
title: "Genetic Diversity of Invasive Pyrus calleryana trees"

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Pyrus calleryana (callery pear) trees were imported from China to the US to combat fireblight disease in European pear in 1917. Those callery pear trees were hugely used as rootstock for several edible pears. Now, these trees are invasive species in most of the eastern and southern states of the US. For our study, P. calleryana samples were collected from China, Japan, Korea and US. Initially, we had 100 samples but at the end, we were limited with only 57 samples as other samples were cutoff due to several reasons. Our study aims at studying the genetic diversity of those trees and evaluate the relatedness of US species with the Asian ones. Microsatellite loci are used for the study.

library(yaml) library(tidyr) library(poppr) library(hierfstat) library(mmod) library(ape) library(magrittr) library(adegenet) library(MASS) library(geiger) library(pegas) library(treemap) library(car) library(agricolae) library(ggplot2) library(foreign) library(plyr) library(caTools)

library(reshape2)

library(ecodist)

```
library(polysat)
library(radiator)
library(diveRsity)
library(doParallel)
library(xlsx)
library(shiny)
library(rJava)
library(PopGenReport)
library(devtools)
library(roxygen2)
library(pegas)
library(lattice)
library(ade4)
library(vegan)
#Loading Genalex datafile
```{r}
tks <- read.genalex("C:/Users/ssapkot1/Desktop/GenalexAsian.csv", ploidy = 2, geo = FALSE, region =
FALSE, genclone = FALSE)
tks
/// GENIND OBJECT ///////
 // 57 individuals; 18 loci; 220 alleles; size: 94.5 Kb
 // Basic content
@tab: 57 x 220
 57 x 220 matrix of allele counts
 @loc.n.all: number of alleles per locus (range: 5-20)
 @loc.fac: locus factor for the 220 columns of @tab
 @all.names: list of allele names for each locus
 @ploidy: ploidy of each individual (range: 2-2)
 @type: codom
@call: read.genalex(genalex = "GenalexAsian.csv", ploidy = 2,
 geo = FALSE, region = FALSE, genclone = FALSE)
 // Optional content
 @pop: population of each individual (group size range: 5-21)
 @strata: a data frame with 1 columns (Pop)
```

```
Doing Clone correction
```

```
missingno(tks, type = "loci", cutoff = 0.99, quiet = FALSE,
freq = FALSE)
setPop(tks) <- ~Pop
tks<-clonecorrect(tks, strata = ~Pop, combine = FALSE, keep = 1)
tks
...
```

No loci with missing values above 99% found.

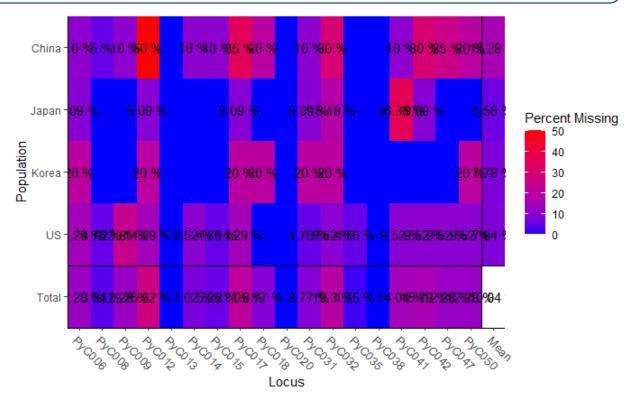
# Displaying the class of datafile

```
class(tks)

[1] "genind"
attr(,"package")
[1] "adegenet"
```

### # Displaying information about loci and populations

```
'``{r}
info_table(tks, plot = TRUE)
'``
```



#### # Basic statistics

```
"\{r\}
summary(tks)
""

// Number of individuals: 57
// Group sizes: 20 11 5 21
// Number of alleles per locus: 10 16 15 13 14 14 18 20 16 13 20 6 13 6 8 7 6
5
// Number of alleles per group: 149 107 46 134
// Percentage of missing data: 10.04 %
// Observed heterozygosity: 0.18 0.47 0.24 0.12 0.42 0.23 0.11 0.71 0.73 0.4
0.77 0.09 0.43 0.95 0.29 0.06 0.24 0.04
// Expected heterozygosity: 0.72 0.86 0.84 0.88 0.83 0.85 0.86 0.91 0.9 0.79
0.91 0.73 0.85 0.76 0.8 0.8 0.75 0.4
```

```
```{r}
BS <- basic.stats(tks)
BS
```

```
$perloc
                                                                         Fis
           НО
                  HS
                          Ηt
                                 Dst
                                        Htp
                                               Dstp
                                                         Fst
                                                                Fstp
Dest
PyC006 0.1250 0.6377 0.6919
                              0.0542 0.7100
                                             0.0723
                                                      0.0784
                                                              0.1018
                                                                      0.8040
0.1996
                             0.1809 0.9470
PyC008 0.3596 0.7058 0.8867
                                             0.2412
                                                     0.2040
                                                             0.2547
                                                                      0.4904
0.8198
PyC009 0.2458 0.8606 0.8460 -0.0146 0.8411 -0.0194 -0.0172 -0.0231
                                                                      0.7143 -
0.1392
PyC012 0.0806 0.7971 0.9160 0.1189 0.9556
                                            0.1586
                                                     0.1298
                                                              0.1659
                                                                      0.8989
0.7814
PyC013 0.4348 0.7552 0.8473
                              0.0921 0.8779
                                             0.1227
                                                      0.1087
                                                              0.1398
                                                                      0.4242
0.5014
PyC014 0.2072 0.7201 0.8704
                              0.1503 0.9205
                                             0.2004
                                                      0.1727
                                                              0.2177
                                                                      0.7122
0.7159
                              0.1960 0.9529
PyC015 0.1187 0.6916 0.8876
                                             0.2613
                                                      0.2208
                                                              0.2742
                                                                      0.8284
0.8473
PyC017 0.5983 0.8403 0.8954
                              0.0551 0.9138
                                             0.0735
                                                      0.0616
                                                              0.0804
                                                                      0.2880
0.4602
PyC018 0.6518 0.8485 0.9063
                             0.0578 0.9256
                                             0.0771
                                                     0.0638
                                                              0.0832
                                                                      0.2319
0.5087
PyC020 0.3872 0.7488 0.7864
                              0.0375 0.7989
                                             0.0500
                                                      0.0477
                                                              0.0626
                                                                      0.4829
0.1993
PyC031 0.8389 0.8707 0.9263
                             0.0556 0.9448
                                             0.0741
                                                     0.0600
                                                              0.0785
                                                                      0.0365
0.5734
PyC032 0.0913 0.5220 0.7302
                             0.2081 0.7996
                                             0.2775
                                                     0.2851
                                                             0.3471
                                                                      0.8252
0.5806
PyC035 0.4091 0.8422 0.8785 0.0362 0.8905
                                             0.0483
                                                     0.0413
                                                             0.0543
0.3063
PyC038 0.9318 0.7585 0.7505 -0.0080 0.7478 -0.0107 -0.0107 -0.0143 -0.2286 -
0.0441
PyC041 0.2938 0.8132 0.8189
                             0.0056 0.8207
                                             0.0075
                                                      0.0069
                                                              0.0091
                                                                      0.6387
0.0402
PyC042 0.0560 0.6428 0.8308
                             0.1879 0.8934
                                             0.2506
                                                     0.2262
                                                              0.2805
                                                                      0.9129
0.7016
PyC047 0.1770 0.6775 0.7646
                             0.0871 0.7936
                                             0.1161
                                                     0.1139
                                                              0.1463
                                                                      0.7387
0.3599
PyC050 0.0312 0.3485 0.3816 0.0330 0.3926
                                             0.0441
                                                     0.0866
                                                             0.1122 0.9103
0.0676
$overall
                                                             Fis
    Но
           HS
                        Dst
                                Htp
                                      Dstp
                                              Fst
                                                     Fstp
```

0.3355 0.7267 0.8120 0.0852 0.8404 0.1136 0.1050 0.1352 0.5384 0.4158

Testing Hardy-Weinberg Equillibrium

```
hw.test(tks, B = 1000) #Rough test. Pr.exact = 0 -> Locus not in HWE.

(tks.HWE <- hw.test(tks, B = 1000)) # performs 1000 permuatations

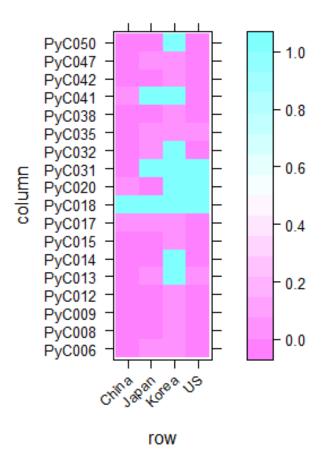
(tks.HWE.pop <- seppop(tks) %>% lapply(hw.test, B = 1000)) #by population

(tks.HWE.mat <- sapply(tks.HWE.pop, "[", i = TRUE, j = 3)) # Take the third column with all rows alpha <- 0.05

tksHWEmat <- tks.HWE.mat

tksHWEmat[tksHWEmat > alpha] <- 1

levelplot(t(tksHWEmat), scales=list(x=list(rot=43)))
```



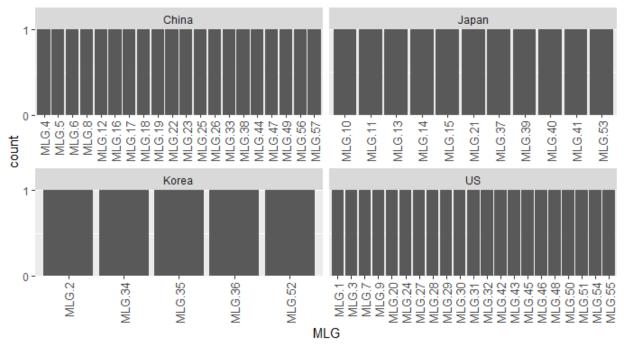
#Looking how uninformatic loci are

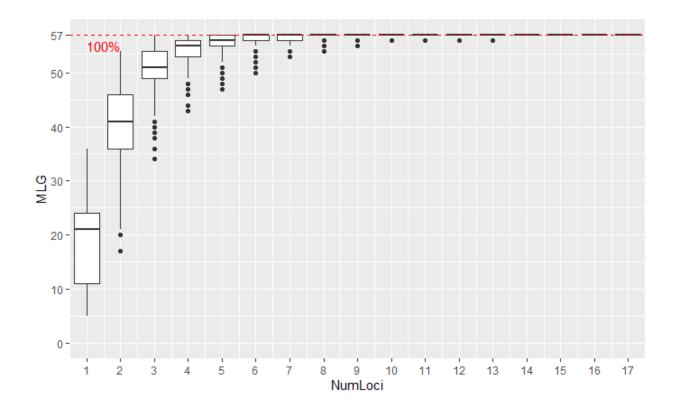
gac

P.tab<-mlg.table(tks)

Data: tks N = 57 MLG = 57

٠,





```
#Linkage disequilibrium (LD)
```

#The index of association

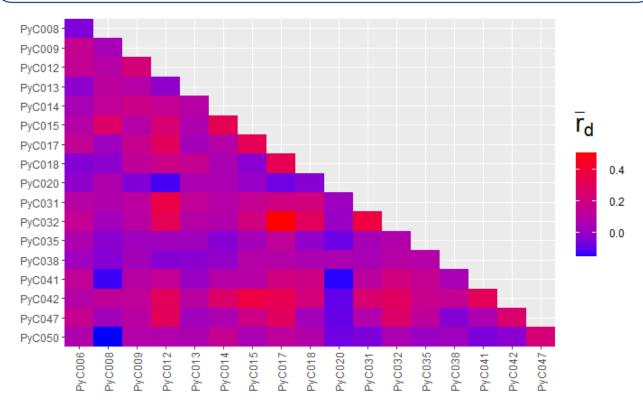
```
tks2 <- popsub(tks)
set.seed(1044)
ia(tks2, hist = TRUE, sample = 999)
...
```

Completed after 6 $\rm m$

Ia p.Ia rbarD p.rD 1.9201013 0.1180000 0.1152366 0.1130000

#Pairwise LD over all loci

```
tkspair <- tks %>% clonecorrect(strata = ~Pop) %>% pair.ia
plot(tkspair, limits = plotrange, label=TRUE, low = "orange", high = "purple")
...
```

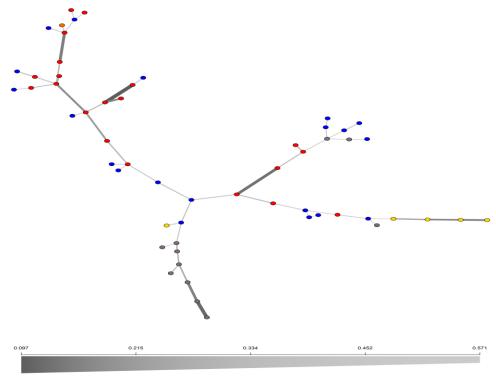


#Minimum spanning network

```
Imsn()
tks_sub <- popsub(tks, blacklist = character(0))
tks_dist <- diss.dist(tks_sub, percent = FALSE, mat = FALSE)
min_span_net <- poppr.msn(tks_sub, tks_dist, showplot = FALSE, include.ties = TRUE)
set.seed(69)
plot_poppr_msn(tks, min_span_net, inds = "ALL", mlg = FALSE, gadj = 6, nodescale = 10,
palette = seasun, cutoff = NULL, quantiles = FALSE, beforecut = TRUE, pop.leg = TRUE,
size.leg = FALSE, scale.leg = TRUE, layfun = igraph::layout_nicely)</pre>
```

POPULATION



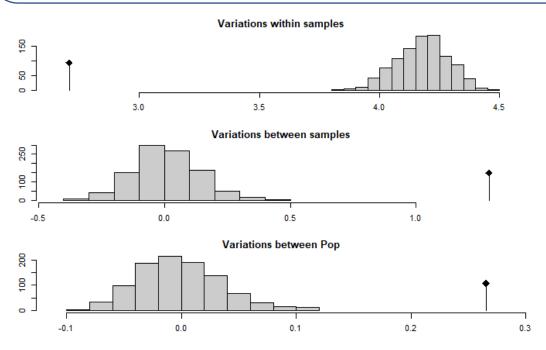


DISTANCE

```
```{r}
tks <- as.genclone(tks)
tks
table (strata(tks, ~Pop))
tksamova <- poppr.amova(tks, ~Pop)
tksamova
This is a genclone object
Genotype information:
 57 original multilocus genotypes
 57 diploid individuals
 18 codominant loci
Population information:
 1 stratum - Pop
 4 populations defined - China, Japan, Korea, US
China Japan Korea
 20
 11
Found 1215 missing values.
13 loci contained missing values greater than 5%
Removing 13 loci: PyC006, PyC009, PyC012, PyC014, PyC015, PyC017, PyC018,
PyC031, PyC032, PyC041, PyC042, PyC047, PyC050 Distance matrix is non-euclidean.
Using quasieuclid correction method. See ?quasieuclid for details.
ade4::amova(samples = xtab, distances = xdist, structures = xstruct)
$results
 Df
 Sum Sq
 Mean Sq
 36.92288 12.307627
Between Pop
 53 280.15363
Between samples Within Pop
 5.285917
 57 154.33570
 2.707644
Within samples
 113 471.41221
 4.171789
Total
$componentsofcovariance
 Sigma
 0.2654095
Variations
 Between Pop
 6.227067
Variations
 Between samples Within Pop 1.2891368
 30.245877
 2.7076439
 Within samples
 63.527056
Variations
Total variations
 4.2621902 100.000000
$statphi
Phi-samples-total 0.36472944
Phi-samples-Pop
 0.32254378
Phi-Pop-total
 0.06227067
```

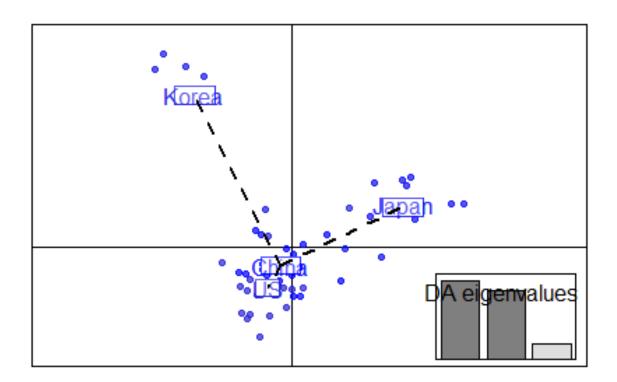
# #Significance testing

```
set.seed(1999)
tkssignif <- randtest(tksamova, nrepet = 999)
plot(tkssignif)
tkssignif
...</pre>
```



#Discriminant analysis of principal components (DAPC)

```
"`{r}
I.col <- seasun(40)
pop(tks) <- tks$pop
dapc.tks <- dapc(tks, var.contrib = TRUE, scale = FALSE, n.pca = 19, n.da = nPop(tks) - 1)
scatter(dapc.tks, col=l.col, cell = 0, cstar = 0, mstree = TRUE, lwd = 2, lty = 2)
...</pre>
```



### **#DAPC** cross-valiation

```
````{r}
set.seed(1044)
pramx <- xvalDapc(tab(tks, NA.method = "mean"), pop(tks))</pre>
system.time(pramx <- xvalDapc(tab(tks, NA.method = "mean"), pop(tks),
                 n.pca = 5:25, n.rep = 10,
                parallel = "multicore", ncpus = 4L))
names(pramx)
pramx[-1]
max(pramx$'Mean Successful Assignment by Number of PCs of PCA')
scatter(dapc.tks, cex = 2, label.inds = FALSE, col = l.col, legend = TRUE, clabel = TRUE, posi.leg =
"bottomleft", scree.pca = FALSE, scree.da = TRUE, posi.pca = "topleft", posi.da = "bottomright", cleg =
0.75, xax = 1, yax = 2, inset.solid = 1, cstar=0)
scatter(dapc.tks, cex = 2, label.inds = NULL, col = l.col, legend = FALSE, clabel = TRUE, posi.leg = "topleft",
scree.pca = FALSE, scree.da = TRUE, posi.pca = "topright", posi.da = "bottomright", cleg = 0.75, xax = 1,
yax = 2, inset.solid = 1, cstar=0)
contrib <- loadingplot(dapc.tks$var.contr, axis = 2, thres = 0.055, lab.jitter = 1)</pre>
```

