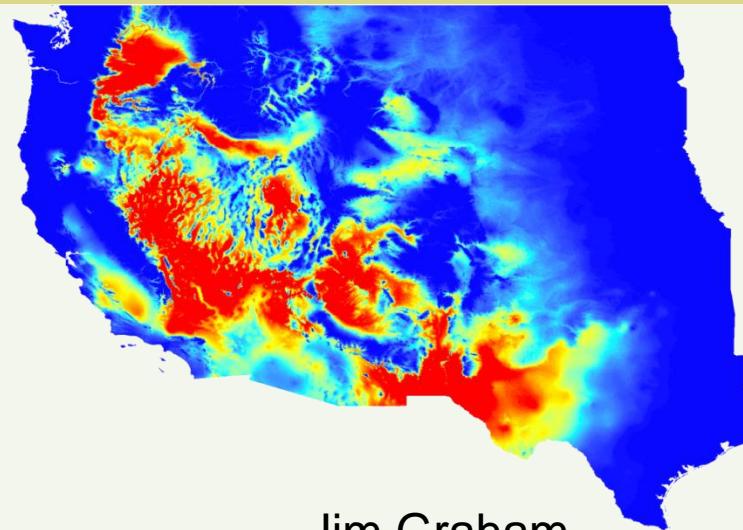


Modeling Potential Distributions of Species at Large Spatial Extents



Jim Graham

Colorado
State
University
Knowledge to Go Places

Greg Newman, Nick Young, Catherine Jarnevich

Natural Resource Ecology Laboratory

Oregon State University / Colorado State University





Jim Graham

- BS CS and Math from California State University at Chico
- 15 Years Image Processing at HP
- 3 Years a CEO for GIS web corp.
- PhD in GIS from Colorado State University, Fort Collins
- 4 Years as Research Scientist at the Natural Resource Ecology Laboratory
- Visiting Professor at OSU



Jim's Research

- Engaging citizen scientists
- Web-based GIS
- Integrating eco-informatics databases
- Global species occurrence databases
- Optimal data access for large spatial databases
- Habitat suitability modeling at large extents
- Risks and impacts of energy production



Invasive Species



Rat attacking New Zealand fantail

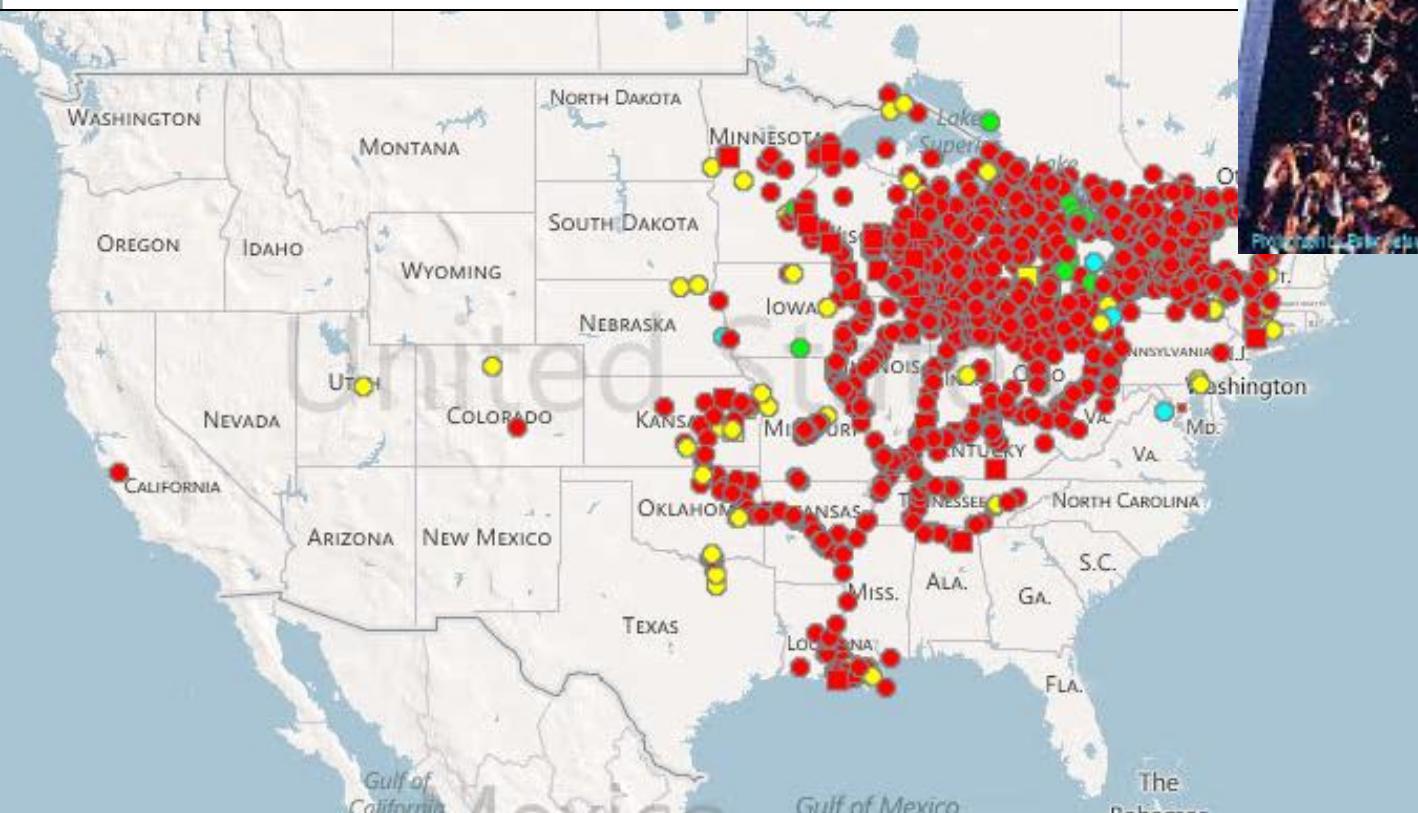
Photo: David Mudge

Mnemiopsis leidyi (comb jelly)





Zebra Mussel Distribution





Predicting Distributions

- Predicting potential species distributions at large spatial and temporal extents
- Given:
 - Limited data
 - Most have unknown uncertainty
 - Most biased/not randomly sampled
 - >90% just “occurrences” or “observations”
 - Lots of species
 - Climate change and other scenarios



Occurrences of Polar Bears



From The Global Biodiversity Information Facility (www.gbif.org, 2011)



Uncertainty in Data

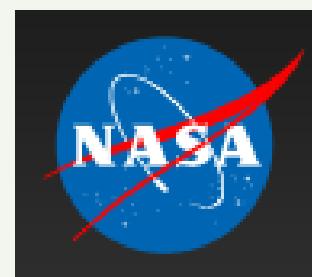
- Experts more accurate in correctly identifying species than volunteers
 - 88% vs. 72%
 - Volunteers: 28% false negative identifications and 1% false positive identifications
 - Experts: 12% false negative identifications and <1% false positive identifications
- Conspicuous vs. Inconspicuous
 - Volunteers correctly identified “easy” species 82% of the time vs. 65% for “difficult” species
 - 62% of false ids for GB were CB



GISIN Organizations



Biodiversity
Information
Standards
T D W G

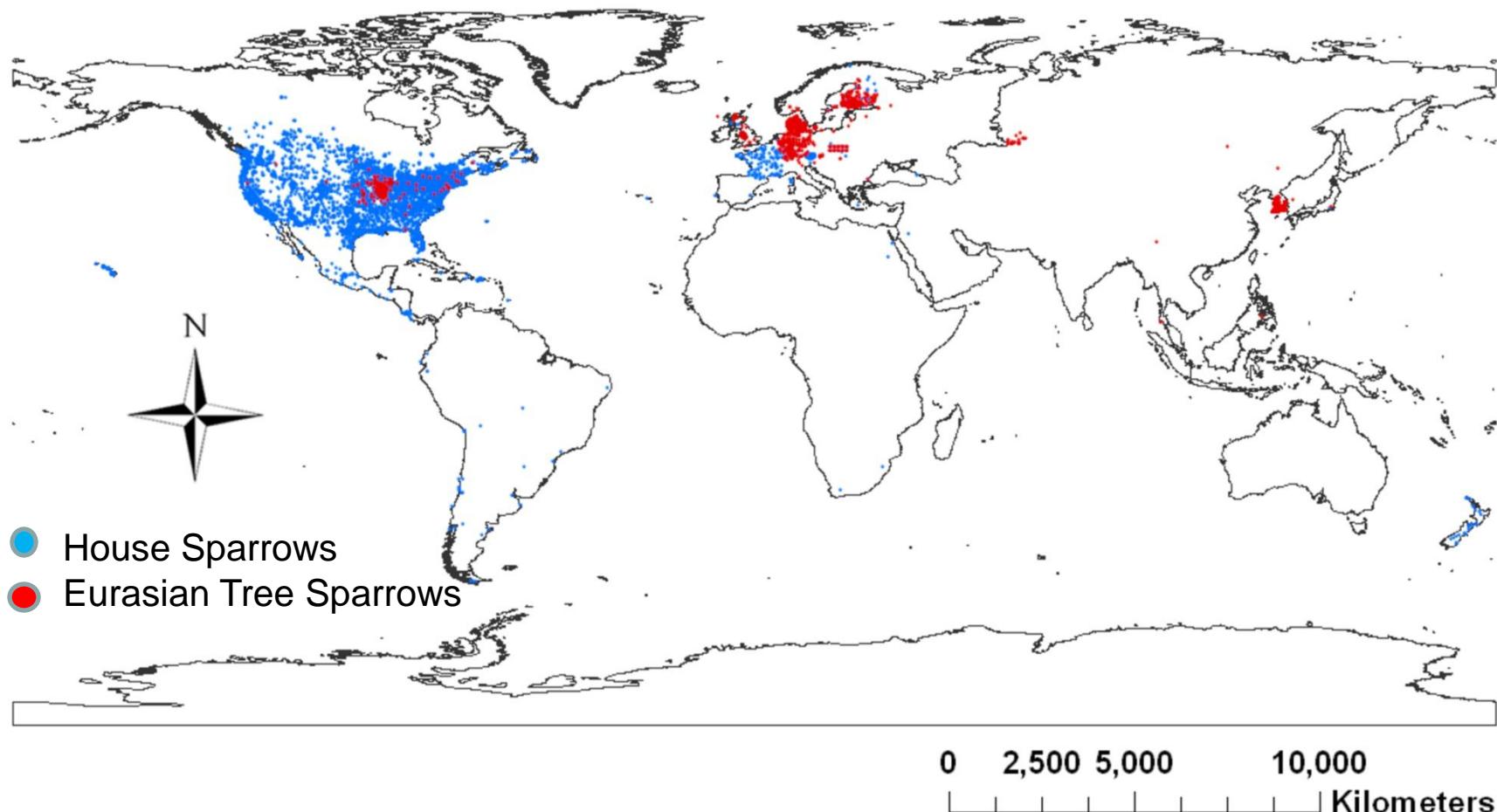


DISCOVER LIFE





Tree Sparrow Occurrences

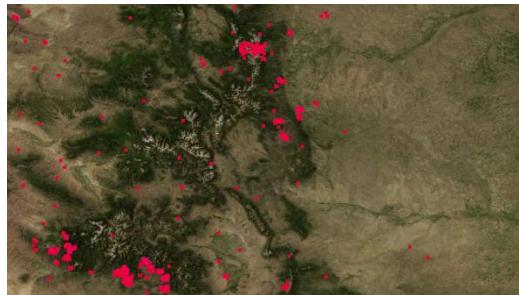


Graham, J., C. Jarnevich, N. Young, G. Newman, T. Stohlgren, How will climate change affect the potential distribution of Eurasian Tree Sparrows (*Passer montanus*)? Current Zoology, 2011.



Modeling Process

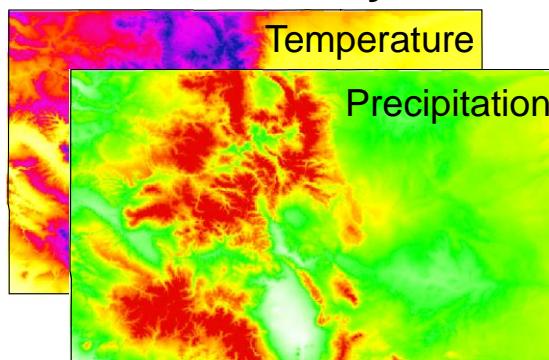
Occurrences



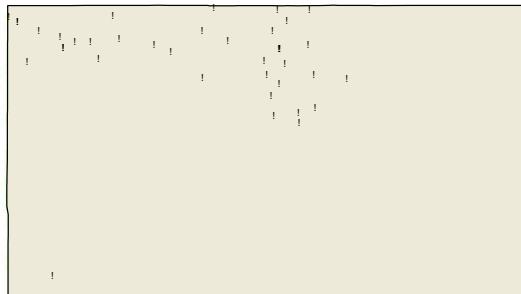
Spreadsheets

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

Environmental Layers



Habitat Suitability Map



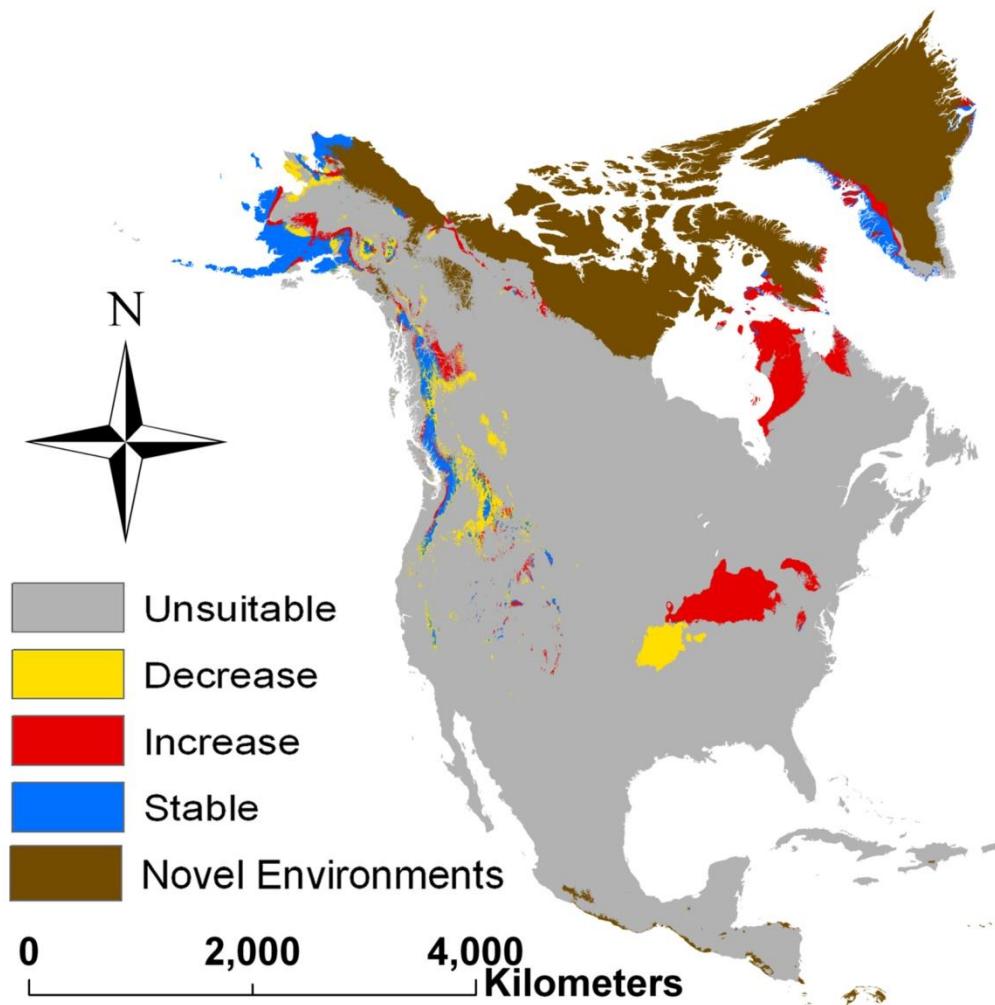
Model Parameters

Variable	Coefficient	P-Value
Intercept	-1.52	0.064
Annual Precip	-0.05	0.0
Annual Temp.	0.61	0.0

Map Generation



Tree Sparrow Model - 2050



Graham, J., C. Jarnevich, N. Young, G. Newman, T. Stohlgren, How will climate change affect the potential distribution of Eurasian Tree Sparrows (*Passer montanus*)? Current Zoology, 2011



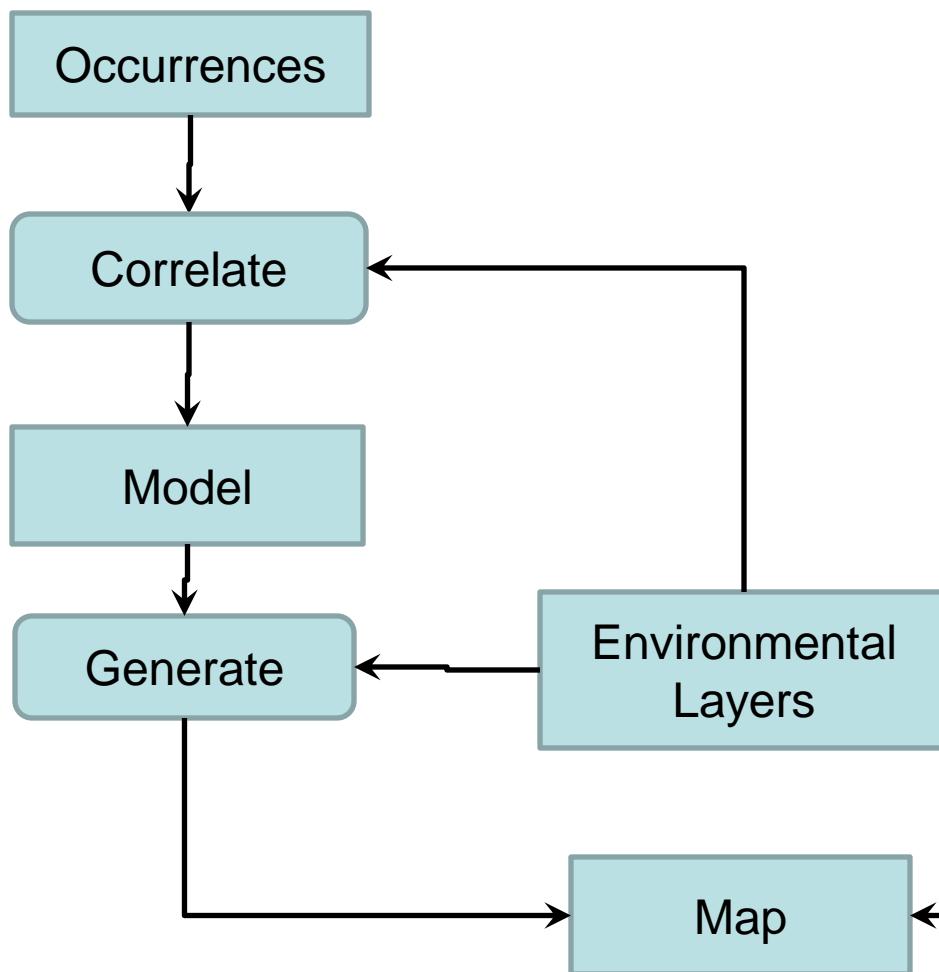
Spatial Modeling Concerns

- Over fitting the data
 - Are we modeling biological/ecological theory?
- What does the model look like?
 - In environmental space vs. geographic space
- Absence points?
 - What do they mean?
- Analysis and representation of uncertainty?
- Can we really model the potential distribution of a species from a sub-sample?

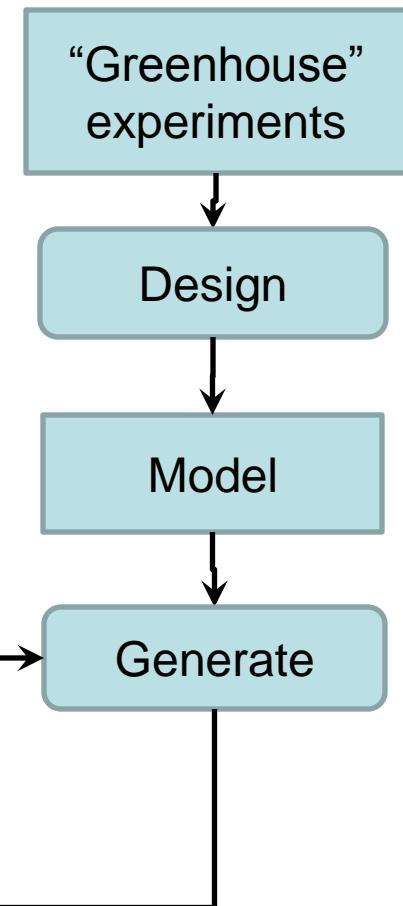


Two Approaches

Occurrence/Presence



Mechanistic





Tamarisk Data

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niiss

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Current Project: **NISS - General User Help**

Location



Edit

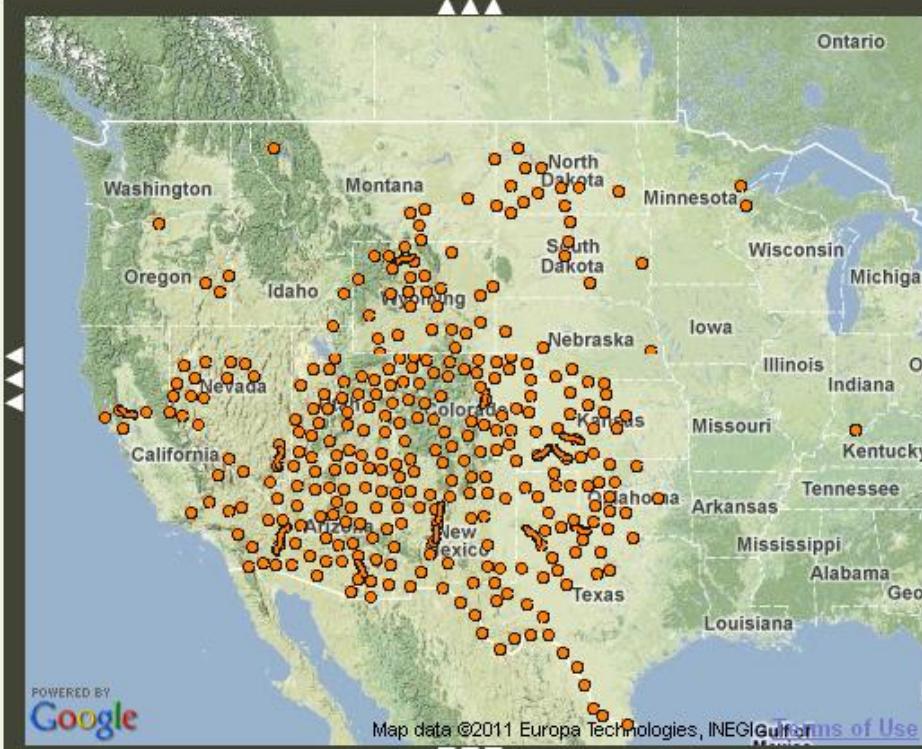
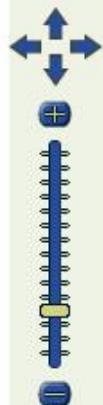
Legend

Plants

Tamarisk

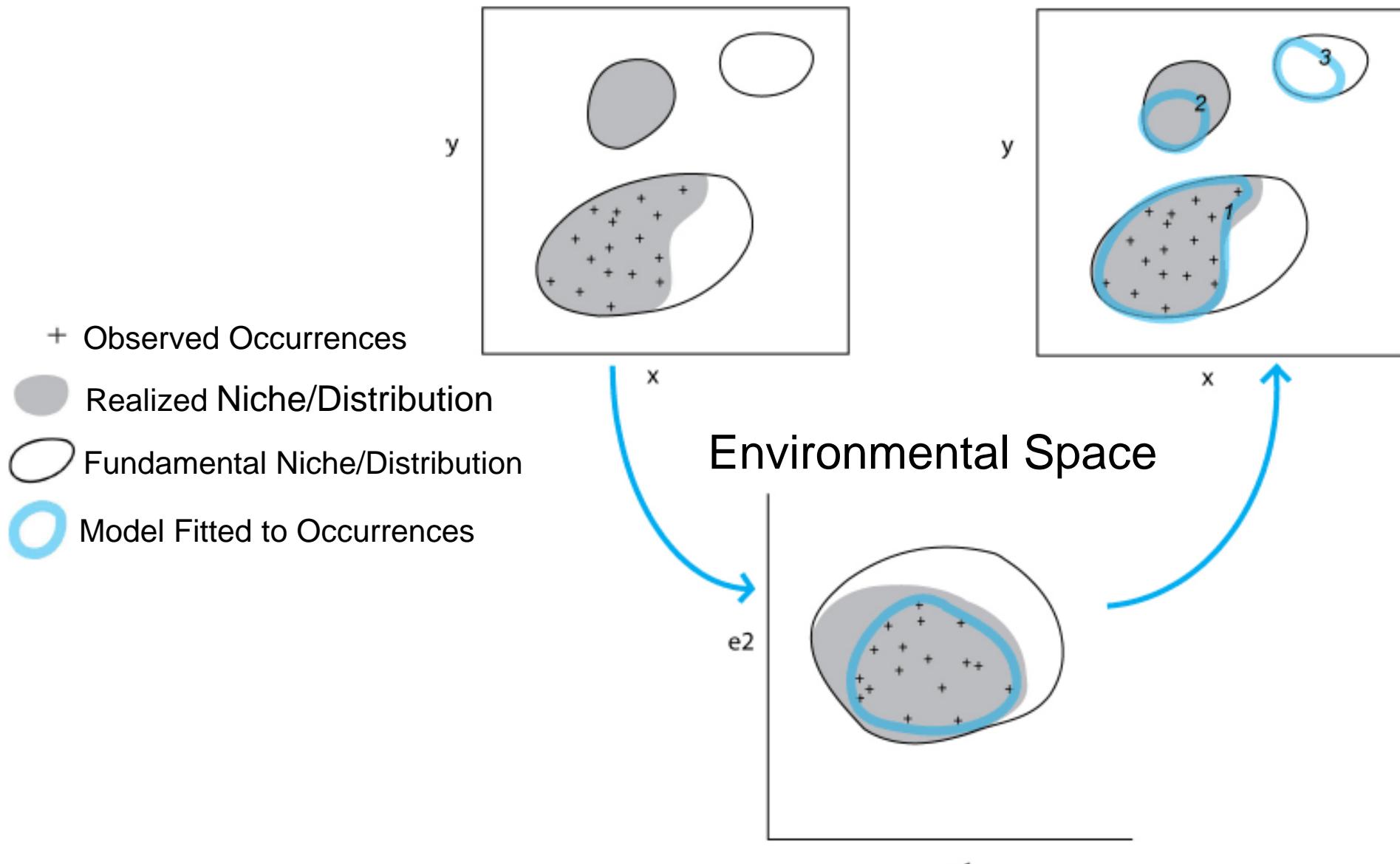
Backgrounds

- Google: Terrain
- Google: Map
- Google: Satellite
- Google: Hybrid



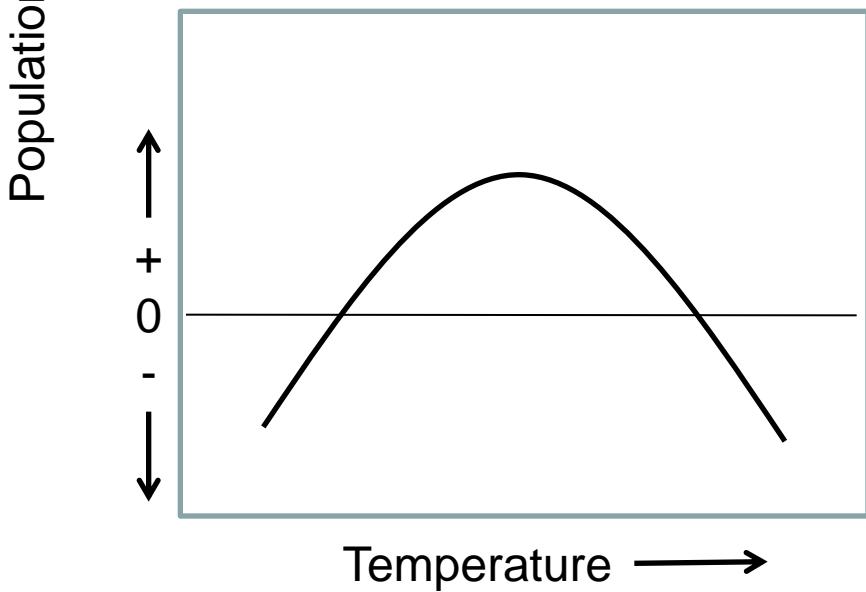
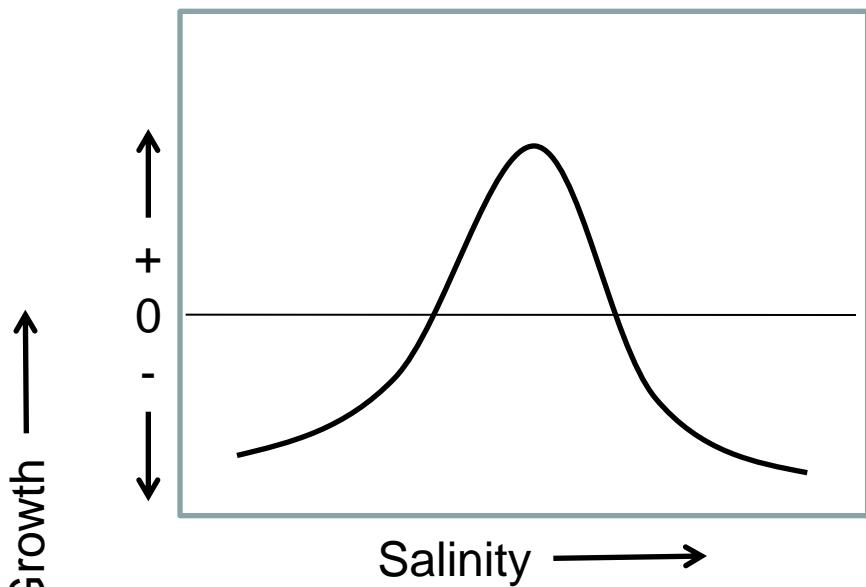
Projection: Google Mercator [Sources](#)

Geographical Space

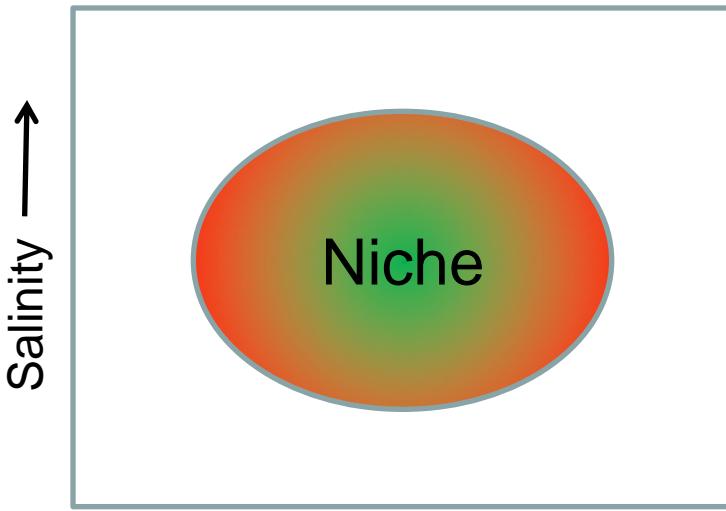


Adapted from Richard Pearson, Center for Biodiversity and Conservation at the American Museum of Natural History

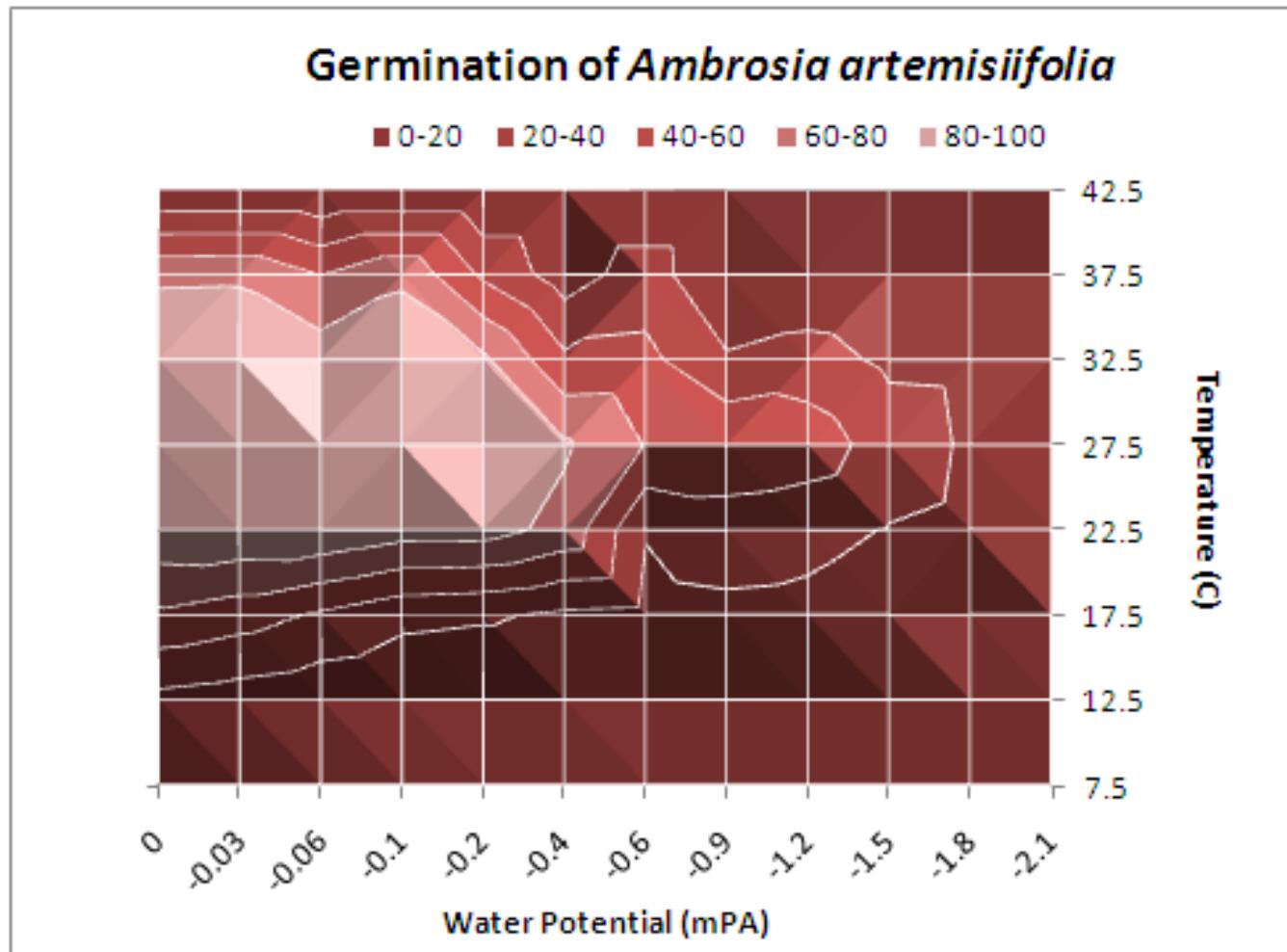
From the Theory of Biogeography



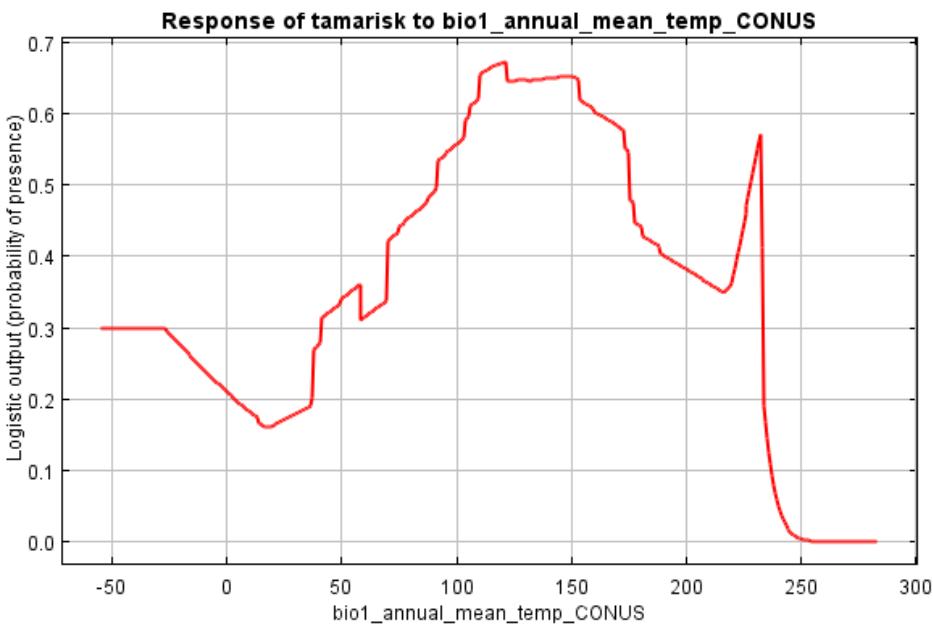
Environmental Space



Germination Percentage



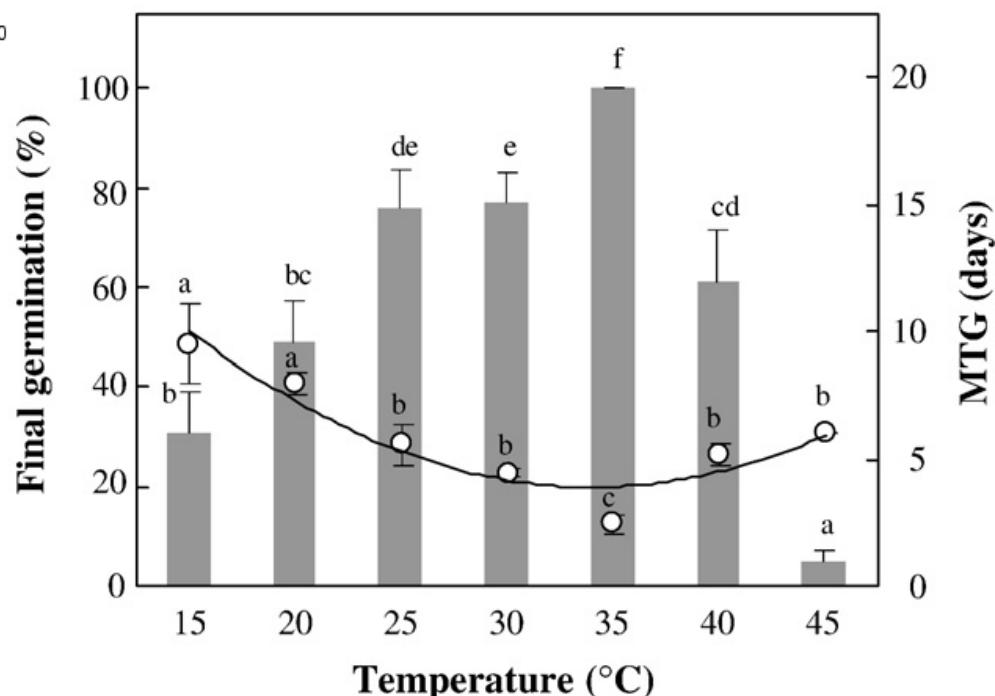
Shrestha, A., E. S. Roman, A. G. Thomas, and C. J. Swanton. 1999. Modeling germination and shoot-radicle elongation of *Ambrosia artemisiifolia*. *Weed Science* 47:557-562.



What should the model look like?

Over-fitting The Data?

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



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.

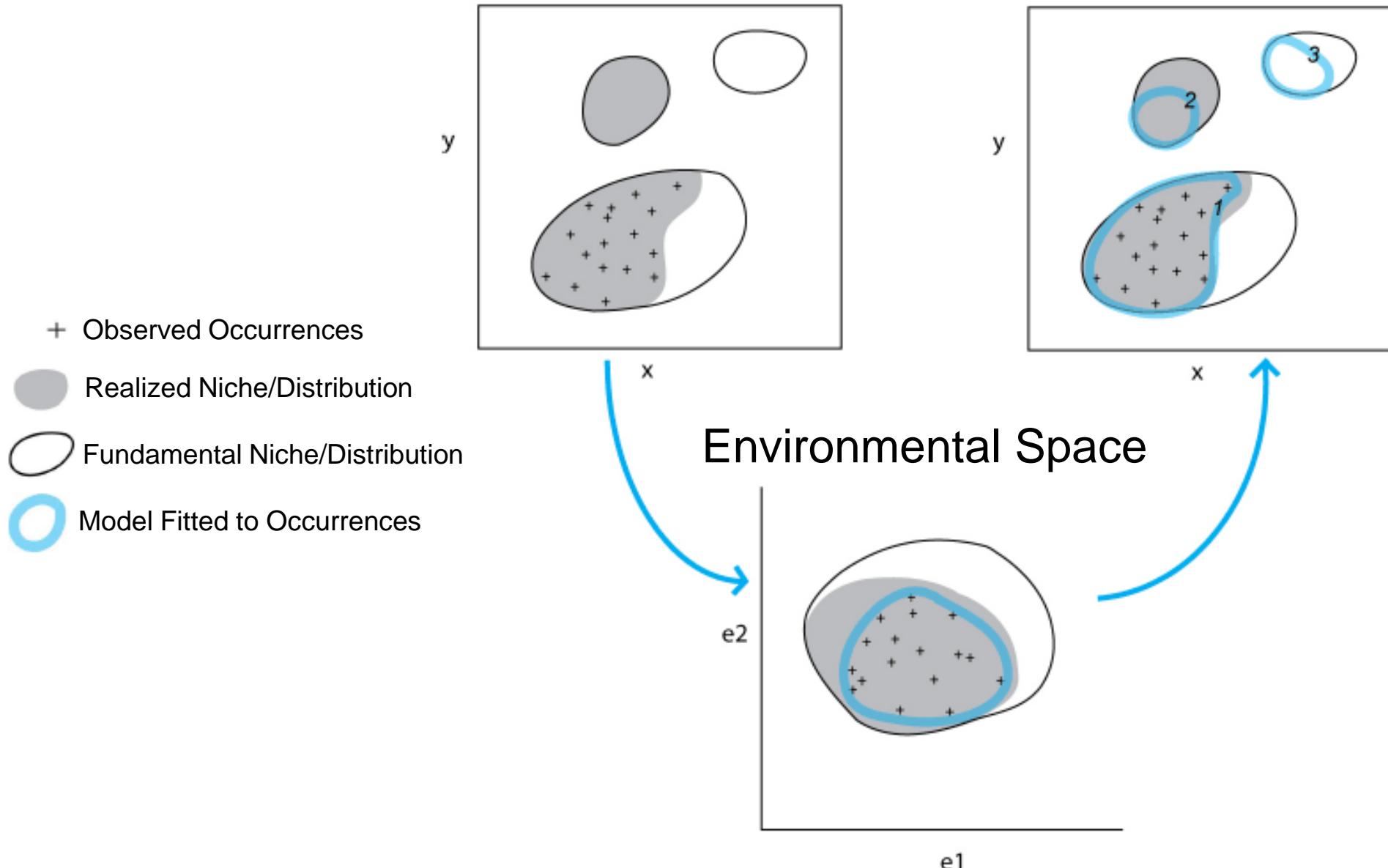


Maxent Model Parameters

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numBackgroundPoints, 10000
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162 Parameters

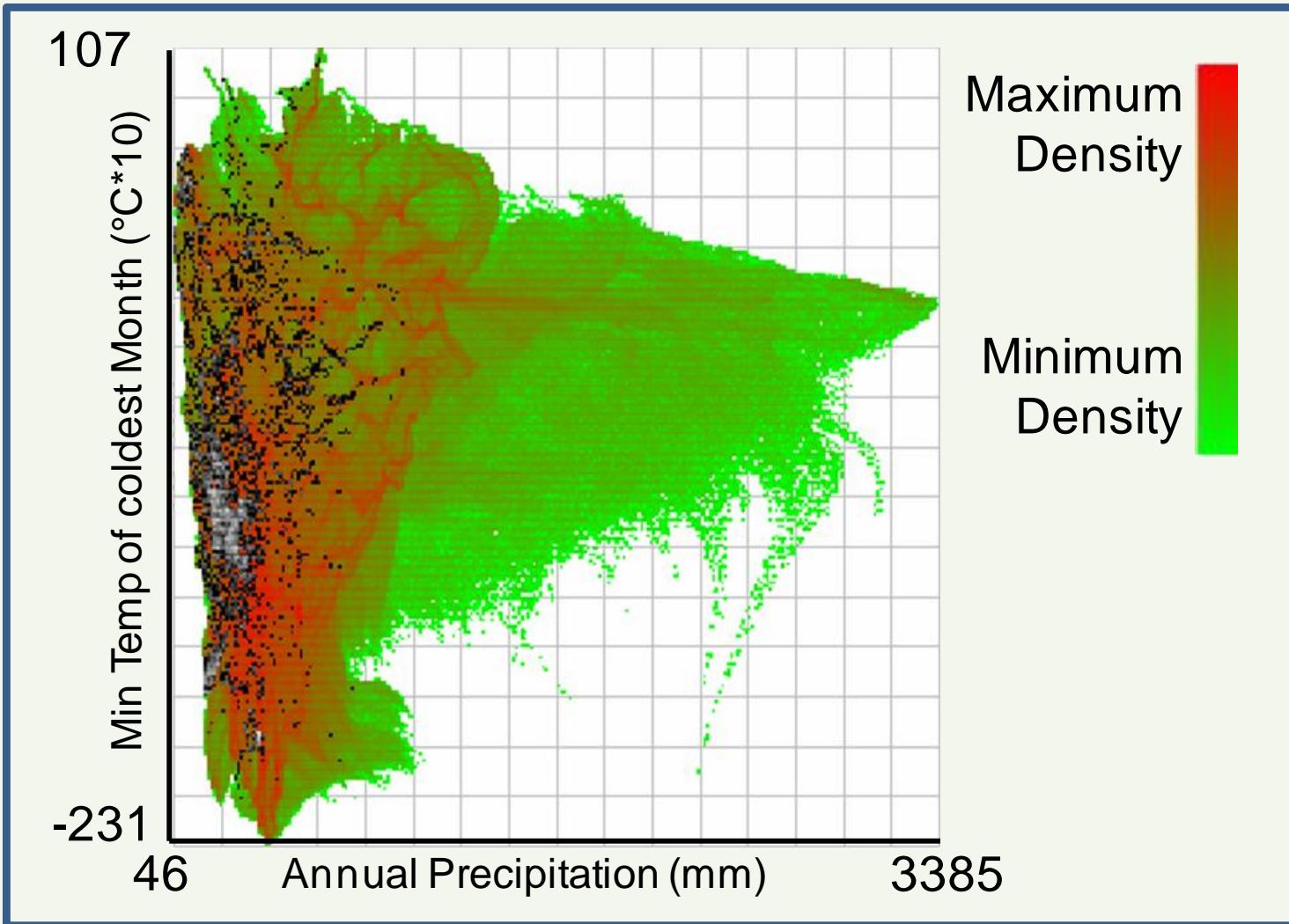
Geographical Space



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



Tamarisk Occurrences





Can we?

- Create a species distribution modeling method that:
 - More closely matches ecological theory?
 - Allows visualization of the model in environmental space?
 - Does not use absence points?
 - Allows integration of physiological knowledge and occurrence data?
 - Allows editing the model to try scenarios?
 - Represents uncertainty?



Some Caveats

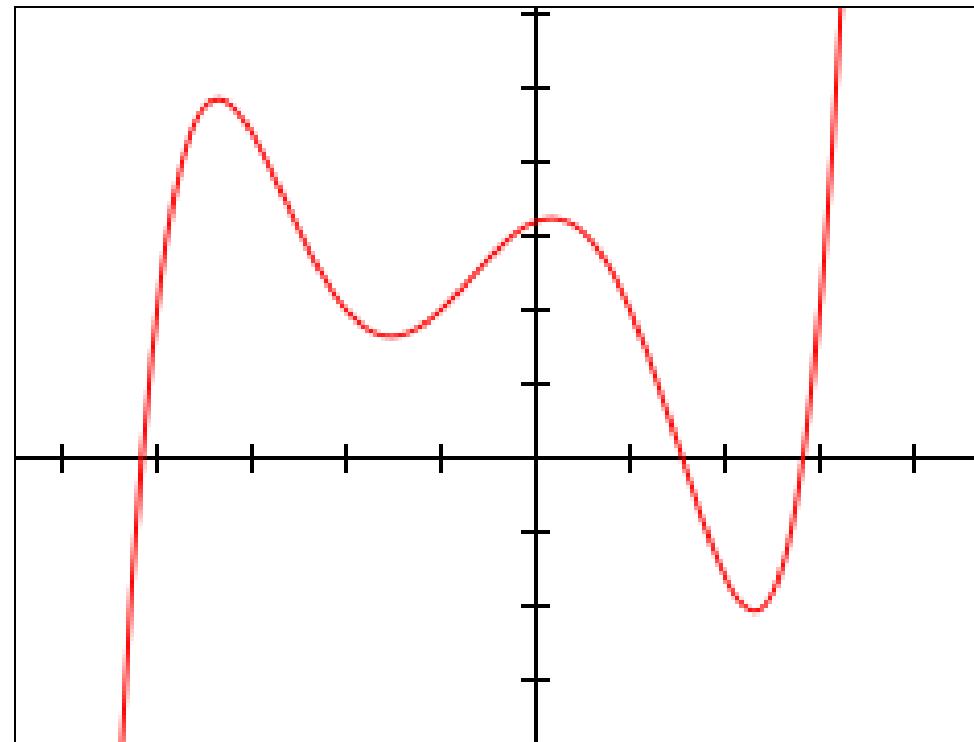
- We are modeling “observations”
 - A. Modeling occurrences with some uncertainty
 - B. Modeling the realized niche if the data is a complete sample for the environmental space the species currently occupies
 - C. Modeling the fundamental niche if B is true and the species is covering its full possible range of habitats
- Habitat Suitability Modeling
 - Predicting the potential species distribution



Problems with Polynomials

$f(x) = a_0 + a_1x + a_2x^2 + \dots + a_nx^n$, where $a_n \neq 0$ and $n \geq 2$

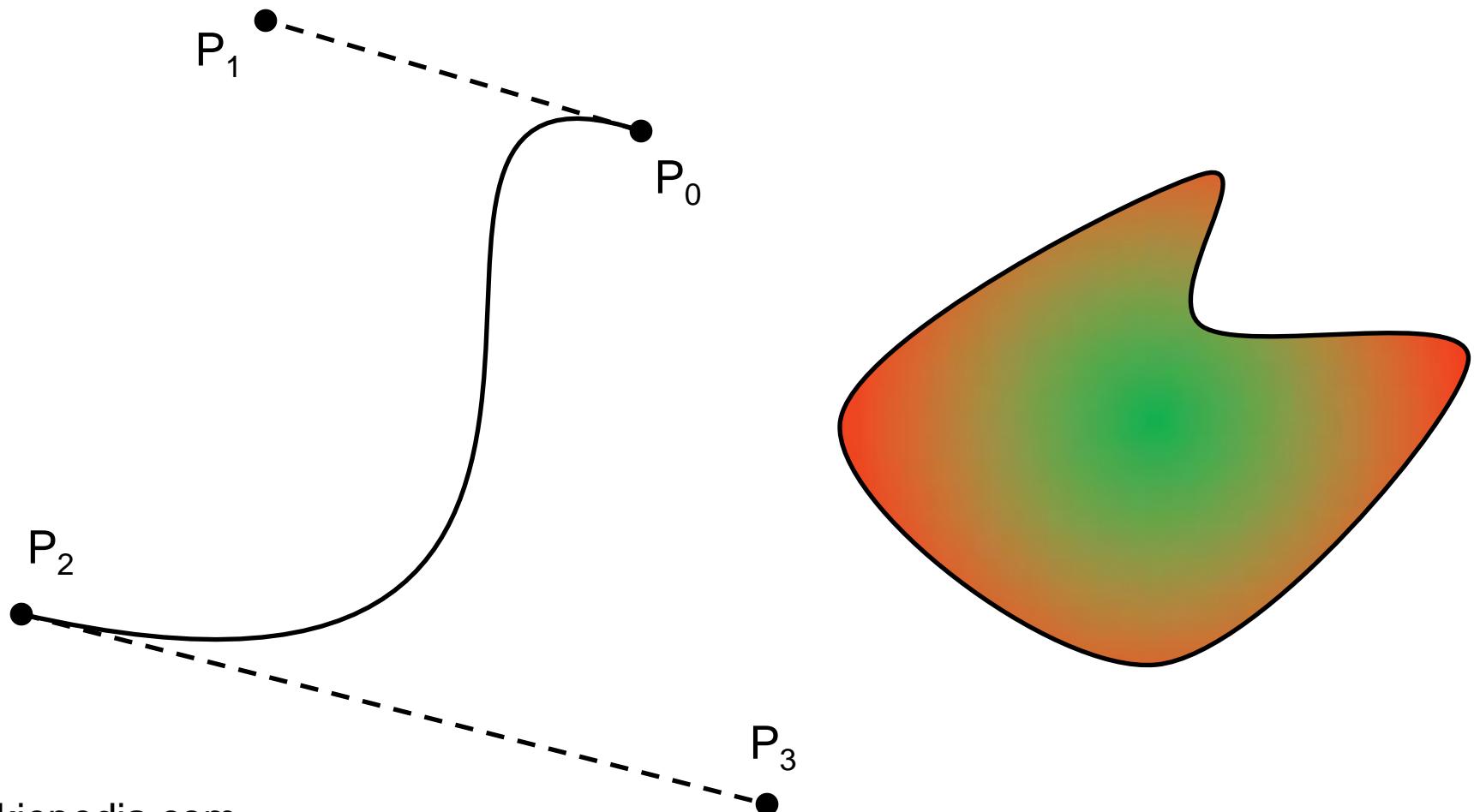
- Lack flexibility
- Not well behaved at boundaries





Bezier and Spline Curves

$$\mathbf{B}(t) = (1-t)^3 \mathbf{P}_0 + 3(1-t)^2 t \mathbf{P}_1 + 3(1-t)t^2 \mathbf{P}_2 + t^3 \mathbf{P}_3 , \quad t \in [0, 1].$$



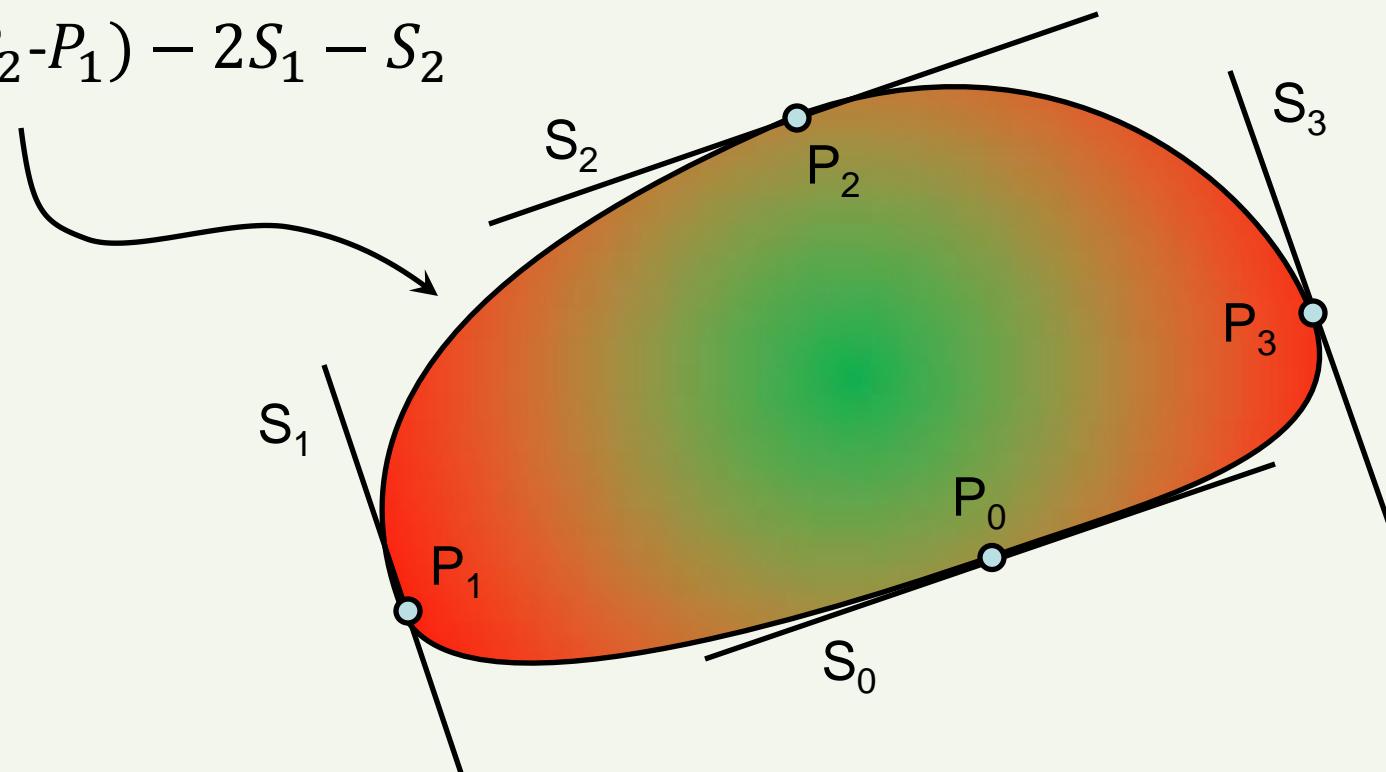


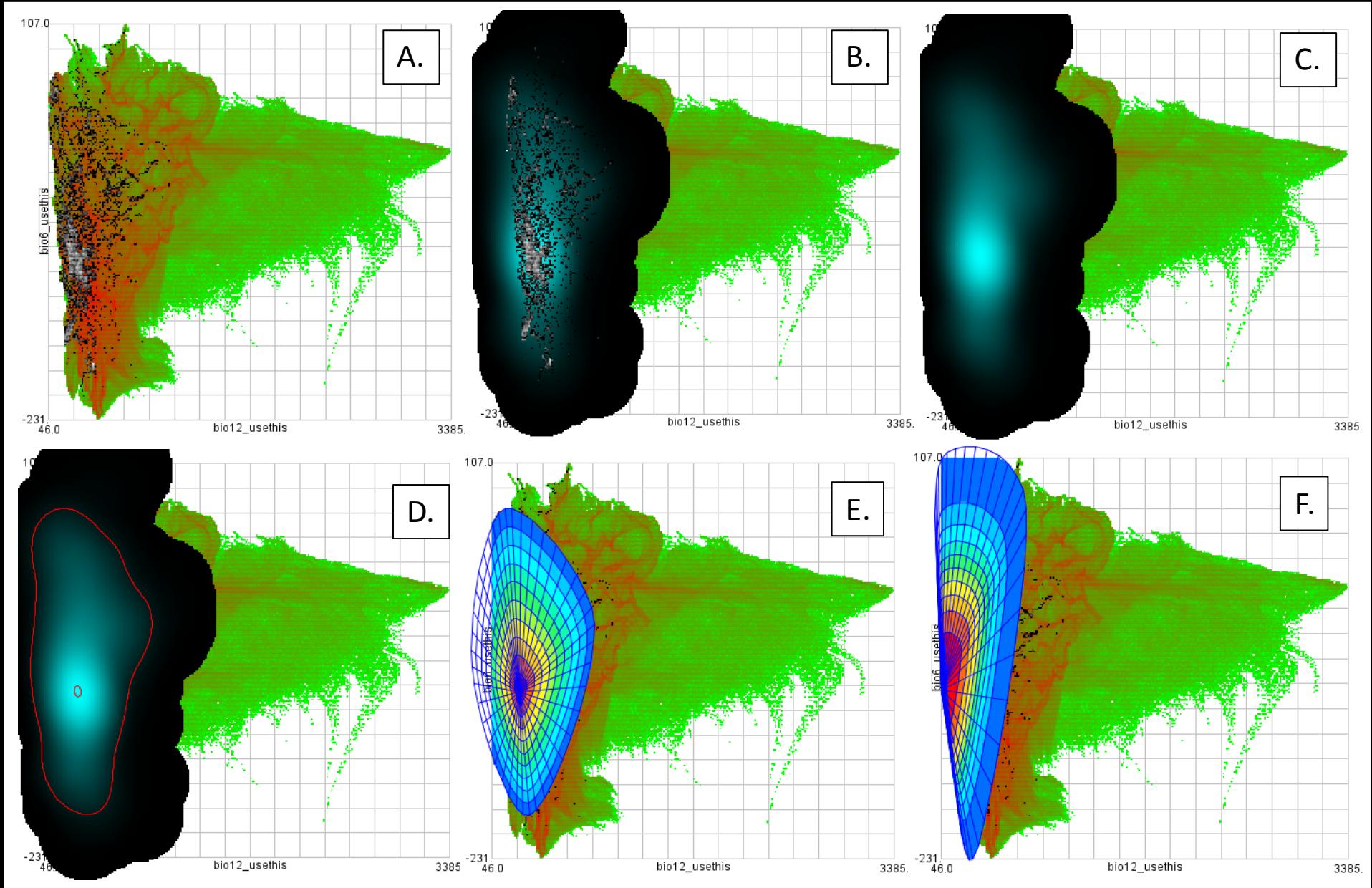
Modified Bezier Curves

$$B(t) = at^3 + at^2 + S_1t + P_1$$

$$a = 2(P_1 - P_2) + S_1 + S_2$$

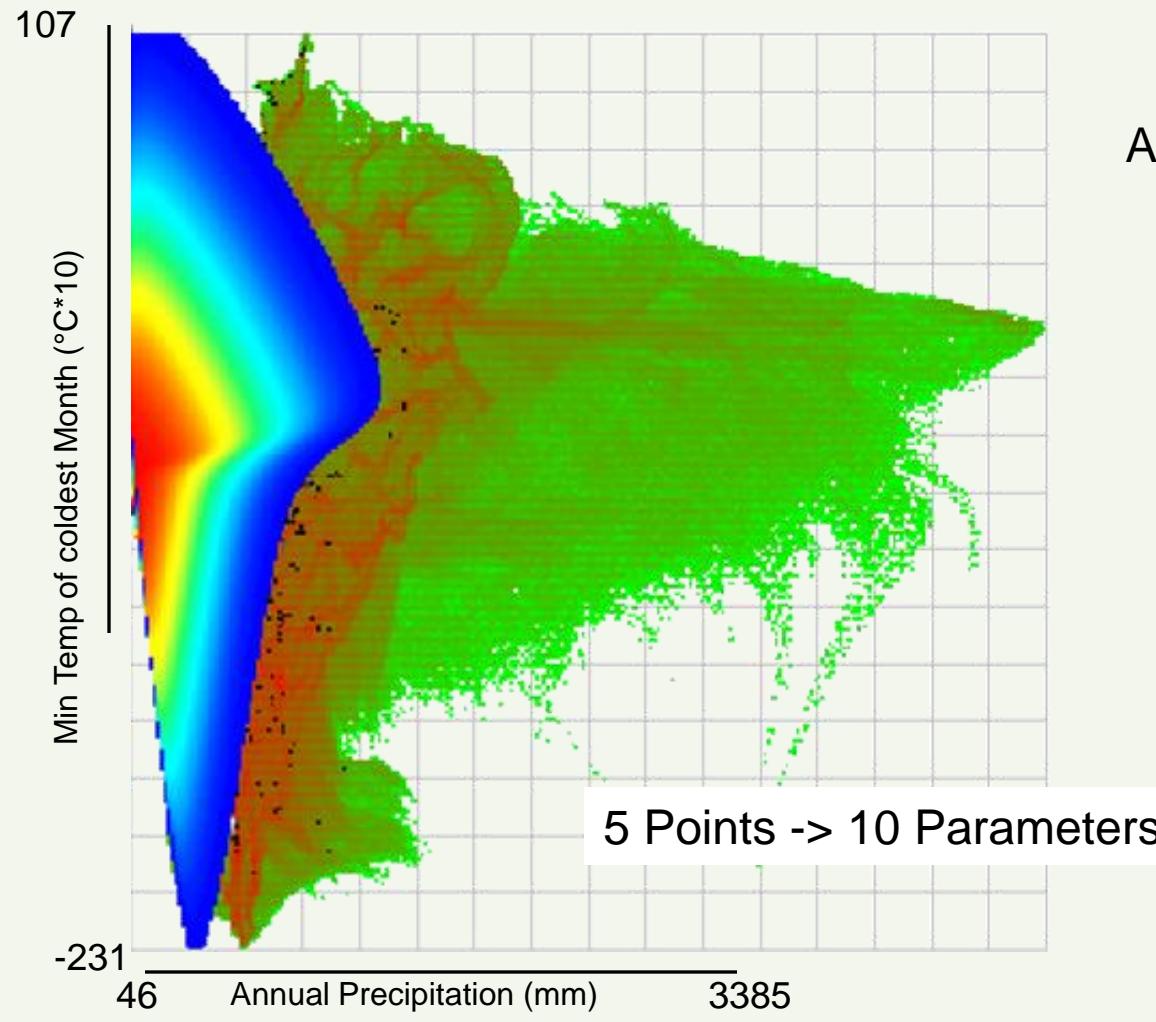
$$b = 3(P_2 - P_1) - 2S_1 - S_2$$







HEMI *Tamarix* Model

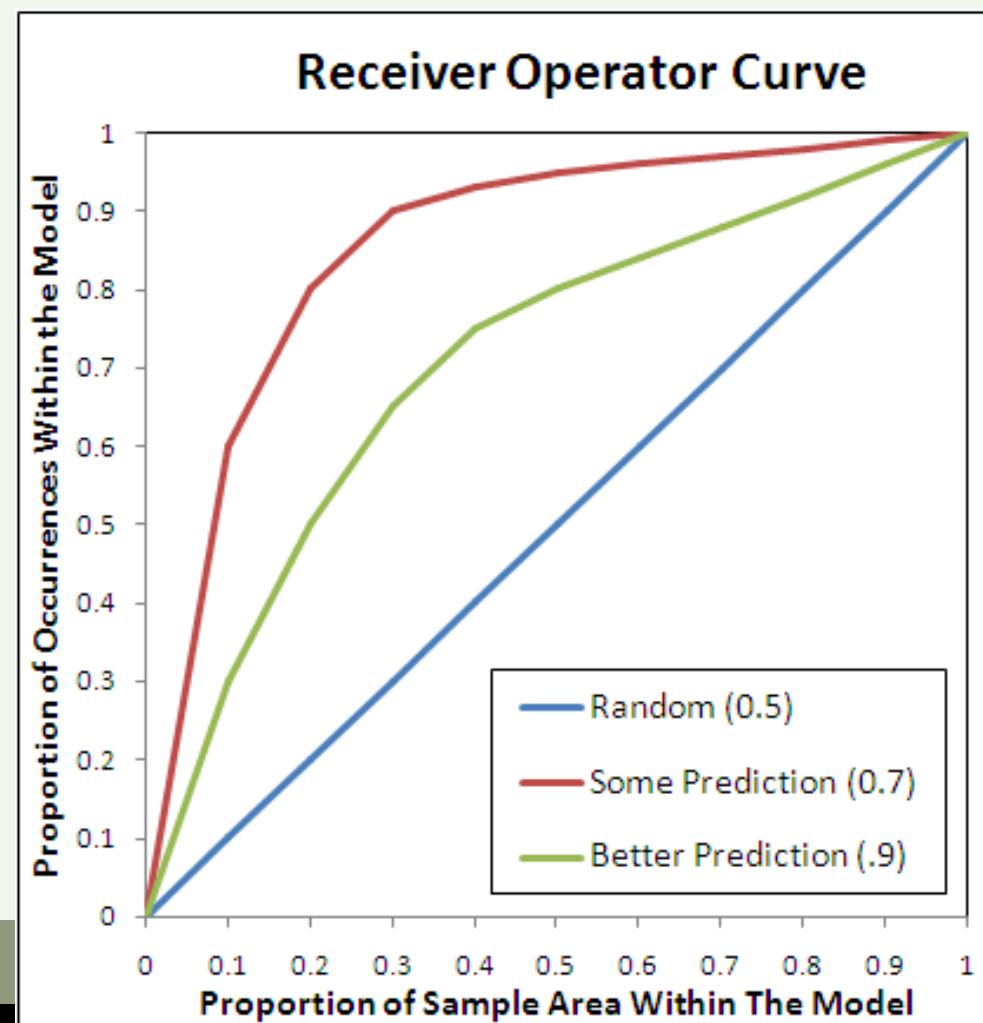


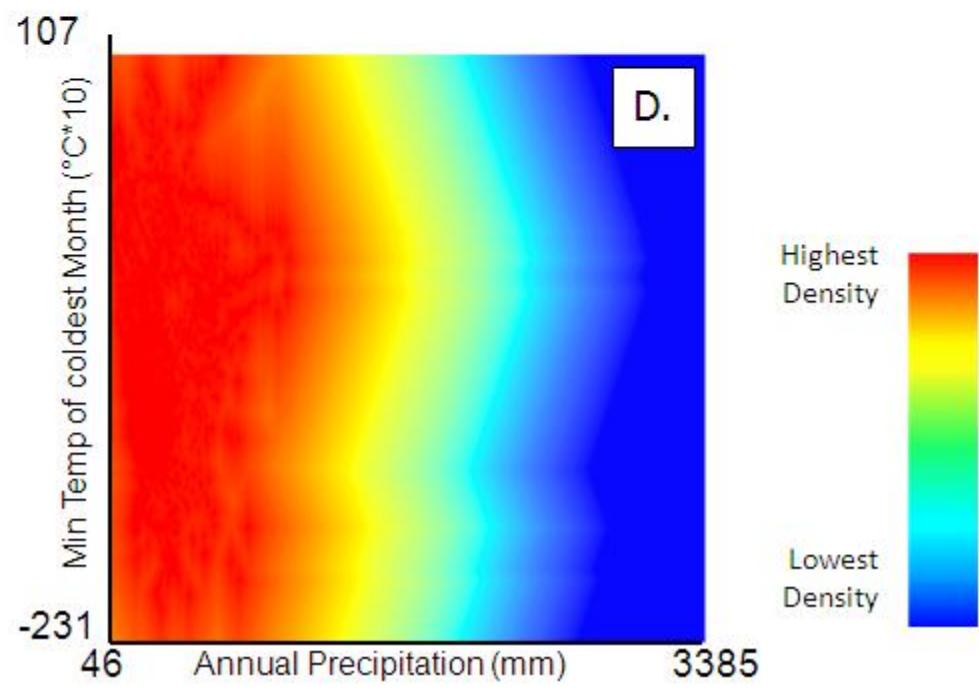
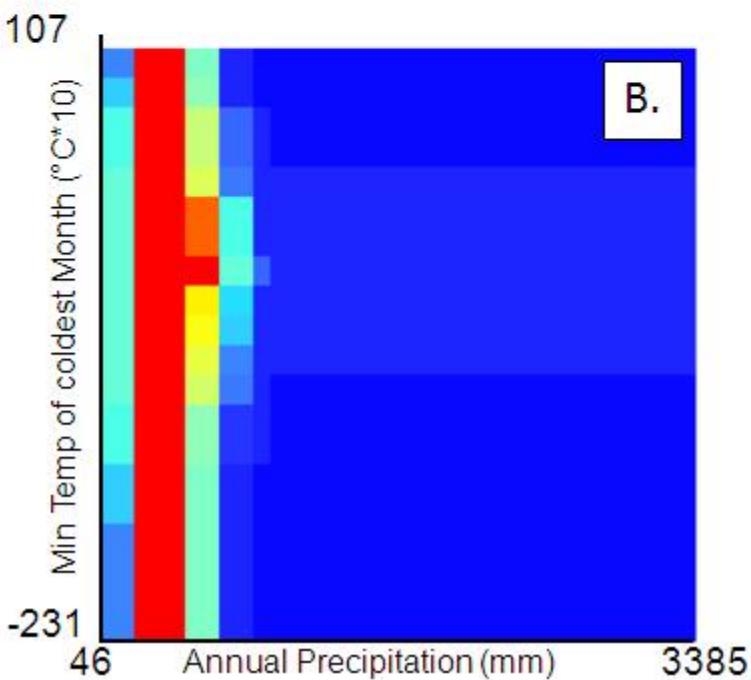
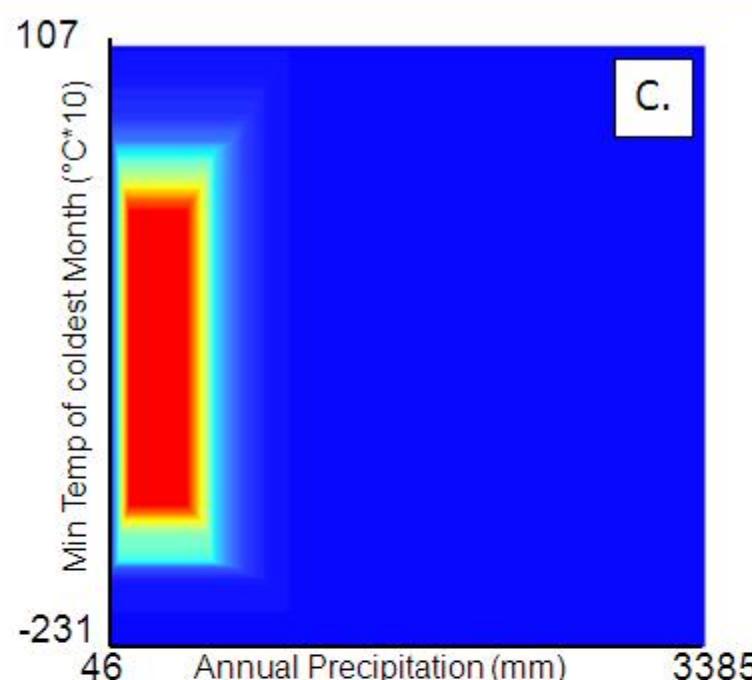
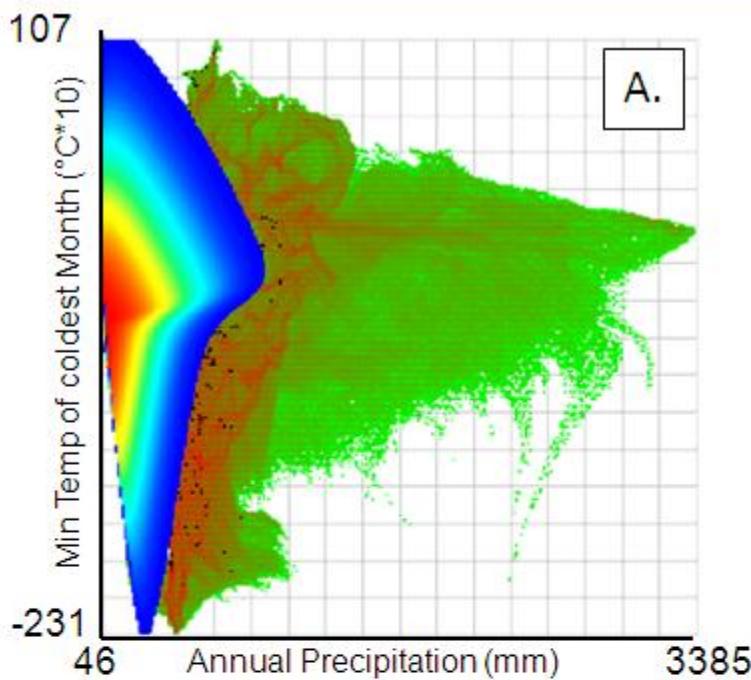


Area Under the Curve Metric

- Area Under the Curve (AUC)

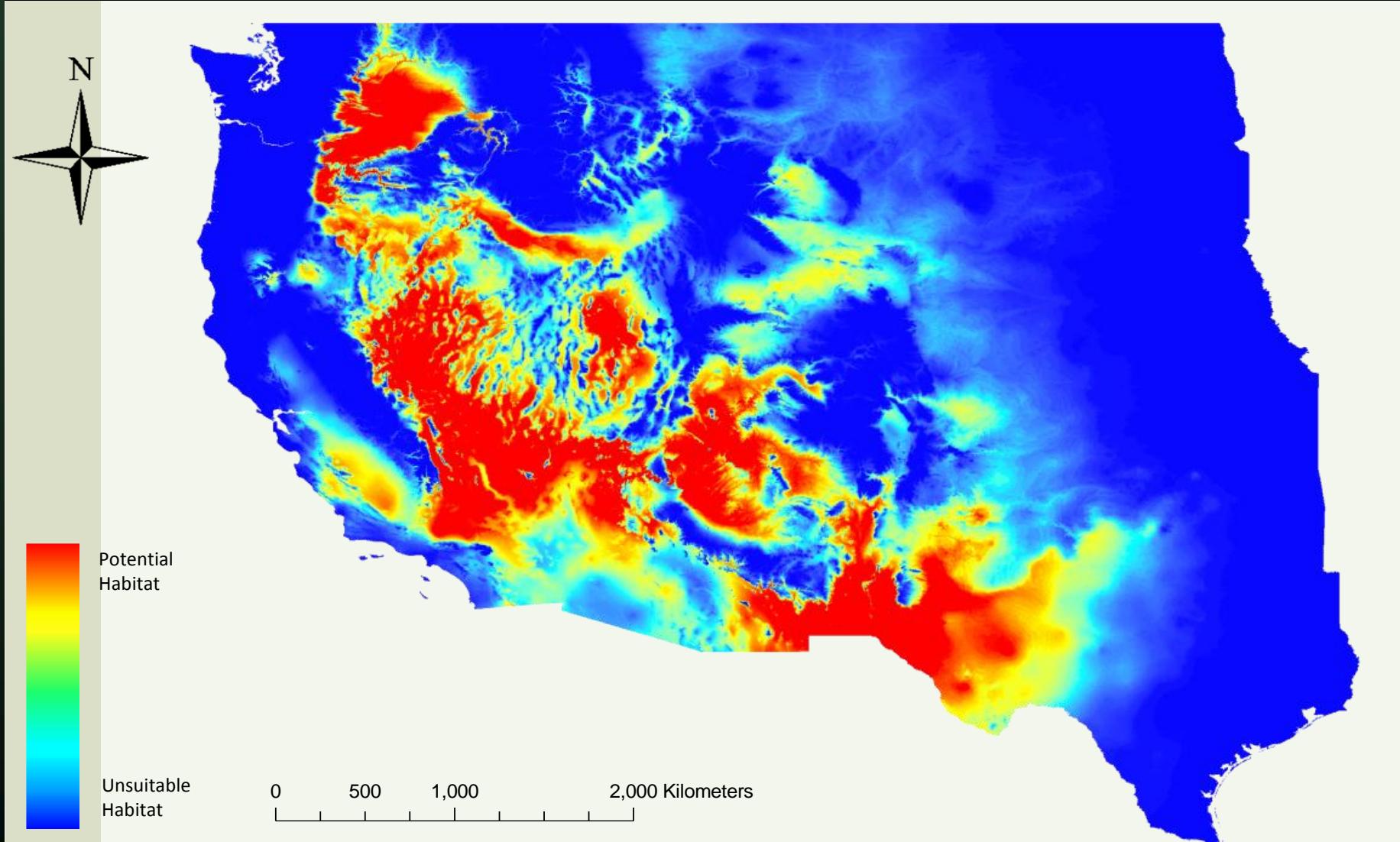
- 1=Perfect
- 0=Worthless





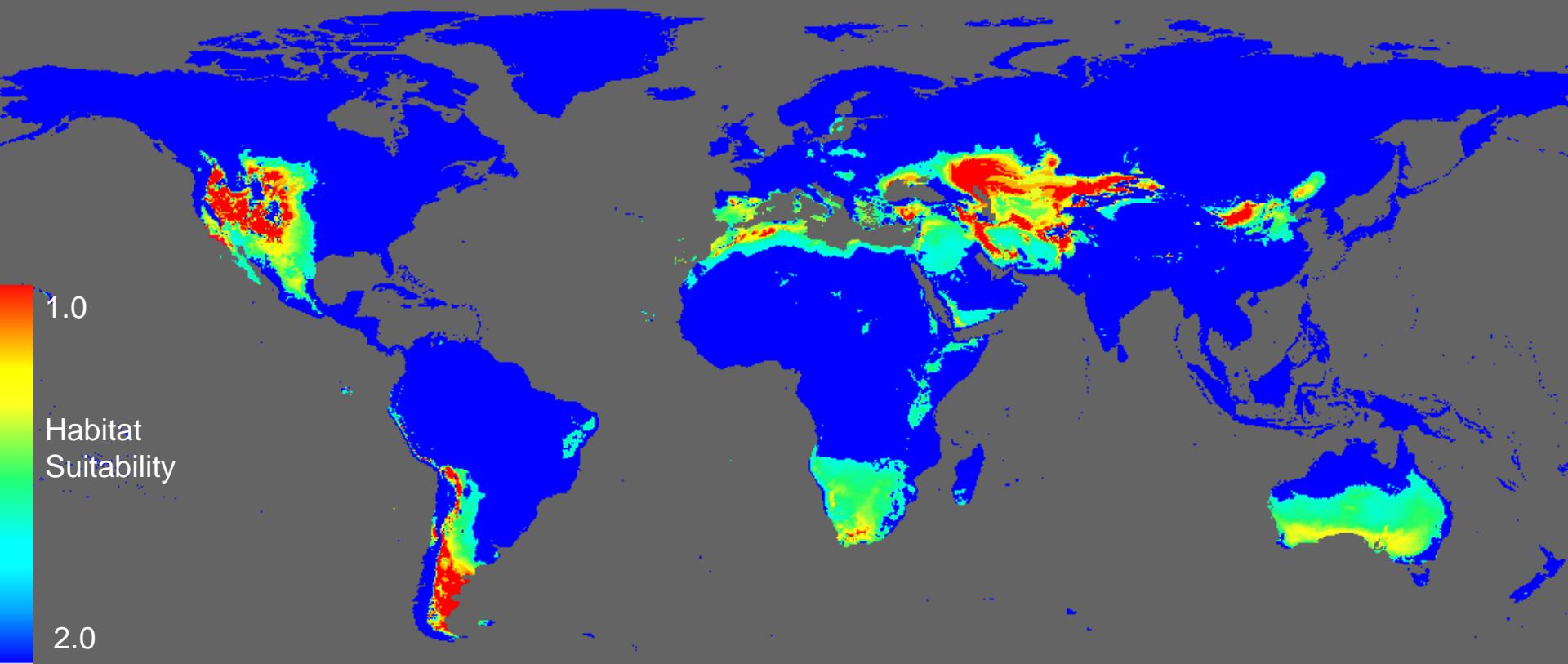


Potential Habitat





Global Tamarisk Map?





Migration Animations

- Jim's web site
 - <http://tinyurl.com/6krghts>
- Gray whale model
 - <http://tinyurl.com/4xtmzho>
- Barn swallows



Conclusions

- We can visualize models in environmental space
 - At least in 2 dimensions
- We can build constrained models and edit the models for scenarios
- We can reduce the complexity of the models
- Absence points are not required
- Categorical variables have to be modeled separately for each category



Next Steps

- Characterize a number of species to determine how to constrain the envelopes
- Develop likelihood model to fit Bezier curves?
- Include uncertainty analysis and error surfaces
- Move HEMI to the web?
- More “good” data!



Modeling Online

Welcome Nicholas Logout | My Profile | December 12th 2009



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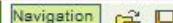
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Navigation



Current Project: NREL Mountain Nyala Project

Location



Legend

Edit

Plants

Tamarisk

GeoRasters

MaxEnt Model Tamari

Backgrounds

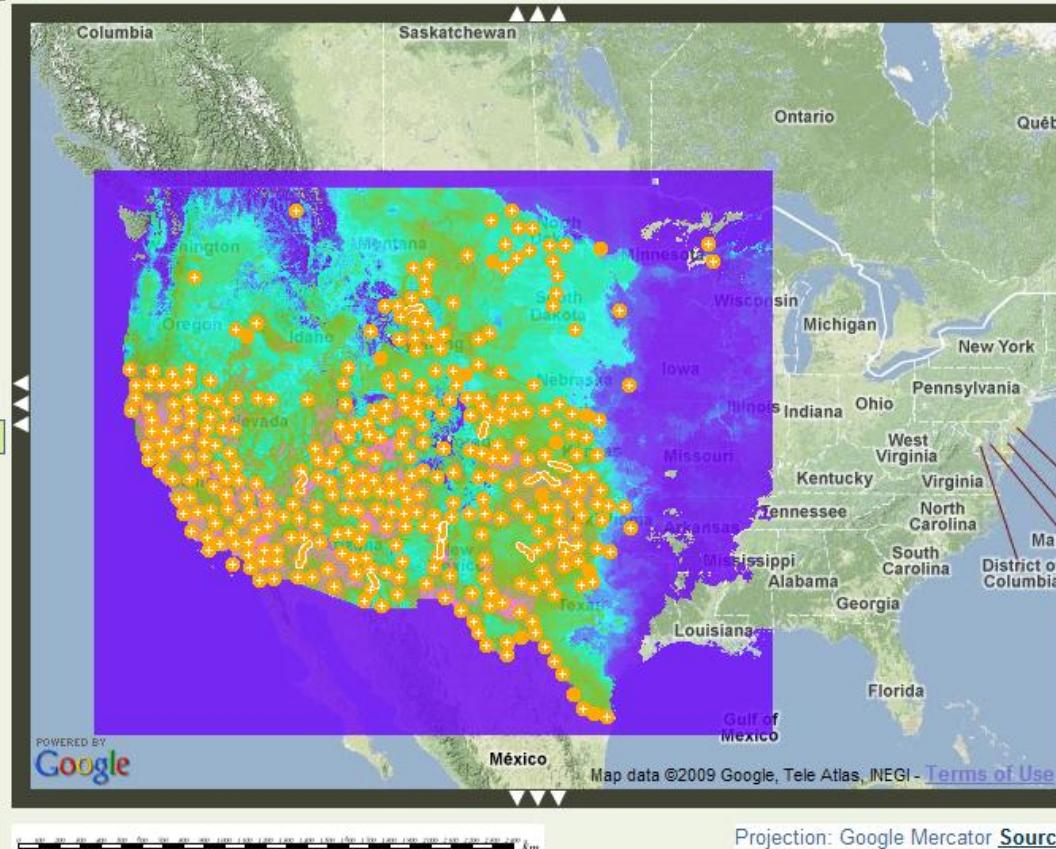
Google: Terrain

Google: Map

Google: Satellite

Google: Hybrid

Tools



Projection: Google Mercator [Sources](#)



Updated 10/29/2009

An IBIS website

Colorado State University



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