

Virginia Mid-Atlantic Forest  
Danielle Brigida  
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Konza Prairie, Kansas  
Joanna Gilkeson/USFWS  
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# Landscape Metrics as Predictors of Avian Species Richness in Grassland vs Forest Biomes

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ANDREW CAMERON

VIRGINIA COMMONWEALTH UNIVERSITY

CENTER FOR ENVIRONMENTAL STUDIES

# Background

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- The loss of grassland and forest ecosystems poses the most serious threat to terrestrial biodiversity (Ceballos et al., 2010; Jaureguiberry et al., 2022)
- Land use change for agriculture, livestock, urbanization, and other forms of human development and its resultant habitat loss is primary driver of this trend, particularly for bird species (Jaureguiberry et al., 2022; Rosenberg et al., 2019)
- Eastern forest and grassland bird species have declined by 27% and 34% respectively since 1970 (NABCI, 2022)
- Among grassland birds, 74% of species have experienced population declines over that period (Lees et al., 2022)

# Research Question

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To what degree can class-level landscape metrics help explain variation in avian species richness in forest vs grassland biomes at a variety of spatial scales?

# Hypothesis

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Avian species richness will be significantly better explained by class-level landscape metrics in grassland rather than forest biomes.

# THE DATA

AVIAN POINT COUNTS

LANDCOVER RASTERS

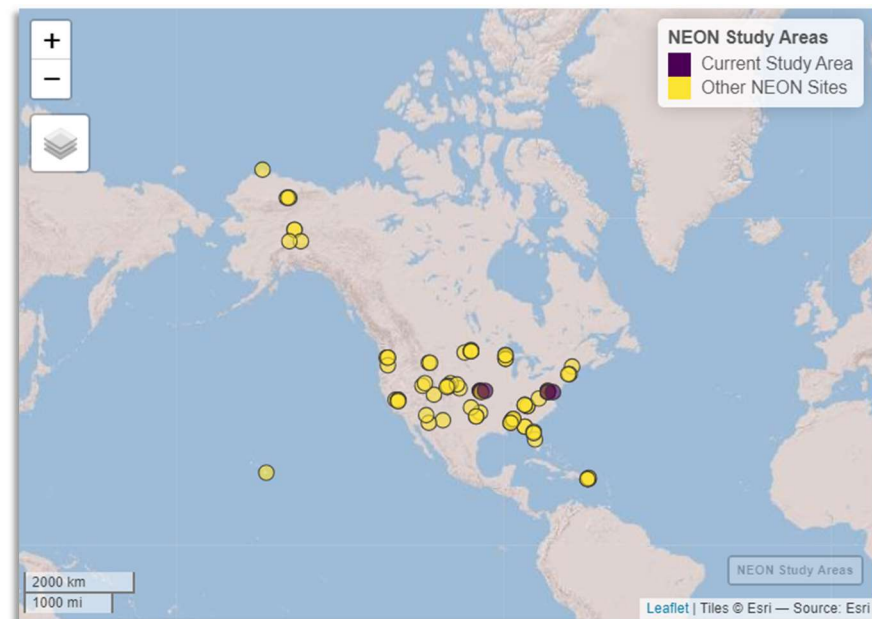
21	2019-06-11 09:17:00	BLAN_001.21.2019-06-11	88	Y	COYE	<i>Geothlypis trichas</i>	species	Common Yellowthroat	NA	singing
21	2019-06-11 09:17:00	BLAN_001.21.2019-06-11	1	Y	BGGN	<i>Polioptila caerulea</i>	species	Blue-gray Gnatcatcher	18	singing
21	2019-06-11 09:17:00	BLAN_001.21.2019-06-11	88	Y	ACFL	<i>Empidonax virescens</i>	species	Acadian Flycatcher	NA	singing
21	2019-06-11 09:17:00	BLAN_001.21.2019-06-11	88	Y	CHSP	<i>Spizella passerina</i>	species	Chipping Sparrow	NA	singing
21	2019-06-11 09:17:00	BLAN_001.21.2019-06-11	5	Y	DOWO	<i>Picoides pubescens</i>	species	Downy Woodpecker	23	singing
21	2019-06-11 09:17:00	BLAN_001.21.2019-06-11	3	Y	NOCA	<i>Cardinalis cardinalis</i>	species	Northern Cardinal	24	calling
21	2019-06-11 09:17:00	BLAN_001.21.2019-06-11	2	Y	CARW	<i>Thryothorus ludovicianus</i>	species	Carolina Wren	15	singing
21	2019-06-11 09:17:00	BLAN_001.21.2019-06-11	3	Y	INBU	<i>Passerina cyanea</i>	species	Indigo Bunting	33	singing
21	2019-06-11 09:17:00	BLAN_001.21.2019-06-11	88	Y	NOPA	<i>Setophaga americana</i>	species	Northern Parula	NA	singing
21	2019-06-11 09:17:00	BLAN_001.21.2019-06-11	6	Y	OROR	<i>Icterus spurius</i>	species	Orchard Oriole	29	calling
21	2019-06-11 09:17:00	BLAN_001.21.2019-06-11	4	N	NA	NA	NA	NA	NA	NA
21	2019-06-11 09:17:00	BLAN_001.21.2019-06-11	1	Y	REVI	<i>Vireo olivaceus</i>	species	Red-eyed Vireo	23	singing
21	2019-06-11 09:17:00	BLAN_001.21.2019-06-11	88	Y	EATO	<i>Pipilo erythrophthalmus</i>	species	Eastern Towhee	NA	singing
21	2019-06-11 09:17:00	BLAN_001.21.2019-06-11	88	Y	EAWP	<i>Contopus virens</i>	species	Eastern Wood-Pewee	NA	singing
21	2019-06-11 09:53:00	BLAN_004.21.2019-06-11	3	Y	BGGN	<i>Polioptila caerulea</i>	species	Blue-gray Gnatcatcher	23	calling
21	2019-06-11 09:53:00	BLAN_004.21.2019-06-11	NA	NA	NA	NA	NA	NA	NA	NA
21	2019-06-11 09:53:00	BLAN_004.21.2019-06-11	NA	NA	WAVI	<i>Vireo gilvus</i>	species	Warbling Vireo	61	singing
21	2019-06-11 09:53:00	BLAN_004.21.2019-06-11	3	Y	INBU	<i>Passerina cyanea</i>	species	Indigo Bunting	162	singing
21	2019-06-11 09:53:00	BLAN_004.21.2019-06-11	2	Y	WAVI	<i>Vireo gilvus</i>	species	Warbling Vireo	171	singing
21	2019-06-11 09:53:00	BLAN_004.21.2019-06-11	88	Y	OROR	<i>Icterus spurius</i>	species	Orchard Oriole	NA	singing
21	2019-06-11 09:53:00	BLAN_004.21.2019-06-11	6	Y	MODO	<i>Zenaida macroura</i>	species	Mourning Dove	61	singing
21	2019-06-11 09:53:00	BLAN_004.21.2019-06-11	88	Y	FISP	<i>Spizella pusilla</i>	species	Field Sparrow	NA	singing
21	2019-06-11 09:53:00	BLAN_004.21.2019-06-11	NA	NA	INBU	<i>Passerina cyanea</i>	species	Indigo Bunting	57	singing
21	2019-06-11 09:53:00	BLAN_004.21.2019-06-11	2	Y	YBCU	<i>Coccyzus americanus</i>	species	Yellow-billed Cuckoo	17	singing
21	2019-06-11 09:53:00	BLAN_004.21.2019-06-11	4	Y	BHCO	<i>Molothrus ater</i>	species	Brown-headed Cowbird	173	singing
21	2019-06-11 09:53:00	BLAN_004.21.2019-06-11	3	Y	EABL	<i>Sialia sialis</i>	species	Eastern Bluebird	148	singing
21	2019-06-11 09:53:00	BLAN_004.21.2019-06-11	2	Y	INBU	<i>Passerina cyanea</i>	species	Indigo Bunting	34	singing

# BIRD POINT COUNT DATA

Accessed through the **National Ecological Observatory Network (NEON)**, a collection of field observation facilities across the United States providing long term ecological data.

Bird count study areas have roughly 10-20 distinct plots within them. Each plot contains points arranged in a 3x3 point grid, with points separated by 250m.

This analysis uses **three years of data (2019-2021)** from three separate study areas in each of the two landscape types.

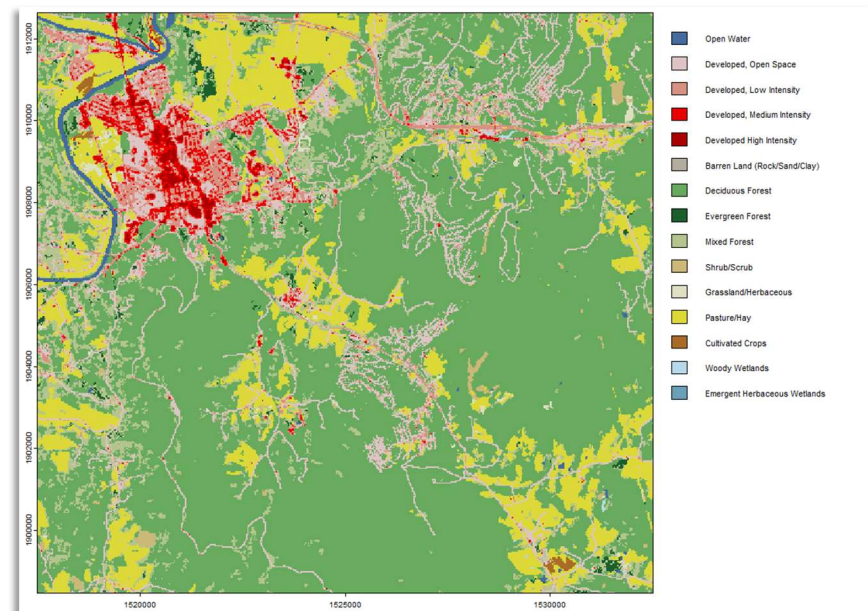




# LAND COVER DATA

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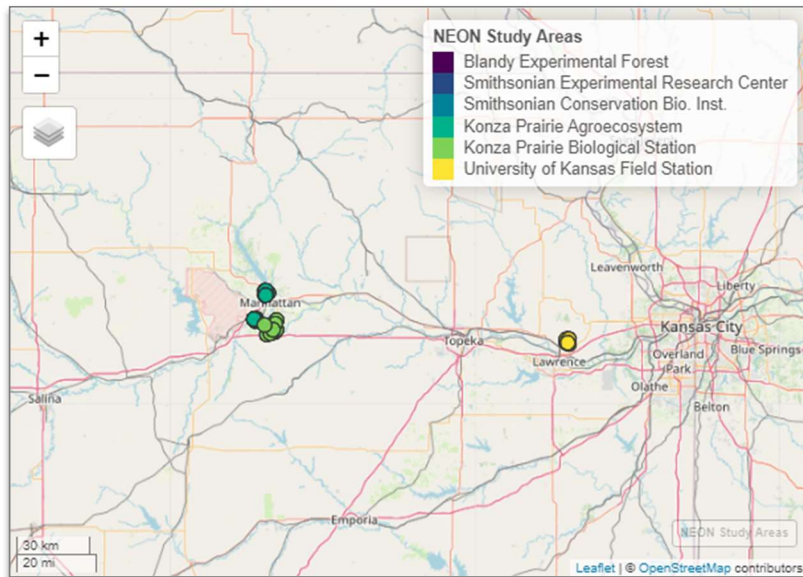
National Land Cover Database (NLCD) rasters with spatial resolution of 30m were accessed using the `FedData` package in R.



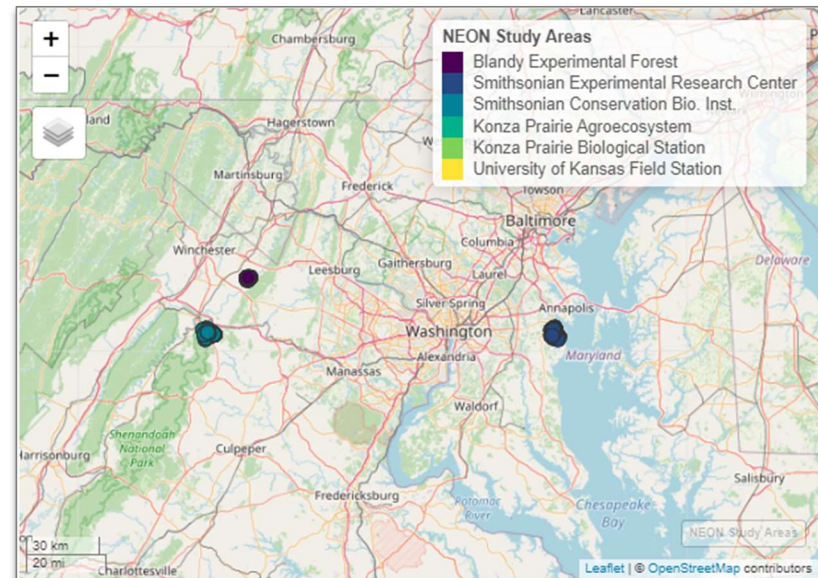
# Study Area Locations

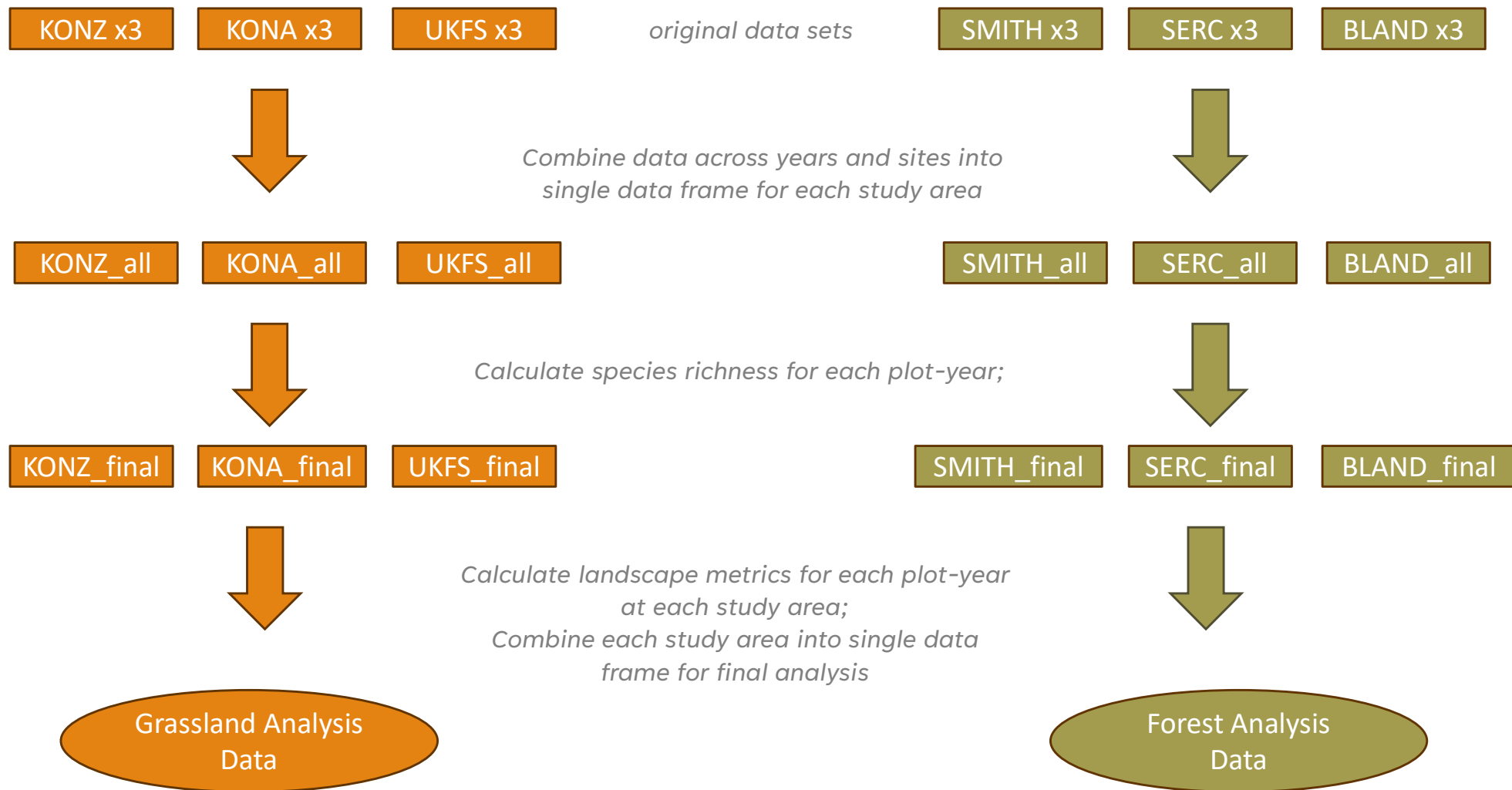


## GRASSLAND SITES



## MID-ATLANTIC FOREST SITES







# Land Cover Categories Following Reclassification

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## GRASSLAND

- **GRASSLAND** ← Grassland/Herbaceous
- **AGRICULTURAL** ← “Pasture/Hay”, “Cultivated Crops”
- **FOREST** ← “Deciduous Forest”, “Evergreen Forest”, “Mixed Forest”

## FOREST

- **FOREST** ← “Deciduous Forest”, “Evergreen Forest”, “Mixed Forest”
- **AGRICULTURAL** ← “Pasture/Hay”, “Cultivated Crops
- **(SUB)URBAN** ← “Developed Medium”, “Developed High

**NA** ← All other land cover classes



# LANDSCAPE METRICS

SPATIAL EXTENTS

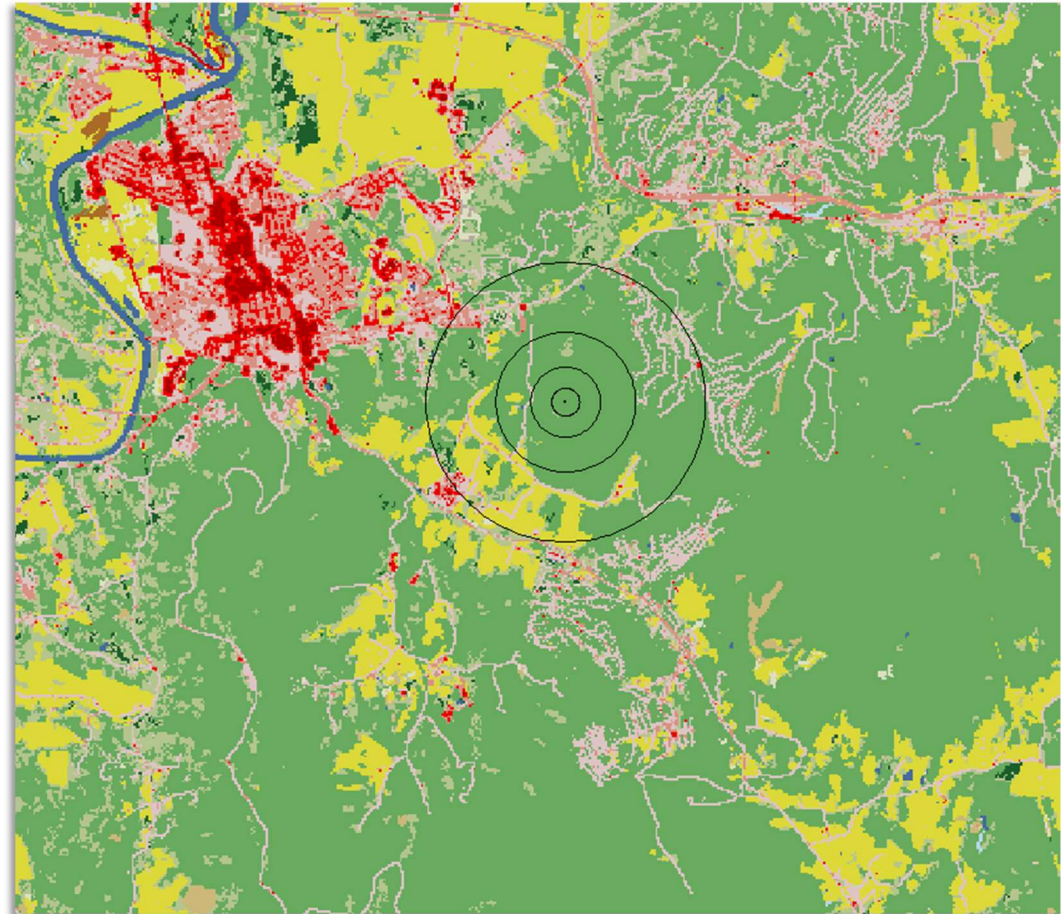
CLASS-LEVEL METRICS

- Open Water
- Developed, Open Sp
- Developed, Low Inte
- Developed, Medium
- Developed High Inte
- Barren Land (Rock/
- Deciduous Forest
- Evergreen Forest
- Mixed Forest
- Shrub/Scrub
- Grassland/Herbaceo
- Pasture/Hay
- Cultivated Crops
- Woody Wetlands
- Emergent Herbaceo

# SPATIAL SCALES

Landscape metrics were calculated for each study area plot-year at four spatial scales.

- 200m
- 500m
- 1000m
- 2000m



*Smithsonian Conservation Biology Institute plot 002 with its four buffers.*

# CLASS- LEVEL LANDSCAPE METRICS

A total of five metrics were selected and calculated for each plot-year at each of the four spatial scales.

- **Proportion of Landscape (PLAND):** Measures the percentage of the landscape covered by a specific land cover class.
- **Largest Patch Index (LPI):** Measures the dominance of the largest patch of a particular land cover class.
- **Aggregation Index (AI):** Measures the degree to which a land cover class is aggregated or dispersed in the landscape.
- **Mean Patch Size:** Represents the average size of patches for a given land cover type.
- **Mean Core Area Size:** Represents the average size of the core areas (interior parts of patches, excluding edges) of land cover class for given cover type.

```
## Both variables model
formula <- as.formula(paste("richness ~ ",
                             paste(var_names, collapse = " + ") ))
```

```
model <-
  lm(formula = formula,
      data = grassland_final,
      na.action = na.omit)
|
all_models[[3]] <- model
```

```
## Null model
null_model <-
  lm(formula = richness ~ 1,
      data = grassland_final,
      na.action = na.omit)

# add null model to model list
all_models[[length(all_models) + 1]] <- null_model
```

```
## ----- CREATE AIC TABLE -----
aic_table <- AICcm.bayes::aictab(all_models)
```

*# AIC table only has model #, not predictors. Loop below creates a new 2 col df; extracts predictors from each model summary; and creates a join column.*

```
mod_names <- data.frame("predictors" = c(rep(NA, length(all_models) )),
                        Modnames = NA)
```

```
for (i in seq_along(all_models)) {
  model <- all_models[[i]]
```

```
  modsum <- summary(model)
```

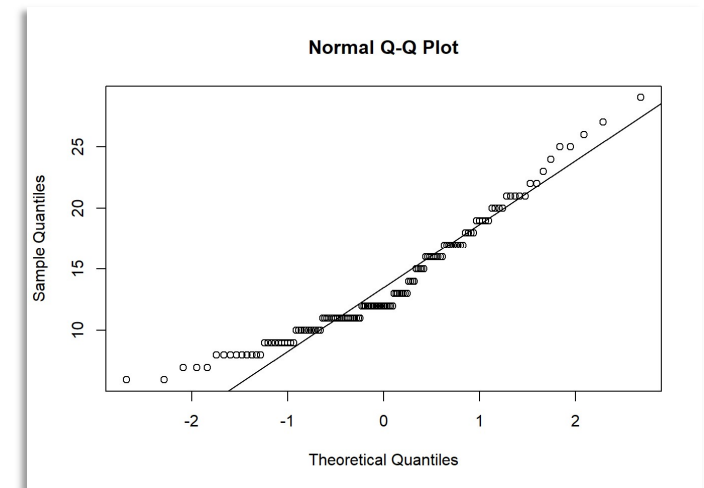
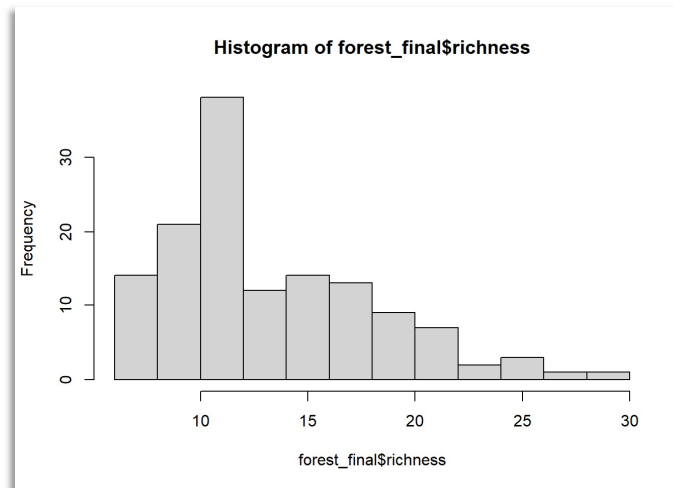
```
  # Extract and concatenate predictor variable names
```

```
  predictors <- rownames(modsum$coefficients)[2:nrow(modsum$coefficients)]
  mod_names[i, 1] <- paste(predictors, collapse = " | ")
```

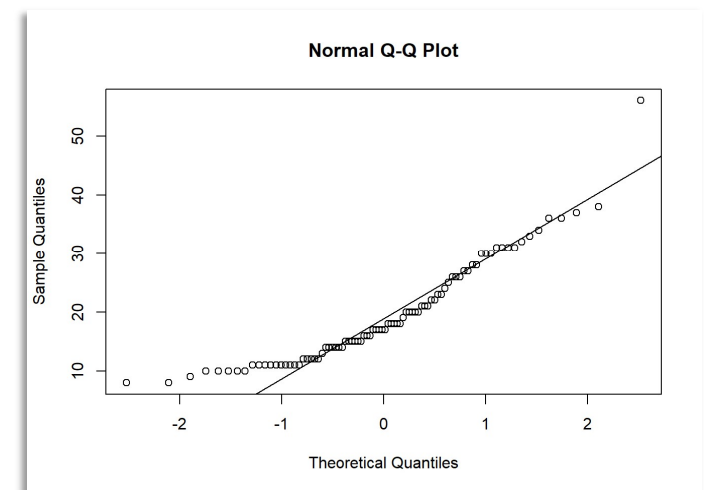
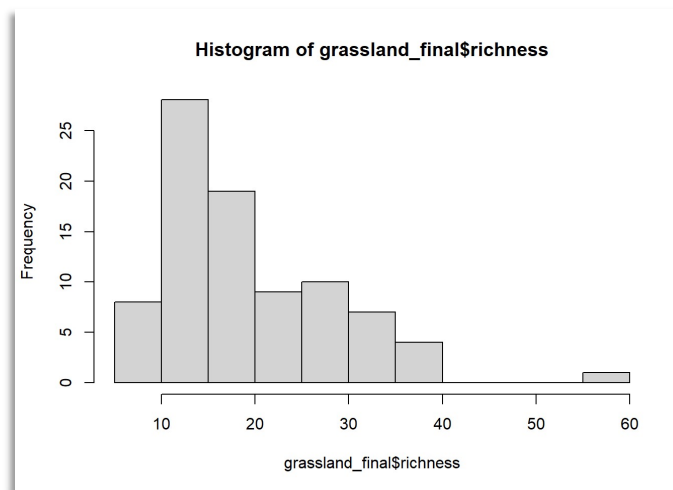
# MODEL SELECTION



## FOREST DATA



## GRASSLAND DATA



# HIERARCHICAL VARIABLE SELECTION

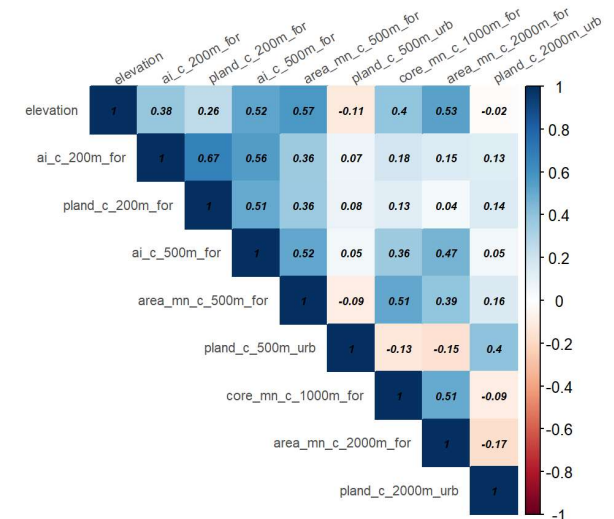
Step 1 Select minimally correlated variables at each spatial extent ( $R < 0.7$ )

Step 2 Group all remaining variables and again select variables with correlation coefficients  $< 0.7$

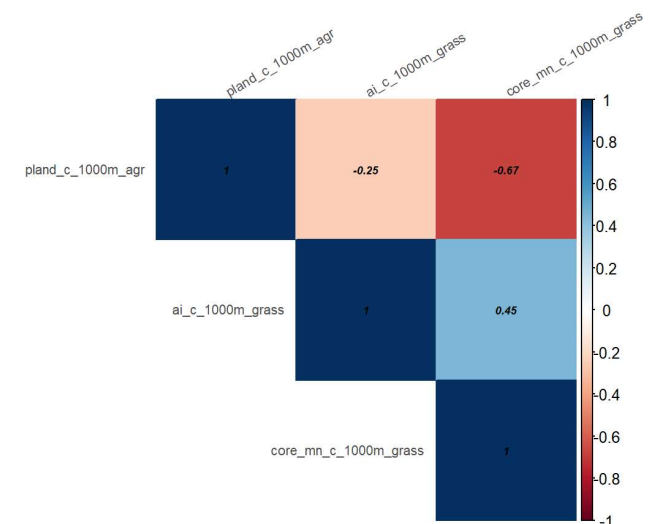
Step 3 Repeat process, lowering threshold to 0.6

*Correlograms following step two of the variable selection process for both forest (top) and grassland (bottom) data*

**Tier 2 Forest LSM Predictors Correlation**



**Tier 2 Grassland LSM Predictors Correlation**



# FINAL VARIABLE SELECTION

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## GRASSLAND

% Agricultural (1000m)

Grassland Aggregation Index

## FOREST

Elevation

% Forest (200m)

% Urban (500m)

Forest Mean Core Area (1000m)

% Urban (2000m)

# MODEL RUNS

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- All combinations of variables used within each data set
  - 4 grassland model runs
  - 22 forest model runs
- Models were then evaluated for goodness of fit using Akaike Information Criterion

```
## 2 VARIABLE MODELS
two_var_combos <- combn(as.character(final_vars_f$var.names), 2, simplify = TRUE)
l <- ncol(two_var_combos)
for (i in 1:ncol(two_var_combos)) {
  formula <- as.formula(paste("richness ~ ",
                              paste(two_var_combos[, i], collapse = " + ")) )

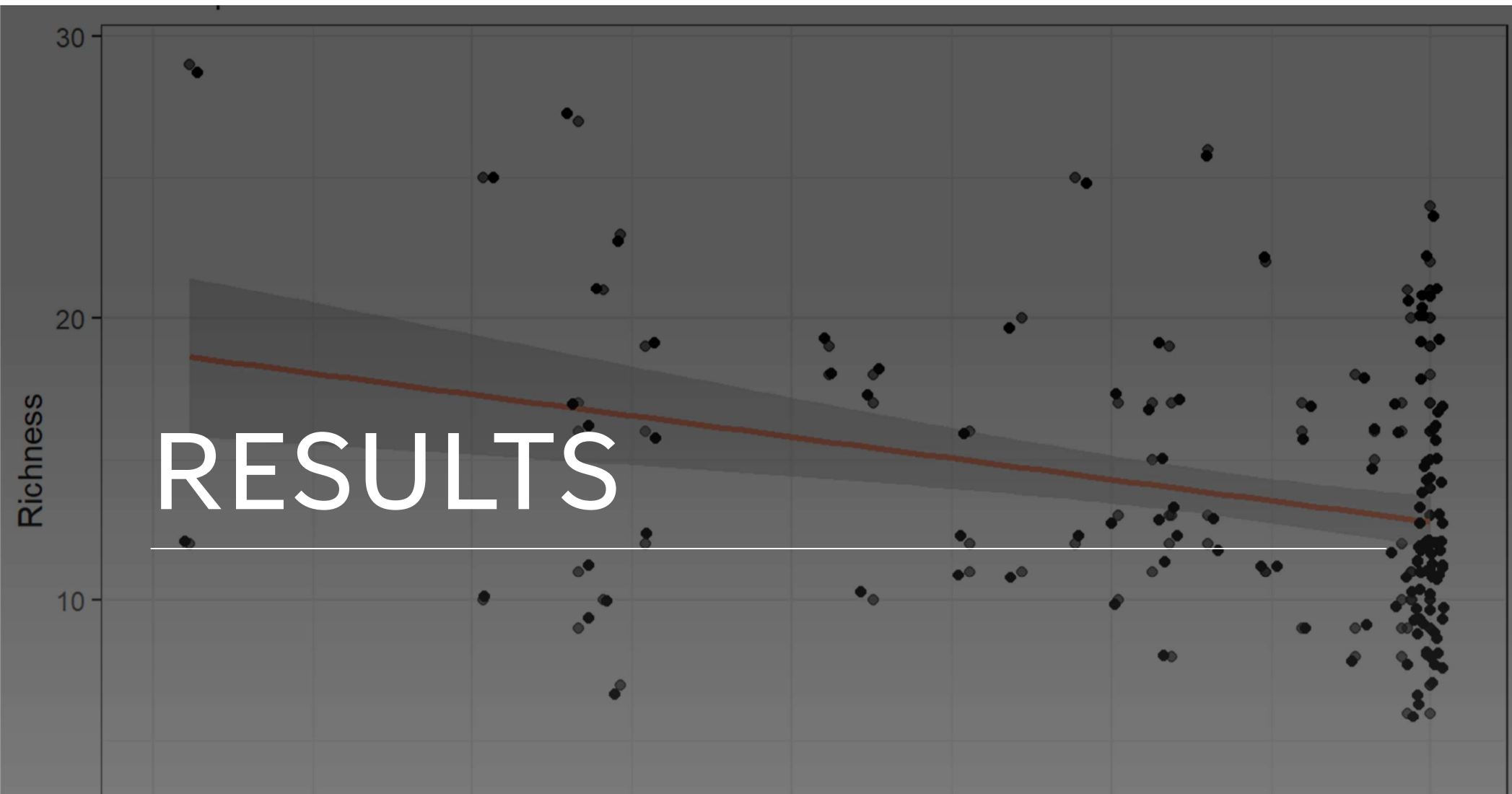
  model <-
    lm(formula = formula,
        data = forest_final,
        na.action = na.omit)

  all_models_f[[i + 1]] <- model
}

## 3 VARIABLE MODELS
three_var_combos <- combn(as.character(final_vars_f$var.names), 3, simplify = TRUE)
l <- ncol(three_var_combos)
for (i in 1:ncol(three_var_combos)) {
  formula <- as.formula(paste("richness ~ ",
                              paste(three_var_combos[, i], collapse = " + ")) )

  model <-
    lm(formula = formula,
        data = forest_final,
        na.action = na.omit)

  all_models_f[[i + 1]] <- model
}
```





### AIC Results for All Grassland Candidate Models

predictors	K	AICc	Delta_AICc	ModelLik	AICcWt	model.num
pland_c_1000m_agr   ai_c_1000m_grass	4	576.9533	0.000000	1.0000000	0.9702911	3
pland_c_1000m_agr	3	583.9256	6.972299	0.0306185	0.0297089	1
NA   (Intercept)	2	622.3568	45.403550	0.0000000	0.0000000	4
ai_c_1000m_grass	3	623.7691	46.815825	0.0000000	0.0000000	2

# AIC Results for All Forest Candidate Models

predictors	K	AICc	Delta_AICc	ModelLik	AICcWt	model.num
elevation   pland_c_200m_for   pland_c_500m_urb	5	794.6300	0.0000000	1.0000000	0.2409743	11
elevation   pland_c_200m_for   pland_c_2000m_urb	5	795.5767	0.9467038	0.6229108	0.1501055	13
elevation   pland_c_200m_for   core_mn_c_1000m_for	5	795.6959	1.0658368	0.5868897	0.1414253	12
elevation   pland_c_200m_for   pland_c_500m_urb   pland_c_2000m_urb	6	795.7279	1.0979093	0.5775532	0.1391755	7
elevation   pland_c_200m_for   pland_c_500m_urb   core_mn_c_1000m_for	6	796.5699	1.9398539	0.3791107	0.0913559	6
elevation   pland_c_200m_for   core_mn_c_1000m_for   pland_c_2000m_urb	6	797.6506	3.0206030	0.2208434	0.0532176	8
elevation   pland_c_200m_for   pland_c_500m_urb   core_mn_c_1000m_for   pland_c_2000m_urb	7	797.7636	3.1336082	0.2087111	0.0502940	21
pland_c_200m_for	3	798.0716	3.4415609	0.1789265	0.0431167	2

## Frequency of Predictor Variables Among Top Candidate Forest Models

Predictor	Freq	Ecosystem		
elevation	4	Mid Atlantic Forest	16	17
pland_c_200m_for	4	Mid Atlantic Forest	2	1
pland_c_2000m_urb	2	Mid Atlantic Forest	18	19
pland_c_500m_urb	2	Mid Atlantic Forest	2	18
core_mn_c_1000m_for	1	Mid Atlantic Forest	13	10

#### Top Forest Model Results

Predictor	Coefficient	Standard_Error	Rsqr.adj	P_Value	Model_rank
Top Ranked					
(Intercept)	18.9253069	1.4444609	0.1199760	0.0000000	1
elevation	-0.0065671	0.0024503	0.1199760	0.0083052	1
pland_c_200m_for	-0.0467381	0.0170303	0.1199760	0.0069130	1
pland_c_500m_urb	-0.3260762	0.2991487	0.1199760	0.2777079	1
Second Ranked					
(Intercept)	18.9349004	1.4495889	0.1137830	0.0000000	2
elevation	-0.0061266	0.0024396	0.1137830	0.0132457	2
pland_c_200m_for	-0.0502426	0.0171679	0.1137830	0.0040418	2
pland_c_2000m_urb	0.1103858	0.2146804	0.1137830	0.6079877	2
Third Ranked					
(Intercept)	18.9991982	1.4563324	0.1130006	0.0000000	3
elevation	-0.0058119	0.0026359	0.1130006	0.0292065	3
pland_c_200m_for	-0.0487403	0.0169858	0.1130006	0.0047950	3
core_mn_c_1000m_for	-0.0060333	0.0156510	0.1130006	0.7004994	3

**Only two of five predictors significant**

- **Elevation**
- **% Forest, 200m**

**Both show a *negative* relationship with species richness.**

**Very similar  $R^2$  values in all three models, with < 12% of species richness variation explained.**

Top Grassland Model Results

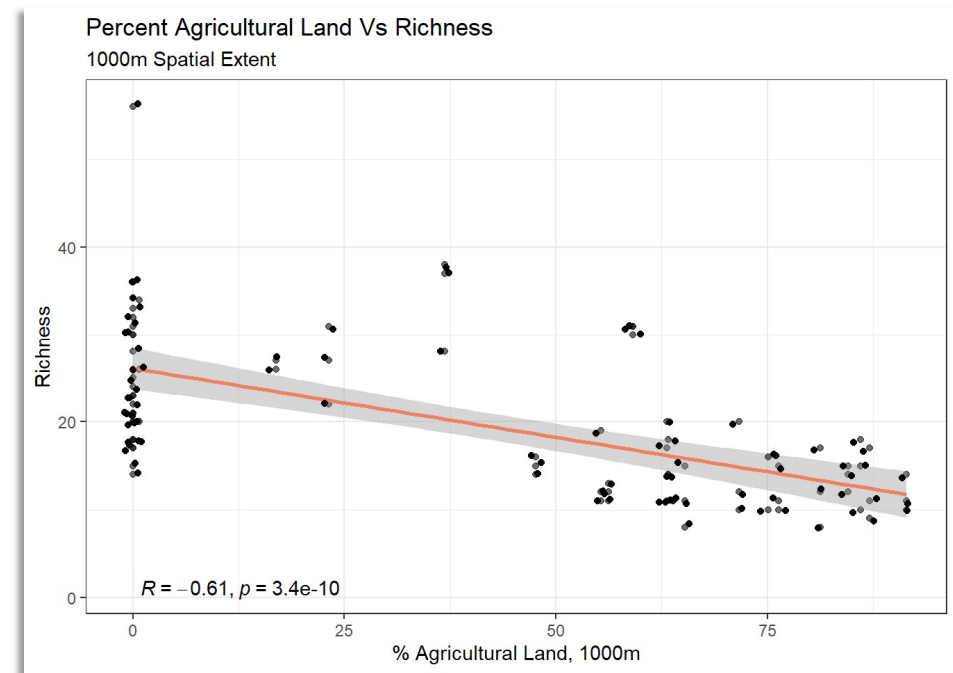
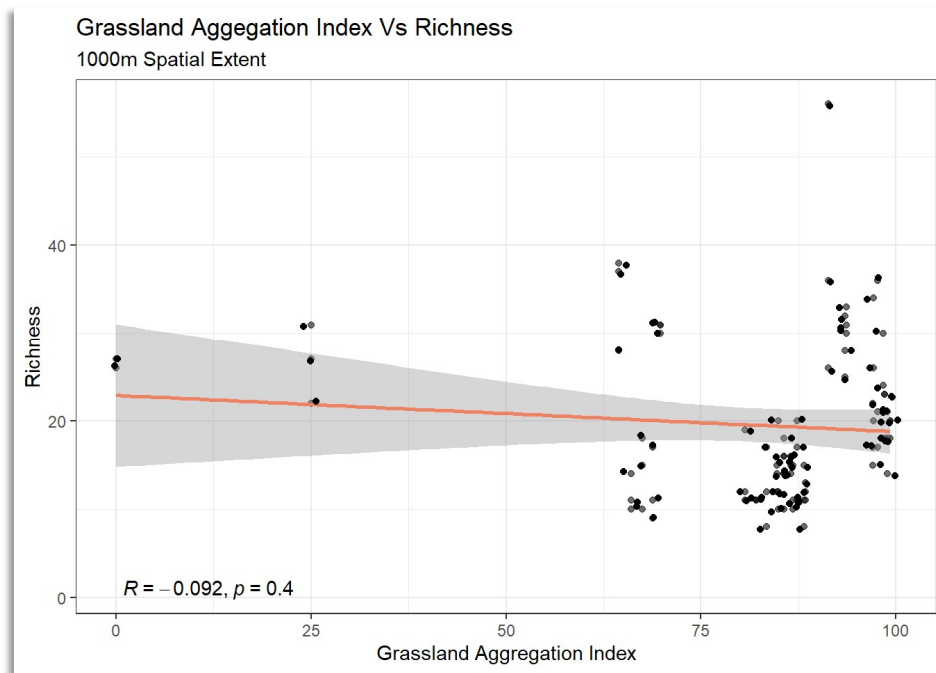
Predictor	Coefficient	Standard_Error	Rsqr.adj	P_Value
(Intercept)	36.2584481	3.5124299	0.4257614	0.0000000
pland_c_1000m_agr	-0.1733121	0.0217046	0.4257614	0.0000000
ai_c_1000m_grass	-0.1154353	0.0377658	0.4257614	0.0030111

**Both predictors significant**

**Significantly higher amount of variation in avian species richness explained by grassland model (42.6%) than forest models (<12%).**

**Increased grassland aggregation has a *negative* relationship with richness**

## Significant Grassland Variable Relationships





## Significant Forest Variable Relationships

