
90 W
75 W
60 W
60 N
45 N
30 N
15 N
0
500
1,000
Kilometers
Douglas-fir Habitat Suitability
High : 0.999
Low : 0
A


N
150 W
135 W
120 W
105 W
90 W
75 W
60 W
60 N
45 N
30 N
15 N
0
500
1,000
Kilometers
Douglas-fir Range
C

Doug-Fir: Environmental Layer Noise Injection


150 W
135 W
120 W
105 W
90 W
75 W
60 W
60 N
45 N
30 N
15 N
N
0
500
1,000
Kilometers
Standard Deviaton of Mean Douglas-fir Habitat Suitability
High : 0.329
Low : 0
B


150 W
135 W
120 W
105 W
90 W
75 W
60 W
60 N
45 N
30 N
15 N
N
0
500
1,000
Kilometers
Coefficient of Variation of Douglas-fir Habitat Suitability
High : 1126.95
Low : 1.095
C

HEMI 2 – Summary

- Noise Injection:
  - Occurrences
  - Environmental Variables/Covariates
- Cross-Validation
- Sensitivity Testing
- Jackknife for environmental variable selection
- Analysis for number of iterations
- Detailed web page outputs
- Monte Carlo methods available for MaxEnt

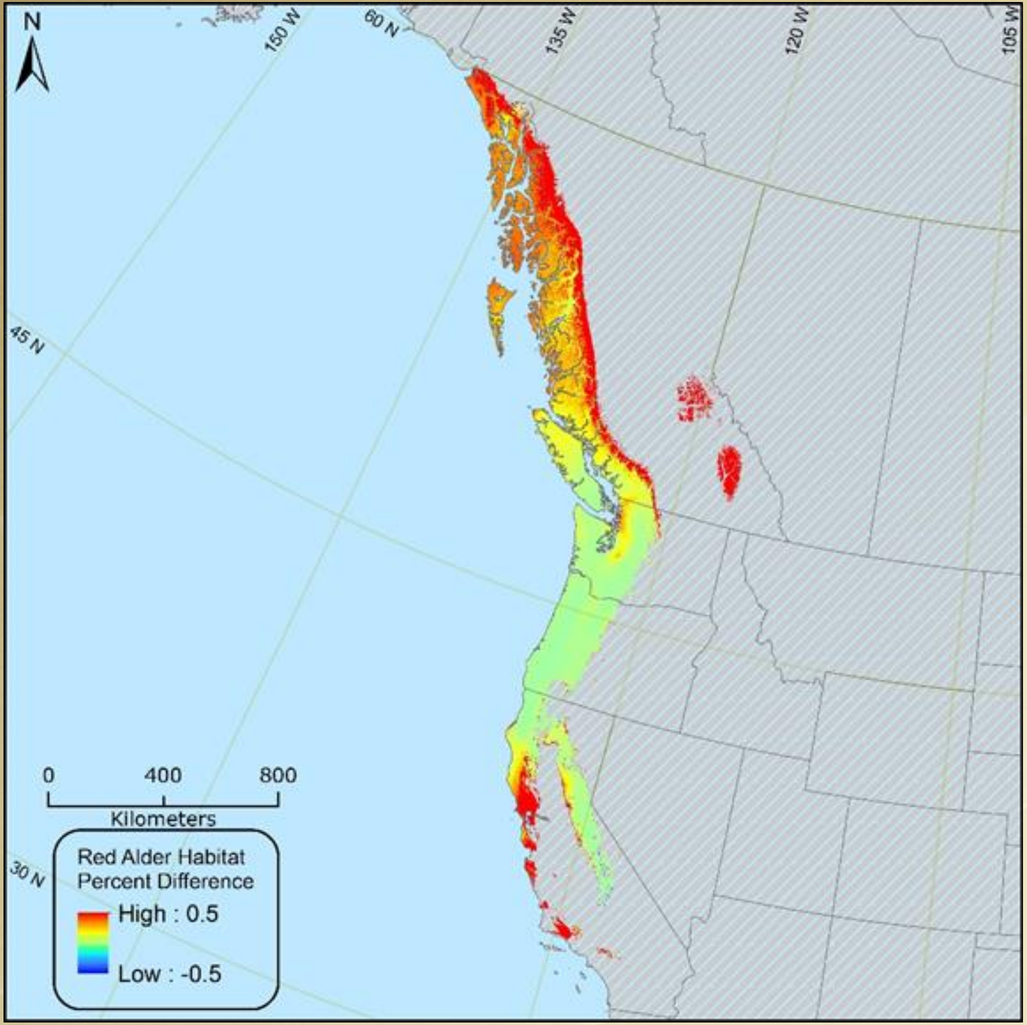
Next Steps

- Memory and performance optimization
- Allowing more complex curves?
- Running models for additional species!
  - Predicting future habitat based on global change with uncertainty maps
- What do you need?

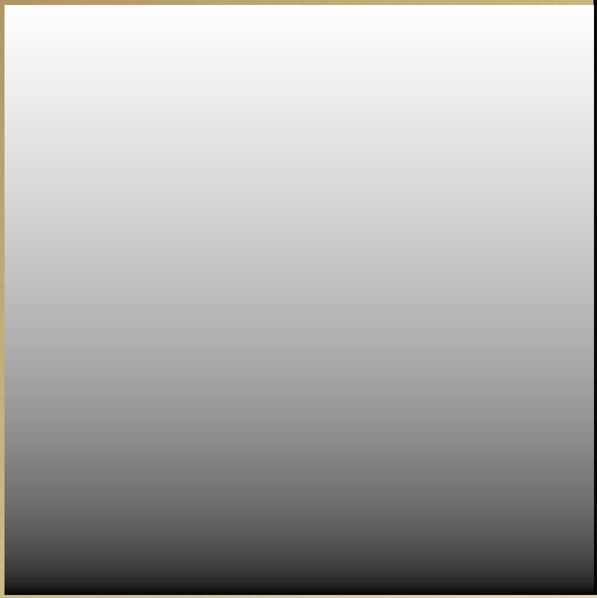
Acknowledgements

- USGS
- Dr. Greg Newman at Colorado State
- WorldClim/BioClim
- For more details, see:
  - More details at gsp.humboldt.edu/hemi2
- Additional References:
  - Sibley, D. (2009). The Sibley guide to trees. New York: Alfred A. Knopf.
  - Forest Inventory Analysis database

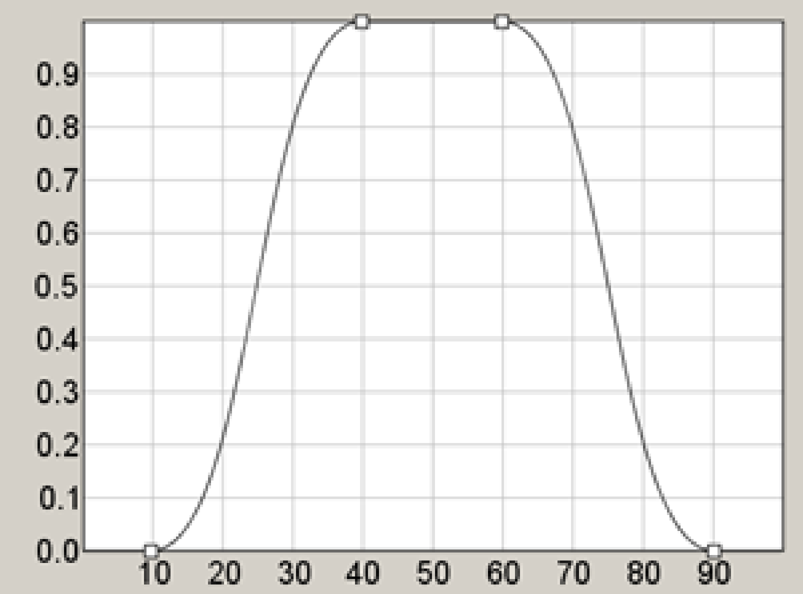
Pocket Slides

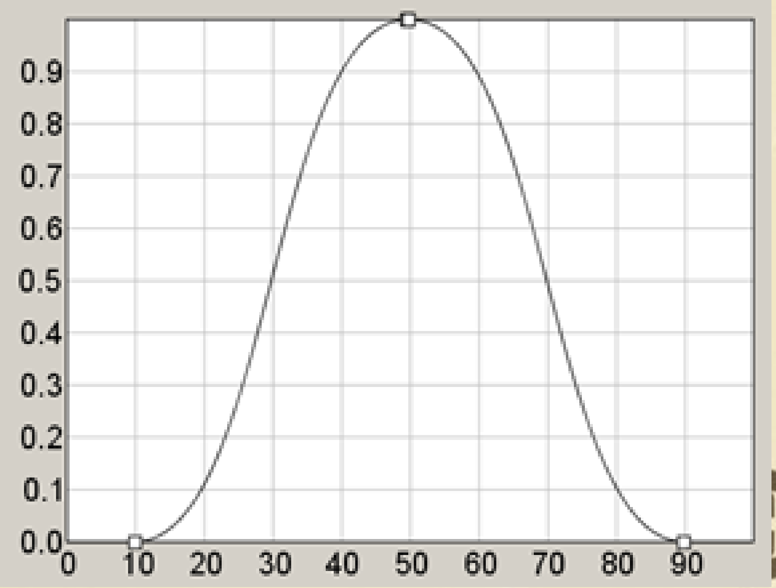

N
150 W
60 N
135 W
120 W
105 W
45 N
30 N
0
400
800
Kilometers
Red Alder Habitat
Percent Difference
High : 0.5
Low : -0.5

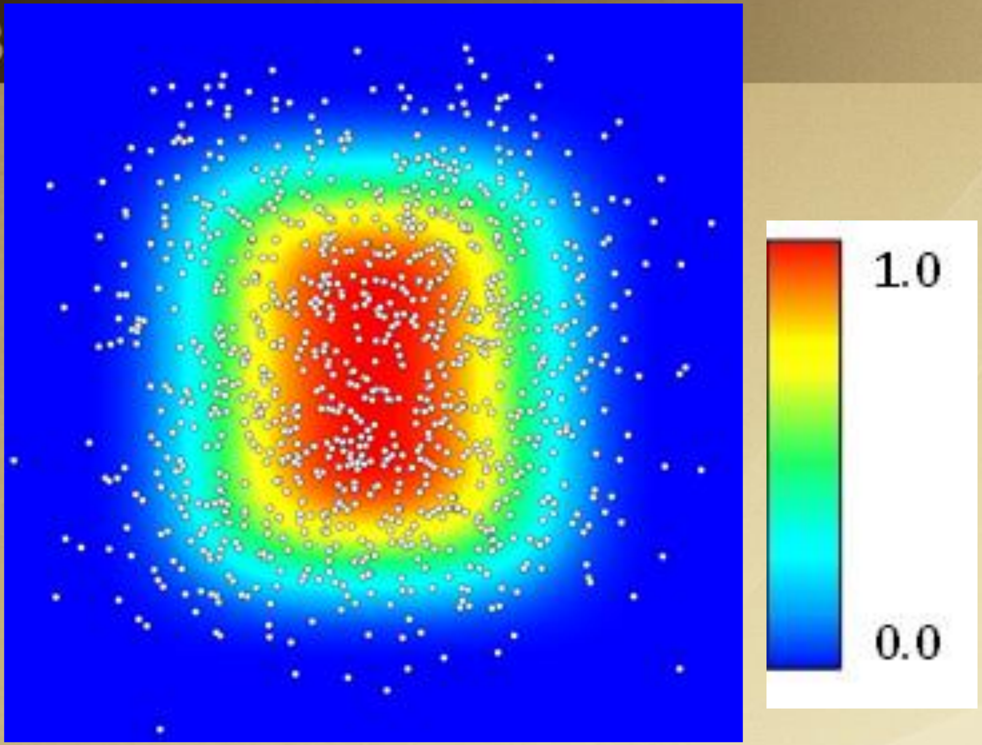
Top
To
Bottom

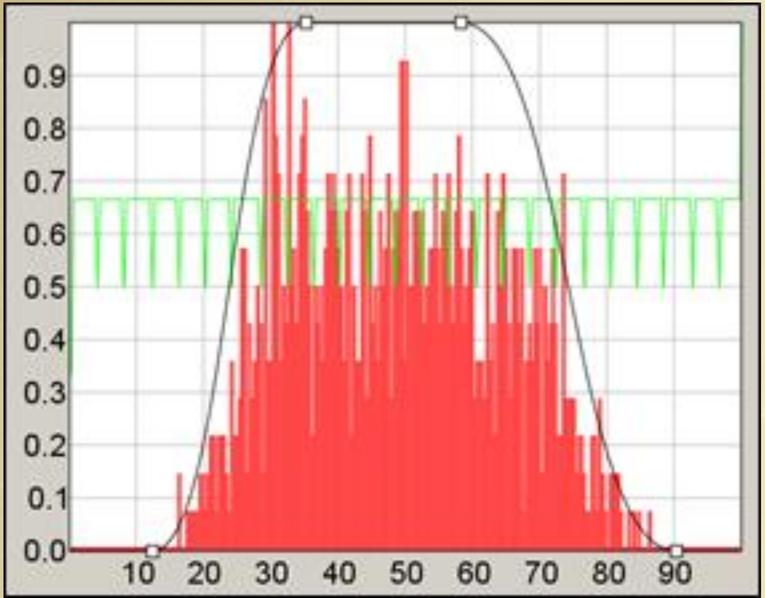


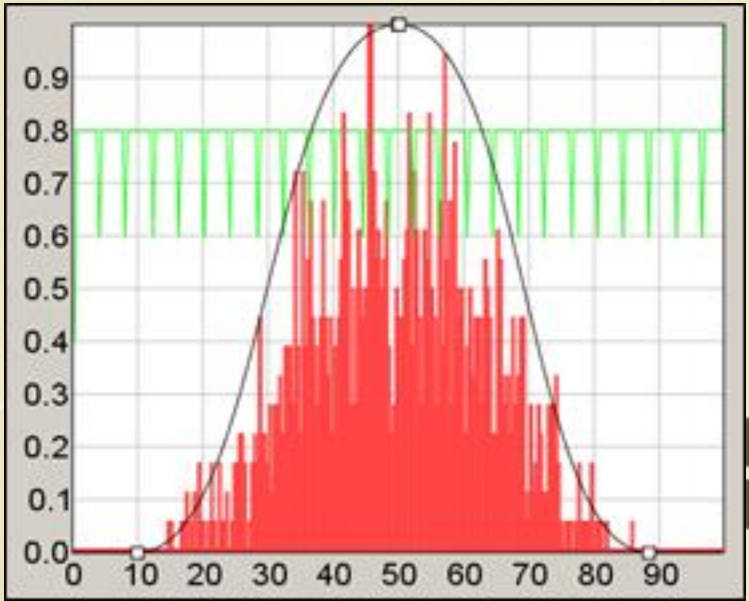
Left
To
Right






1.0
0.0


0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
10
20
30
40
50
60
70
80
90


0.9
0.8
0.7
0.6
0.5
0.4
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0.2
0.1
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40
50
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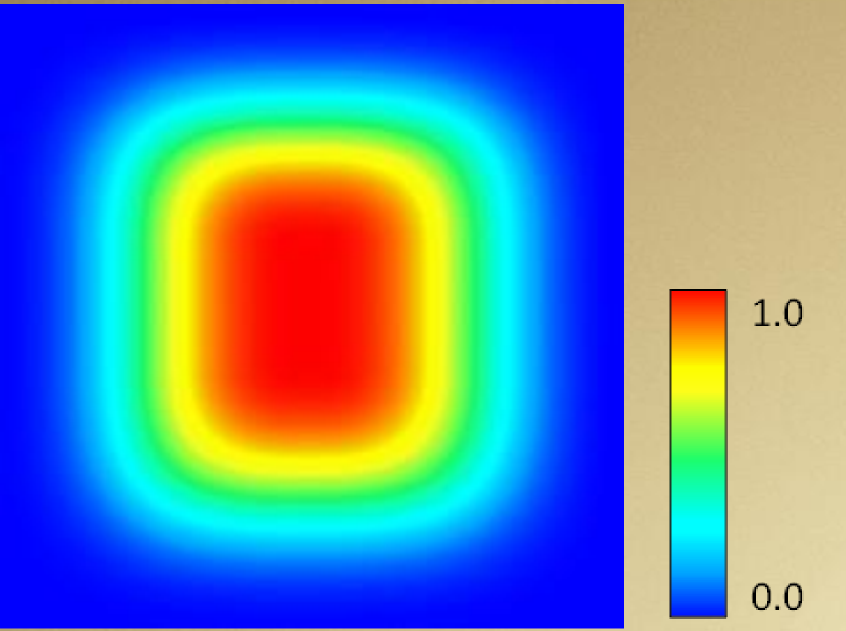
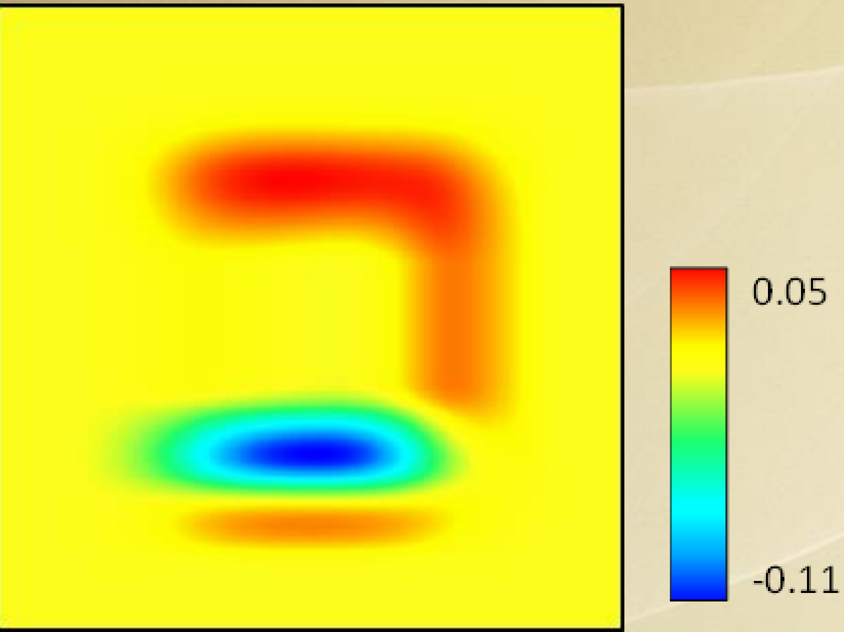
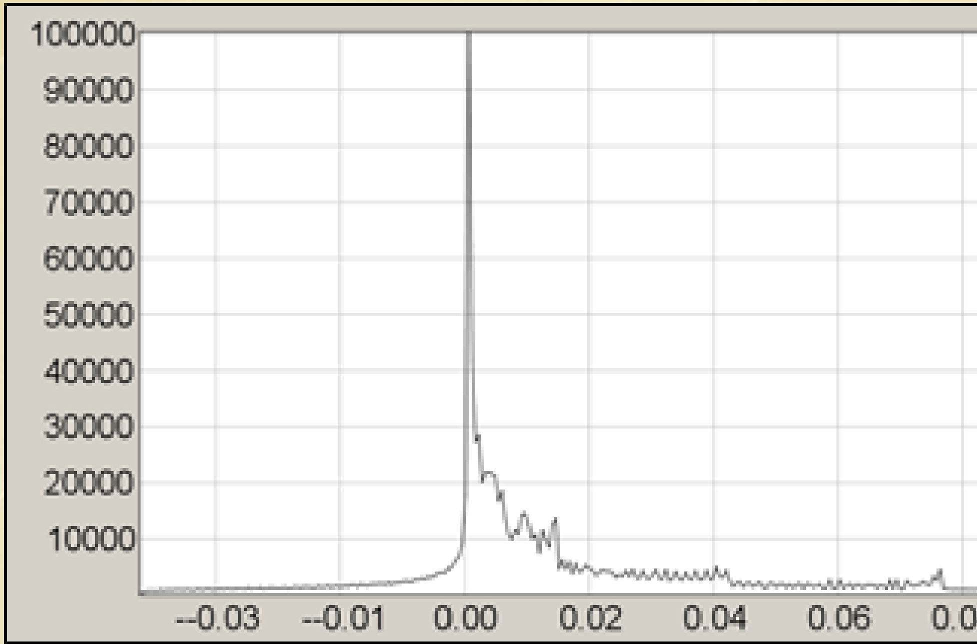
70
80
90


1.0
0.0


0.05
-0.11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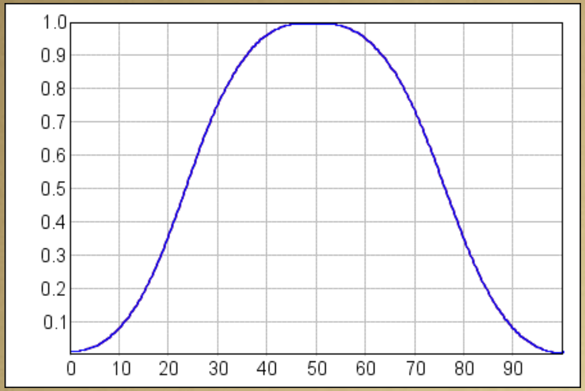
90000
80000
70000
60000
50000
40000
30000
20000
10000
--0.03
--0.01
0.00
0.02
0.04
0.06
0.0


1.0
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
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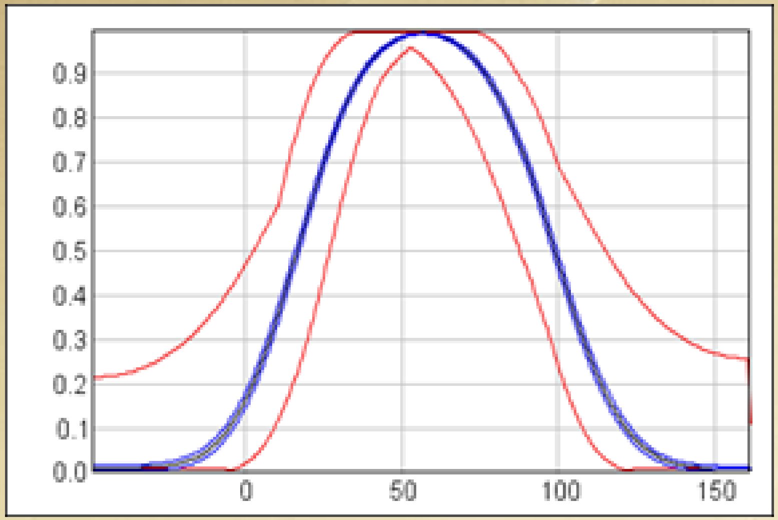
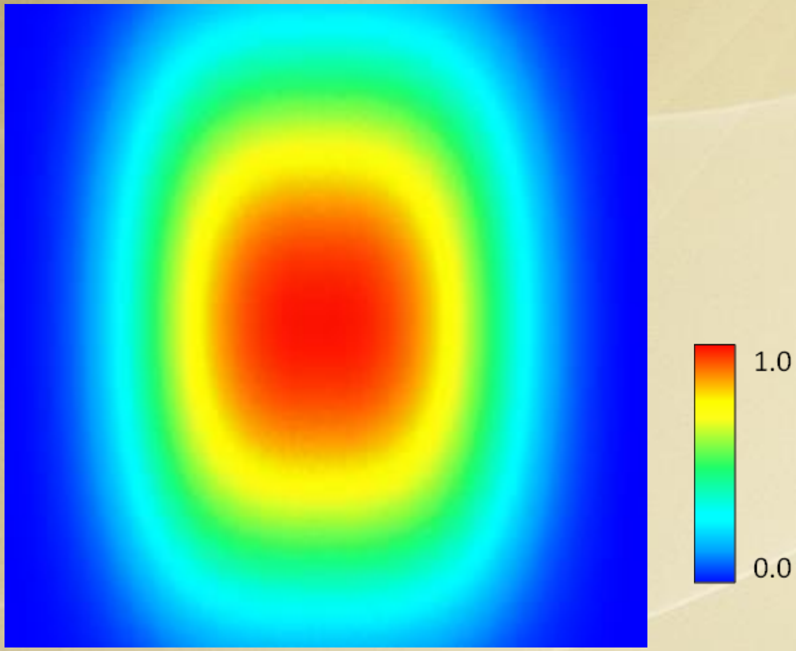
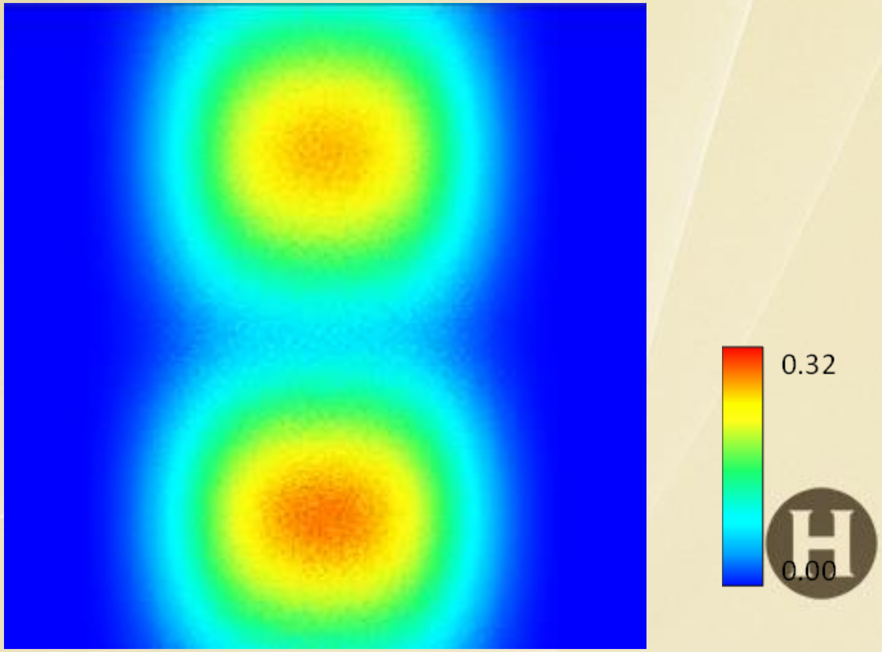
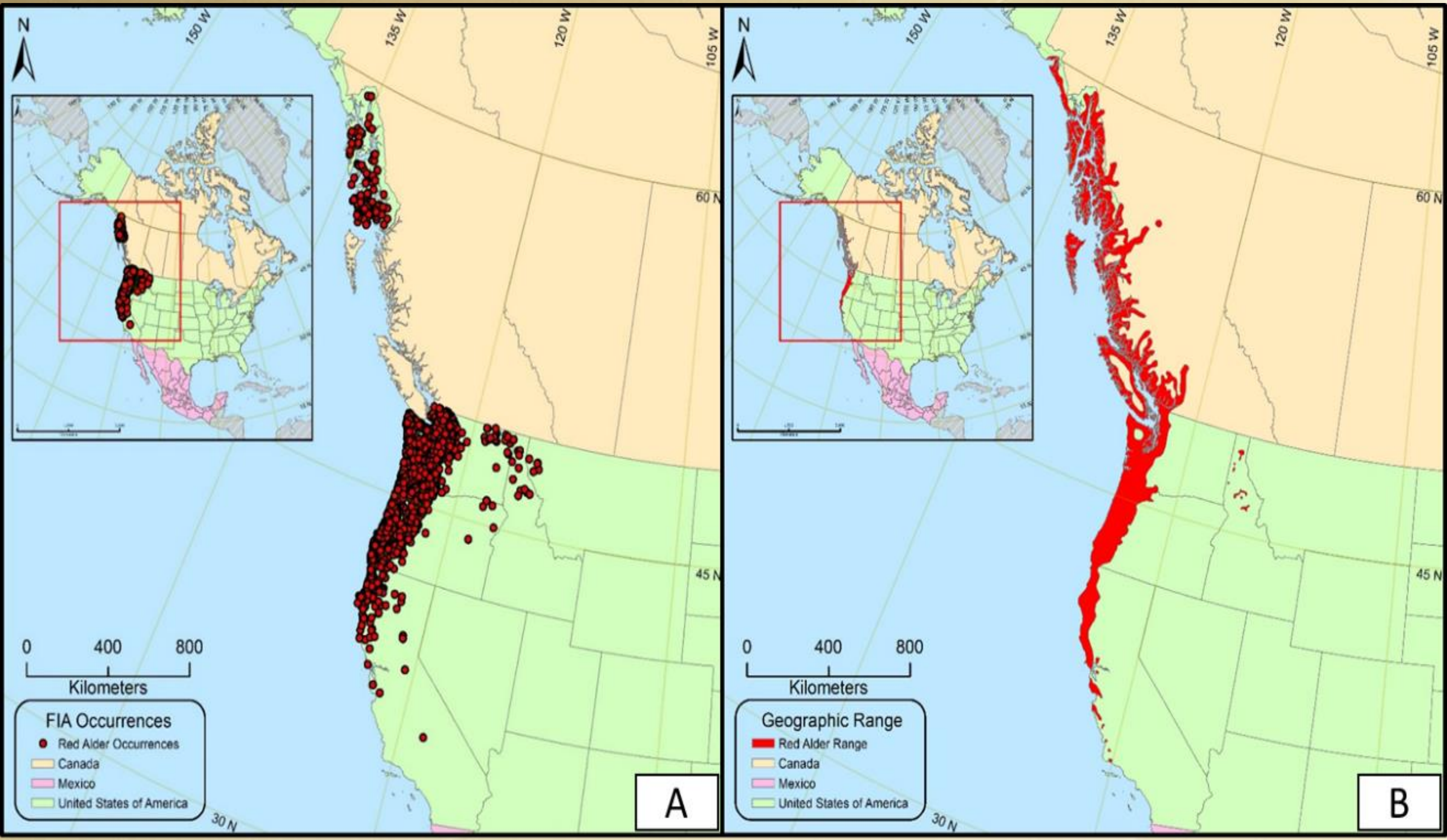
40
50
60
70
80
90


0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
0
50
100
150

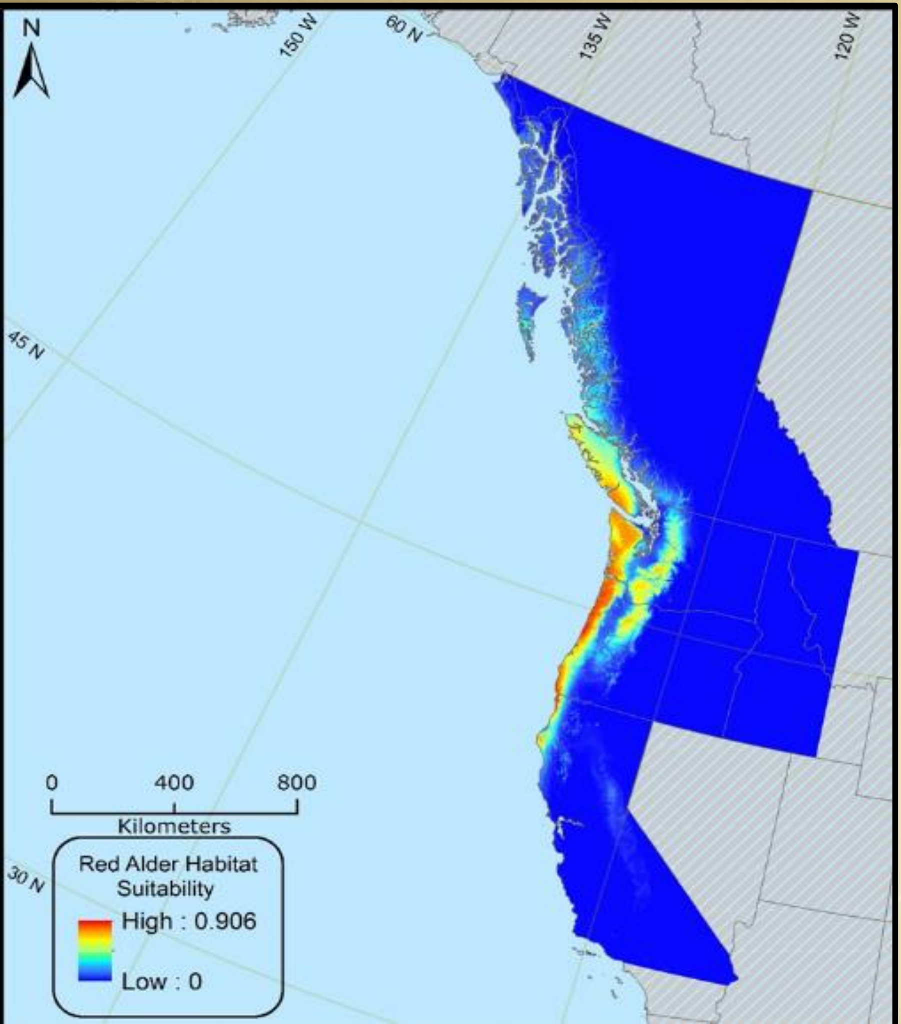

1.0
0.0


0.32
0.00

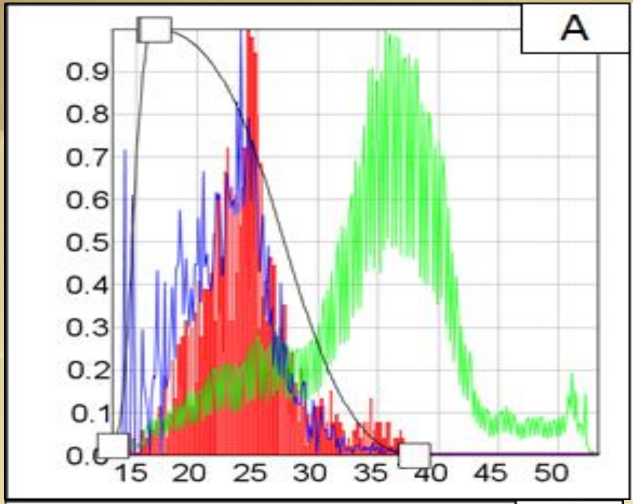
Red Alder


N
150 W
135 W
120 W
105 W
60 N
45 N
30 N
0
400
800
Kilometers
FIA Occurrences
● Red Alder Occurrences
Canada
Mexico
United States of America
A
Geographic Range
🟥 Red Alder Range
Canada
Mexico
United States of America
B

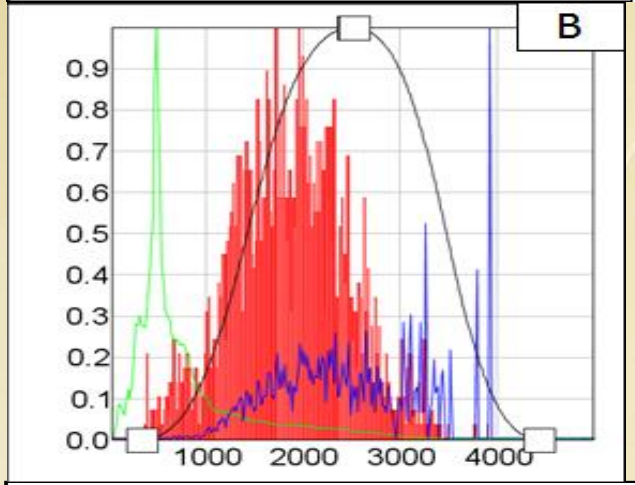
Red Alder


N
150 W
60 N
135 W
120 W
45 N
30 N
0
400
800
Kilometers
Red Alder Habitat Suitability
High : 0.906
Low : 0

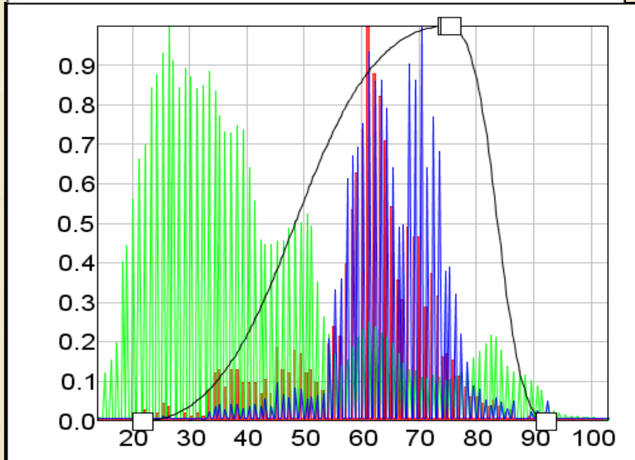
Average Temperature (C*10)



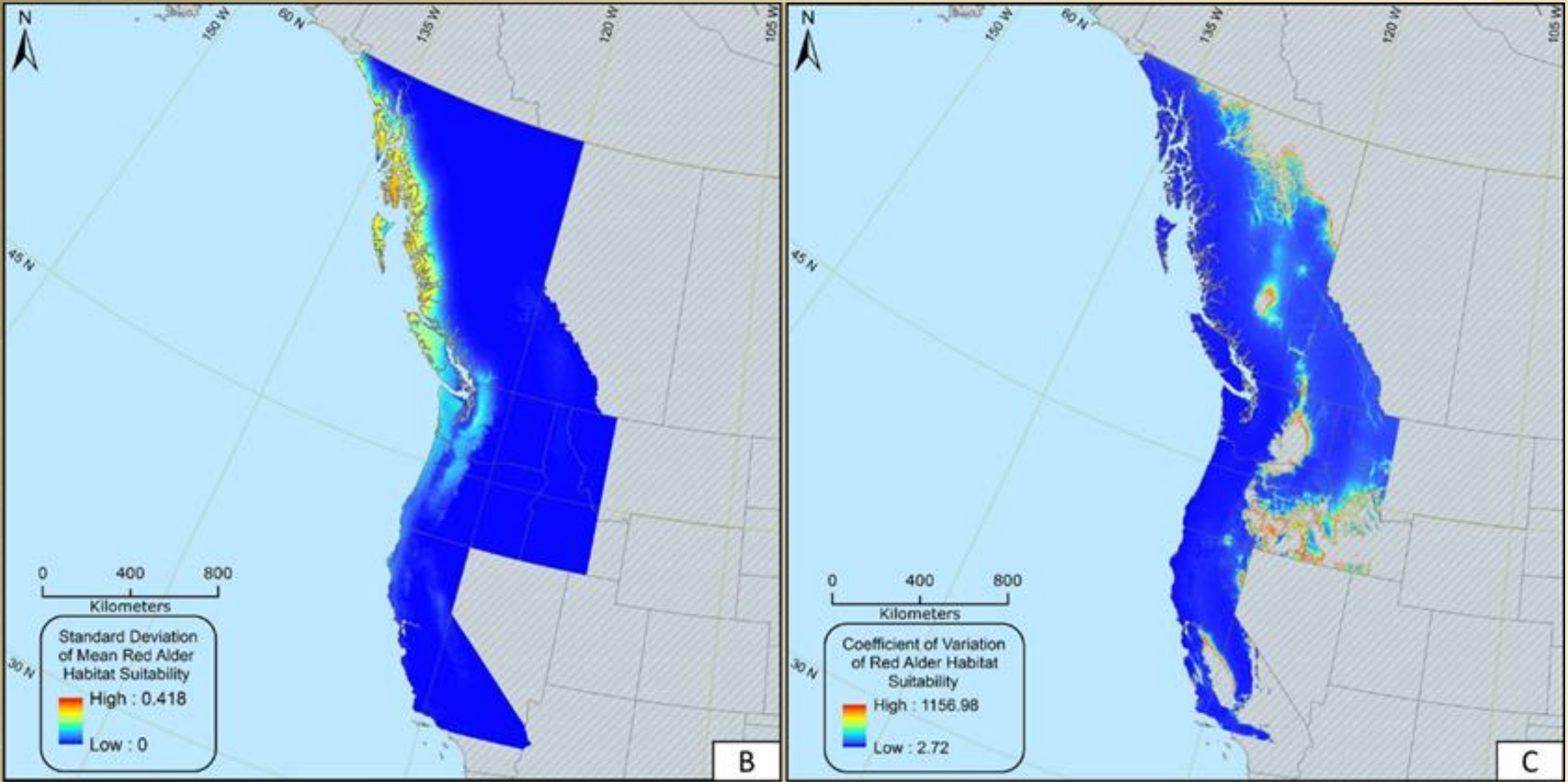
Annual Precip (mm)



Coefficient of variation for Precip.



Red Alder


N
150 W
60 N
135 W
120 W
105 W
45 N
30 N
0
400
800
Kilometers
Standard Deviation of Mean Red Alder Habitat Suitability
High : 0.418
Low : 0
B
N
150 W
60 N
135 W
120 W
105 W
45 N
30 N
0
400
800
Kilometers
Coefficient of Variation of Red Alder Habitat Suitability
High : 1156.98
Low : 2.72
C