

Uganda tsetse PopGen: PCA, diversity, CSE

Norah Saarman

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RStudio Configuration: - **R version:** R 4.4.0 (Geospatial packages)
- **Number of cores:** 4 (up to 32 available)
- **Account:** saarman-np
- **Partition:** saarman-shared-np (allows multiple simultaneous jobs)
- **Memory per job:** 100G (cluster limit: 1000G total; avoid exceeding half)

```
library(adegenet)
library(geosphere)
library(igraph)
library(scatterplot3d)
library(ggplot2)
library(dplyr)
library(hierfstat)
library(pegas)
library(PopGenReport)
library(poppr)
library(sf)
library(rnaturalearth)
library(rnaturalearthdata)
library(cowplot)
library(viridis)
```

Importing data as genind object from .gen

```
# 1. Genepop .gen file "./input/Gff_11loci_allsites_genepop.gen"
Gff.genind <- read.genepop("../input/Gff_11loci_allsites_genepop.gen", ncode = 3)
```

```
##
## Converting data from a Genepop .gen file to a genind object...
##
##
## File description: Glossina fuscipes fuscipes Uganda, all sites, 11 loci, GpCAG133 has a lot of miss
##
## ...done.
```

```
# Metadata with base R function read.csv()
Gff <- read.csv("../input/Gff_11loci_allsites_indinfo.txt", header=TRUE, sep = "\t")

# Add site code to @pop slot
Gff.genind@pop <- as.factor(Gff$SiteCode)

# Check genind object
```

```
Gff.genind
```

```
## /// GENIND OBJECT ///////////  
##  
## // 2,736 individuals; 11 loci; 162 alleles; size: 1.9 Mb  
##  
## // Basic content  
## @tab: 2736 x 162 matrix of allele counts  
## @loc.n.all: number of alleles per locus (range: 7-28)  
## @loc.fac: locus factor for the 162 columns of @tab  
## @all.names: list of allele names for each locus  
## @ploidy: ploidy of each individual (range: 2-2)  
## @type: codom  
## @call: read.genepop(file = "../input/Gff_11loci_allsites_genepop.gen",  
## ncode = 3)  
##  
## // Optional content  
## @pop: population of each individual (group size range: 8-236)
```

```
summary(Gff.genind)
```

```
##  
## // Number of individuals: 2736  
## // Group sizes: 19 20 25 15 10 8 20 15 20 20 9 24 25 26 25 13 17 25 20 20 17 15 13 21 25 37 20 26 15  
## // Number of alleles per locus: 27 7 17 8 10 15 9 13 28 10 18  
## // Number of alleles per group: 65 65 65 61 52 50 60 60 59 57 52 54 69 66 57 50 50 59 56 56 55 60 59  
## // Percentage of missing data: 3.25 %  
## // Observed heterozygosity: 0.72 0.44 0.51 0.2 0.59 0.51 0.33 0.43 0.71 0.51 0.65  
## // Expected heterozygosity: 0.85 0.63 0.69 0.23 0.71 0.73 0.5 0.56 0.87 0.7 0.84
```

Visualize genetic variation with PCA

All samples:

```
# replace NAs with locus means for PCA  
gen_tab <- tab(Gff.genind, NA.method = "mean")  
  
# Compute PCA on the subset  
pca_result3 <- dudi.pca(gen_tab, cent = FALSE, scale = TRUE, scannf = FALSE, nf = 4)  
  
# Extract percent variance explained for PC1 and PC2  
var_explained <- round(100 * pca_result3$eig / sum(pca_result3$eig), 1)  
  
# Generate 86 visually distinct colors  
set.seed(123) # for reproducibility  
n_pops <- nlevels(pop(Gff.genind))  
color_palette <- colorRampPalette(c("red", "orange", "yellow", "green", "cyan", "blue", "purple"))(n_pops)  
  
# Map population levels to colors  
site_levels <- levels(pop(Gff.genind))  
site_colors <- setNames(color_palette, site_levels)  
  
# Get color for each individual  
pop_colors <- site_colors[as.character(pop(Gff.genind))]
```

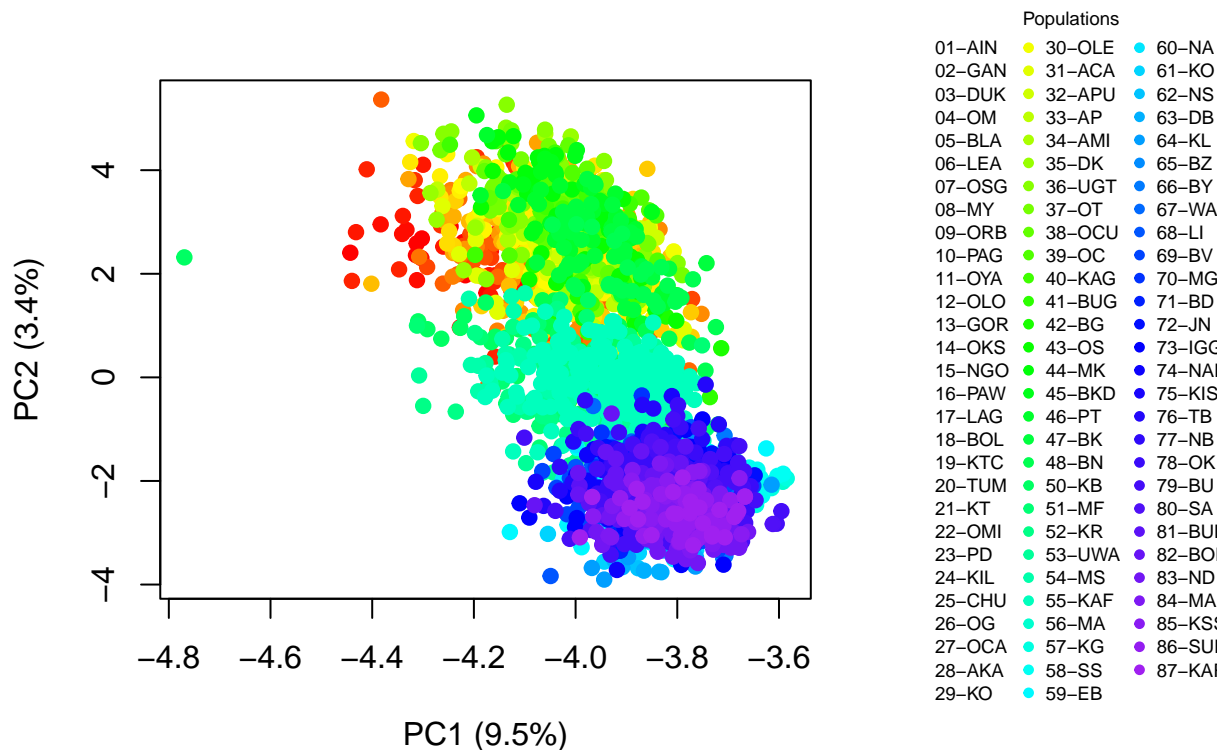
```

# Layout: 2 panels (main plot + legend)
layout(matrix(c(1, 2), nrow = 1), widths = c(6, 2.5))

# PCA plot
#pdf("../figures/PCA-all-2D.pdf", width = 14, height = 10)
par(mar = c(5, 4, 4, 2))
plot(pca_result3$li[, 1:2],
     col = pop_colors,
     pch = 19,
     xlab = paste0("PC1 (", var_explained[1], "%)"),
     ylab = paste0("PC2 (", var_explained[2], "%)"))

# Legend panel
par(mar = c(1,1,1,1)) # increase space to avoid clipping
plot.new()
legend("center",
      legend = site_levels,
      col = site_colors,
      pch = 19,
      cex = 0.6,
      title = "Populations",
      ncol = 3,
      bty = "n") # <- no border

```



```

#dev.off()

# 3D PCA plot
#pdf("../figures/PCA-all-3D.pdf", width = 14, height = 10)
par(mar = c(5, 4, 4, 2))
s3d <- scatterplot3d(pca_result3$li[, c(1,3,2)],

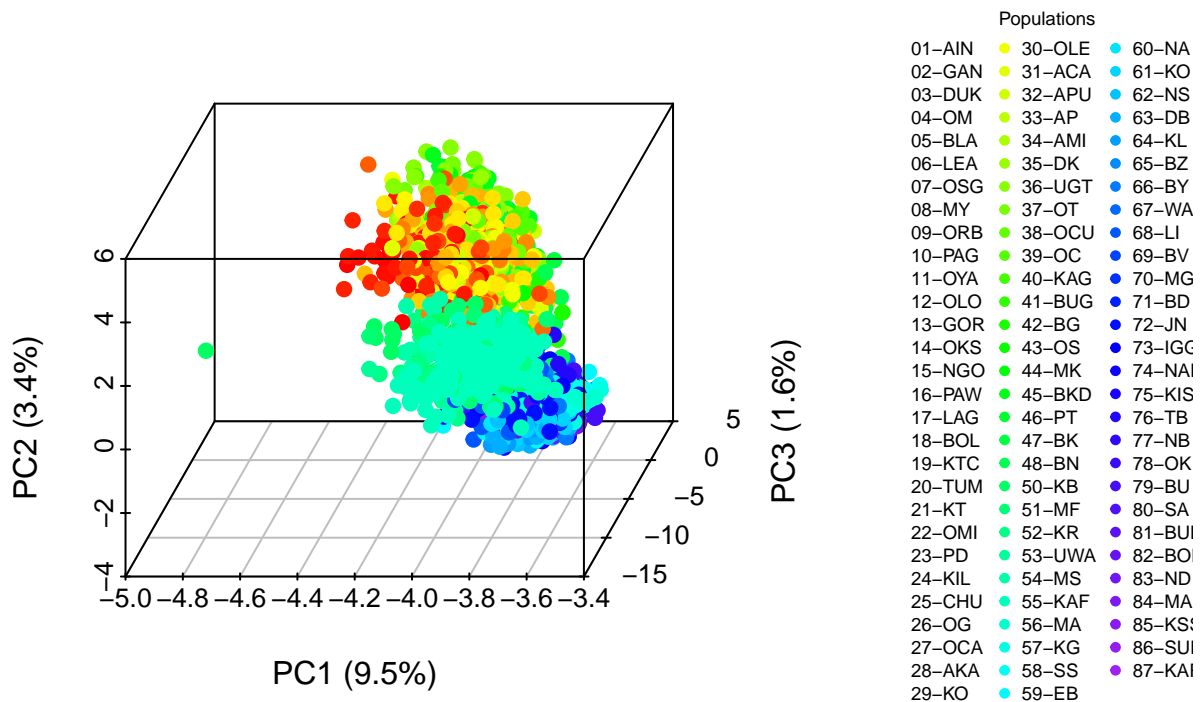
```

```

color = pop_colors,
pch = 19,
xlab = paste0("PC1 (", var_explained[1], "%)", # horizontal
ylab = paste0("PC3 (", var_explained[3], "%)", # depth
zlab = paste0("PC2 (", var_explained[2], "%)", # vertical
angle = 55,
box = TRUE)

# Legend panel
par(mar = c(1, 1, 1, 1))
plot.new()
legend("center",
      legend = site_levels,
      col = site_colors,
      pch = 19,
      cex = 0.6,
      title = "Populations",
      ncol = 3,
      bty = "n")

```



```
#dev.off()
```

Considering K=2 by Evano method

```
# Add K2 cluster combining "south" and "west" into "south"
Gff$K2 <- ifelse(Gff$SiteMajCluster %in% c("south", "west"), "south", Gff$SiteMajCluster)
```

PCA for each K2 clusters separately

```
# PCA for each K2 cluster separately
for (region in c("north", "south")) {
  genind_sub <- Gff.genind[pop(Gff.genind) %in% Gff$SiteCode[Gff$K2 == region]]
}
```

```

# Replace NAs with locus means for PCA
gen_tab <- tab(genind_sub, NA.method = "mean")
pca_result <- dudi.pca(gen_tab, cent = FALSE, scale = TRUE, scannf = FALSE, nf = 4)
var_explained <- round(100 * pca_result$eig / sum(pca_result$eig), 1)
# Color palette
set.seed(123)
n_pops <- nlevels(pop(genind_sub))
palette <- colorRampPalette(c("red", "orange", "yellow", "green", "cyan", "blue", "purple"))(n_pops)
site_levels <- levels(pop(genind_sub))
site_colors <- setNames(palette, site_levels)
pop_colors <- site_colors[as.character(pop(genind_sub))]
layout(matrix(c(1, 2), nrow = 1), widths = c(6, 2.5))

# 2D PCA plot
#pdf(paste0("../figures/PCA-", region, "-2D.pdf"), width = 14, height = 10)
par(mar = c(5, 4, 4, 2))
plot(pca_result$li[, 1:2],
      col = pop_colors,
      pch = 19,
      xlab = paste0("PC1 (", var_explained[1], "%)"),
      ylab = paste0("PC2 (", var_explained[2], "%)"))
# Legend
par(mar = c(1, 1, 1, 1))
plot.new()
legend("center",
      legend = site_levels,
      col = site_colors,
      pch = 19,
      cex = 0.6,
      title = "Populations",
      ncol = 2,
      bty = "n")
#dev.off()

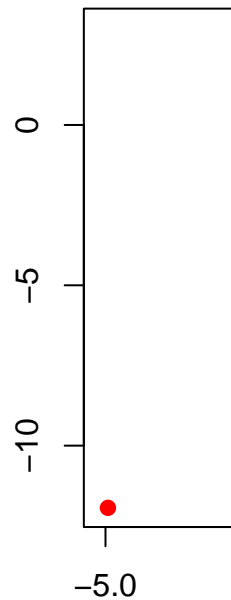
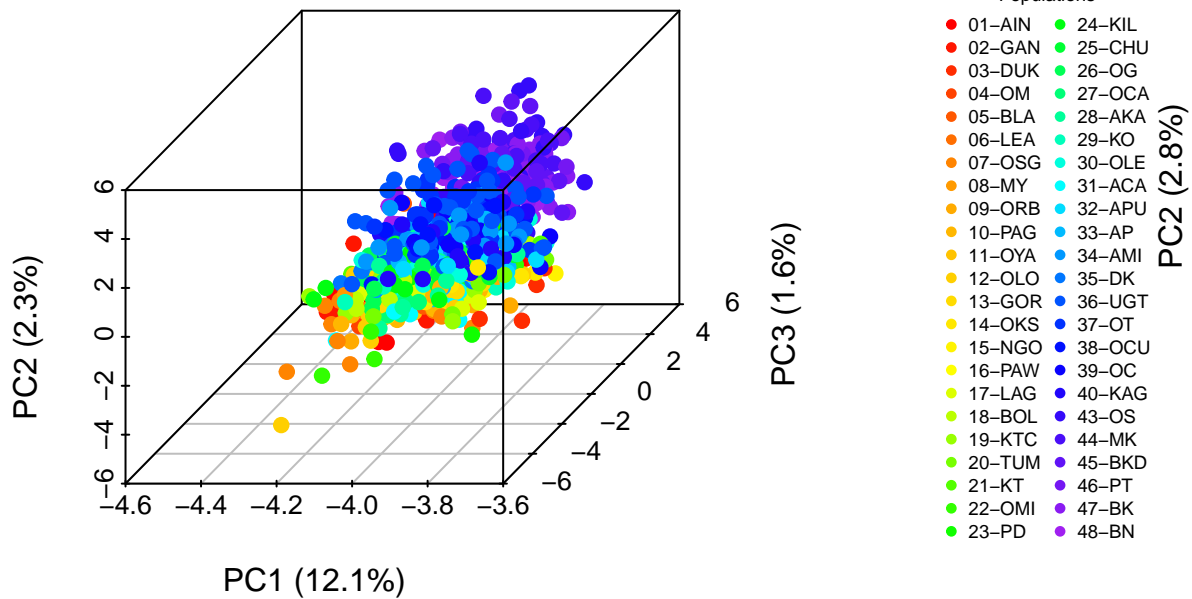
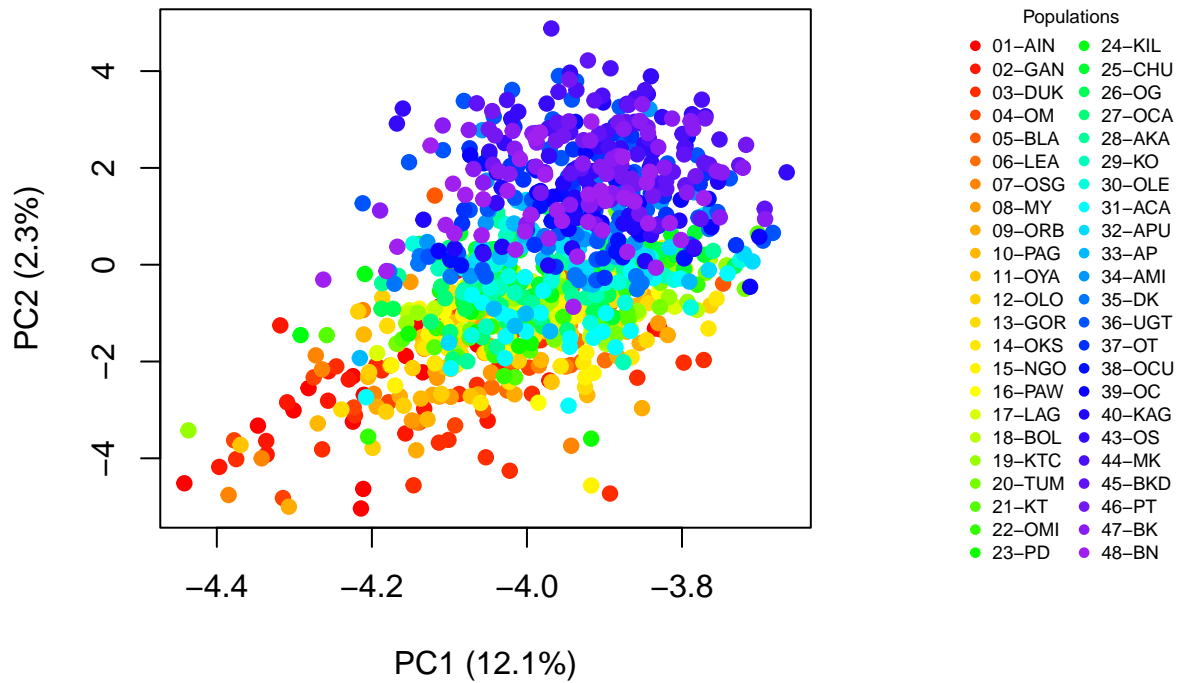
# 3D PCA plot
#pdf(paste0("../figures/PCA-", region, "-3D.pdf"), width = 14, height = 10)
par(mar = c(5, 1, 4, 2))
scatterplot3d(x = pca_result$li[, 1], # horizontal
              y = pca_result$li[, 3], # depth
              z = pca_result$li[, 2], # vertical
              color = pop_colors,
              pch = 19,
              xlab = paste0("PC1 (", var_explained[1], "%)"),
              ylab = paste0("PC3 (", var_explained[3], "%)"),
              zlab = paste0("PC2 (", var_explained[2], "%)"),
              angle = 55,
              box = TRUE)
par(mar = c(1, 1, 1, 1))
plot.new()
legend("center",
      legend = site_levels,
      col = site_colors,
      pch = 19,

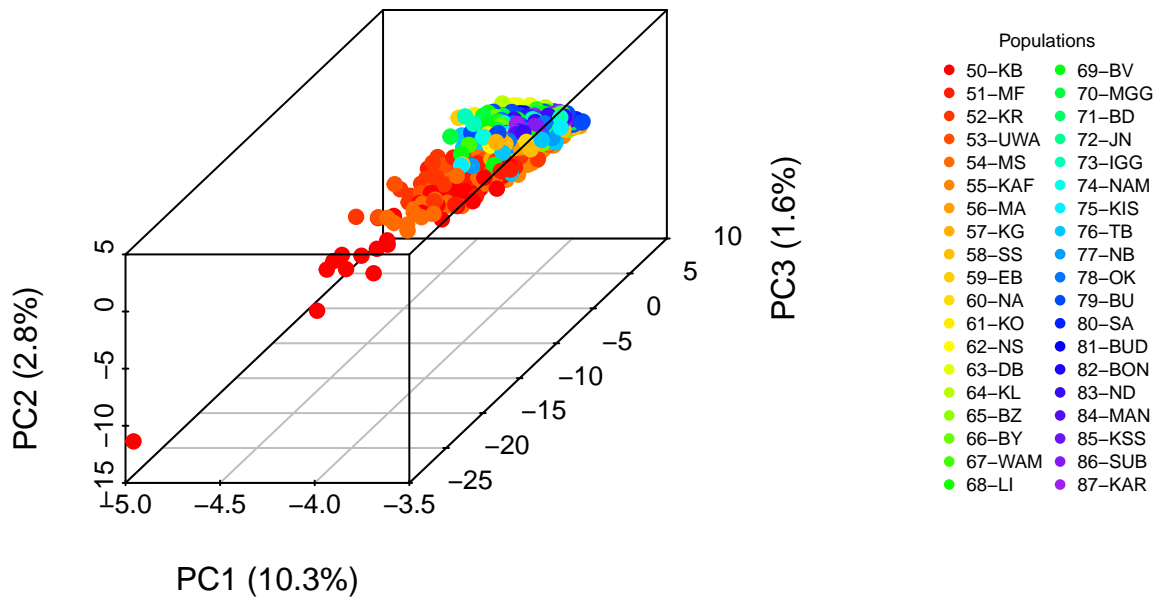
```

```

cex = 0.6,
title = "Populations",
ncol = 2,
bty = "n")
#dev.off()
}

```





Choosing sites for Random Forest (K=2)

Filter out any `Gff$Cluster == nogroup` to avoid admixed individuals, which will inflate the genetic distance within each geographic region.

Filtering for only largest/most complete genetic sample from each 5 km radius for gps within each `Gff$SiteMajCluster` independently so that we get best samples from both north and south of the river/Lake Kyoga dividing north and south.

```
# Create filtered copy of Gff excluding 'nogroup'
```

```
Gff_filt <- Gff[Gff$Cluster != "nogroup", ]
```

```
# Ensure Gff$SiteCode matches pop(Gff.genind)
```

```
Gff_filt$SiteCode <- as.character(Gff_filt$SiteCode)
```

```
pop_names <- as.character(pop(Gff.genind))
```

```
if (!all(pop_names == Gff_filt$SiteCode)) {
```

```
  Gff_filt <- Gff_filt[match(pop_names, Gff_filt$SiteCode), ]
```

```
  stopifnot(all(as.character(pop(Gff.genind)) == Gff_filt$SiteCode))
```

```
}
```

```
## Warning in pop_names == Gff_filt$SiteCode: longer object length is not a
```

```
## multiple of shorter object length
```

```
# Initialize storage
```

```
selected_sites <- character()
```

```
report_list <- list()
```

```
# Loop through each K2 cluster separately (north/south)
```

```
for (region in c("north", "south")) {
```

```
  Gff_sub <- Gff_filt[Gff_filt$K2 == region, ]
```

```
  # Build coordinate matrix
```

```
  xy <- cbind(lon = Gff_sub$SiteLong, lat = Gff_sub$SiteLat)
```

```
  dist_mat <- distm(xy, fun = distHaversine)
```

```
  # Define adjacency for <2 km
```

```
  threshold_m <- 2000
```

```
  adj_mat <- dist_mat < threshold_m
```

```

# Create undirected graph of close sites
g <- graph_from_adjacency_matrix(adj_mat, mode = "undirected", diag = FALSE)
clust_ids <- components(g)$membership
# For each 5km cluster, pick the SiteCode with the most individuals in Gff.genind
for (cid in unique(clust_ids)) {
  site_group <- Gff_sub$SiteCode[clust_ids == cid]
  counts <- table(pop(Gff.genind)[pop(Gff.genind) %in% site_group])
  best_site <- names(which.max(counts))
  selected_sites <- c(selected_sites, best_site)
  report_list[[best_site]] <- site_group
}
}

# Subset Gff and Gff.genind to selected sites
Gff_rf <- Gff_filt[Gff_filt$SiteCode %in% selected_sites, ]
Gff.genind_rf <- Gff.genind[pop(Gff.genind) %in% selected_sites]

# Report selected SiteCodes by region
print(split(Gff_rf$SiteCode, Gff_rf$K2))

```

```

## $north
## [1] "01-AIN" "01-AIN" "01-AIN" "01-AIN" "01-AIN" "01-AIN" "01-AIN" "01-AIN" "01-AIN"
## [9] "01-AIN" "01-AIN" "01-AIN" "01-AIN" "01-AIN" "01-AIN" "01-AIN" "01-AIN" "01-AIN"
## [17] "01-AIN" "01-AIN" "01-AIN" "02-GAN" "02-GAN" "02-GAN" "02-GAN" "02-GAN" "02-GAN"
## [25] "02-GAN" "02-GAN" "02-GAN" "02-GAN" "02-GAN" "02-GAN" "02-GAN" "02-GAN" "02-GAN"
## [33] "02-GAN" "02-GAN" "02-GAN" "02-GAN" "02-GAN" "02-GAN" "02-GAN" "02-GAN" "03-DUK"
## [41] "03-DUK" "03-DUK" "03-DUK" "03-DUK" "03-DUK" "03-DUK" "03-DUK" "03-DUK" "03-DUK"
## [49] "03-DUK" "03-DUK" "03-DUK" "03-DUK" "03-DUK" "03-DUK" "03-DUK" "03-DUK" "03-DUK"
## [57] "03-DUK" "03-DUK" "03-DUK" "03-DUK" "03-DUK" "03-DUK" "03-DUK" "03-DUK" "03-DUK"
## [65] "05-BLA" "05-BLA" "05-BLA" "05-BLA" "05-BLA" "05-BLA" "05-BLA" "05-BLA" "05-BLA"
## [73] "05-BLA" "05-BLA" "06-LEA" "06-LEA" "06-LEA" "06-LEA" "06-LEA" "06-LEA" "06-LEA"
## [81] "06-LEA" "06-LEA" "07-OSG" "07-OSG" "07-OSG" "07-OSG" "07-OSG" "07-OSG" "07-OSG"
## [89] "07-OSG" "07-OSG" "07-OSG" "07-OSG" "07-OSG" "07-OSG" "07-OSG" "07-OSG" "07-OSG"
## [97] "07-OSG" "07-OSG" "07-OSG" "07-OSG" "07-OSG" "07-OSG" "07-OSG" "08-MY" "08-MY"
## [105] "08-MY" "08-MY" "08-MY" "08-MY" "08-MY" "08-MY" "08-MY" "08-MY" "08-MY"
## [113] "08-MY" "08-MY" "08-MY" "08-MY" "08-MY" "09-ORB" "09-ORB" "09-ORB" "09-ORB"
## [121] "09-ORB" "09-ORB" "09-ORB" "09-ORB" "09-ORB" "09-ORB" "09-ORB" "09-ORB" "09-ORB"
## [129] "09-ORB" "09-ORB" "09-ORB" "09-ORB" "09-ORB" "09-ORB" "09-ORB" "09-ORB" "09-ORB"
## [137] "09-ORB" "10-PAG" "10-PAG" "10-PAG" "10-PAG" "10-PAG" "10-PAG" "10-PAG" "10-PAG"
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## [153] "10-PAG" "10-PAG" "10-PAG" "10-PAG" "10-PAG" "10-PAG" "11-OYA" "11-OYA" "11-OYA"
## [161] "11-OYA" "11-OYA" "11-OYA" "11-OYA" "11-OYA" "11-OYA" "11-OYA" "12-OLO" "12-OLO"
## [169] "12-OLO" "12-OLO" "12-OLO" "12-OLO" "12-OLO" "12-OLO" "12-OLO" "12-OLO" "12-OLO"
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## [185] "12-OLO" "12-OLO" "12-OLO" "12-OLO" "12-OLO" "12-OLO" "12-OLO" "14-OKS" "14-OKS"
## [193] "14-OKS" "14-OKS" "14-OKS" "14-OKS" "14-OKS" "14-OKS" "14-OKS" "14-OKS" "14-OKS"
## [201] "14-OKS" "14-OKS" "14-OKS" "14-OKS" "14-OKS" "14-OKS" "14-OKS" "14-OKS" "14-OKS"
## [209] "14-OKS" "14-OKS" "14-OKS" "14-OKS" "14-OKS" "14-OKS" "14-OKS" "14-OKS" "14-OKS"
## [217] "15-NGO" "15-NGO" "15-NGO" "15-NGO" "15-NGO" "15-NGO" "15-NGO" "15-NGO" "15-NGO"
## [225] "15-NGO" "15-NGO" "15-NGO" "15-NGO" "15-NGO" "15-NGO" "15-NGO" "15-NGO" "15-NGO"
## [233] "15-NGO" "15-NGO" "15-NGO" "15-NGO" "15-NGO" "15-NGO" "15-NGO" "15-NGO" "15-NGO"
## [241] "15-NGO" "16-PAW" "16-PAW" "16-PAW" "16-PAW" "16-PAW" "16-PAW" "16-PAW" "16-PAW"
## [249] "16-PAW" "16-PAW" "16-PAW" "16-PAW" "16-PAW" "16-PAW" "16-PAW" "17-LAG" "17-LAG"
## [257] "17-LAG" "17-LAG" "17-LAG" "17-LAG" "17-LAG" "17-LAG" "17-LAG" "17-LAG" "17-LAG"

```


##	[265]	"17-LAG"	"17-LAG"	"17-LAG"	"17-LAG"	"17-LAG"	"17-LAG"	"17-LAG"	"18-BOL"
##	[273]	"18-BOL"	"18-BOL"	"18-BOL"	"18-BOL"	"18-BOL"	"18-BOL"	"18-BOL"	"18-BOL"
##	[281]	"18-BOL"	"18-BOL"	"18-BOL"	"18-BOL"	"18-BOL"	"18-BOL"	"18-BOL"	"18-BOL"
##	[289]	"18-BOL"	"18-BOL"	"18-BOL"	"18-BOL"	"18-BOL"	"18-BOL"	"18-BOL"	"18-BOL"
##	[297]	"19-KTC"	"19-KTC"	"19-KTC"	"19-KTC"	"19-KTC"	"19-KTC"	"19-KTC"	"19-KTC"
##	[305]	"19-KTC"	"19-KTC"	"19-KTC"	"19-KTC"	"19-KTC"	"19-KTC"	"19-KTC"	"19-KTC"
##	[313]	"19-KTC"	"19-KTC"	"19-KTC"	"19-KTC"	"20-TUM"	"20-TUM"	"20-TUM"	"20-TUM"
##	[321]	"20-TUM"	"20-TUM"	"20-TUM"	"20-TUM"	"20-TUM"	"20-TUM"	"20-TUM"	"20-TUM"
##	[329]	"20-TUM"	"20-TUM"	"20-TUM"	"20-TUM"	"20-TUM"	"20-TUM"	"20-TUM"	"20-TUM"
##	[337]	"21-KT"	"21-KT"	"21-KT"	"21-KT"	"21-KT"	"21-KT"	"21-KT"	"21-KT"
##	[345]	"21-KT"	"21-KT"	"21-KT"	"21-KT"	"21-KT"	"21-KT"	"21-KT"	"21-KT"
##	[353]	"21-KT"	"22-OMI"	"22-OMI"	"22-OMI"	"22-OMI"	"22-OMI"	"22-OMI"	"22-OMI"
##	[361]	"22-OMI"	"22-OMI"	"22-OMI"	"22-OMI"	"22-OMI"	"22-OMI"	"22-OMI"	"22-OMI"
##	[369]	"23-PD"	"23-PD"	"23-PD"	"23-PD"	"23-PD"	"23-PD"	"23-PD"	"23-PD"
##	[377]	"23-PD"	"23-PD"	"23-PD"	"23-PD"	"23-PD"	"24-KIL"	"24-KIL"	"24-KIL"
##	[385]	"24-KIL"	"24-KIL"	"24-KIL"	"24-KIL"	"24-KIL"	"24-KIL"	"24-KIL"	"24-KIL"
##	[393]	"24-KIL"	"24-KIL"	"24-KIL"	"24-KIL"	"24-KIL"	"24-KIL"	"24-KIL"	"24-KIL"
##	[401]	"24-KIL"	"24-KIL"	"25-CHU"	"25-CHU"	"25-CHU"	"25-CHU"	"25-CHU"	"25-CHU"
##	[409]	"25-CHU"	"25-CHU"	"25-CHU"	"25-CHU"	"25-CHU"	"25-CHU"	"25-CHU"	"25-CHU"
##	[417]	"25-CHU"	"25-CHU"	"25-CHU"	"25-CHU"	"25-CHU"	"25-CHU"	"25-CHU"	"25-CHU"
##	[425]	"25-CHU"	"25-CHU"	"25-CHU"	"26-OG"	"26-OG"	"26-OG"	"26-OG"	"26-OG"
##	[433]	"26-OG"	"26-OG"	"26-OG"	"26-OG"	"26-OG"	"26-OG"	"26-OG"	"26-OG"
##	[441]	"26-OG"	"26-OG"	"26-OG"	"26-OG"	"26-OG"	"26-OG"	"26-OG"	"26-OG"
##	[449]	"26-OG"	"26-OG"	"26-OG"	"26-OG"	"26-OG"	"26-OG"	"26-OG"	"26-OG"
##	[457]	"26-OG"	"26-OG"	"26-OG"	"26-OG"	"26-OG"	"26-OG"	"26-OG"	"26-OG"
##	[465]	"27-OCA"	"27-OCA"	"27-OCA"	"27-OCA"	"27-OCA"	"27-OCA"	"27-OCA"	"27-OCA"
##	[473]	"27-OCA"	"27-OCA"	"27-OCA"	"27-OCA"	"27-OCA"	"27-OCA"	"27-OCA"	"27-OCA"
##	[481]	"27-OCA"	"27-OCA"	"27-OCA"	"27-OCA"	"28-AKA"	"28-AKA"	"28-AKA"	"28-AKA"
##	[489]	"28-AKA"	"28-AKA"	"28-AKA"	"28-AKA"	"28-AKA"	"28-AKA"	"28-AKA"	"28-AKA"
##	[497]	"28-AKA"	"28-AKA"	"28-AKA"	"28-AKA"	"28-AKA"	"28-AKA"	"28-AKA"	"28-AKA"
##	[505]	"28-AKA"	"28-AKA"	"28-AKA"	"28-AKA"	"28-AKA"	"28-AKA"	"30-OLE"	"30-OLE"
##	[513]	"30-OLE"	"30-OLE"	"30-OLE"	"30-OLE"	"30-OLE"	"30-OLE"	"30-OLE"	"30-OLE"
##	[521]	"30-OLE"	"30-OLE"	"30-OLE"	"30-OLE"	"30-OLE"	"30-OLE"	"30-OLE"	"30-OLE"
##	[529]	"30-OLE"	"30-OLE"	"30-OLE"	"30-OLE"	"30-OLE"	"30-OLE"	"31-ACA"	"31-ACA"
##	[537]	"31-ACA"	"31-ACA"	"31-ACA"	"31-ACA"	"31-ACA"	"31-ACA"	"31-ACA"	"31-ACA"
##	[545]	"31-ACA"	"31-ACA"	"31-ACA"	"31-ACA"	"31-ACA"	"31-ACA"	"31-ACA"	"31-ACA"
##	[553]	"31-ACA"	"31-ACA"	"31-ACA"	"31-ACA"	"31-ACA"	"31-ACA"	"31-ACA"	"32-APU"
##	[561]	"32-APU"	"32-APU"	"32-APU"	"32-APU"	"32-APU"	"32-APU"	"32-APU"	"32-APU"
##	[569]	"32-APU"	"32-APU"	"32-APU"	"32-APU"	"32-APU"	"32-APU"	"32-APU"	"32-APU"
##	[577]	"32-APU"	"32-APU"	"32-APU"	"32-APU"	"32-APU"	"32-APU"	"32-APU"	"32-APU"
##	[585]	"32-APU"	"32-APU"	"32-APU"	"32-APU"	"33-AP"	"33-AP"	"33-AP"	"33-AP"
##	[593]	"33-AP"	"33-AP"	"33-AP"	"33-AP"	"33-AP"	"33-AP"	"33-AP"	"33-AP"
##	[601]	"33-AP"	"33-AP"	"33-AP"	"36-UGT"	"36-UGT"	"36-UGT"	"36-UGT"	"36-UGT"
##	[609]	"36-UGT"	"36-UGT"	"36-UGT"	"36-UGT"	"36-UGT"	"36-UGT"	"36-UGT"	"36-UGT"
##	[617]	"36-UGT"	"36-UGT"	"36-UGT"	"36-UG				

[illegible]

[illegible]

[illegible]

[illegible]

```
## [1465] "83-ND" "83-ND" "83-ND" "83-ND" "83-ND" "83-ND" "83-ND" "83-ND" "83-ND"
## [1473] "83-ND" "83-ND" "83-ND" "83-ND" "84-MAN" "84-MAN" "84-MAN" "84-MAN" "84-MAN"
## [1481] "84-MAN" "84-MAN" "84-MAN" "84-MAN" "84-MAN" "84-MAN" "84-MAN" "84-MAN" "84-MAN"
## [1489] "84-MAN" "84-MAN" "84-MAN" "84-MAN" "84-MAN" "84-MAN" "84-MAN" "84-MAN" "84-MAN"
## [1497] "84-MAN" "84-MAN" "84-MAN" "84-MAN" "84-MAN" "84-MAN" "84-MAN" "84-MAN" "84-MAN"
## [1505] "84-MAN" "84-MAN" "84-MAN" "84-MAN" "84-MAN" "84-MAN" "84-MAN" "84-MAN" "85-KSS"
## [1513] "85-KSS" "85-KSS" "85-KSS" "85-KSS" "85-KSS" "85-KSS" "85-KSS" "85-KSS" "85-KSS"
## [1521] "85-KSS" "85-KSS" "85-KSS" "85-KSS" "85-KSS" "85-KSS" "85-KSS" "85-KSS" "85-KSS"
## [1529] "85-KSS" "85-KSS" "85-KSS" "85-KSS" "85-KSS" "85-KSS" "85-KSS" "85-KSS" "85-KSS"
## [1537] "85-KSS" "85-KSS" "85-KSS" "85-KSS" "85-KSS" "85-KSS" "85-KSS" "85-KSS" "85-KSS"
## [1545] "85-KSS" "85-KSS" "86-SUB" "86-SUB" "86-SUB" "86-SUB" "86-SUB" "86-SUB" "86-SUB"
## [1553] "86-SUB" "86-SUB" "86-SUB" "86-SUB" "86-SUB" "86-SUB" "86-SUB" "86-SUB" "86-SUB"
## [1561] "86-SUB" "86-SUB" "86-SUB" "86-SUB" "86-SUB" "86-SUB" "86-SUB" "86-SUB" "86-SUB"
## [1569] "86-SUB" "86-SUB" "87-KAR" "87-KAR" "87-KAR" "87-KAR" "87-KAR" "87-KAR" "87-KAR"
## [1577] "87-KAR" "87-KAR" "87-KAR" "87-KAR" "87-KAR" "87-KAR" "87-KAR" "87-KAR" "87-KAR"
## [1585] "87-KAR" "87-KAR" "87-KAR" "87-KAR" "87-KAR" "87-KAR" "87-KAR" "87-KAR" "87-KAR"
## [1593] "87-KAR" "87-KAR"
```

```
# Report groupings and selected representative from each 5km cluster
report_df <- data.frame(
  selected = names(report_list),
  group = sapply(report_list, function(x) paste(sort(unique(x)), collapse = ", ")),
  row.names = NULL
)
print(report_df)
```

```
##      selected      group
## 1    01-AIN      01-AIN
## 2    02-GAN      02-GAN
## 3    03-DUK      03-DUK, 04-OM
## 4    05-BLA      05-BLA
## 5    06-LEA      06-LEA
## 6    07-OSG      07-OSG
## 7     08-MY      08-MY
## 8    09-ORB      09-ORB
## 9    10-PAG      10-PAG
## 10   11-OYA      11-OYA
## 11   12-OLO      12-OLO
## 12   14-OKS      13-GOR, 14-OKS
## 13   15-NGO      15-NGO
## 14   16-PAW      16-PAW
## 15   17-LAG      17-LAG
## 16   18-BOL      18-BOL
## 17   19-KTC      19-KTC
## 18   20-TUM      20-TUM
## 19   21-KT       21-KT
## 20   22-OMI      22-OMI
## 21   23-PD       23-PD
## 22   24-KIL      24-KIL
## 23   25-CHU      25-CHU
## 24   26-OG       26-OG
## 25   27-OCA      27-OCA
## 26   28-AKA      28-AKA
## 27   30-OLE      29-KO, 30-OLE
## 28   31-ACA      31-ACA
```

```

## 29 32-APU 32-APU
## 30 33-AP 33-AP
## 31 36-UGT 34-AMI, 35-DK, 36-UGT
## 32 37-OT 37-OT
## 33 38-OCU 38-OCU, 39-OC
## 34 40-KAG 40-KAG
## 35 43-OS 43-OS
## 36 44-MK 44-MK
## 37 45-BKD 45-BKD
## 38 46-PT 46-PT
## 39 47-BK 47-BK
## 40 48-BN 48-BN
## 41 50-KB 50-KB
## 42 51-MF 51-MF
## 43 52-KR 52-KR, 53-UWA
## 44 54-MS 54-MS
## 45 55-KAF 55-KAF
## 46 56-MA 56-MA
## 47 57-KG 57-KG
## 48 58-SS 58-SS
## 49 59-EB 59-EB
## 50 60-NA 60-NA
## 51 61-KO 61-KO
## 52 62-NS 62-NS
## 53 63-DB 63-DB
## 54 64-KL 64-KL
## 55 65-BZ 65-BZ
## 56 66-BY 66-BY
## 57 67-WAM 67-WAM
## 58 68-LI 68-LI
## 59 69-BV 69-BV
## 60 70-MGG 70-MGG
## 61 71-BD 71-BD
## 62 72-JN 72-JN
## 63 73-IGG 73-IGG
## 64 74-NAM 74-NAM
## 65 75-KIS 75-KIS
## 66 76-TB 76-TB, 77-NB
## 67 78-OK 78-OK
## 68 79-BU 79-BU, 80-SA
## 69 81-BUD 81-BUD
## 70 82-BON 82-BON
## 71 83-ND 83-ND
## 72 84-MAN 84-MAN
## 73 85-KSS 85-KSS
## 74 86-SUB 86-SUB
## 75 87-KAR 87-KAR

```

Remove smaller sample size(s) of any 2-3 sites within 2 km of each other: 04-OM, 29-KO, 13-GOR, 34-AMI, 35-DK, 39-OC, 53-UWA, 77-NB, 80-SA

Brings total site count down to 75.

```
Gff.genind_rf # group size 8-236
```

```
## /// GENIND OBJECT //////////
```

```
##
## // 2,532 individuals; 11 loci; 162 alleles; size: 1.8 Mb
##
## // Basic content
##   @tab: 2532 x 162 matrix of allele counts
##   @loc.n.all: number of alleles per locus (range: 7-28)
##   @loc.fac: locus factor for the 162 columns of @tab
##   @all.names: list of allele names for each locus
##   @ploidy: ploidy of each individual (range: 2-2)
##   @type: codon
##   @call: .local(x = x, i = i, j = j, drop = drop)
##
## // Optional content
##   @pop: population of each individual (group size range: 8-236)
table(pop(Gff.genind_rf))
```

```
##
## 01-AIN 02-GAN 03-DUK 05-BLA 06-LEA 07-OSG 08-MY 09-ORB 10-PAG 11-OYA 12-OLO
##      19      20      25      10      8      20      15      20      20      9      24
## 14-OKS 15-NGO 16-PAW 17-LAG 18-BOL 19-KTC 20-TUM 21-KT 22-OMI 23-PD 24-KIL
##      26      25      13      17      25      20      20      17      15      13      21
## 25-CHU 26-OG 27-OCA 28-AKA 30-OLE 31-ACA 32-APU 33-AP 36-UGT 37-OT 38-OCU
##      25      37      20      26      24      25      29      15      64      40      25
## 40-KAG 43-OS 44-MK 45-BKD 46-PT 47-BK 48-BN 50-KB 51-MF 52-KR 54-MS
##      20      32      24      24      26      40      40      40      38      55      30
## 55-KAF 56-MA 57-KG 58-SS 59-EB 60-NA 61-KO 62-NS 63-DB 64-KL 65-BZ
##      236     33      32      40      35      33      40      16      32      40      18
## 66-BY 67-WAM 68-LI 69-BV 70-MGG 71-BD 72-JN 73-IGG 74-NAM 75-KIS 76-TB
##      62      14      46      60      59      35      40      65      15      8      28
## 78-OK 79-BU 81-BUD 82-BON 83-ND 84-MAN 85-KSS 86-SUB 87-KAR
##      119     119      24      24      40      35      35      24      24
```

Too imbalanced... - Downsample 55-KAF, 78-OK, 79-BU to N individuals (e.g., 50) - Remove sites with fewer than n=15

```
# Set thresholds
min_n <- 15
max_n <- 50

# Compute sample sizes per population
pop_sizes <- table(pop(Gff.genind_rf))

# Keep populations with n >= min_n
pops_to_keep <- names(pop_sizes[pop_sizes >= min_n])

# Indices to retain
inds_keep <- unlist(lapply(pops_to_keep, function(p) {
  inds <- which(pop(Gff.genind_rf) == p)
  if (length(inds) > max_n) {
    sample(inds, max_n) # downsample
  } else {
    inds # keep as-is
  }
}))
```



```
#Subset both genind and metadata
```

```
Gff.genind_rf <- Gff.genind_rf[inds_keep]
```

```
Gff_rf <- Gff_rf[inds_keep, ]
```

```
# Re-check population sizes
```

```
Gff.genind_rf
```

```
## /// GENIND OBJECT //////////
```

```
##
```

```
## // 2,068 individuals; 11 loci; 162 alleles; size: 1.5 Mb
```

```
##
```

```
## // Basic content
```

```
## @tab: 2068 x 162 matrix of allele counts
```

```
## @loc.n.all: number of alleles per locus (range: 7-28)
```

```
## @loc.fac: locus factor for the 162 columns of @tab
```

```
## @all.names: list of allele names for each locus
```

```
## @ploidy: ploidy of each individual (range: 2-2)
```

```
## @type: codom
```

```
## @call: .local(x = x, i = i, j = j, drop = drop)
```

```
##
```

```
## // Optional content
```

```
## @pop: population of each individual (group size range: 15-50)
```

```
summary(Gff.genind_rf)
```

```
##
```

```
## // Number of individuals: 2068
```

```
## // Group sizes: 19 20 25 20 15 20 20 24 26 25 17 25 20 20 17 15 21 25 37 20 26 24 25 29 15 50 40 25 1
```

```
## // Number of alleles per locus: 26 7 16 8 10 12 9 13 28 9 18
```

```
## // Number of alleles per group: 65 65 65 60 60 59 57 54 66 57 50 59 56 56 55 60 61 62 70 59 61 58 66
```

```
## // Percentage of missing data: 2.51 %
```

```
## // Observed heterozygosity: 0.71 0.47 0.5 0.19 0.59 0.52 0.32 0.39 0.71 0.51 0.63
```

```
## // Expected heterozygosity: 0.85 0.63 0.69 0.23 0.71 0.73 0.51 0.55 0.87 0.7 0.84
```

```
table(pop(Gff.genind_rf))
```

```
##
```

```
## 01-AIN 02-GAN 03-DUK 07-OSG 08-MY 09-ORB 10-PAG 12-OLO 14-OKS 15-NGO 17-LAG
```

```
## 19 20 25 20 15 20 20 24 26 25 17
```

```
## 18-BOL 19-KTC 20-TUM 21-KT 22-OMI 24-KIL 25-CHU 26-OG 27-OCA 28-AKA 30-OLE
```

```
## 25 20 20 17 15 21 25 37 20 26 24
```

```
## 31-ACA 32-APU 33-AP 36-UGT 37-OT 38-OCU 40-KAG 43-OS 44-MK 45-BKD 46-PT
```

```
## 25 29 15 50 40 25 20 32 24 24 26
```

```
## 47-BK 48-BN 50-KB 51-MF 52-KR 54-MS 55-KAF 56-MA 57-KG 58-SS 59-EB
```

```
## 40 40 40 38 50 30 50 33 32 40 35
```

```
## 60-NA 61-KO 62-NS 63-DB 64-KL 65-BZ 66-BY 68-LI 69-BV 70-MGG 71-BD
```

```
## 33 40 16 32 40 18 50 46 50 50 35
```

```
## 72-JN 73-IGG 74-NAM 76-TB 78-OK 79-BU 81-BUD 82-BON 83-ND 84-MAN 85-KSS
```

```
## 40 50 15 28 50 50 24 24 40 35 35
```

```
## 86-SUB 87-KAR
```

```
## 24 24
```

```
length(unique(Gff_rf$SiteCode))
```

```
## [1] 68
```

Now 68 pops with group size ranges from 15-50.

Genetic diversity

Estimate allelic richness (standardized/rarefied) with pegas

```
genind_hf <- genind2hierfstat(Gff.genind_rf)

# This function rarefies allelic richness to the smallest sample size
allelic_richness <- allelic.richness(genind_hf)

# Extract mean rarefied allelic richness per population
mean_ar <- colMeans(allelic_richness$Ar, na.rm = TRUE)
mean_ar
```

```
##   01-AIN   02-GAN   03-DUK   07-OSG   08-MY   09-ORB   10-PAG   12-OLO
## 4.583157 4.260748 4.324919 4.298275 4.085127 4.124468 3.989337 3.799450
##   14-OKS   15-NGO   17-LAG   18-BOL   19-KTC   20-TUM   21-KT    22-OMI
## 4.158996 4.035677 3.671817 3.970963 4.001584 3.920779 3.954186 4.306697
##   24-KIL   25-CHU   26-OG    27-OCA   28-AKA   30-OLE   31-ACA   32-APU
## 4.053850 3.882766 4.005494 4.195913 3.955369 3.790632 4.011672 3.736532
##   33-AP    36-UGT   37-OT    38-OCU   40-KAG   43-OS    44-MK    45-BKD
## 3.819058 3.615759 3.491427 3.415275 3.498529 3.352508 2.731920 2.899221
##   46-PT    47-BK    48-BN    50-KB    51-MF    52-KR    54-MS    55-KAF
## 2.999925 3.098557 3.452087 3.821452 4.047632 4.130584 3.607622 3.158181
##   56-MA    57-KG    58-SS    59-EB    60-NA    61-KO    62-NS    63-DB
## 2.297347 2.260882 2.463630 2.910498 2.463815 2.444742 2.715141 2.465209
##   64-KL    65-BZ    66-BY    68-LI    69-BV    70-MGG    71-BD    72-JN
## 2.742293 2.972306 3.202754 3.409572 3.228719 3.301905 3.203263 2.776018
##   73-IGG   74-NAM    76-TB    78-OK    79-BU    81-BUD    82-BON    83-ND
## 3.238009 3.443531 3.045357 3.088576 3.127337 3.124326 3.088781 2.251466
##   84-MAN   85-KSS    86-SUB    87-KAR
## 2.628454 2.433326 2.108145 2.310008
```

Most diversity stats use poppr

```
# Compute per-population stats
div_stats <- poppr(Gff.genind_rf)

# View a summary table
div_stats
```

```
##      Pop      N  MLG eMLG      SE      H      G lambda  E.5  Hexp      Ia
## 1  01-AIN    19   19 15.0 1.33e-07 2.94   19.0  0.947 1.000 0.721  0.04162
## 2  02-GAN    20   20 15.0 1.50e-07 3.00   20.0  0.950 1.000 0.695 -0.02912
## 3  03-DUK    25   25 15.0 4.18e-07 3.22   25.0  0.960 1.000 0.687  0.01829
## 4  07-OSG    20   20 15.0 1.50e-07 3.00   20.0  0.950 1.000 0.685 -0.28441
## 5   08-MY    15   15 15.0 0.00e+00 2.71   15.0  0.933 1.000 0.638  0.00679
## 6  09-ORB    20   20 15.0 1.50e-07 3.00   20.0  0.950 1.000 0.646 -0.06216
## 7  10-PAG    20   20 15.0 1.50e-07 3.00   20.0  0.950 1.000 0.649  0.00277
## 8  12-OLO    24   24 15.0 4.63e-07 3.18   24.0  0.958 1.000 0.608  0.01274
## 9  14-OKS    26   26 15.0 2.46e-07 3.26   26.0  0.962 1.000 0.622 -0.08768
## 10 15-NGO    25   25 15.0 4.18e-07 3.22   25.0  0.960 1.000 0.645 -0.06576
## 11 17-LAG    17   17 15.0 0.00e+00 2.83   17.0  0.941 1.000 0.570  0.65876
## 12 18-BOL    25   25 15.0 4.18e-07 3.22   25.0  0.960 1.000 0.614  0.06185
## 13 19-KTC    20   20 15.0 1.50e-07 3.00   20.0  0.950 1.000 0.634  0.17083
```

## 14	20-TUM	20	20	15.0	1.50e-07	3.00	20.0	0.950	1.000	0.603	0.12220
## 15	21-KT	17	17	15.0	0.00e+00	2.83	17.0	0.941	1.000	0.633	0.07529
## 16	22-OMI	15	15	15.0	0.00e+00	2.71	15.0	0.933	1.000	0.632	0.31473
## 17	24-KIL	21	21	15.0	0.00e+00	3.04	21.0	0.952	1.000	0.642	0.09284
## 18	25-CHU	25	25	15.0	4.18e-07	3.22	25.0	0.960	1.000	0.599	0.09597
## 19	26-OG	37	37	15.0	9.13e-07	3.61	37.0	0.973	1.000	0.621	-0.11078
## 20	27-OCA	20	20	15.0	1.50e-07	3.00	20.0	0.950	1.000	0.666	-0.08867
## 21	28-AKA	26	26	15.0	2.46e-07	3.26	26.0	0.962	1.000	0.618	0.06542
## 22	30-OLE	24	24	15.0	4.63e-07	3.18	24.0	0.958	1.000	0.597	0.11002
## 23	31-ACA	25	25	15.0	4.18e-07	3.22	25.0	0.960	1.000	0.606	0.20404
## 24	32-APU	29	29	15.0	9.38e-07	3.37	29.0	0.966	1.000	0.601	-0.06391
## 25	33-AP	15	15	15.0	0.00e+00	2.71	15.0	0.933	1.000	0.606	0.34404
## 26	36-UGT	50	50	15.0	0.00e+00	3.91	50.0	0.980	1.000	0.585	0.08853
## 27	37-OT	40	40	15.0	1.80e-06	3.69	40.0	0.975	1.000	0.571	0.06462
## 28	38-OCU	25	25	15.0	4.18e-07	3.22	25.0	0.960	1.000	0.568	-0.05678
## 29	40-KAG	20	20	15.0	1.50e-07	3.00	20.0	0.950	1.000	0.570	0.29471
## 30	43-OS	32	32	15.0	0.00e+00	3.47	32.0	0.969	1.000	0.540	0.01320
## 31	44-MK	24	24	15.0	4.63e-07	3.18	24.0	0.958	1.000	0.431	-0.10228
## 32	45-BKD	24	24	15.0	4.63e-07	3.18	24.0	0.958	1.000	0.451	-0.06728
## 33	46-PT	26	26	15.0	2.46e-07	3.26	26.0	0.962	1.000	0.511	-0.01831
## 34	47-BK	40	40	15.0	1.80e-06	3.69	40.0	0.975	1.000	0.504	0.11078
## 35	48-BN	40	40	15.0	1.80e-06	3.69	40.0	0.975	1.000	0.578	0.28780
## 36	50-KB	40	40	15.0	1.80e-06	3.69	40.0	0.975	1.000	0.583	-0.10537
## 37	51-MF	38	38	15.0	0.00e+00	3.64	38.0	0.974	1.000	0.636	-0.01558
## 38	52-KR	50	50	15.0	0.00e+00	3.91	50.0	0.980	1.000	0.655	-0.00793
## 39	54-MS	30	30	15.0	6.09e-07	3.40	30.0	0.967	1.000	0.581	0.14182
## 40	55-KAF	50	50	15.0	0.00e+00	3.91	50.0	0.980	1.000	0.497	0.03315
## 41	56-MA	33	33	15.0	0.00e+00	3.50	33.0	0.970	1.000	0.304	0.24065
## 42	57-KG	32	32	15.0	0.00e+00	3.47	32.0	0.969	1.000	0.315	-0.00445
## 43	58-SS	40	40	15.0	1.80e-06	3.69	40.0	0.975	1.000	0.341	0.04044
## 44	59-EB	35	35	15.0	9.66e-07	3.56	35.0	0.971	1.000	0.487	0.42852
## 45	60-NA	33	33	15.0	0.00e+00	3.50	33.0	0.970	1.000	0.467	0.13936
## 46	61-KO	40	40	15.0	1.80e-06	3.69	40.0	0.975	1.000	0.383	-0.07328
## 47	62-NS	16	16	15.0	0.00e+00	2.77	16.0	0.938	1.000	0.407	0.16855
## 48	63-DB	32	32	15.0	0.00e+00	3.47	32.0	0.969	1.000	0.424	-0.04743
## 49	64-KL	40	40	15.0	1.80e-06	3.69	40.0	0.975	1.000	0.479	0.05266
## 50	65-BZ	18	18	15.0	1.05e-07	2.89	18.0	0.944	1.000	0.486	0.06400
## 51	66-BY	50	50	15.0	0.00e+00	3.91	50.0	0.980	1.000	0.509	0.09059
## 52	68-LI	46	46	15.0	0.00e+00	3.83	46.0	0.978	1.000	0.524	-0.00226
## 53	69-BV	50	50	15.0	0.00e+00	3.91	50.0	0.980	1.000	0.534	-0.02767
## 54	70-MGG	50	50	15.0	0.00e+00	3.91	50.0	0.980	1.000	0.519	-0.05398
## 55	71-BD	35	35	15.0	9.66e-07	3.56	35.0	0.971	1.000	0.511	-0.11040
## 56	72-JN	40	40	15.0	1.80e-06	3.69	40.0	0.975	1.000	0.444	0.06943
## 57	73-IGG	50	50	15.0	0.00e+00	3.91	50.0	0.980	1.000	0.528	0.04277
## 58	74-NAM	15	15	15.0	0.00e+00	2.71	15.0	0.933	1.000	0.545	-0.17373
## 59	76-TB	28	28	15.0	0.00e+00	3.33	28.0	0.964	1.000	0.512	-0.00191
## 60	78-OK	50	50	15.0	0.00e+00	3.91	50.0	0.980	1.000	0.514	-0.09053
## 61	79-BU	50	50	15.0	0.00e+00	3.91	50.0	0.980	1.000	0.502	0.11748
## 62	81-BUD	24	24	15.0	4.63e-07	3.18	24.0	0.958	1.000	0.511	0.06376
## 63	82-BON	24	24	15.0	4.63e-07	3.18	24.0	0.958	1.000	0.537	0.34967
## 64	83-ND	40	40	15.0	1.80e-06	3.69	40.0	0.975	1.000	0.354	0.20419
## 65	84-MAN	35	35	15.0	9.66e-07	3.56	35.0	0.971	1.000	0.396	0.07113
## 66	85-KSS	35	35	15.0	9.66e-07	3.56	35.0	0.971	1.000	0.362	-0.05269
## 67	86-SUB	24	24	15.0	4.63e-07	3.18	24.0	0.958	1.000	0.289	0.04648

```

## 68 87-KAR    24    23 14.6 4.85e-01 3.12    22.2  0.955 0.977 0.375  0.03373
## 69 Total 2068 2067 15.0 7.01e-03 7.63 2066.0  1.000 1.000 0.664  0.75189
##      rbarD      File
## 1   0.004200 Gff.genind_rf
## 2  -0.002956 Gff.genind_rf
## 3   0.001847 Gff.genind_rf
## 4  -0.028581 Gff.genind_rf
## 5   0.000700 Gff.genind_rf
## 6  -0.006376 Gff.genind_rf
## 7   0.000282 Gff.genind_rf
## 8   0.001282 Gff.genind_rf
## 9  -0.008886 Gff.genind_rf
## 10 -0.006648 Gff.genind_rf
## 11  0.067972 Gff.genind_rf
## 12  0.006248 Gff.genind_rf
## 13  0.017287 Gff.genind_rf
## 14  0.012386 Gff.genind_rf
## 15  0.007744 Gff.genind_rf
## 16  0.032072 Gff.genind_rf
## 17  0.009369 Gff.genind_rf
## 18  0.009782 Gff.genind_rf
## 19 -0.011138 Gff.genind_rf
## 20 -0.009091 Gff.genind_rf
## 21  0.006631 Gff.genind_rf
## 22  0.011256 Gff.genind_rf
## 23  0.020782 Gff.genind_rf
## 24 -0.006480 Gff.genind_rf
## 25  0.035299 Gff.genind_rf
## 26  0.009062 Gff.genind_rf
## 27  0.006541 Gff.genind_rf
## 28 -0.005804 Gff.genind_rf
## 29  0.029830 Gff.genind_rf
## 30  0.001346 Gff.genind_rf
## 31 -0.010768 Gff.genind_rf
## 32 -0.007719 Gff.genind_rf
## 33 -0.001955 Gff.genind_rf
## 34  0.011300 Gff.genind_rf
## 35  0.032032 Gff.genind_rf
## 36 -0.010561 Gff.genind_rf
## 37 -0.001562 Gff.genind_rf
## 38 -0.000800 Gff.genind_rf
## 39  0.014381 Gff.genind_rf
## 40  0.003590 Gff.genind_rf
## 41  0.028274 Gff.genind_rf
## 42 -0.000513 Gff.genind_rf
## 43  0.004714 Gff.genind_rf
## 44  0.048785 Gff.genind_rf
## 45  0.015967 Gff.genind_rf
## 46 -0.008711 Gff.genind_rf
## 47  0.024362 Gff.genind_rf
## 48 -0.005514 Gff.genind_rf
## 49  0.005902 Gff.genind_rf
## 50  0.007225 Gff.genind_rf
## 51  0.009545 Gff.genind_rf

```

```
## 52 -0.000231 Gff.genind_rf
## 53 -0.002889 Gff.genind_rf
## 54 -0.006035 Gff.genind_rf
## 55 -0.012401 Gff.genind_rf
## 56  0.007418 Gff.genind_rf
## 57  0.004767 Gff.genind_rf
## 58 -0.019502 Gff.genind_rf
## 59 -0.000215 Gff.genind_rf
## 60 -0.010430 Gff.genind_rf
## 61  0.012353 Gff.genind_rf
## 62  0.008090 Gff.genind_rf
## 63  0.043995 Gff.genind_rf
## 64  0.025826 Gff.genind_rf
## 65  0.009257 Gff.genind_rf
## 66 -0.006982 Gff.genind_rf
## 67  0.007154 Gff.genind_rf
## 68  0.004515 Gff.genind_rf
## 69  0.075992 Gff.genind_rf
```

Hierfstat, separating by pop and rarefying to min samples size with 100 replications with own code:

```
# Set rarefaction parameters
# Minimum number of individuals per population to include
min_n <- 15

# Number of random resampling repetitions per population
n_reps <- 100

# Split the genind object by population
# seppop() returns a list of genind objects, one for each population
pop_list <- seppop(Gff.genind_rf)

# For each pop, repeat random sampling n_reps times
# For each replicate:
# - Randomly sample min_n individuals (with no replacement)
# - Convert to hierfstat format
# - Run basic.stats()
# - Extract and average FIS, Ho (observed heterozygosity), and He (expected heterozygosity)
results <- lapply(names(pop_list), function(pname) {
  g <- pop_list[[pname]]
  # Skip populations with fewer than min_n individuals
  if (nInd(g) < min_n) return(NULL)
  # Repeat rarefied sampling n_reps times
  replicate(n_reps, {
    # Randomly sample min_n individuals
    inds <- sample(1:nInd(g), min_n)
    g_sub <- g[inds, ]
    # Convert to hierfstat format and compute basic stats
    hf <- genind2hierfstat(g_sub)
    bs <- basic.stats(hf)
    # Return vector of average values across loci
    c(
      FIS = mean(bs$Fis, na.rm = TRUE),
      Ho  = mean(bs$Ho, na.rm = TRUE),
      He  = mean(bs$Hs, na.rm = TRUE)
    )
  })
})
```

```

    )
  }) |>
    t() |>                                # transpose so each row = one replicate
    as.data.frame()                       # convert to data frame for easy averaging
})

# Average results across replicates for each population
# Keep only populations where stats were successfully computed
names(results) <- names(pop_list)[sapply(results, is.data.frame)]

# Compute mean FIS, Ho, He across replicates
summary_stats <- do.call(rbind, lapply(results, function(df) {
  colMeans(df, na.rm = TRUE)
}))

# Format as a final summary table
summary_df <- data.frame(
  Population = rownames(summary_stats),
  round(summary_stats, 3), # round to 3 decimal places
  row.names = NULL
)

```

Compile results from the three code chunks into one data frame

```

# Convert allelic richness (mean_ar) to a data frame
ar_df <- data.frame(
  Population = names(mean_ar),
  Allelic_Richness = as.numeric(mean_ar),
  row.names = NULL
)

# Convert poppr results (div_stats) to a data frame
# (assumes div_stats has rownames corresponding to populations)
div_stats_df <- data.frame(
  Population = div_stats$Pop,
  div_stats[, setdiff(names(div_stats), "Pop") ],
  row.names = NULL
)

# Merge all three data frames by "Population"
# Use Reduce() for a sequential full join
summary_df <- Reduce(function(x, y) {
  merge(x, y, by = "Population", all = TRUE)
}, list(ar_df, div_stats_df, summary_df))

# Save the combined summary to a CSV file
#write.csv(summary_df, "../input/summary_df.csv", row.names = FALSE)

# Print the final table
print(summary_df)

```

##	Population	Allelic_Richness	N	MLG	eMLG	SE	H
## 1	01-AIN	4.583157	19	19	15.00000	1.332800e-07	2.944439
## 2	02-GAN	4.260748	20	20	15.00000	1.504944e-07	2.995732

## 3	03-DUK	4.324919	25	25	15.00000	4.182955e-07	3.218876
## 4	07-OSG	4.298275	20	20	15.00000	1.504944e-07	2.995732
## 5	08-MY	4.085127	15	15	15.00000	0.000000e+00	2.708050
## 6	09-ORB	4.124468	20	20	15.00000	1.504944e-07	2.995732
## 7	10-PAG	3.989337	20	20	15.00000	1.504944e-07	2.995732
## 8	12-OLO	3.799450	24	24	15.00000	4.626565e-07	3.178054
## 9	14-OKS	4.158996	26	26	15.00000	2.457562e-07	3.258097
## 10	15-NGO	4.035677	25	25	15.00000	4.182955e-07	3.218876
## 11	17-LAG	3.671817	17	17	15.00000	0.000000e+00	2.833213
## 12	18-BOL	3.970963	25	25	15.00000	4.182955e-07	3.218876
## 13	19-KTC	4.001584	20	20	15.00000	1.504944e-07	2.995732
## 14	20-TUM	3.920779	20	20	15.00000	1.504944e-07	2.995732
## 15	21-KT	3.954186	17	17	15.00000	0.000000e+00	2.833213
## 16	22-OMI	4.306697	15	15	15.00000	0.000000e+00	2.708050
## 17	24-KIL	4.053850	21	21	15.00000	0.000000e+00	3.044522
## 18	25-CHU	3.882766	25	25	15.00000	4.182955e-07	3.218876
## 19	26-OG	4.005494	37	37	15.00000	9.127493e-07	3.610918
## 20	27-OCA	4.195913	20	20	15.00000	1.504944e-07	2.995732
## 21	28-ACA	3.955369	26	26	15.00000	2.457562e-07	3.258097
## 22	30-OLE	3.790632	24	24	15.00000	4.626565e-07	3.178054
## 23	31-ACA	4.011672	25	25	15.00000	4.182955e-07	3.218876
## 24	32-APU	3.736532	29	29	15.00000	9.377082e-07	3.367296
## 25	33-AP	3.819058	15	15	15.00000	0.000000e+00	2.708050
## 26	36-UGT	3.615759	50	50	15.00000	0.000000e+00	3.912023
## 27	37-OT	3.491427	40	40	15.00000	1.803964e-06	3.688879
## 28	38-OCU	3.415275	25	25	15.00000	4.182955e-07	3.218876
## 29	40-KAG	3.498529	20	20	15.00000	1.504944e-07	2.995732
## 30	43-OS	3.352508	32	32	15.00000	0.000000e+00	3.465736
## 31	44-MK	2.731920	24	24	15.00000	4.626565e-07	3.178054
## 32	45-BKD	2.899221	24	24	15.00000	4.626565e-07	3.178054
## 33	46-PT	2.999925	26	26	15.00000	2.457562e-07	3.258097
## 34	47-BK	3.098557	40	40	15.00000	1.803964e-06	3.688879
## 35	48-BN	3.452087	40	40	15.00000	1.803964e-06	3.688879
## 36	50-KB	3.821452	40	40	15.00000	1.803964e-06	3.688879
## 37	51-MF	4.047632	38	38	15.00000	0.000000e+00	3.637586
## 38	52-KR	4.130584	50	50	15.00000	0.000000e+00	3.912023
## 39	54-MS	3.607622	30	30	15.00000	6.085806e-07	3.401197
## 40	55-KAF	3.158181	50	50	15.00000	0.000000e+00	3.912023
## 41	56-MA	2.297347	33	33	15.00000	0.000000e+00	3.496508
## 42	57-KG	2.260882	32	32	15.00000	0.000000e+00	3.465736
## 43	58-SS	2.463630	40	40	15.00000	1.803964e-06	3.688879
## 44	59-EB	2.910498	35	35	15.00000	9.657056e-07	3.555348
## 45	60-NA	2.463815	33	33	15.00000	0.000000e+00	3.496508
## 46	61-KO	2.444742	40	40	15.00000	1.803964e-06	3.688879
## 47	62-NS	2.715141	16	16	15.00000	0.000000e+00	2.772589
## 48	63-DB	2.465209	32	32	15.00000	0.000000e+00	3.465736
## 49	64-KL	2.742293	40	40	15.00000	1.803964e-06	3.688879
## 50	65-BZ	2.972306	18	18	15.00000	1.053671e-07	2.890372
## 51	66-BY	3.202754	50	50	15.00000	0.000000e+00	3.912023
## 52	68-LI	3.409572	46	46	15.00000	0.000000e+00	3.828641
## 53	69-BV	3.228719	50	50	15.00000	0.000000e+00	3.912023
## 54	70-MGG	3.301905	50	50	15.00000	0.000000e+00	3.912023
## 55	71-BD	3.203263	35	35	15.00000	9.657056e-07	3.555348
## 56	72-JN	2.776018	40	40	15.00000	1.803964e-06	3.688879

## 57	73-IGG	3.238009	50	50	15.00000	0.000000e+00	3.912023	
## 58	74-NAM	3.443531	15	15	15.00000	0.000000e+00	2.708050	
## 59	76-TB	3.045357	28	28	15.00000	0.000000e+00	3.332205	
## 60	78-OK	3.088576	50	50	15.00000	0.000000e+00	3.912023	
## 61	79-BU	3.127337	50	50	15.00000	0.000000e+00	3.912023	
## 62	81-BUD	3.124326	24	24	15.00000	4.626565e-07	3.178054	
## 63	82-BON	3.088781	24	24	15.00000	4.626565e-07	3.178054	
## 64	83-ND	2.251466	40	40	15.00000	1.803964e-06	3.688879	
## 65	84-MAN	2.628454	35	35	15.00000	9.657056e-07	3.555348	
## 66	85-KSS	2.433326	35	35	15.00000	9.657056e-07	3.555348	
## 67	86-SUB	2.108145	24	24	15.00000	4.626565e-07	3.178054	
## 68	87-KAR	2.310008	24	23	14.61957	4.854937e-01	3.120292	
## 69	Total		NA	2068	2067	14.99995	7.011983e-03	7.633667
##	G	lambda	E.5	Hexp	Ia	rbarD		
## 1	19.00000	0.9473684	1.0000000	0.7208808	0.041616591	0.0042002802		
## 2	20.00000	0.9500000	1.0000000	0.6948870	-0.029117292	-0.0029556143		
## 3	25.00000	0.9600000	1.0000000	0.6866765	0.018290805	0.0018470585		
## 4	20.00000	0.9500000	1.0000000	0.6853279	-0.284413207	-0.0285812567		
## 5	15.00000	0.9333333	1.0000000	0.6384535	0.006791379	0.0006995413		
## 6	20.00000	0.9500000	1.0000000	0.6458834	-0.062158096	-0.0063755282		
## 7	20.00000	0.9500000	1.0000000	0.6489510	0.002766823	0.0002824040		
## 8	24.00000	0.9583333	1.0000000	0.6077979	0.012742568	0.0012822709		
## 9	26.00000	0.9615385	1.0000000	0.6217202	-0.087681707	-0.0088864910		
## 10	25.00000	0.9600000	1.0000000	0.6452916	-0.065758420	-0.0066475919		
## 11	17.00000	0.9411765	1.0000000	0.5699336	0.658758970	0.0679723412		
## 12	25.00000	0.9600000	1.0000000	0.6142299	0.061851960	0.0062484109		
## 13	20.00000	0.9500000	1.0000000	0.6344010	0.170825520	0.0172873245		
## 14	20.00000	0.9500000	1.0000000	0.6033110	0.122202089	0.0123856772		
## 15	17.00000	0.9411765	1.0000000	0.6328068	0.075291161	0.0077435310		
## 16	15.00000	0.9333333	1.0000000	0.6319086	0.314726418	0.0320724946		
## 17	21.00000	0.9523810	1.0000000	0.6418541	0.092842924	0.0093691731		
## 18	25.00000	0.9600000	1.0000000	0.5991458	0.095967779	0.0097815036		
## 19	37.00000	0.9729730	1.0000000	0.6206347	-0.110778501	-0.0111377650		
## 20	20.00000	0.9500000	1.0000000	0.6660260	-0.088671148	-0.0090910872		
## 21	26.00000	0.9615385	1.0000000	0.6180584	0.065423613	0.0066307659		
## 22	24.00000	0.9583333	1.0000000	0.5974624	0.110023484	0.0112558835		
## 23	25.00000	0.9600000	1.0000000	0.6062798	0.204039654	0.0207819184		
## 24	29.00000	0.9655172	1.0000000	0.6007143	-0.063913591	-0.0064798638		
## 25	15.00000	0.9333333	1.0000000	0.6058752	0.344038061	0.0352989160		
## 26	50.00000	0.9800000	1.0000000	0.5845777	0.088533996	0.0090617988		
## 27	40.00000	0.9750000	1.0000000	0.5707955	0.064618140	0.0065406477		
## 28	25.00000	0.9600000	1.0000000	0.5679406	-0.056782035	-0.0058040628		
## 29	20.00000	0.9500000	1.0000000	0.5702670	0.294709961	0.0298300587		
## 30	32.00000	0.9687500	1.0000000	0.5400839	0.013204821	0.0013463203		
## 31	24.00000	0.9583333	1.0000000	0.4307979	-0.102279586	-0.0107682308		
## 32	24.00000	0.9583333	1.0000000	0.4514068	-0.067275704	-0.0077192455		
## 33	26.00000	0.9615385	1.0000000	0.5114544	-0.018314825	-0.0019553909		
## 34	40.00000	0.9750000	1.0000000	0.5043689	0.110779966	0.0113004959		
## 35	40.00000	0.9750000	1.0000000	0.5778481	0.287803253	0.0320317006		
## 36	40.00000	0.9750000	1.0000000	0.5830840	-0.105366399	-0.0105605272		
## 37	38.00000	0.9736842	1.0000000	0.6357320	-0.015579471	-0.0015622365		
## 38	50.00000	0.9800000	1.0000000	0.6545189	-0.007927994	-0.0008004312		
## 39	30.00000	0.9666667	1.0000000	0.5809571	0.141824546	0.0143805742		
## 40	50.00000	0.9800000	1.0000000	0.4967772	0.033145778	0.0035901824		


```

## 41 33.00000 0.9696970 1.0000000 0.3043507 0.240653955 0.0282741339
## 42 32.00000 0.9687500 1.0000000 0.3154762 -0.004454101 -0.0005129762
## 43 40.00000 0.9750000 1.0000000 0.3409243 0.040438533 0.0047139646
## 44 35.00000 0.9714286 1.0000000 0.4873703 0.428520444 0.0487853405
## 45 33.00000 0.9696970 1.0000000 0.4669210 0.139357083 0.0159667239
## 46 40.00000 0.9750000 1.0000000 0.3827947 -0.073278338 -0.0087109335
## 47 16.00000 0.9375000 1.0000000 0.4065526 0.168554828 0.0243624995
## 48 32.00000 0.9687500 1.0000000 0.4241162 -0.047432175 -0.0055144322
## 49 40.00000 0.9750000 1.0000000 0.4789701 0.052661988 0.0059018944
## 50 18.00000 0.9444444 1.0000000 0.4859334 0.063996759 0.0072245000
## 51 50.00000 0.9800000 1.0000000 0.5089285 0.090590732 0.0095454847
## 52 46.00000 0.9782609 1.0000000 0.5244826 -0.002258499 -0.0002305685
## 53 50.00000 0.9800000 1.0000000 0.5339183 -0.027672346 -0.0028892877
## 54 50.00000 0.9800000 1.0000000 0.5193046 -0.053979384 -0.0060350933
## 55 35.00000 0.9714286 1.0000000 0.5112005 -0.110396274 -0.0124005298
## 56 40.00000 0.9750000 1.0000000 0.4444438 0.069428837 0.0074180714
## 57 50.00000 0.9800000 1.0000000 0.5277465 0.042767647 0.0047670215
## 58 15.00000 0.9333333 1.0000000 0.5446010 -0.173733618 -0.0195023913
## 59 28.00000 0.9642857 1.0000000 0.5119924 -0.001908985 -0.0002147069
## 60 50.00000 0.9800000 1.0000000 0.5141629 -0.090534755 -0.0104298411
## 61 50.00000 0.9800000 1.0000000 0.5019481 0.117483054 0.0123526285
## 62 24.00000 0.9583333 1.0000000 0.5110280 0.063755017 0.0080899078
## 63 24.00000 0.9583333 1.0000000 0.5366809 0.349669262 0.0439954174
## 64 40.00000 0.9750000 1.0000000 0.3537687 0.204194236 0.0258259005
## 65 35.00000 0.9714286 1.0000000 0.3963515 0.071133644 0.0092574112
## 66 35.00000 0.9714286 1.0000000 0.3622693 -0.052692176 -0.0069824976
## 67 24.00000 0.9583333 1.0000000 0.2894485 0.046481546 0.0071543028
## 68 22.15385 0.9548611 0.9769483 0.3752051 0.033730644 0.0045145283
## 69 2066.00193 0.9995160 0.9997036 0.6643510 0.751892157 0.0759915177
##      File      FIS      Ho      He
## 1 Gff.genind_rf 0.041 0.691 0.721
## 2 Gff.genind_rf 0.189 0.570 0.698
## 3 Gff.genind_rf 0.155 0.575 0.688
## 4 Gff.genind_rf 0.137 0.585 0.689
## 5 Gff.genind_rf 0.082 0.576 0.641
## 6 Gff.genind_rf 0.195 0.532 0.649
## 7 Gff.genind_rf 0.160 0.550 0.651
## 8 Gff.genind_rf 0.036 0.587 0.608
## 9 Gff.genind_rf 0.074 0.562 0.620
## 10 Gff.genind_rf 0.044 0.620 0.645
## 11 Gff.genind_rf 0.138 0.488 0.569
## 12 Gff.genind_rf 0.046 0.582 0.614
## 13 Gff.genind_rf 0.072 0.575 0.636
## 14 Gff.genind_rf 0.043 0.564 0.606
## 15 Gff.genind_rf 0.126 0.557 0.637
## 16 Gff.genind_rf 0.155 0.560 0.635
## 17 Gff.genind_rf 0.048 0.604 0.641
## 18 Gff.genind_rf 0.003 0.593 0.601
## 19 Gff.genind_rf 0.016 0.623 0.622
## 20 Gff.genind_rf 0.014 0.641 0.667
## 21 Gff.genind_rf -0.011 0.621 0.617
## 22 Gff.genind_rf 0.027 0.577 0.597
## 23 Gff.genind_rf 0.044 0.569 0.607
## 24 Gff.genind_rf 0.068 0.556 0.603

```

```
## 25 Gff.genind_rf 0.085 0.556 0.608
## 26 Gff.genind_rf 0.082 0.536 0.584
## 27 Gff.genind_rf 0.050 0.538 0.570
## 28 Gff.genind_rf -0.003 0.555 0.569
## 29 Gff.genind_rf 0.204 0.479 0.574
## 30 Gff.genind_rf 0.066 0.514 0.547
## 31 Gff.genind_rf -0.064 0.459 0.432
## 32 Gff.genind_rf 0.068 0.417 0.453
## 33 Gff.genind_rf 0.068 0.484 0.514
## 34 Gff.genind_rf 0.087 0.458 0.503
## 35 Gff.genind_rf 0.084 0.524 0.578
## 36 Gff.genind_rf -0.011 0.591 0.581
## 37 Gff.genind_rf 0.009 0.629 0.635
## 38 Gff.genind_rf 0.096 0.593 0.657
## 39 Gff.genind_rf 0.056 0.553 0.578
## 40 Gff.genind_rf 0.081 0.464 0.495
## 41 Gff.genind_rf -0.100 0.340 0.304
## 42 Gff.genind_rf 0.009 0.309 0.314
## 43 Gff.genind_rf 0.031 0.322 0.341
## 44 Gff.genind_rf 0.024 0.469 0.488
## 45 Gff.genind_rf -0.105 0.508 0.466
## 46 Gff.genind_rf 0.023 0.375 0.385
## 47 Gff.genind_rf 0.102 0.386 0.407
## 48 Gff.genind_rf -0.027 0.440 0.424
## 49 Gff.genind_rf 0.023 0.482 0.478
## 50 Gff.genind_rf 0.074 0.457 0.487
## 51 Gff.genind_rf 0.032 0.489 0.510
## 52 Gff.genind_rf 0.002 0.529 0.525
## 53 Gff.genind_rf 0.072 0.498 0.534
## 54 Gff.genind_rf 0.014 0.511 0.520
## 55 Gff.genind_rf 0.014 0.506 0.510
## 56 Gff.genind_rf 0.024 0.433 0.443
## 57 Gff.genind_rf 0.081 0.490 0.530
## 58 Gff.genind_rf -0.026 0.559 0.544
## 59 Gff.genind_rf 0.026 0.495 0.512
## 60 Gff.genind_rf 0.012 0.507 0.512
## 61 Gff.genind_rf 0.073 0.463 0.498
## 62 Gff.genind_rf 0.066 0.485 0.511
## 63 Gff.genind_rf -0.072 0.574 0.537
## 64 Gff.genind_rf -0.012 0.361 0.354
## 65 Gff.genind_rf -0.008 0.402 0.394
## 66 Gff.genind_rf 0.053 0.339 0.360
## 67 Gff.genind_rf 0.030 0.287 0.294
## 68 Gff.genind_rf 0.296 0.260 0.377
## 69 Gff.genind_rf      NA      NA      NA
```

Cavalli-Sforza and Edwards' Distance (CSE)

Pairwise within cluster "north"

```
# Subset genind and metadata
meta_sub <- Gff_rf[Gff_rf$K2 == "north", ]
gen_sub <- Gff.genind_rf[pop(Gff.genind_rf) %in% meta_sub$SiteCode]
```

```

# Convert to genpop (aggregates by population)
genpop_sub <- genind2genpop(gen_sub)

##
## Converting data from a genind to a genpop object...
##
## ...done.

# Compute Cavalli-Sforza and Edwards' distance
cse_dist <- dist.genpop(genpop_sub, method = 2) # method = 2 (CSE distance)

# Display as a matrix
cse_north <- as.matrix(cse_dist)

```

Pairwise within cluster "south"

```

# Subset genind and metadata
meta_sub <- Gff_rf[Gff_rf$K2 == "south", ]
gen_sub <- Gff.genind_rf[pop(Gff.genind_rf) %in% meta_sub$SiteCode]

# Convert to genpop (aggregates by population)
genpop_sub <- genind2genpop(gen_sub)

##
## Converting data from a genind to a genpop object...
##
## ...done.

# Compute Cavalli-Sforza and Edwards' distance
cse_dist <- dist.genpop(genpop_sub, method = 2) # method = 2 (CSE distance)

# Display as a matrix
cse_south <- as.matrix(cse_dist)

```

Combine CSE output into a single dataframe for downstream analysis:

```

# Create a metadata data frame for coordinates and cluster
meta_coords <- unique(Gff_rf[, c("SiteCode", "SiteLat", "SiteLong", "K2")])
names(meta_coords) <- c("SiteCode", "lat", "long", "cluster")

# Process the "north" CSE matrix
north_df <- as.data.frame(as.table(cse_north), stringsAsFactors = FALSE)
names(north_df) <- c("Var1", "Var2", "CSEdistance")

# Keep only one triangle (Var1 < Var2 alphabetically)
north_df <- subset(north_df, Var1 < Var2)

# Merge to get lat1, long1, and Pop1_cluster
north_df <- merge(
  north_df,
  meta_coords,
  by.x = "Var1",
  by.y = "SiteCode",
  all.x = TRUE,
  suffixes = c("", ".ignore")
)
names(north_df)[names(north_df) == "lat"] <- "lat1"

```

```

names(north_df)[names(north_df) == "long"]      <- "long1"
names(north_df)[names(north_df) == "cluster"]    <- "Pop1_cluster"

# Merge to get lat2, long2, and Pop2_cluster
north_df <- merge(
  north_df,
  meta_coords,
  by.x = "Var2",
  by.y = "SiteCode",
  all.x = TRUE,
  suffixes = c("", ".ignore")
)
names(north_df)[names(north_df) == "lat"]        <- "lat2"
names(north_df)[names(north_df) == "long"]       <- "long2"
names(north_df)[names(north_df) == "cluster"]    <- "Pop2_cluster"
# Select and order columns
north_df <- north_df[, c(
  "Var1", "Var2", "CSEdistance",
  "lat1", "long1", "lat2", "long2",
  "Pop1_cluster", "Pop2_cluster"
)]

# Process the "south" CSE matrix (analogous steps)
south_df <- as.data.frame(as.table(cse_south), stringsAsFactors = FALSE)
names(south_df) <- c("Var1", "Var2", "CSEdistance")
south_df <- subset(south_df, Var1 < Var2)
south_df <- merge(
  south_df,
  meta_coords,
  by.x = "Var1",
  by.y = "SiteCode",
  all.x = TRUE,
  suffixes = c("", ".ignore")
)
names(south_df)[names(south_df) == "lat"]        <- "lat1"
names(south_df)[names(south_df) == "long"]       <- "long1"
names(south_df)[names(south_df) == "cluster"]    <- "Pop1_cluster"
south_df <- merge(
  south_df,
  meta_coords,
  by.x = "Var2",
  by.y = "SiteCode",
  all.x = TRUE,
  suffixes = c("", ".ignore")
)
names(south_df)[names(south_df) == "lat"]        <- "lat2"
names(south_df)[names(south_df) == "long"]       <- "long2"
names(south_df)[names(south_df) == "cluster"]    <- "Pop2_cluster"
south_df <- south_df[, c(
  "Var1", "Var2", "CSEdistance",
  "lat1", "long1", "lat2", "long2",
  "Pop1_cluster", "Pop2_cluster"
)]

```

```

# Combine "north" and "south" results
cse_combined <- rbind(north_df, south_df)

# Save to CSV
#write.csv(cse_combined, "../input/Gff_11loci_68sites_cse.csv", row.names = FALSE)

# View the first few rows
head(cse_combined)

```

```

##      Var1  Var2 CSEdistance  lat1  long1  lat2  long2 Pop1_cluster
## 1 01-AIN 02-GAN    0.2424627 3.3044 31.1191 3.2521 31.1231      north
## 2 01-AIN 03-DUK    0.3169412 3.3044 31.1191 3.2671 31.1352      north
## 3 02-GAN 03-DUK    0.3076377 3.2521 31.1231 3.2671 31.1352      north
## 4 03-DUK 07-OSG    0.4064882 3.2671 31.1352 3.2110 31.7253      north
## 5 02-GAN 07-OSG    0.3732382 3.2521 31.1231 3.2110 31.7253      north
## 6 01-AIN 07-OSG    0.3726589 3.3044 31.1191 3.2110 31.7253      north
##   Pop2_cluster
## 1         north
## 2         north
## 3         north
## 4         north
## 5         north
## 6         north

```

Create density plots of CSEdistance for each cluster

```

# Capitalize or rename cluster labels ("Northern"/"Southern")
cse_combined <- cse_combined %>%
  mutate(
    Pop1_cluster = case_when(
      Pop1_cluster == "north" ~ "Northern",
      Pop1_cluster == "south" ~ "Southern",
      TRUE ~ Pop1_cluster
    ),
    Pop2_cluster = case_when(
      Pop2_cluster == "north" ~ "Northern",
      Pop2_cluster == "south" ~ "Southern",
      TRUE ~ Pop2_cluster
    )
  )
# Create two density plots (one for "Northern", one for "Southern")
cluster_names <- unique(
  cse_combined$Pop1_cluster[cse_combined$Pop1_cluster == cse_combined$Pop2_cluster]
)
density_plots <- lapply(cluster_names, function(cl) {
  df <- filter(cse_combined, Pop1_cluster == cl & Pop2_cluster == cl)
  ggplot(df, aes(x = CSEdistance)) +
    geom_density(fill = "grey80", color = "black") +
    labs(
      title = paste0(cl, " Genetic Cluster"),
      x = "CSE Distance",
      y = "Density"
    ) +
    theme_minimal() +
    theme(

```

```

    plot.title = element_text(size = 12, face = "bold", hjust = 0.5),
    axis.title = element_text(size = 10),
    axis.text = element_text(size = 9)
  )
})
# Turn each row into an sf LINESTRING, colored by CSE
lines_list <- lapply(seq_len(nrow(cse_combined)), function(i) {
  coords <- matrix(
    c(
      cse_combined$long1[i], cse_combined$lat1[i],
      cse_combined$long2[i], cse_combined$lat2[i]
    ),
    ncol = 2,
    byrow = TRUE
  )
  st_linestring(coords)
})
lines_sf <- st_sf(
  geometry = st_sfc(lines_list, crs = 4326),
  CSE = cse_combined$CSEdistance
)
# 5. Load Uganda outline as an sf object
uganda <- ne_countries(scale = "medium", country = "Uganda", returnclass = "sf")

# 6. Build the map with reversed "magma" (yellow→purple) and
#    move legend to the right, vertically centered
map_plot <- ggplot() +
  geom_sf(data = uganda, fill = "white", color = "black") +
  geom_sf(
    data = lines_sf,
    aes(color = CSE),
    size = 0.6
  ) +
  scale_color_viridis_c(
    name = "CSE",
    option = "magma", # use the "magma" palette
    direction = -1    # reverse so low = yellow, high = purple
  ) +
  theme_void() +
  theme(
    # place legend at (x=0.95, y=0.50) relative to entire panel
    legend.position = c(1.3, 0.50),
    legend.background = element_rect(fill = alpha("white", 0.6), color = NA),
    legend.title = element_text(size = 9),
    legend.text = element_text(size = 8)
  )
)

```

```

## Warning: A numeric 'legend.position' argument in 'theme()' was deprecated in ggplot2
## 3.5.0.
## i Please use the 'legend.position.inside' argument of 'theme()' instead.
## This warning is displayed once every 8 hours.
## Call 'lifecycle::last_lifecycle_warnings()' to see where this warning was
## generated.

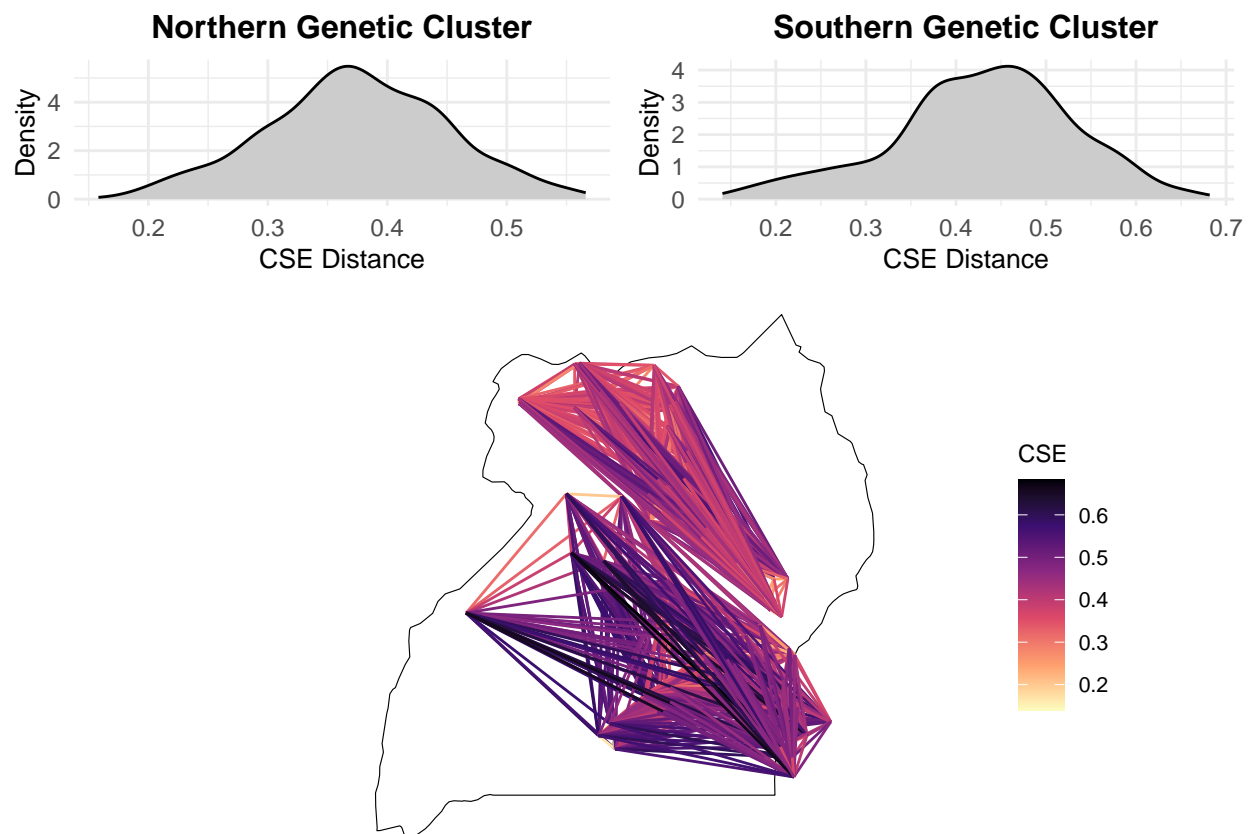
```

```

# 7. Combine the two density plots (top) and the map (bottom)
top_row <- plot_grid(
  plotlist = density_plots,
  nrow = 1,
  rel_widths = rep(1, length(density_plots))
)
final_figure <- plot_grid(
  top_row,
  map_plot,
  ncol = 1,
  rel_heights = c(1, 2)
)

# Display CSE density plots
#pdf("../figures/CSE_density.pdf", width = 14, height = 10)
final_figure

```



```

#dev.off()

```