CORRELATION ANALYSIS

These correlation coefficients provide information about the strength and direction of the relationships between each pair of variables and the "risk_score." Here's a brief interpretation of the results:

```
> cor(nri_data$population, nri_data$risk_score)
[1] 0.3739231
> cor(nri_data$buildvalue, nri_data$risk_score)
[1] 0.3976655
> cor(nri_data$agrivalue, nri_data$risk_score)
[1] 0.1807788
> cor(nri_data$area, nri_data$risk_score)
[1] -0.02216815
> cor(nri_data$eal_score, nri_data$risk_score)
[1] 0.9893131
> cor(nri_data$sovi_score, nri_data$risk_score)
[1] 0.3023887
> cor(nri_data$resl_score, nri_data$risk_score)
[1] 0.2043117
```

Population, Building Value, and SOVI Score have positive correlations with Risk Score, indicating that higher values in these variables tend to be associated with higher risk scores.

Agriculture Value has a relatively weaker positive correlation with Risk Score.

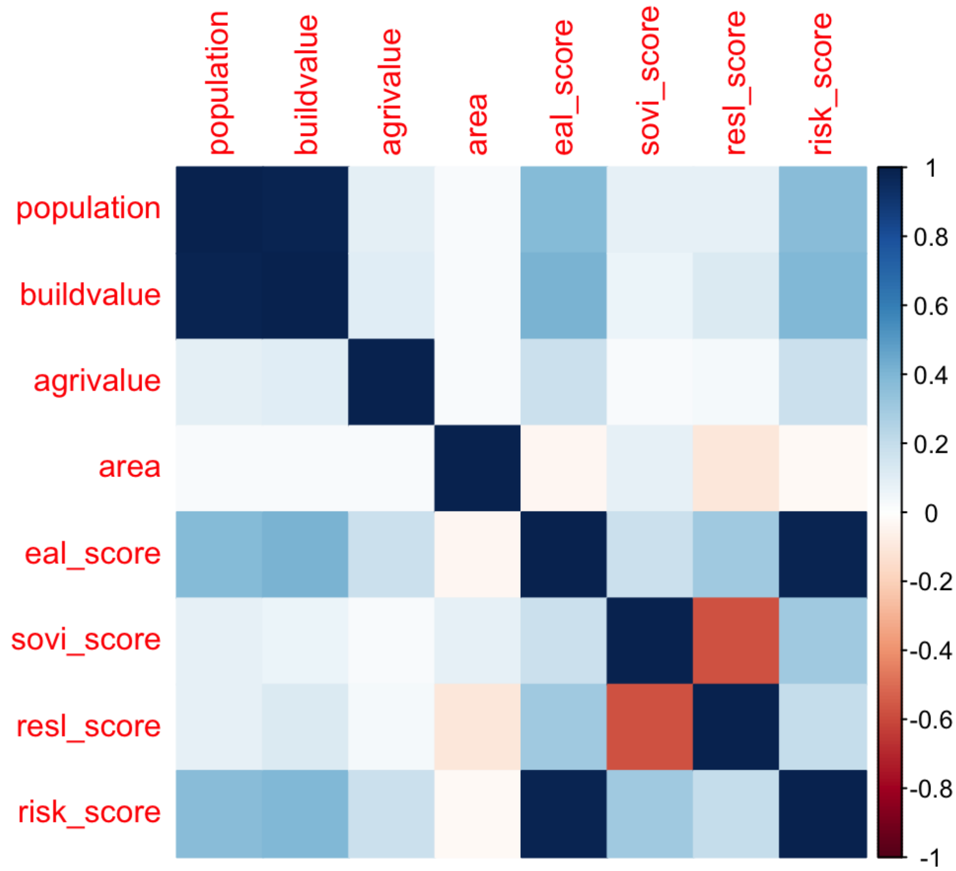
Area has a very weak negative correlation with Risk Score, suggesting that larger areas might be associated with slightly lower risk scores.

Expected Annual Loss (EAL) Score has a very strong positive correlation with Risk Score, indicating that as EAL Score increases, Risk Score increases significantly.

Social Vulnerability (SOVI) Score has a moderate positive correlation with Risk Score, suggesting that higher SOVI Scores are associated with higher risk scores.

Community Resilience (RESL) Score also has a positive correlation with Risk Score, but it's relatively weaker compared to other variables.

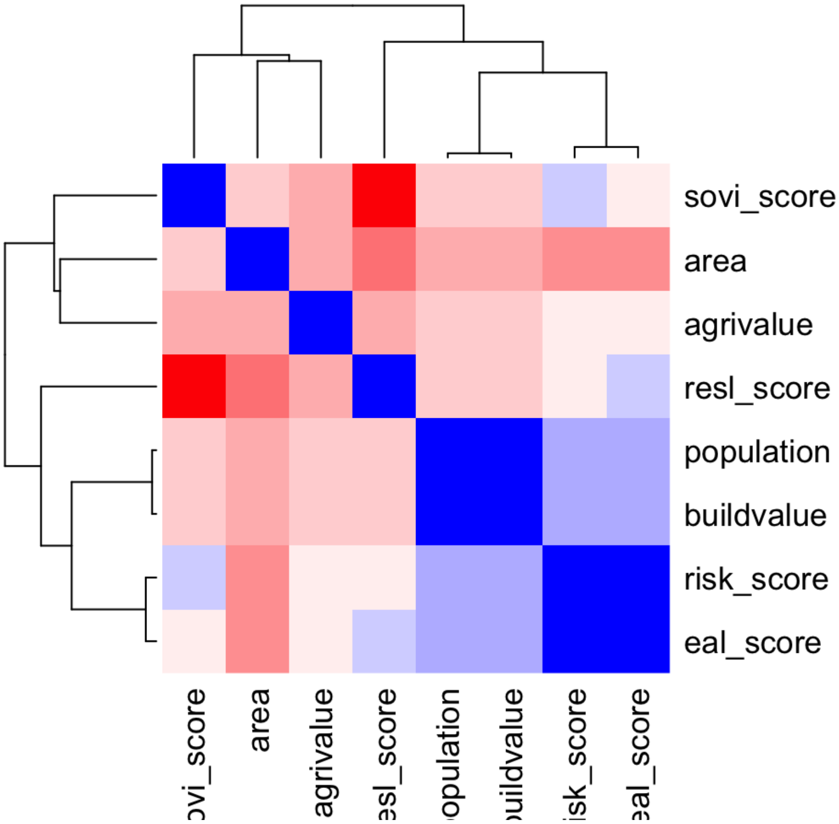
Overall, these correlations provide insights into how each variable is related to the overall risk score.



The intensity of the color in each cell of the plot represents the strength of the correlation between two variables. A darker color (e.g., dark blue) indicates a stronger correlation, while a lighter color (e.g., light yellow) indicates a weaker correlation.

The diagonal line from the top left to the bottom right typically contains perfect correlations (correlation of 1) because each variable is perfectly correlated with itself.

Variables with a positive correlation will have a positive color, typically in shades of blue. This means that as one variable increases, the other tends to increase as well. The darker the blue, the stronger the positive correlation. Variables with a negative correlation will have a negative color, typically in shades of red. This means that as one variable increases, the other tends to decrease. The darker the red, the stronger the negative correlation.



The heatmap created using the heatmap function and the corrplot visualization serve similar purposes in that they both display the correlations between variables in a dataset.

MULTIPLE LINEAR REGRESSION ANALYSIS

Since we are primarily interested in understanding the overall risk of natural disasters and its relationship with various factors (e.g., population, building value, agriculture value, etc.), we want to focus on the overall risk score as the dependent variable and include only relevant predictor variables that are likely to influence overall risk.

```
> summary(multiple_regression_model)

Call:
lm(formula = risk_score ~ population + buildvalue + agrivalue +
    area + eal_score + sovi_score + resl_score, data = nri_data)

Residuals:
     Min       1Q   Median       3Q      Max
-11.4252  -1.3410   0.0218   1.3058  11.6349

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept) -1.516e+00  1.568e-01  -9.667  < 2e-16 ***
population  -4.307e-06  6.744e-07  -6.387 1.95e-10 ***
buildvalue   2.063e-11  4.110e-12   5.020 5.46e-07 ***
agrivalue   -5.350e-10  1.427e-10  -3.750  0.00018 ***
area         9.642e-07  1.048e-05   0.092  0.92671
eal_score    9.938e-01  1.789e-03 555.403  < 2e-16 ***
sovi_score   9.584e-02  1.897e-03  50.530  < 2e-16 ***
resl_score  -4.163e-02  1.970e-03 -21.130  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 2.236 on 3135 degrees of freedom
Multiple R-squared:  0.994,     Adjusted R-squared:  0.994
F-statistic: 7.437e+04 on 7 and 3135 DF,  p-value: < 2.2e-16
```

The results from the multiple linear regression model provide insights into how various predictor variables are associated with the dependent variable, which is the "risk_score" in the analysis. Here's an interpretation of the key findings:

The "Pr(>|t|)" column provides p-values for each coefficient. In this summary, you can see that several predictor variables (population, buildvalue, agrivalue, eal_score, sovi_score, and resl_score) have p-values less than 0.05, indicating that they are statistically significant predictors of risk_score. The "Pr(>|t|)" column also shows that the intercept term is statistically significant.

The "Multiple R-squared" value is 0.994, indicating that the model explains a significant proportion of the variance in risk_score. This suggests that the combination of predictor variables in the model is highly effective in explaining the variation in the dependent variable.

```
> summary(multiple_regression_model)$coefficient
                 Estimate   Std. Error     t value     Pr(>|t|)
(Intercept) -1.516271e+00 1.568447e-01  -9.66733987 8.337459e-22
population  -4.306885e-06 6.743641e-07  -6.38658730 1.947156e-10
buildvalue   2.063069e-11 4.109884e-12   5.01977503 5.461910e-07
agrivalue   -5.349914e-10 1.426747e-10  -3.74972764 1.802251e-04
area         9.641750e-07 1.048110e-05   0.09199177 9.267105e-01
eal_score    9.937798e-01 1.789294e-03 555.40339864 0.000000e+00
sovi_score   9.583938e-02 1.896677e-03  50.53016773 0.000000e+00
resl_score  -4.162521e-02 1.969991e-03 -21.12964958 9.283199e-93
```

Population (Population Estimate): For every one-unit increase in population, the estimated "risk_score" decreases by approximately -4.31 units. This suggests that higher population areas tend to have lower risk scores, all else being equal.

Building Value (Buildvalue Estimate): For every one-unit increase in building value, the estimated "risk_score" increases by approximately 2.06 units. This implies that areas with higher building values tend to have higher risk scores, assuming other factors remain constant.

Agriculture Value (Agrivalue Estimate): For every one-unit increase in agriculture value, the estimated "risk_score" decreases by approximately -5.35 units. This suggests that areas with higher agricultural values tend to have lower risk scores, holding other variables constant.

Area (Area Estimate): The "area" variable does not appear to have a significant effect on the "risk_score" because the coefficient estimate is close to zero (9.64e-07). In other words, changes in the area of an area do not appear to be strongly associated with changes in risk scores.

Expected Annual Loss Score (Eal_score Estimate): For every one-unit increase in the expected annual loss score (eal_score), the estimated "risk_score" increases by approximately 0.994 units. This suggests that higher EAL scores are associated with higher risk scores.

Social Vulnerability Score (Sovi_score Estimate): For every one-unit increase in the social vulnerability score (sovi_score), the estimated "risk_score" increases by approximately 0.096 units. This implies that higher social vulnerability scores are associated with higher risk scores.

Community Resilience Score (Resl_score Estimate): For every one-unit increase in the community resilience score (resl_score), the estimated "risk_score" decreases by approximately -0.042 units. This suggests that higher community resilience scores are associated with lower risk scores.

In summary, the multiple linear regression model provides estimates of how changes in each predictor variable are associated with changes in the "risk_score." Some variables, such as population, building value, agriculture value, social vulnerability score, and community reliance score, appear to have statistically significant associations with the "risk_score," while others, like area, do not appear to be significant in this model.

```
> confint(multiple_regression_model)
                    2.5 %        97.5 %
(Intercept) -1.823799e+00 -1.208742e+00
population  -5.629125e-06 -2.984645e-06
buildvalue   1.257236e-11  2.868903e-11
agrivalue   -8.147367e-10 -2.552460e-10
area        -1.958634e-05  2.151469e-05
eal_score    9.902715e-01  9.972881e-01
sovi_score   9.212053e-02  9.955824e-02
resl_score  -4.548781e-02 -3.776261e-02
```

area: The confidence interval for the area coefficient includes zero. This suggests that the area variable may not have a statistically significant effect on the risk_score. In other words, changes in the area may not be associated with changes in the risk_score in a statistically meaningful way, at least based on this model.

All other variables have confidence intervals for these coefficients that do not include zero, indicating that these variables have statistically significant effects on the risk_score.

VALIDATION ANALYSIS

The cross-validated results for the multiple linear regression model are as follows:

```
Linear Regression

3143 samples
   7 predictor

No pre-processing
Resampling: Cross-Validated (5 fold)
Summary of sample sizes: 2514, 2514, 2515, 2515, 2514
Resampling results:

  RMSE      Rsquared   MAE
  2.255888  0.9939221  1.684458

Tuning parameter 'intercept' was held constant at a value of TRUE
```

Root Mean Squared Error (RMSE): Approximately 2.255888
R-squared (Rsquared): Approximately 0.9939221
Mean Absolute Error (MAE): Approximately 1.684458
These performance metrics provide insights into how well the regression model is performing:

RMSE: This metric measures the average prediction error of the linear regression model. An RMSE of approximately 2.255888 means that, on average, the predicted risk_score values from the model are off by around 2.255888 units from the actual risk_score values in the dataset.

R-squared (Rsquared): R-squared measures the goodness of fit of the linear regression model. An R-squared value of approximately 0.9939221 indicates that the model can explain approximately 99.39% of the variance in the risk_score variable. In other words, the model does an excellent job of capturing and explaining the variability in risk_score based on the predictor variables.

MAE: MAE represents the average absolute difference between the model's predictions and the actual risk_score values. An MAE of approximately 1.684458 means that, on average, the model's predictions are off by about 1.684458 units from the actual values.

In summary, the RMSE and MAE values are relatively low, indicating that the regression model is making accurate predictions. The R-squared value is very high, suggesting that the model explains a significant portion of the variance in the risk_score, indicating strong predictive power. These results suggest that the multiple linear regression model is performing very well in predicting the risk_score based on the chosen predictor variables. It has a high degree of explanatory power (as indicated by the high R-squared value) and makes relatively accurate predictions (as indicated by the low RMSE and MAE values).

VULNERABILITY / RESILIENCE RATIO

Calculating the vulnerability-to-resilience ratio can provide valuable insights into disaster risk assessment and preparedness. This ratio helps assess the balance between a community's vulnerability (its susceptibility to negative impacts from disasters) and its resilience (its ability to bounce back and recover from disasters).

```
> cat("Ratio of Vulnerability to Resilience:", vulnerability_to_resilience_ratio, "\n")
Ratio of Vulnerability to Resilience: -2.302436
```

I used the coefficients from the multiple regression model to calculate the ratio of vulnerability to resilience because these coefficients represent the estimated effect of each predictor variable on the outcome variable (risk_score) while holding other variables constant.

In this context, the coefficients tell us how much the risk score is expected to change for a one-unit change in the predictor variable, assuming all other variables remain constant. By dividing the coefficient of sovi_score by the coefficient of resl_score, we are essentially calculating the change in risk score associated with a one-unit change in social vulnerability relative to a one-unit change in community resilience.

So, when I calculated the ratio of vulnerability to resilience using the coefficients, I was quantifying the relative impact of changes in social vulnerability (sovi_score) compared to changes in community resilience (resl_score) on the risk score. This ratio provides insights into the relationship between vulnerability and resilience in the context of the regression model.

The calculated ratio of vulnerability to resilience is approximately -2.302436. This ratio suggests that for every one-unit increase in the social vulnerability score (sovi_score), there is an expected decrease of approximately 2.302 units in the resilience score (resl_score) based on the multiple regression model.

A negative ratio like this implies that as vulnerability increases, resilience tends to decrease, which is an important insight for assessing the impact of social vulnerability on community resilience in the context of natural disaster risk.