**Introduction:**

In this inquiry, we employed data derived from an observational study on vegetation, focusing on the percentage of plant cover within designated square meter areas. Alongside the percentage of plant cover, the dataset encompasses insights into various abiotic factors present within the squares, such as annual precipitation, estimated potassium (K) concentrations, and incoming radiation. The objective of this investigation is to leverage the accumulated data to inspect the impact of diverse abiotic factors on the occurrence of exotic and native herbs and grasses. Specifically, we aim to determine whether these two categories of flora display patterns of resource competition or if one demonstrates superior adaptability to certain environmental conditions compared to the other.

**Methods:**

In the preliminary phase of our study, we established distinct categories for the examination of herbaceous vegetation, classifying them into two groups: exotic and native herbs and grasses. The exotic category encompassed both perennial and annual herbs and grasses, whereas the native group exclusively comprised perennial herbs and grasses.

To initiate our investigation, we performed an exploratory analysis of the response variables, namely the percentage cover of exotic and native herbs and grasses. This initial examination aimed to analyze the inherent distribution patterns within the dataset. Consequently, we generated two histograms to visually represent the distribution of exotic and native plants (Figure 1).

Subsequently, we identified nine abiotic factors deemed pertinent to our study and incorporated them into our preliminary model. Employing a general linear model (GLM) with a Poisson distribution served as the initial step in our modeling process. Recognizing the presence of overdispersion in our data, as discerned through the previous Poisson GLM, we opted for a negative binomial distribution to better accommodate this inherent characteristic.

Following this, we systematically constructed simplified models by iteratively excluding various abiotic factors. This iterative approach resulted in the formulation of seven distinct models, each subject to evaluation to ascertain the most fitting one. Model assessments were conducted based on the Akaike Information Criterion (AIC).

In the final phase of our analysis, we compared the impacts of different abiotic factors on exotic and native herbs and grasses. This comparative analysis was presented in tabular form, and the results were visually depicted using a barplot, illustrating the effects along with their corresponding standard errors.

**Results:**

We commenced our analysis by examining the distribution of our response variable, exotic and native herbs and grasses.

Both histograms resembled a Poisson distribution, prompting the application of a Generalized Linear Model (GLM) with a Poisson distribution.

We initiated the modeling process with a regular GLM using the Poisson family. However, the native model exhibited substantial residual deviance 5377.7 on 336 degrees of freedom, and the exotic model 5567.8 on 336 degrees of freedom, indicating serious overdispersion in both models. Given this concern, we used a negative binomial distribution similar to the Poisson distribution but with an additional parameter addressing disproportionate variance.

Afterward, we constructed simplified models by iteratively excluding various abiotic factors.

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| Model | AIC | logLik | weight |
| glm.nb(data = data, NativePlant\_cover~annual\_precipitation+  precipitation\_warmest\_quarter+precipitation\_coldest\_quarte+ MrVBF+K\_perc) | 2547.315 | -1266.658 | 0.54 |
| glm.nb(data = data, NativePlant\_cover~annual\_precipitation+  precipitation\_warmest\_quarter+precipitation\_coldest\_quarte+ MrVBF+K\_perc+Th\_ppm) | 2549.312 | 1266.656 | 0.20 |
| glm.nb(data = data, NativePlant\_cover~annual\_precipitation+  MrVBF+K\_perc) | 2550.503 | -1270.252 | 0.11 |
| glm.nb(data = data, NativePlant\_cover~annual\_precipitation+  precipitation\_warmest\_quarter+precipitation\_coldest\_quarte+ MrVBF+K\_perc+Th\_ppm+U\_ppm) | 2551.046 | -1266.523 | 0.08 |
| glm.nb(data = data, NativePlant\_cover~ MrVBF+K\_perc) | 2552.241 | -1272.121 | 0.05 |
| glm.nb(data = data, NativePlant\_cover~annual\_precipitation+  precipitation\_warmest\_quarter+precipitation\_coldest\_quarte+ MrVBF+K\_perc+Th\_ppm+U\_ppm+SRad\_Jan+SRad\_Jul) | 2553.503 | -1265.751 | 0.02 |
| glm.nb(data = data, NativePlant\_cover~ 1) | 2568.071 | -1282.036 | 0.00 |

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| --- | --- | --- | --- |
| Model | AIC | logLik | weight |
| glm.nb(data = data, ExoticPlant\_cover~annual\_precipitation+  precipitation\_warmest\_quarter+precipitation\_coldest\_quarte+ MrVBF+K\_perc) | 2912.759 | -1449.380 | 0.64 |
| glm.nb(data = data, ExoticPlant\_cover~annual\_precipitation+  precipitation\_warmest\_quarter+precipitation\_coldest\_quarte+ MrVBF+K\_perc+Th\_ppm) | 2914.758 | -1449.379 | 0.24 |
| glm.nb(data = data, ExoticPlant\_cover~annual\_precipitation+  precipitation\_warmest\_quarter+precipitation\_coldest\_quarte+ MrVBF+K\_perc+Th\_ppm+U\_ppm) | 2916.602 | -1449.301 | 0.09 |
| glm.nb(data = data, ExoticPlant\_cover~annual\_precipitation+  precipitation\_warmest\_quarter+precipitation\_coldest\_quarte+ MrVBF+K\_perc+Th\_ppm+U\_ppm+SRad\_Jan+SRad\_Jul) | 2919.191 | -1448.595 | 0.03 |
| glm.nb(data = data, ExoticPlant\_cover~annual\_precipitation+  MrVBF+K\_perc) | 2939.227 | -1460.114 | 0.00 |
| glm.nb(data = data, ExoticPlant\_cover~ MrVBF+K\_perc) | 2953.902 | -1472.951 | 0.00 |
| glm.nb(data = data, ExoticPlant\_cover~ 1) | 3005.154 | -1500.577 | 0.00 |

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| General linear model negative binomial distribution (NativePlant\_cover ~ annual\_precipitation + precipitation\_warmest\_quarter + precipitation\_coldest\_quarter + +MrVBF + K\_perc) | | | | | |
| Coefficients: | Estimate | Std. Error | Z value | P(<|z|) |
| Intercept | 3.1624 | 1.2950 | 2.442 | 0.0146 |
| annual\_precipitation | -0.0258 | 0.0117 | -2.202 | 0.0277 |
| Precipitation\_warmest\_quarter | 0.0642 | 0.4126 | 1.557 | 0.1195 |
| Precipitation\_coldest\_quarter | 0.0462 | 0.1902 | 2428 | 0.0152 |
| MrVBF | -0.1701 | 0.0363 | -4.694 | 2.69e-06 |
| K\_perc | -0.2713 | 0.1461 | -1.857 | 0.0633 |

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| General linear model negative binomial distribution (ExoticPlant\_cover ~ annual\_precipitation + precipitation\_warmest\_quarter + precipitation\_coldest\_quarter + +MrVBF + K\_perc) | | | | | |
| Coefficients: | Estimate | Std. Error | Z value | P(<|z|) |
| Intercept | 2.2514 | 0.9620 | 2.340 | 0.0193 |
| annual\_precipitation | 0.0342 | 0.0087 | 3.936 | 9.28e-05 |
| Precipitation\_warmest\_quarter | -0.0879 | 0.0306 | -2.873 | 0.0041 |
| Precipitation\_coldest\_quarter | -0.0576 | 0.0141 | -4.089 | 4.33e-05 |
| MrVBF | -0.0210 | 0.0271 | -0.777 | 0.4372 |
| K\_perc | 0.57042 | 0.1092 | 5.225 | 1.74e-07 |