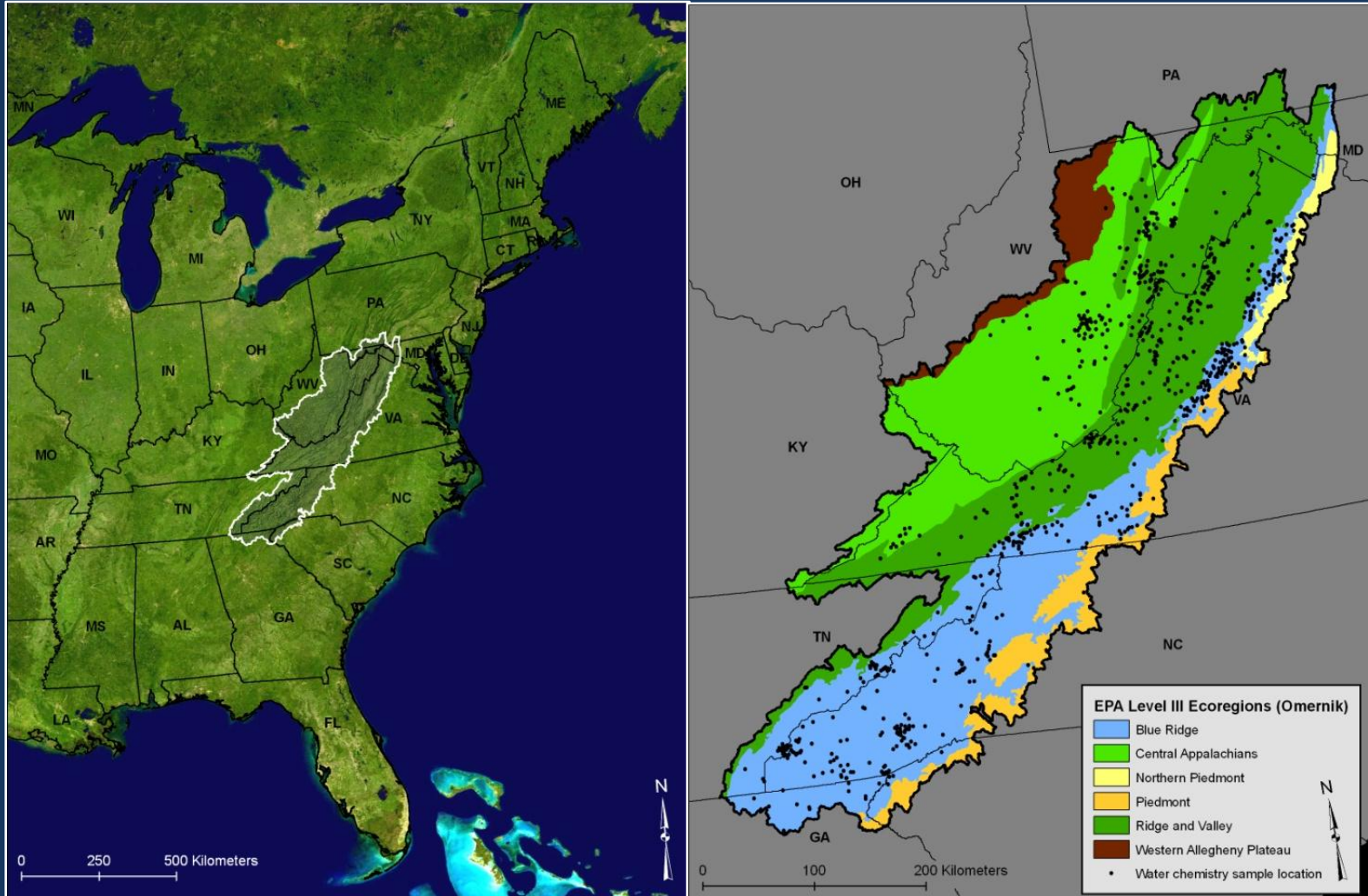


# Implementing a DSS to assess CLs of atmospheric S deposition in the SE US



Paul Hessburg, Keith Reynolds,  
Timothy Sullivan, Nick Povak, Brion Salter,  
Todd McDonnell, Bill Jackson

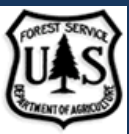
# Study area



- Study Area Size: 14.3 MM ha (35.4 MM ac)
- Domain: Ridge & Valley, Appalachian Plateau ecoregions in VA, WV; Blue Ridge ecoregion in VA, WV, NC, TN

# EMDS, logic, & decisions

- ❑ Spatial decision support for environmental analysis and planning in *ArcMap*
- ❑ Logic modeling
  - To assess environmental state(s)
- ❑ Decision modeling
  - To prioritize landscape elements based on environmental states & mgr. considerations



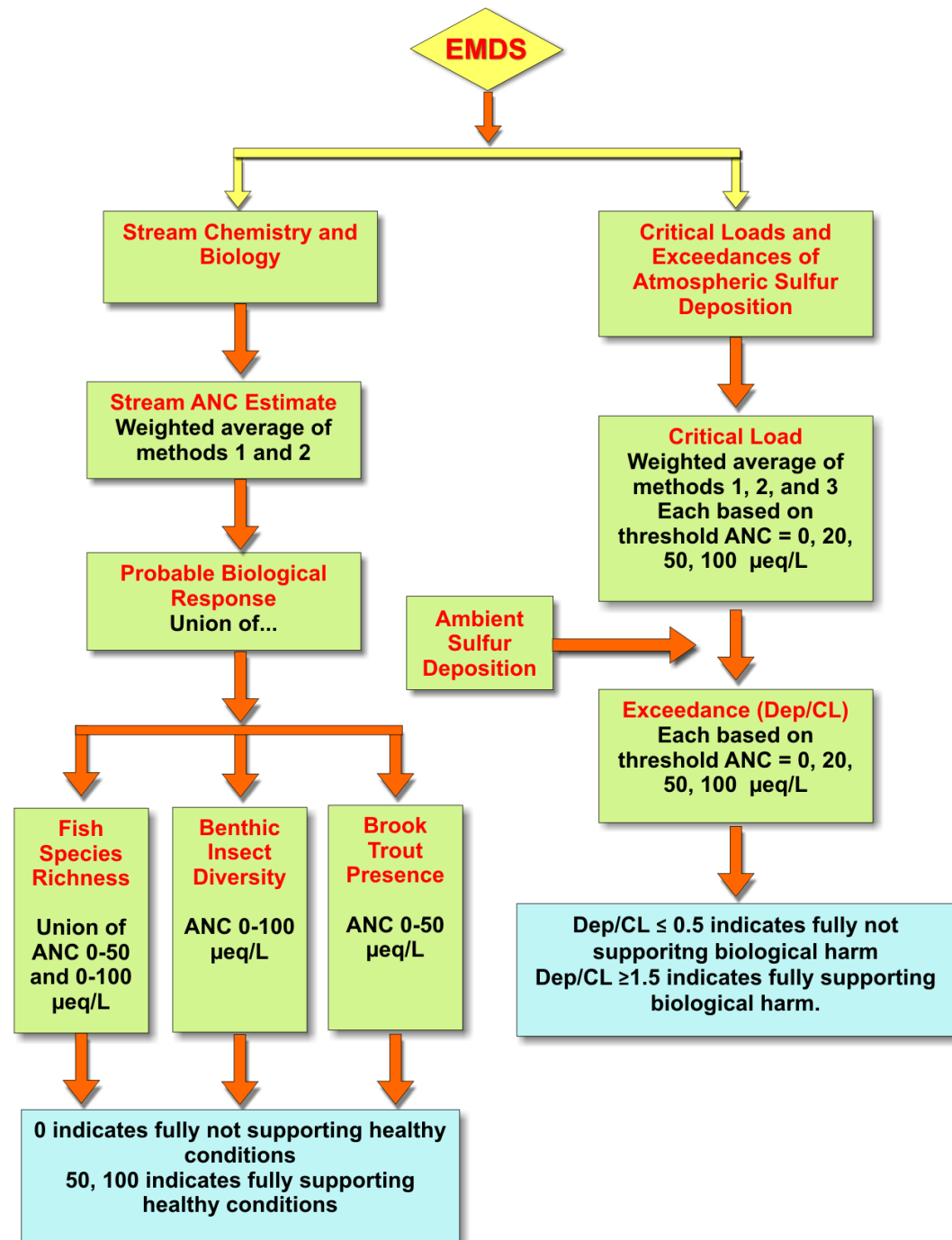
# Logic for CL

## CL methods:

- 1) MAGIC
- 2) Water chemistry
- 3) bgc ANC/BCw predictions

## ANC methods:

- 1) Water chemistry
- 2) bgc ANC predictions





# Predicting ANC/BCw in SE US streams: Status of current modeling efforts



Paul Hessburg, Keith Reynolds, Nick Povak, Brion Salter  
USDA-FS, PNW Res. Sta.

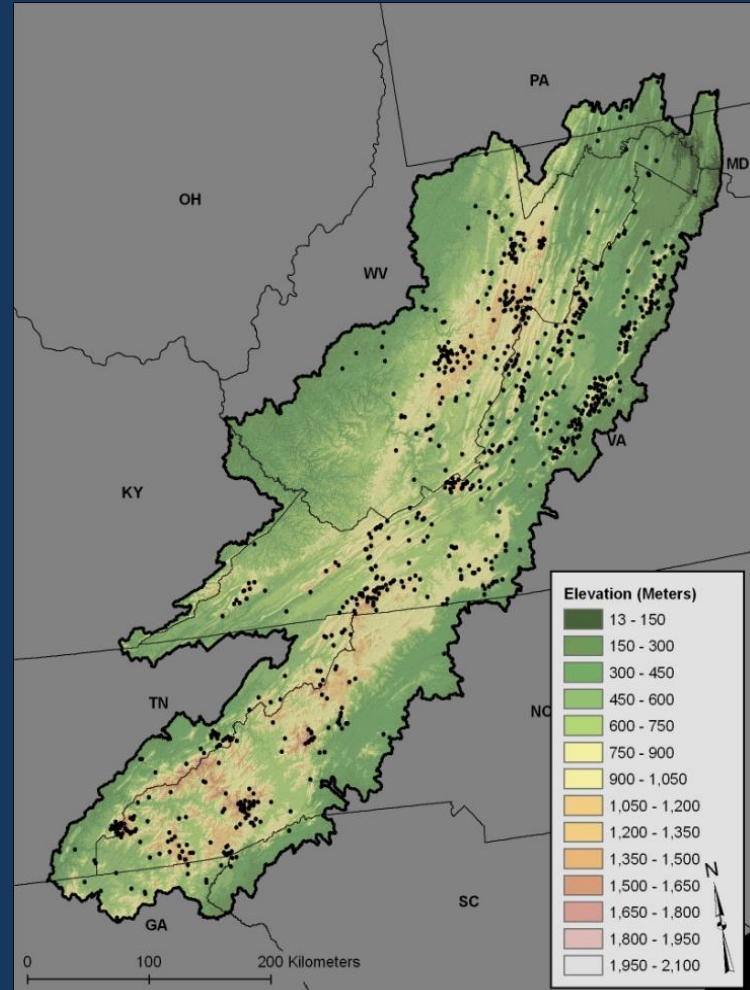
Tim Sullivan, Todd McDonnell, E&S Env. Chem., Corvallis, OR

# Background

- Post-hoc modeling effort
- Predict continuous ANC/BCw from training data
- Water chemistry data, existing water quality databases
- Water chemistry sites represented by most recent spring sample
- 933 total sites with water chemistry, ANC values
- 140/933 sites have estimated BCw via MAGIC
- BCw + ANC used to estimate CL
- BCw results not shown, similar modeling approach



# Study area

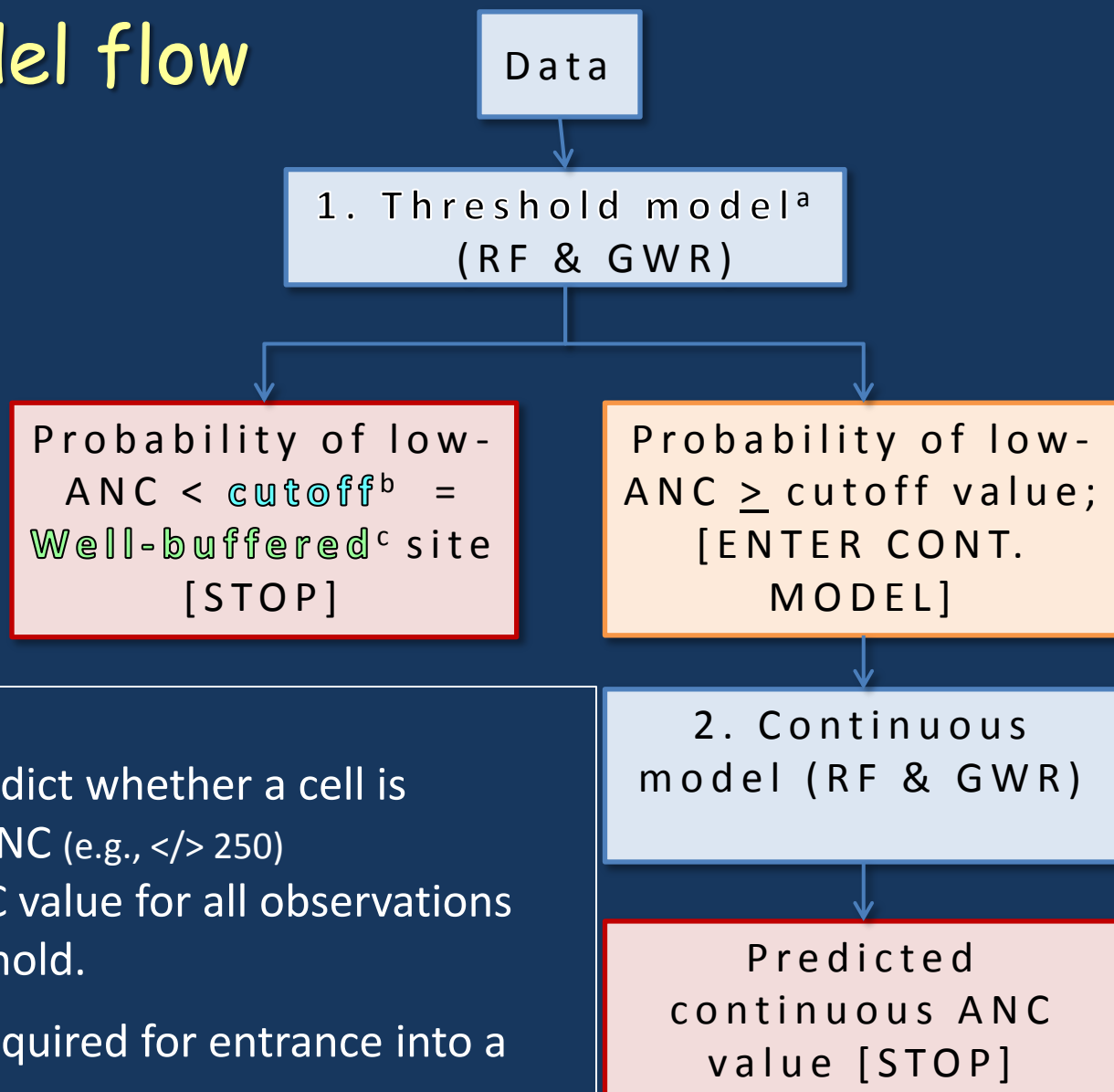


# Methods

- Started with 56 potential predictors, incl. topo., soil, climatic, lithologic, vegetation, & SO<sub>x</sub> dep. vars (wet, dry, total)
- Eliminated sig. multi-collinearity → 33 vars
- Submitted the database of these 33 vars to a “Gatekeeper” modeling approach



# Gatekeeper model flow



## <sup>a</sup> Threshold model

1<sup>st</sup> uses a binary model to predict whether a cell is above/below a threshold ANC (e.g., </> 250)

2<sup>nd</sup> predicts a continuous ANC value for all observations predicted below that threshold.

<sup>b</sup> **Cutoff value:** probability required for entrance into a continuous model

<sup>c</sup> **Well-buffered:** ANC threshold value above which sites are considered well-buffered.

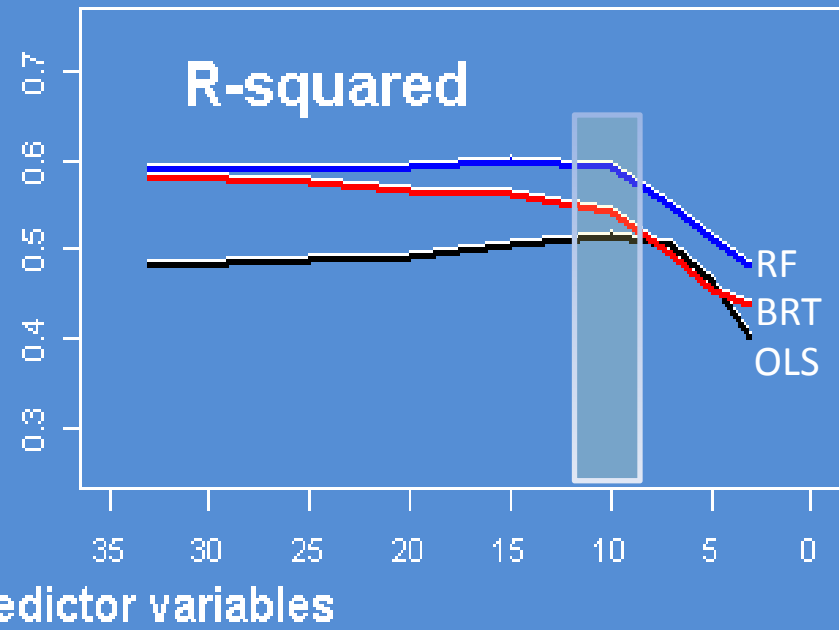
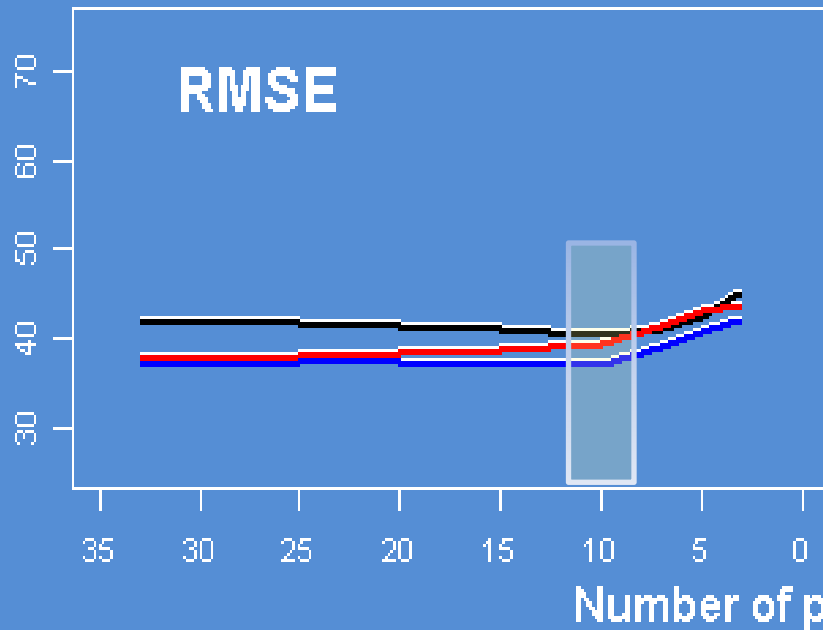
# Results

## Important predictors (% var. explained)

Threshold model--ANC $\leq$ 250 $\mu\text{eq/L}$		Continuous model--ANC < 250	
Carbonaceous lithology	(17.7)	Siliceous lithology	(24.3)
Percent public land	(17.6)	No. of GS Days w/ $T > 32.2^\circ\text{C}$	(18.2)
Percent forest cover	(15.2)	Dry sulfur deposition	(11.3)
Consec. day w/ $\text{VPD} > 750\text{pa}, T > 10^\circ\text{C}$	(9.7)	Max # Days w/o PCP, $T > 10^\circ\text{C}$	(10.1)
Soil pH	(8.7)	Soil pH	(8.3)
95 %-tile diurnal GS surface TMP	(7.5)	Percent soil clay	(7.6)
Non-GS precipitation	(6.8)	Topographic wetness index	(6.2)
Percent soil clay	(6.8)	Percent mixed-conifer cover	(5.8)
Flow accumulation	(5.4)	Percent forest cover	(4.9)
GS days $> 5.6^\circ\text{C}$	(4.6)	Flow accumulation	(3.3)

**Data Sources:** Ameriflux, PRISM, STATSGO, EPA-CMAQ, NED, NLCD2000, E&S Env Chem

# How we got to 10 predictors, continuous

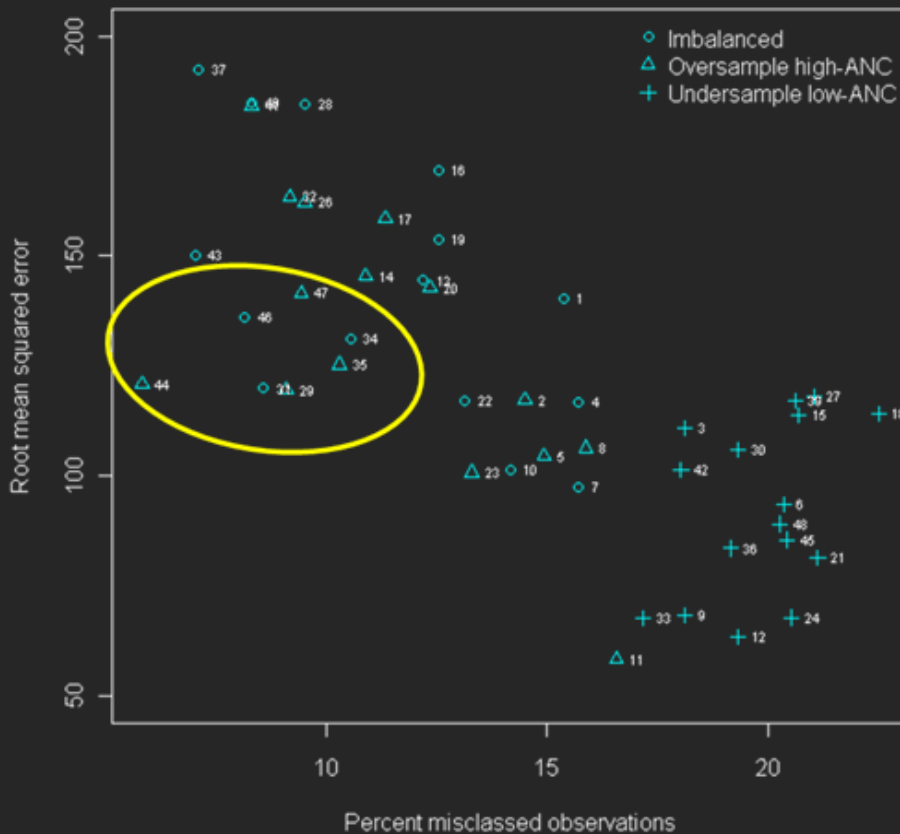


# Scatterplot of Gatekeeper model performance

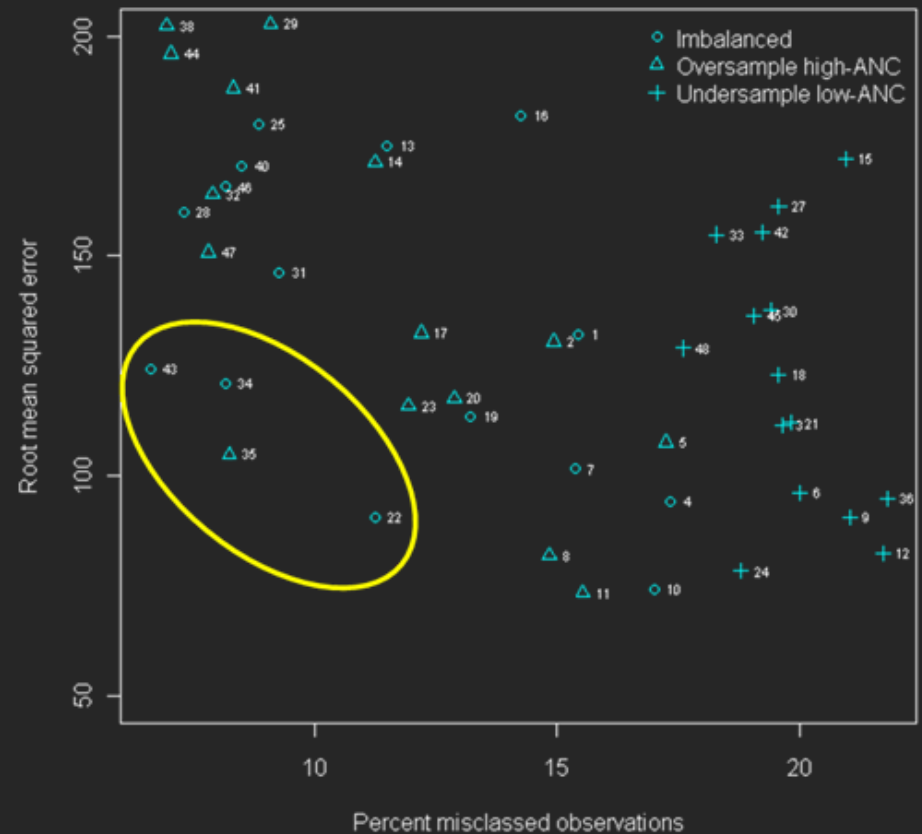
48 unique combinations of the data, ea. RF & GWR, (3x4x4) below

1. Design balancing (3x): imbalanced<sub>as is</sub>, oversampled ANC<sub>hi</sub>, undersampled ANC<sub>low</sub>)
2. Varying the ANC threshold (4x): [150, 200, 250, 300],
3. Varying the cutoff (4x): [0.4, 0.5, 0.6, 0.7]

Random forest



Geographically weighted regression



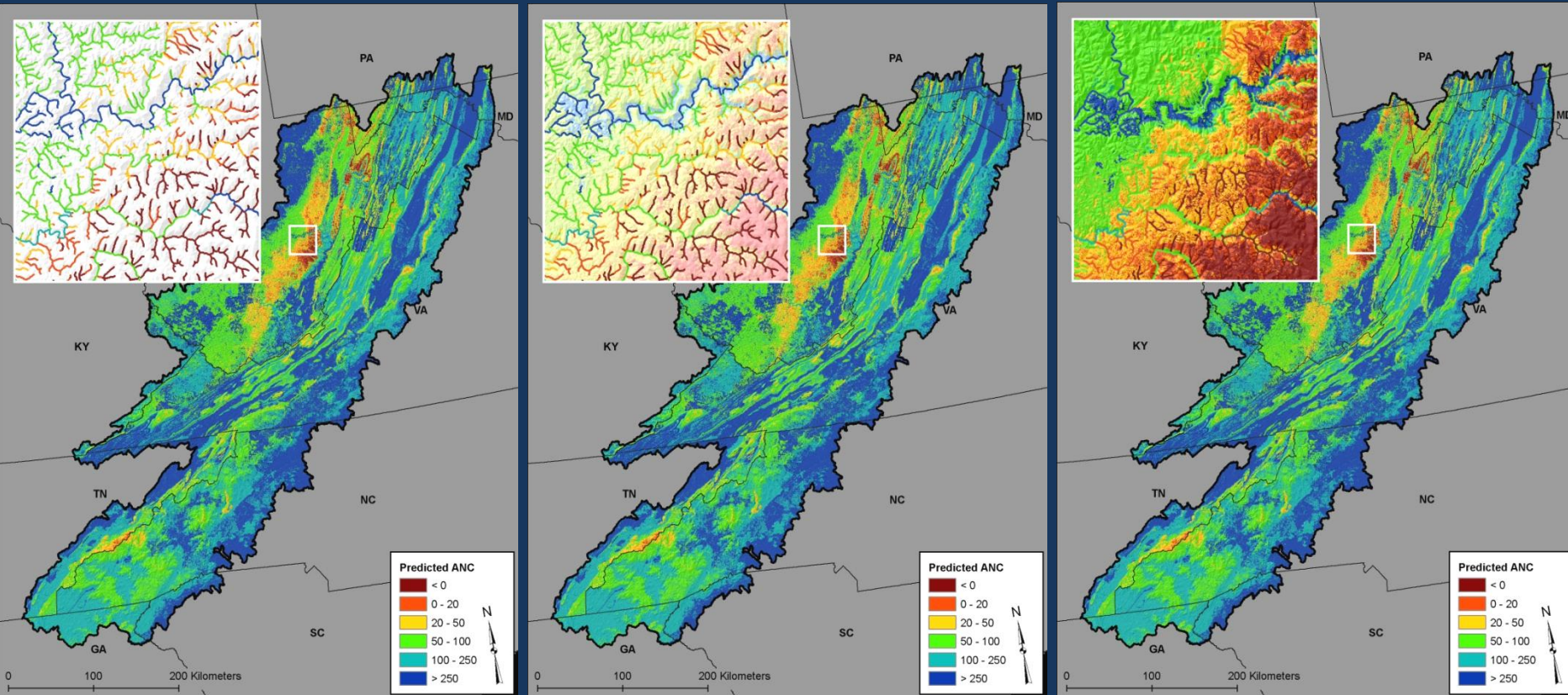


# Best performing models

ID	Continuous model	Data sampling	Low ANC threshold	Prob. cutoff	Misclass. Rate (%)	RF RMSE	Gatekeeper RMSE
31	RF	Imbalanced	250	0.6	8.6	292.1	119.9
34	RF	Imbalanced	250	0.7	10.6	326.3	131.2
46	RF	Imbalanced	300	0.7	8.2	324.5	136.2
29	RF	Oversample	250	0.5	9.1	293.5	119.5
35	RF	Oversample	250	0.7	10.3	339.8	125.3
44	RF	Oversample	300	0.6	5.8	301.6	120.9
47	RF	Oversample	300	0.7	9.4	293.0	141.6
22	GWR	Imbalanced	200	0.7	11.2	341.5	90.7
34	GWR	Imbalanced	250	0.7	8.2	279.5	121.0
43	GWR	Imbalanced	300	0.6	6.6	338.0	124.3
35	GWR	Oversample	250	0.7	8.2	309.6	104.9

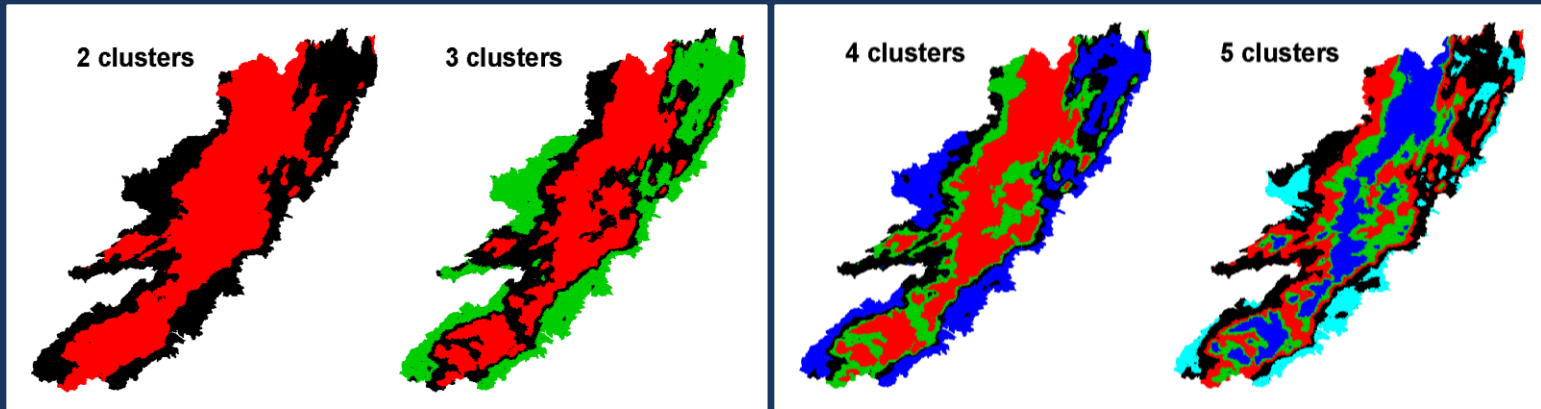
# Predicted ANC, 250, 0.5, RF

- Can be specified w/ geographic variants to the model

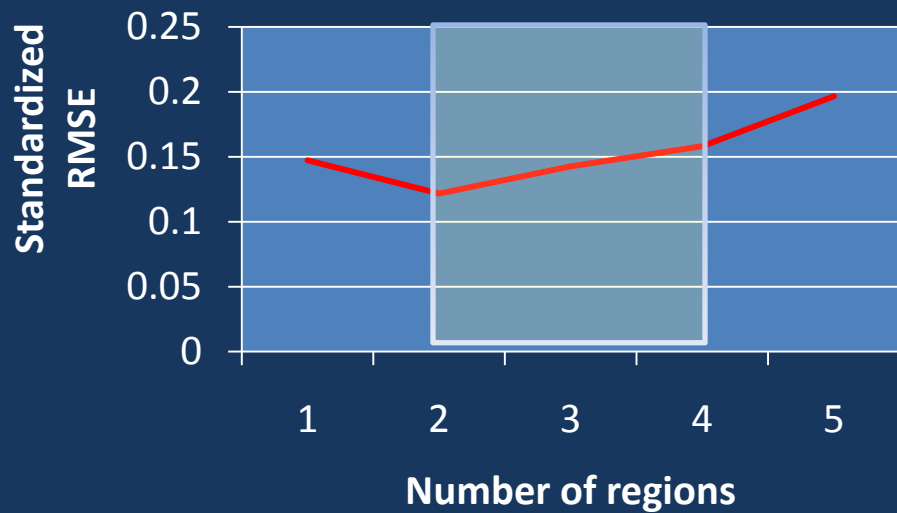


**Note:** We are predicting for 159 MM grid cells using 933 sampled cells;  
Stream networks represented by 4MM cells, more tractable, 1/40<sup>th</sup>

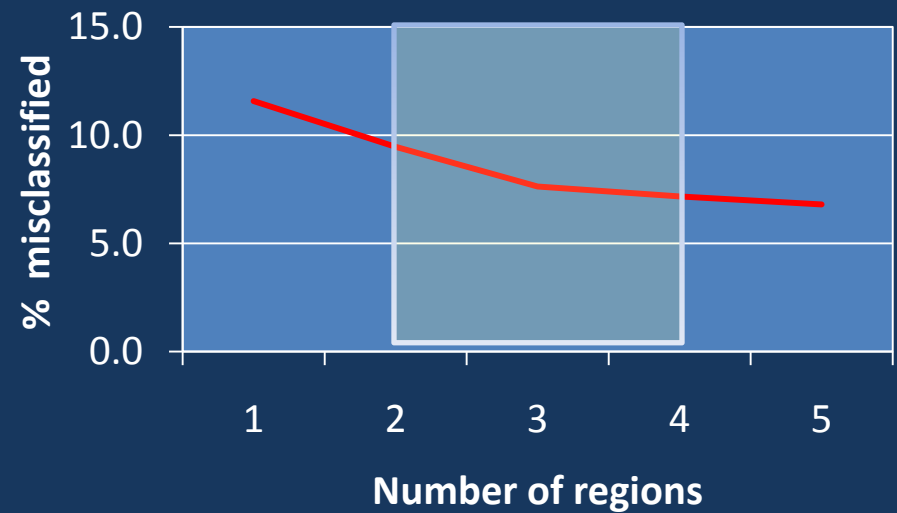
# K-means clustered top 10 predictors into 2-5 regions



Gatekeeper model

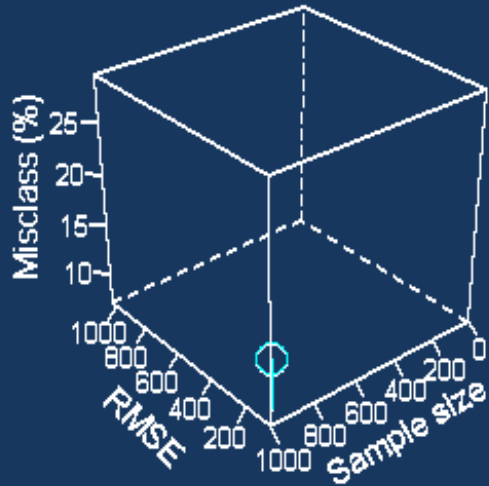


Gatekeeper model

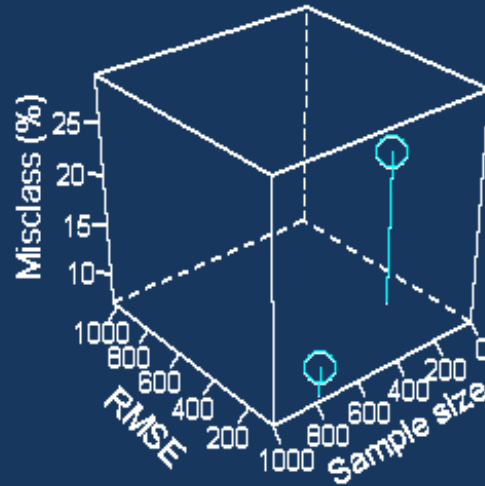


\*RF model performance statistics for modeled regions

Cluster 1

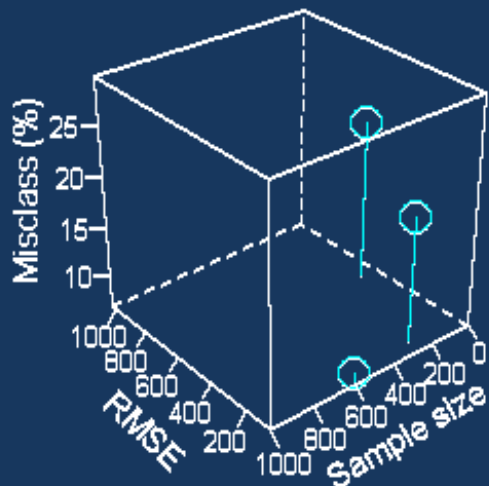


Cluster 2

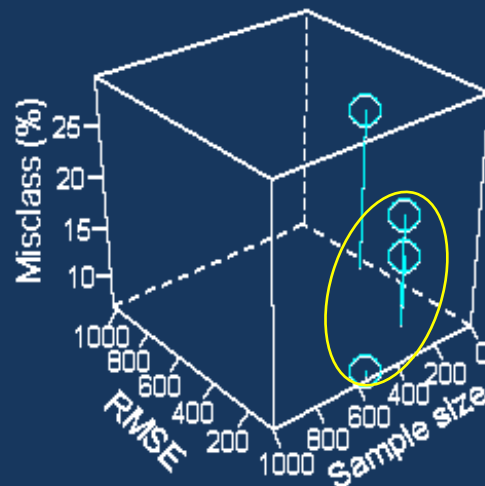


- Results: some regions are undersampled
- Geographic variation in predictors likely exists
- Cannot be shown with this imbalanced sample

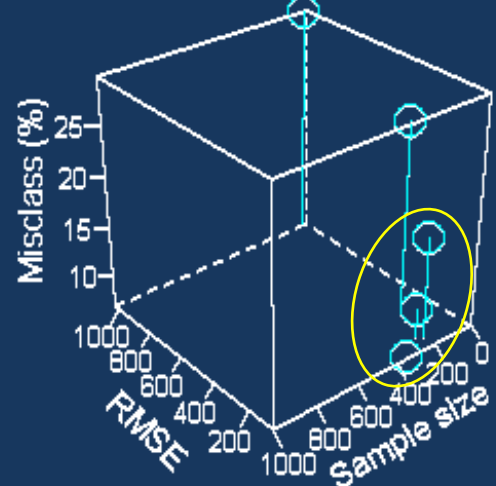
Cluster 3



Cluster 4



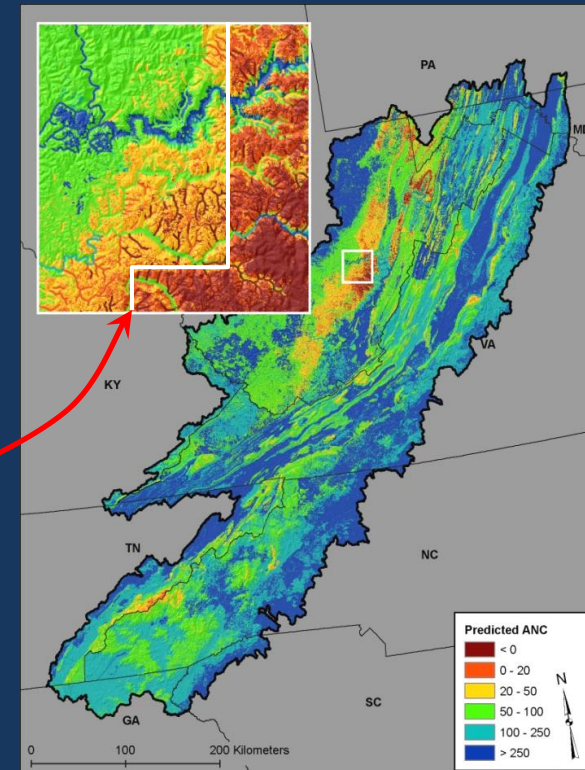
Cluster 5





# Summary

- ANC predictive model (imbalanced design) is reasonably robust to prediction & stable:
  - Gatekeeper model with RF explains ~60% of the multi-variance
  - Balancing design would:
    - Improve variance explained
    - Expose geographic variants
  - Highest uncertainty – what drives high ANC
    - Affects overall model predictions, low + high
- Lack of QC & evenness in data scaling w/ soils & geology data reduces model sensitivity
  - Better data → better model specificity
- Dry S deposition was leading predictor
  - expected to see wet S-deposition a stronger predictor in continuous model







Thank you

Questions?

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