Association of Stress and connectivity in UK lakes with beetles species richness

Kuan Wang

1 Introduction

Global biodiversity is facing greater challenge nowadays due to the acceleration of climate change and human industrial revolution(Butchart et al. 2010). According to (Wiens 2016; Abell et al. 2008), Although biodiversity of freshwater is declining at higher rates compared with terrestrial and marine, its ecosystem is somewhat overlooked by the conservation community. Due to the limited human resources, identifying crucial areas for conservation is becoming problematic in reaching efficient biodiversity preservation.(Margules and Pressey 2000; Myers et al. 2000) In the intricate UK's freshwater ecosystems, connectivity and stressors play pivotal roles that greatly influence biodiversity and ecosystem functionality.

For most of the inland aquatic habitats, water beetles' richness is the perfect indicator for checking the biodiversity and conservation of freshwater. The existance of some specific species are also critical in determine water quality and habitat stability.(Bilton, Ribera, and Edward 2019) In the Mediterranean region, water beetles exists in nearly all types of freshwater and brackish environments because of its high species richness.(Ribera 2000) At the same time, water beetles have been employed to identify priority conservation zones.(Sánchez-Fernández et al. 2004)

Therefore the "Hydroscape" project funded by the UK Natural Environment Research Council (NERC). This project delves deep into the exploration of the interactions between stressors and connectivity and how they affect biodiversity and ecosystem functionality in the UK's freshwater systems. With a spotlight on some specific species such as beetles, the project aims to demystify the mutual effects of stress and connectivity on the species diversity.

Finally, this project would like to extend heartfelt gratitude to Dr. Alan Law and Dr. Philip Taylor for providing precious data on response and explanatory variables, which form the establishment of this program.

The objective of this program is to answer the following questions:
(i) What are the main relationships between species richness and surrounding land cover stressors?
(ii) What is the primary correlation between species diversity in freshwaters and connectivity to its buffers?
(iii) Does the association between species distribution and stress factors change depending on connectivity to other nearby freshwaters?

2 Methodology

2.1 Study area and dataset

This study is based on Great Britain islands(Some offshore islands not included: Isle of Man, Shetlands etc.), an island in the North Atlantic Ocean with an area of 209,331 km^2 and contains over 40,000 water bodies in total.(Source,2012)(Hughes et al. 2004) From the illustrated map below, it is clear that most of the lake samples come from the middle part of the island, which are northern and central England.

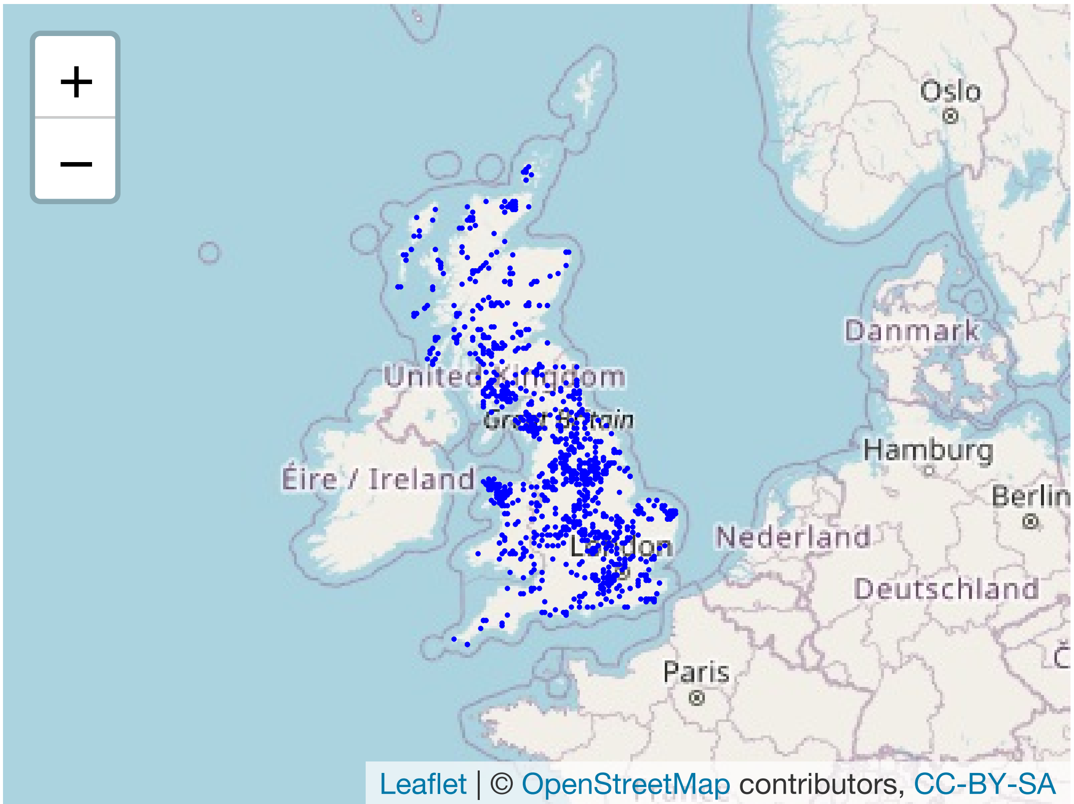

Figure 1: Map of the study area(Great Britain island) with all lake samples marked in blue.

The secondary dataset we used in this project is base on the compilation from Dr. Alan Law and Dr. Philip Taylor from the project NERC. The collected dataset comprises 1418 samples from various lakes throughout the UK and each of them have 26 different variables. They are categorized they belongs to three facet concerning the lakes: Lake typology, Connectivity and Stressors. The following table shows the data summary of response variable and numerical variables for lake geology features :

Variable	Missing number	Mean	S.D	Median
nSpecies	0	12.83	14.45	8
Lake.area	0	116.84	614.99	6.57
Lake.alltitude	0	109.51	126.15	67
Lake.depth	0	4.62	6.61	3.28
Lake.volume	0	19886151.76	215002635.82	157125.48
Lake.perimeter	0	4.91	14.09	1.37

Connectivity and stressor variables are the major components of this regression analysis. In this dataset, connectivity variables are structural connectivity which refers to the arrangement of elements within landscapes, including the spatial layout of landscape units and the physical features of the surrounding buffer areas.(Zhang et al. (2021)) Another part of the explanatory variable refers to nature and human interactions to lake surroundings, which refers to stressors. The table below shows the explanation of all variables.

Connectivity Variables	Explanation
Land.slope	Mean slope of 2km buffer around lake/ degree
Land.lakearea	Percentage of 2km buffer around lake covered by lakes/ %
Land.pondarea	Percentage of 2km buffer around lake covered by ponds/ %
Land.riverlength	Total length of rivers in 2km buffer around lake/ km
Land.Canallength	Total length of canals in 2km buffer around lake/ km
Land.obstacles	Total number of obstacles in 2km buffer around lake
Land.lakeper	Total perimeter of all other lakes in 2km buffer around lake/ km
Land.pondper	Total perimeter of all ponds in 2km buffer around lake/ km
Land.lakecount	Total number of other lakes in 2km buffer around lake
Land.pondcount	Total number of ponds in 2km buffer around lake

Stressor Variables	Explanation
Land.Agricultural	Percentage of agricultural land cover in 2km buffer around lake
Land.urban	Percentage of urban land cover in 2km buffer around lake
Land.MeanT	Mean temperature of 2km buffer around lake
Land.Rainfall	Mean annual rainfall of 2km buffer around lake
Land.fishing	Normalised measure of number of visits for fish- ing purposes in 2km buffer around lake
Land.watersports	Normalised measure of number of visits for watersport purposes in 2km buffer around lake
Land.allvisit	Normalised measure of number of visits for all pur- poses in 2km buffer around lake

Figure 2. shows the boxplot of all the stressor and connectivity variables. It is clear that majority of the sample data in some connectivity variables are around value zero(Land.lakearea, Land.Canallength), and the actual realiable datapoints are made by outliers. Therefore, Land.Canallength should not be included in the model since it only has 166 non-zero values.

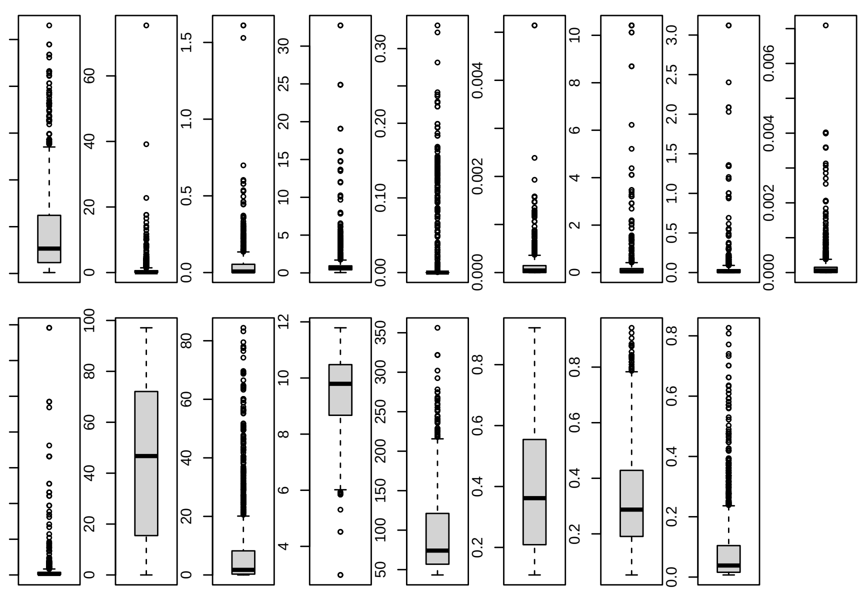

Figure 2: Boxplots of stress and connectivity variables

2.2 Models implemented

Given that this is a regression problem, a Generalized Linear Model(GLM) will typically be the first choice for incorporating all the variables. The response variable in this case is a count variable, which is the number of species in a certain sample. Poisson/Quasi-poisson/Negative binomial GLM should be considered based on different level of dispersion. Here is the negative binomial model used in this case:

$$Y \sim NB(\mu, k), Y_i \sim NB(\mu_i, k)$$

$$E(Y_i) = \mu_i, Var(Y_i) = \mu_i + \mu_i^2/k$$

Where the response variable Y have mean μ and variance $\mu + \mu^2/k$is related to both poisson parameter μ and dispersion variable k. μ^2/k converges to zero if k is large enough, then the whole distribution converges to poisson distribution.

$$g(\mu_i) = log(\mu_i)$$

$$g(\mu) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_p x_p$$

The link function $g(\mu)$ is also logarithmic with β_i represents the coefficients for different variables and x_i corresponds to different connectivity/stressor variables.

2.3 Model checking

The Akaike Information Criterion (AIC), is a metric for evaluating the goodness of fit when selecting the most appropriate model from among multiple fitted options. The AIC is calculated as follows:

$$AIC = -2log(MLE) + 2k$$

Where k indicates the estimated parameters in the model, and MLE stands for Maximum likelihood estimate of this model. Given a multiple choice of models, the model with the lowest AIC value is considered the most preferred choice with its maximized MLE and lowest possible parameters.

Overdispersion is checked via the dispersion parameter ϕ, where:

$$\phi = D/(n - p)$$

D refers to the residual deviance and $n - p$ is the degrees of freedom. a relative high value with $\phi > 10$ indicates a serious overdispersion of this model.

3 Data analysis

3.1 Correlation between explanatory variables and response variable

The correlations between each explanatory variable versus the response variable is plotted as Figure 3. Most of the connectivity variables have weak negative correlations against richness, the stress variables are appeared to be more active and correlated. “Land.Agricultural” and “Land.MeanT” shows the most positive correlation and “landscape_2km_Mean.slope..degrees.” shows the most negative correlation, which is definitely unexpected. Overall, all variables do not show clear relationship against the response variable, we need further plots to discover.

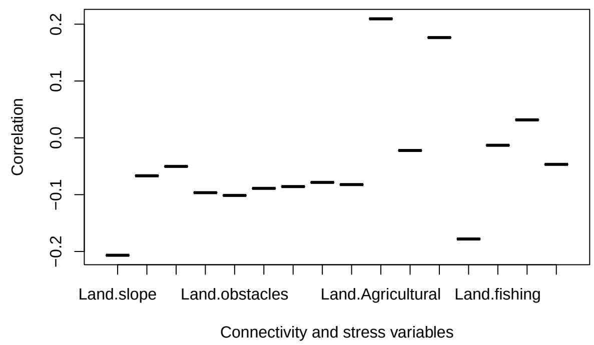

Figure 3: Correlations between response variable and different covariates

3.2 Correlation plots

Figure 4 are the correlation plots for each explanatory variable, correlations between each variables have shown some similarities, such as Land.watersports/Land.allvisit and Land.pondper/Land.poundcount. For these variables which might have muticolinearity, some of them need to be deleted to improve the model's performance.

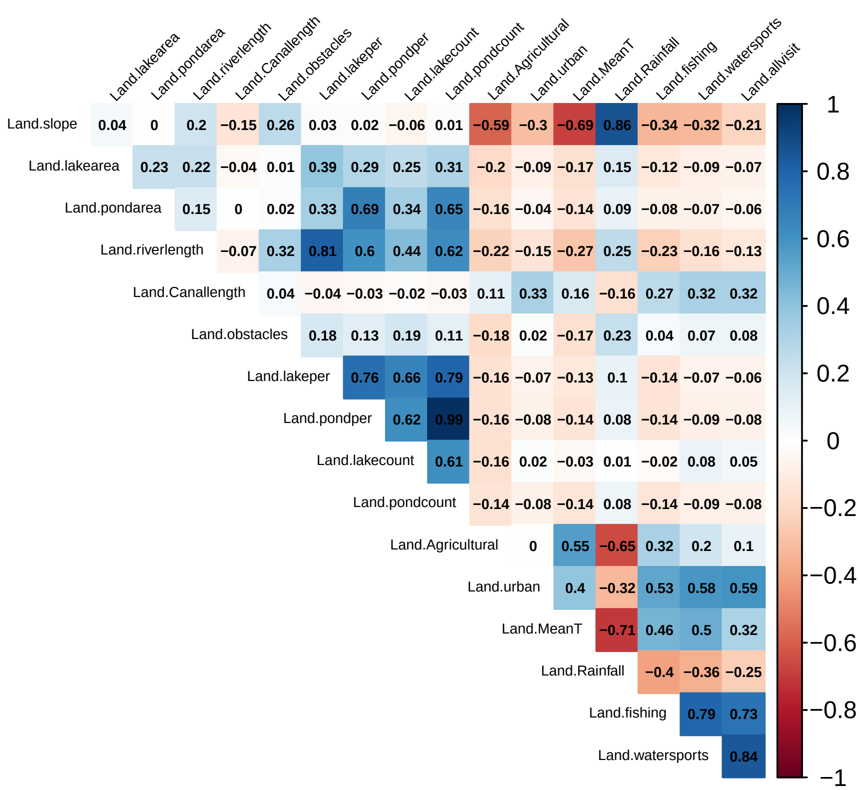

Figure 4: Correlations of different variables

3.3 Scatter plots

Figure 5 are scatter plots from all stress variables against species richness. It is clear that there is no strong linear pattern for all these variables, Agriculture and Mean temperature are left skewed and Urban, Rainfall, Visits are right skewed, the rest are ramdomly placed.

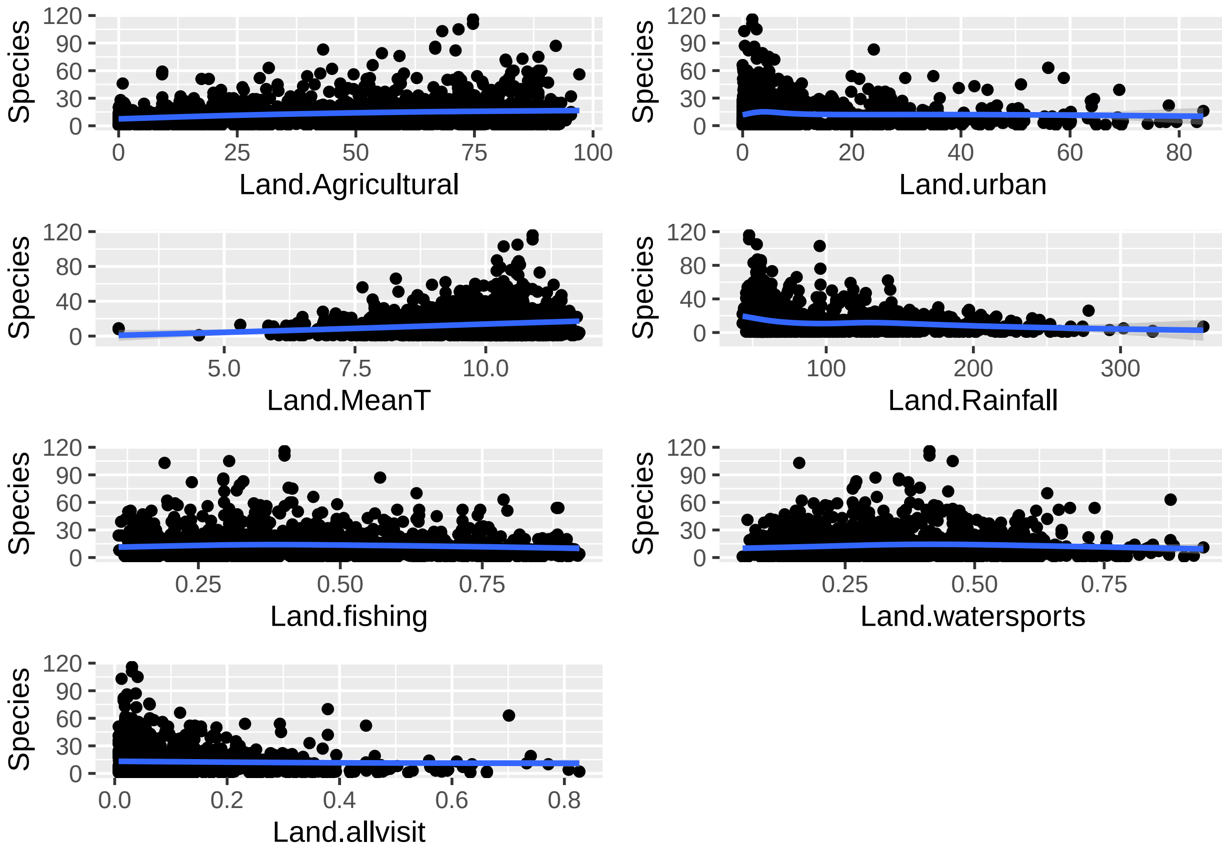

Figure 5: Scatter plots of different stress variables against nSpecies

Figure 6 shows scatter plots from all connectivity variables against species richness. Most of the variables are very right skewed, and there is no clear linear relationship from these variables can be reached.

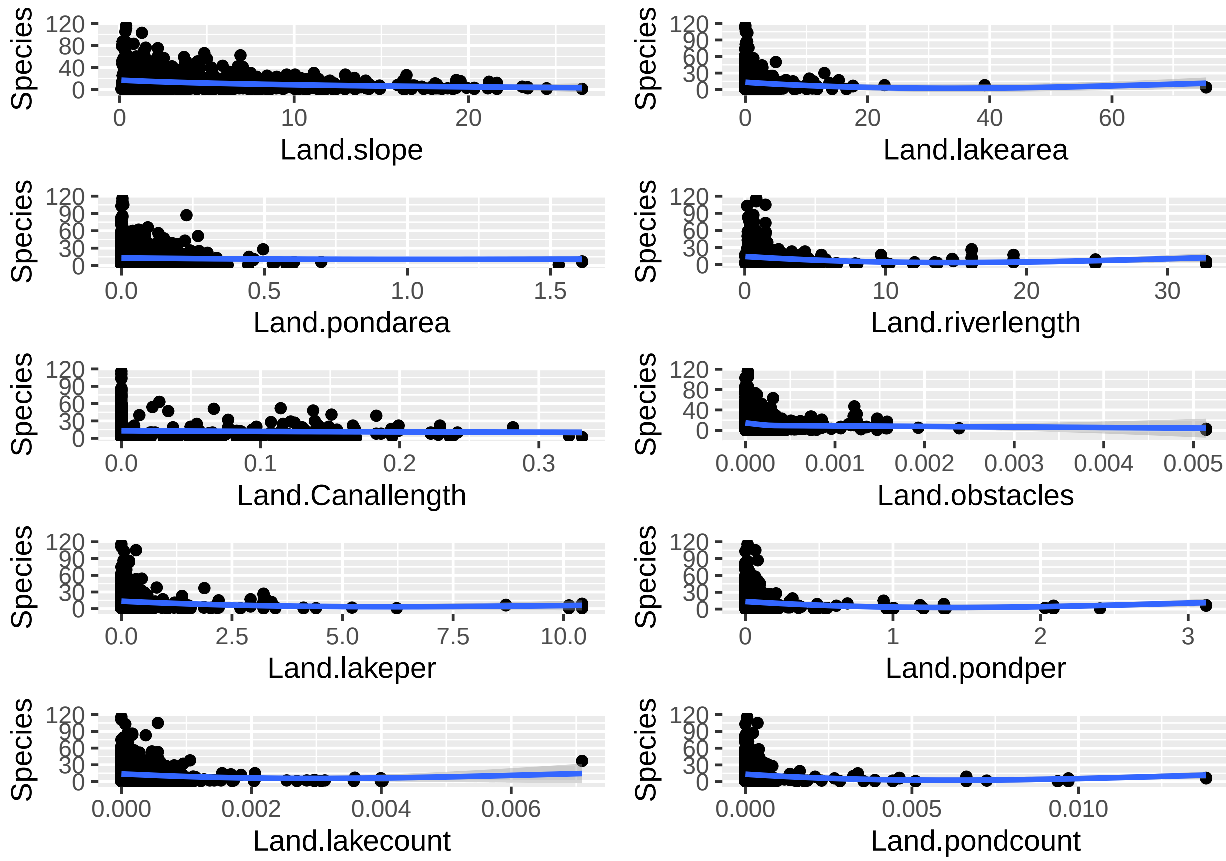

Figure 6: Scatter plots of different connectivity variables against nSpecies

3.4 Fit the generalised linear model

From the scatterplots and corrplots above, there are some variables shows high colinearity with other variables(Land.allvisit,Land.pondcount,Land.lakecount), though they should be excluded to the model building. In order to discover what specific variable interfere the species richness, the GLM model for count variables is fitted in to stressor variables. Firstly, the data was fitted with poisson GLM model, the result shows a severe overdispersion with residual deviance: 16142 on 1411 degrees of freedom with the dispersion ratio = 11.63. Therefore, a negative binomial model is implemented to solve this problem. There are several updates to optimize the model by deleting colinear items and adding interaction terms.

The Rootograms in Figure 7 from poisson GLM(left) and negative binomial GLM(right) simply show the goodness of fit from two models. Histogram of negative binomial model is "standing" on the x_axis, differ from "hanging" graph from poisson GLM graph. Which shows there is much more deviation from the poisson GLM model.

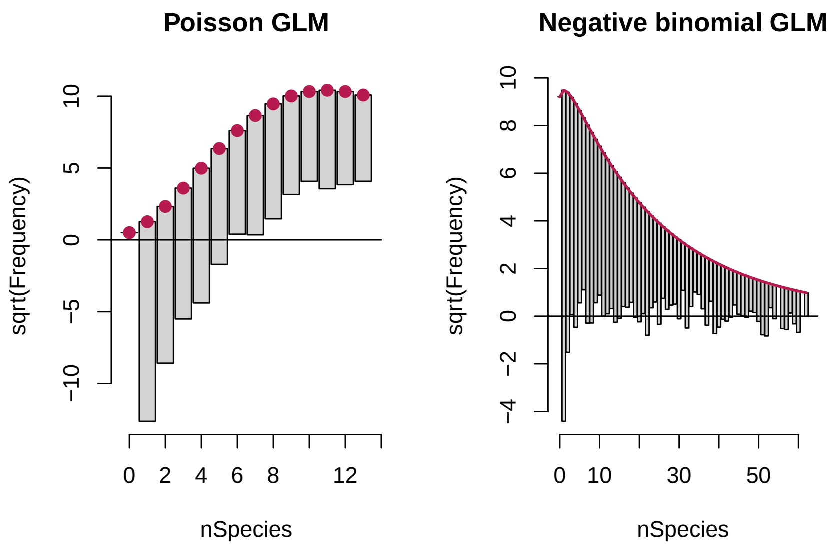

Figure 7: Rootgram of two GLM models

The overdispersion problem from poisson GLM model occurs again among the connectivity variables. Poisson GLM model returns a residual deviance of 16255 on 1410 degrees of freedom with a dispersion ratio of 11.51. Unlike the stressor model above, the p-value for connectivity variables are relatively high, only “Land.slope” and “Land.obstacles” have p-value less than 0.05. Then after adding all the possible interaction terms, AIC stepwised regression is applied to eliminate the unrelated variables.

Rootograms in Figure 8 show the difference in deviation for both models again. Negative binomial model displays a better dispersion.

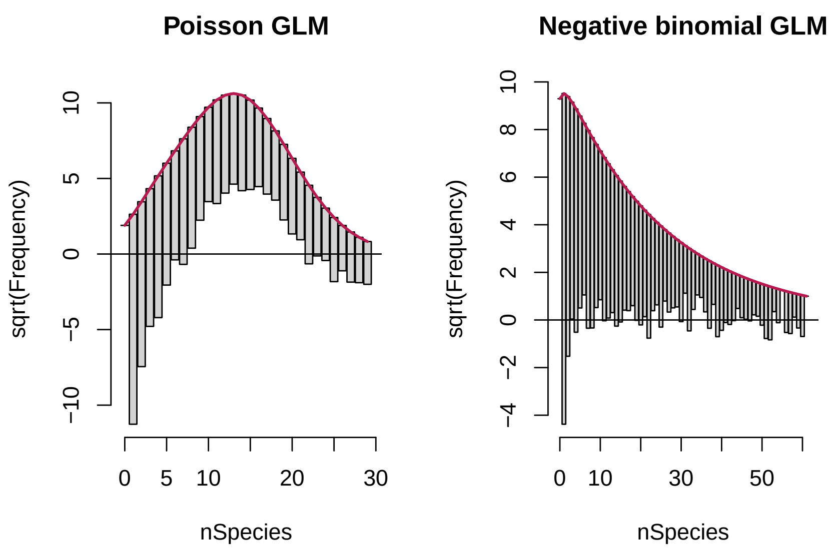

Figure 8: Rootgram of two GLM models

Figure 7 shows the VIF values of both GLM model, result shows no strict multicolinearity between all explanatory variables in both models.

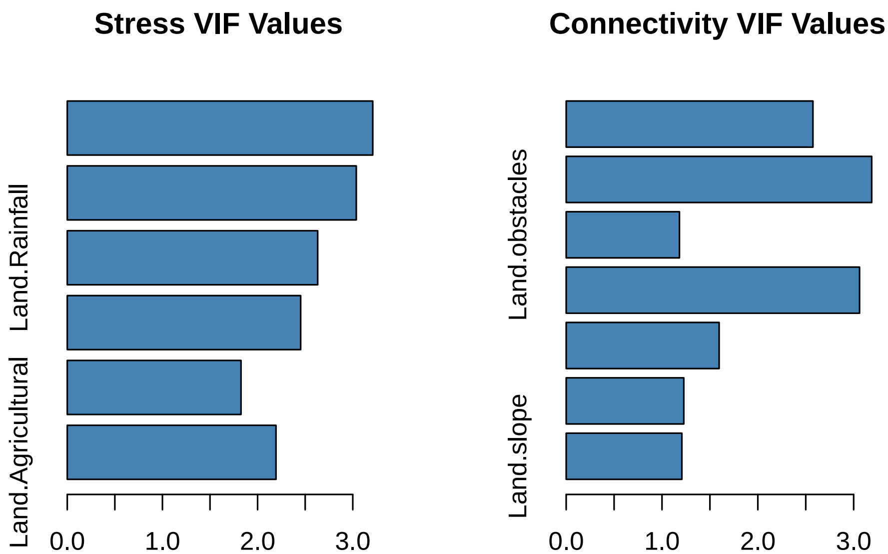

Figure 9: Barplot of vif values of GLM model

The third research question seeks some correlations between two categories of variables, we need to find the interaction effects between connectivity and stressors covariates. After filtering the parameters, there are 6 variables for stressors and 7 for connectivity. There is no need to discover interactions among each and every variable. Consequently, interaction between every pair is found and every significant p-value is selected to build up the new model. AIC stepwised regression is implemented to reach the optimised model.

4 Result

4.1 Stressor variables GLM

From the anova table we can conclude that from the nature stressors, “Land.MeanT” shows the best significance related to the species richness, with every 1 degree increase in Mean temperature reflets around 0.20 increases in species richness. Both human stressors: “Land.fishing” and “Land.watersports” have implications on species richness, the intriguing part is the visits for watersports do help the rich of species of beetles. And the interaction of Rainfall/Agricultural do have good implications on beetles richness.

Variable	Estimated coef	S.D	Deviance	p-value	Significance
(Intercept)	0.9574	0.554	NA	NA	.
Land.Agricultural	-0.0019	0.003	93.915	3.29302535644872e-22	
Land.urban	-0.0042	0.003	0.109	0.74091199783768	
Land.MeanT	0.201	0.064	17.784	2.47447062662019e-05	**
Land.Rainfall	0.0067	0.004	4.189	0.0406865567635433	
Land.fishing	-0.8148	0.208	14.232	0.000161594418330648	***
Land.watersports	0.5531	0.265	4.22	0.0399487557159468	*
Land.MeanT:Land.Rainfall	-0.0012	0.001	0.195	0.658608929267719	*
Land.Agricultural:Land.Rainfall	1e-04	0	8.947	0.00277850913155813	**

From the model comparison table, the optimal model is chosen by choosing the model with lowest AIC value, which is the one with two interaction terms.

Model	Theta	2*log-lik	p-value	AIC
Original Model	1.17	-10049.11	NA	10065
+Land.Rainfall*Land.MeanT	1.17	-10048.92	0.659582169115958	10067
+Land.Rainfall*Land.Agricultural	1.18	-10039.99	0.00281382807659958	10060

4.2 Connectivity variables GLM

For all the connectivity variables, all the selected covariates are showing the strict significance i contribution to the model. However, the result of coefficients are differ of the expectation. Since the “Land.lakeper” and “Land.pondper” have negative relationship with species richness, every 1 increase in pond count in 2km buffer will leads to an decrease in species richness around 1.14.

Variable	Estimated coef	S.D	Deviance	p-value	Significance
(Intercept)	2.8394	0.037	NA	NA	***
Land.slope	-0.0668	0.006	106.523	5.66209535556184e-25	***
Land.riverlength	0.0504	0.019	5.934	0.0148507379936801	**
Land.lakeper	-0.2999	0.082	14.316	0.000154514405657573	***
Land.pondper	-1.141	0.027	2.77	0.096020356928661	***
Land.lakeper:Land.pondper	0.167	0.044	13.052	0.000303020706164011	***

From the model comparisons, the preferred model is chosed to be the stepwised model after adding the interaction terms, with the smallest AIC value.

Model	Theta	2*log-lik	p-value	AIC
Original Model	1.18	-10040.75	NA	10066
+Interaction terms	1.17	-10048.1	1	10057
Stepwised	1.18	-10035.04	0.00145615358245987	10055

4.3 Stressor variables GLM with connectivity interactions

In the model of all stress variables with interactions with connectivities,“Land.pondarea”,“Land.pondper”,“Land.obstacles” have the most interaction effects with all the stressor variables, and “Land.pondarea” shows the most dominating effects, with its positive interaction with “Land.MeanT” and negative effect with “Land.watersports”.

Variable	Estimated coef	S.D	Deviance	p-value	Significance
(Intercept)	1.9012	0.335	NA	NA	***
Land.Agricultural	0.0057	0.001	95.524	1.46132320397766e-22	***
Land.MeanT	0.0653	0.032	13.546	0.000232799737218864	*
Land.Rainfall	-0.0011	0.001	2.018	0.155458535732575	
Land.fishing	-1.1987	0.232	21.187	4.16607555209906e-06	***
Land.watersports	1.08	0.296	3.624	0.0569502770213958	***
Land.MeanT:Land.pondarea	0.3352	0.121	0.579	0.446628082483432	**
Land.MeanT:Land.pondper	-0.2663	0.09	18.789	1.45970508913309e-05	**
Land.Rainfall:Land.pondarea	-0.009	0.006	2.023	0.154936756585443	
Land.Rainfall:Land.lakeper	0.001	0.001	0.079	0.778879589513227	
Land.fishing:Land.pondarea	4.7106	2.437	0	0.99665281464223	.
Land.watersports:Land.pondarea	-11.7398	4.093	3.397	0.0653139060265435	**
Land.watersports:Land.obstacles	-928.2565	307.2	7.094	0.00773615990468198	**
Land.watersports:Land.lakeper	-0.6249	0.322	1.641	0.20015308308652	.
Land.watersports:Land.pondper	8.6261	3.71	4.193	0.0405985638860527	*

In the model comparison part, two models from the original stressors GLM were compared to the model with connectivity interactions, finally the stepwised model with smallest AIC value is chosed to be the optimal model.

Model	Theta	2*log-lik	p-value	AIC
Original Model	1.17	-10049.11	NA	10065
Optimized stress model	1.18	-10039.99	0.0104701656723788	10060
+connectivity interaction terms	1.2	-10012.6	0.000122201140464795	10052
Stepwised	1.2	-10009.92	0.74933661308767	10045

5 Discussion and limitations

5.1 Other approaches

5.1.1 Gaussian GLM

Other than using count response variable in the case above, we can transform the response to continuous variable by create the species density(species richness/lake area) to replace it. After doing the log transformation to the new response variable, we can employ the gaussian GLM model to replace the overdipersed poisson model. The summary output indicates a strict decrease in AIC value, however, replace the response covariate is simply facing a enormous loss in data details and accuracy.

```
##
## Call:
## glm(formula = log(richness_density) ~ Land.Agricultural + Land.urban +
##     Land.MeanT + Land.Rainfall + Land.fishing + Land.watersports +
##     Land.fishing:Land.watersports, family = gaussian(), data = beetles)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -7.6450  -1.1998   0.2056   1.4948   4.9898
##
## Coefficients:
##                                Estimate Std. Error t value Pr(>|t|)
## (Intercept)                   -2.503892   0.735593  -3.404 0.000683 ***
## Land.Agricultural              0.002794   0.002812   0.994 0.320463
## Land.urban                     0.009953   0.005479   1.817 0.069480 .
## Land.MeanT                     0.409791   0.070779   5.790 8.68e-09 ***
## Land.Rainfall                 -0.005904   0.001790  -3.299 0.000994 ***
## Land.fishing                  -0.511403   0.673028  -0.760 0.447469
## Land.watersports              -6.107704   1.032986  -5.913 4.22e-09 ***
## Land.fishing:Land.watersports  5.439414   1.582746   3.437 0.000606 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for gaussian family taken to be 4.514856)
##
##     Null deviance: 7282.5  on 1417  degrees of freedom
## Residual deviance: 6365.9  on 1410  degrees of freedom
## AIC: 6171.5
##
## Number of Fisher Scoring iterations: 2
```

5.1.2 Visualise using generalised additive model(GAM)

Now we introduce the Gerneralised Additive Model(GAM), it is the non parametric regression on all variables, using smooth functions feature variables. Therefore the non-linear model is formed as:

$$g(\mu) = \beta_0 + f(x_1) + f(x_2) + ... + f(x_p)$$

Where y is the response variable: Species richness, μ is Expected value of y, and $f(x_i)$ corresponds to the smooth functions for each explanatory variable to form non-linear relationship against y. One of the most common used spline function is the thin plate spline:

$$f(x) = \beta_0 + \beta_1 x + \sum_{k=1}^{K} u_k |x - \kappa_k|^3$$

Where κ_k are invidual knots of the smooth function and K represents the total number of knots.

In this example, we use negative binomial gam model to fit the data and thin plate spline function is applied on each of the covariates. The outcome is quite ideal, as every component appears to be significant in this model. As shown in the Figure 10., the quantiles plotted against deviance residuals line mostly fall within the 95% confidence interval, and the scatterplot of the residuals displays a relatively good degree of randomness. From the visualization of different covariates in Figure 11., 95% confidence interval fits perfectly between the lines of best fit. However, the R^2 value from this model is too low that the result from this model is not realiable enough to support this model.

```
##
## Family: Negative Binomial(1.205)
## Link function: log
##
## Formula:
## nSpecies ~ s(Land.Agricultural) + s(Land.urban) + s(Land.MeanT) +
##     s(Land.Rainfall) + s(Land.fishing) + s(Land.watersports)
##
## Parametric coefficients:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)  2.49117    0.02544   97.94   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Approximate significance of smooth terms:
##                        edf Ref.df Chi.sq  p-value
## s(Land.Agricultural) 3.1772      9 44.135  < 2e-16 ***
## s(Land.urban)        1.7907      9  5.128  0.03955 *
## s(Land.MeanT)        0.5230      9  1.098  0.14093
## s(Land.Rainfall)     4.8755      9 27.356 4.50e-06 ***
## s(Land.fishing)      0.9461      9 17.298 7.95e-06 ***
## s(Land.watersports)  1.9922      9  8.115  0.00716 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## R-sq.(adj) =  0.0914   Deviance explained = 11.2%
## -REML = 5025.8  Scale est. = 1         n = 1418
```

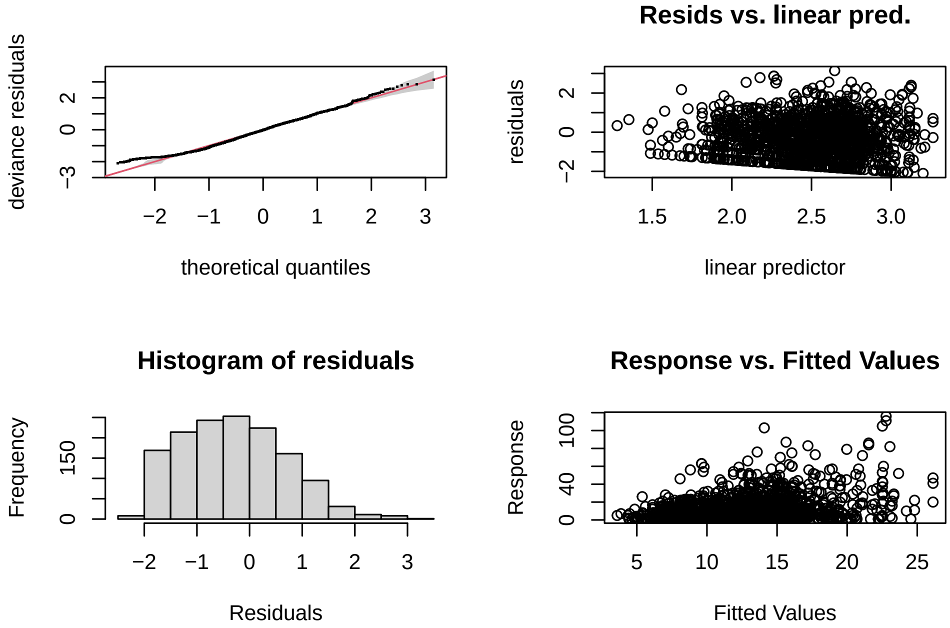

Figure 10: Summary of the negative binomial GAM model on stress variables

```
##
## Method: REML   Optimizer: outer newton
## full convergence after 10 iterations.
## Gradient range [-0.0007515432,0.00263018]
## (score 5025.808 & scale 1).
## Hessian positive definite, eigenvalue range [0.0001900516,648.9791].
## Model rank =  55 / 55
##
## Basis dimension (k) checking results. Low p-value (k-index<1) may
## indicate that k is too low, especially if edf is close to k'.
##
##                         k'   edf k-index p-value
## s(Land.Agricultural) 9.000 3.177    0.83   0.005 **
## s(Land.urban)        9.000 1.791    0.81  <2e-16 ***
## s(Land.MeanT)        9.000 0.523    0.81  <2e-16 ***
## s(Land.Rainfall)     9.000 4.875    0.83  <2e-16 ***
## s(Land.fishing)      9.000 0.946    0.84   0.005 **
## s(Land.watersports)  9.000 1.992    0.86   0.015 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

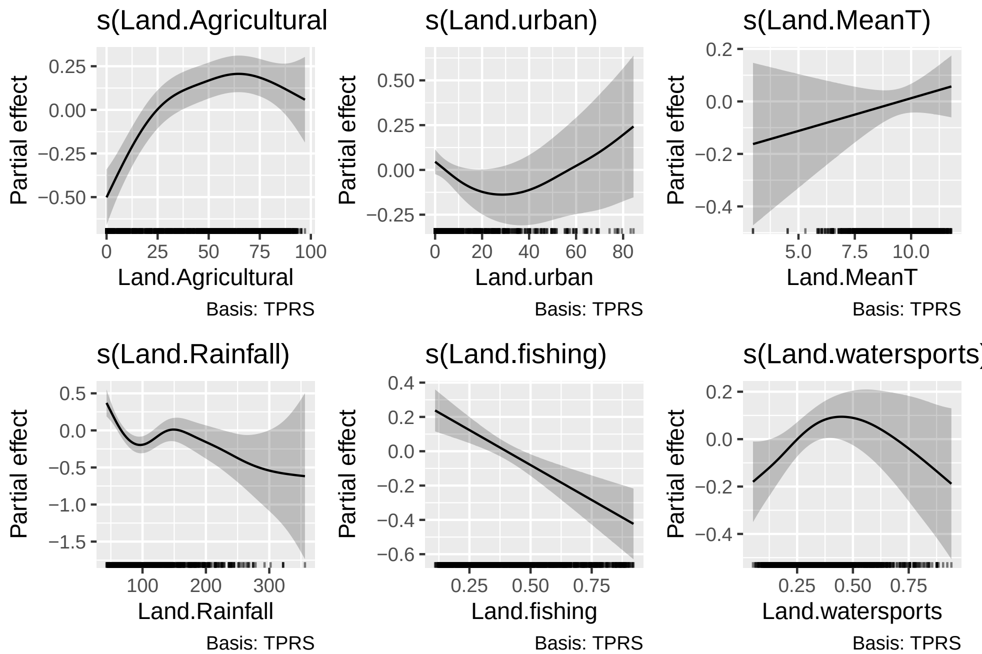

Figure 11: Summary of the negative binomial GAM model on stress variables

5.2 Limitations

The results from models above have reveal a measurable degree of uncertainty and bias. For example, from the connectivity GLM model, both “Land.lakeper” and “Land.pondper” have negative impact on species richness, the result might be affected by a group of large lakes which have small beetles richness. A reasonable explanation for why “Land.watersports” have a positive impact on species richness could be that people are tend to visit beautiful places with rich species richness, therefore a positive coefficient could not involve the positive effect of the human activities. Overall, even though every model have some results that are not matching the common sense, the overall results are relatively good and connected.

6 Conclusion

This research project uses GLM models to discover all the possible linear relationships between species richness and all the connectivity and stressors covariates. Given that the response variable is a count variable and overdispersion occurs when applying a Poisson model to the data, then negative binomial model is addressed and least AIC is used for filtering the models. Results have shown the significance on specific variables: “Land.MeanT”, “Land.watersports” and “Land.riverlength” etc have good impact on species richness. Moreover, “Land.fishing”, “Land.lakeper” etc have negative affect on the diversity. On the other hand, the variables: “Land.pondarea”,“Land.pondper”,“Land.obstacles” from the connectivity have interactions with some of the stressors variables which do have influence on species richness.

7 Bibliography and reference

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