final project result analysis

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R Markdown

This is an R Markdown document. Markdown is a simple formatting syntax for authoring HTML, PDF, and MS Word documents. For more details on using R Markdown see http://rmarkdown.rstudio.com (http://rmarkdown.rstudio.com).

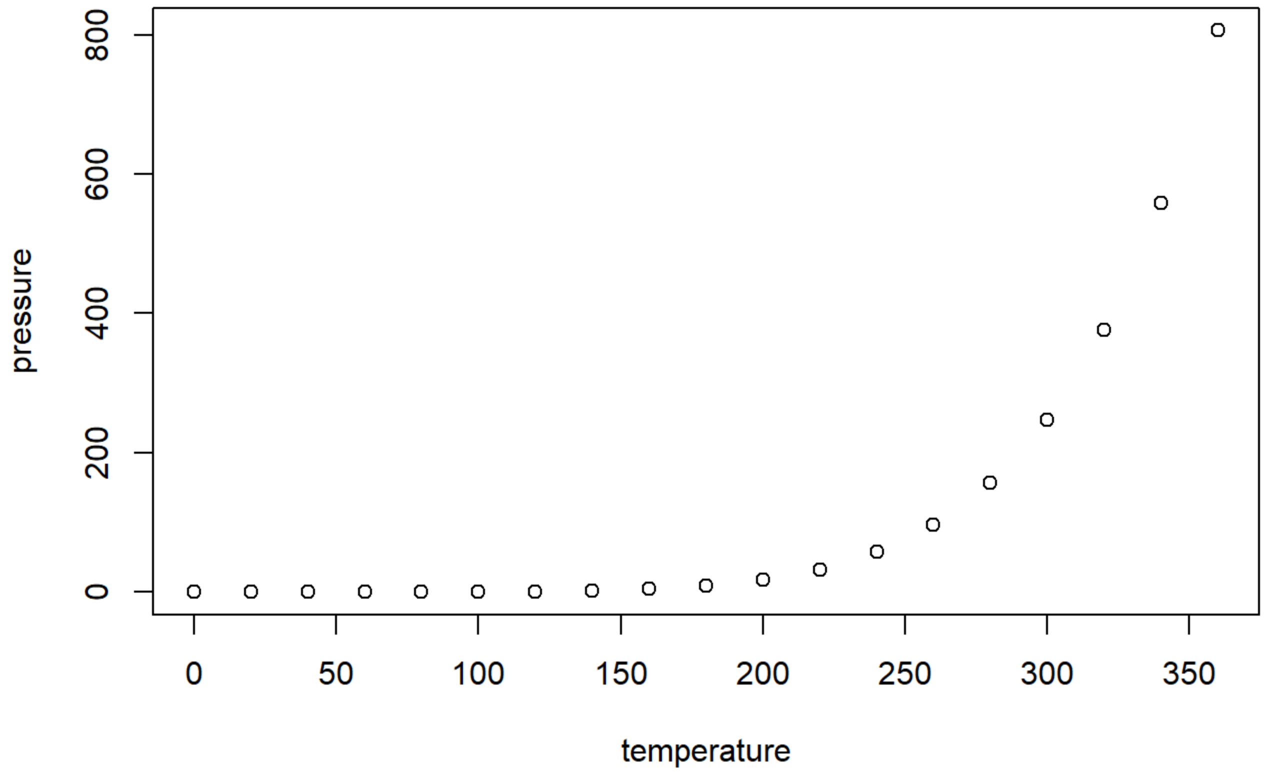
When you click the **Knit** button a document will be generated that includes both content as well as the output of any embedded R code chunks within the document. You can embed an R code chunk like this:

```
summary(cars)
```

```
##      speed           dist       
##  Min.   : 4.0   Min.   :  2.00  
##  1st Qu.:12.0   1st Qu.: 26.00  
##  Median :15.0   Median : 36.00  
##  Mean   :15.4   Mean   : 42.98  
##  3rd Qu.:19.0   3rd Qu.: 56.00  
##  Max.   :25.0   Max.   :120.00
```

Including Plots

You can also embed plots, for example:



Note that the `echo = FALSE` parameter was added to the code chunk to prevent printing of the R code that generated the plot.

```
# Set the working directory
setwd("C:/Users/mt1468/OneDrive - USNH/Desktop/rice final project")

# Load the data
rice_data <- read.csv("Rice.csv")

# View the first few rows of the dataset
head(rice_data)
```

```
##       landraces  PH_cm  ET.P PL_cm   FG.P  UG.P X1000SW_gm GY_t.ha
## 1      Laldigha 124.10 36.86 21.23 116.50  9.96      19.48    5.75
## 2      Laldigha 125.67 34.30 21.90 100.50 10.96      20.20    5.77
## 3      Laldigha 150.13 10.67 22.80 110.00 20.34      36.96    3.19
## 4 Lokhsmi digha 131.40 21.63 25.83 114.70 16.83      20.14    4.65
## 5 Lokhsmi digha 130.07 23.36 22.60 111.56 14.78      20.70    4.75
## 6 Lokhsmi digha 156.50 11.67 22.80 125.00 21.67      33.21    2.93
```

```
# Basic summary statistics
summary(rice_data)
```

```
##   landraces             PH_cm            ET.P           PL_cm      
##  Length:33          Min.   :112.3   Min.   : 9.00   Min.   :20.66  
##  Class :character   1st Qu.:130.1   1st Qu.:11.67   1st Qu.:22.80  
##  Mode  :character   Median :137.0   Median :16.30   Median :24.13  
##                     Mean   :138.0   Mean   :17.43   Mean   :24.12  
##                     3rd Qu.:150.1   3rd Qu.:21.66   3rd Qu.:25.30  
##                     Max.   :160.1   Max.   :36.86   Max.   :26.63  
##       FG.P            UG.P         X1000SW_gm       GY_t.ha     
##  Min.   : 97.3   Min.   : 9.48   Min.   :18.49   Min.   :1.460  
##  1st Qu.:107.8   1st Qu.:13.50   1st Qu.:20.49   1st Qu.:2.910  
##  Median :113.5   Median :16.83   Median :23.70   Median :3.220  
##  Mean   :117.0   Mean   :18.30   Mean   :26.72   Mean   :3.659  
##  3rd Qu.:119.0   3rd Qu.:21.33   3rd Qu.:32.90   3rd Qu.:4.690  
##  Max.   :170.7   Max.   :36.00   Max.   :44.74   Max.   :5.770
```

```
# Standard deviation for each numeric trait
apply(rice_data[, -c(1,2)], 2, sd) # Assuming columns 1 and 2 are Variety and Replication
```

```
##       ET.P      PL_cm       FG.P       UG.P X1000SW_gm    GY_t.ha 
##   7.013549   1.594246  17.555456   6.550851   7.133205   1.250112
```

```
# ANOVA for Plant Height
plant_height_aov <- aov(PH_cm ~ landraces, data = rice_data)
summary(plant_height_aov)
```

```
##             Df Sum Sq Mean Sq F value Pr(>F)
## landraces   10   1899   189.9   1.325  0.278
## Residuals   22   3154   143.4
```

```
# Post-hoc analysis using Tukey's HSD
TukeyHSD(plant_height_aov)
```

```
##   Tukey multiple comparisons of means
##     95% family-wise confidence level
##
## Fit: aov(formula = PH_cm ~ landraces, data = rice_data)
##
## $landraces
##                                   diff       lwr       upr     p adj
## Bidigha-Bandorjhata        -10.0666667 -45.01425 24.880915 0.9918632
## Debmoni-Bandorjhata          3.5400000 -31.40758 38.487582 0.9999992
## Jabra-Bandorjhata          -10.3666667 -45.31425 24.580915 0.9898869
## Kachkalam-Bandorjhata       -6.3100000 -41.25758 28.637582 0.9998287
## Laldigha-Bandorjhata       -15.4666667 -50.41425 19.480915 0.8736964
## Lokhsmi digha-Bandorjhata   -9.4433333 -44.39092 25.504248 0.9949937
## Modhudigha-Bandorjhata     -22.9900000 -57.93758 11.957582 0.4365044
## Najirshail-Bandorjhata     -12.8200000 -47.76758 22.127582 0.9568401
## Rangadigha-Bandorjhata     -13.1000000 -48.04758 21.847582 0.9506344
## Sishumaty-Bandorjhata      -21.2033333 -56.15092 13.744248 0.5461538
## Debmoni-Bidigha             13.6066667 -21.34092 48.554248 0.9379029
## Jabra-Bidigha               -0.3000000 -35.24758 34.647582 1.0000000
## Kachkalam-Bidigha            3.7566667 -31.19092 38.704248 0.9999986
## Laldigha-Bidigha            -5.4000000 -40.34758 29.547582 0.9999581
## Lokhsmi digha-Bidigha        0.6233333 -34.32425 35.570915 1.0000000
## Modhudigha-Bidigha         -12.9233333 -47.87092 22.024248 0.9546170
## Najirshail-Bidigha          -2.7533333 -37.70092 32.194248 0.9999999
## Rangadigha-Bidigha          -3.0333333 -37.98092 31.914248 0.9999998
## Sishumaty-Bidigha          -11.1366667 -46.08425 23.810915 0.9830855
## Jabra-Debmoni              -13.9066667 -48.85425 21.040915 0.9294222
## Kachkalam-Debmoni           -9.8500000 -44.79758 25.097582 0.9930903
## Laldigha-Debmoni           -19.0066667 -53.95425 15.940915 0.6848677
## Lokhsmi digha-Debmoni      -12.9833333 -47.93092 21.964248 0.9532903
## Modhudigha-Debmoni         -26.5300000 -61.47758  8.417582 0.2552170
## Najirshail-Debmoni         -16.3600000 -51.30758 18.587582 0.8332391
## Rangadigha-Debmoni         -16.6400000 -51.58758 18.307582 0.8193832
## Sishumaty-Debmoni          -24.7433333 -59.69092 10.204248 0.3394134
## Kachkalam-Jabra              4.0566667 -30.89092 39.004248 0.9999971
## Laldigha-Jabra              -5.1000000 -40.04758 29.847582 0.9999752
## Lokhsmi digha-Jabra          0.9233333 -34.02425 35.870915 1.0000000
## Modhudigha-Jabra           -12.6233333 -47.57092 22.324248 0.9608587
## Najirshail-Jabra            -2.4533333 -37.40092 32.494248 1.0000000
## Rangadigha-Jabra            -2.7333333 -37.68092 32.214248 0.9999999
## Sishumaty-Jabra            -10.8366667 -45.78425 24.110915 0.9860577
## Laldigha-Kachkalam          -9.1566667 -44.10425 25.790915 0.9960618
## Lokhsmi digha-Kachkalam     -3.1333333 -38.08092 31.814248 0.9999998
## Modhudigha-Kachkalam       -16.6800000 -51.62758 18.267582 0.8173609
## Najirshail-Kachkalam        -6.5100000 -41.45758 28.437582 0.9997741
## Rangadigha-Kachkalam        -6.7900000 -41.73758 28.157582 0.9996730
## Sishumaty-Kachkalam        -14.8933333 -49.84092 20.054248 0.8964435
## Lokhsmi digha-Laldigha       6.0233333 -28.92425 40.970915 0.9998869
## Modhudigha-Laldigha         -7.5233333 -42.47092 27.424248 0.9992096
## Najirshail-Laldigha          2.6466667 -32.30092 37.594248 1.0000000
## Rangadigha-Laldigha          2.3666667 -32.58092 37.314248 1.0000000
## Sishumaty-Laldigha          -5.7366667 -40.68425 29.210915 0.9999272
```

```
## Modhudigha-Lokhsmi digha  -13.5466667 -48.49425 21.400915 0.9395140
## Najirshail-Lokhsmi digha   -3.3766667 -38.32425 31.570915 0.9999995
## Rangadigha-Lokhsmi digha   -3.6566667 -38.60425 31.290915 0.9999989
## Sishumaty-Lokhsmi digha   -11.7600000 -46.70758 23.187582 0.9753997
## Najirshail-Modhudigha      10.1700000 -24.77758 45.117582 0.9912204
## Rangadigha-Modhudigha       9.8900000 -25.05758 44.837582 0.9928756
## Sishumaty-Modhudigha        1.7866667 -33.16092 36.734248 1.0000000
## Rangadigha-Najirshail      -0.2800000 -35.22758 34.667582 1.0000000
## Sishumaty-Najirshail       -8.3833333 -43.33092 26.564248 0.9980557
## Sishumaty-Rangadigha       -8.1033333 -43.05092 26.844248 0.9985286
```

```
# ANOVA for Effective_.tiller_per_plant
Effective_.tiller_per_plant_aov <- aov(ET.P ~ landraces, data = rice_data)
summary(Effective_.tiller_per_plant_aov)
```

```
##             Df Sum Sq Mean Sq F value Pr(>F)
## landraces   10    612   61.20     1.4  0.244
## Residuals   22    962   43.73
```

```
# Post-hoc analysis using Tukey's HSD
TukeyHSD(Effective_.tiller_per_plant_aov)
```

```
##   Tukey multiple comparisons of means
##     95% family-wise confidence level
##
## Fit: aov(formula = ET.P ~ landraces, data = rice_data)
##
## $landraces
##                                  diff        lwr       upr     p adj
## Bidigha-Bandorjhata         4.7900000 -14.511527 24.091527 0.9974409
## Debmoni-Bandorjhata         1.8800000 -17.421527 21.181527 0.9999995
## Jabra-Bandorjhata           7.5566667 -11.744861 26.858194 0.9358347
## Kachkalam-Bandorjhata       4.8966667 -14.404861 24.198194 0.9969480
## Laldigha-Bandorjhata       14.5900000  -4.711527 33.891527 0.2600734
## Lokhsmi digha-Bandorjhata   6.2000000 -13.101527 25.501527 0.9821160
## Modhudigha-Bandorjhata     -1.9666667 -21.268194 17.334861 0.9999992
## Najirshail-Bandorjhata      8.1200000 -11.181527 27.421527 0.9034458
## Rangadigha-Bandorjhata      4.5133333 -14.788194 23.814861 0.9984227
## Sishumaty-Bandorjhata       1.6100000 -17.691527 20.911527 0.9999999
## Debmoni-Bidigha            -2.9100000 -22.211527 16.391527 0.9999666
## Jabra-Bidigha               2.7666667 -16.534861 22.068194 0.9999790
## Kachkalam-Bidigha           0.1066667 -19.194861 19.408194 1.0000000
## Laldigha-Bidigha            9.8000000  -9.501527 29.101527 0.7600002
## Lokhsmi digha-Bidigha       1.4100000 -17.891527 20.711527 1.0000000
## Modhudigha-Bidigha         -6.7566667 -26.058194 12.544861 0.9680254
## Najirshail-Bidigha          3.3300000 -15.971527 22.631527 0.9998859
## Rangadigha-Bidigha         -0.2766667 -19.578194 19.024861 1.0000000
## Sishumaty-Bidigha          -3.1800000 -22.481527 16.121527 0.9999247
## Jabra-Debmoni               5.6766667 -13.624861 24.978194 0.9905048
## Kachkalam-Debmoni           3.0166667 -16.284861 22.318194 0.9999535
## Laldigha-Debmoni           12.7100000  -6.591527 32.011527 0.4351584
## Lokhsmi digha-Debmoni       4.3200000 -14.981527 23.621527 0.9989032
## Modhudigha-Debmoni         -3.8466667 -23.148194 15.454861 0.9995921
## Najirshail-Debmoni          6.2400000 -13.061527 25.541527 0.9812976
## Rangadigha-Debmoni          2.6333333 -16.668194 21.934861 0.9999868
## Sishumaty-Debmoni          -0.2700000 -19.571527 19.031527 1.0000000
## Kachkalam-Jabra            -2.6600000 -21.961527 16.641527 0.9999855
## Laldigha-Jabra              7.0333333 -12.268194 26.334861 0.9586182
## Lokhsmi digha-Jabra        -1.3566667 -20.658194 17.944861 1.0000000
## Modhudigha-Jabra           -9.5233333 -28.824861  9.778194 0.7878208
## Najirshail-Jabra            0.5633333 -18.738194 19.864861 1.0000000
## Rangadigha-Jabra           -3.0433333 -22.344861 16.258194 0.9999495
## Sishumaty-Jabra            -5.9466667 -25.248194 13.354861 0.9866856
## Laldigha-Kachkalam          9.6933333  -9.608194 28.994861 0.7708846
## Lokhsmi digha-Kachkalam     1.3033333 -17.998194 20.604861 1.0000000
## Modhudigha-Kachkalam       -6.8633333 -26.164861 12.438194 0.9646023
## Najirshail-Kachkalam        3.2233333 -16.078194 22.524861 0.9999149
## Rangadigha-Kachkalam       -0.3833333 -19.684861 18.918194 1.0000000
## Sishumaty-Kachkalam        -3.2866667 -22.588194 16.014861 0.9998986
## Lokhsmi digha-Laldigha     -8.3900000 -27.691527 10.911527 0.8849564
## Modhudigha-Laldigha       -16.5566667 -35.858194  2.744861 0.1374406
## Najirshail-Laldigha        -6.4700000 -25.771527 12.831527 0.9760330
## Rangadigha-Laldigha       -10.0766667 -29.378194  9.224861 0.7309396
## Sishumaty-Laldigha        -12.9800000 -32.281527  6.321527 0.4068570
```

```
## Modhudigha-Lokhsmi digha   -8.1666667 -27.468194 11.134861 0.9003869
## Najirshail-Lokhsmi digha    1.9200000 -17.381527 21.221527 0.9999993
## Rangadigha-Lokhsmi digha   -1.6866667 -20.988194 17.614861 0.9999998
## Sishumaty-Lokhsmi digha    -4.5900000 -23.891527 14.711527 0.9981890
## Najirshail-Modhudigha      10.0866667  -9.214861 29.388194 0.7298687
## Rangadigha-Modhudigha       6.4800000 -12.821527 25.781527 0.9757816
## Sishumaty-Modhudigha        3.5766667 -15.724861 22.878194 0.9997843
## Rangadigha-Najirshail      -3.6066667 -22.908194 15.694861 0.9997678
## Sishumaty-Najirshail       -6.5100000 -25.811527 12.791527 0.9750156
## Sishumaty-Rangadigha       -2.9033333 -22.204861 16.398194 0.9999673
```

```
# ANOVA for Panicle_length._cm
Panicle_length._cm_aov <- aov(PL_cm ~ landraces, data = rice_data)
summary(Panicle_length._cm_aov)
```

```
##             Df Sum Sq Mean Sq F value Pr(>F)
## landraces   10  26.89   2.689   1.086  0.413
## Residuals   22  54.44   2.475
```

```
# Post-hoc analysis using Tukey's HSD
TukeyHSD(Panicle_length._cm_aov)
```

```
##   Tukey multiple comparisons of means
##     95% family-wise confidence level
##
## Fit: aov(formula = PL_cm ~ landraces, data = rice_data)
##
## $landraces
##                                   diff       lwr      upr     p adj
## Bidigha-Bandorjhata       -1.59000000 -6.181686 3.001686 0.9702251
## Debmoni-Bandorjhata       -1.32333333 -5.915019 3.268352 0.9918312
## Jabra-Bandorjhata         -1.64666667 -6.238352 2.945019 0.9626153
## Kachkalam-Bandorjhata     -0.33333333 -4.925019 4.258352 1.0000000
## Laldigha-Bandorjhata      -3.29666667 -7.888352 1.295019 0.3217848
## Lokhsmi digha-Bandorjhata -1.53000000 -6.121686 3.061686 0.9769835
## Modhudigha-Bandorjhata    -0.85333333 -5.445019 3.738352 0.9997787
## Najirshail-Bandorjhata    -0.06333333 -4.655019 4.528352 1.0000000
## Rangadigha-Bandorjhata    -1.48666667 -6.078352 3.105019 0.9811028
## Sishumaty-Bandorjhata     -0.54333333 -5.135019 4.048352 0.9999965
## Debmoni-Bidigha            0.26666667 -4.325019 4.858352 1.0000000
## Jabra-Bidigha             -0.05666667 -4.648352 4.535019 1.0000000
## Kachkalam-Bidigha          1.25666667 -3.335019 5.848352 0.9944769
## Laldigha-Bidigha          -1.70666667 -6.298352 2.885019 0.9531516
## Lokhsmi digha-Bidigha      0.06000000 -4.531686 4.651686 1.0000000
## Modhudigha-Bidigha         0.73666667 -3.855019 5.328352 0.9999409
## Najirshail-Bidigha         1.52666667 -3.065019 6.118352 0.9773222
## Rangadigha-Bidigha         0.10333333 -4.488352 4.695019 1.0000000
## Sishumaty-Bidigha          1.04666667 -3.545019 5.638352 0.9987225
## Jabra-Debmoni             -0.32333333 -4.915019 4.268352 1.0000000
## Kachkalam-Debmoni          0.99000000 -3.601686 5.581686 0.9991992
## Laldigha-Debmoni          -1.97333333 -6.565019 2.618352 0.8916748
## Lokhsmi digha-Debmoni     -0.20666667 -4.798352 4.385019 1.0000000
## Modhudigha-Debmoni         0.47000000 -4.121686 5.061686 0.9999991
## Najirshail-Debmoni         1.26000000 -3.331686 5.851686 0.9943636
## Rangadigha-Debmoni        -0.16333333 -4.755019 4.428352 1.0000000
## Sishumaty-Debmoni          0.78000000 -3.811686 5.371686 0.9999008
## Kachkalam-Jabra            1.31333333 -3.278352 5.905019 0.9922818
## Laldigha-Jabra            -1.65000000 -6.241686 2.941686 0.9621284
## Lokhsmi digha-Jabra        0.11666667 -4.475019 4.708352 1.0000000
## Modhudigha-Jabra           0.79333333 -3.798352 5.385019 0.9998844
## Najirshail-Jabra           1.58333333 -3.008352 6.175019 0.9710399
## Rangadigha-Jabra           0.16000000 -4.431686 4.751686 1.0000000
## Sishumaty-Jabra            1.10333333 -3.488352 5.695019 0.9980287
## Laldigha-Kachkalam        -2.96333333 -7.555019 1.628352 0.4624814
## Lokhsmi digha-Kachkalam   -1.19666667 -5.788352 3.395019 0.9962235
## Modhudigha-Kachkalam      -0.52000000 -5.111686 4.071686 0.9999977
## Najirshail-Kachkalam       0.27000000 -4.321686 4.861686 1.0000000
## Rangadigha-Kachkalam      -1.15333333 -5.745019 3.438352 0.9971811
## Sishumaty-Kachkalam       -0.21000000 -4.801686 4.381686 1.0000000
## Lokhsmi digha-Laldigha     1.76666667 -2.825019 6.358352 0.9421488
## Modhudigha-Laldigha        2.44333333 -2.148352 7.035019 0.7099300
## Najirshail-Laldigha        3.23333333 -1.358352 7.825019 0.3463722
## Rangadigha-Laldigha        1.81000000 -2.781686 6.401686 0.9332031
## Sishumaty-Laldigha         2.75333333 -1.838352 7.345019 0.5618292
```

```
## Modhudigha-Lokhsmi digha   0.67666667 -3.915019 5.268352 0.9999729
## Najirshail-Lokhsmi digha   1.46666667 -3.125019 6.058352 0.9828046
## Rangadigha-Lokhsmi digha   0.04333333 -4.548352 4.635019 1.0000000
## Sishumaty-Lokhsmi digha    0.98666667 -3.605019 5.578352 0.9992217
## Najirshail-Modhudigha      0.79000000 -3.801686 5.381686 0.9998887
## Rangadigha-Modhudigha     -0.63333333 -5.225019 3.958352 0.9999853
## Sishumaty-Modhudigha       0.31000000 -4.281686 4.901686 1.0000000
## Rangadigha-Najirshail     -1.42333333 -6.015019 3.168352 0.9860907
## Sishumaty-Najirshail      -0.48000000 -5.071686 4.111686 0.9999989
## Sishumaty-Rangadigha       0.94333333 -3.648352 5.535019 0.9994696
```

```
# ANOVA for Filled_grain_per_panicle
Filled_grain_per_panicle_aov <- aov(FG.P ~ landraces, data = rice_data)
summary(Filled_grain_per_panicle_aov)
```

```
##             Df Sum Sq Mean Sq F value Pr(>F)
## landraces   10   1876   187.6   0.517   0.86
## Residuals   22   7986   363.0
```

```
# Post-hoc analysis using Tukey's HSD
TukeyHSD(Filled_grain_per_panicle_aov)
```

```
##   Tukey multiple comparisons of means
##     95% family-wise confidence level
##
## Fit: aov(formula = FG.P ~ landraces, data = rice_data)
##
## $landraces
##                                  diff       lwr      upr     p adj
## Bidigha-Bandorjhata         2.3766667 -53.23353 57.98686 1.0000000
## Debmoni-Bandorjhata        19.6266667 -35.98353 75.23686 0.9662762
## Jabra-Bandorjhata           8.0933333 -47.51686 63.70353 0.9999759
## Kachkalam-Bandorjhata       7.3300000 -48.28019 62.94019 0.9999904
## Laldigha-Bandorjhata        1.2400000 -54.37019 56.85019 1.0000000
## Lokhsmi digha-Bandorjhata   9.3266667 -46.28353 64.93686 0.9999116
## Modhudigha-Bandorjhata     22.0166667 -33.59353 77.62686 0.9314806
## Najirshail-Bandorjhata      8.4200000 -47.19019 64.03019 0.9999652
## Rangadigha-Bandorjhata      2.9866667 -52.62353 58.59686 1.0000000
## Sishumaty-Bandorjhata      19.8766667 -35.73353 75.48686 0.9634043
## Debmoni-Bidigha            17.2500000 -38.36019 72.86019 0.9860219
## Jabra-Bidigha               5.7166667 -49.89353 61.32686 0.9999991
## Kachkalam-Bidigha           4.9533333 -50.65686 60.56353 0.9999998
## Laldigha-Bidigha           -1.1366667 -56.74686 54.47353 1.0000000
## Lokhsmi digha-Bidigha       6.9500000 -48.66019 62.56019 0.9999942
## Modhudigha-Bidigha         19.6400000 -35.97019 75.25019 0.9661273
## Najirshail-Bidigha          6.0433333 -49.56686 61.65353 0.9999985
## Rangadigha-Bidigha          0.6100000 -55.00019 56.22019 1.0000000
## Sishumaty-Bidigha          17.5000000 -38.11019 73.11019 0.9845172
## Jabra-Debmoni             -11.5333333 -67.14353 44.07686 0.9994248
## Kachkalam-Debmoni         -12.2966667 -67.90686 43.31353 0.9990090
## Laldigha-Debmoni          -18.3866667 -73.99686 37.22353 0.9781686
## Lokhsmi digha-Debmoni     -10.3000000 -65.91019 45.31019 0.9997852
## Modhudigha-Debmoni          2.3900000 -53.22019 58.00019 1.0000000
## Najirshail-Debmoni        -11.2066667 -66.81686 44.40353 0.9995508
## Rangadigha-Debmoni        -16.6400000 -72.25019 38.97019 0.9892220
## Sishumaty-Debmoni           0.2500000 -55.36019 55.86019 1.0000000
## Kachkalam-Jabra            -0.7633333 -56.37353 54.84686 1.0000000
## Laldigha-Jabra             -6.8533333 -62.46353 48.75686 0.9999949
## Lokhsmi digha-Jabra         1.2333333 -54.37686 56.84353 1.0000000
## Modhudigha-Jabra           13.9233333 -41.68686 69.53353 0.9972526
## Najirshail-Jabra            0.3266667 -55.28353 55.93686 1.0000000
## Rangadigha-Jabra           -5.1066667 -60.71686 50.50353 0.9999997
## Sishumaty-Jabra            11.7833333 -43.82686 67.39353 0.9993091
## Laldigha-Kachkalam         -6.0900000 -61.70019 49.52019 0.9999983
## Lokhsmi digha-Kachkalam     1.9966667 -53.61353 57.60686 1.0000000
## Modhudigha-Kachkalam       14.6866667 -40.92353 70.29686 0.9958092
## Najirshail-Kachkalam        1.0900000 -54.52019 56.70019 1.0000000
## Rangadigha-Kachkalam       -4.3433333 -59.95353 51.26686 0.9999999
## Sishumaty-Kachkalam        12.5466667 -43.06353 68.15686 0.9988272
## Lokhsmi digha-Laldigha      8.0866667 -47.52353 63.69686 0.9999760
## Modhudigha-Laldigha        20.7766667 -34.83353 76.38686 0.9516284
## Najirshail-Laldigha         7.1800000 -48.43019 62.79019 0.9999921
## Rangadigha-Laldigha         1.7466667 -53.86353 57.35686 1.0000000
## Sishumaty-Laldigha         18.6366667 -36.97353 74.24686 0.9760698
```

```
## Modhudigha-Lokhsmi digha   12.6900000 -42.92019 68.30019 0.9987109
## Najirshail-Lokhsmi digha   -0.9066667 -56.51686 54.70353 1.0000000
## Rangadigha-Lokhsmi digha   -6.3400000 -61.95019 49.27019 0.9999976
## Sishumaty-Lokhsmi digha    10.5500000 -45.06019 66.16019 0.9997347
## Najirshail-Modhudigha     -13.5966667 -69.20686 42.01353 0.9977303
## Rangadigha-Modhudigha     -19.0300000 -74.64019 36.58019 0.9724704
## Sishumaty-Modhudigha       -2.1400000 -57.75019 53.47019 1.0000000
## Rangadigha-Najirshail      -5.4333333 -61.04353 50.17686 0.9999994
## Sishumaty-Najirshail       11.4566667 -44.15353 67.06686 0.9994568
## Sishumaty-Rangadigha       16.8900000 -38.72019 72.50019 0.9879880
```

```
# ANOVA for Unfilled_grain_per_panicle
Unfilled_grain_per_panicle_aov <- aov(UG.P ~ landraces, data = rice_data)
summary(Unfilled_grain_per_panicle_aov)
```

```
##             Df Sum Sq Mean Sq F value Pr(>F)
## landraces   10  275.7   27.57   0.553  0.834
## Residuals   22 1097.5   49.89
```

```
# Post-hoc analysis using Tukey's HSD
TukeyHSD(Unfilled_grain_per_panicle_aov)
```

```
##   Tukey multiple comparisons of means
##     95% family-wise confidence level
##
## Fit: aov(formula = UG.P ~ landraces, data = rice_data)
##
## $landraces
##                                   diff       lwr      upr     p adj
## Bidigha-Bandorjhata         3.06666667 -17.54929 23.68262 0.9999705
## Debmoni-Bandorjhata         1.15333333 -19.46262 21.76929 1.0000000
## Jabra-Bandorjhata           3.71000000 -16.90596 24.32596 0.9998336
## Kachkalam-Bandorjhata       3.48666667 -17.12929 24.10262 0.9999046
## Laldigha-Bandorjhata       -2.72333333 -23.33929 17.89262 0.9999902
## Lokhsmi digha-Bandorjhata   1.28333333 -19.33262 21.89929 1.0000000
## Modhudigha-Bandorjhata      7.31000000 -13.30596 27.92596 0.9652437
## Najirshail-Bandorjhata      1.34000000 -19.27596 21.95596 1.0000000
## Rangadigha-Bandorjhata     -2.93666667 -23.55262 17.67929 0.9999802
## Sishumaty-Bandorjhata       4.33333333 -16.28262 24.94929 0.9993549
## Debmoni-Bidigha            -1.91333333 -22.52929 18.70262 0.9999997
## Jabra-Bidigha               0.64333333 -19.97262 21.25929 1.0000000
## Kachkalam-Bidigha           0.42000000 -20.19596 21.03596 1.0000000
## Laldigha-Bidigha           -5.79000000 -26.40596 14.82596 0.9932736
## Lokhsmi digha-Bidigha      -1.78333333 -22.39929 18.83262 0.9999998
## Modhudigha-Bidigha          4.24333333 -16.37262 24.85929 0.9994610
## Najirshail-Bidigha         -1.72666667 -22.34262 18.88929 0.9999999
## Rangadigha-Bidigha         -6.00333333 -26.61929 14.61262 0.9911775
## Sishumaty-Bidigha           1.26666667 -19.34929 21.88262 1.0000000
## Jabra-Debmoni               2.55666667 -18.05929 23.17262 0.9999946
## Kachkalam-Debmoni           2.33333333 -18.28262 22.94929 0.9999977
## Laldigha-Debmoni           -3.87666667 -24.49262 16.73929 0.9997545
## Lokhsmi digha-Debmoni       0.13000000 -20.48596 20.74596 1.0000000
## Modhudigha-Debmoni          6.15666667 -14.45929 26.77262 0.9893763
## Najirshail-Debmoni          0.18666667 -20.42929 20.80262 1.0000000
## Rangadigha-Debmoni         -4.09000000 -24.70596 16.52596 0.9996078
## Sishumaty-Debmoni           3.18000000 -17.43596 23.79596 0.9999587
## Kachkalam-Jabra            -0.22333333 -20.83929 20.39262 1.0000000
## Laldigha-Jabra             -6.43333333 -27.04929 14.18262 0.9854133
## Lokhsmi digha-Jabra        -2.42666667 -23.04262 18.18929 0.9999967
## Modhudigha-Jabra            3.60000000 -17.01596 24.21596 0.9998729
## Najirshail-Jabra           -2.37000000 -22.98596 18.24596 0.9999974
## Rangadigha-Jabra           -6.64666667 -27.26262 13.96929 0.9816511
## Sishumaty-Jabra             0.62333333 -19.99262 21.23929 1.0000000
## Laldigha-Kachkalam         -6.21000000 -26.82596 14.40596 0.9886866
## Lokhsmi digha-Kachkalam    -2.20333333 -22.81929 18.41262 0.9999987
## Modhudigha-Kachkalam        3.82333333 -16.79262 24.43929 0.9997828
## Najirshail-Kachkalam       -2.14666667 -22.76262 18.46929 0.9999990
## Rangadigha-Kachkalam       -6.42333333 -27.03929 14.19262 0.9855738
## Sishumaty-Kachkalam         0.84666667 -19.76929 21.46262 1.0000000
## Lokhsmi digha-Laldigha      4.00666667 -16.60929 24.62262 0.9996722
## Modhudigha-Laldigha        10.03333333 -10.58262 30.64929 0.8003783
## Najirshail-Laldigha         4.06333333 -16.55262 24.67929 0.9996295
## Rangadigha-Laldigha        -0.21333333 -20.82929 20.40262 1.0000000
## Sishumaty-Laldigha          7.05666667 -13.55929 27.67262 0.9724233
```

```
## Modhudigha-Lokhsmi digha    6.02666667 -14.58929 26.64262 0.9909201
## Najirshail-Lokhsmi digha    0.05666667 -20.55929 20.67262 1.0000000
## Rangadigha-Lokhsmi digha   -4.22000000 -24.83596 16.39596 0.9994860
## Sishumaty-Lokhsmi digha     3.05000000 -17.56596 23.66596 0.9999719
## Najirshail-Modhudigha      -5.97000000 -26.58596 14.64596 0.9915352
## Rangadigha-Modhudigha     -10.24666667 -30.86262 10.36929 0.7809078
## Sishumaty-Modhudigha       -2.97666667 -23.59262 17.63929 0.9999776
## Rangadigha-Najirshail      -4.27666667 -24.89262 16.33929 0.9994236
## Sishumaty-Najirshail        2.99333333 -17.62262 23.60929 0.9999764
## Sishumaty-Rangadigha        7.27000000 -13.34596 27.88596 0.9664579
```

```
# ANOVA for X1000_seed_weight_gm
X1000_seed_weight_gm_aov <- aov(X1000SW_gm ~ landraces, data = rice_data)
summary(X1000_seed_weight_gm_aov)
```

```
##             Df Sum Sq Mean Sq F value Pr(>F)
## landraces   10  285.2   28.52   0.467  0.894
## Residuals   22 1343.1   61.05
```

```
# Post-hoc analysis using Tukey's HSD
TukeyHSD(X1000_seed_weight_gm_aov)
```

```
##   Tukey multiple comparisons of means
##     95% family-wise confidence level
##
## Fit: aov(formula = X1000SW_gm ~ landraces, data = rice_data)
##
## $landraces
##                                    diff       lwr      upr     p adj
## Bidigha-Bandorjhata       -4.23000000 -27.03592 18.57592 0.9997825
## Debmoni-Bandorjhata       -4.56000000 -27.36592 18.24592 0.9995803
## Jabra-Bandorjhata          0.25666667 -22.54926 23.06259 1.0000000
## Kachkalam-Bandorjhata     -7.14666667 -29.95259 15.65926 0.9849718
## Laldigha-Bandorjhata      -4.89666667 -27.70259 17.90926 0.9992270
## Lokhsmi digha-Bandorjhata -5.76000000 -28.56592 17.04592 0.9970544
## Modhudigha-Bandorjhata    -4.64333333 -27.44926 18.16259 0.9995092
## Najirshail-Bandorjhata    -0.86000000 -23.66592 21.94592 1.0000000
## Rangadigha-Bandorjhata    -8.86000000 -31.66592 13.94592 0.9387035
## Sishumaty-Bandorjhata     -0.30000000 -23.10592 22.50592 1.0000000
## Debmoni-Bidigha           -0.33000000 -23.13592 22.47592 1.0000000
## Jabra-Bidigha              4.48666667 -18.31926 27.29259 0.9996354
## Kachkalam-Bidigha         -2.91666667 -25.72259 19.88926 0.9999928
## Laldigha-Bidigha          -0.66666667 -23.47259 22.13926 1.0000000
## Lokhsmi digha-Bidigha     -1.53000000 -24.33592 21.27592 1.0000000
## Modhudigha-Bidigha        -0.41333333 -23.21926 22.39259 1.0000000
## Najirshail-Bidigha         3.37000000 -19.43592 26.17592 0.9999722
## Rangadigha-Bidigha        -4.63000000 -27.43592 18.17592 0.9995212
## Sishumaty-Bidigha          3.93000000 -18.87592 26.73592 0.9998871
## Jabra-Debmoni              4.81666667 -17.98926 27.62259 0.9993280
## Kachkalam-Debmoni         -2.58666667 -25.39259 20.21926 0.9999977
## Laldigha-Debmoni          -0.33666667 -23.14259 22.46926 1.0000000
## Lokhsmi digha-Debmoni     -1.20000000 -24.00592 21.60592 1.0000000
## Modhudigha-Debmoni        -0.08333333 -22.88926 22.72259 1.0000000
## Najirshail-Debmoni         3.70000000 -19.10592 26.50592 0.9999346
## Rangadigha-Debmoni        -4.30000000 -27.10592 18.50592 0.9997487
## Sishumaty-Debmoni          4.26000000 -18.54592 27.06592 0.9997685
## Kachkalam-Jabra           -7.40333333 -30.20926 15.40259 0.9807566
## Laldigha-Jabra            -5.15333333 -27.95926 17.65259 0.9988121
## Lokhsmi digha-Jabra       -6.01666667 -28.82259 16.78926 0.9958438
## Modhudigha-Jabra          -4.90000000 -27.70592 17.90592 0.9992225
## Najirshail-Jabra          -1.11666667 -23.92259 21.68926 1.0000000
## Rangadigha-Jabra          -9.11666667 -31.92259 13.68926 0.9275316
## Sishumaty-Jabra           -0.55666667 -23.36259 22.24926 1.0000000
## Laldigha-Kachkalam         2.25000000 -20.55592 25.05592 0.9999994
## Lokhsmi digha-Kachkalam    1.38666667 -21.41926 24.19259 1.0000000
## Modhudigha-Kachkalam       2.50333333 -20.30259 25.30926 0.9999983
## Najirshail-Kachkalam       6.28666667 -16.51926 29.09259 0.9941639
## Rangadigha-Kachkalam      -1.71333333 -24.51926 21.09259 1.0000000
## Sishumaty-Kachkalam        6.84666667 -15.95926 29.65259 0.9889595
## Lokhsmi digha-Laldigha    -0.86333333 -23.66926 21.94259 1.0000000
## Modhudigha-Laldigha        0.25333333 -22.55259 23.05926 1.0000000
## Najirshail-Laldigha        4.03666667 -18.76926 26.84259 0.9998565
## Rangadigha-Laldigha       -3.96333333 -26.76926 18.84259 0.9998782
## Sishumaty-Laldigha         4.59666667 -18.20926 27.40259 0.9995502
```

```
## Modhudigha-Lokhsmi digha   1.11666667 -21.68926 23.92259 1.0000000
## Najirshail-Lokhsmi digha   4.90000000 -17.90592 27.70592 0.9992225
## Rangadigha-Lokhsmi digha  -3.10000000 -25.90592 19.70592 0.9999872
## Sishumaty-Lokhsmi digha    5.46000000 -17.34592 28.26592 0.9980866
## Najirshail-Modhudigha      3.78333333 -19.02259 26.58926 0.9999199
## Rangadigha-Modhudigha     -4.21666667 -27.02259 18.58926 0.9997885
## Sishumaty-Modhudigha       4.34333333 -18.46259 27.14926 0.9997255
## Rangadigha-Najirshail     -8.00000000 -30.80592 14.80592 0.9675890
## Sishumaty-Najirshail       0.56000000 -22.24592 23.36592 1.0000000
## Sishumaty-Rangadigha       8.56000000 -14.24592 31.36592 0.9502328
```

```
# ANOVA for Grain_yield_tonn_per_ha
Grain_yield_tonn_per_ha_aov <- aov(GY_t.ha ~ landraces, data = rice_data)
summary(Grain_yield_tonn_per_ha_aov)
```

```
##             Df Sum Sq Mean Sq F value  Pr(>F)
## landraces   10  34.14   3.414   4.733 0.00114 **
## Residuals   22  15.87   0.721
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
# Post-hoc analysis using Tukey's HSD
TukeyHSD(Grain_yield_tonn_per_ha_aov)
```

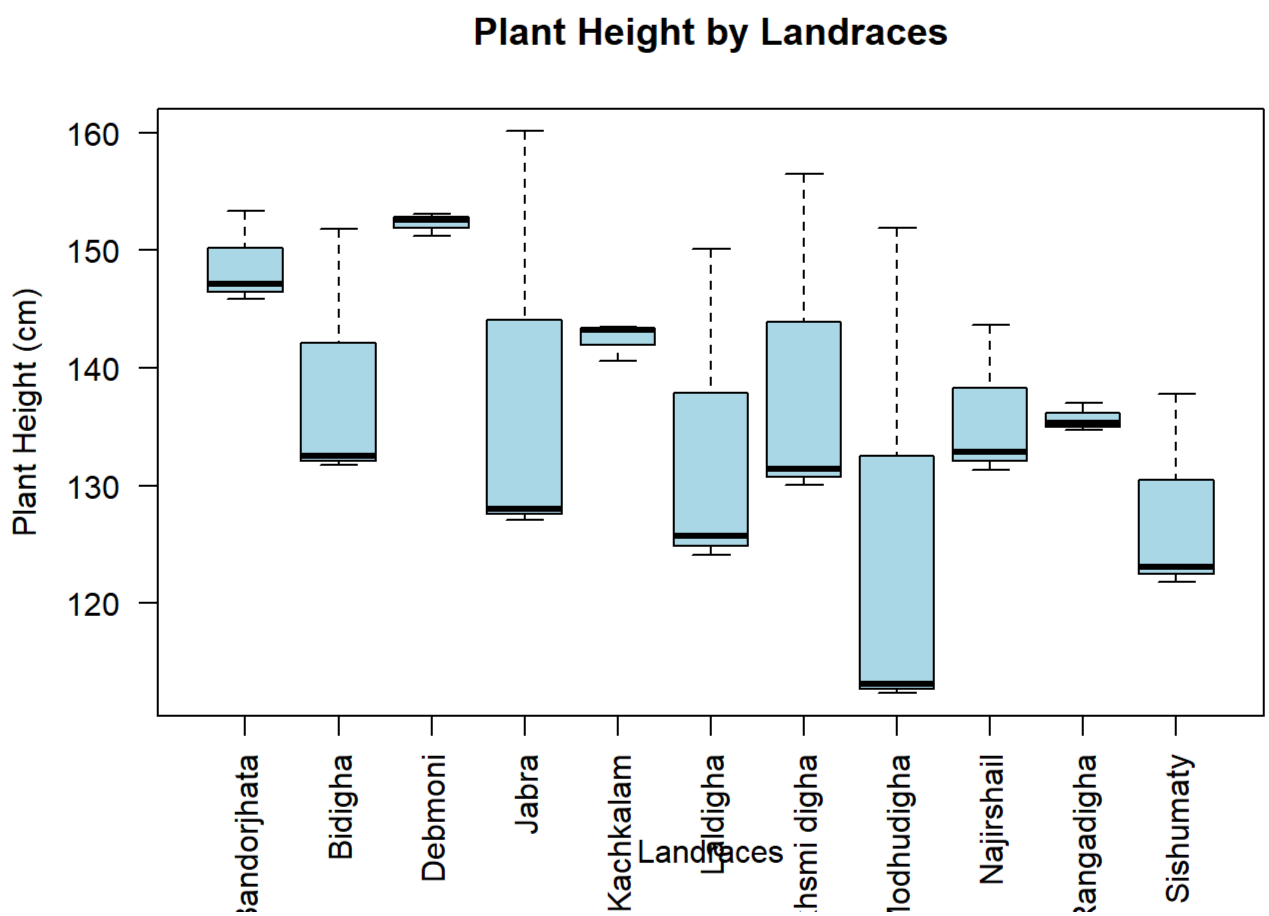
```
##   Tukey multiple comparisons of means
##     95% family-wise confidence level
##
## Fit: aov(formula = GY_t.ha ~ landraces, data = rice_data)
##
## $landraces
##                                 diff         lwr        upr     p adj
## Bidigha-Bandorjhata       -1.44333333 -3.92227115  1.0356045 0.6004799
## Debmoni-Bandorjhata       -0.72666667 -3.20560449  1.7522712 0.9907332
## Jabra-Bandorjhata          0.92000000 -1.55893782  3.3989378 0.9535879
## Kachkalam-Bandorjhata     -1.87333333 -4.35227115  0.6056045 0.2603736
## Laldigha-Bandorjhata       1.11000000 -1.36893782  3.5889378 0.8659422
## Lokhsmi digha-Bandorjhata  0.31666667 -2.16227115  2.7956045 0.9999929
## Modhudigha-Bandorjhata    -0.81333333 -3.29227115  1.6656045 0.9792908
## Najirshail-Bandorjhata     1.01000000 -1.46893782  3.4889378 0.9191970
## Rangadigha-Bandorjhata    -0.88000000 -3.35893782  1.5989378 0.9649824
## Sishumaty-Bandorjhata      0.90666667 -1.57227115  3.3856045 0.9576379
## Debmoni-Bidigha            0.71666667 -1.76227115  3.1956045 0.9916389
## Jabra-Bidigha              2.36333333 -0.11560449  4.8422712 0.0705253
## Kachkalam-Bidigha         -0.43000000 -2.90893782  2.0489378 0.9998802
## Laldigha-Bidigha           2.55333333  0.07439551  5.0322712 0.0398665
## Lokhsmi digha-Bidigha      1.76000000 -0.71893782  4.2389378 0.3358799
## Modhudigha-Bidigha         0.63000000 -1.84893782  3.1089378 0.9969048
## Najirshail-Bidigha         2.45333333 -0.02560449  4.9322712 0.0540054
## Rangadigha-Bidigha         0.56333333 -1.91560449  3.0422712 0.9987548
## Sishumaty-Bidigha          2.35000000 -0.12893782  4.8289378 0.0733284
## Jabra-Debmoni              1.64666667 -0.83227115  4.1256045 0.4233851
## Kachkalam-Debmoni         -1.14666667 -3.62560449  1.3322712 0.8425458
## Laldigha-Debmoni           1.83666667 -0.64227115  4.3156045 0.2834026
## Lokhsmi digha-Debmoni      1.04333333 -1.43560449  3.5222712 0.9032111
## Modhudigha-Debmoni        -0.08666667 -2.56560449  2.3922712 1.0000000
## Najirshail-Debmoni         1.73666667 -0.74227115  4.2156045 0.3529746
## Rangadigha-Debmoni        -0.15333333 -2.63227115  2.3256045 1.0000000
## Sishumaty-Debmoni          1.63333333 -0.84560449  4.1122712 0.4343631
## Kachkalam-Jabra           -2.79333333 -5.27227115 -0.3143955 0.0187853
## Laldigha-Jabra             0.19000000 -2.28893782  2.6689378 0.9999999
## Lokhsmi digha-Jabra       -0.60333333 -3.08227115  1.8756045 0.9978128
## Modhudigha-Jabra          -1.73333333 -4.21227115  0.7456045 0.3554579
## Najirshail-Jabra           0.09000000 -2.38893782  2.5689378 1.0000000
## Rangadigha-Jabra          -1.80000000 -4.27893782  0.6789378 0.3077802
## Sishumaty-Jabra           -0.01333333 -2.49227115  2.4656045 1.0000000
## Laldigha-Kachkalam         2.98333333  0.50439551  5.4622712 0.0101744
## Lokhsmi digha-Kachkalam    2.19000000 -0.28893782  4.6689378 0.1155599
## Modhudigha-Kachkalam       1.06000000 -1.41893782  3.5389378 0.8945508
## Najirshail-Kachkalam       2.88333333  0.40439551  5.3622712 0.0140714
## Rangadigha-Kachkalam       0.99333333 -1.48560449  3.4722712 0.9265225
## Sishumaty-Kachkalam        2.78000000  0.30106218  5.2589378 0.0196016
## Lokhsmi digha-Laldigha    -0.79333333 -3.27227115  1.6856045 0.9825729
## Modhudigha-Laldigha       -1.92333333 -4.40227115  0.5556045 0.2311592
## Najirshail-Laldigha       -0.10000000 -2.57893782  2.3789378 1.0000000
## Rangadigha-Laldigha       -1.99000000 -4.46893782  0.4889378 0.1960944
## Sishumaty-Laldigha        -0.20333333 -2.68227115  2.2756045 0.9999999
```

```
## Modhudigha-Lokhsmi digha  -1.13000000 -3.60893782  1.3489378 0.8534257
## Najirshail-Lokhsmi digha   0.69333333 -1.78560449  3.1722712 0.9934815
## Rangadigha-Lokhsmi digha  -1.19666667 -3.67560449  1.2822712 0.8075937
## Sishumaty-Lokhsmi digha    0.59000000 -1.88893782  3.0689378 0.9981765
## Najirshail-Modhudigha      1.82333333 -0.65560449  4.3022712 0.2921122
## Rangadigha-Modhudigha     -0.06666667 -2.54560449  2.4122712 1.0000000
## Sishumaty-Modhudigha       1.72000000 -0.75893782  4.1989378 0.3654914
## Rangadigha-Najirshail     -1.89000000 -4.36893782  0.5889378 0.2503549
## Sishumaty-Najirshail      -0.10333333 -2.58227115  2.3756045 1.0000000
## Sishumaty-Rangadigha       1.78666667 -0.69227115  4.2656045 0.3169745
```

```
print(Grain_yield_tonn_per_ha_aov)
```

```
## Call:
##    aov(formula = GY_t.ha ~ landraces, data = rice_data)
##
## Terms:
##                 landraces Residuals
## Sum of Squares   34.14039  15.86860
## Deg. of Freedom        10        22
##
## Residual standard error: 0.8492938
## Estimated effects may be unbalanced
```

```
# Boxplot for Plant Height
boxplot(PH_cm ~ landraces, data = rice_data, main = "Plant Height by Landraces",
        xlab = "Landraces", ylab = "Plant Height (cm)", las = 2, col = "lightblue")
```




```
summary(rice_data)
```

```
##   landraces              PH_cm            ET.P            PL_cm      
##  Length:33          Min.   :112.3   Min.   : 9.00   Min.   :20.66  
##  Class :character   1st Qu.:130.1   1st Qu.:11.67   1st Qu.:22.80  
##  Mode  :character   Median :137.0   Median :16.30   Median :24.13  
##                     Mean   :138.0   Mean   :17.43   Mean   :24.12  
##                     3rd Qu.:150.1   3rd Qu.:21.66   3rd Qu.:25.30  
##                     Max.   :160.1   Max.   :36.86   Max.   :26.63  
##       FG.P             UG.P          X1000SW_gm       GY_t.ha     
##  Min.   : 97.3   Min.   : 9.48   Min.   :18.49   Min.   :1.460  
##  1st Qu.:107.8   1st Qu.:13.50   1st Qu.:20.49   1st Qu.:2.910  
##  Median :113.5   Median :16.83   Median :23.70   Median :3.220  
##  Mean   :117.0   Mean   :18.30   Mean   :26.72   Mean   :3.659  
##  3rd Qu.:119.0   3rd Qu.:21.33   3rd Qu.:32.90   3rd Qu.:4.690  
##  Max.   :170.7   Max.   :36.00   Max.   :44.74   Max.   :5.770
```

```
# Load necessary library
library(ggplot2)
library(dplyr)
```

```
## 
## Attaching package: 'dplyr'
```

```
## The following objects are masked from 'package:stats':
##
##     filter, lag
```

```
## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union
```

```r
library(tidyverse)
```

```
## ── Attaching core tidyverse packages ──────────────────────── tidyverse 2.0.0 ──
## ✔ forcats   1.0.0     ✔ stringr   1.5.1
## ✔ lubridate 1.9.3     ✔ tibble    3.2.1
## ✔ purrr     1.0.2     ✔ tidyr     1.3.1
## ✔ readr     2.1.5
```

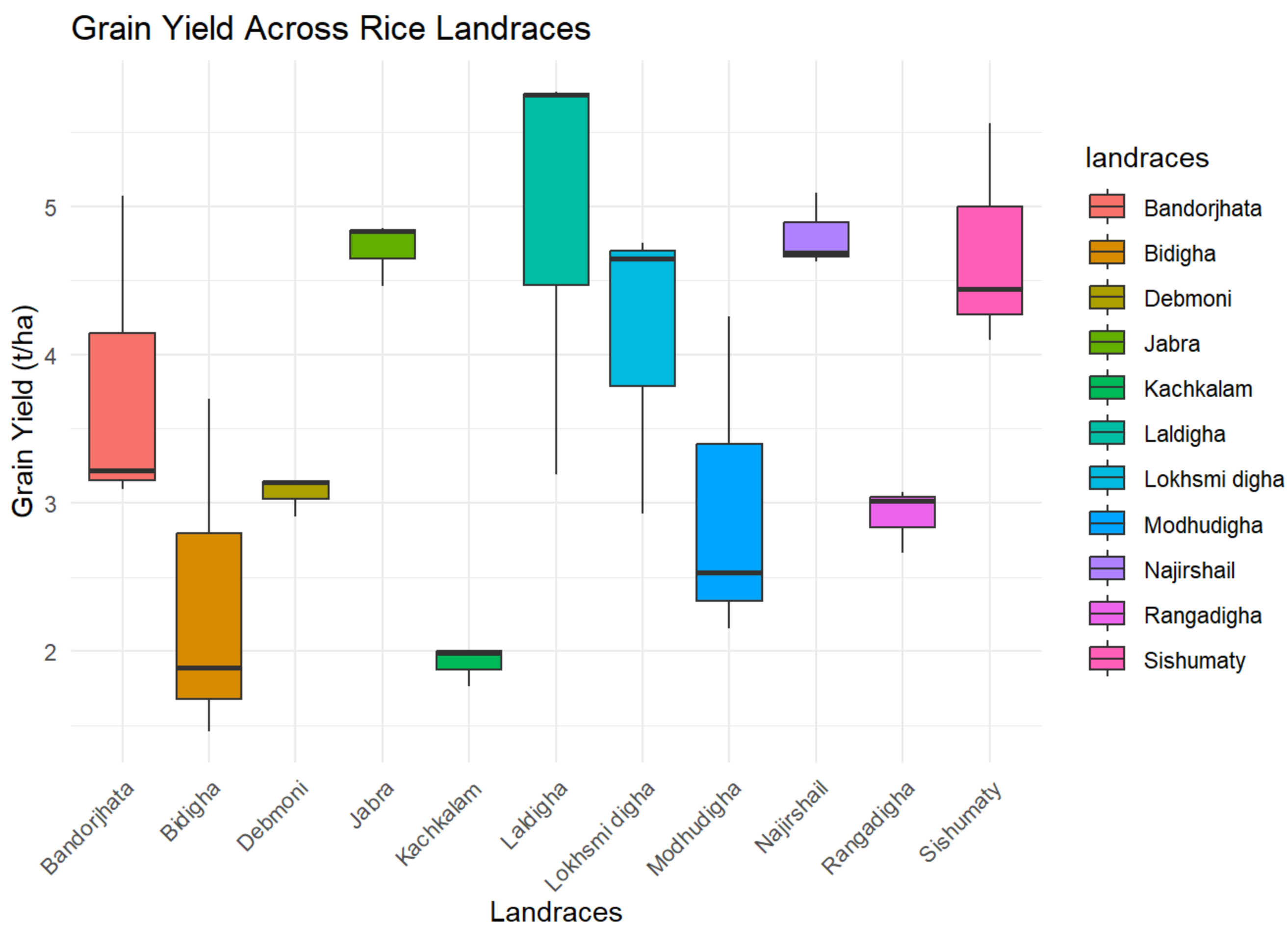
```
## ── Conflicts ────────────────────────────────────────── tidyverse_conflicts() ──
## ✖ dplyr::filter() masks stats::filter()
## ✖ dplyr::lag()    masks stats::lag()
## ℹ Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to becom
e errors
```

```r
# Read the dataset
rice_data <- read.csv("Rice.csv")

# Ensure the Landraces column is treated as a factor
rice_data$landraces <- as.factor(rice_data$landraces)

# Perform ANOVA for each quantitative trait
traits <- c(" PH_cm", "ET.P", "PL_cm",
            "FG.P", "UG.P",
            "X1000SW_gm", "GY_t.ha")

# Loop through traits to run ANOVA and display results
for (trait in traits) {
  print(paste("ANOVA for:", trait))
  formula <- as.formula(paste(trait, "~ landraces"))
  anova_result <- aov(formula, data = rice_data)
  print(summary(anova_result))

  # Post-hoc test if significant
  if (summary(anova_result)[[1]][["Pr(>F)"]][1] < 0.05) {
    print("Tukey HSD Results:")
    print(TukeyHSD(anova_result))
  }
}
```

```
## [1] "ANOVA for:  PH_cm"
##             Df Sum Sq Mean Sq F value Pr(>F)
## landraces   10   1899   189.9   1.325  0.278
## Residuals   22   3154   143.4
## [1] "ANOVA for: ET.P"
##             Df Sum Sq Mean Sq F value Pr(>F)
## landraces   10    612   61.20     1.4  0.244
## Residuals   22    962   43.73
## [1] "ANOVA for: PL_cm"
##             Df Sum Sq Mean Sq F value Pr(>F)
## landraces   10  26.89   2.689   1.086  0.413
## Residuals   22  54.44   2.475
## [1] "ANOVA for: FG.P"
##             Df Sum Sq Mean Sq F value Pr(>F)
## landraces   10   1876   187.6   0.517   0.86
## Residuals   22   7986   363.0
## [1] "ANOVA for: UG.P"
##             Df Sum Sq Mean Sq F value Pr(>F)
## landraces   10  275.7   27.57   0.553  0.834
## Residuals   22 1097.5   49.89
## [1] "ANOVA for: X1000SW_gm"
##             Df Sum Sq Mean Sq F value Pr(>F)
## landraces   10  285.2   28.52   0.467  0.894
## Residuals   22 1343.1   61.05
## [1] "ANOVA for: GY_t.ha"
##             Df Sum Sq Mean Sq F value  Pr(>F)
## landraces   10  34.14   3.414   4.733 0.00114 **
## Residuals   22  15.87   0.721
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## [1] "Tukey HSD Results:"
##   Tukey multiple comparisons of means
##     95% family-wise confidence level
##
## Fit: aov(formula = formula, data = rice_data)
##
## $landraces
##                                  diff         lwr        upr     p adj
## Bidigha-Bandorjhata       -1.44333333 -3.92227115  1.0356045 0.6004799
## Debmoni-Bandorjhata       -0.72666667 -3.20560449  1.7522712 0.9907332
## Jabra-Bandorjhata          0.92000000 -1.55893782  3.3989378 0.9535879
## Kachkalam-Bandorjhata     -1.87333333 -4.35227115  0.6056045 0.2603736
## Laldigha-Bandorjhata       1.11000000 -1.36893782  3.5889378 0.8659422
## Lokhsmi digha-Bandorjhata  0.31666667 -2.16227115  2.7956045 0.9999929
## Modhudigha-Bandorjhata    -0.81333333 -3.29227115  1.6656045 0.9792908
## Najirshail-Bandorjhata     1.01000000 -1.46893782  3.4889378 0.9191970
## Rangadigha-Bandorjhata    -0.88000000 -3.35893782  1.5989378 0.9649824
## Sishumaty-Bandorjhata      0.90666667 -1.57227115  3.3856045 0.9576379
## Debmoni-Bidigha            0.71666667 -1.76227115  3.1956045 0.9916389
## Jabra-Bidigha              2.36333333 -0.11560449  4.8422712 0.0705253
## Kachkalam-Bidigha         -0.43000000 -2.90893782  2.0489378 0.9998802
## Laldigha-Bidigha           2.55333333  0.07439551  5.0322712 0.0398665
```

```
## Lokhsmi digha-Bidigha      1.76000000 -0.71893782  4.2389378 0.3358799
## Modhudigha-Bidigha         0.63000000 -1.84893782  3.1089378 0.9969048
## Najirshail-Bidigha         2.45333333 -0.02560449  4.9322712 0.0540054
## Rangadigha-Bidigha         0.56333333 -1.91560449  3.0422712 0.9987548
## Sishumaty-Bidigha          2.35000000 -0.12893782  4.8289378 0.0733284
## Jabra-Debmoni              1.64666667 -0.83227115  4.1256045 0.4233851
## Kachkalam-Debmoni         -1.14666667 -3.62560449  1.3322712 0.8425458
## Laldigha-Debmoni           1.83666667 -0.64227115  4.3156045 0.2834026
## Lokhsmi digha-Debmoni      1.04333333 -1.43560449  3.5222712 0.9032111
## Modhudigha-Debmoni        -0.08666667 -2.56560449  2.3922712 1.0000000
## Najirshail-Debmoni         1.73666667 -0.74227115  4.2156045 0.3529746
## Rangadigha-Debmoni        -0.15333333 -2.63227115  2.3256045 1.0000000
## Sishumaty-Debmoni          1.63333333 -0.84560449  4.1122712 0.4343631
## Kachkalam-Jabra           -2.79333333 -5.27227115 -0.3143955 0.0187853
## Laldigha-Jabra             0.19000000 -2.28893782  2.6689378 0.9999999
## Lokhsmi digha-Jabra       -0.60333333 -3.08227115  1.8756045 0.9978128
## Modhudigha-Jabra          -1.73333333 -4.21227115  0.7456045 0.3554579
## Najirshail-Jabra           0.09000000 -2.38893782  2.5689378 1.0000000
## Rangadigha-Jabra          -1.80000000 -4.27893782  0.6789378 0.3077802
## Sishumaty-Jabra           -0.01333333 -2.49227115  2.4656045 1.0000000
## Laldigha-Kachkalam         2.98333333  0.50439551  5.4622712 0.0101744
## Lokhsmi digha-Kachkalam    2.19000000 -0.28893782  4.6689378 0.1155599
## Modhudigha-Kachkalam       1.06000000 -1.41893782  3.5389378 0.8945508
## Najirshail-Kachkalam       2.88333333  0.40439551  5.3622712 0.0140714
## Rangadigha-Kachkalam       0.99333333 -1.48560449  3.4722712 0.9265225
## Sishumaty-Kachkalam        2.78000000  0.30106218  5.2589378 0.0196016
## Lokhsmi digha-Laldigha    -0.79333333 -3.27227115  1.6856045 0.9825729
## Modhudigha-Laldigha       -1.92333333 -4.40227115  0.5556045 0.2311592
## Najirshail-Laldigha       -0.10000000 -2.57893782  2.3789378 1.0000000
## Rangadigha-Laldigha       -1.99000000 -4.46893782  0.4889378 0.1960944
## Sishumaty-Laldigha        -0.20333333 -2.68227115  2.2756045 0.9999999
## Modhudigha-Lokhsmi digha  -1.13000000 -3.60893782  1.3489378 0.8534257
## Najirshail-Lokhsmi digha   0.69333333 -1.78560449  3.1722712 0.9934815
## Rangadigha-Lokhsmi digha  -1.19666667 -3.67560449  1.2822712 0.8075937
## Sishumaty-Lokhsmi digha    0.59000000 -1.88893782  3.0689378 0.9981765
## Najirshail-Modhudigha      1.82333333 -0.65560449  4.3022712 0.2921122
## Rangadigha-Modhudigha     -0.06666667 -2.54560449  2.4122712 1.0000000
## Sishumaty-Modhudigha       1.72000000 -0.75893782  4.1989378 0.3654914
## Rangadigha-Najirshail     -1.89000000 -4.36893782  0.5889378 0.2503549
## Sishumaty-Najirshail      -0.10333333 -2.58227115  2.3756045 1.0000000
## Sishumaty-Rangadigha       1.78666667 -0.69227115  4.2656045 0.3169745
```

```
#  Visualize one of the traits (e.g., Grain Yield) with boxplot
ggplot(rice_data, aes(x = landraces, y = GY_t.ha, fill = landraces)) +
  geom_boxplot() +
  labs(title = "Grain Yield Across Rice Landraces",
       x = "Landraces",
       y = "Grain Yield (t/ha)") +
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))
```




```
# Load necessary libraries
library(corrplot)
```

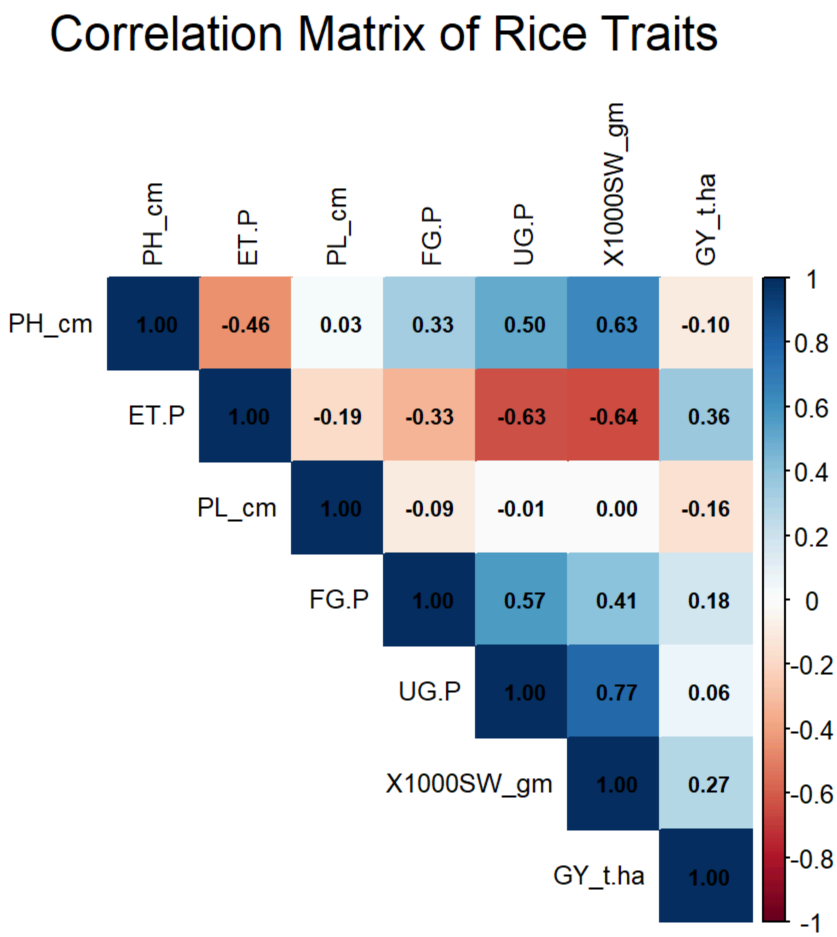
```
## Warning: package 'corrplot' was built under R version 4.4.2
```

```
## corrplot 0.95 loaded
```

```
# Load the data
data <- read.csv("Rice.csv")

# Select only numerical columns for correlation analysis
numerical_data <- data %>% select(-landraces)

# Calculate the correlation matrix
correlation_matrix <- cor(numerical_data, method = "pearson")

# Print the correlation matrix
print(correlation_matrix)
```

```
##                 PH_cm       ET.P         PL_cm        FG.P        UG.P
## PH_cm       1.00000000 -0.4571490  0.0317375835  0.33478369  0.50145249
## ET.P       -0.45714899  1.0000000 -0.1862510384 -0.33485353 -0.63456864
## PL_cm       0.03173758 -0.1862510  1.0000000000 -0.09056327 -0.00858839
## FG.P        0.33478369 -0.3348535 -0.0905632681  1.00000000  0.56786839
## UG.P        0.50145249 -0.6345686 -0.0085883897  0.56786839  1.00000000
## X1000SW_gm  0.63383133 -0.6433562  0.0005785448  0.40534473  0.77389234
## GY_t.ha    -0.10052966  0.3618132 -0.1596718126  0.18238939  0.06454855
##              X1000SW_gm     GY_t.ha
## PH_cm       0.6338313289 -0.10052966
## ET.P       -0.6433562357  0.36181325
## PL_cm       0.0005785448 -0.15967181
## FG.P        0.4053447259  0.18238939
## UG.P        0.7738923402  0.06454855
## X1000SW_gm  1.0000000000  0.27020846
## GY_t.ha     0.2702084587  1.00000000
```

```
# Adjust outer margins for the main title
par(oma = c(0, 0, 3, 0)) # Bottom, left, top, right margins for the outer area

# Visualize the correlation matrix as a heatmap
corrplot(correlation_matrix, method = "color", type = "upper",
         tl.col = "black", tl.cex = 0.8, number.cex = 0.7,
         addCoef.col = "black")

# Add the title
mtext("Correlation Matrix of Rice Traits", outer = TRUE, cex = 1.5, col = "black", line = 1)
```




```
# Reset graphical parameters
par(oma = c(0, 0, 0, 0))
```

```
# Load necessary libraries
library(tidyverse)
library(heatmaply)
```

```
## Warning: package 'heatmaply' was built under R version 4.4.2
```

```
## Loading required package: plotly
```

```
## Warning: package 'plotly' was built under R version 4.4.2
```

```
##
## Attaching package: 'plotly'
```

```
## The following object is masked from 'package:ggplot2':
##
##     last_plot
```

```
## The following object is masked from 'package:stats':
##
##     filter
```

```
## The following object is masked from 'package:graphics':
##
##     layout
```

```
## Loading required package: viridis
```

```
## Warning: package 'viridis' was built under R version 4.4.2
```

```
## Loading required package: viridisLite
```

```
##
## ======================
## Welcome to heatmaply version 1.5.0
##
## Type citation('heatmaply') for how to cite the package.
## Type ?heatmaply for the main documentation.
##
## The github page is: https://github.com/talgalili/heatmaply/
## Please submit your suggestions and bug-reports at: https://github.com/talgalili/heatmaply/iss
ues
## You may ask questions at stackoverflow, use the r and heatmaply tags:
##   https://stackoverflow.com/questions/tagged/heatmaply
## ======================
```

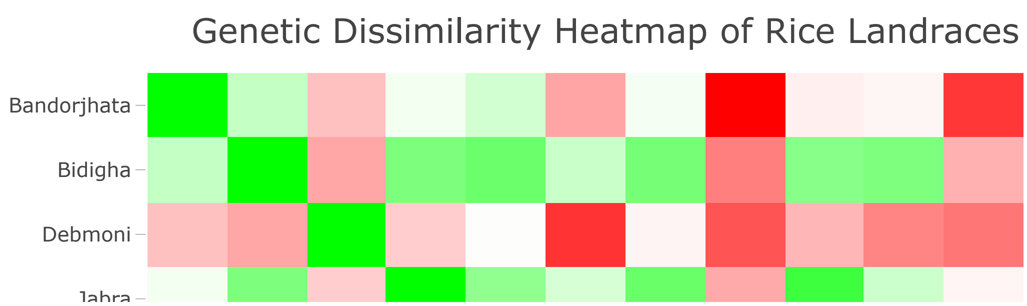
```
# Load the data
data <- read.csv("Rice.csv")

# Inspect the structure of the data
str(data)
```

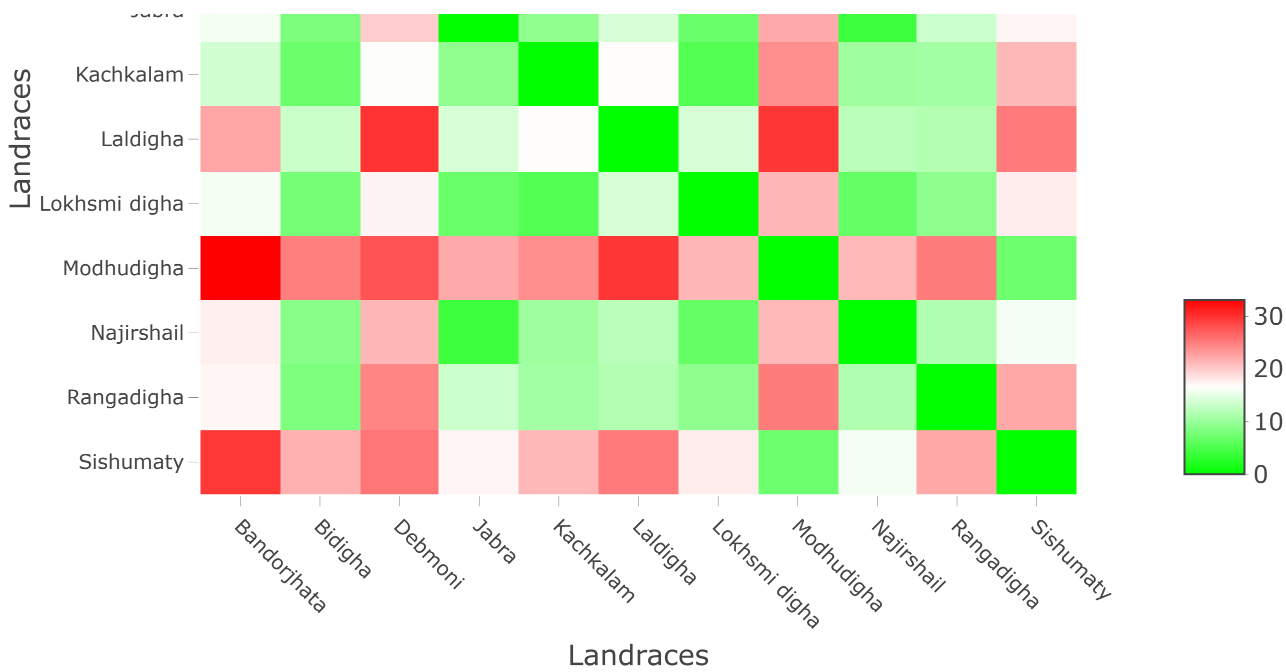
```
## 'data.frame':    33 obs. of  8 variables:
##  $ landraces : chr  "Laldigha" "Laldigha" "Laldigha" "Lokhsmi digha" ...
##  $ PH_cm     : num  124 126 150 131 130 ...
##  $ ET.P      : num  36.9 34.3 10.7 21.6 23.4 ...
##  $ PL_cm     : num  21.2 21.9 22.8 25.8 22.6 ...
##  $ FG.P      : num  116 100 110 115 112 ...
##  $ UG.P      : num  9.96 10.96 20.34 16.83 14.78 ...
##  $ X1000SW_gm: num  19.5 20.2 37 20.1 20.7 ...
##  $ GY_t.ha   : num  5.75 5.77 3.19 4.65 4.75 2.93 4.83 4.85 4.46 2.15 ...
```

```
# Calculate the mean across replications for each landrace
# Assuming the dataset contains columns: "Landrace", "Replication", and trait columns
data_mean <- data %>%
  group_by(landraces) %>%
  summarise(across(where(is.numeric), mean, na.rm = TRUE))
```

```
## Warning: There was 1 warning in `summarise()`.
## ℹ In argument: `across(where(is.numeric), mean, na.rm = TRUE)`.
## ℹ In group 1: `landraces = "Bandorjhata"`.
## Caused by warning:
## ! The `...` argument of `across()` is deprecated as of dplyr 1.1.0.
## Supply arguments directly to `.fns` through an anonymous function instead.
##
##   # Previously
##   across(a:b, mean, na.rm = TRUE)
##
##   # Now
##   across(a:b, \(x) mean(x, na.rm = TRUE))
```

```
# Remove the "Landrace" column for distance computation
traits_data <- data_mean %>% select(-landraces)

# Compute Euclidean distance for dissimilarity
distance_matrix <- dist(traits_data, method = "euclidean")

# Convert to a matrix for heatmap visualization
distance_matrix <- as.matrix(distance_matrix)

# Add row and column names (Landrace names)
rownames(distance_matrix) <- data_mean$landraces
colnames(distance_matrix) <- data_mean$landraces

# Plot the heatmap
heatmaply(
  distance_matrix,
  main = "Genetic Dissimilarity Heatmap of Rice Landraces",
  xlab = "Landraces",
  ylab = "Landraces",
  colors = colorRampPalette(c("green", "white", "red"))(100),
  dendrogram = "none", # Exclude hierarchical clustering
  plot_method = "plotly"
)
```

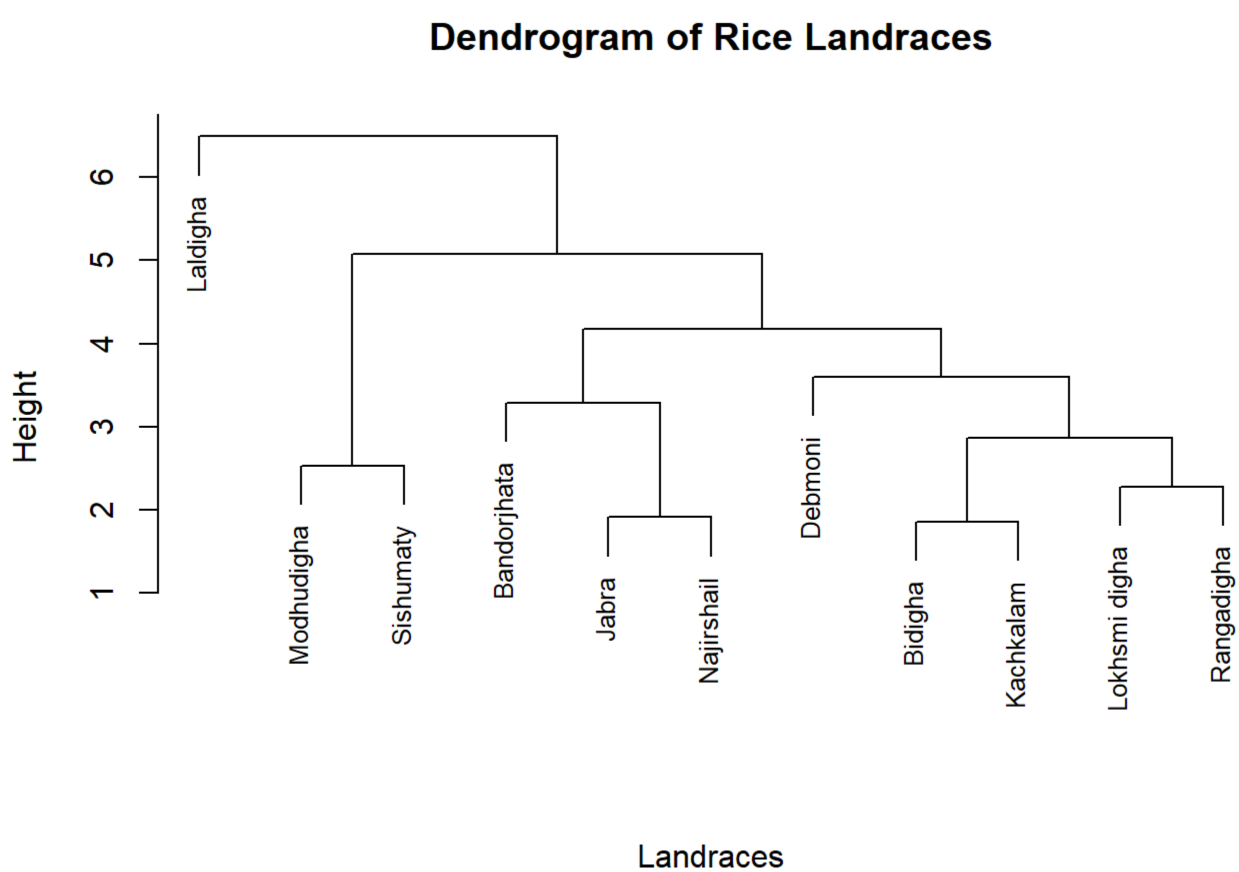




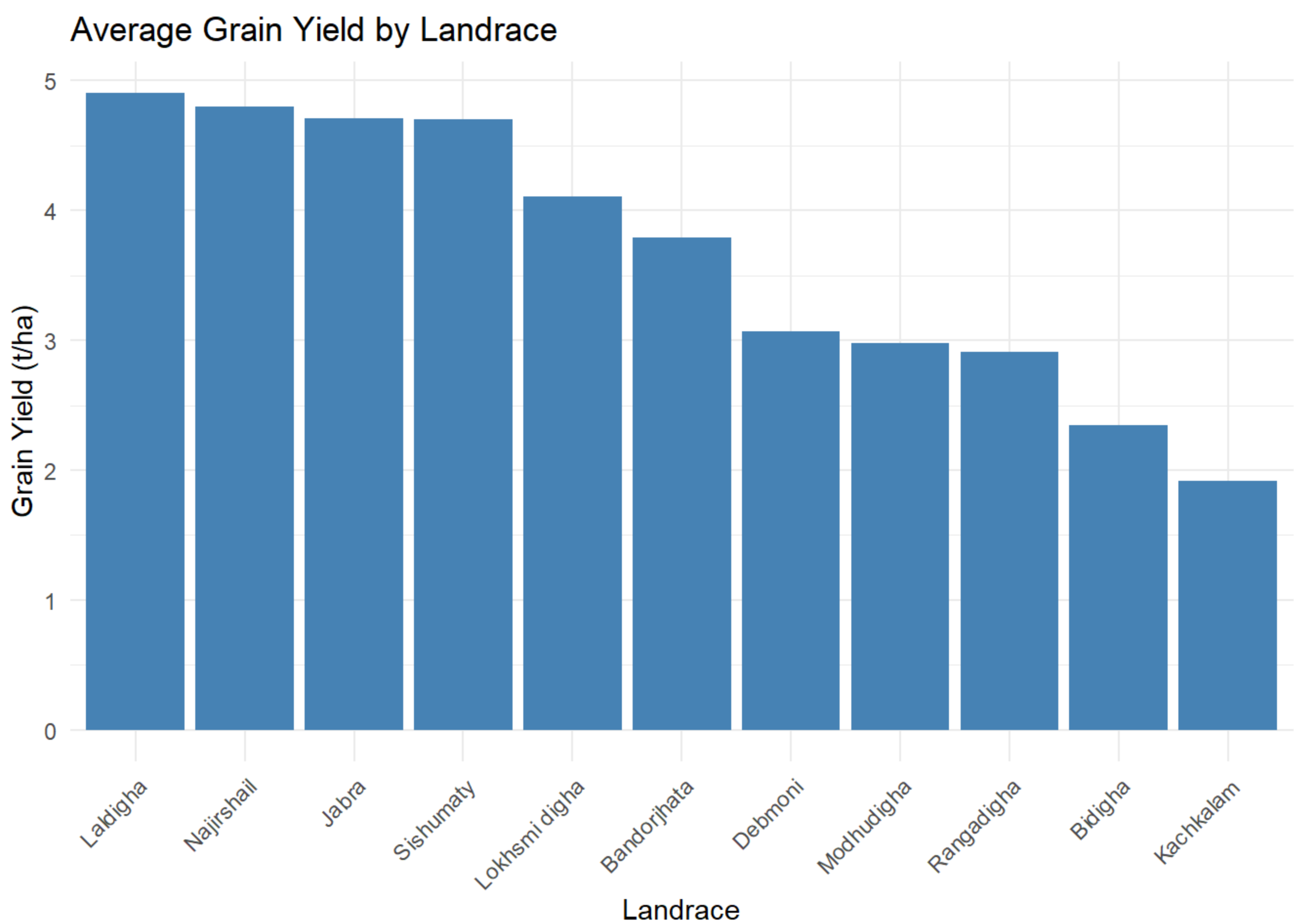

```r
# Load necessary libraries
library(ggplot2)
library(cluster)

# Read the dataset and ensure it is a data frame
rice_data <- read.csv("Rice.csv")

# Check the structure of the dataset
str(rice_data)
```

```
## 'data.frame':    33 obs. of  8 variables:
##  $ landraces : chr  "Laldigha" "Laldigha" "Laldigha" "Lokhsmi digha" ...
##  $ PH_cm     : num  124 126 150 131 130 ...
##  $ ET.P      : num  36.9 34.3 10.7 21.6 23.4 ...
##  $ PL_cm     : num  21.2 21.9 22.8 25.8 22.6 ...
##  $ FG.P      : num  116 100 110 115 112 ...
##  $ UG.P      : num  9.96 10.96 20.34 16.83 14.78 ...
##  $ X1000SW_gm: num  19.5 20.2 37 20.1 20.7 ...
##  $ GY_t.ha   : num  5.75 5.77 3.19 4.65 4.75 2.93 4.83 4.85 4.46 2.15 ...
```

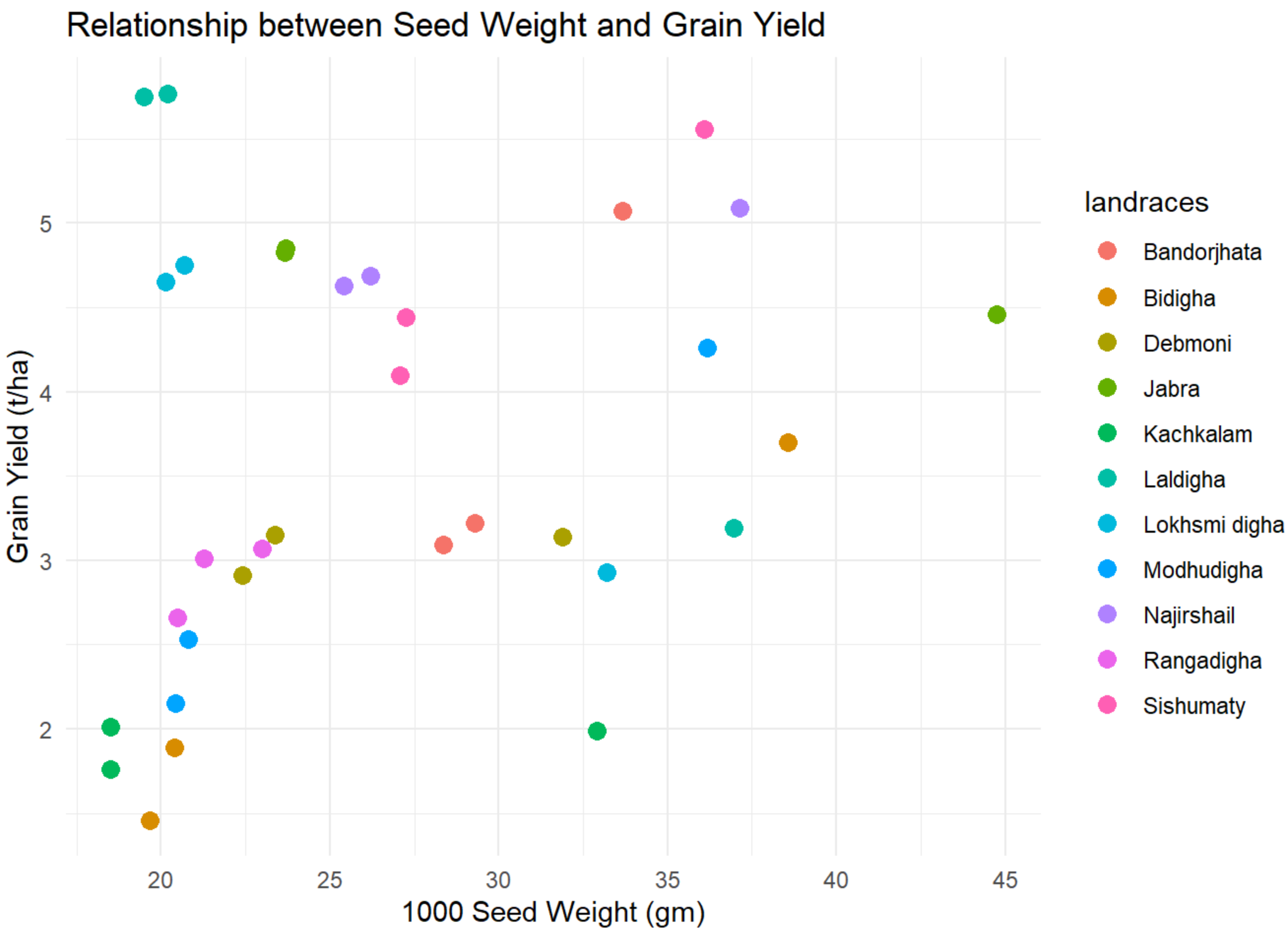
```r
# Ensure the dataset is treated as a data frame
rice_data <- as.data.frame(rice_data)

# Aggregate the data by 'landraces' (mean across replications)
# Assuming the first column is 'landraces' and the rest are numeric
aggregated_data <- aggregate(. ~ landraces, data = rice_data, FUN = mean)

# Exclude the first non-numeric column ('landraces') for clustering
numeric_data <- aggregated_data[, -1]  # Remove the first column (landraces)

# Normalize the numeric data
normalized_data <- scale(numeric_data)

# Compute the distance matrix
distance_matrix <- dist(normalized_data, method = "euclidean")

# Perform hierarchical clustering (complete linkage)
hc <- hclust(distance_matrix, method = "complete")

# Plot the dendrogram with landrace labels
plot(hc, labels = aggregated_data$landraces, main = "Dendrogram of Rice Landraces",
     xlab = "Landraces", sub = "", cex = 0.8)
```



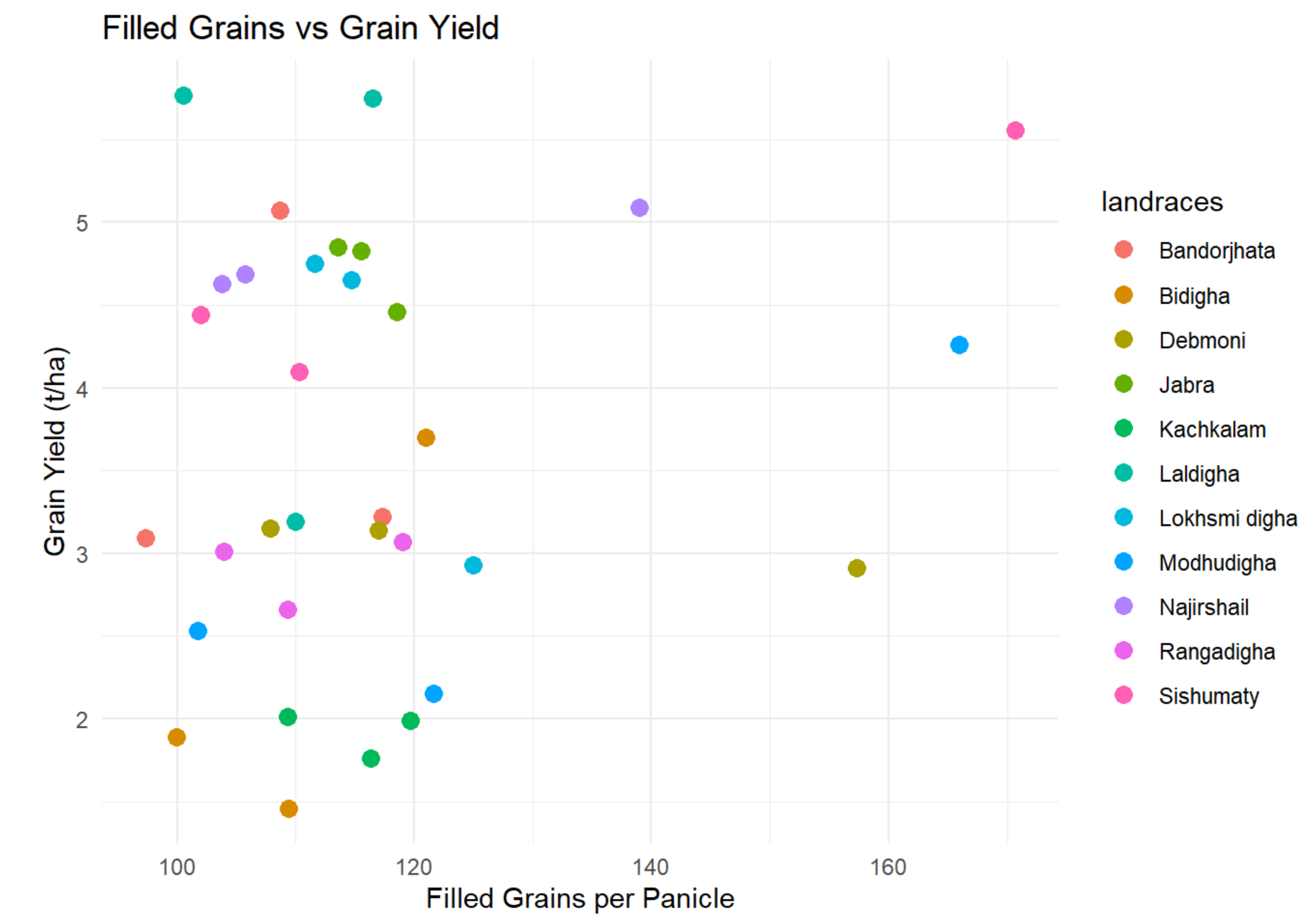
```r
# Load necessary libraries
library(ggplot2)
library(dplyr)

# Read the dataset
data <- read.csv("Rice.csv")

# Aggregate data by landraces to calculate means for plotting
agg_data <- data %>%
  group_by(landraces) %>%
  summarise(across(PH_cm:GY_t.ha, mean))

# Bar Plot: Average Grain Yield (GY_t/ha) for each landrace
ggplot(agg_data, aes(x = reorder(landraces, -GY_t.ha), y = GY_t.ha)) +
  geom_bar(stat = "identity", fill = "steelblue") +
  labs(title = "Average Grain Yield by Landrace", x = "Landrace", y = "Grain Yield (t/ha)") +
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))
```



```
# Scatter Plot: Relationship between Seed Weight and Grain Yield
ggplot(data, aes(x = X1000SW_gm, y = GY_t.ha, color = landraces)) +
  geom_point(size = 3) +
  labs(title = "Relationship between Seed Weight and Grain Yield",
       x = "1000 Seed Weight (gm)", y = "Grain Yield (t/ha)") +
  theme_minimal()
```




```
# Scatter Plot: Filled Grains vs Grain Yield
ggplot(data, aes(x = FG.P, y = GY_t.ha, color = landraces)) +
  geom_point(size = 3) +
  labs(title = "Filled Grains vs Grain Yield",
       x = "Filled Grains per Panicle", y = "Grain Yield (t/ha)") +
  theme_minimal()
```


Filled Grains vs Grain Yield
Grain Yield (t/ha)
5
4
3
2
100
120
140
160
Filled Grains per Panicle
landraces
Bandorjhata
Bidigha
Debmoni
Jabra
Kachkalam
Laldigha
Lokhsmi digha
Modhudigha
Najirshail
Rangadigha
Sishumaty