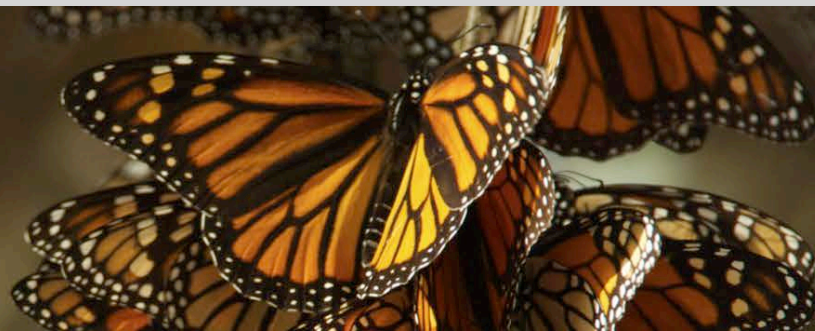


Western milkweed and monarch breeding habitat suitability modeling review

Joe Engler, Liz Cruz, & Madeline Steele,
February 18th, 2016, 8:00 am Pacific



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FOR INVERTEBRATE CONSERVATION



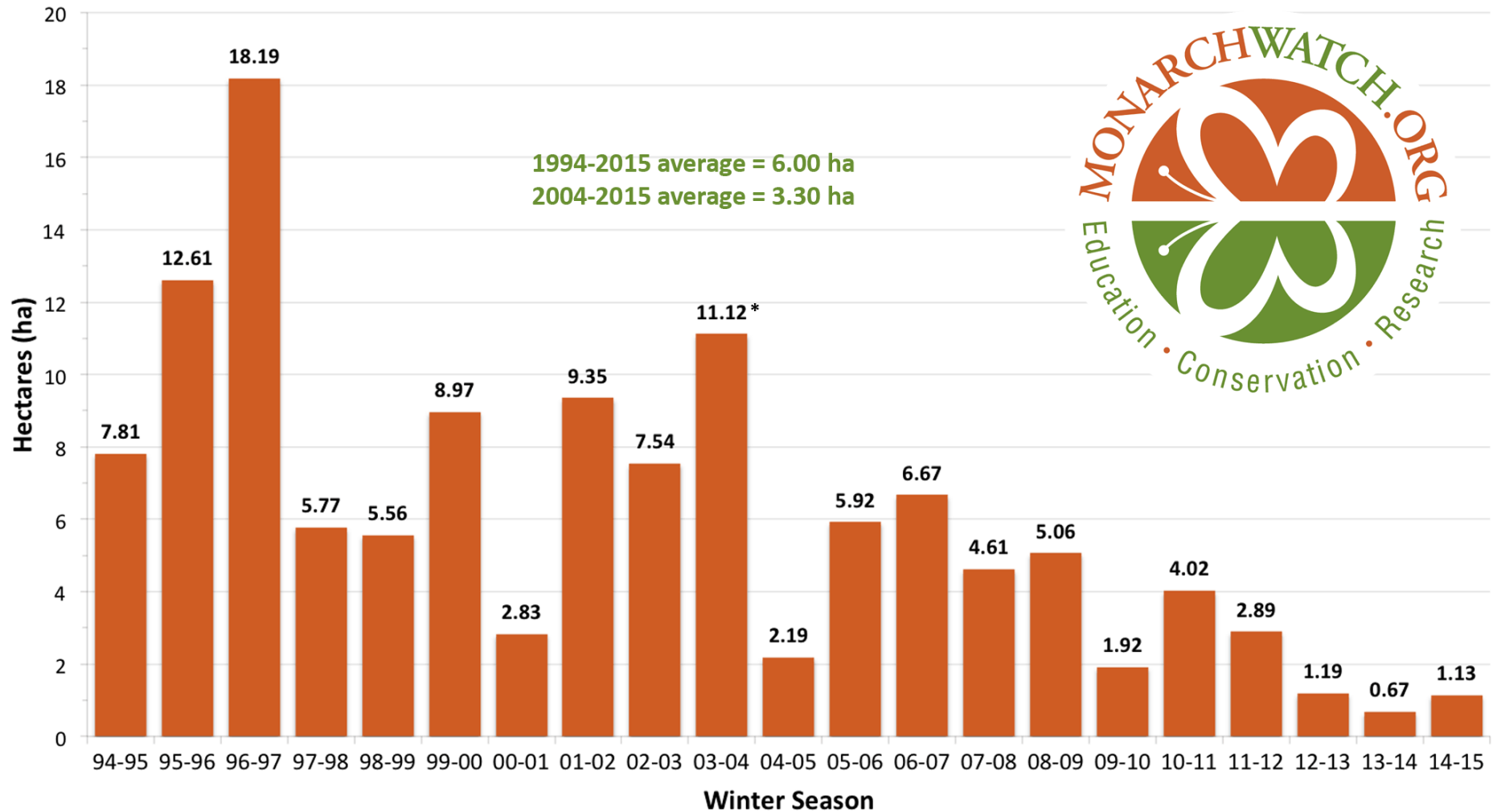


Meeting outline

- Motivation for project
- Milkweed and monarch database development
- Modeling methods
 - MaxEnt
 - Mitigating for sampling bias
 - Environmental variable selection
 - Defining the background
 - Model tuning
- Results review
- Discussion



Total Area Occupied by Monarch Colonies at Overwintering Sites in Mexico



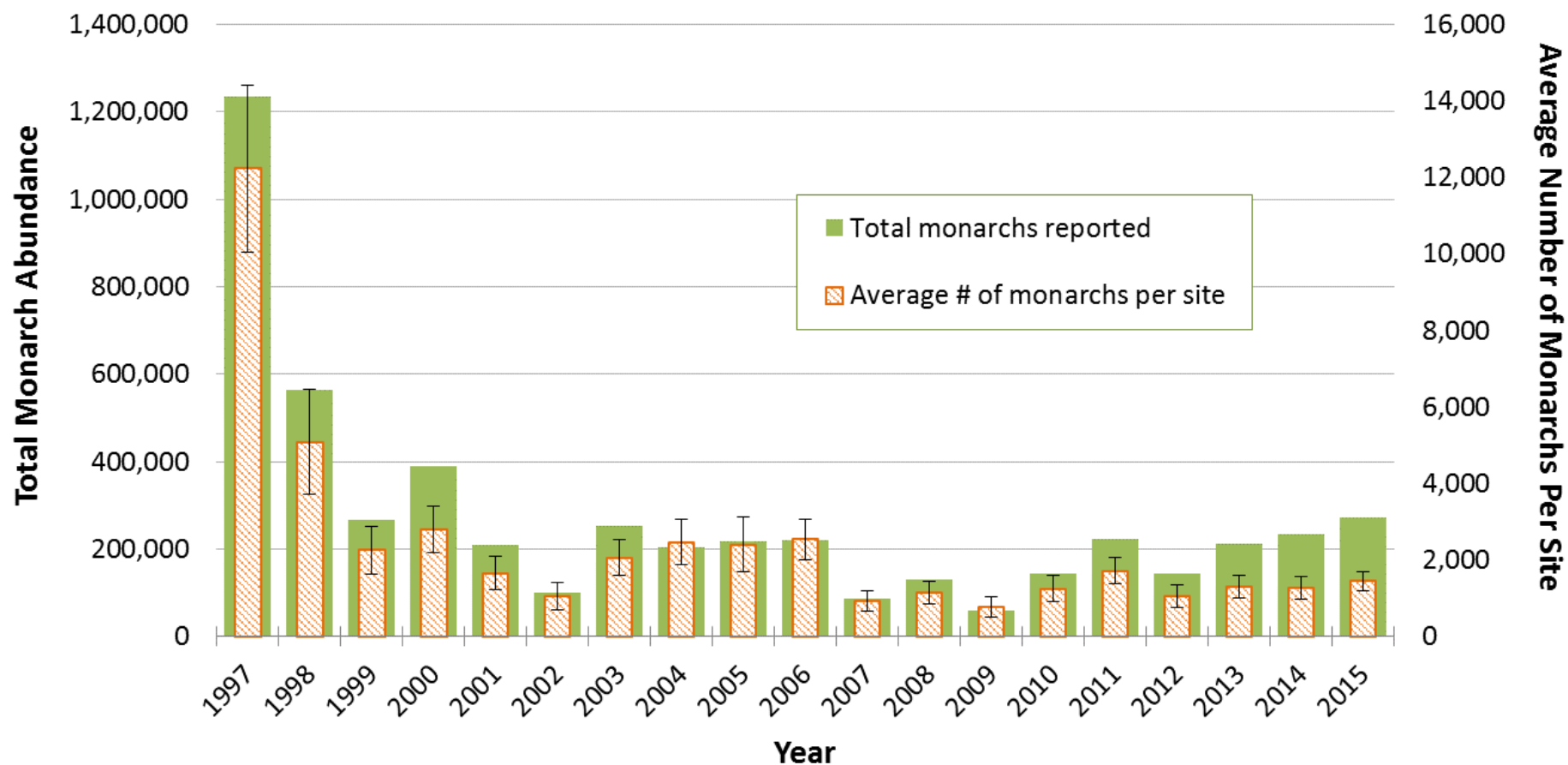
Data for 1994-2003 collected by personnel of the Monarch Butterfly Biosphere Reserve (MBBR) of the National Commission of Natural Protected Areas (CONANP) in Mexico. Data for 2003-2014 collected by World Wildlife Fund Mexico in coordination with the Directorate of the MBBR.

* Represents colony sizes measured in November of 2003 before the colonies consolidated. Measures obtained in January 2004 indicated the population was much smaller, possibly 8-9 hectares. CT

Western Monarch Thanksgiving Count

Total and Average Abundance Estimates w/ Standard Error of the Means
at 76-187 Overwintering Sites from 1997-2015
(Monroe *et al.* 2016)

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Western Monarch Overwintering Habitat

In the fall and winter, monarchs are found clustering in hundreds of coastal California groves

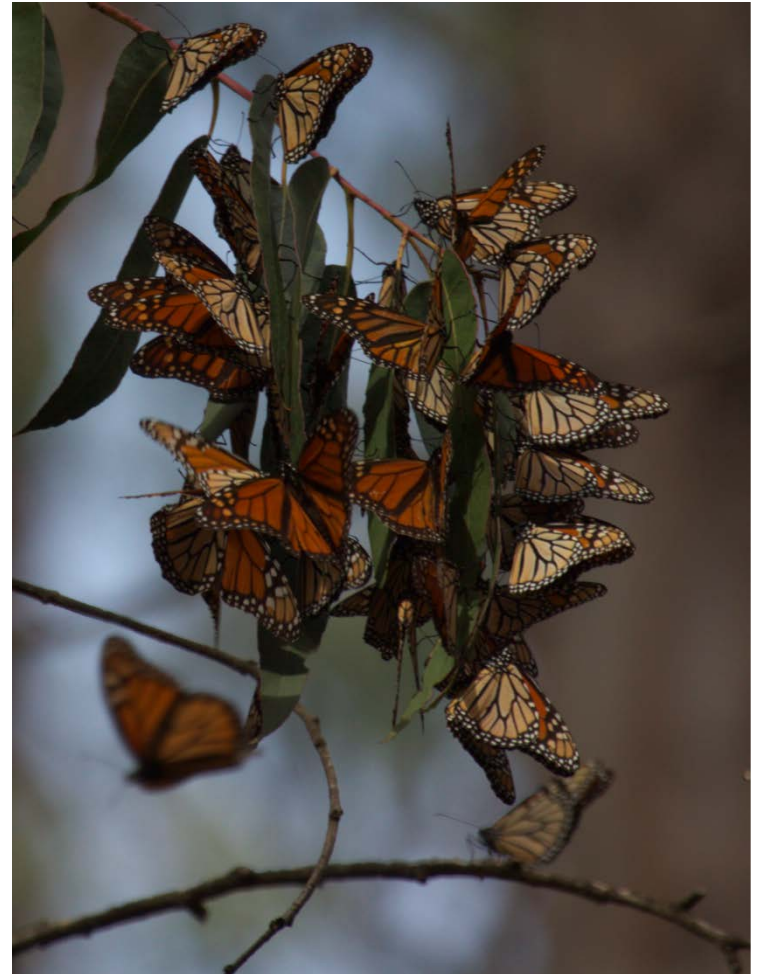
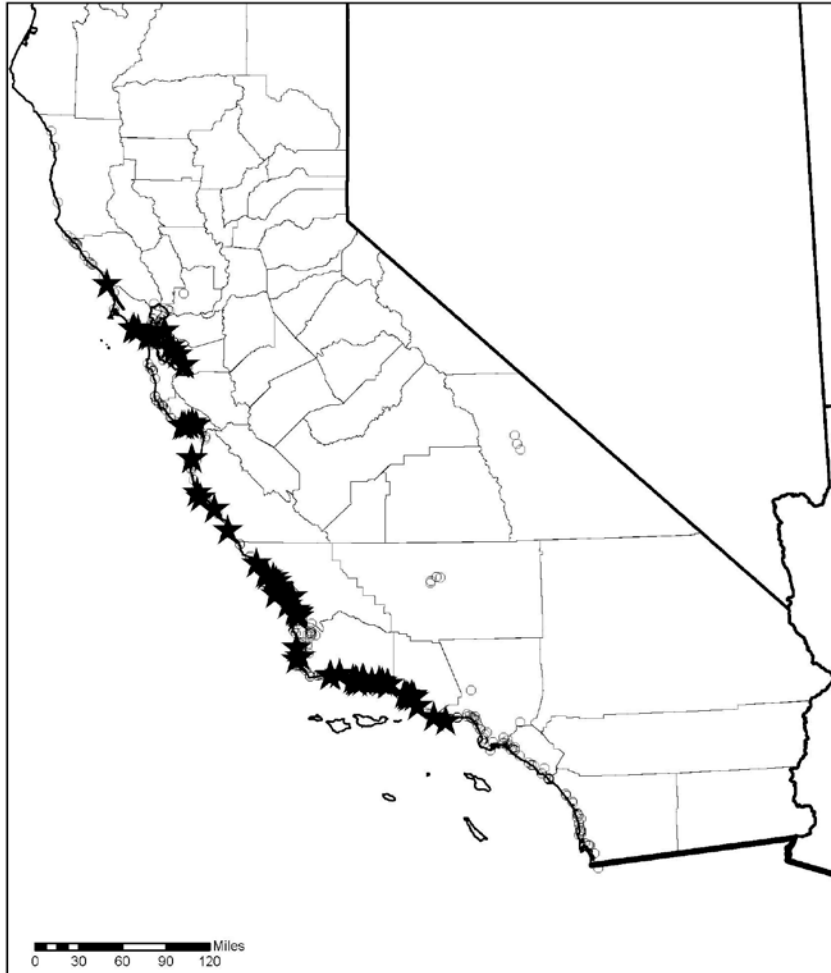
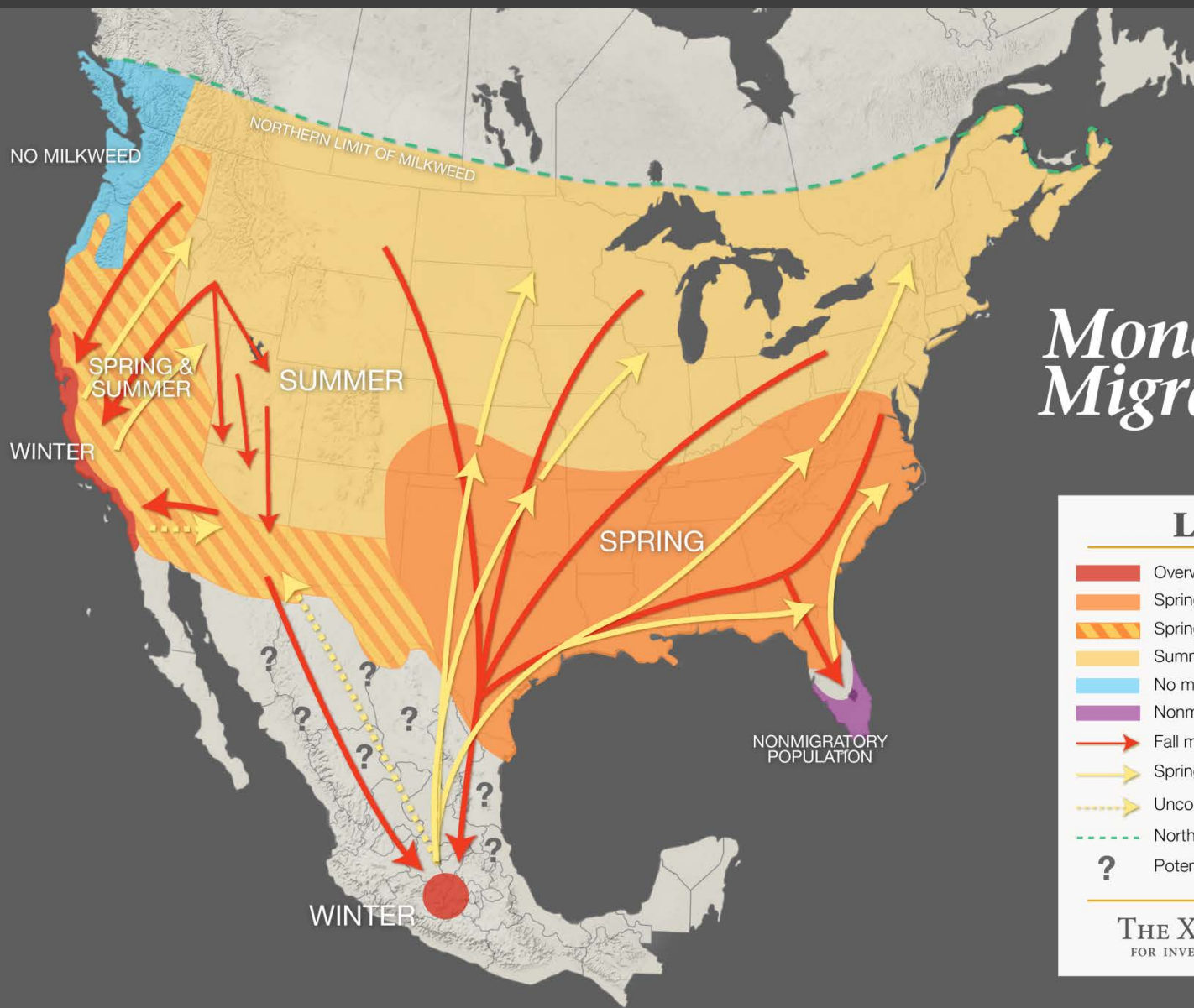


Photo: The Xerces Society/Carly Voight



Monarch Migration

Spring & Fall



LEGEND

- Overwintering areas
- Spring breeding areas
- Spring & summer breeding areas
- Summer breeding areas
- No milkweed - no breeding area
- Nonmigratory population
- Fall migration
- Spring migration
- Unconfirmed migration
- Northern limit of milkweed
- ? Potential monarch breeding habitat

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Dingle et al. 2005

Distribution of western monarchs throughout the year

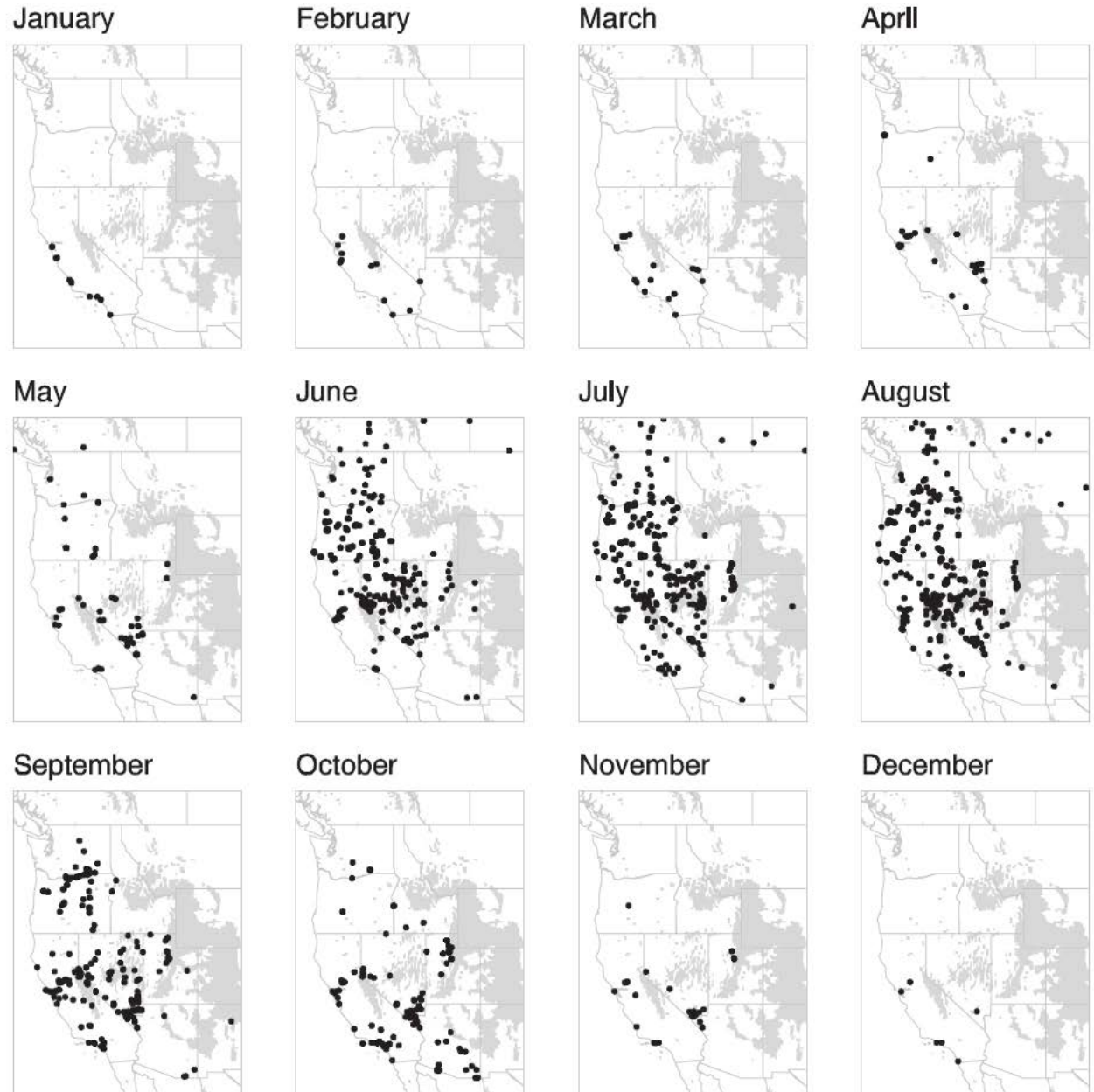
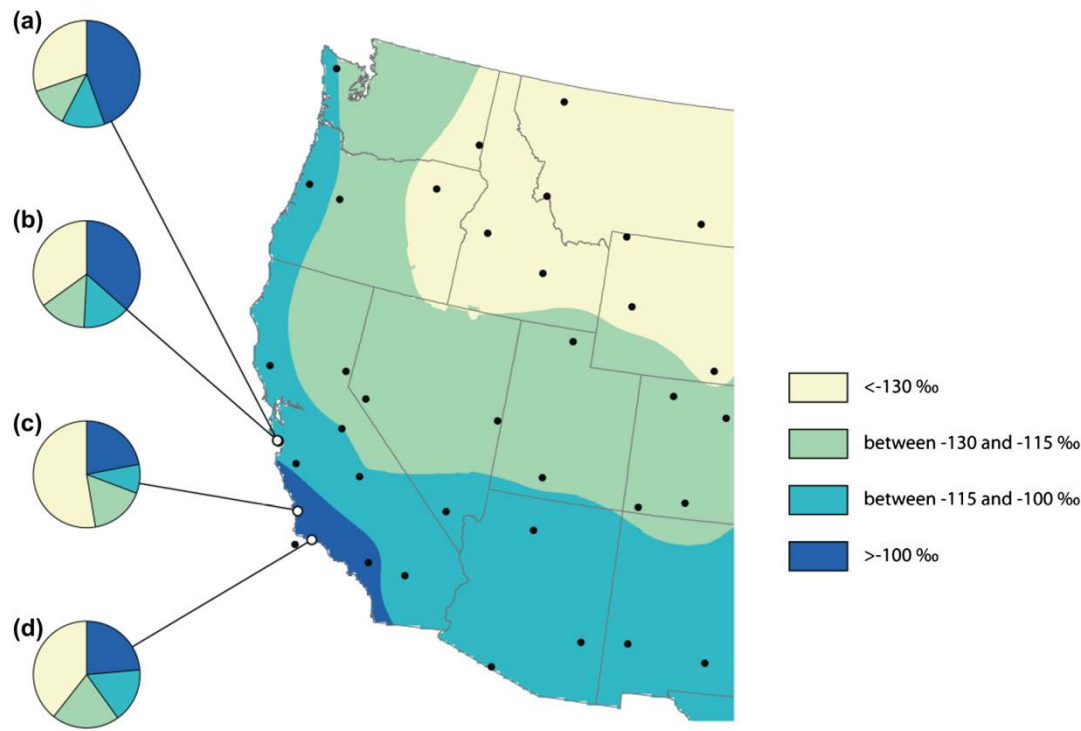


Figure 1. Collection records for monarch butterflies in western North America. Grey shaded areas are above 2000 m elevation.

Monarch Natal Habitat

We understand general regional patterns in monarch natal habitat suitability, but higher resolution maps would be very useful



Yang et al. 2015



Stephens and Frey 2010



The need for a habitat suitability model

- Identification of priority monarch areas needed for efficient use of limited funds
- We know that geographic features, climate variability, and milkweed availability influence monarch habitat distribution
- Species distribution models can quantify these relationships and help us prioritize landscapes



Project objectives

- Consolidate existing western milkweed and monarch records
- Collect new data for milkweed and monarchs (2015-2020)
- Compile geospatial data layers that may influence milkweed & monarch distributions



Objectives, continued

- Produce coarse-scale models that predict important regions for key milkweed species and for monarchs themselves.
- Use models to help prioritize landscapes and to guide surveys that can refine next year's models
- **An iterative process**



Primary Objectives

Build a database to house the large, and growing, collection of milkweed and monarch breeding observation records held by The Xerces Society.

Collect and incorporate USFWS milkweed field surveys and western milkweed and monarch breeding records from a variety of other sources.

Convert data to spatial format to be used in the western milkweed habitat suitability model.

How did we get the data?

- Request for data sent to researchers, herbariums, and other (FWS) regional biologists
- Obtained through agreements with Xerces/FWS
- Returned FWS field survey forms and other field surveys
- Downloads from online consortiums and herbariums
- ArcGIS online web mapping application
- Social Media

Main Providers:

- The Xerces Society
- US Fish & Wildlife
- SEINet
- Bureau of Land Management
- US Forest Service
- National Park Service
- Consortium of Pacific Northwest Herbaria
- Consortium of California Herbaria
- iNaturalist
- National Phenology Network
- BISON (USGS)
- OSU Herbarium (Oregon Plant Atlas)
- Journey North
- Hugh Dingle (UC Davis)
- Monarch Larva Monitoring Project (MLMP)
- Flickr
- GBIF

Original Source Data:

65 Universities

13 Government agencies

10 Botanical Gardens

7 Consortiums

6 Conservation Organizations

6 Museums

5 Research Organizations

6 Other

Major Challenges:

- 92 input files in dozens of unique formats
- Cross-walking to new database structure
- Interpreting data (no explanation of fields)
- Inconsistent data values
- Poor or unknown location accuracy
- Datasets lacking information we sought
- Duplicates (mostly overlaps between data sources)

The Numbers

Began with a single spreadsheet of ~8,000 records shared by Xerces and ended with roughly...

- 28,000 total records (still many known duplicates to contend with)

- 60 data providers

- 90 input files

- 61% of records are for our target milkweed species and 26% of those records have a high enough accuracy level to be used in model

- 19% of records for monarch, 24% of those have good accuracy

- Only 12% of the total “good” monarch records indicate breeding activity

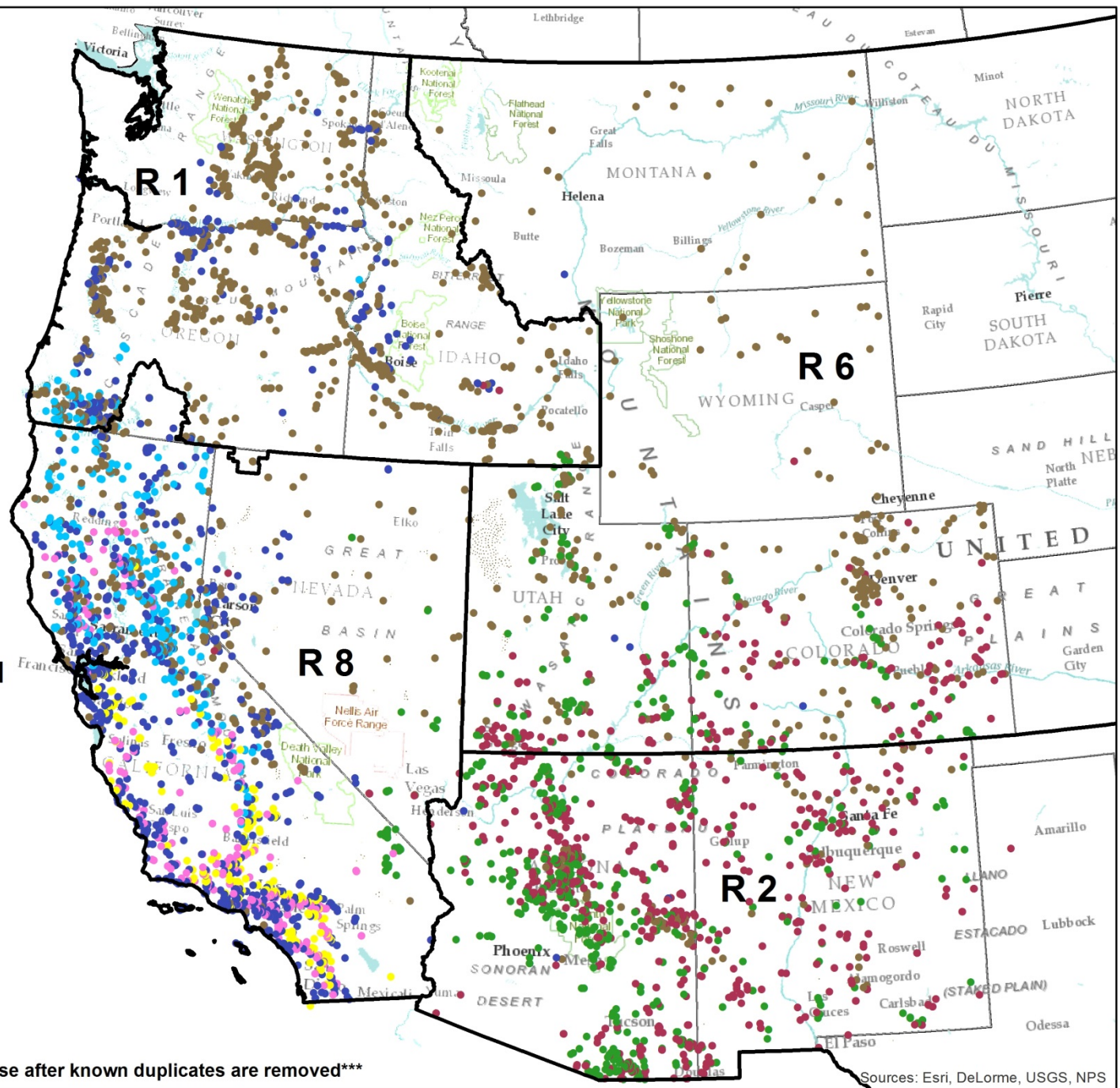
ProviderName	SourceFile	LocAccuracyCode	WindSpeed
RecordID	RecordDate_vbtlm	LocationRemarks	Precipitation
ProviderContact	RecordDate	LocReview	CloudCover_pct
ProviderNotes	RecordMonth	CoordinateUncertainty_m	Phenology
DatasetDate	RecordDay	GeoreferencedBy	PlantStructure
AddedBy	RecordYear	Habitat	PatchSize_m2
AddedDate	RecordedBy	IsUrban_YN	AvgPlantHeight_in
CompilationNotes	RecordedBy_Lastname	VegRemarks	PlantCount
DataRemarks	RecordedBy_Firstname	Breeding_YN	StemCount
Share_YN	RecordedBy_Contact	Lifestage	MaturePlantCount
ConsortiumDatabase	Recorder_Affiliation	Count	ImmaturePlantCount
ConsortiumUniqueID	Locality	AdultCount	FloweringPlantCount
OriginalSource	NearestCity	LarvaeCount	PlantCount_ImmaturePods
OriginalSourceID	State	PupaeCount	PlantCount_MaturePods
CatalogNum	County	EggCount	PodCollectionCount
CollectionNum	LandMgr	ObservationTime	EstimationMethod
BasisofRecord	LandMgrType	MonarchPopRemarks	PlantPopRemarks
SurveyType	Latitude	BehaviorNotes	OtherRemarks
Genus	Longitude	NectarFamilyUsed	Literature_YN
Species	VerbatimElevation	NectarSpeciesUsed	
ScientificName	DataProjection	NectarFamilyObserved	
VernacularName	Datum	NectarSpeciesObserved	
	GeoreferenceSource	Temperature_F	

13,817 Records

Observations

Target Milkweed, All

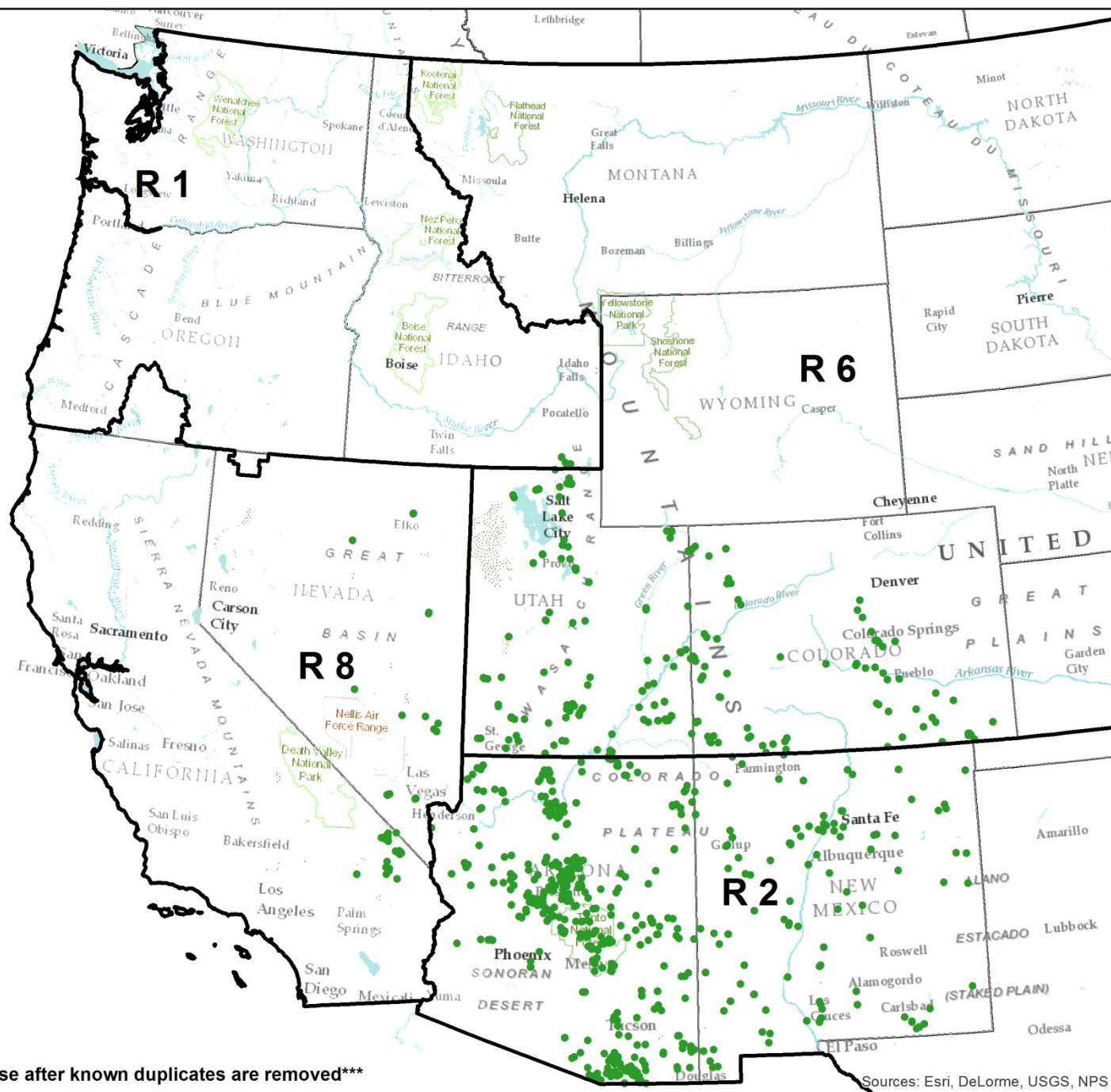
- Eriocarpa
- Asperula
- Californica
- Cordifolia
- Fascicularis
- Speciosa
- Subverticillata



Number of records will decrease after known duplicates are removed

Sources: Esri, DeLorme, USGS, NPS

1,996 Records



Observations

• Asperula

Number of records will decrease after known duplicates are removed

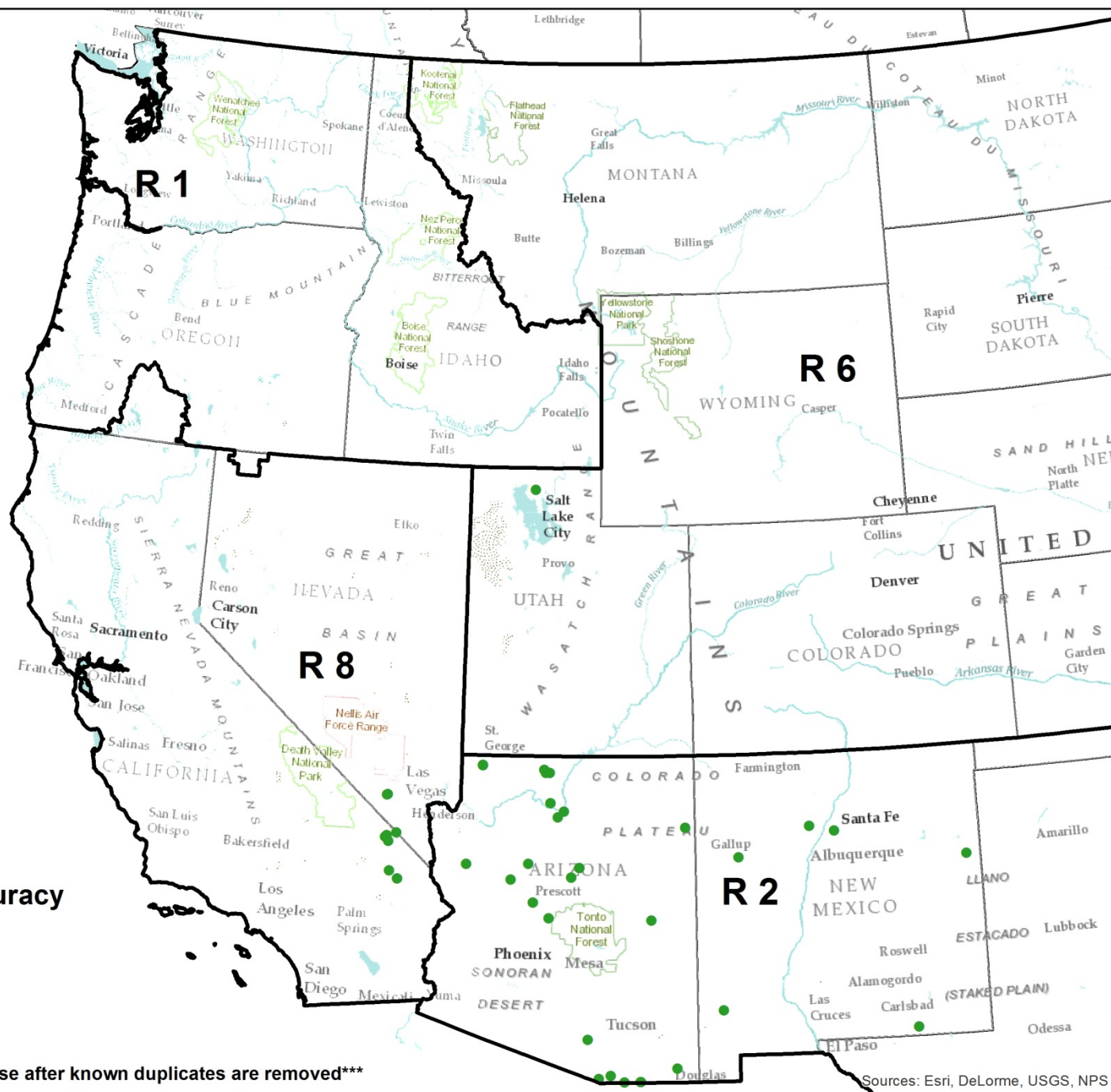
Sources: Esri, DeLorme, USGS, NPS

56 Records

Medium to High Accuracy
Observations

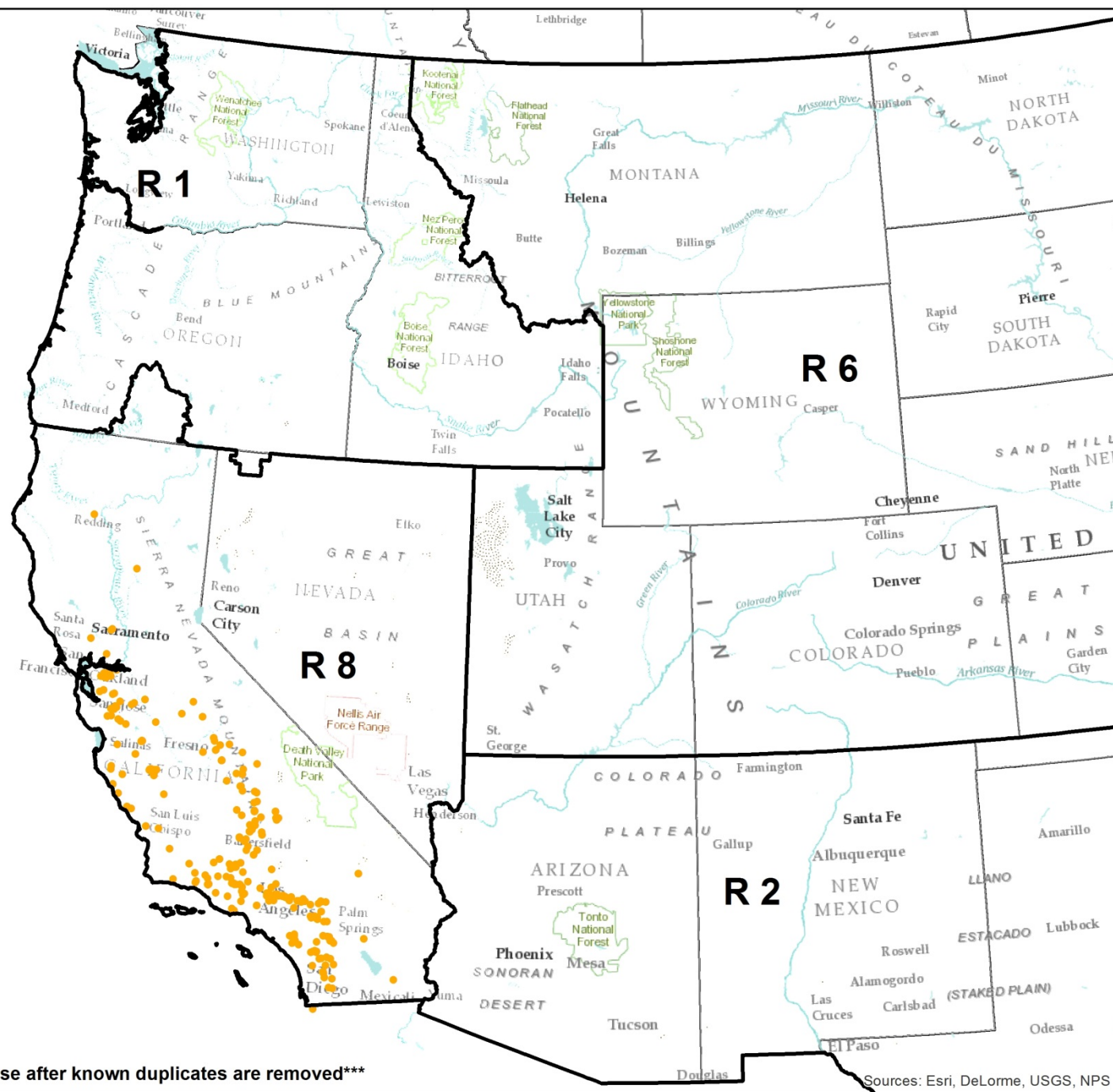
● Asperula

Number of records will decrease after known duplicates are removed



Sources: Esri, DeLorme, USGS, NPS

605 Records



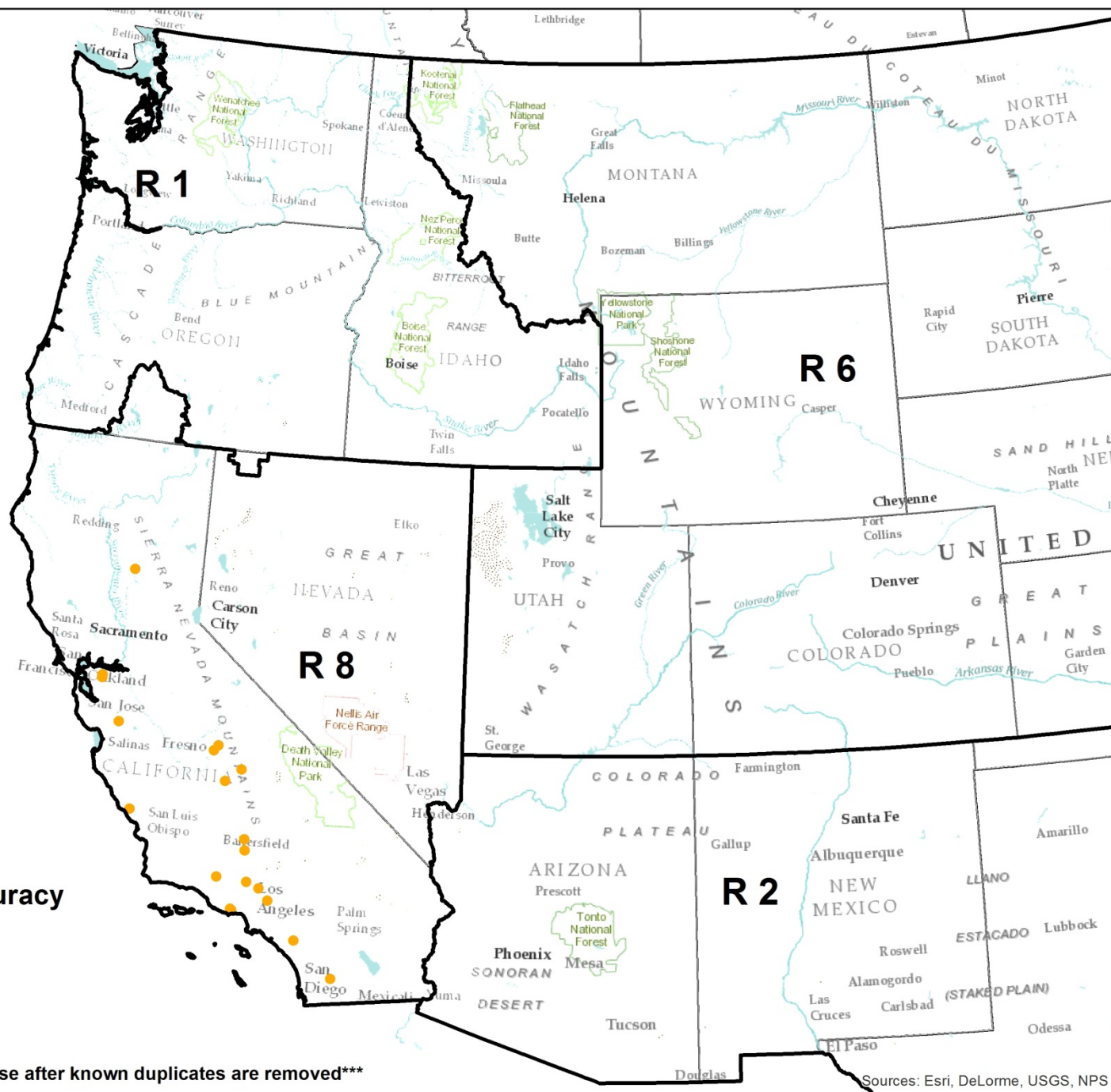
Observations

• Californica

Number of records will decrease after known duplicates are removed

Sources: Esri, DeLorme, USGS, NPS

20 Records



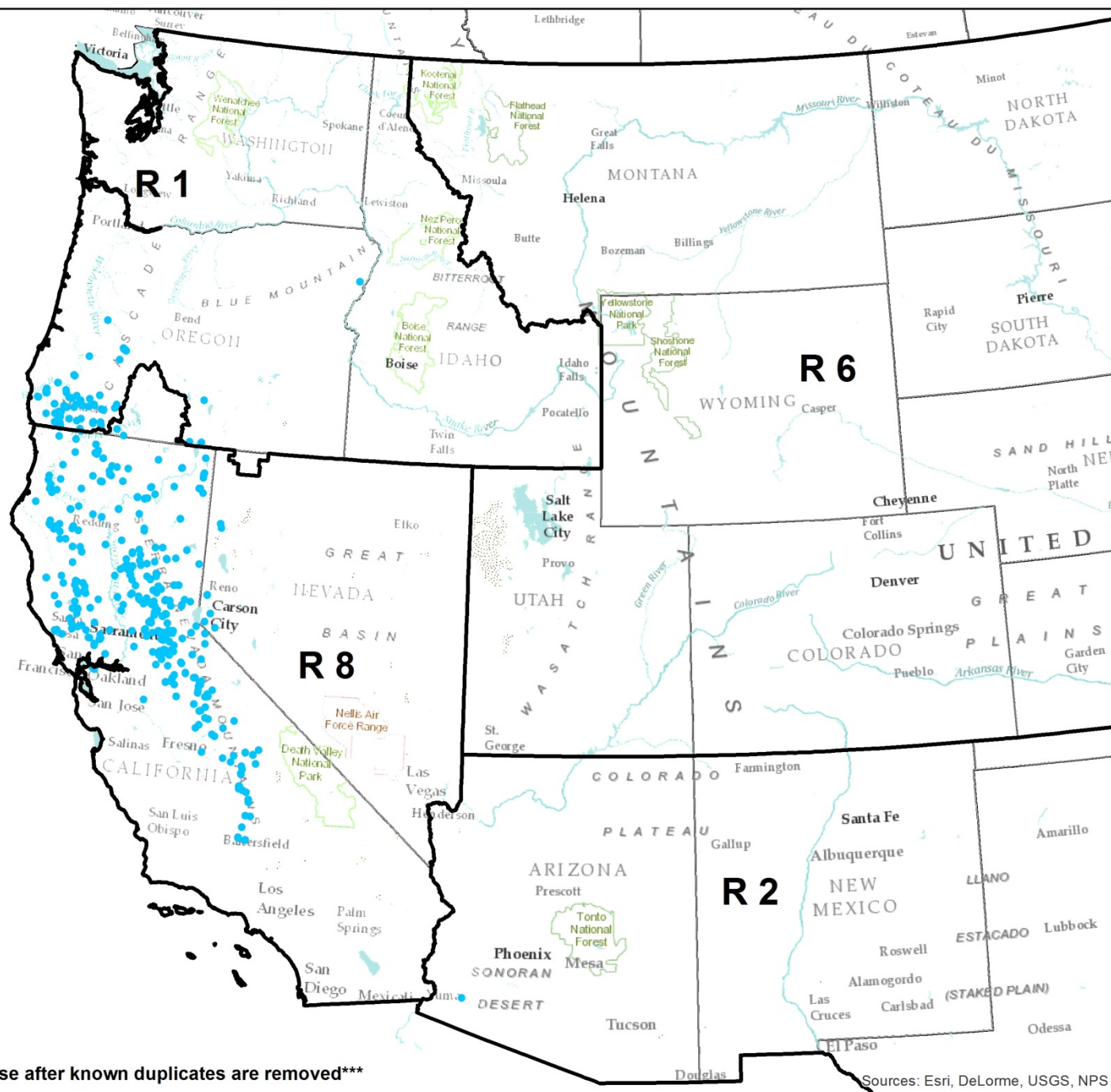
Medium to High Accuracy
Observations

● California

Number of records will decrease after known duplicates are removed

Sources: Esri, DeLorme, USGS, NPS

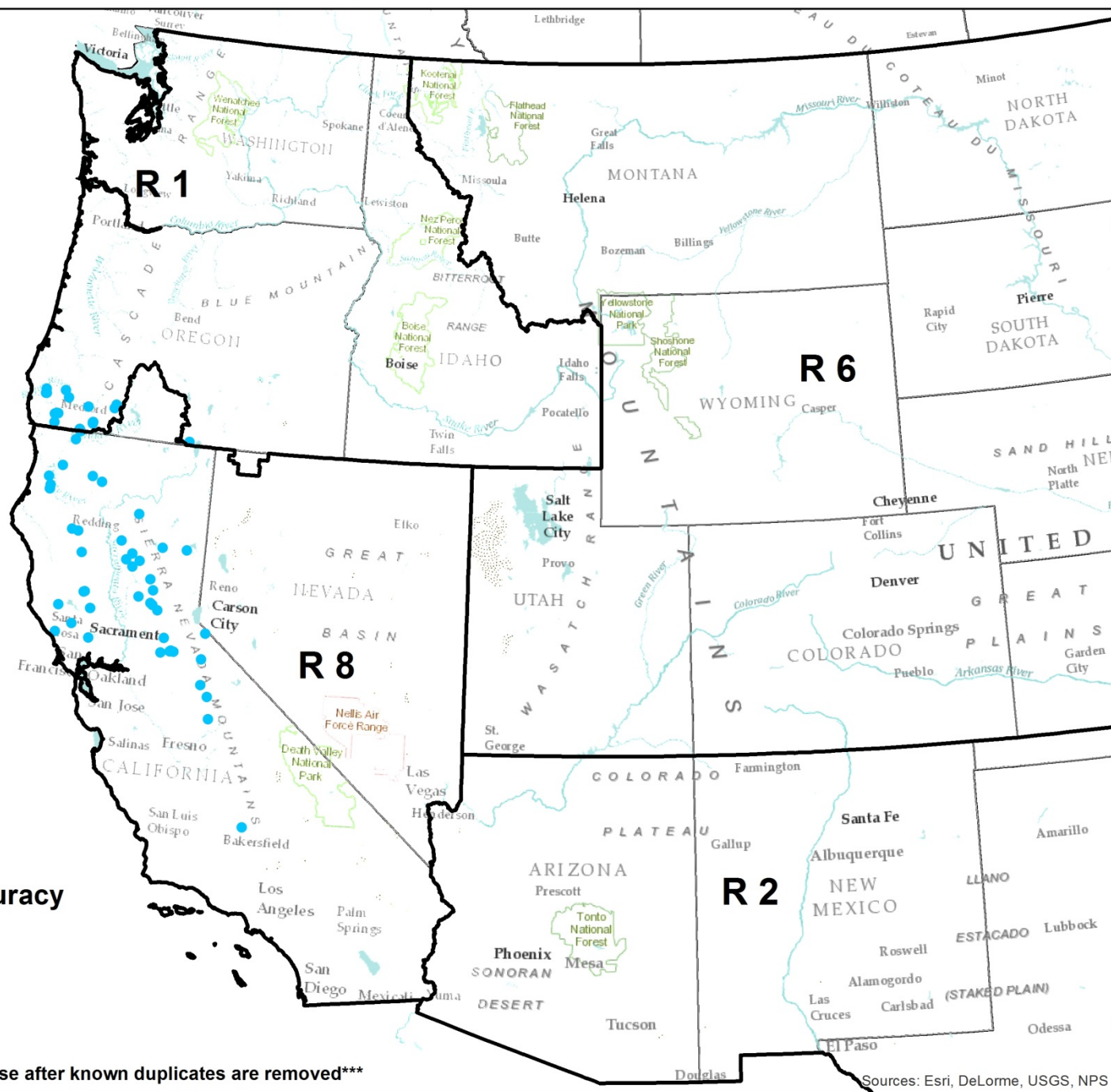
933 Records



Number of records will decrease after known duplicates are removed

Sources: Esri, DeLorme, USGS, NPS

65 Records



Medium to High Accuracy
Observations

• Cordifolia

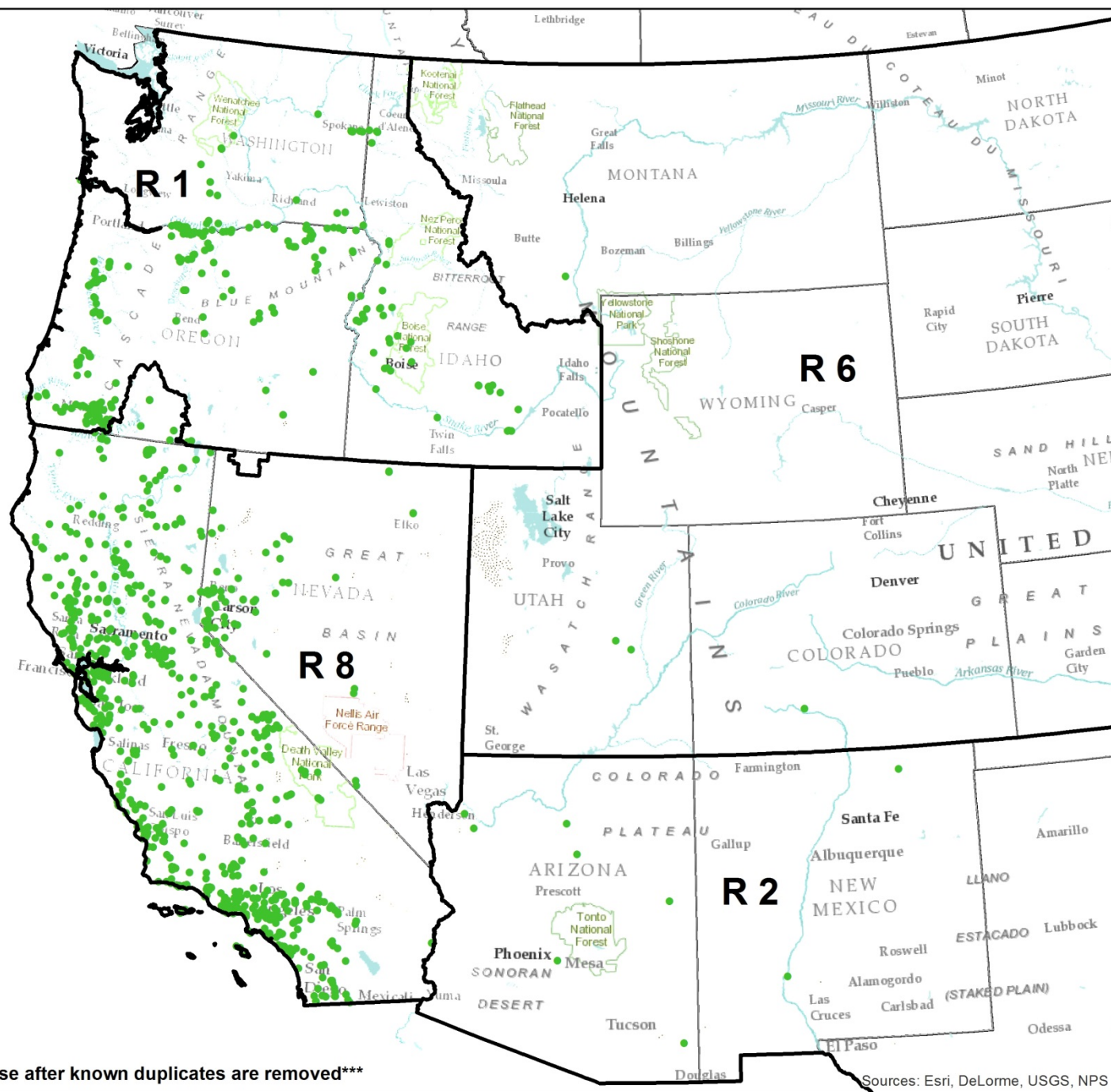
Number of records will decrease after known duplicates are removed

Sources: Esri, DeLorme, USGS, NPS

2,666 Records

Observations

• Fascicularis



Number of records will decrease after known duplicates are removed

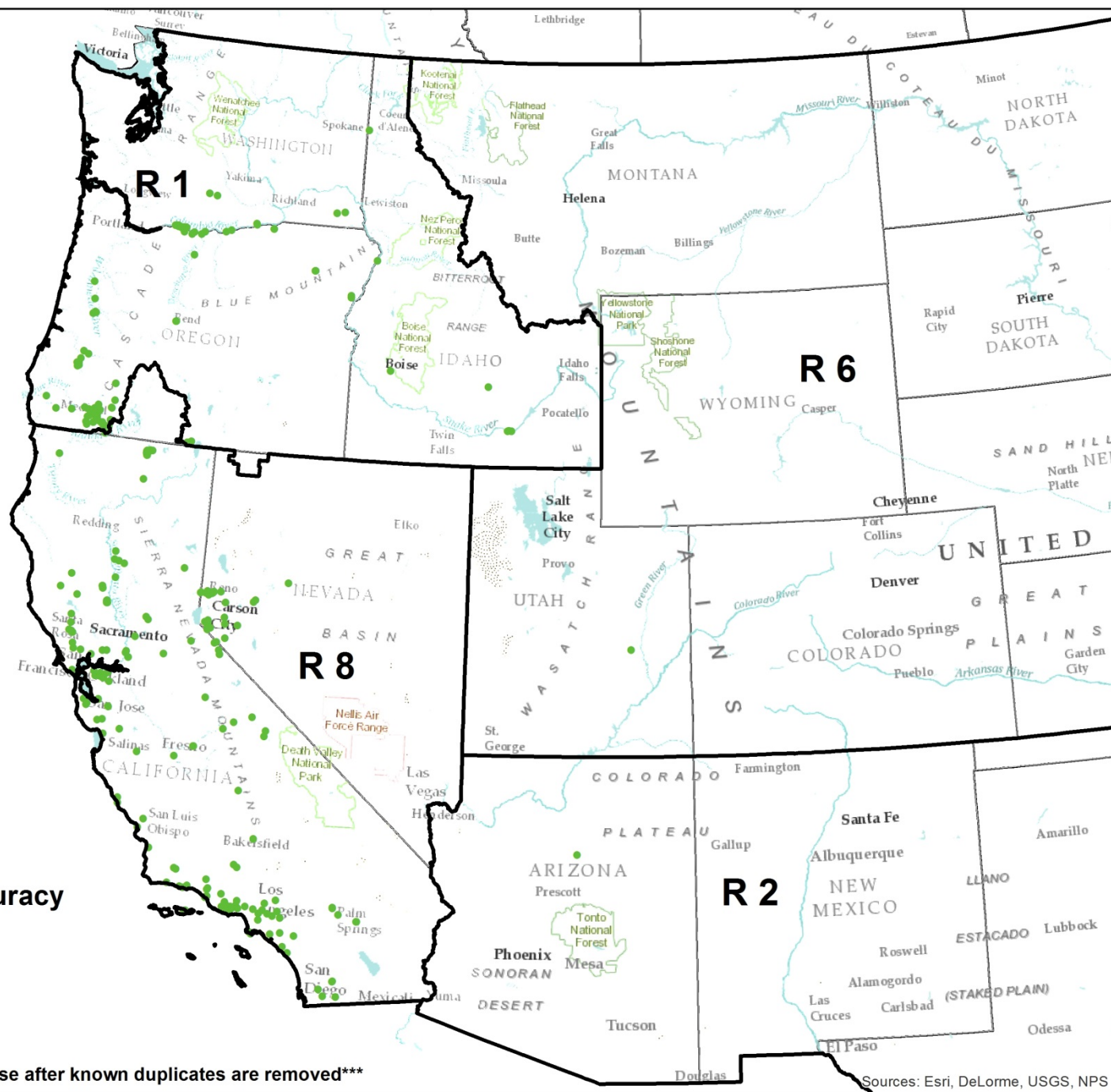
Sources: Esri, DeLorme, USGS, NPS

683 Records

Medium to High Accuracy
Observations

• Fascicularis

Number of records will decrease after known duplicates are removed

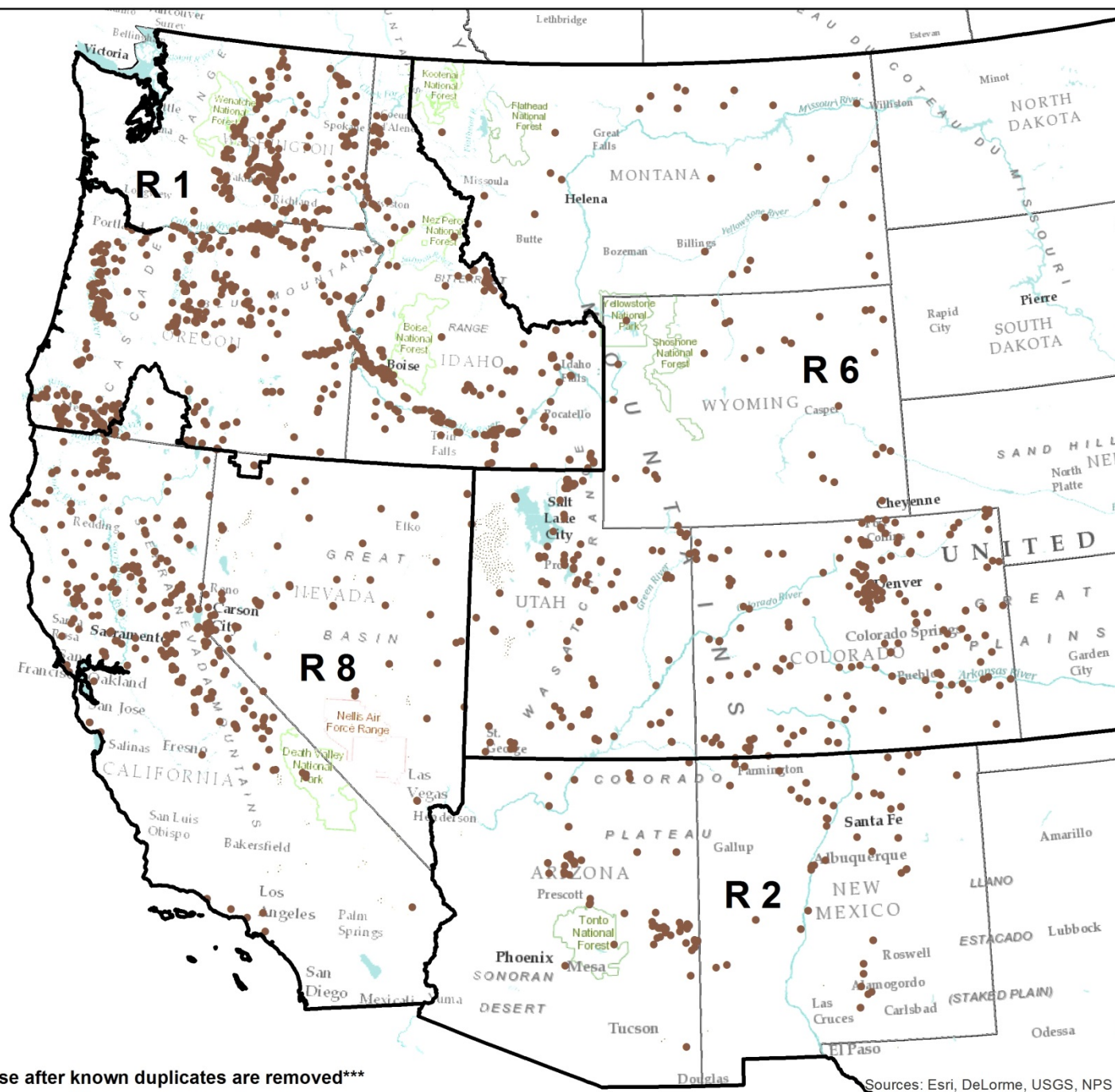


Sources: Esri, DeLorme, USGS, NPS

5,137 Records

Observations

• Speciosa



Number of records will decrease after known duplicates are removed

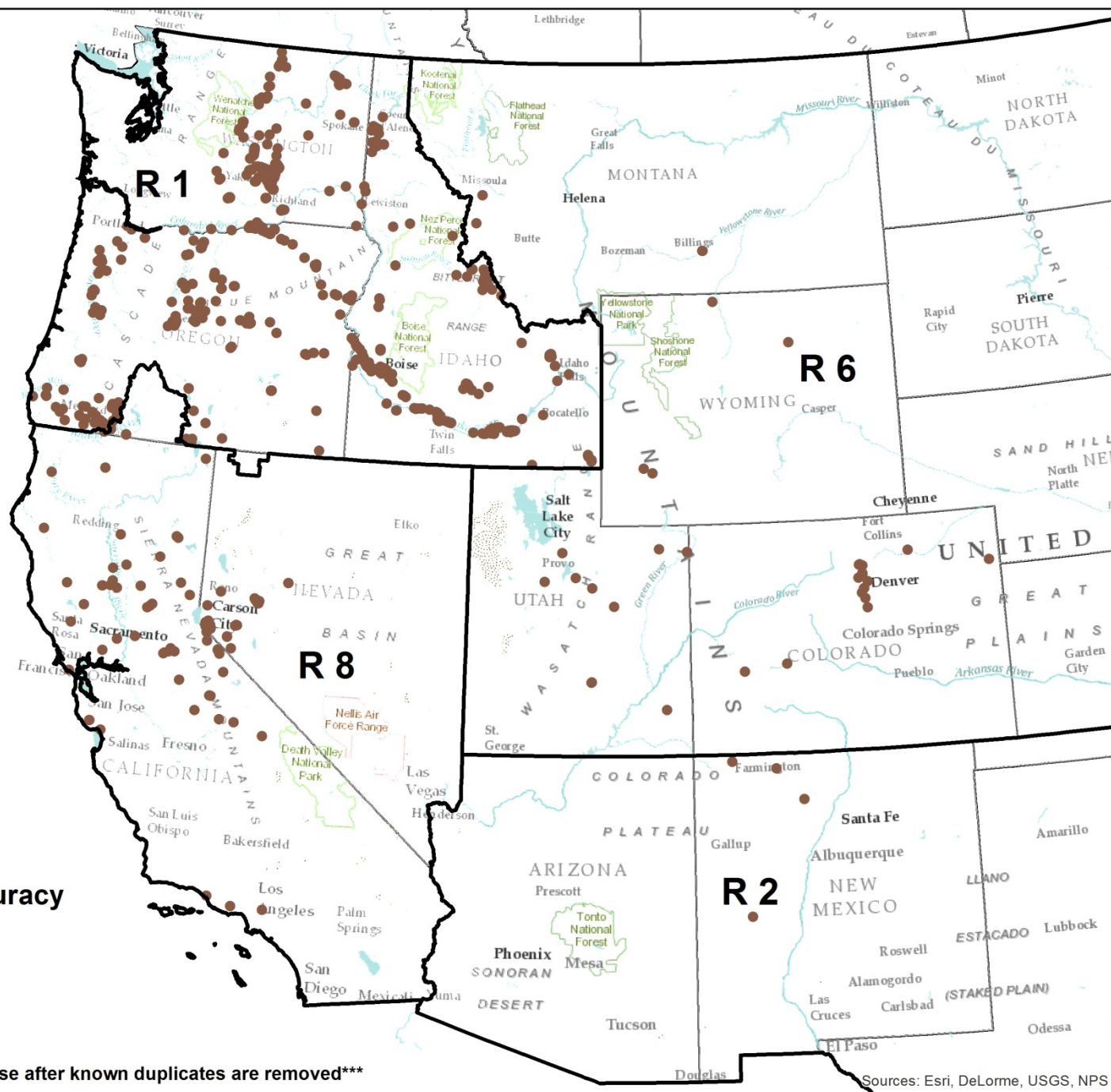
Sources: Esri, DeLorme, USGS, NPS

2,597 Records

Medium to High Accuracy
Observations

● Speciosa

Number of records will decrease after known duplicates are removed

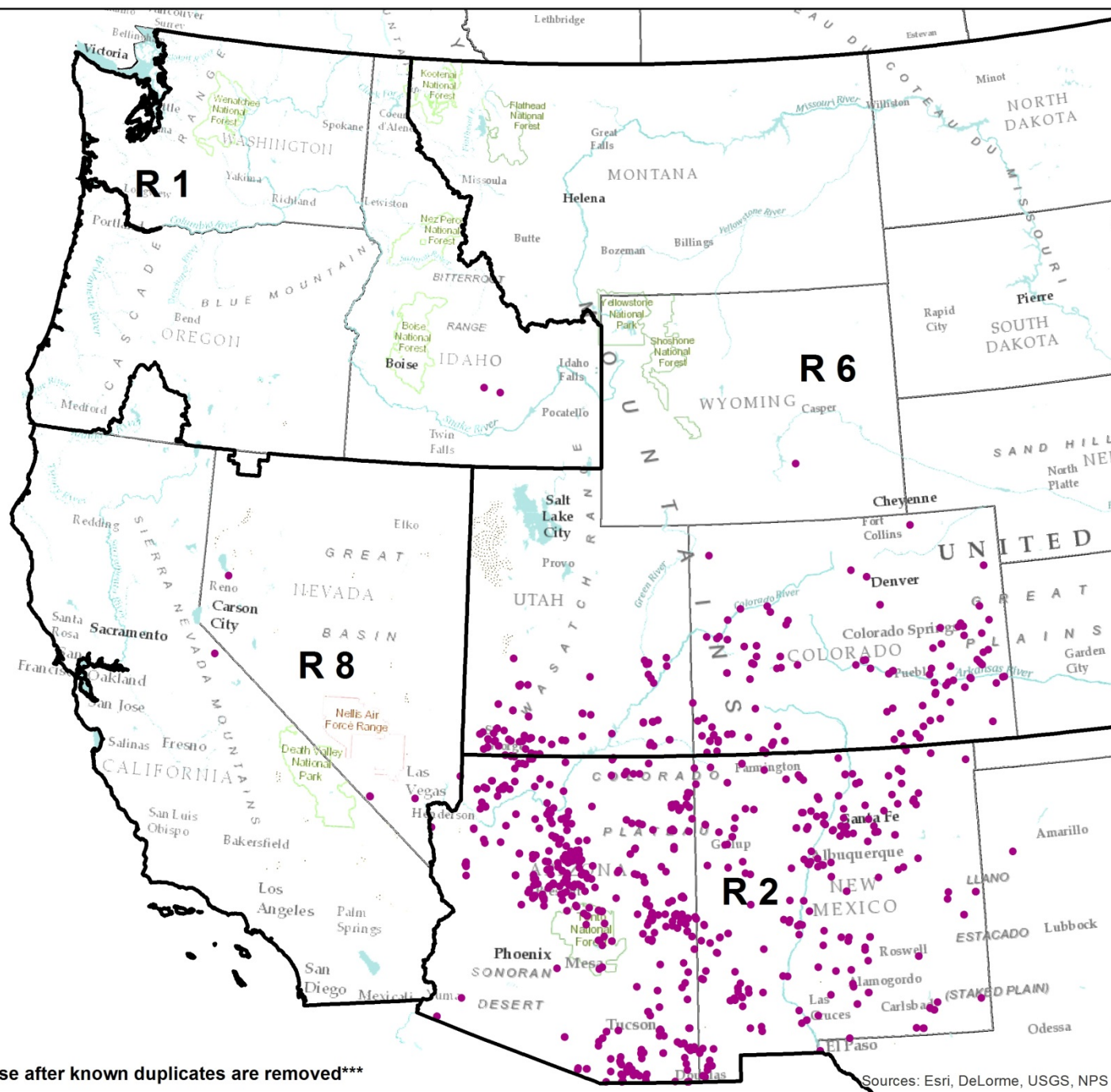


Sources: Esri, DeLorme, USGS, NPS

1,819 Records

Observations

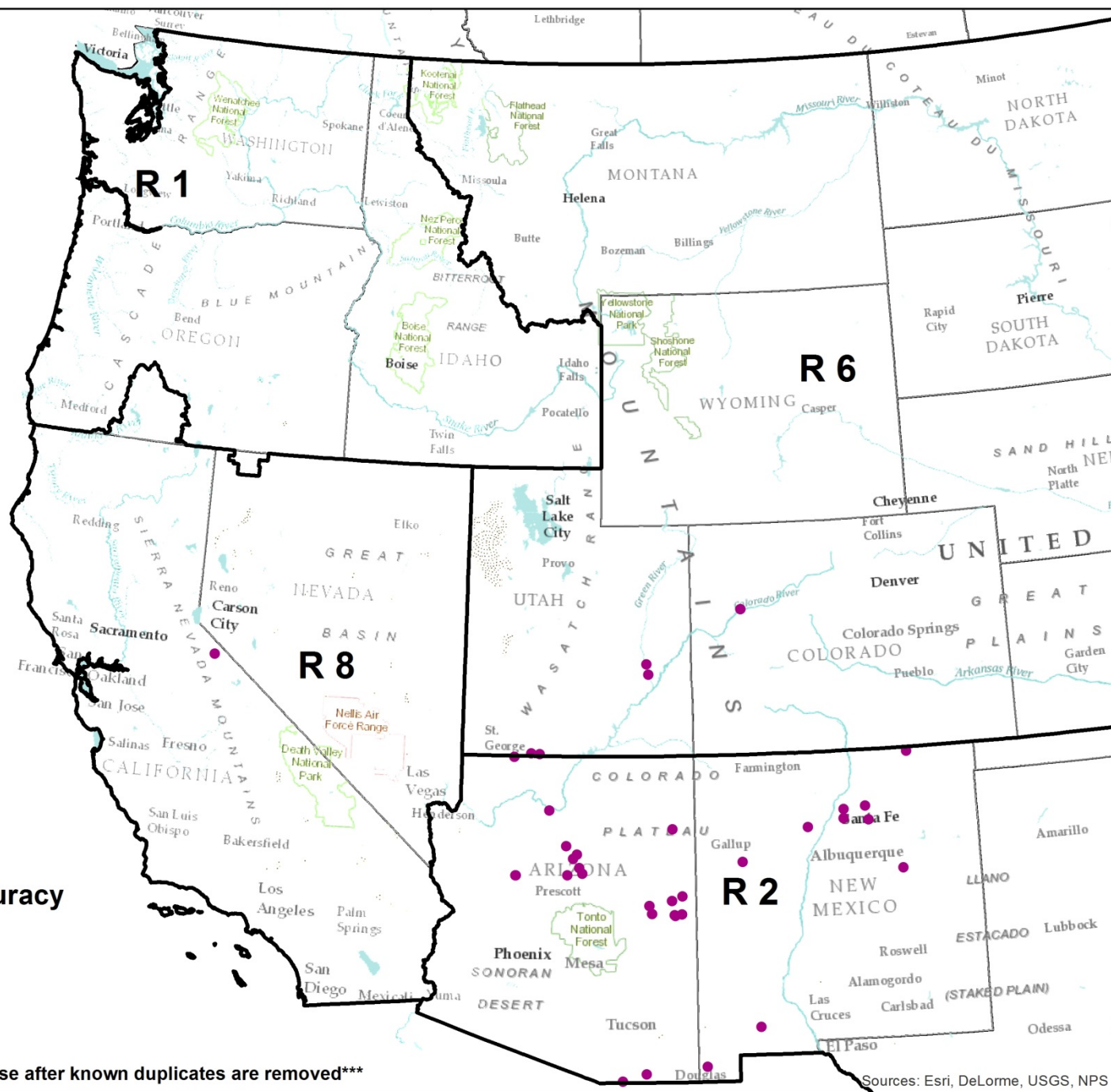
• Subverticillata



Number of records will decrease after known duplicates are removed

Sources: Esri, DeLorme, USGS, NPS

181 Records



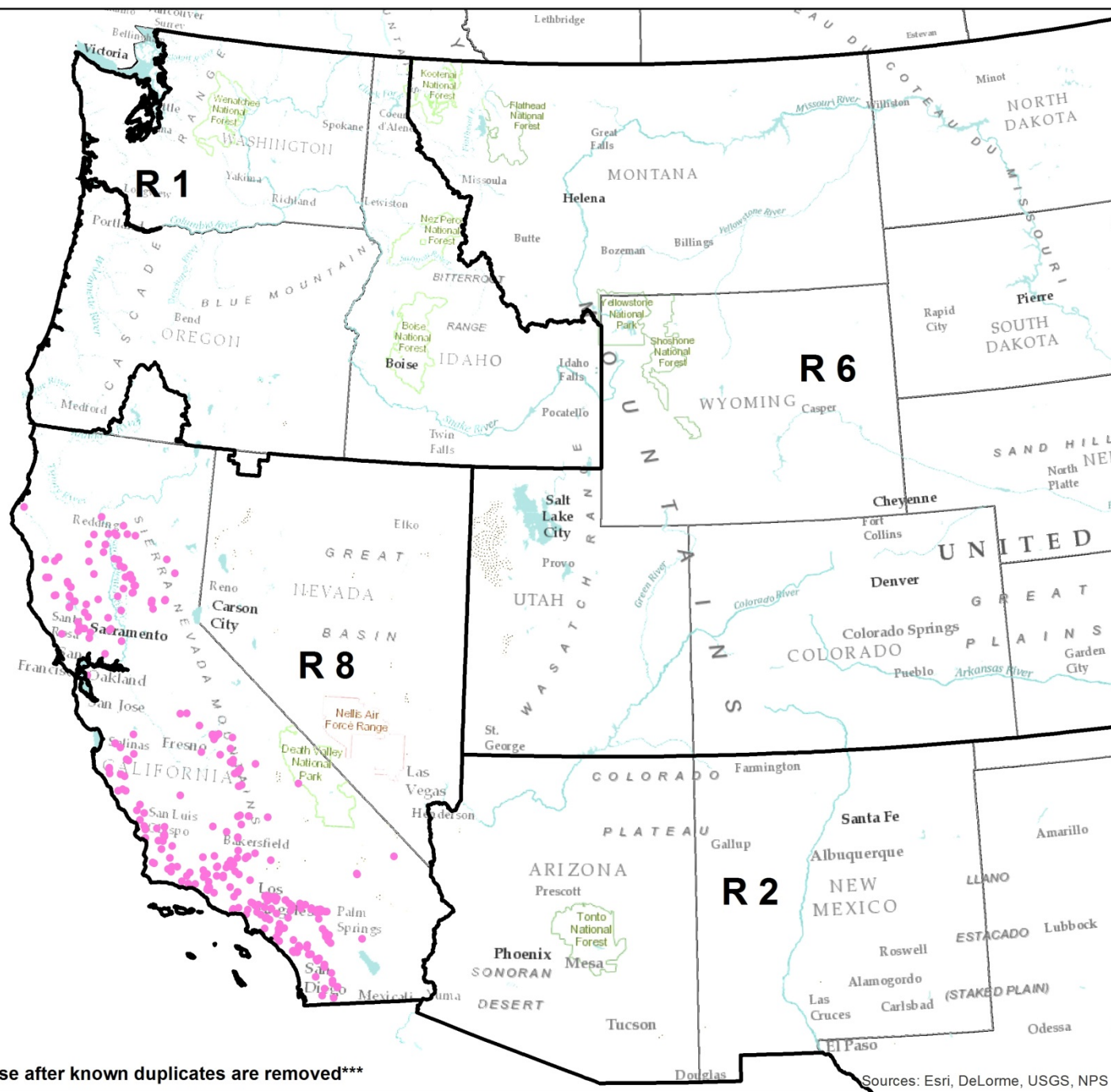
Medium to High Accuracy Observations

• Subverticillata

Number of records will decrease after known duplicates are removed

Sources: Esri, DeLorme, USGS, NPS

664 Records



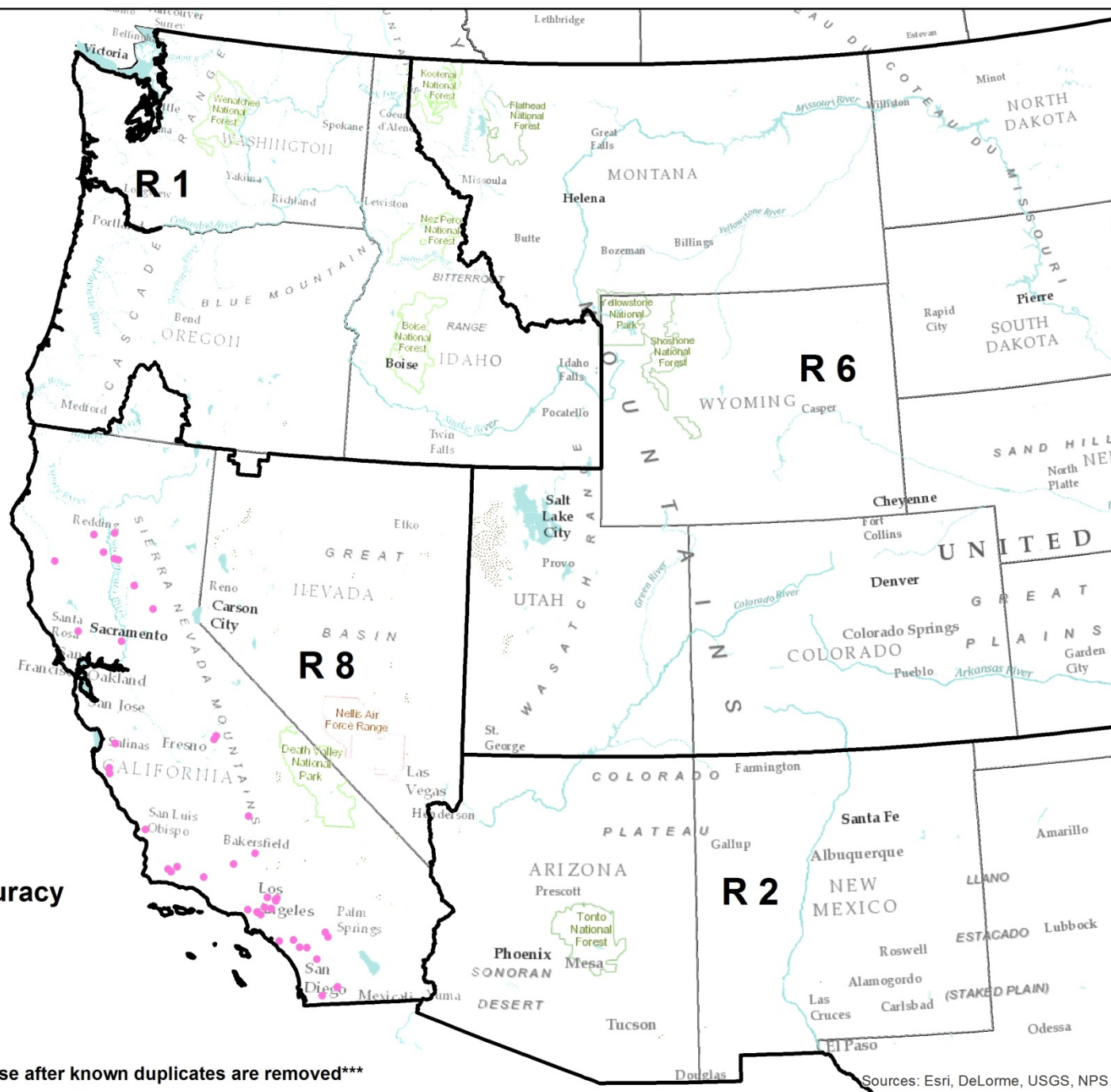
Observations

• Eriocarpa

Number of records will decrease after known duplicates are removed

Sources: Esri, DeLorme, USGS, NPS

48 Records



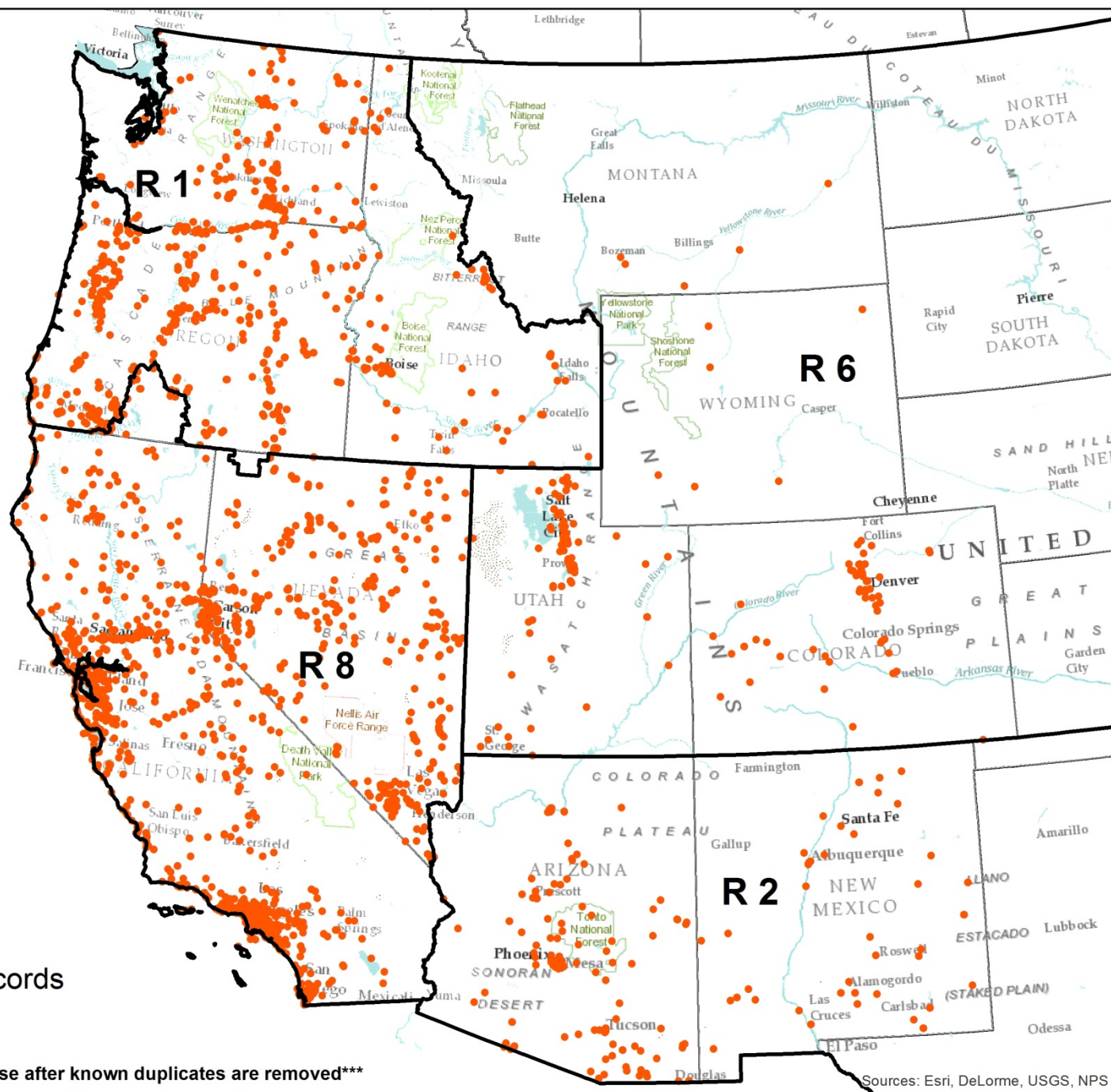
Medium to High Accuracy
Observations

• Eriocarpa

Number of records will decrease after known duplicates are removed

Sources: Esri, DeLorme, USGS, NPS

5,283 Records



Observations

- All Monarch Records

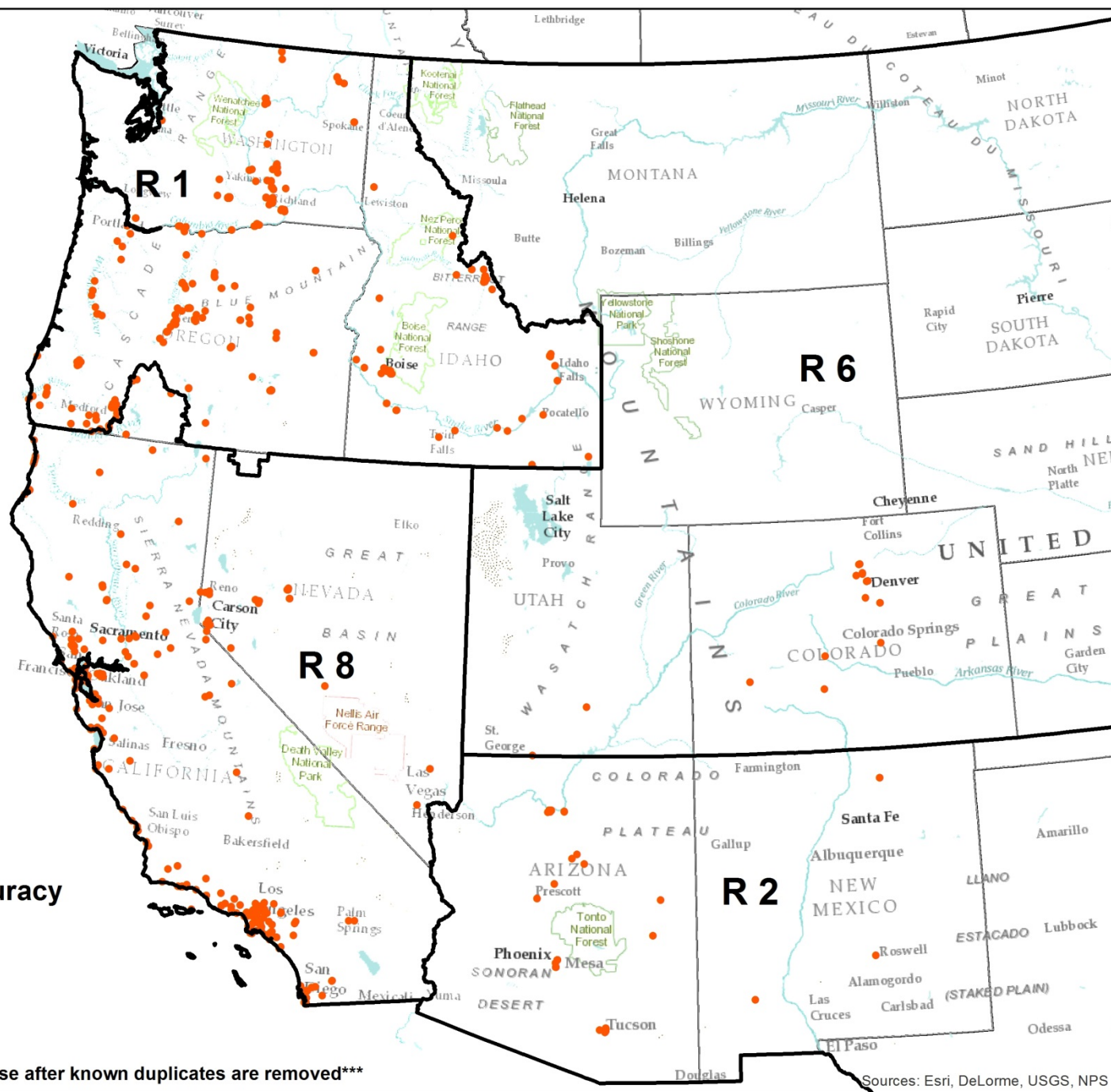
Number of records will decrease after known duplicates are removed

Sources: Esri, DeLorme, USGS, NPS

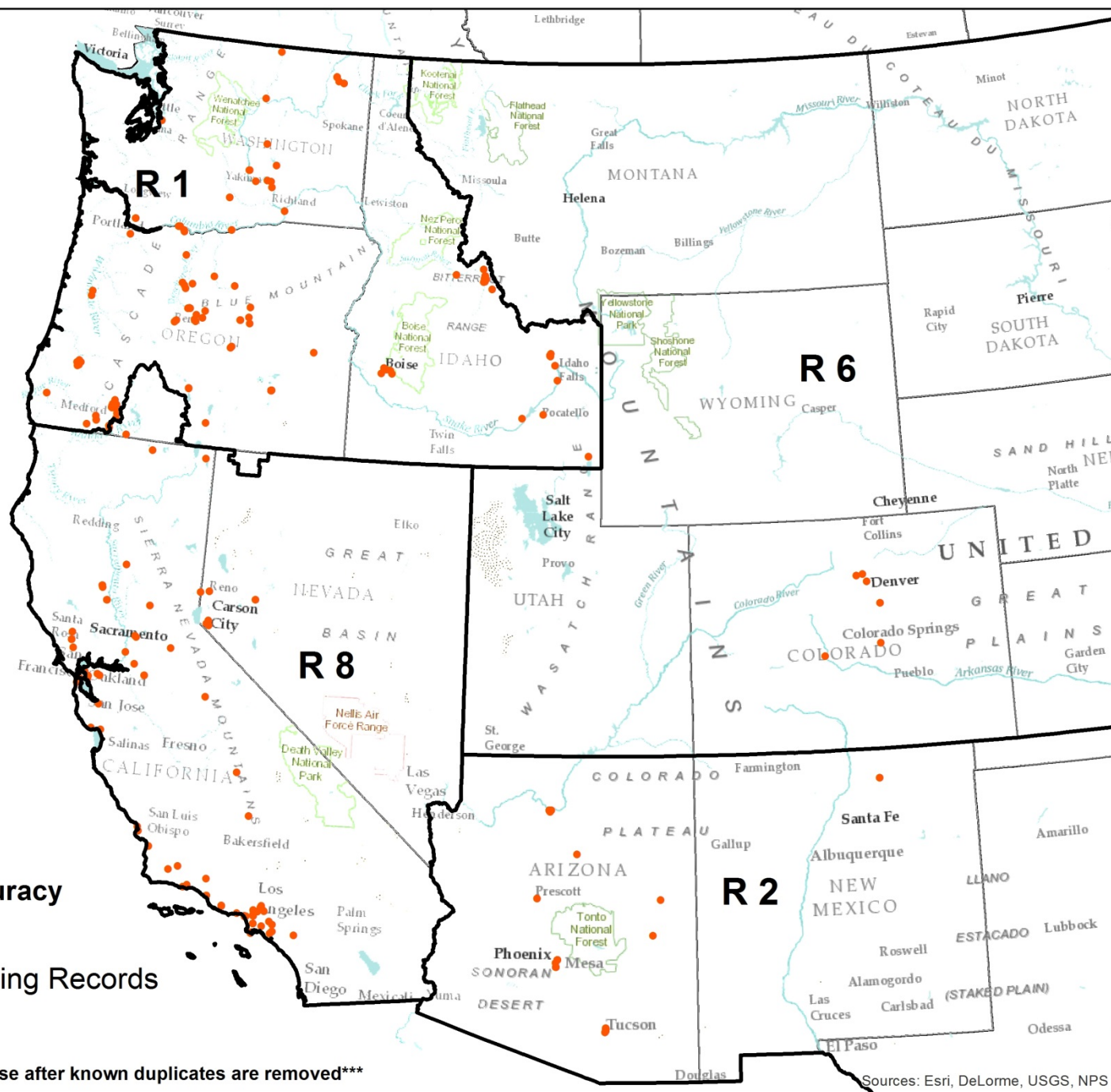
1,256 Records

Medium to High Accuracy
Observations

• Monarch



612 Records



Medium to High Accuracy
Observations

• Monarch, Breeding Records

Number of records will decrease after known duplicates are removed

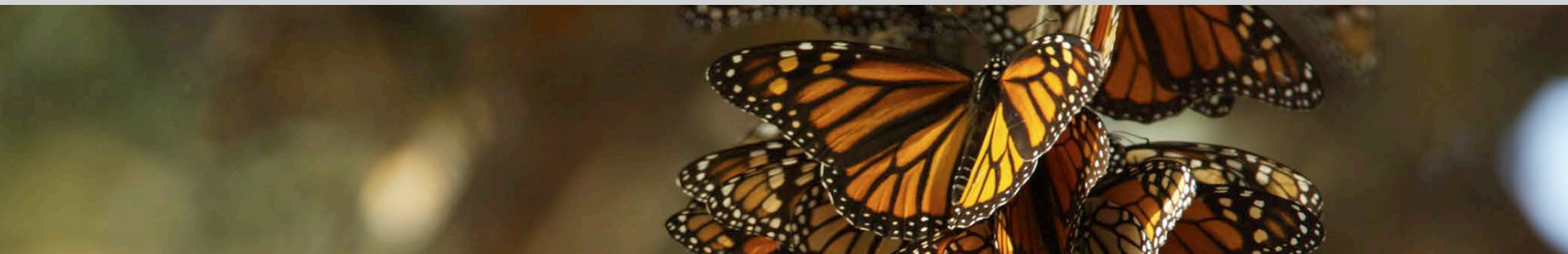
Sources: Esri, DeLorme, USGS, NPS

What's next?

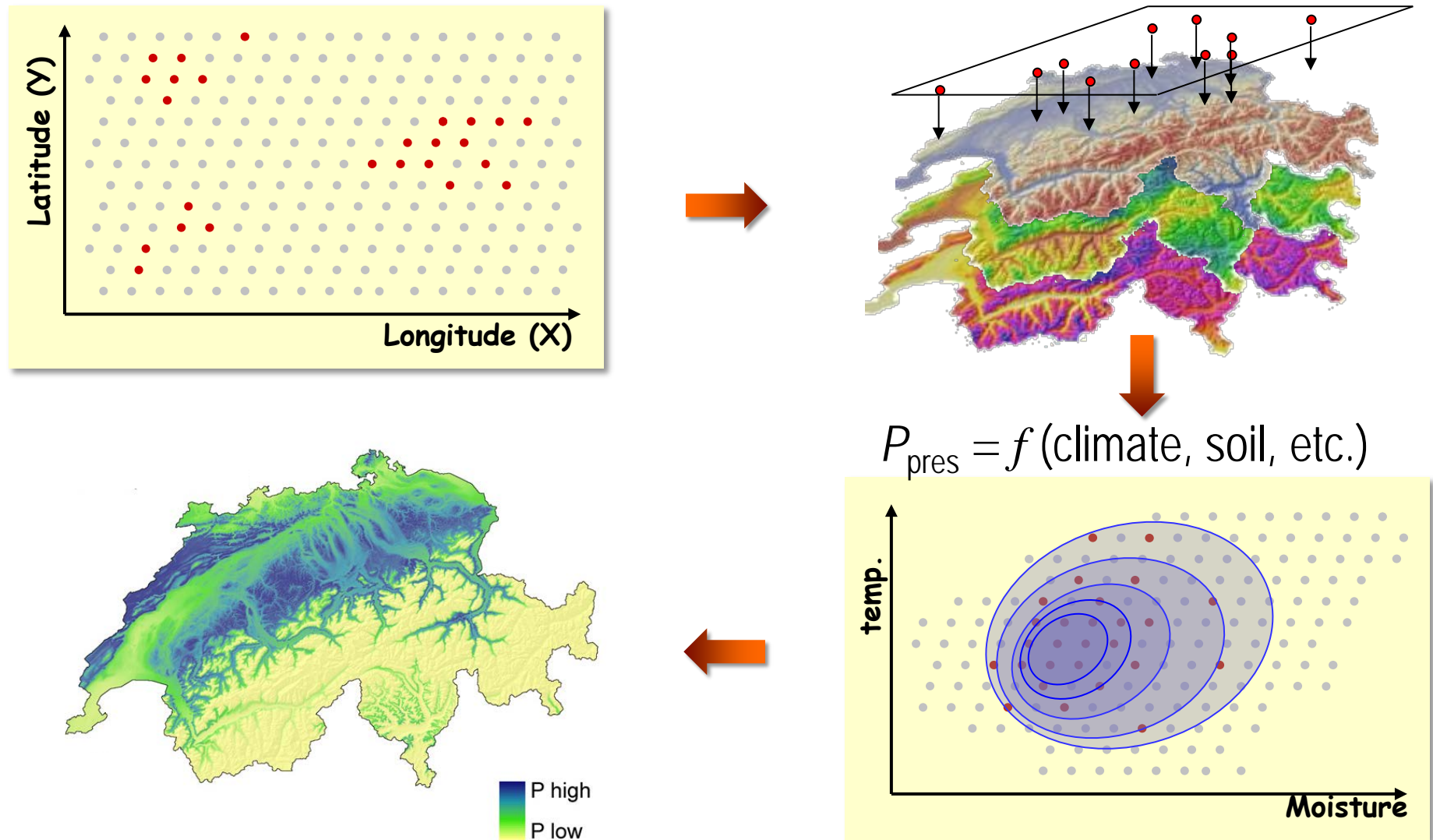
- Continue to standardize data
- Remove duplicates
- Break up into relational tables (normalize data)
- Create useful queries for end-users
- Fill the data gaps
- Compile notes and document the process
- **Increase number of georeferenced records**
- Share!

Modeling methods

- MaxEnt, the modeling tool
- Defining the analysis area for each species
- Mitigating for sampling bias
- Environmental covariate selection
- Model calibration and selection



Species Distribution Modeling Basics



MaxEnt, the modeling tool

"The idea of Maxent is to estimate a target probability distribution by finding the probability distribution of maximum entropy (i.e., that is most spread out, or closest to uniform), subject to a set of constraints that represent our incomplete information about the target distribution. The information available about the target distribution [is]... a set of real-valued variables... and the constraints are that the expected value of each feature should match its empirical average."

- Philips et al. 2006

Why MaxEnt

- Presence only data
- Explore complex relationships with environment (with user control of allowed complexity)
- Considered good for small data sets
- Performs well relative to other machine learning models (e.g., Random Forests) when they are run with presence/pseudo-absence data (Elith et al. 2006)
- Fairly well documented and studied

Defining the geographic background for each species

- Known to have strong effect on the model outputs
- Using a calibrated buffer approach described in VanDerWal et al. 2009

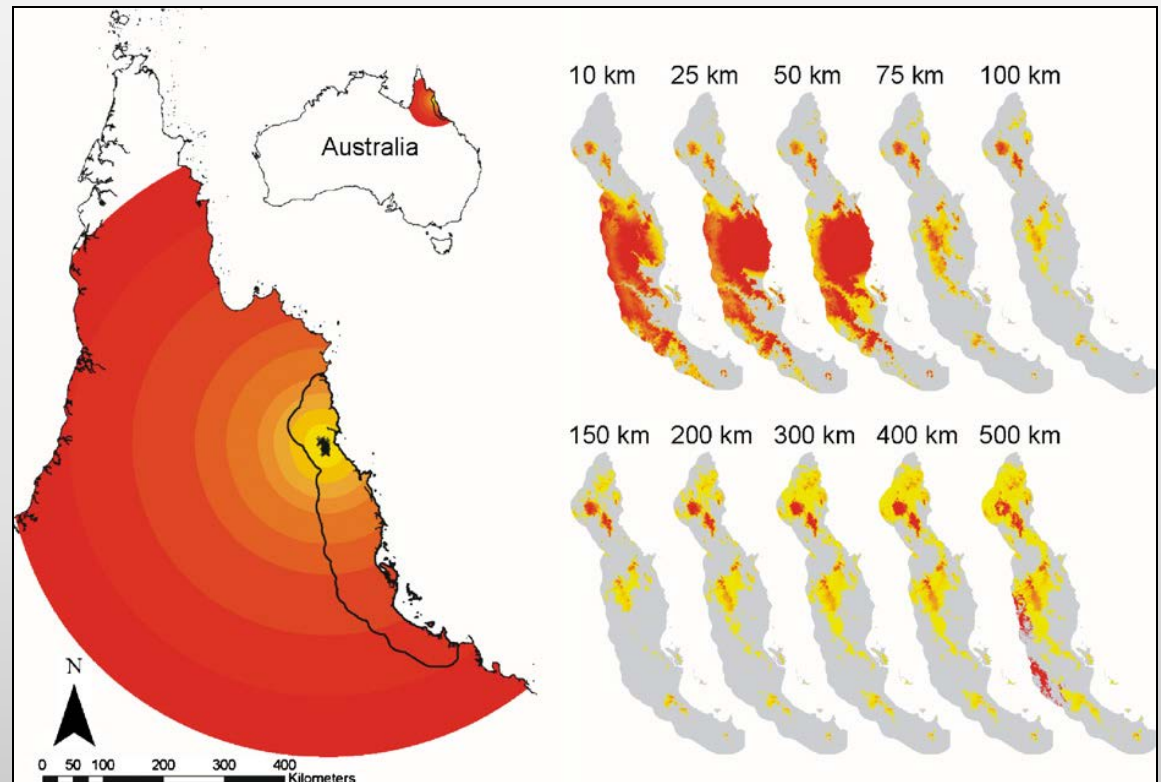


Fig. 1, VanderWal et al. 2009, Ecological Modelling

Across 12 species, results improve;
then plateaued

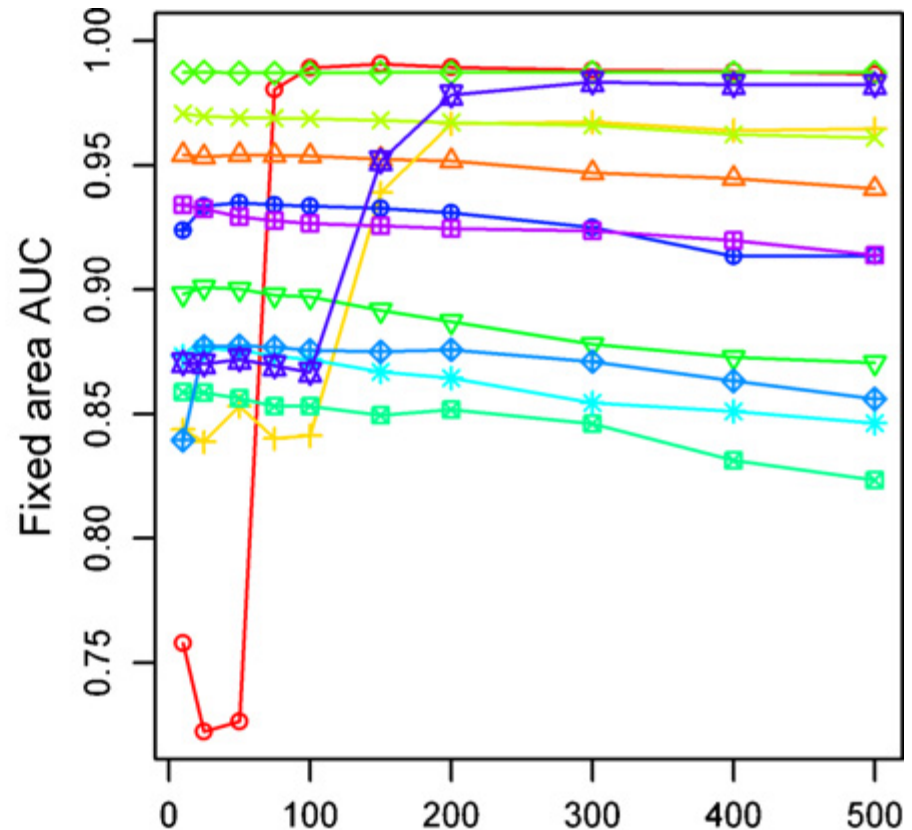
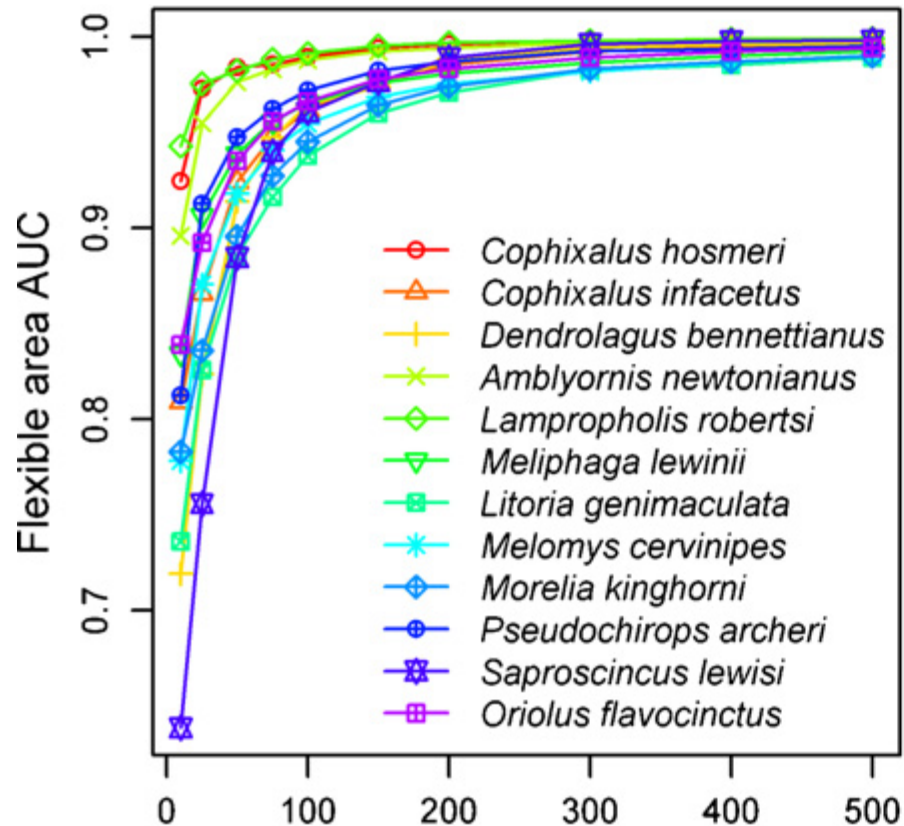


Fig. 2, VanderWal et al. 2009, Ecological Modelling

Similar findings in Iturbide et al. 2015

And they released an R package that makes this buffer calibration much easier!

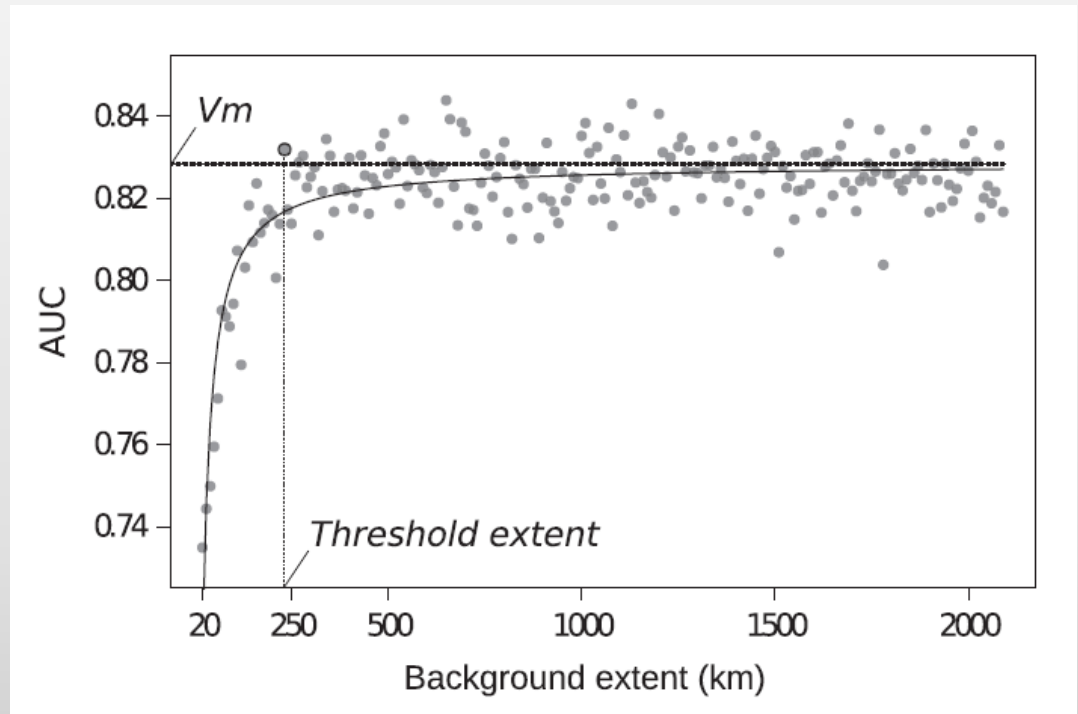
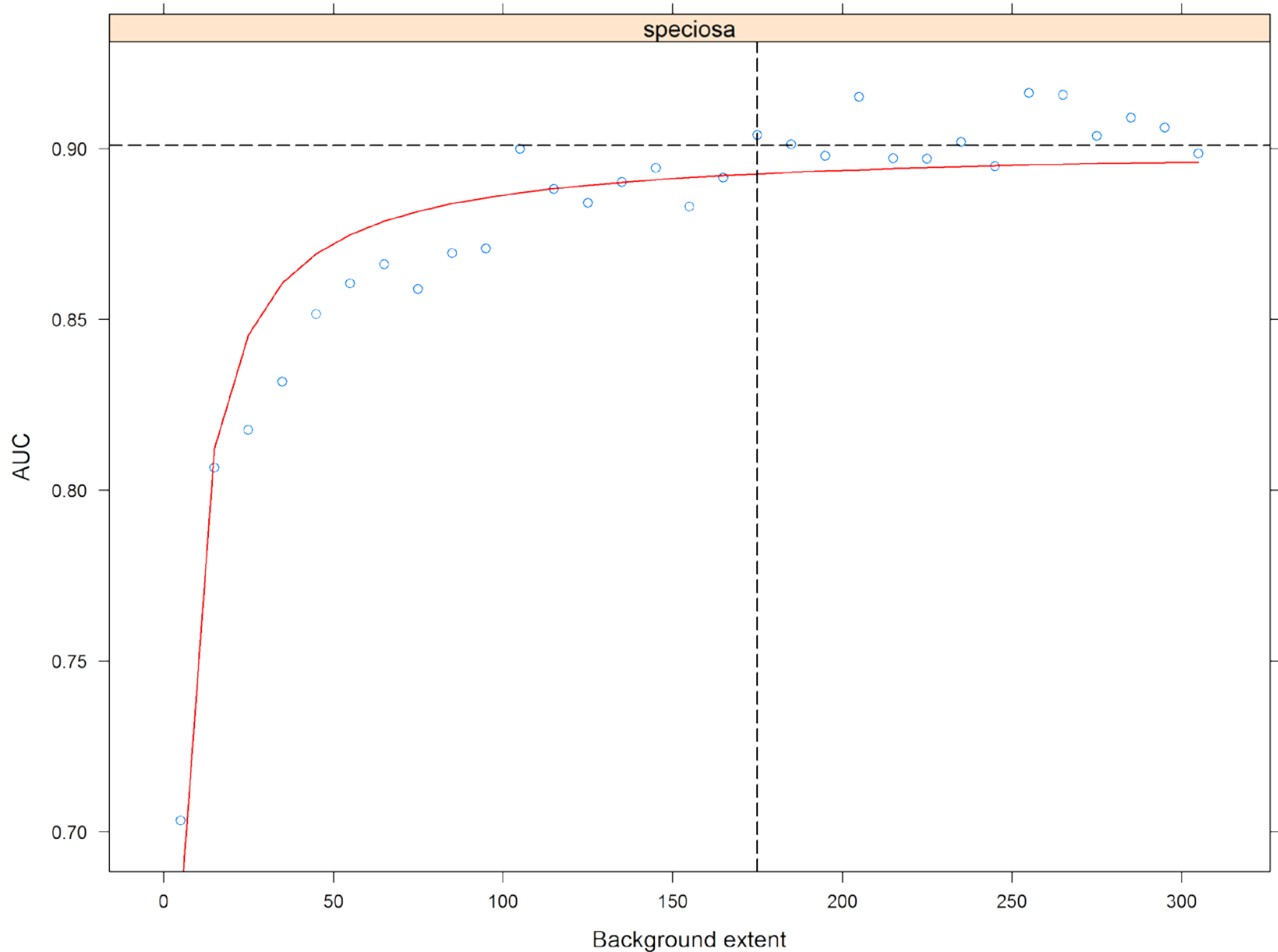


Fig. 3, Iturbide et al. 2015, Ecological Modelling

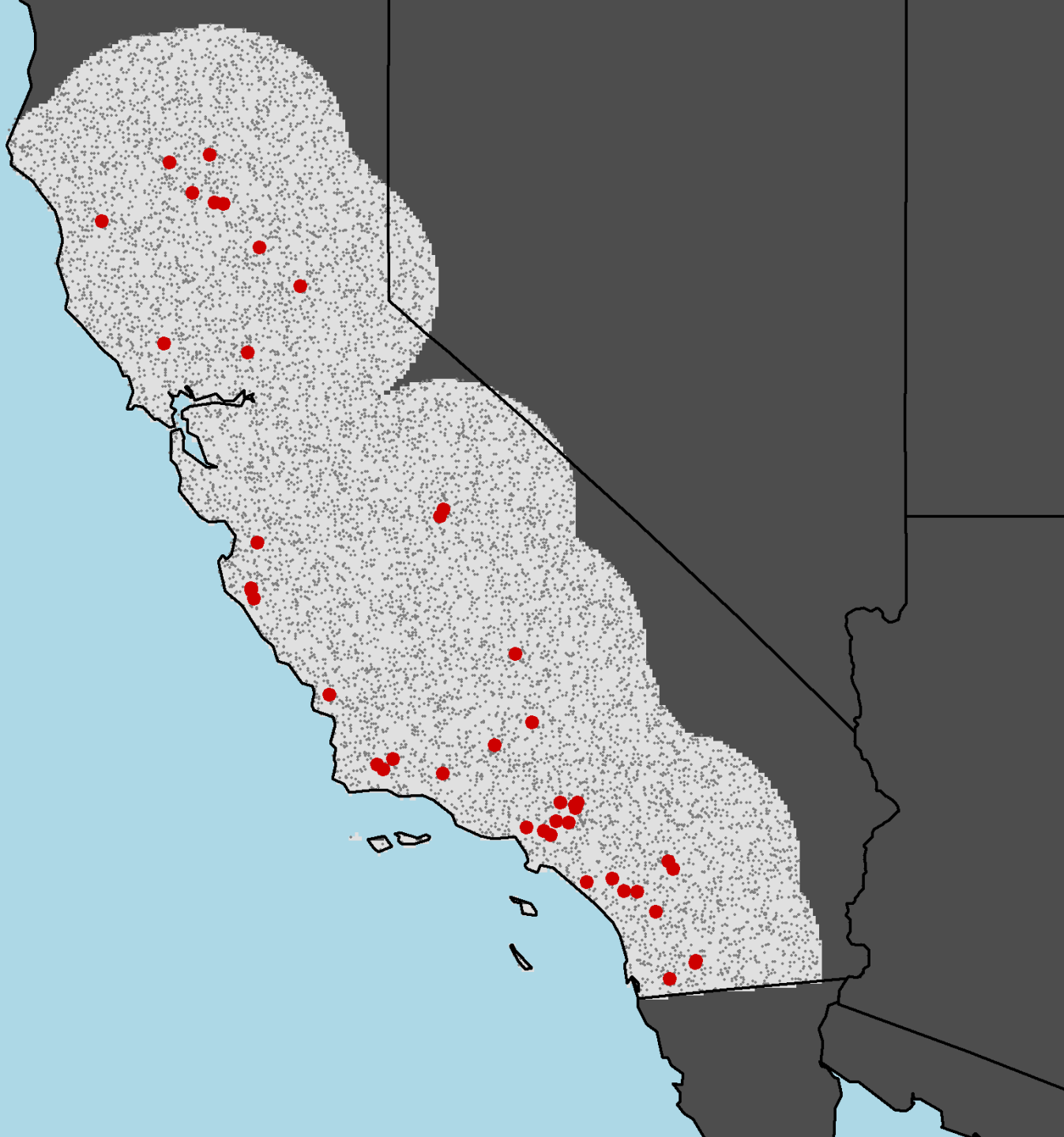
Example background extent selection with our data



A. eriocarpa

background and medium
resolution occurrences

- Presence
- Background sample
- Background



Correction for sampling bias

- Serious problem in many data sets, including ours
- Fourcade et al. did a particularly thorough exploration:
 - Developed 36 artificially biased datasets (3 species X 4 types of biases X 3 intensity levels)
 - For each, tried 5 different bias correction methods

Mitigating for sampling bias: results from Fourcade et al. 2014

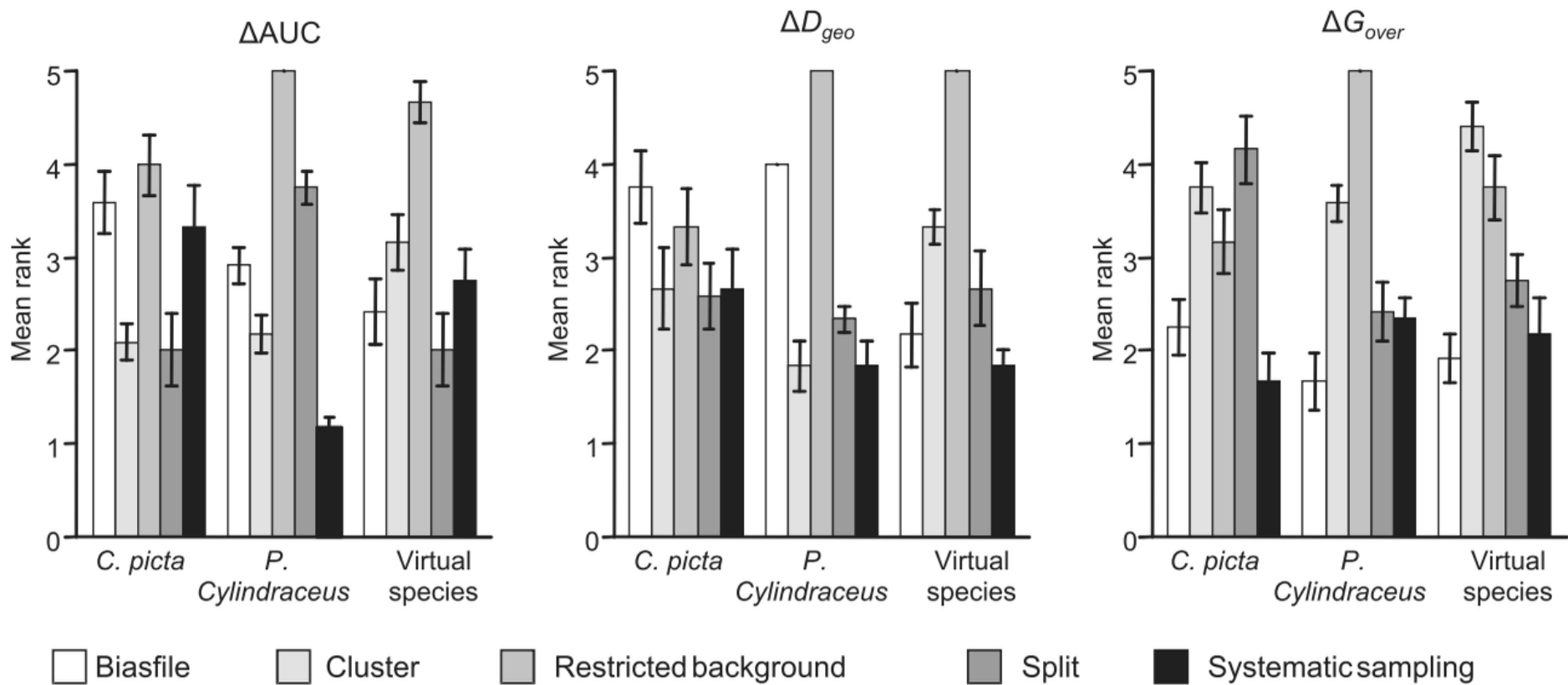


Figure 5. Rank of each method to correct sampling bias. Mean ranks \pm standard-error for the performance of each method to correct sampling bias for each species (*Chrysemys picta*: left, *Plethodon cylindraceus*: center, *virtual species*: right), following 3 measures of correction performance: ΔAUC (left), ΔD_{geo} (centre), and ΔG_{over} (right). For each type of bias and bias intensity, the method which results in the most efficient correction is set to 1 whereas the least powerful method is set to 5. The plotted values are the mean rank across the 4 types of bias and 3 intensities. doi:10.1371/journal.pone.0097122.g005

Environmental Covariates

- Based on expert input and data availability
- Study domain is conterminous US, west of continental divide
- 25 total in current candidate set
 - (More on selection of best subset for each species later)
- Experimented with 3 resolutions: 90m, 270m, and 900m pixels
- 270 seemed most reasonable given resolution of inputs and accuracy of points

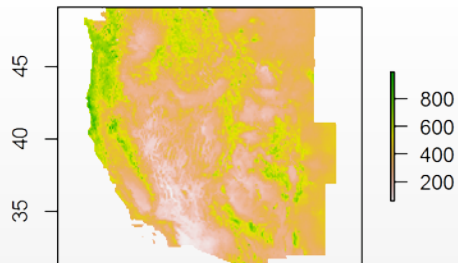
	Covariates: PRISM Climate Variables			
	Variable name	Source	Original Resolution	Time period
1	Mean Annual temp.	PRISM	~900m pixels	30 year avg: 1981-2010
2	Mean Annual precip.	PRISM	~900m pixels	30 year avg: 1981-2010
3	Mean precip. of the Warmest Quarter	PRISM	~900m pixels	30 year avg: 1981-2010
4	Mean precip. of the Coldest Quarter	PRISM	~900m pixels	30 year avg: 1981-2010
5	Mean temp. of the Warmest Quarter	PRISM	~900m pixels	30 year avg: 1981-2010
6	Mean temp. of the coldest quarter	PRISM	~900m pixels	30 year avg: 1981-2010
7	Max temp. of the warmest month	PRISM	~900m pixels	30 year avg: 1981-2010
8	Minimum temp. of the coldest month	PRISM	~900m pixels	30 year avg: 1981-2010
9	temp. annual range	PRISM	~900m pixels	30 year avg: 1981-2010

Covariates: Land cover, soil, and other

	Variable name	Source	Original Resolution	Time period
10	Topsoil (0-30cm) bulk density	SSURGO patched with STATSGO	varies	n/a
11	Topsoil (0-30cm) clay fraction	SSURGO patched with STATSGO	varies	n/a
12	Topsoil (0-30cm) sand fraction	SSURGO patched with STATSGO	varies	n/a
13	Topsoil (0-30cm) silt fraction	SSURGO patched with STATSGO	varies	n/a
14	Topsoil (0-30cm) pH	SSURGO patched with STATSGO	varies	n/a
15	Slope	Derived from 30m DEM (3DEP)	30m pixels	n/a
16	Aspect	Derived from 30m DEM (3DEP)	30m pixels	n/a
17	Compound Topographic Index (CTI)	Derived from 90m DEM (SRTM)	90m pixels	n/a
18	Distance to water	Derived from (NHD)	Calculated at 90m resolution	n/a
19	Reclassified LANDFIRE Existing Vegetation Type	LANDFIRE	30m pixels	2011
20	Percent natural within 1 km	LANDFIRE	30m pixels	2011

	Covariates: Other Climate Variables			
	Variable name	Source	Original Resolution	Time period
21	Mean Actual Evapotranspiration (AET)	AdaptWest	~900m pixels	30 year avg: 1981-2010
22	Mean Climatic Water Deficit, 1980-2009	AdaptWest	~900m pixels	30 year avg: 1981-2010
23	Mean precip. Seasonality (Coefficient of Variation)	BIOCLIM	~900m pixels	50 year avg: 1950-2000
24	Mean temp. Seasonality (standard deviation *100)	BIOCLIM	~900m pixels	50 year avg: 1950-2000
25	Annual Mean Degree Days	ClimateWNA	~900m pixels	30 year avg: 1961-1990

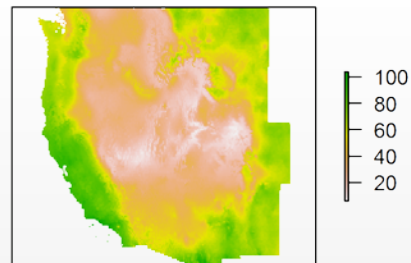
AET_annual_mean_270m



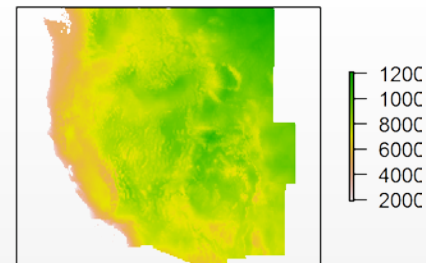
aspect_270m



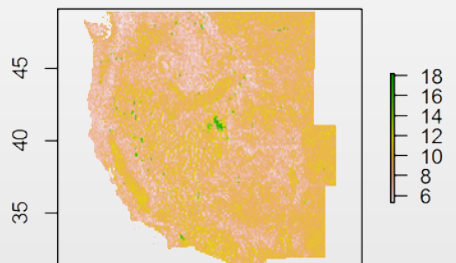
bioclim_ppt_seasonality_270m



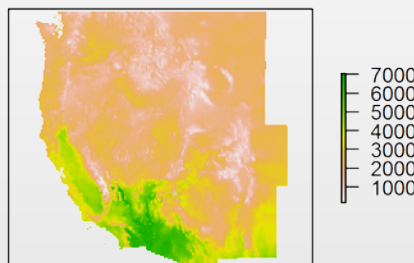
bioclim_temp_seasonality_270m



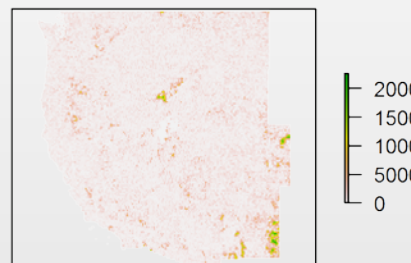
CTI_270m



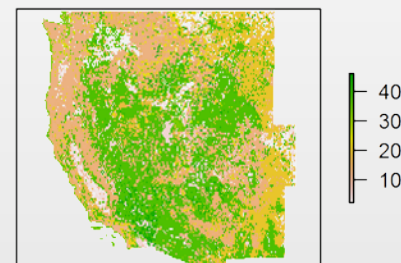
degree_days_5C_270m



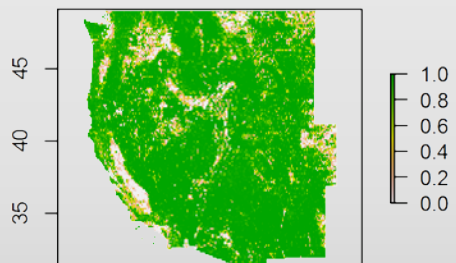
distance_to_water_270m



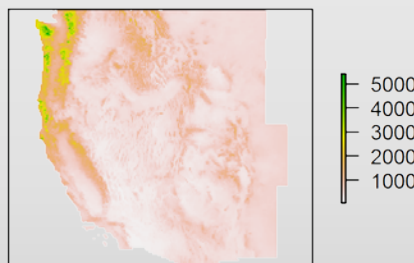
LF_EVT_rc_270m



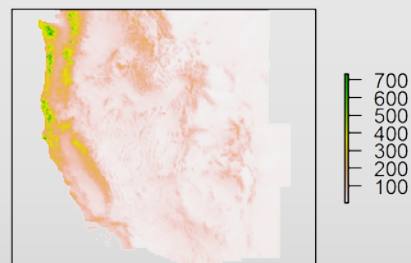
percent_nat_1km_270m



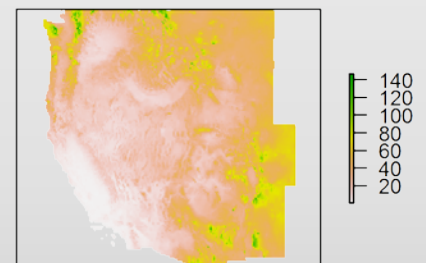
PRISM_ppt_annual_270m



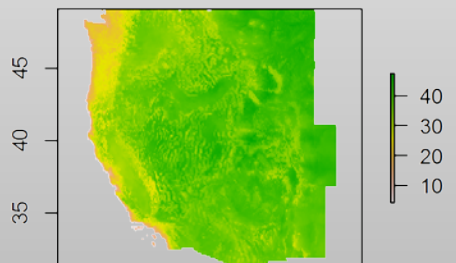
PRISM_ppt_coldest_quarter_270m



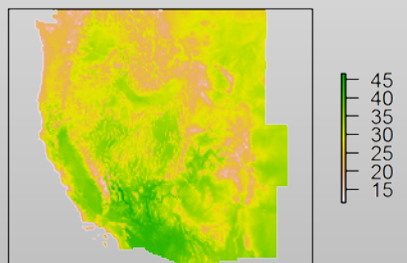
PRISM_ppt_warmest_quarter_270m



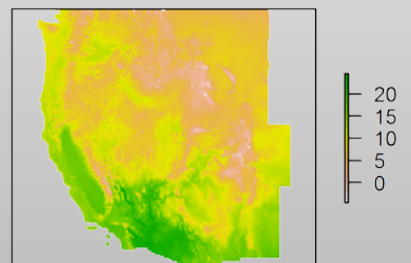
PRISM_temp_range_270m



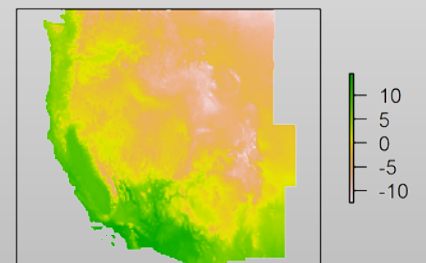
RISM_tmax_warmest_month_270m



PRISM_tmean_annual_270m



RISM_tmean_coldest_quarter_270m





Selection of uncorrelated subsets of covariates for each species

- Multicollinearity can lead to unpredictable results and make models difficult to interpret
- Did initial runs with all variables to get “permutation importance” scores for each
- Reran with an uncorrelated subset
 - From each correlated group of variables, selected the one with highest permutation importance

Example variable selection: *A. eriocarpa*

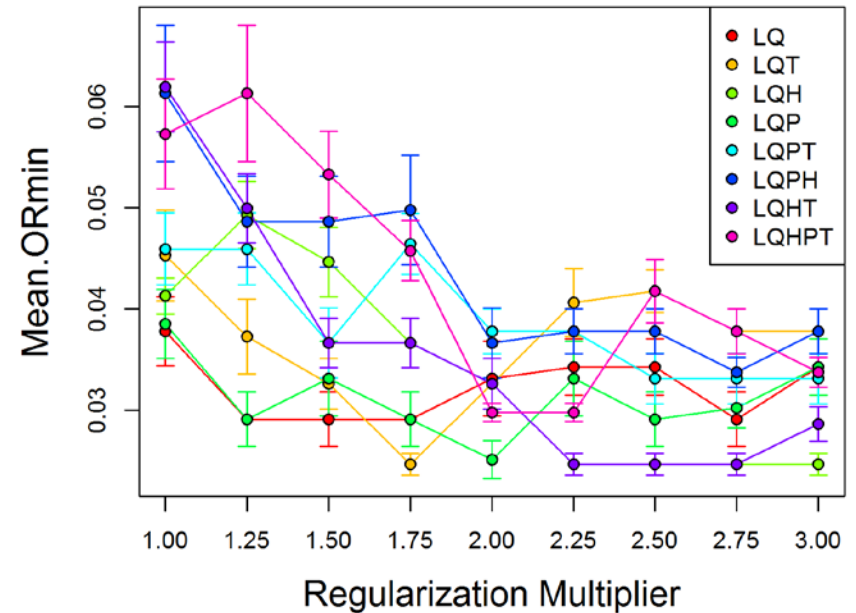
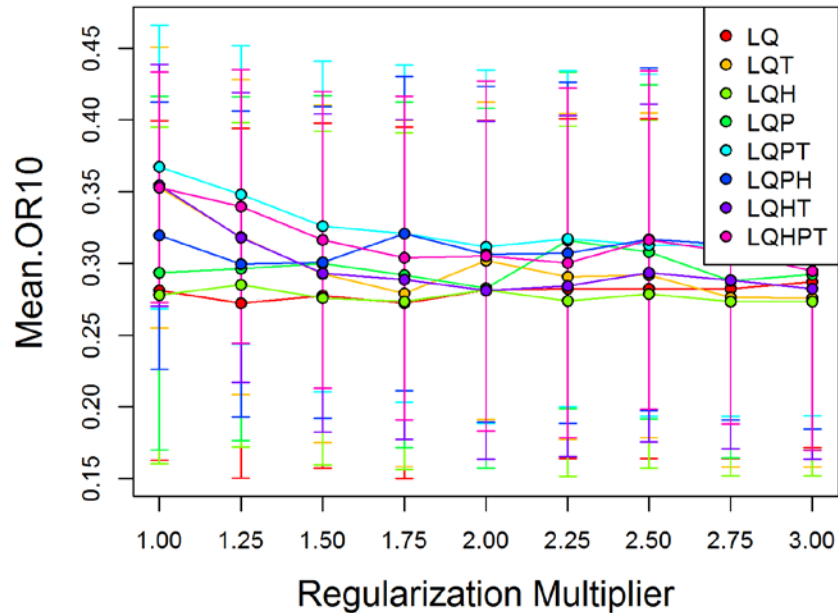
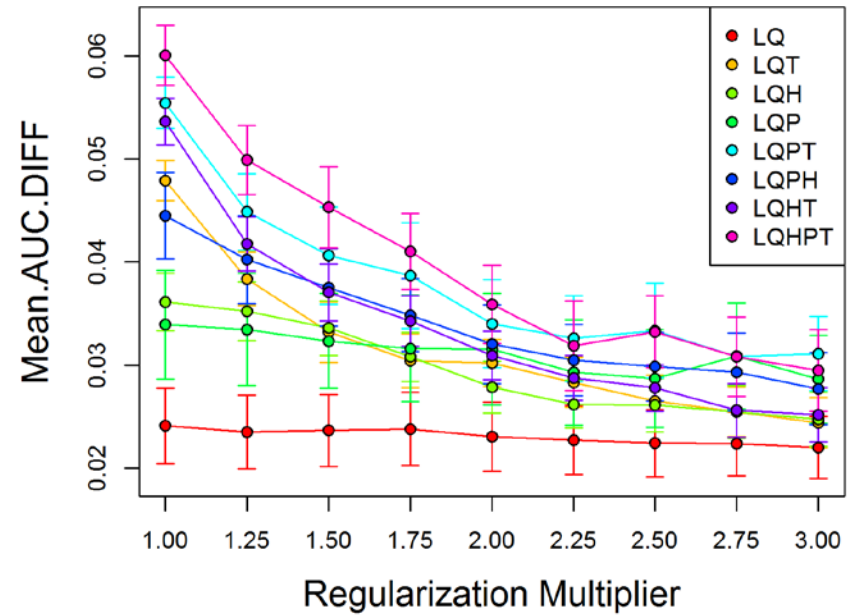
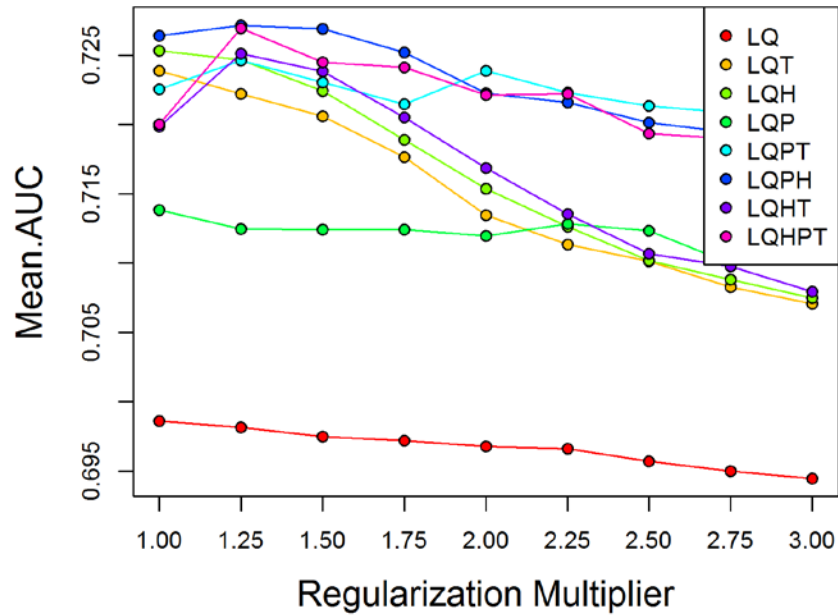
- **water deficit annual: 43.89%**
 - *degree days 5C*: 2.63%
 - *tmean annual*: 2.16%
 - *tmax warmest month*: 0%
 - *tmean warmest quarter*: 0.11%
 - *AET annual mean*: 0.97%
- **ppt warmest quarter: 12.74%**
- **ppt annual: 11.28%**
 - *tmean coldest quarter*: 0%
 - *Topsoil pH*: 0%
- **temp range: 5.22%**
 - *temp seasonality*: 4.81%
- **LANDFIRE reclass: 5.07%**
- **ppt seasonality: 3.64%**
 - *tmin coldest month*: 0.72%
- **aspect: 2.20%**
- **slope: 1.62%**
- **distance to water: 1.44%**
- **topsoil clay fraction: 1.42%**
- topsoil silt fraction: 0.09%
- combined topographic index: 0%
- ppt coldest quarter: 0%
- topsoil bulk density: 0%
- topsoil sand fraction: 0%

Calibrating MaxEnt

- Two important parameters
 - Regularization Multiplier (RM)
 - Tightness of fit
 - Allowed “Feature Classes” (FCs)
 - Types of mathematical relationships explored by MaxEnt
 - Include Linear, Quadratic, Hinge, Product, and Threshold
 - Numerous recent emphasize the importance of tuning/calibrating these parameters
 - ENMeval (Muscarella et al. 2014) now makes it relatively easy to do so.
 - For each run, tried 8 FC combos X 9 RMs = 72 models

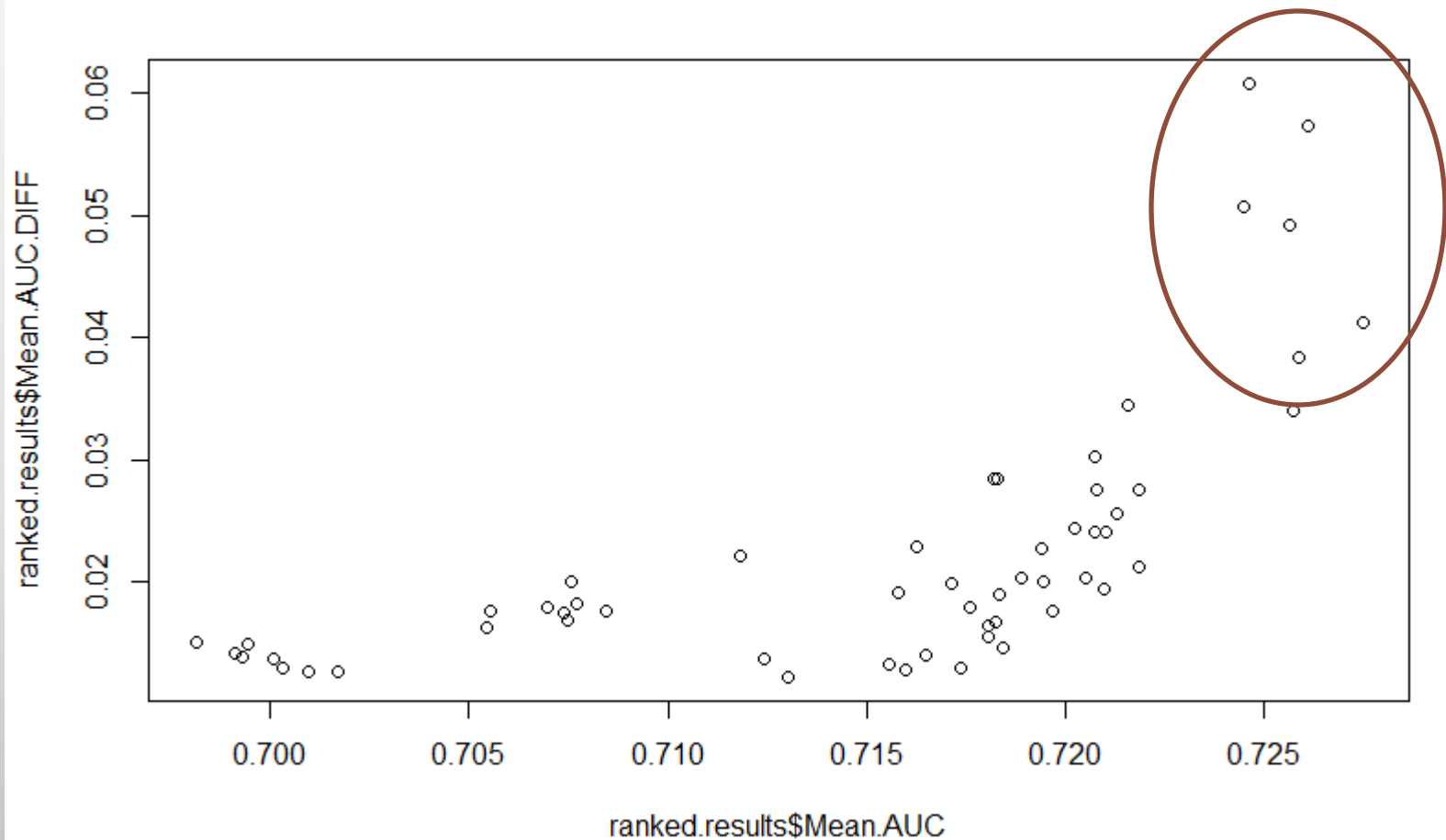


Example ENMeval calibration outputs for monarch breeding habitat suitability



AUC vs. AUC DIFF:

Finding overfit models



Model selection

- No accepted standard metric.
- AUC is often used on its own, but does not adequately penalize overfitting
- We are selecting models by
 - First removing anything below a 0.7 AUC
 - Removing models that are in the bottom quadrant for any of the three overfitting metrics
 - Sorting those that remain by AUC, and inspecting the top several versions (usually very similar)

A. eriocarpa

AUC = 0.71 AUC.diff=0.08, RM=1.5

water deficit annual: 43.0%

ppt annual: 26.8%

temp range: 7.3%

ppt seasonality: 6.0%

ppt warmest quarter: 4.2%

slope: 3.9%

LANDFIRE reclass: 3.1%

aspect: 2.5%

Topsoil Clay Fraction: 2.4%

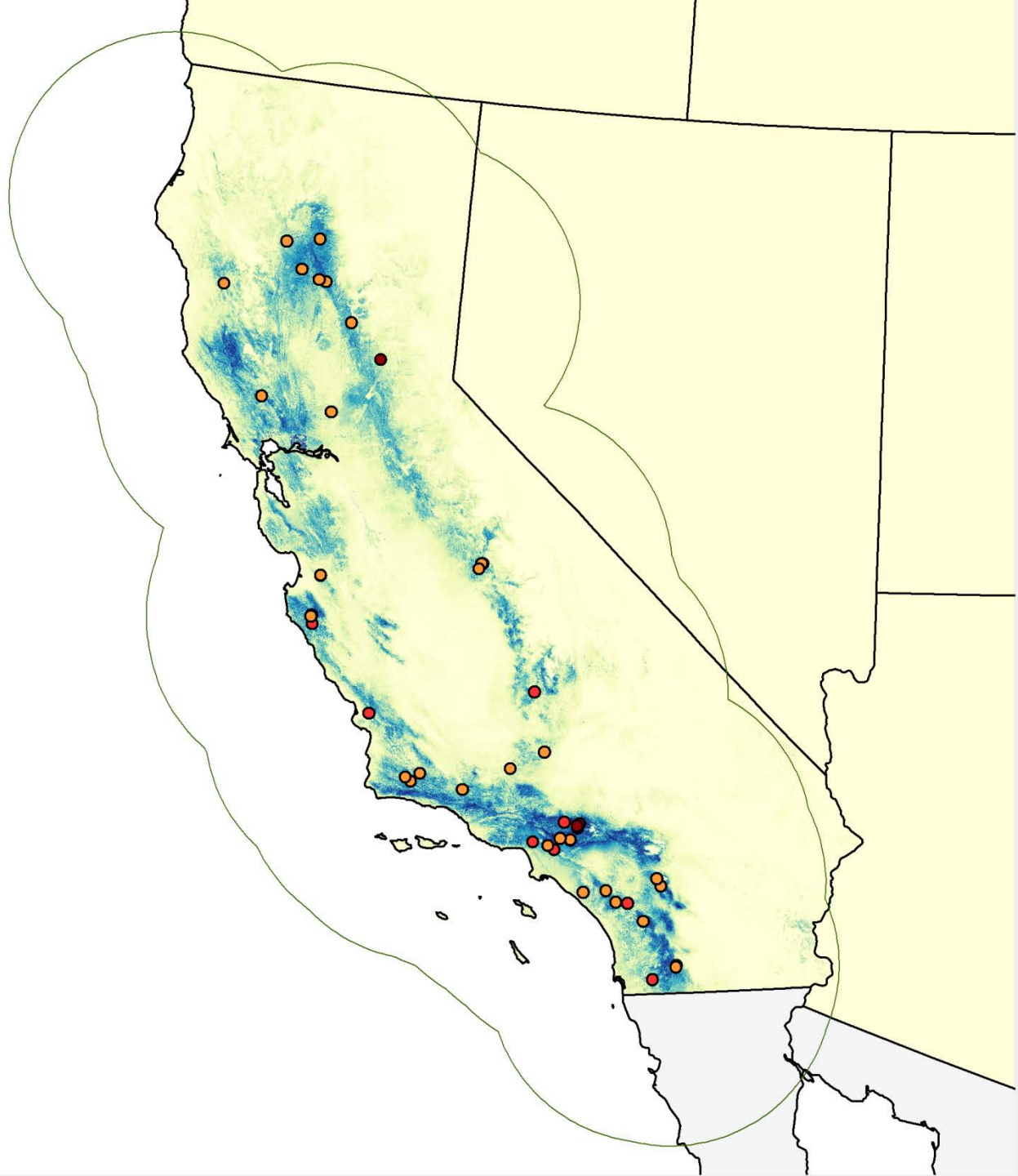
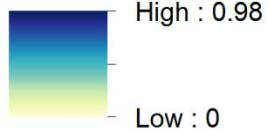
distance to water: 0.7%

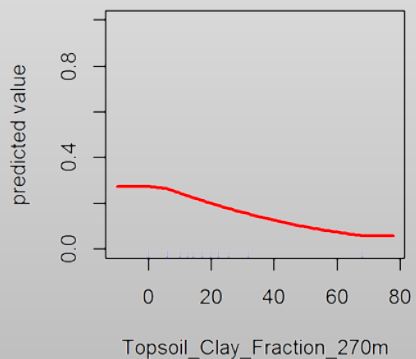
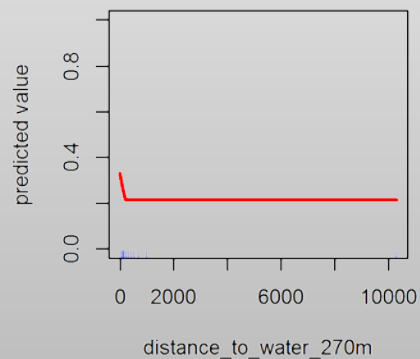
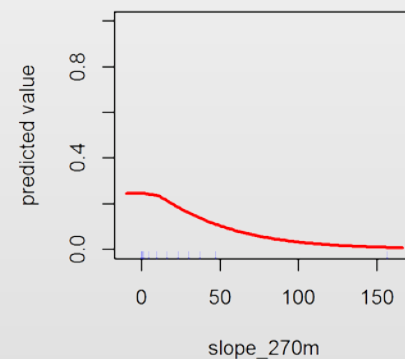
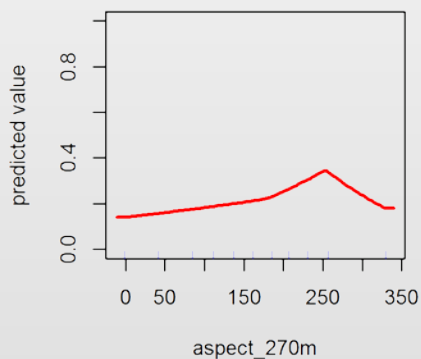
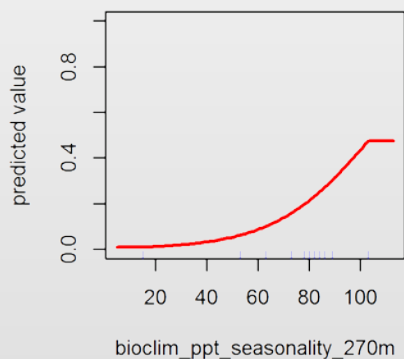
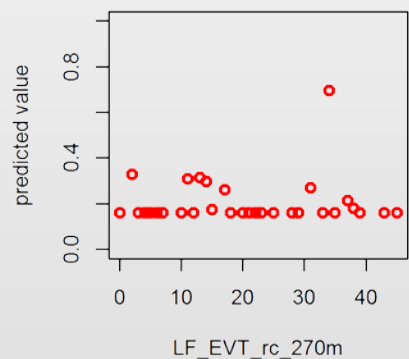
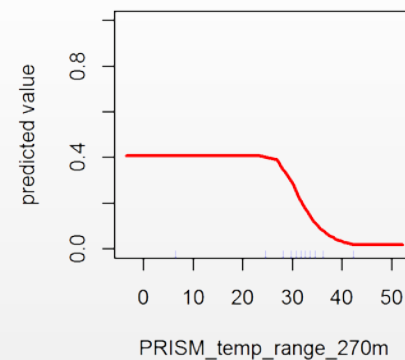
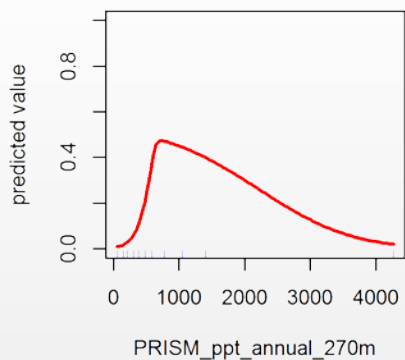
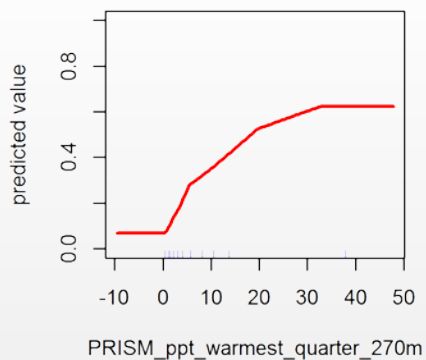
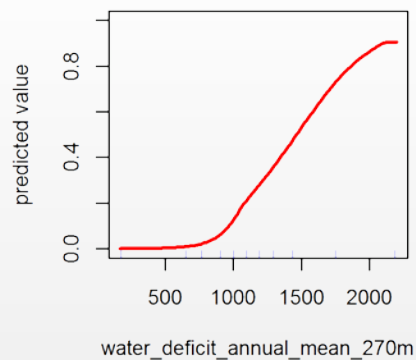
Points by accuracy class

- High
- Medium-High
- Medium

Modeling extent

Relative Habitat Suitability





A. fascicularis

AUC = 0.73 AUC.diff=0.02, RM=2.25

ppt coldest quarter: 23.7%

tmean coldest quarter: 21.5%

ppt warmest quarter: 17.8%

LANDFIRE reclass: 9.7%

Topsoil Silt Fraction: 7.8%

ppt seasonality: 6.1%

Topsoil Bulk Density: 5.5%

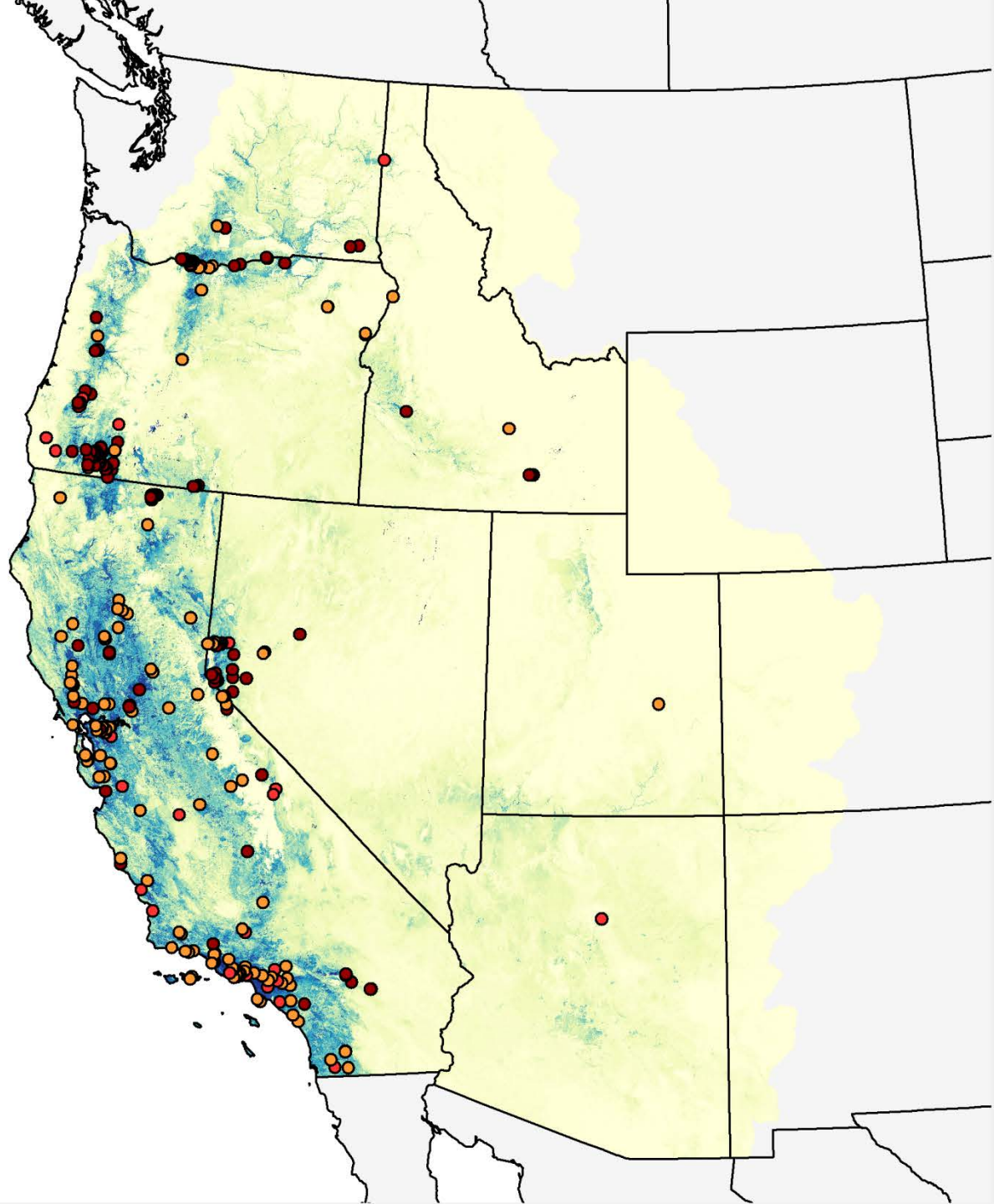
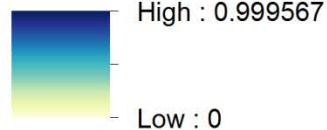
slope: 5.0%

distance to water: 2.8%

Points by accuracy class

- High
- Medium-High
- Medium

Relative Habitat Suitability



A. speciosa

AUC = 0.7 AUC.diff=0.03, RM=2.25

tmin coldest month: 23.9%

tmax warmest month: 16.1%

ppt warmest quarter: 14.2%

temp seasonality: 12.6%

slope: 11.5%

distance to water: 9.2%

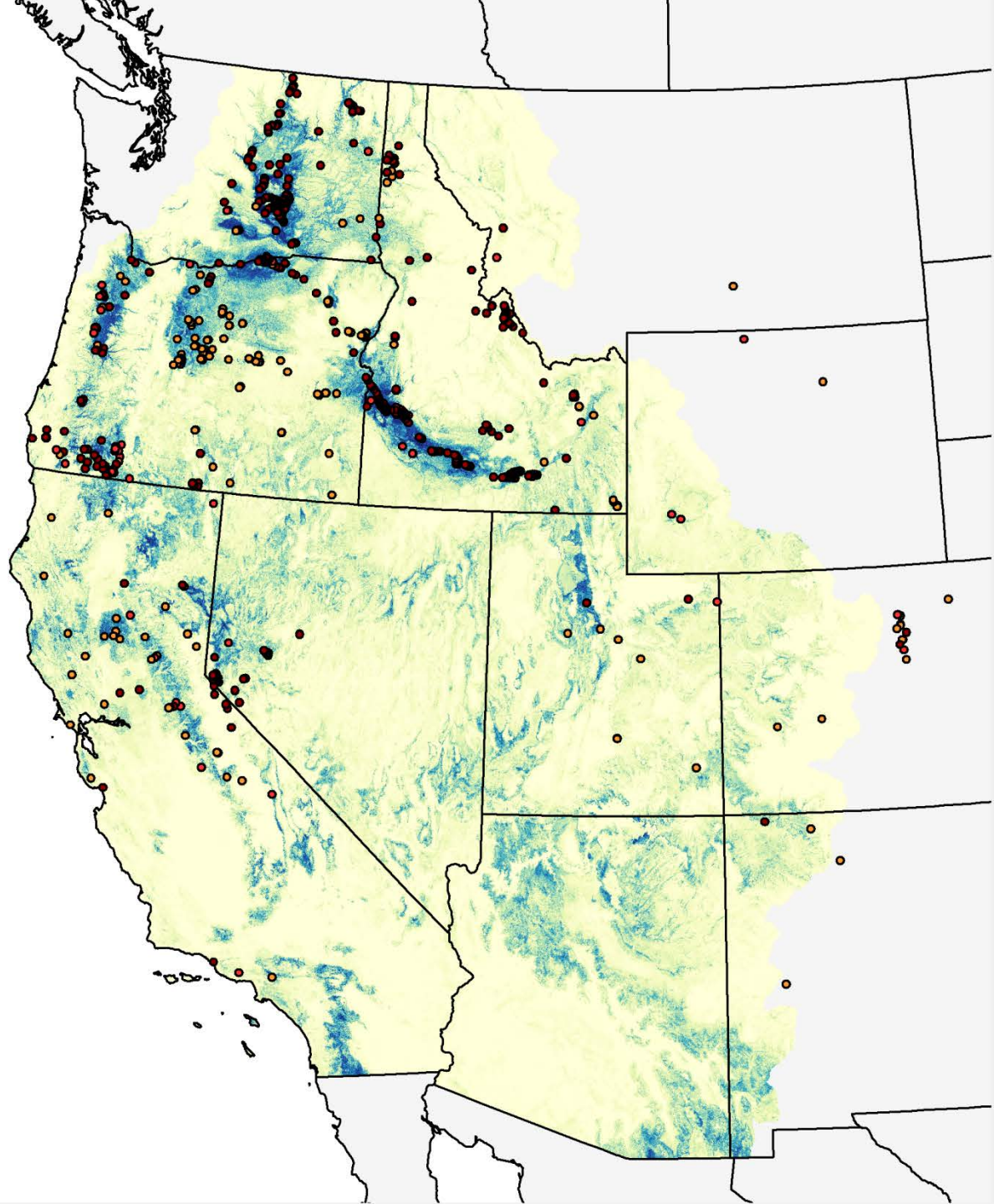
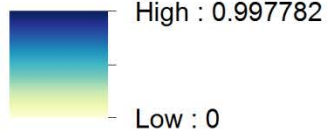
ppt coldest quarter: 8.3%

Topsoil Silt Fraction: 4.2%

Points by accuracy class

- High
- Medium-High
- Medium

Relative Habitat Suitability






Effect of spatial inaccuracy in data on species distribution models

- Graham et al 2008
 - Moved each coordinate with a random number drawn from the normal distribution with a mean of zero and a standard deviation of 5 km
 - Found MaxEnt was largely unaffected by these errors
 - But, many of the errors in the milkweed and monarch database could be far greater than 5km.



A. asperula

AUC = 0.71; AUC.diff=0.05, RM=1.5


ppt seasonality: 32.1%
ppt coldest quarter: 21.7%
AET annual mean: 16.3%
ppt warmest quarter: 9.2%
tmean warmest quarter: 6.6%
distance to water: 6.3%
LANDFIRE reclass: 3.7%
slope: 3.6%
Topsoil Silt Fraction: 0.6%

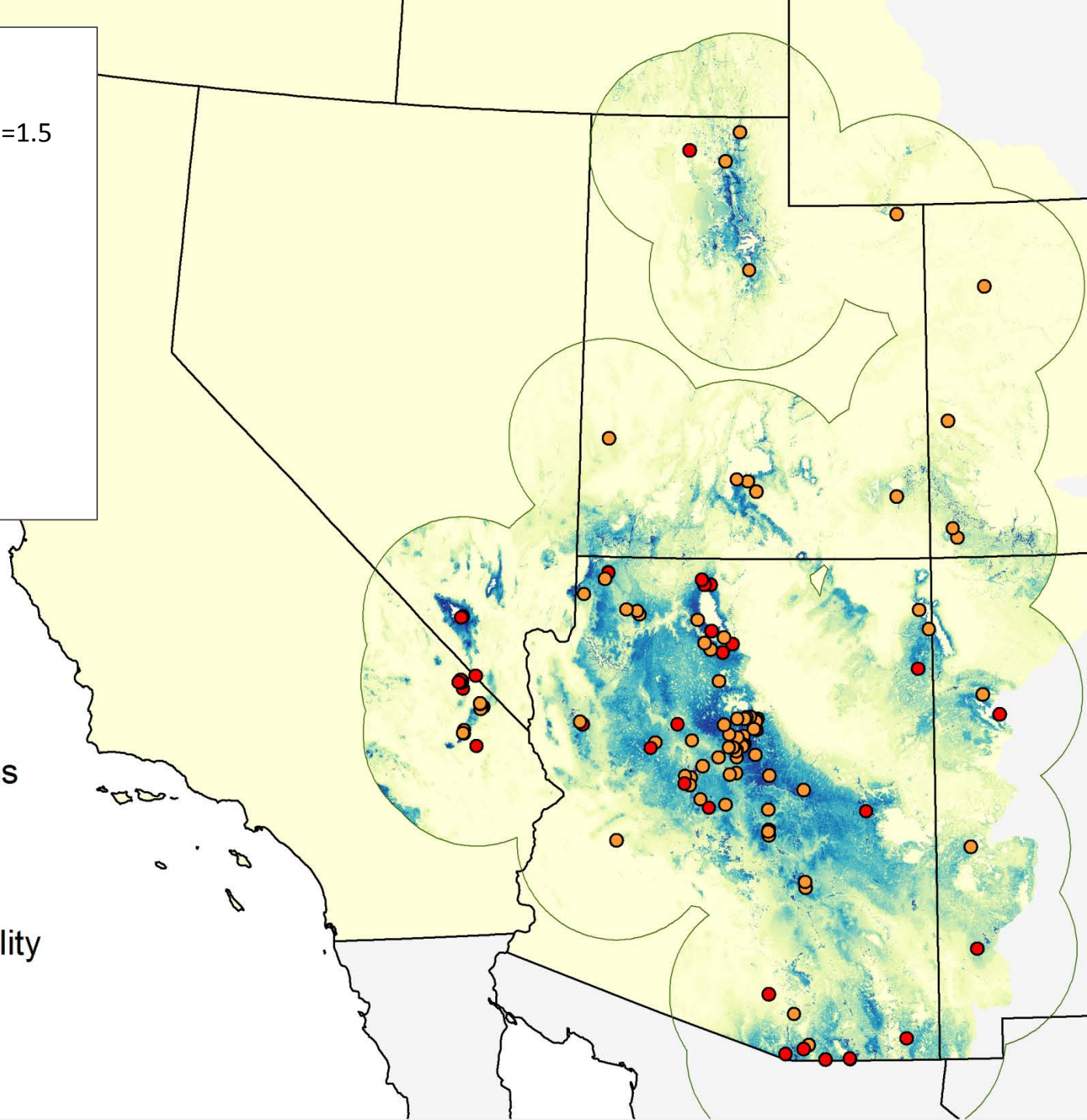
 Modeling extent

Points by accuracy class

-  Medium or better
-  Low (but not vague)

Relative Habitat Suitability


 High : 0.999626
Low : 0





A. cordifolia

AUC = 0.72; AUC.diff=0.03, RM=1.75


ppt annual: 28.2%
tmin coldest month: 15.0%
temp range: 12.9%
water deficit annual : 11.9%
ppt warmest quarter: 8.6%
slope: 6.1%
Topsoil Silt Fraction: 6.1%
LANDFIRE reclass: 5.1%
distance to water: 4.5%
aspect: 1.5%

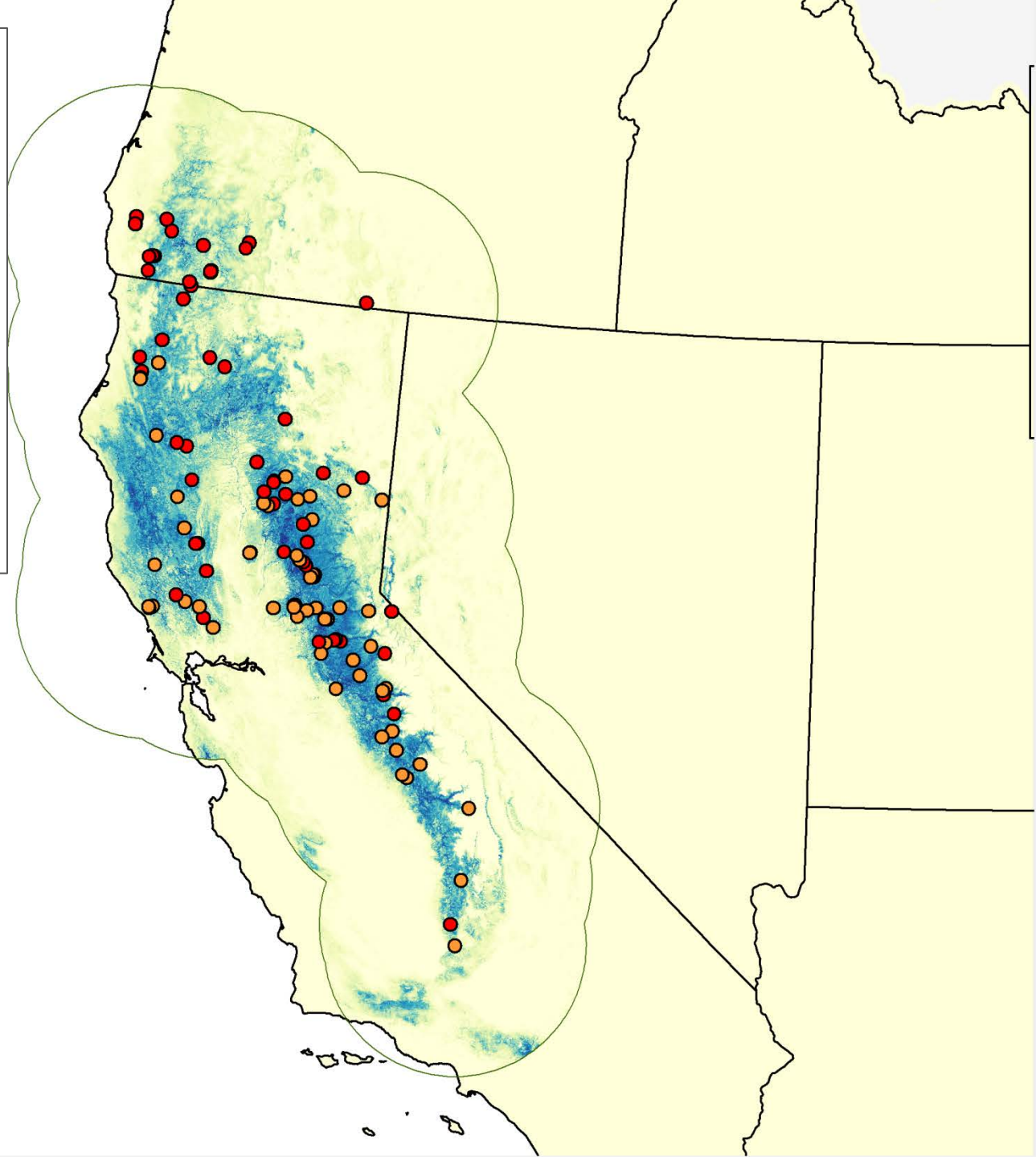
 Modeling extent

Points by accuracy class

-  Medium or better
-  Low (but not vague)

Relative Habitat Suitability


 High : 0.975831
Low : 0



Monarch breeding

AUC = 0.7; AUC.diff=0.06, RM=1.25

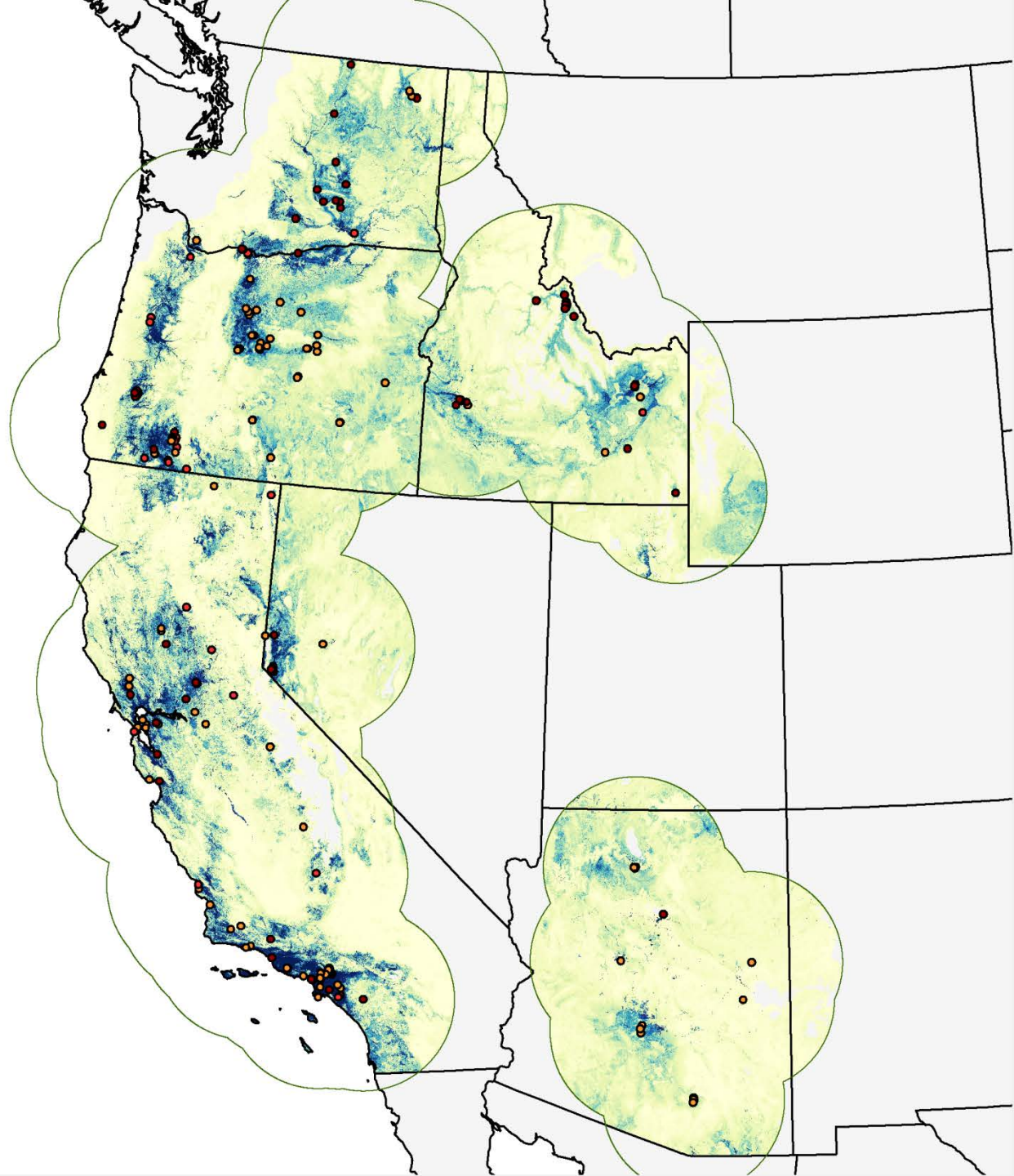
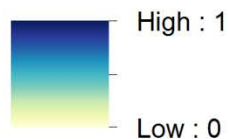
fascicularis model: 41.6%
speciosa model: 22.7%
tmean warmest quarter: 9.7%
AET annual mean: 5.5%
ppt warmest quarter: 4.1%
eriocarpa model: 3.4%
ppt seasonality: 2.9%
asperula model: 2.8%
slope: 2.5%
Topsoil Sand Fraction: 1.5%
cordifolia model: 1.3%
Topsoil Clay Fraction: 1.1%
distance to water: 0.9%

 Modeling extent

Points by accuracy class

- High
- Medium-High
- Medium

Relative Habitat Suitability



Potential improvements

- Near term
 - Can run with different variable subsets
- Long term
 - **More species data -> better models**
 - Improve variables
 - Rivers instead of all minor waterways
 - Recent climate variables instead of long-term avgs.
 - Ensemble of model types
 - Model regions separately
 - Finer models of key regions
 - Seasonal suitability models
 - Climate change modeling

Potential uses

- Guide surveys
 - For example, speciosa model could be mapped with roads and public lands in NV to help inform sampling locations this summer
- Help point to regions of higher potential value for restoration
 - This sort of application probably only appropriate in CA and PNW with these models
- Need to be validated, and new runs



Thank you!

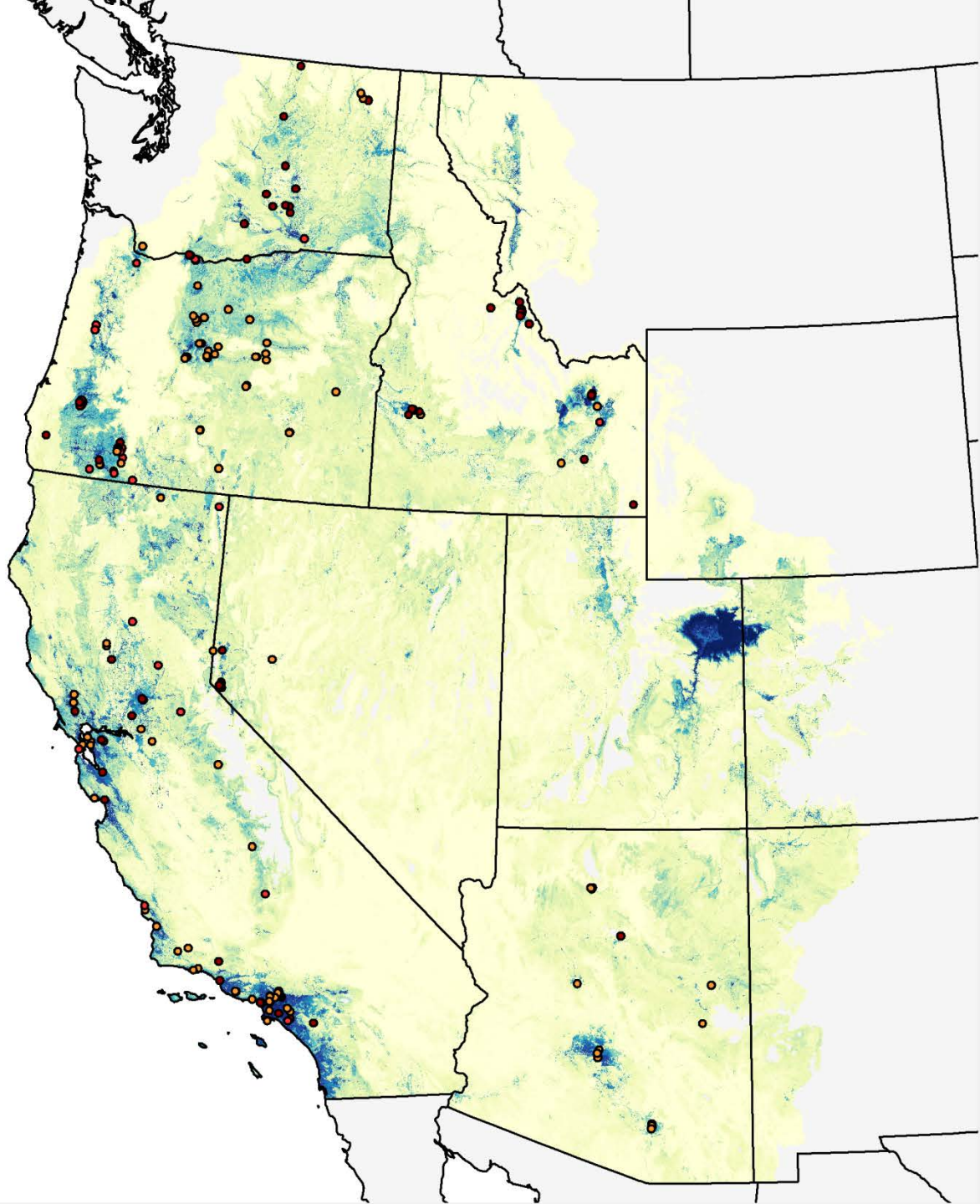
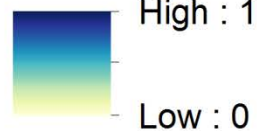
Appendix Slides

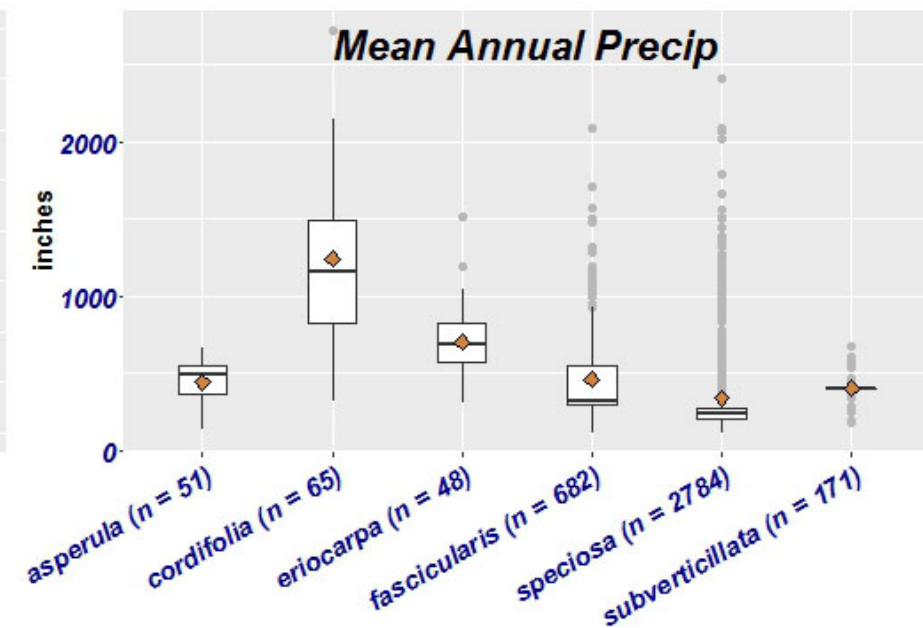
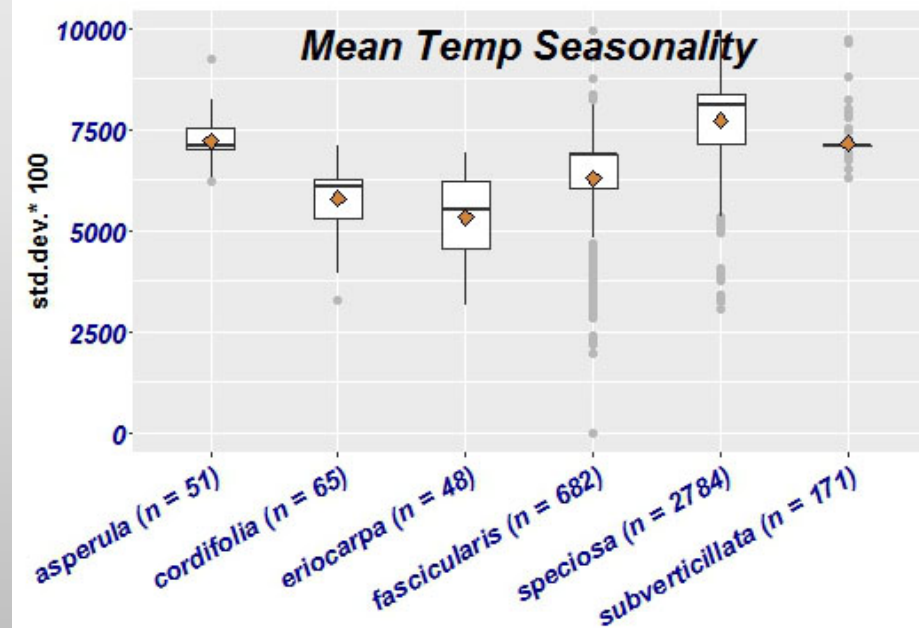
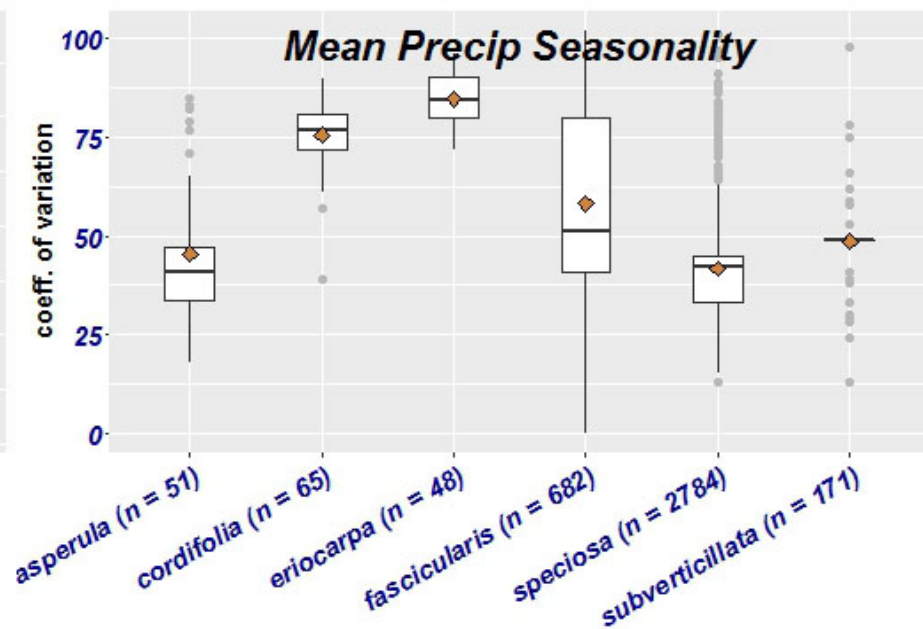
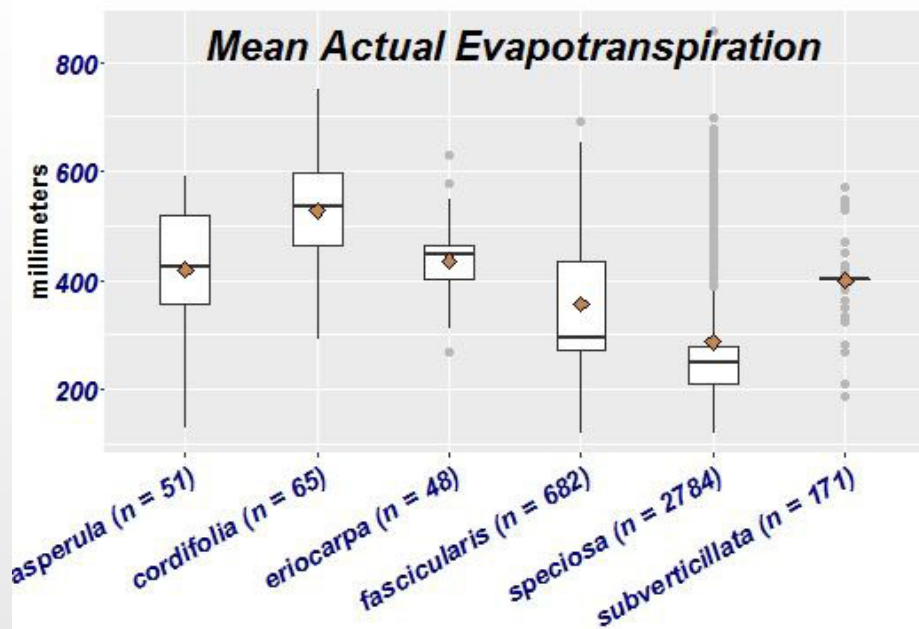
Monarch breeding, projected across large unsampled areas

Points by accuracy class

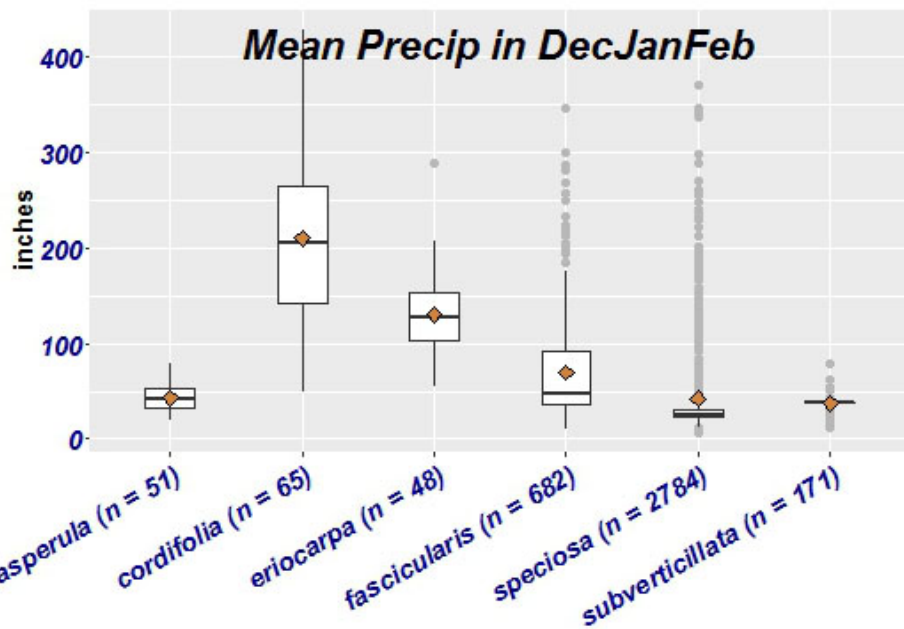
- High
- Medium-High
- Medium

Relative Habitat Suitability

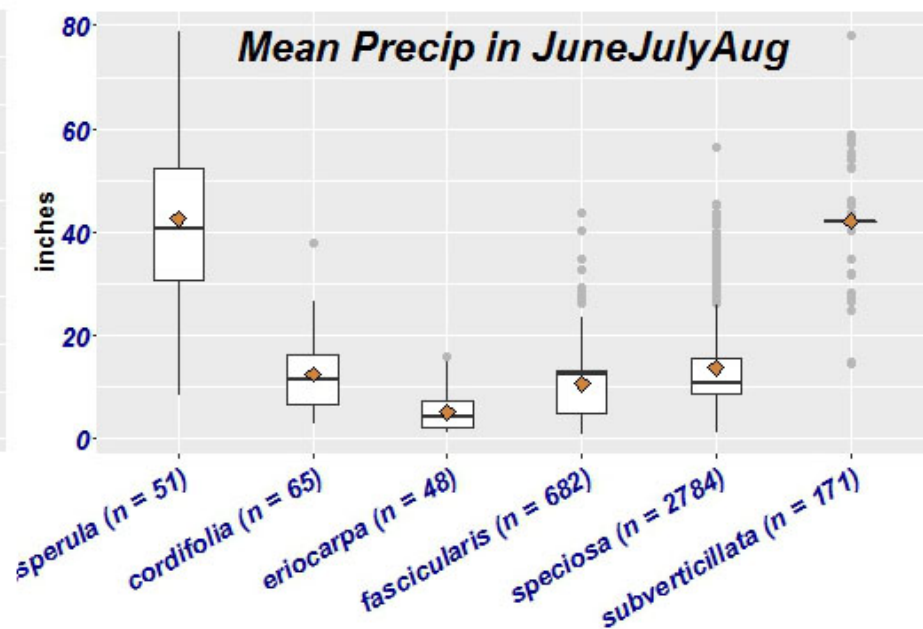




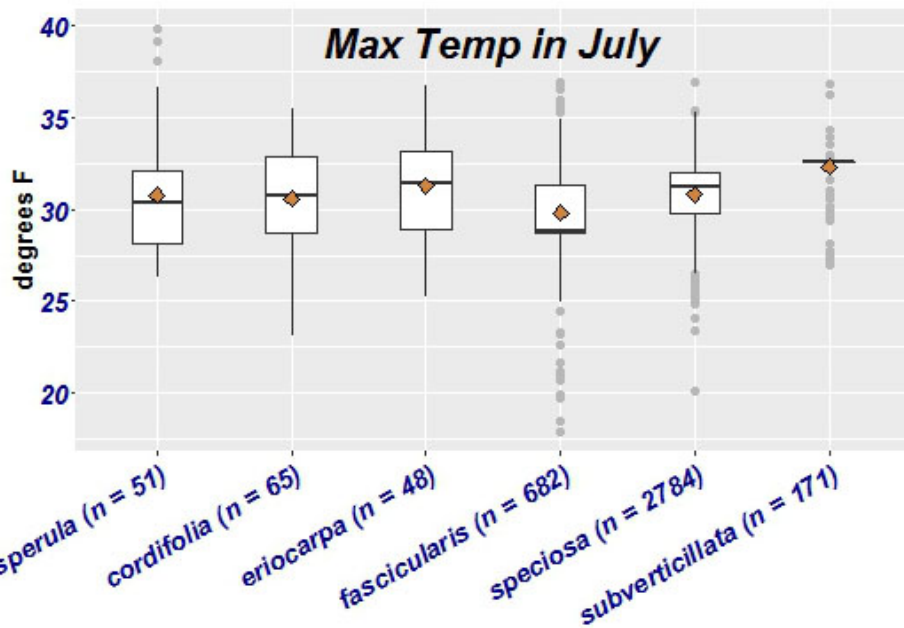
Mean Precip in DecJanFeb



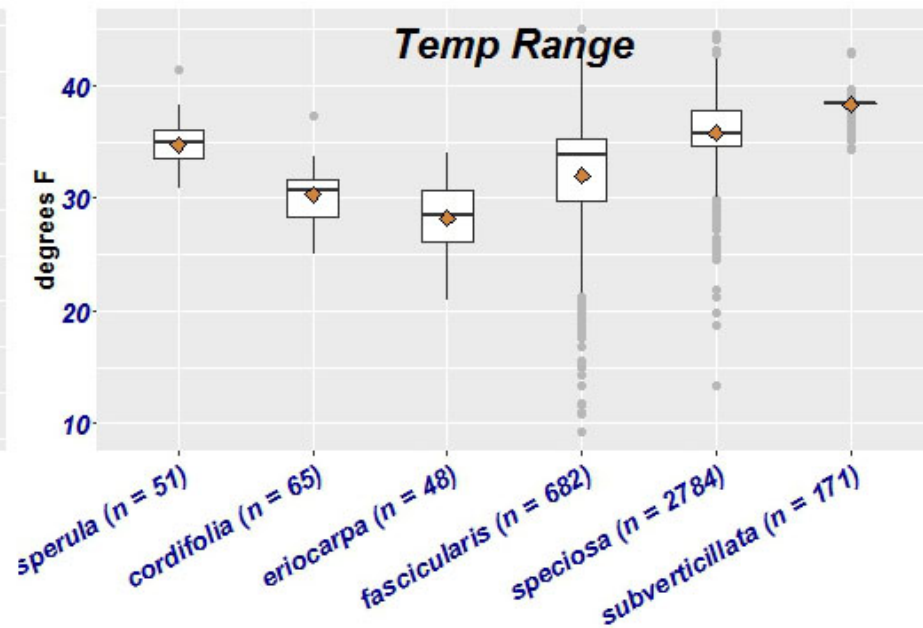
Mean Precip in JuneJulyAug

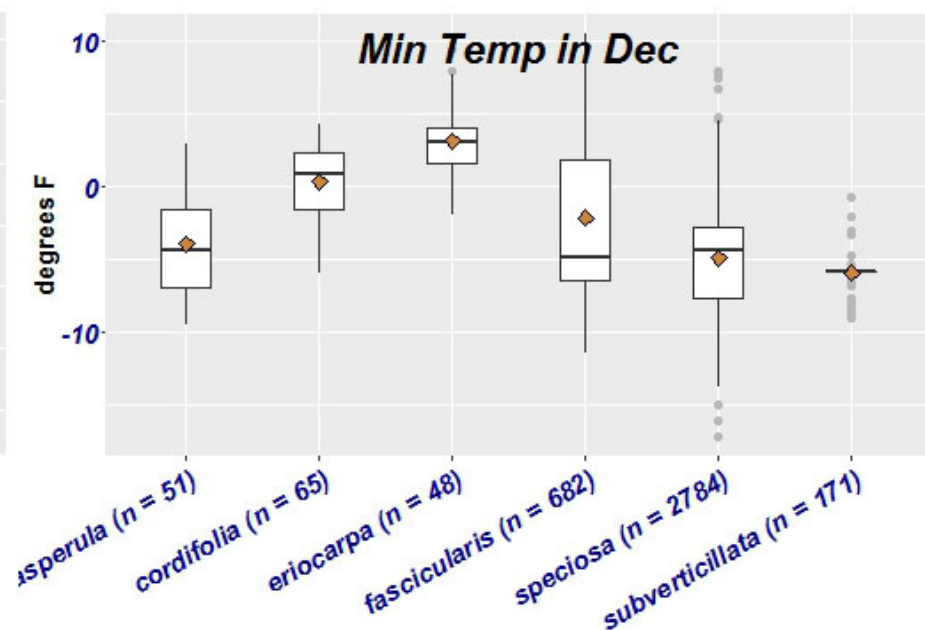
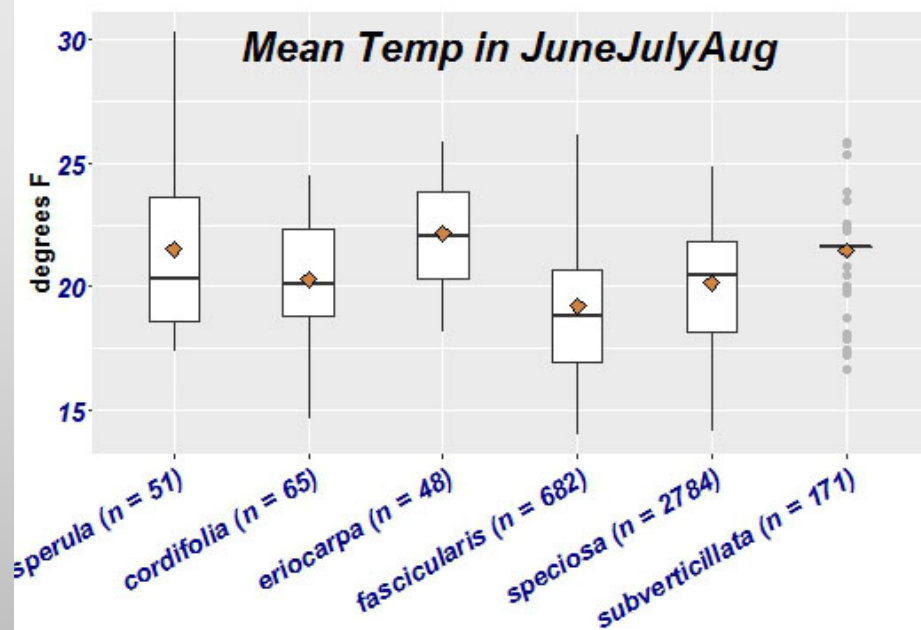
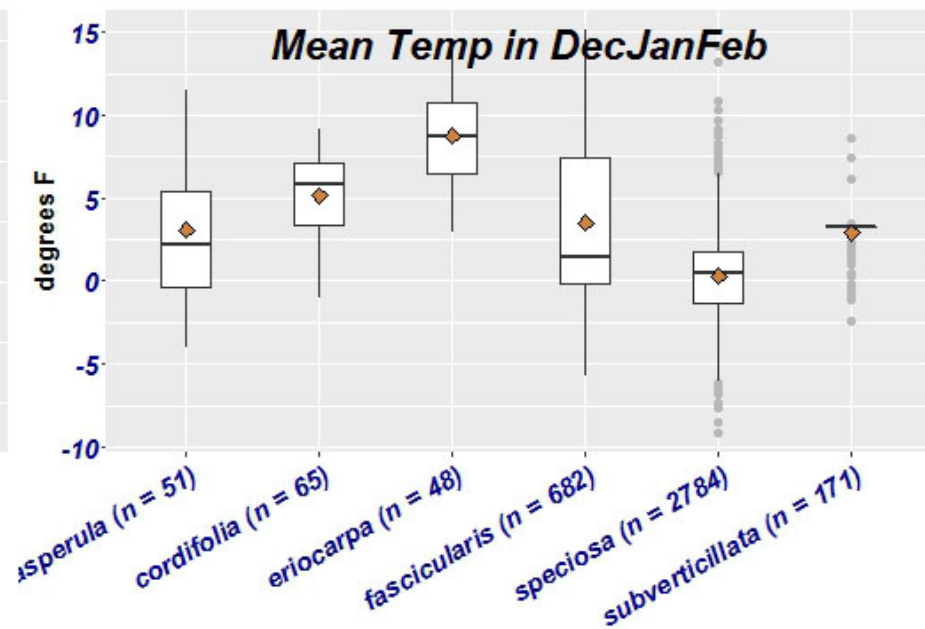
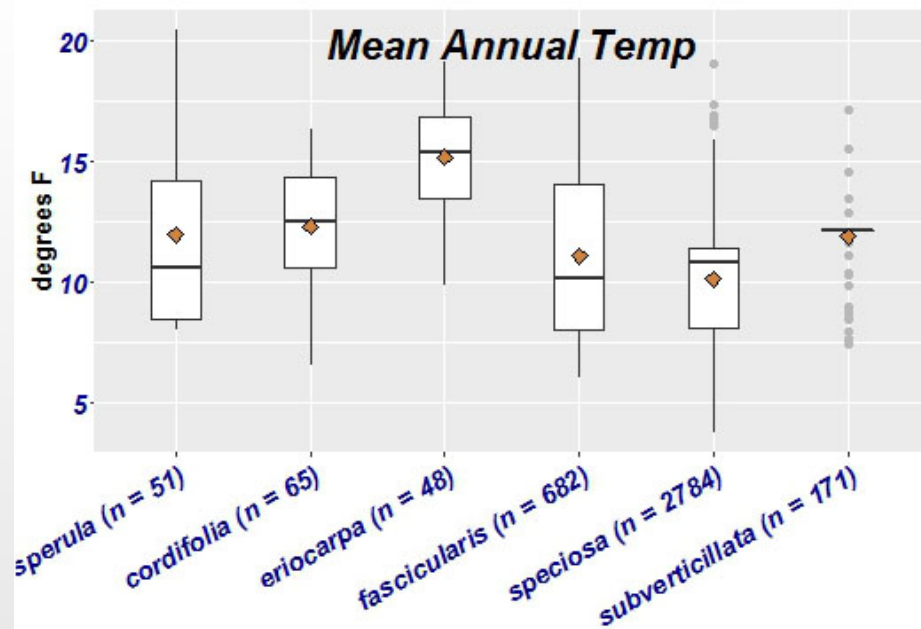


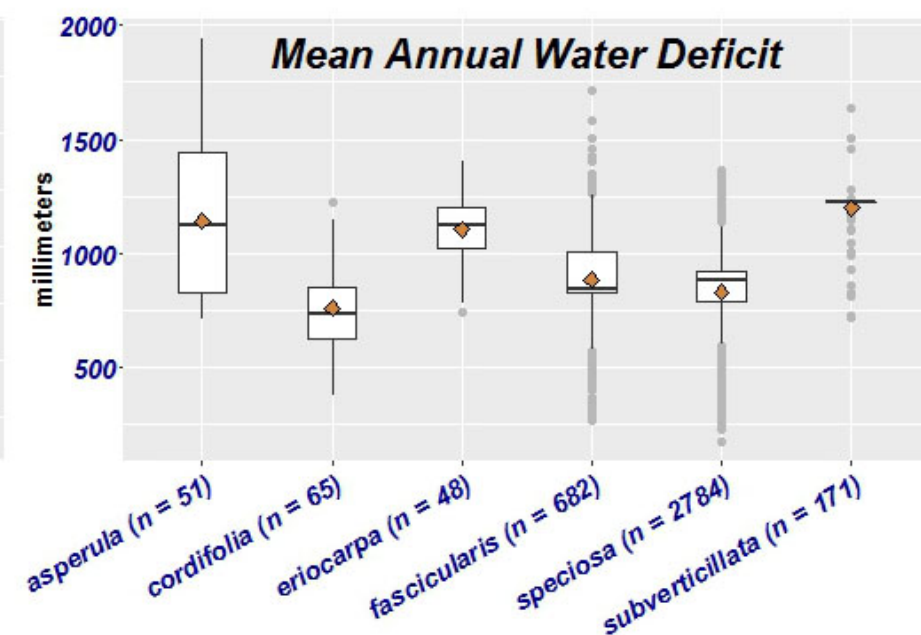
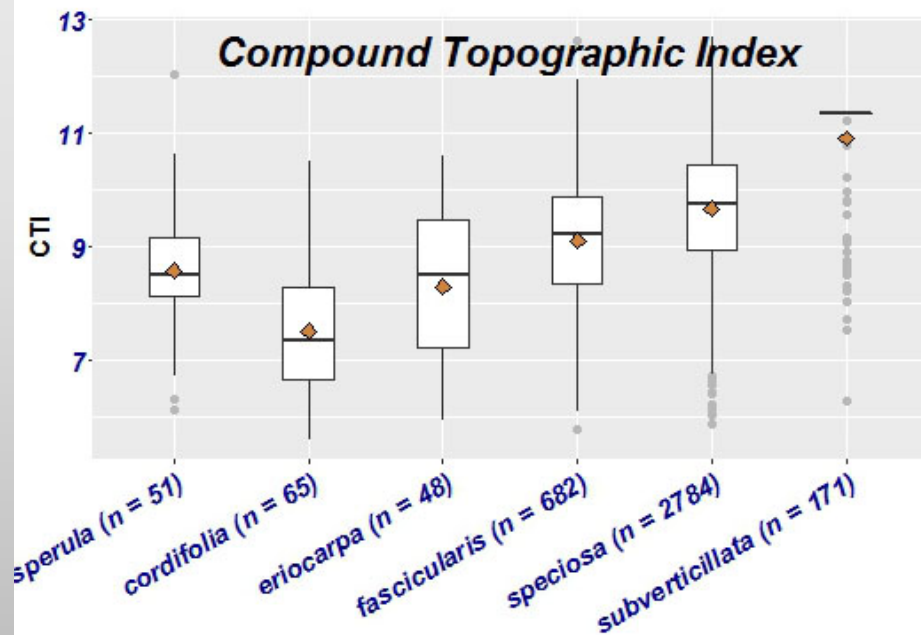
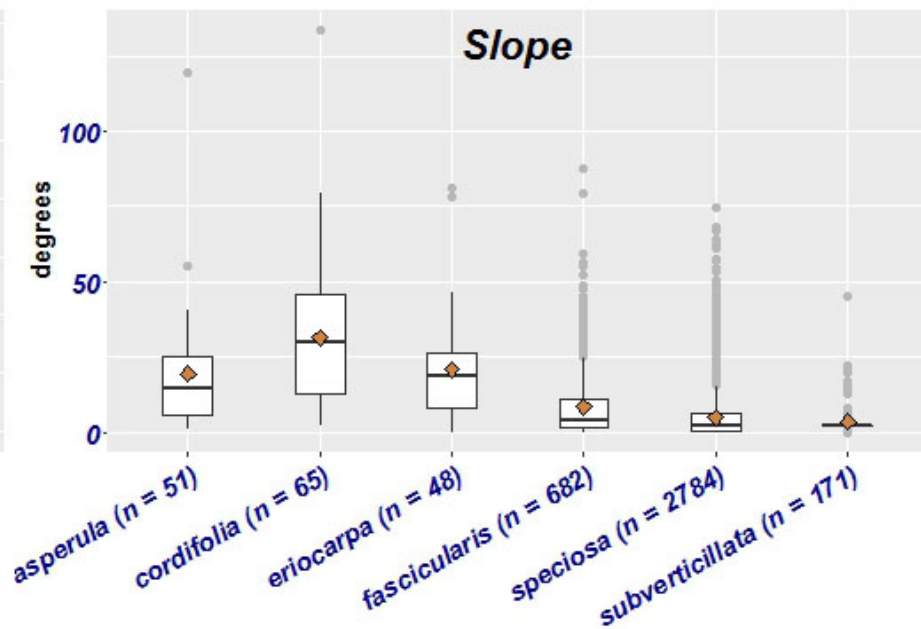
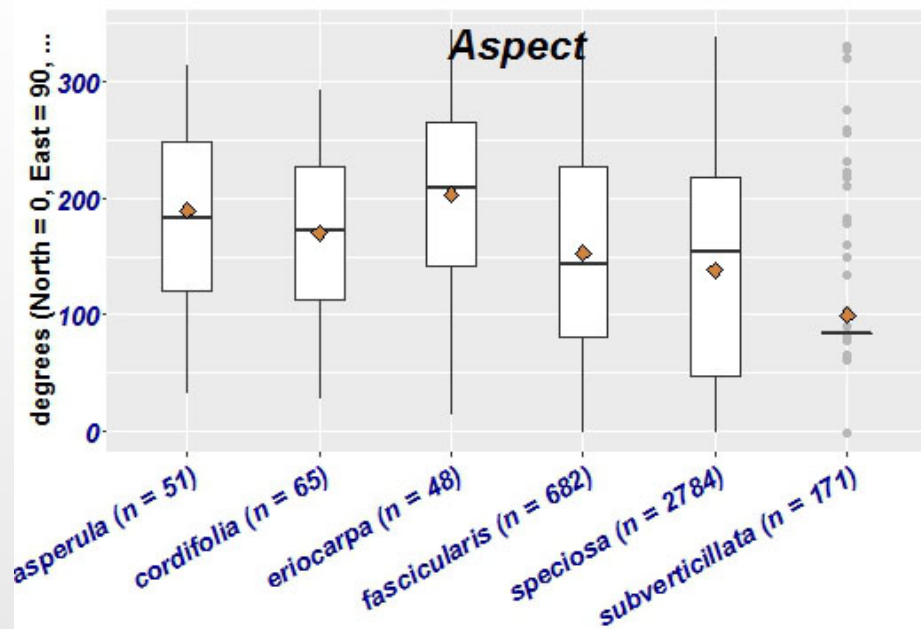
Max Temp in July



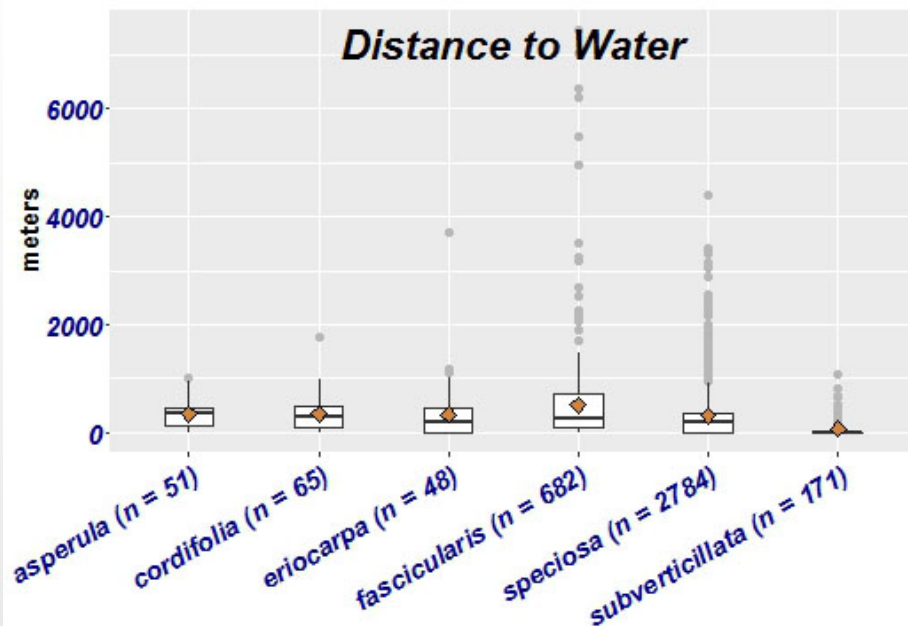
Temp Range



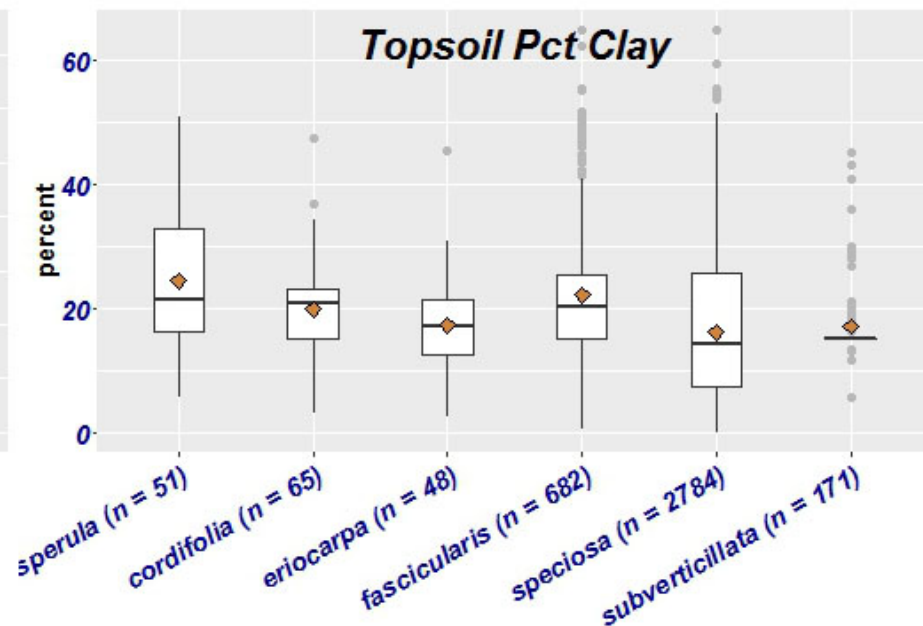




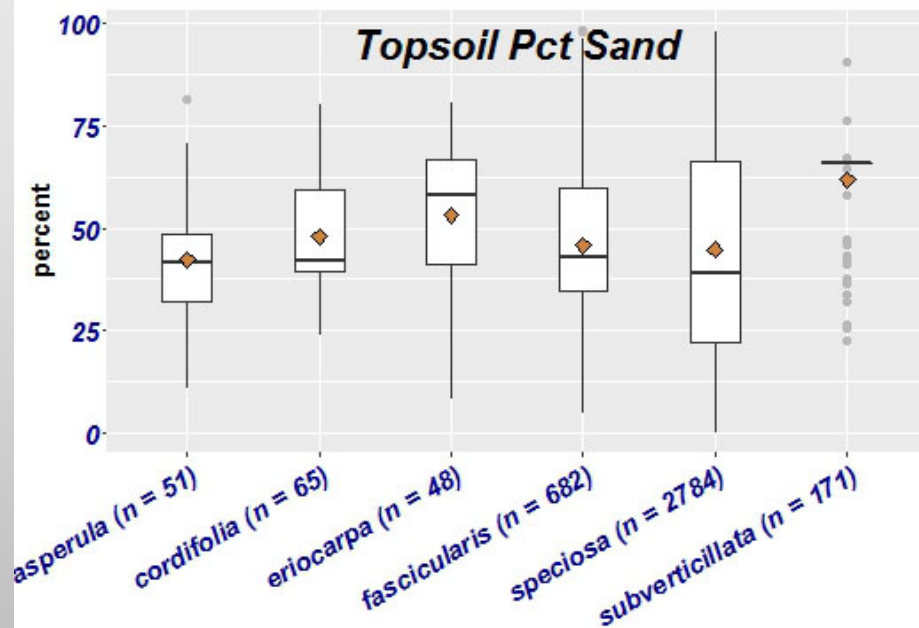
Distance to Water



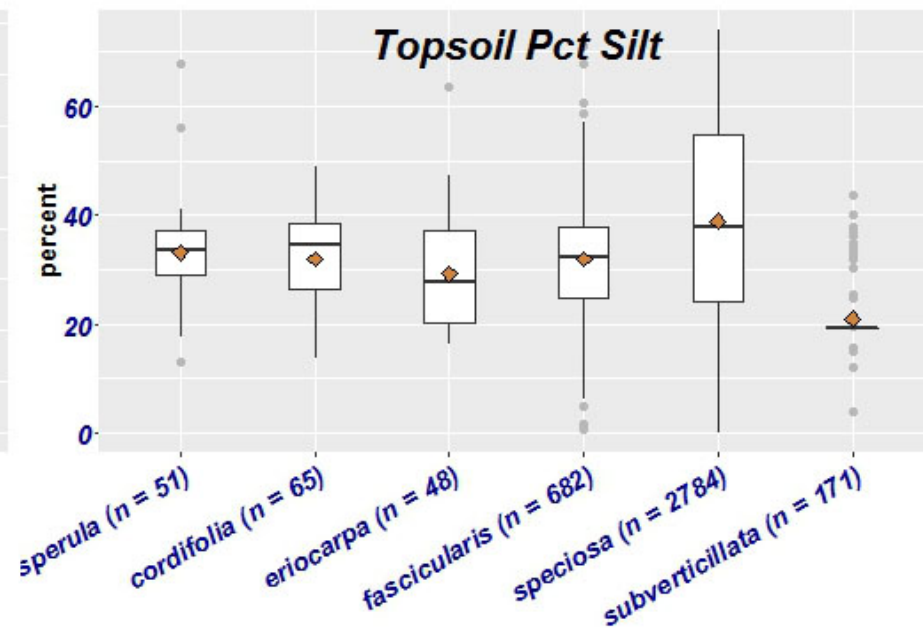
Topsoil Pct Clay

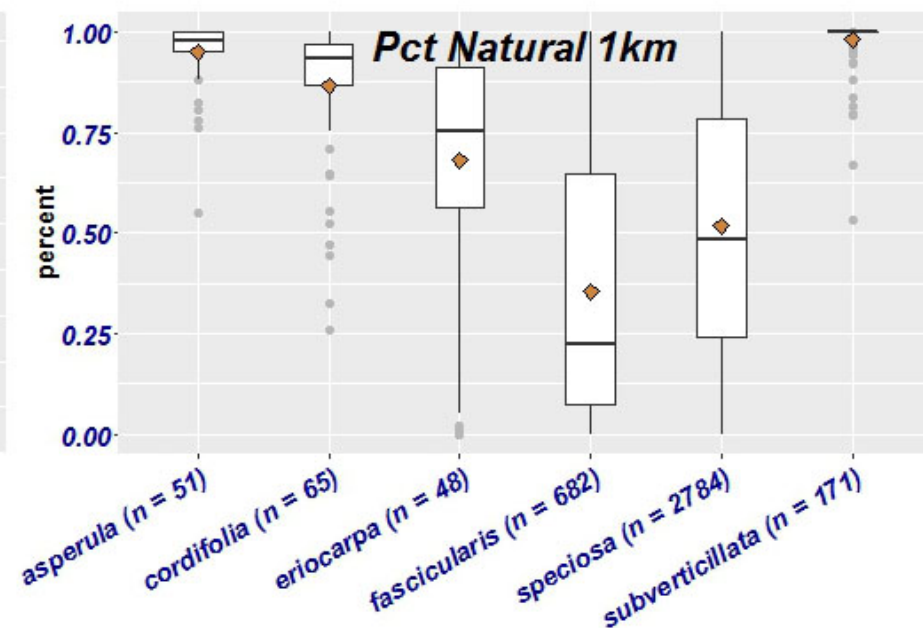
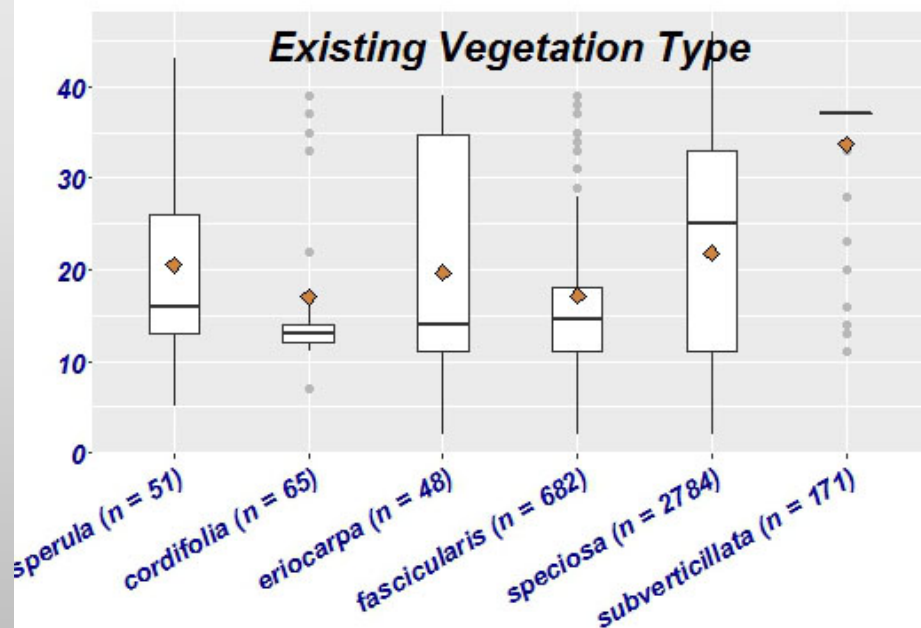
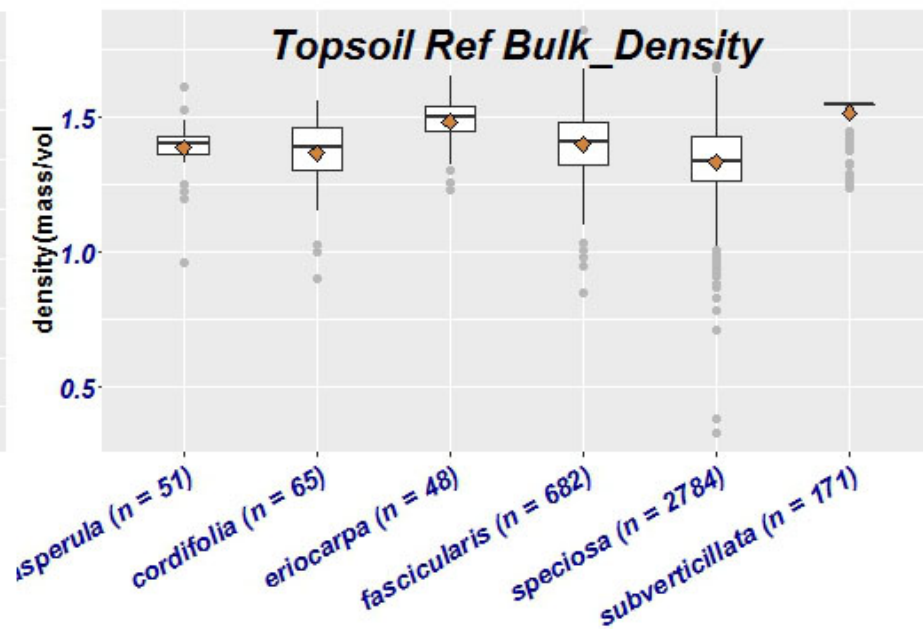
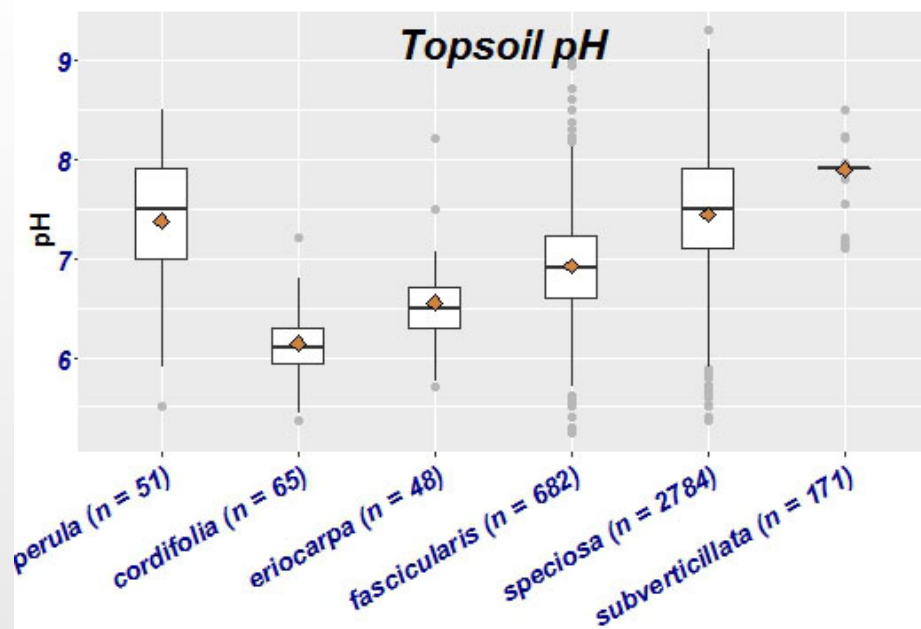


Topsoil Pct Sand



Topsoil Pct Silt

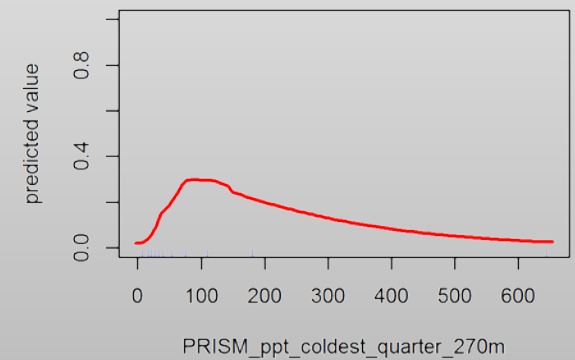
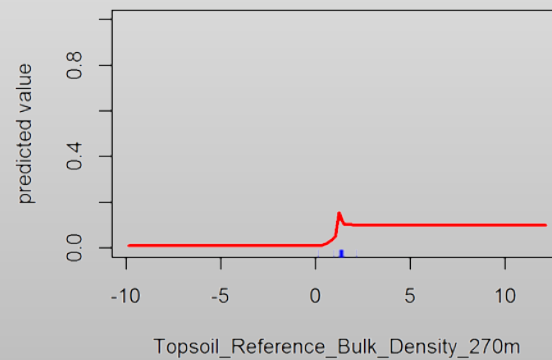
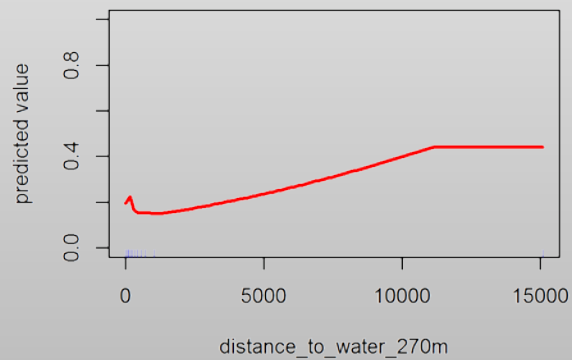
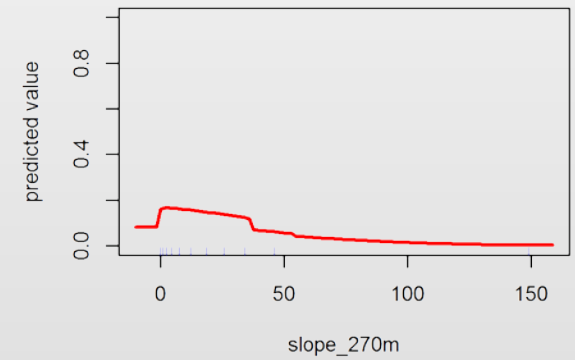
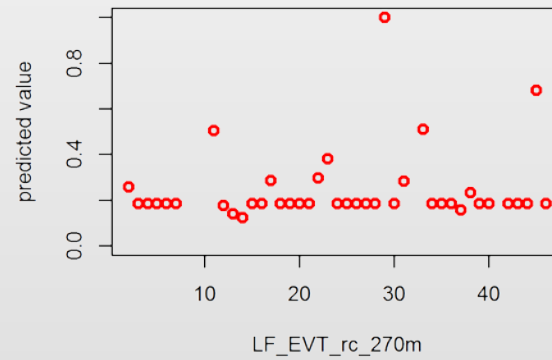
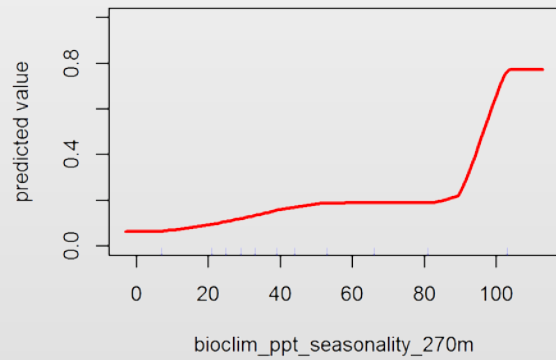
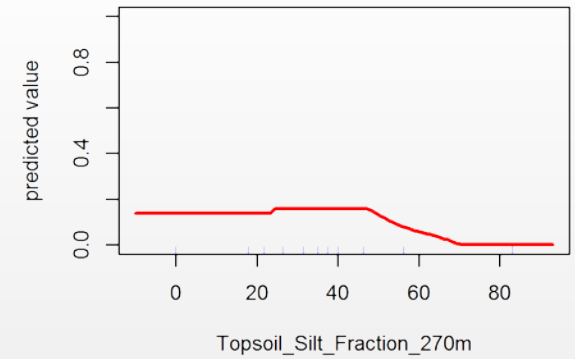
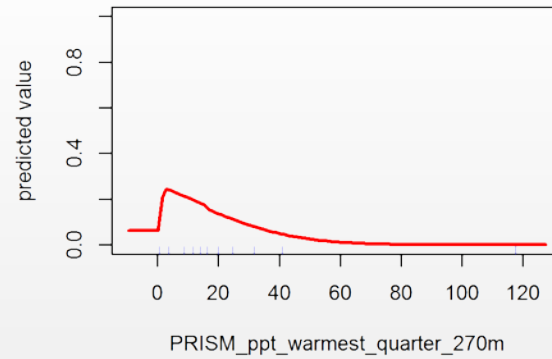
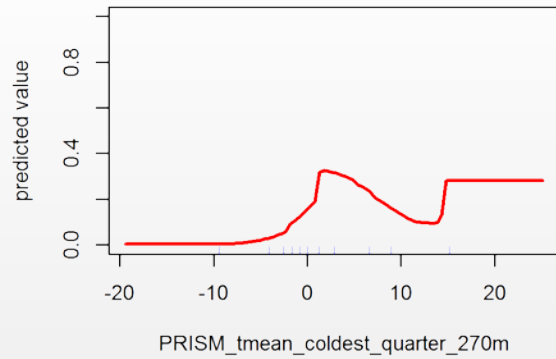




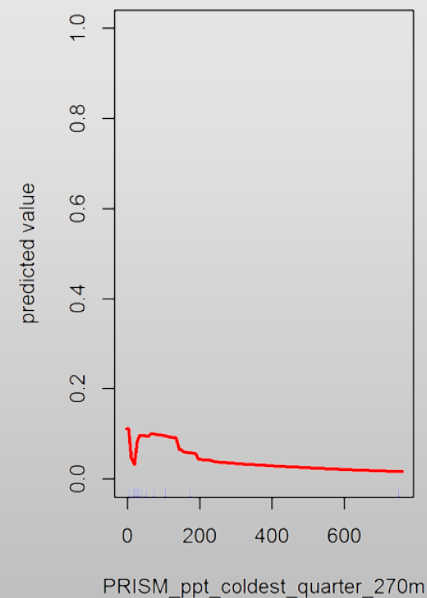
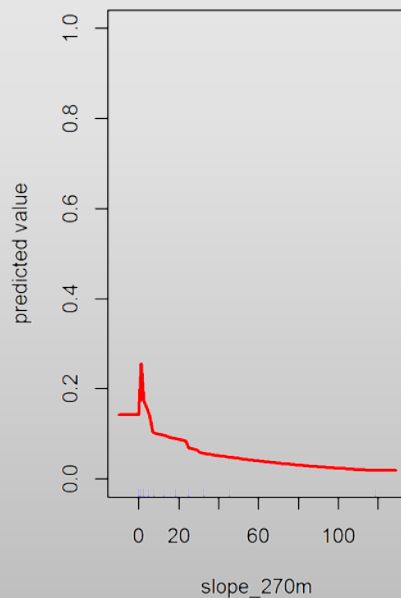
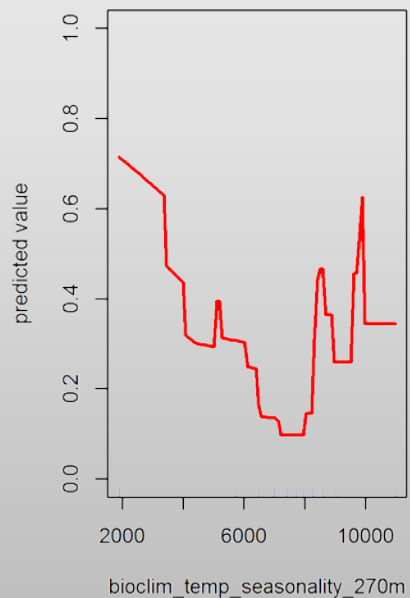
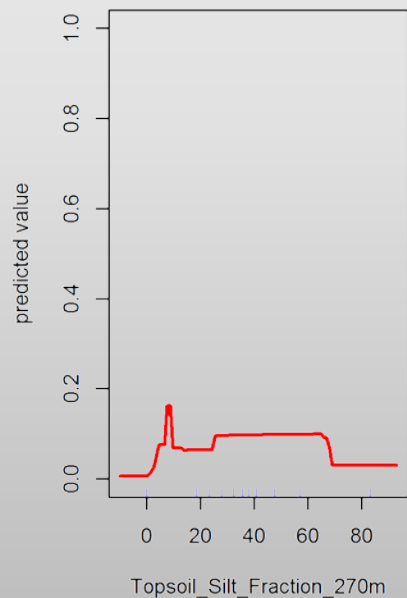
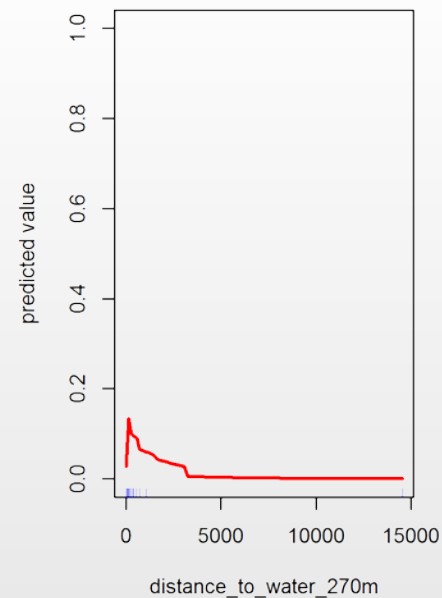
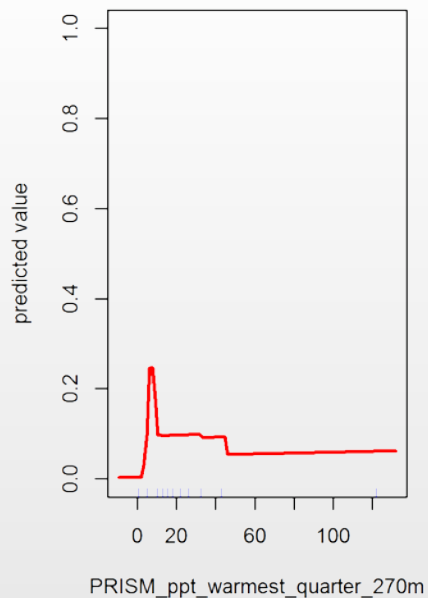
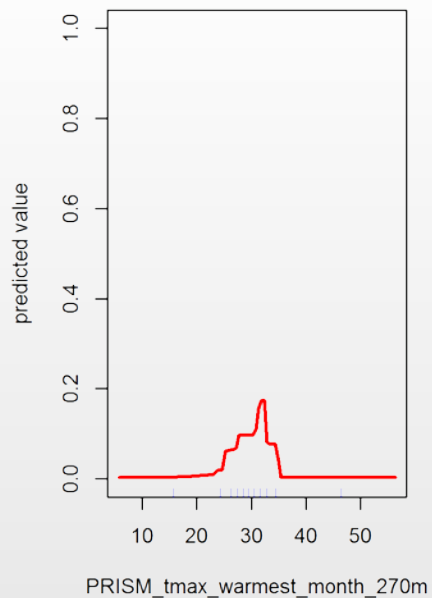
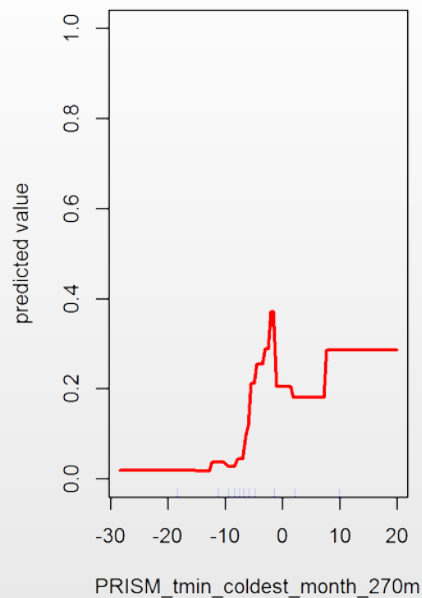
Model evaluation metrics

Metric	Description
AUC Test	Measures goodness of fit. Probability that a randomly-drawn presence has a <i>higher score than a randomly drawn background location</i> . Tends to be lower for generalist species.
AUC Diff	“The difference between the AUC value based on training localities (i.e. AUCTRAIN) and AUCTEST (AUCTRAIN - AUCTEST). If AUCTRAIN < AUCTEST, the returned value is zero. Value of AUCDIFF is expected to be positively associated with the degree of model overfitting” (Muscarella et al. 2014)
ORMTP (‘Minimum Training Presence’ omission rate)	“indicates the proportion of test localities with suitability values (MAXENT relative occurrence rates) lower than that associated with the lowest-ranking training locality. Omission rates greater than the expectation of zero typically indicate model overfitting.
OR10 (10% training omission rate)	indicates the proportion of test localities with suitability values (MAXENT relative occurrence rates) lower than that excluding the 10% of training localities with the lowest predicted suitability. Omission rates greater than the expectation of 10% typically indicate model overfitting

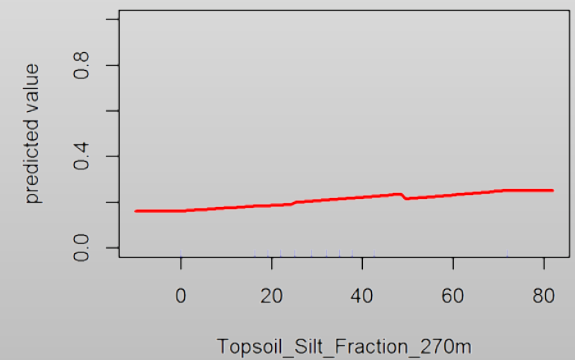
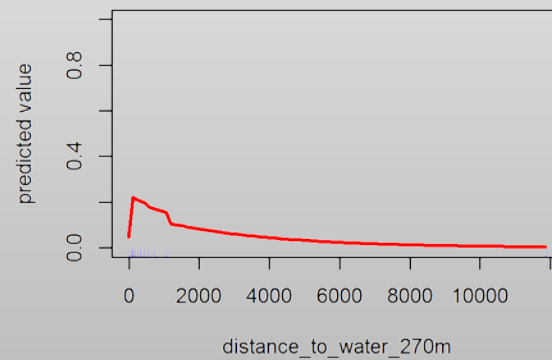
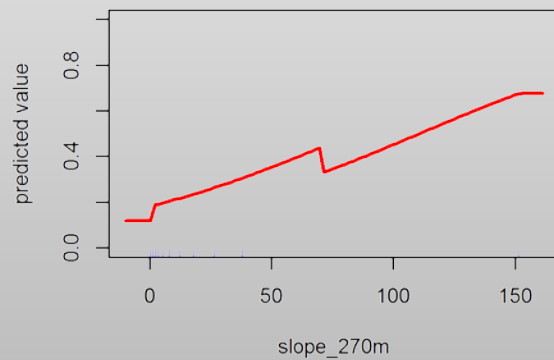
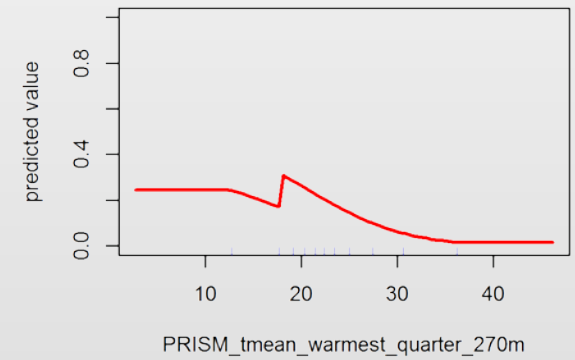
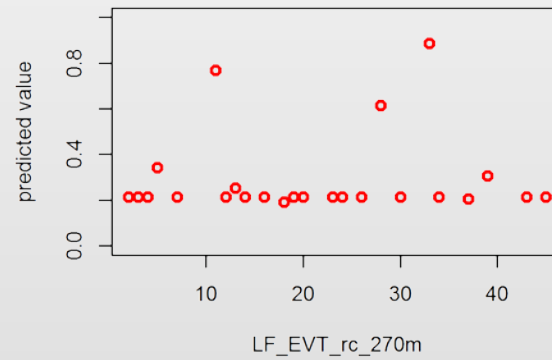
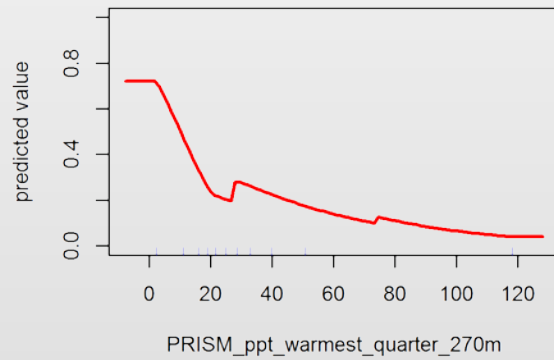
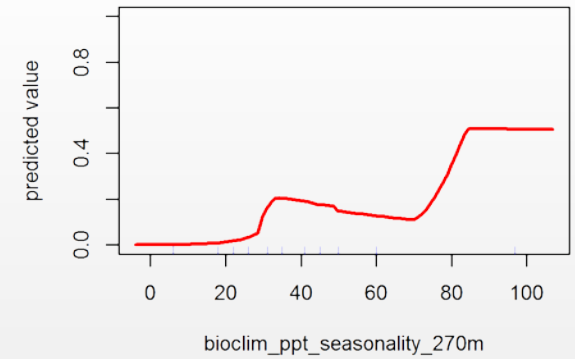
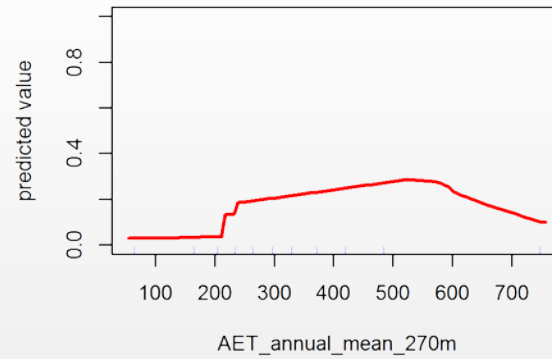
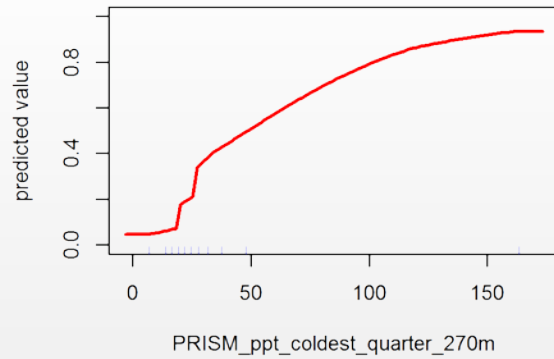
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A. speciosa



A. asperula



A. cordifolia

