

agricolae tutorial (Version 1.2-7)

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Preface

The following document was developed to facilitate the use of agricolae package in R, it is understood that the user knows the statistical methodology for the design and analysis of experiments and through the use of the functions programmed in agricolae facilitate the generation of the field book experimental design and their analysis. The first part document describes the use of graph.freq role is complementary to the *hist* function of R functions to facilitate the collection of statistics and frequency table, statistics or grouped data histogram based training grouped data and graphics as frequency polygon or ogive; second part is the development of experimental plans and numbering of the units as used in an agricultural experiment; a third part corresponding to the comparative tests and finally provides agricolae miscellaneous additional functions applied in agricultural research and stability functions, soil consistency, late blight simulation and others.

1 Introduction

The package **agricolae** offers a broad functionality in the design of experiments, especially for experiments in agriculture and improvements of plants, which can also be used for other purposes. It contains the following designs: lattice, alpha, cyclic, balanced incomplete block designs, complete randomized blocks, Latin, Graeco-Latin, augmented block designs, split plot and strip plot. It also has several procedures of experimental data analysis, such as the comparisons of treatments of Waller-Duncan, Bonferroni, Duncan, Student-Newman-Keuls, Scheffe, Ryan, Einot and Gabriel and Welsch multiple range test or the classic LSD and Tukey; and non-parametric comparisons, such as Kruskal-Wallis, Friedman, Durbin, Median and Waerden, stability analysis, and other procedures applied in genetics, as well as procedures in biodiversity and descriptive statistics, [De Mendiburu \(2009\)](#)

1.1 Installation

The main program of **R** should be already installed in the platform of your computer (*Windows, Linux or MAC*). If it is not installed yet, you can download it from the R project (www.r-project.org) of a repository CRAN, [R Core Team \(2017\)](#).

`> install.packages("agricolae")` Once the agricolae package is installed, it needs to be made accessible to the current **R** session by the command:

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```
> library(agricolae)
```

For online help facilities or the details of a particular command (such as the function `waller.test`) you can type:

```
> help(package="agricolae")
> help(waller.test)
```

For a complete functionality, **agricolae** requires other packages

MASS: for the generalized inverse used in the function *PBIB.test*

nlme: for the methods REML and LM in *PBIB.test*

klaR: for the function *triplot* used in the function *AMMI*

Cluster: for the use of the function *consensus*

spdep: for the between genotypes spatial relation in biplot of the function *AMMI*

algDesign: for the balanced incomplete block design *design.bib*

1.2 Use in R

Since **agricolae** is a package of functions, these are operational when they are called directly from the console of **R** and are integrated to all the base functions of **R**. The following orders are frequent:

```
> detach(package:agricolae) # detach package agricole
> library(agricolae) # Load the package to the memory
> designs<-apropos("design")
> print(designs[substr(designs,1,6)=="design"], row.names=FALSE)

[1] "design.ab"      "design.alpha"  "design.bib"
[4] "design.crd"     "design.cyclic" "design.dau"
[7] "design.graeco"  "design.lattice" "design.lsd"
[10] "design.rcbd"    "design.split"  "design.strip"
[13] "design.youden"
```

For the use of symbols that do not appear in the keyboard in Spanish, such as:

~, [,], &, ^, |. <, >, {, }, \% or others, use the table ASCII code.

```
> library(agricolae) # Load the package to the memory:
```

In order to continue with the command line, do not forget to close the open windows with any R order. For help:

```
help(graph.freq)
? (graph.freq)
str(normal.freq)
example(join.freq)
```

1.3 Data set in agricolae

```
> A<-as.data.frame(data(package="agricolae")$results[,3:4])
> A[,2]<-paste(substr(A[,2],1,35),"..",sep=".")
> head(A)
```

	Item	Title
1	CIC	Data for late blight of potatoes...
2	Chz2006	Data amendment Carhuaz 2006...
3	ComasOxapampa	Data AUDPC Comas - Oxapampa...
4	DC	Data for the analysis of carolina g...
5	Glycoalkaloids	Data Glycoalkaloids...
6	Hco2006	Data amendment Huanuco 2006...

2 Descriptive statistics

The package **agricolae** provides some complementary functions to the **R** program, specifically for the management of the histogram and function *hist*.

2.1 Histogram

The histogram is constructed with the function *graph.freq* and is associated to other functions: *polygon.freq*, *table.freq*, *stat.freq*. See Figures: [1](#), [2](#) and [3](#) for more details.

Example. Data generated in **R** . (students' weight).

```
> weight<-c( 68, 53, 69.5, 55, 71, 63, 76.5, 65.5, 69, 75, 76, 57, 70.5, 71.5, 56, 81.5,
+           69, 59, 67.5, 61, 68, 59.5, 56.5, 73, 61, 72.5, 71.5, 59.5, 74.5, 63)
> print(summary(weight))
```

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
53.00	59.88	68.00	66.45	71.50	81.50

2.2 Statistics and Frequency tables

Statistics: mean, median, mode and standard deviation of the grouped data.

```
> stat.freq(h1)
```

```
$variance
[1] 51.37655
```

```
$mean
[1] 66.6
```

```
$median
[1] 68.36
```

```
$mode
[- -] mode
[1,] 67.4 72.2 70.45455
```

Frequency tables: Use *table.freq*, *stat.freq* and *summary*

The *table.freq* is equal to *summary()*

```

> par(mfrow=c(1,2),mar=c(4,4,0,1),cex=0.6)
> h1<- graph.freq(weight,col=colors()[84],frequency=1,las=2,density=20,ylim=c(0,12),ylab="Frequency")
> x<-h1$breaks
> h2<- plot(h1, frequency =2, axes= FALSE,ylim=c(0,0.4),xlab="weight",ylab="Relative (%)")
> polygon.freq(h2, col=colors()[84], lwd=2, frequency =2)
> axis(1,x,cex=0.6,las=2)
> y<-seq(0,0.4,0.1)
> axis(2, y,y*100,cex=0.6,las=1)

```

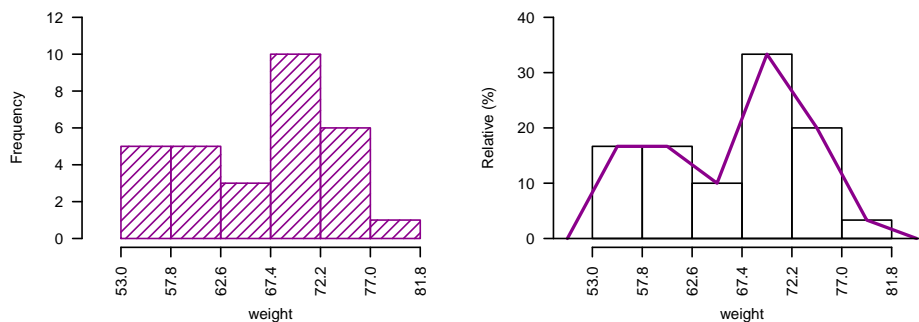


Figure 1: Absolute and relative frequency with polygon.

Limits class: **Lower and Upper**

Class point: **Main**

Frequency: **Frequency**

Percentage frequency: **Percentage**

Cumulative frequency: **CF**

Cumulative percentage frequency: **CPF**

```
> print(summary(h1),row.names=FALSE)
```

Lower	Upper	Main	Frequency	Percentage	CF	CPF
53.0	57.8	55.4	5	16.7	5	16.7
57.8	62.6	60.2	5	16.7	10	33.3
62.6	67.4	65.0	3	10.0	13	43.3
67.4	72.2	69.8	10	33.3	23	76.7
72.2	77.0	74.6	6	20.0	29	96.7
77.0	81.8	79.4	1	3.3	30	100.0

2.3 Histogram manipulation functions

You can extract information from a histogram such as class intervals *intervals.freq*, attract new intervals with the *sturges.freq* function or to join classes with *join.freq* function. It is also possible to reproduce the graph with the same creator *graph.freq* or function *plot* and overlay normal function with *normal.freq* be it a histogram in absolute scale, relative or density . The following examples illustrates these properties.

```
> sturges.freq(weight)
```

```

$maximum
[1] 81.5

$minimum
[1] 53

$amplitude
[1] 29

$classes
[1] 6

$interval
[1] 4.8

$breaks
[1] 53.0 57.8 62.6 67.4 72.2 77.0 81.8

```

```
> intervals.freq(h1)
```

```

      lower upper
[1,]  53.0  57.8
[2,]  57.8  62.6
[3,]  62.6  67.4
[4,]  67.4  72.2
[5,]  72.2  77.0
[6,]  77.0  81.8

```

```

> join.freq(h1,1:3) -> h3
> print(summary(h3))

```

	Lower	Upper	Main	Frequency	Percentage	CF	CPF
1	53.0	67.4	60.2	13	43.3	13	43.3
2	67.4	72.2	69.8	10	33.3	23	76.7
3	72.2	77.0	74.6	6	20.0	29	96.7
4	77.0	81.8	79.4	1	3.3	30	100.0

2.4 hist() and graph.freq() based on grouped data

The *hist* and *graph.freq* have the same characteristics, only *f2* allows build histogram from grouped data.

```

0-10 (3)
10-20 (8)
20-30 (15)
30-40 (18)
40-50 (6)

```

```
> print(summary(h5),row.names=FALSE)
```

```

> par(mfrow=c(1,2),mar=c(4,4,0,1),cex=0.8)
> plot(h3, frequency=2,col=colors()[84],ylim=c(0,0.6),axes=FALSE,xlab="weight",ylab="%",border=0)
> y<-seq(0,0.6,0.2)
> axis(2,y,y*100,las=2)
> axis(1,h3$breaks)
> normal.freq(h3,frequency=2,col=colors()[90])
> ogive.freq(h3,col=colors()[84],xlab="weight")

```

	weight	RCF
1	53.0	0.0000
2	67.4	0.4333
3	72.2	0.7667
4	77.0	0.9667
5	81.8	1.0000
6	86.6	1.0000

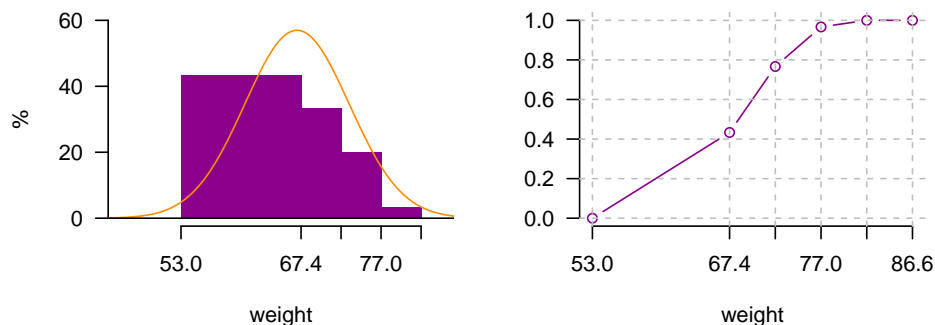


Figure 2: Join frequency and relative frequency with normal and Ogive.

```

> par(mfrow=c(1,2),mar=c(4,3,2,1),cex=0.6)
> h4<-hist(weight,xlab="Classes (h4)")
> table.freq(h4)
> # this is possible
> # hh<-graph.freq(h4,plot=FALSE)
> # summary(hh)
> # new class
> classes <- c(0, 10, 20, 30, 40, 50)
> freq <- c(3, 8, 15, 18, 6)
> h5 <- graph.freq(classes,counts=freq, xlab="Classes (h5)",main="Histogram grouped data")

```

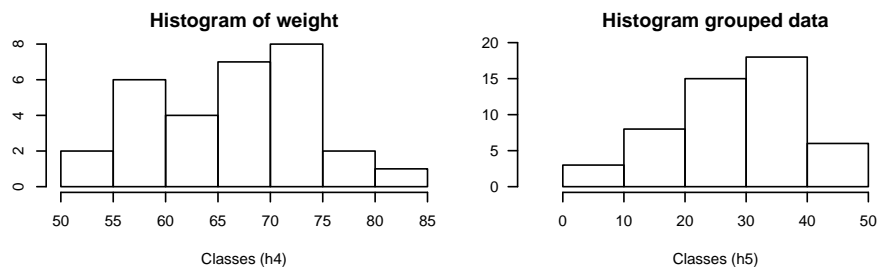


Figure 3: hist() function and histogram defined class

Lower	Upper	Main	Frequency	Percentage	CF	CPF
0	10	5	3	6	3	6
10	20	15	8	16	11	22
20	30	25	15	30	26	52
30	40	35	18	36	44	88
40	50	45	6	12	50	100

3 Experiment designs

The package **agricolae** presents special functions for the creation of the field book for experimental designs. Due to the random generation, this package is quite used in agricultural research.

For this generation, certain parameters are required, as for example the name of each treatment, the number of repetitions, and others, according to the design, [Cochran and Cox \(1957\)](#); [kueh \(2000\)](#); [Le Clerg and Leonard and Erwin and Warren and Andrew \(1992\)](#); [Montgomery \(2002\)](#). There are other parameters of random generation, as the seed to reproduce the same random generation or the generation method (See the reference manual of **agricolae** .

<http://cran.at.r-project.org/web/packages/agricolae/agricolae.pdf>

Important parameters in the generation of design:

series: A constant that is used to set numerical tag blocks , eg number = 2, the labels will be : 101, 102, for the first row or block, 201, 202, for the following , in the case of completely randomized design, the numbering is sequential.

design: Some features of the design requested agricolae be applied specifically to design.ab(factorial) or design.split (split plot) and their possible values are: "rcbd", "crd" and "lsd".

seed: The seed for the random generation and its value is any real value, if the value is zero, it has no reproducible generation, in this case copy of value of the outdesign\$parameters.

kinds: the random generation method, by default "Super-Duper".

first: For some designs is not required random the first repetition, especially in the block design, if you want to switch to random, change to TRUE.

randomization: TRUE or FALSE. If false, randomization is not performed

Output design:

parameters: the input to generation design, include the seed to generation random, if seed=0, the program generate one value and it is possible reproduce the design.

book: field book

statistics: the information statistics the design for example efficiency index, number of treatments.

sketch: distribution of treatments in the field.

The enumeration of the plots

zigzag is a function that allows you to place the numbering of the plots in the direction of serpentine: The zigzag is output generated by one design: blocks, Latin square, graeco, split plot, strip plot, into blocks factorial, balanced incomplete block, cyclic lattice, alpha and augmented blocks.

fieldbook: output zigzag, contain field book.

3.1 Completely randomized design

It generates completely a randomized design with equal or different repetition. "Random" uses the methods of number generation in R. The seed is by `set.seed(seed, kinds)`. They only require the names of the treatments and the number of their repetitions and its parameters are:

```
> str(design.crd)

function (trt, r, serie = 2, seed = 0, kinds = "Super-Duper",
  randomization = TRUE)

> trt <- c("A", "B", "C")
> repeticion <- c(4, 3, 4)
> outdesign <- design.crd(trt,r=repeticion,seed=777,serie=0)
> book1 <- outdesign$book
> head(book1)

  plots r trt
1     1 1  B
2     2 1  A
3     3 2  A
4     4 1  C
5     5 2  C
6     6 3  A
```

```
Excel:write.csv(book1,"book1.csv",row.names=FALSE)
```

3.2 Randomized complete block design

It generates field book and sketch to Randomized Complete Block Design. "Random" uses the methods of number generation in R. The seed is by `set.seed(seed, kinds)`. They require the names of the treatments and the number of blocks and its parameters are:

```
> str(design.rcbd)

function (trt, r, serie = 2, seed = 0, kinds = "Super-Duper",
  first = TRUE, continue = FALSE, randomization = TRUE)

> trt <- c("A", "B", "C", "D", "E")
> repeticion <- 4
> outdesign <- design.rcbd(trt,r=repeticion, seed=-513, serie=2)
> # book2 <- outdesign$book
> book2<- zigzag(outdesign) # zigzag numeration
> print(outdesign$sketch)

      [,1] [,2] [,3] [,4] [,5]
[1,] "D"  "B"  "C"  "E"  "A"
[2,] "E"  "A"  "D"  "B"  "C"
[3,] "E"  "D"  "B"  "A"  "C"
[4,] "A"  "E"  "C"  "B"  "D"
```



```
> print(matrix(book2[,1],byrow = TRUE, ncol = 5))
```

```
      [,1] [,2] [,3] [,4] [,5]
[1,]  101  102  103  104  105
[2,]  205  204  203  202  201
[3,]  301  302  303  304  305
[4,]  405  404  403  402  401
```

3.3 Latin square design

It generates Latin Square Design. "Random" uses the methods of number generation in R. The seed is by set.seed(seed, kinds). They require the names of the treatments and its parameters are:

```
> str(design.lsd)
```

```
function (trt, serie = 2, seed = 0, kinds = "Super-Duper",
         first = TRUE, randomization = TRUE)
```

```
> trt <- c("A", "B", "C", "D")
> outdesign <- design.lsd(trt, seed=543, serie=2)
> print(outdesign$sketch)
```

```
      [,1] [,2] [,3] [,4]
[1,] "C"  "A"  "B"  "D"
[2,] "D"  "B"  "C"  "A"
[3,] "B"  "D"  "A"  "C"
[4,] "A"  "C"  "D"  "B"
```

Serpentine enumeration:

```
> book <- zigzag(outdesign)
> print(matrix(book[,1],byrow = TRUE, ncol = 4))
```

```
      [,1] [,2] [,3] [,4]
[1,]  101  102  103  104
[2,]  204  203  202  201
[3,]  301  302  303  304
[4,]  404  403  402  401
```

3.4 Graeco-Latin designs

A graeco - latin square is a KxK pattern that permits the study of k treatments simultaneously with three different blocking variables, each at k levels. The function is only for squares of the odd numbers and even numbers (4, 8, 10 and 12). They require the names of the treatments of each factor of study and its parameters are:

```
> str(design.graeco)
```

```
function (trt1, trt2, serie = 2, seed = 0, kinds = "Super-Duper",
         randomization = TRUE)
```

```
> trt1 <- c("A", "B", "C", "D")
> trt2 <- 1:4
> outdesign <- design.graeco(trt1,trt2, seed=543, serie=2)
> print(outdesign$sketch)
```

```
      [,1] [,2] [,3] [,4]
[1,] "A 1" "D 4" "B 3" "C 2"
[2,] "D 3" "A 2" "C 1" "B 4"
[3,] "B 2" "C 3" "A 4" "D 1"
[4,] "C 4" "B 1" "D 2" "A 3"
```

Serpentine enumeration:

```
> book <- zigzag(outdesign)
> print(matrix(book[,1],byrow = TRUE, ncol = 4))
```

```
      [,1] [,2] [,3] [,4]
[1,] 101 102 103 104
[2,] 204 203 202 201
[3,] 301 302 303 304
[4,] 404 403 402 401
```

3.5 Youden design

Such designs are referred to as Youden squares since they were introduced by Youden (1937) after Yates (1936) considered the special case of column equal to number treatment minus 1. "Random" uses the methods of number generation in R. The seed is by set.seed(seed, kinds). They require the names of the treatments of each factor of study and its parameters are:

```
> str(design.youden)

function (trt, r, serie = 2, seed = 0, kinds = "Super-Duper",
  first = TRUE, randomization = TRUE)

> varieties<-c("perricholi","yungay","maria bonita","tomasa")
> r<-3
> outdesign <-design.youden(varieties,r,serie=2,seed=23)
> print(outdesign$sketch)
```

```
      [,1]      [,2]      [,3]
[1,] "maria bonita" "perricholi" "tomasa"
[2,] "yungay"      "tomasa"      "maria bonita"
[3,] "tomasa"      "yungay"      "perricholi"
[4,] "perricholi"  "maria bonita" "yungay"
```

```
> book <- outdesign$book
> print(book) # field book.
```

```
plots row col varieties
1      101   1   1 maria bonita
```

```

2    102    1    2    perricholi
3    103    1    3          tomasa
4    201    2    1          yungay
5    202    2    2          tomasa
6    203    2    3 maria bonita
7    301    3    1          tomasa
8    302    3    2          yungay
9    303    3    3    perricholi
10   401    4    1    perricholi
11   402    4    2 maria bonita
12   403    4    3          yungay

```

```
> print(matrix(as.numeric(book[,1]),byrow = TRUE, ncol = r))
```

```

      [,1] [,2] [,3]
[1,]  101  102  103
[2,]  201  202  203
[3,]  301  302  303
[4,]  401  402  403

```

Serpentine enumeration:

```

> book <- zigzag(outdesign)
> print(matrix(as.numeric(book[,1]),byrow = TRUE, ncol = r))

```

```

      [,1] [,2] [,3]
[1,]  101  102  103
[2,]  203  202  201
[3,]  301  302  303
[4,]  403  402  401

```

3.6 Balanced Incomplete Block Designs

Creates Randomized Balanced Incomplete Block Design. "Random" uses the methods of number generation in R. The seed is by set.seed(seed, kinds). They require the names of the treatments and the size of the block and its parameters are:

```

> str(design.bib)

function (trt, k, r = NULL, serie = 2, seed = 0, kinds = "Super-Duper",
  maxRep = 20, randomization = TRUE)

> trt <- c("A", "B", "C", "D", "E" )
> k <- 4
> outdesign <- design.bib(trt,k, seed=543, serie=2)

```

```

Parameters BIB
=====
Lambda      : 3

```

```
treatmeans : 5
Block size : 4
Blocks      : 5
Replication: 4
```

```
Efficiency factor 0.9375
```

```
<<< Book >>>
```

```
> book5 <- outdesign$book
> outdesign$statistics
```

```
      lambda treatmeans blockSize blocks r Efficiency
values      3          5         4     5 4      0.9375
```

```
> outdesign$parameters
```

```
$design
[1] "bib"
```

```
$trt
[1] "A" "B" "C" "D" "E"
```

```
$k
[1] 4
```

```
$serie
[1] 2
```

```
$seed
[1] 543
```

```
$kinds
[1] "Super-Duper"
```

According to the produced information, they are five blocks of size 4, being the matrix:

```
> outdesign$sketch
```

```
      [,1] [,2] [,3] [,4]
[1,] "D"  "B"  "E"  "C"
[2,] "B"  "A"  "C"  "D"
[3,] "D"  "B"  "E"  "A"
[4,] "E"  "A"  "C"  "D"
[5,] "B"  "C"  "E"  "A"
```

It can be observed that the treatments have four repetitions. The parameter lambda has three repetitions, which means that a couple of treatments are together on three occasions. For example, B and E are found in the blocks I, II and V.

Serpentine enumeration:

```
> book <- zigzag(outdesign)
> matrix(book[,1],byrow = TRUE, ncol = 4)
```

```
      [,1] [,2] [,3] [,4]
[1,]  101  102  103  104
[2,]  204  203  202  201
[3,]  301  302  303  304
[4,]  404  403  402  401
[5,]  501  502  503  504
```

3.7 Cyclic designs

They require the names of the treatments, the size of the block and the number of repetitions. This design is used for 6 to 30 treatments. The repetitions are a multiple of the size of the block; if they are six treatments and the size is 3, then the repetitions can be 6, 9, 12, etc. and its parameters are:

```
> str(design.cyclic)

function (trt, k, r, serie = 2, rowcol = FALSE, seed = 0,
  kinds = "Super-Duper", randomization = TRUE)

> trt <- c("A", "B", "C", "D", "E", "F" )
> outdesign <- design.cyclic(trt,k=3, r=6, seed=543, serie=2)
```

```
cyclic design
Generator block basic:
1 2 4
1 3 2
```

```
Parameters
=====
treatmeans : 6
Block size : 3
Replication: 6
```

```
> book6 <- outdesign$book
> outdesign$sketch[[1]]
```

```
      [,1] [,2] [,3]
[1,] "A"  "E"  "D"
[2,] "D"  "F"  "C"
[3,] "A"  "D"  "B"
[4,] "A"  "C"  "F"
[5,] "C"  "B"  "E"
[6,] "B"  "E"  "F"
```

```
> outdesign$sketch[[2]]
```

	[,1]	[,2]	[,3]
[1,]	"B"	"D"	"C"
[2,]	"C"	"A"	"B"
[3,]	"F"	"A"	"B"
[4,]	"C"	"D"	"E"
[5,]	"E"	"A"	"F"
[6,]	"F"	"E"	"D"

12 blocks of 4 treatments each have been generated. **Serpentine enumeration:**

```
> book <- zigzag(outdesign)
> array(book$plots,c(3,6,2))->X
> t(X[, ,1])
```

	[,1]	[,2]	[,3]
[1,]	101	102	103
[2,]	106	105	104
[3,]	107	108	109
[4,]	112	111	110
[5,]	113	114	115
[6,]	118	117	116

```
> t(X[, ,2])
```

	[,1]	[,2]	[,3]
[1,]	201	202	203
[2,]	206	205	204
[3,]	207	208	209
[4,]	212	211	210
[5,]	213	214	215
[6,]	218	217	216

3.8 Lattice designs

SIMPLE and TRIPLE lattice designs. It randomizes treatments in $k \times k$ lattice. They require a number of treatments of a perfect square; for example 9, 16, 25, 36, 49, etc. and its parameters are:

```
> str(design.lattice)
```

```
function (trt, r = 3, serie = 2, seed = 0, kinds = "Super-Duper",
  randomization = TRUE)
```

They can generate a simple lattice (2 rep.) or a triple lattice (3 rep.) generating a triple lattice design for 9 treatments 3×3

```
> trt<-letters[1:9]
> outdesign <-design.lattice(trt, r = 3, serie = 2, seed = 33,
+   kinds = "Super-Duper")
```

```

Lattice design,  triple    3 x 3

Efficiency factor
(E ) 0.7272727

<<< Book >>>

> book7 <- outdesign$book
> outdesign$parameters

$design
[1] "lattice"

$type
[1] "triple"

$trt
[1] "a" "b" "c" "d" "e" "f" "g" "h" "i"

$r
[1] 3

$serie
[1] 2

$seed
[1] 33

$kinds
[1] "Super-Duper"

> outdesign$sketch

$rep1
      [,1] [,2] [,3]
[1,] "i"  "d"  "a"
[2,] "b"  "c"  "e"
[3,] "h"  "f"  "g"

$rep2
      [,1] [,2] [,3]
[1,] "c"  "f"  "d"
[2,] "b"  "h"  "i"
[3,] "e"  "g"  "a"

$rep3
      [,1] [,2] [,3]
[1,] "e"  "h"  "d"
[2,] "b"  "f"  "a"
[3,] "c"  "g"  "i"

```

```
> head(book7)
```

```
  plots r block trt
1   101 1     1   i
2   102 1     1   d
3   103 1     1   a
4   104 1     2   b
5   105 1     2   c
6   106 1     2   e
```

Serpentine enumeration:

```
> book <- zigzag(outdesign)
> array(book$plots,c(3,3,3)) -> X
> t(X[, ,1])
```

```
      [,1] [,2] [,3]
[1,]  101  102  103
[2,]  106  105  104
[3,]  107  108  109
```

```
> t(X[, ,2])
```

```
      [,1] [,2] [,3]
[1,]  201  202  203
[2,]  206  205  204
[3,]  207  208  209
```

```
> t(X[, ,3])
```

```
      [,1] [,2] [,3]
[1,]  301  302  303
[2,]  306  305  304
[3,]  307  308  309
```

3.9 Alpha designs

Generates an alpha designs starting from the alpha design fixing under the series formulated by Patterson and Williams. These designs are generated by the alpha arrangements. They are similar to the lattice designs, but the tables are rectangular s by k (with s blocks and $k < s$ columns. The number of treatments should be equal to $s*k$ and all the experimental units $r*s*k$ (r replications) and its parameters are:

```
> str(design.alpha)
```

```
function (trt, k, r, serie = 2, seed = 0, kinds = "Super-Duper",
  randomization = TRUE)
```

```
> trt <- letters[1:15]
> outdesign <- design.alpha(trt,k=3,r=2,seed=543)
```


Alpha Design (0,1) - Serie I

Parameters Alpha Design

=====

Treatmeans : 15

Block size : 3

Blocks : 5

Replication: 2

Efficiency factor

(E) 0.6363636

<<< Book >>>

```
> book8 <- outdesign$book
```

```
> outdesign$statistics
```

	treatments	blocks	Efficiency
values	15	5	0.6363636

```
> outdesign$sketch
```

\$rep1

	[,1]	[,2]	[,3]
[1,]	"l"	"m"	"e"
[2,]	"g"	"c"	"i"
[3,]	"o"	"k"	"d"
[4,]	"h"	"f"	"j"
[5,]	"a"	"n"	"b"

\$rep2

	[,1]	[,2]	[,3]
[1,]	"o"	"a"	"m"
[2,]	"l"	"k"	"g"
[3,]	"d"	"n"	"h"
[4,]	"j"	"b"	"c"
[5,]	"f"	"i"	"e"

```
> # codification of the plots
```

```
> A<-array(book8[,1], c(3,5,2))
```

```
> t(A[, ,1])
```

	[,1]	[,2]	[,3]
[1,]	101	102	103
[2,]	104	105	106
[3,]	107	108	109
[4,]	110	111	112
[5,]	113	114	115

```
> t(A[, ,2])
```

```

      [,1] [,2] [,3]
[1,]  201  202  203
[2,]  204  205  206
[3,]  207  208  209
[4,]  210  211  212
[5,]  213  214  215

```

Serpentine enumeration:

```

> book <- zigzag(outdesign)
> A<-array(book[,1], c(3,5,2))
> t(A[, ,1])

```

```

      [,1] [,2] [,3]
[1,]  101  102  103
[2,]  106  105  104
[3,]  107  108  109
[4,]  112  111  110
[5,]  113  114  115

```

```

> t(A[, ,2])

```

```

      [,1] [,2] [,3]
[1,]  201  202  203
[2,]  206  205  204
[3,]  207  208  209
[4,]  212  211  210
[5,]  213  214  215

```

3.10 Augmented block designs

These are designs for two types of treatments: the control treatments (common) and the increased treatments. The common treatments are applied in complete randomized blocks, and the increased treatments, at random. Each treatment should be applied in any block once only. It is understood that the common treatments are of a greater interest; the standard error of the difference is much smaller than when between two increased ones in different blocks. The function `design.dau()` achieves this purpose and its parameters are:

```

> str(design.dau)

function (trt1, trt2, r, serie = 2, seed = 0, kinds = "Super-Duper",
  name = "trt", randomization = TRUE)

> rm(list=ls())
> trt1 <- c("A", "B", "C", "D")
> trt2 <- c("t", "u", "v", "w", "x", "y", "z")
> outdesign <- design.dau(trt1, trt2, r=5, seed=543, serie=2)
> book9 <- outdesign$book
> with(book9,by(trt, block,as.character))

```

```

block: 1
[1] "D" "C" "A" "u" "B" "t"
-----
block: 2
[1] "D" "z" "C" "A" "v" "B"
-----
block: 3
[1] "C" "w" "B" "A" "D"
-----
block: 4
[1] "A" "C" "D" "B" "y"
-----
block: 5
[1] "C" "B" "A" "D" "x"

```

Serpentine enumeration:

```

> book <- zigzag(outdesign)
> with(book,by(plots, block, as.character))

```

```

block: 1
[1] "101" "102" "103" "104" "105" "106"
-----
block: 2
[1] "206" "205" "204" "203" "202" "201"
-----
block: 3
[1] "301" "302" "303" "304" "305"
-----
block: 4
[1] "405" "404" "403" "402" "401"
-----
block: 5
[1] "501" "502" "503" "504" "505"

> head(book)

```

	plots	block	trt
1	101	1	D
2	102	1	C
3	103	1	A
4	104	1	u
5	105	1	B
6	106	1	t

For augmented completely randomized design, use the function `design.crd()`.

3.11 Split plot designs

These designs have two factors, one is applied in plots and is defined as **trt1** in a randomized complete block design; and a second factor as **trt2** , which is applied in the subplots of each plot applied at

random. The function `design.split()` permits to find the experimental plan for this design and its parameters are:

```
> str(design.split)

function (trt1, trt2, r = NULL, design = c("rcbd",
      "crd", "lsd"), serie = 2, seed = 0, kinds = "Super-Duper",
      first = TRUE, randomization = TRUE)

>
```

Aplication

```
> trt1<-c("A","B","C","D")
> trt2<-c("a","b","c")
> outdesign <-design.split(trt1,trt2,r=3,serie=2,seed=543)
> book10 <- outdesign$book
> head(book10)

  plots splots block trt1 trt2
1   101      1     1    A    c
2   101      2     1    A    a
3   101      3     1    A    b
4   102      1     1    D    b
5   102      2     1    D    c
6   102      3     1    D    a

> p<-book10$trt1[seq(1,36,3)]
> q<-NULL
> for(i in 1:12)
+ q <- c(q,paste(book10$trt2[3*(i-1)+1],book10$trt2[3*(i-1)+2], book10$trt2[3*(i-1)+3]))
```

In plots:

```
> print(t(matrix(p,c(4,3))))

      [,1] [,2] [,3] [,4]
[1,] "A"  "D"  "B"  "C"
[2,] "A"  "C"  "B"  "D"
[3,] "A"  "C"  "B"  "D"
```

In sub plots (split plot)

```
> print(t(matrix(q,c(4,3))))

      [,1]      [,2]      [,3]      [,4]
[1,] "c a b" "b c a" "b c a" "a b c"
[2,] "b a c" "a b c" "a c b" "b c a"
[3,] "a b c" "a c b" "a c b" "c a b"
```

Serpentine enumeration:

```
> book <- zigzag(outdesign)
> head(book,5)

  plots splots block trt1 trt2
1   101      1    1    A    c
2   101      2    1    A    a
3   101      3    1    A    b
4   102      1    1    D    b
5   102      2    1    D    c
```

3.12 Strip-plot designs

These designs are used when there are two types of treatments (factors) and are applied separately in large plots, called bands, in a vertical and horizontal direction of the block, obtaining the divided blocks. Each block constitutes a repetition and its parameters are:

```
> str(design.strip)

function (trt1, trt2, r, serie = 2, seed = 0, kinds = "Super-Duper",
  randomization = TRUE)
```

Aplication

```
> trt1<-c("A","B","C","D")
> trt2<-c("a","b","c")
> outdesign <-design.strip(trt1,trt2,r=3,serie=2,seed=543)
> book11 <- outdesign$book
> head(book11)
```

```
  plots block trt1 trt2
1   101      1    A    a
2   102      1    A    b
3   103      1    A    c
4   104      1    D    a
5   105      1    D    b
6   106      1    D    c
```

```
> t3<-paste(book11$trt1, book11$trt2)
> B1<-t(matrix(t3[1:12],c(4,3)))
> B2<-t(matrix(t3[13:24],c(3,4)))
> B3<-t(matrix(t3[25:36],c(3,4)))
> print(B1)
```

```
      [,1] [,2] [,3] [,4]
[1,] "A a" "A b" "A c" "D a"
[2,] "D b" "D c" "B a" "B b"
[3,] "B c" "C a" "C b" "C c"
```

```
> print(B2)
```

```
      [,1] [,2] [,3]
[1,] "D a" "D b" "D c"
[2,] "A a" "A b" "A c"
[3,] "B a" "B b" "B c"
[4,] "C a" "C b" "C c"
```

```
> print(B3)
```

```
      [,1] [,2] [,3]
[1,] "B b" "B c" "B a"
[2,] "D b" "D c" "D a"
[3,] "C b" "C c" "C a"
[4,] "A b" "A c" "A a"
```

Serpentine enumeration:

```
> book <- zigzag(outdesign)
> head(book)
```

```
plots block trt1 trt2
1   101     1    A    a
2   102     1    A    b
3   103     1    A    c
4   106     1    D    a
5   105     1    D    b
6   104     1    D    c
```

```
> array(book$plots,c(3,4,3))->X
> t(X[, ,1])
```

```
      [,1] [,2] [,3]
[1,]  101  102  103
[2,]  106  105  104
[3,]  107  108  109
[4,]  112  111  110
```

```
> t(X[, ,2])
```

```
      [,1] [,2] [,3]
[1,]  201  202  203
[2,]  206  205  204
[3,]  207  208  209
[4,]  212  211  210
```

```
> t(X[, ,3])
```

```
      [,1] [,2] [,3]
[1,]  301  302  303
[2,]  306  305  304
[3,]  307  308  309
[4,]  312  311  310
```

3.13 Factorial

The full factorial of n factors applied to an experimental design (CRD, RCBD and LSD) is common and this procedure in **agricolae** applies the factorial to one of these three designs and its parameters are:

```
> str(design.ab)

function (trt, r = NULL, serie = 2, design = c("rcbd",
  "crd", "lsd"), seed = 0, kinds = "Super-Duper",
  first = TRUE, randomization = TRUE)
```

To generate the factorial, you need to create a vector of levels of each factor, the method automatically generates up to 25 factors and "r" repetitions.

```
> trt <- c(4,2,3) # three factors with 4,2 and 3 levels.
```

to crd and rcbd designs, it is necessary to value "r" as the number of repetitions, this can be a vector if unequal to equal or constant repetition (recommended).

```
> trt<-c(3,2) # factorial 3x2
> outdesign <- design.ab(trt, r=3, serie=2)
> book12 <- outdesign$book
> head(book12) # print of the field book
```

```
plots block A B
1  101      1 3 1
2  102      1 2 2
3  103      1 1 1
4  104      1 1 2
5  105      1 3 2
6  106      1 2 1
```

Serpentine enumeration:

```
> book <- zigzag(outdesign)
> head(book)
```

```
plots block A B
1  101      1 3 1
2  102      1 2 2
3  103      1 1 1
4  104      1 1 2
5  105      1 3 2
6  106      1 2 1
```

factorial 2 x 2 x 2 with 5 replications in completely randomized design.

```
> trt<-c(2,2,2)
> crd<-design.ab(trt, r=5, serie=2,design="crd")
> names(crd)
```

```

[1] "parameters" "book"

> crd$parameters

$design
[1] "factorial"

$trt
[1] "1 1 1" "1 1 2" "1 2 1" "1 2 2" "2 1 1" "2 1 2" "2 2 1"
[8] "2 2 2"

$r
[1] 5 5 5 5 5 5 5 5

$serie
[1] 2

$seed
[1] 970386955

$kinds
[1] "Super-Duper"

[[7]]
[1] TRUE

$applied
[1] "crd"

> head(crd$book)

  plots r A B C
1   101 1 2 2 1
2   102 1 1 1 2
3   103 1 2 1 2
4   104 1 2 1 1
5   105 1 2 2 2
6   106 2 2 1 2

```

4 Multiple comparisons

For the analyses, the following functions of **agricolae** are used: *LSD.test*, *HSD.test*, *duncan.test*, *scheffe.test*, *waller.test*, *SNK.test*, *REGW.test*, [Steel and Torry and Dickey \(1997\)](#); [Hsu \(1996\)](#) and *durbin.test*, *kruskal*, *friedman*, *waerden.test* and *Median.test*, [Conover \(1999\)](#).

For every statistical analysis, the data should be organized in columns. For the demonstration, the **agricolae** database will be used.

The sweetpotato data correspond to a completely random experiment in field with plots of 50 sweet potato plants, subjected to the virus effect and to a control without virus (See the reference manual of the package).


```
> data(sweetpotato)
> model<-aov(yield~virus, data=sweetpotato)
> cv.model(model)
```

```
[1] 17.1666
```

```
> with(sweetpotato,mean(yield))
```

```
[1] 27.625
```

Model parameters: Degrees of freedom and variance of the error:

```
> df<-df.residual(model)
> MSerror<-deviance(model)/df
```

4.1 The Least Significant Difference (LSD)

It includes the multiple comparison through the method of the minimum significant difference (Least Significant Difference), [Steel and Torry and Dickey \(1997\)](#).

```
> # comparison <- LSD.test(yield,virus,df,MSerror)
> LSD.test(model, "virus",console=TRUE)
```

Study: model ~ "virus"

LSD t Test for yield

Mean Square Error: 22.48917

virus, means and individual (95 %) CI

	yield	std r		LCL	UCL	Min	Max
cc	24.40000	3.609709	3	18.086268	30.71373	21.7	28.5
fc	12.86667	2.159475	3	6.552935	19.18040	10.6	14.9
ff	36.33333	7.333030	3	30.019601	42.64707	28.0	41.8
oo	36.90000	4.300000	3	30.586268	43.21373	32.1	40.4

Alpha: 0.05 ; DF Error: 8

Critical Value of t: 2.306004

least Significant Difference: 8.928965

Treatments with the same letter are not significantly different.

	yield	groups
oo	36.90000	a
ff	36.33333	a
cc	24.40000	b
fc	12.86667	c

In the function `LSD.test`, the multiple comparison was carried out. In order to obtain the probabilities of the comparisons, it should be indicated that groups are not required; thus:

```
> # comparison <- LSD.test(yield, virus,df, MSerror, group=FALSE)
> outLSD <-LSD.test(model, "virus", group=FALSE,console=TRUE)
```

Study: model ~ "virus"

LSD t Test for yield

Mean Square Error: 22.48917

virus, means and individual (95 %) CI

	yield	std r		LCL	UCL	Min	Max
cc	24.40000	3.609709	3	18.086268	30.71373	21.7	28.5
fc	12.86667	2.159475	3	6.552935	19.18040	10.6	14.9
ff	36.33333	7.333030	3	30.019601	42.64707	28.0	41.8
oo	36.90000	4.300000	3	30.586268	43.21373	32.1	40.4

Alpha: 0.05 ; DF Error: 8

Critical Value of t: 2.306004

Comparison between treatments means

	difference	pvalue	signif.	LCL	UCL
cc - fc	11.5333333	0.0176	*	2.604368	20.462299
cc - ff	-11.9333333	0.0151	*	-20.862299	-3.004368
cc - oo	-12.5000000	0.0121	*	-21.428965	-3.571035
fc - ff	-23.4666667	0.0003	***	-32.395632	-14.537701
fc - oo	-24.0333333	0.0003	***	-32.962299	-15.104368
ff - oo	-0.5666667	0.8873		-9.495632	8.362299

Signif. codes:

0 *** 0.001 ** 0.01 * 0.05 . 0.1 ' ' 1

```
> options(digits=2)
```

```
> print(outLSD)
```

\$statistics

MSerror	Df	Mean	CV	t.value	LSD
22	8	28	17	2.3	8.9

\$parameters

test	p.adjusted	name.t	ntr	alpha
Fisher-LSD	none	virus	4	0.05

\$means

	yield	std r	LCL	UCL	Min	Max	Q25	Q50	Q75
cc	24	3.6	3	18.1	31	22	28	22	23

```

fc    13 2.2 3   6.6 19  11  15  12  13  14
ff    36 7.3 3  30.0 43  28  42  34  39  40
oo    37 4.3 3  30.6 43  32  40  35  38  39

$comparison
      difference pvalue signif.  LCL  UCL
cc - fc      11.53 0.0176      *   2.6 20.5
cc - ff     -11.93 0.0151      * -20.9 -3.0
cc - oo     -12.50 0.0121      * -21.4 -3.6
fc - ff     -23.47 0.0003     *** -32.4 -14.5
fc - oo     -24.03 0.0003     *** -33.0 -15.1
ff - oo      -0.57 0.8873      -9.5   8.4

$groups
NULL

attr(,"class")
[1] "group"

```

4.2 holm, hommel, hochberg, bonferroni, BH, BY, fdr

With the function *LSD.test* we can make adjustments to the probabilities found, as for example the adjustment by Bonferroni, holm and other options see Adjust P-values for Multiple Comparisons, function *p.adjust(stats)*, [R Core Team \(2017\)](#).

```
> LSD.test(model, "virus", group=FALSE, p.adj= "bon", console=TRUE)
```

```
Study: model ~ "virus"
```

```
LSD t Test for yield
P value adjustment method: bonferroni
```

```
Mean Square Error: 22
```

```
virus, means and individual ( 95 %) CI
```

```

      yield std r  LCL UCL Min Max
cc    24 3.6 3 18.1 31 22 28
fc    13 2.2 3   6.6 19 11 15
ff    36 7.3 3 30.0 43 28 42
oo    37 4.3 3 30.6 43 32 40

```

```
Alpha: 0.05 ; DF Error: 8
Critical Value of t: 3.5
```

```
Comparison between treatments means
```

```

      difference pvalue signif.  LCL  UCL
cc - fc      11.53 0.1058      -1.9 25.00
cc - ff     -11.93 0.0904      . -25.4  1.54

```

```
cc - oo      -12.50 0.0725      . -26.0   0.97
fc - ff      -23.47 0.0018     ** -36.9 -10.00
fc - oo      -24.03 0.0015     ** -37.5 -10.56
ff - oo      -0.57 1.0000      -14.0  12.90
```

```
> out<-LSD.test(model, "virus", group=TRUE, p.adj= "holm")
> print(out$group)
```

```
      yield groups
oo      37      a
ff      36      a
cc      24      b
fc      13      c
```

```
> out<-LSD.test(model, "virus", group=FALSE, p.adj= "holm")
> print(out$comparison)
```

```
      difference pvalue signif.
cc - fc         11.53 0.0484      *
cc - ff        -11.93 0.0484      *
cc - oo        -12.50 0.0484      *
fc - ff        -23.47 0.0015     **
fc - oo        -24.03 0.0015     **
ff - oo         -0.57 0.8873
```

Other comparison tests can be applied, such as *duncan*, *Student-Newman-Keuls*, *tukey* and *waller-duncan*

For *Duncan*, use the function *duncan.test*; for *Student-Newman-Keuls*, the function *SNK.test*; for *Tukey*, the function *HSD.test*; for *Scheffe*, the function *scheffe.test* and for *Waller-Duncan*, the function *waller.test*. The arguments are the same. *Waller* also requires the value of F-calculated of the ANOVA treatments. If the model is used as a parameter, this is no longer necessary.

4.3 Duncan's New Multiple-Range Test

It corresponds to the Duncan's Test, [Steel and Torry and Dickey \(1997\)](#).

```
> duncan.test(model, "virus", console=TRUE)
```

```
Study: model ~ "virus"
```

```
Duncan's new multiple range test
for yield
```

```
Mean Square Error: 22
```

```
virus, means
```

```
      yield std r Min Max
cc      24 3.6 3  22  28
```

fc	13	2.2	3	11	15
ff	36	7.3	3	28	42
oo	37	4.3	3	32	40

Alpha: 0.05 ; DF Error: 8

Critical Range
 2 3 4
 8.9 9.3 9.5

Means with the same letter are not significantly different.

	yield	groups
oo	37	a
ff	36	a
cc	24	b
fc	13	c

4.4 Student-Newman-Keuls

Student, Newman and Keuls helped to improve the Newman-Keuls test of 1939, which was known as the Keuls method, [Steel and Torry and Dickey \(1997\)](#).

```
> # SNK.test(model, "virus", alpha=0.05,console=TRUE)
> SNK.test(model, "virus", group=FALSE,console=TRUE)
```

Study: model ~ "virus"

Student Newman Keuls Test
 for yield

Mean Square Error: 22

virus, means

	yield	std	r	Min	Max
cc	24	3.6	3	22	28
fc	13	2.2	3	11	15
ff	36	7.3	3	28	42
oo	37	4.3	3	32	40

Comparison between treatments means

	difference	pvalue	signif.	LCL	UCL
cc - fc	11.53	0.0176	*	2.6	20.5
cc - ff	-11.93	0.0151	*	-20.9	-3.0
cc - oo	-12.50	0.0291	*	-23.6	-1.4
fc - ff	-23.47	0.0008	***	-34.5	-12.4
fc - oo	-24.03	0.0012	**	-36.4	-11.6
ff - oo	-0.57	0.8873		-9.5	8.4

4.5 Ryan, Einot and Gabriel and Welsch

Multiple range tests for all pairwise comparisons, to obtain a confident inequalities multiple range tests, [Hsu \(1996\)](#).

```
> # REGW.test(model, "virus", alpha=0.05,console=TRUE)
> REGW.test(model, "virus", group=FALSE,console=TRUE)
```

Study: model ~ "virus"

Ryan, Einot and Gabriel and Welsch multiple range test
for yield

Mean Square Error: 22

virus, means

	yield	std	r	Min	Max
cc	24	3.6	3	22	28
fc	13	2.2	3	11	15
ff	36	7.3	3	28	42
oo	37	4.3	3	32	40

Comparison between treatments means

	difference	pvalue	signif.	LCL	UCL
cc - fc	11.53	0.0350	*	0.91	22.16
cc - ff	-11.93	0.0360	*	-23.00	-0.87
cc - oo	-12.50	0.0482	*	-24.90	-0.10
fc - ff	-23.47	0.0006	***	-34.09	-12.84
fc - oo	-24.03	0.0007	***	-35.10	-12.97
ff - oo	-0.57	0.9873		-11.19	10.06

4.6 Tukey's W Procedure (HSD)

This studentized range test, created by Tukey in 1953, is known as the Tukey's HSD (Honestly Significant Differences), [Steel and Torry and Dickey \(1997\)](#).

```
> outHSD<- HSD.test(model, "virus",console=TRUE)
```

Study: model ~ "virus"

HSD Test for yield

Mean Square Error: 22

virus, means

	yield	std	r	Min	Max
cc	24	3.6	3	22	28

```
fc    13 2.2 3  11  15
ff    36 7.3 3  28  42
oo    37 4.3 3  32  40
```

Alpha: 0.05 ; DF Error: 8
Critical Value of Studentized Range: 4.5

Minimum Significant Difference: 12

Treatments with the same letter are not significantly different.

```
      yield groups
oo    37      a
ff    36     ab
cc    24     bc
fc    13      c
```

```
> outHSD
```

```
$statistics
  MSerror Df Mean CV MSD
      22  8   28 17  12
```

```
$parameters
  test name.t ntr StudentizedRange alpha
  Tukey  virus   4           4.5  0.05
```

```
$means
      yield std r Min Max Q25 Q50 Q75
cc    24 3.6 3  22  28  22  23  26
fc    13 2.2 3  11  15  12  13  14
ff    36 7.3 3  28  42  34  39  40
oo    37 4.3 3  32  40  35  38  39
```

```
$comparison
NULL
```

```
$groups
      yield groups
oo    37      a
ff    36     ab
cc    24     bc
fc    13      c
```

```
attr("class")
[1] "group"
```

4.7 Waller-Duncan's Bayesian K-Ratio T-Test

Duncan continued the multiple comparison procedures, introducing the criterion of minimizing both experimental errors; for this, he used the Bayes' theorem, obtaining one new test called Waller-Duncan,

Waller and Duncan (1969); Steel and Torry and Dickey (1997).

```
> # variance analysis:
> anova(model)
```

Analysis of Variance Table

```
Response: yield
      Df Sum Sq Mean Sq F value    Pr(>F)
virus    3   1170      390    17.3 0.00073 ***
Residuals  8    180       22
---
```

Signif. codes:

```
0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
> with(sweetpotato,waller.test(yield,virus,df,MSerror,Fc= 17.345, group=FALSE,console=TRUE))
```

Study: yield ~ virus

Waller-Duncan K-ratio t Test for yield

This test minimizes the Bayes risk under additive loss and certain other assumptions

```
      . . . . .
K ratio          100.0
Error Degrees of Freedom    8.0
Error Mean Square          22.5
F value                   17.3
Critical Value of Waller    2.2
```

virus, means

```
      yield std r Min Max
cc      24 3.6 3  22  28
fc      13 2.2 3  11  15
ff      36 7.3 3  28  42
oo      37 4.3 3  32  40
```

Comparison between treatments means

```
      Difference significant
cc - fc      11.53      TRUE
cc - ff     -11.93      TRUE
cc - oo     -12.50      TRUE
fc - ff     -23.47      TRUE
fc - oo     -24.03      TRUE
ff - oo      -0.57     FALSE
```

In another case with only invoking the model object:

```
> outWaller <- waller.test(model, "virus", group=FALSE,console=FALSE)
```


The found object *outWaller* has information to make other procedures.

```
> names(outWaller)

[1] "statistics" "parameters" "means"      "comparison"
[5] "groups"

> print(outWaller$comparison)

      Difference significant
cc - fc      11.53      TRUE
cc - ff     -11.93      TRUE
cc - oo     -12.50      TRUE
fc - ff     -23.47      TRUE
fc - oo     -24.03      TRUE
ff - oo      -0.57     FALSE
```

It is indicated that the virus effect "ff" is not significant to the control "oo".

```
> outWaller$statistics

      Mean Df CV MSerror F.Value Waller CriticalDifference
      28  8 17    22      17    2.2              8.7
```

4.8 Scheffe's Test

This method, created by Scheffe in 1959, is very general for all the possible contrasts and their confidence intervals. The confidence intervals for the averages are very broad, resulting in a very conservative test for the comparison between treatment averages, [Steel and Torry and Dickey \(1997\)](#).

```
> # analysis of variance:
> scheffe.test(model,"virus", group=TRUE,console=TRUE,
+ main="Yield of sweetpotato\nDealt with different virus")
```

```
Study: Yield of sweetpotato
Dealt with different virus
```

```
Scheffe Test for yield
```

```
Mean Square Error   : 22
```

```
virus,  means
```

```
      yield std r Min Max
cc      24 3.6 3  22  28
fc      13 2.2 3  11  15
ff      36 7.3 3  28  42
oo      37 4.3 3  32  40
```

Alpha: 0.05 ; DF Error: 8
Critical Value of F: 4.1

Minimum Significant Difference: 14

Means with the same letter are not significantly different.

	yield	groups
oo	37	a
ff	36	a
cc	24	ab
fc	13	b

The minimum significant value is very high. If you require the approximate probabilities of comparison, you can use the option *group=FALSE*.

```
> outScheffe <- scheffe.test(model,"virus", group=FALSE, console=TRUE)
```

Study: model ~ "virus"

Scheffe Test for yield

Mean Square Error : 22

virus, means

	yield	std	r	Min	Max
cc	24	3.6	3	22	28
fc	13	2.2	3	11	15
ff	36	7.3	3	28	42
oo	37	4.3	3	32	40

Alpha: 0.05 ; DF Error: 8
Critical Value of F: 4.1

Comparison between treatments means

	Difference	pvalue	sig	LCL	UCL
cc - fc	11.53	0.0978	.	-1	24.067
cc - ff	-11.93	0.0855	.	-24	0.600
cc - oo	-12.50	0.0706	.	-25	0.034
fc - ff	-23.47	0.0023	**	-36	-10.933
fc - oo	-24.03	0.0020	**	-37	-11.500
ff - oo	-0.57	0.9991		-13	11.967

4.9 Multiple comparison in factorial treatments

In a factorial combined effects of the treatments. Comparative tests: *LSD*, *HSD*, *Waller-Duncan*, *Duncan*, *Scheffé*, *SNK* can be applied.

```
> # modelABC <-aov (y ~ A * B * C, data)
> # compare <-LSD.test (modelABC, c ("A", "B", "C"),console=TRUE)
```

The comparison is the combination of A:B:C.

Data RCBD design with a factorial clone x nitrogen. The response variable yield.

```
> yield <-scan (text =
+ "6 7 9 13 16 20 8 8 9
+ 7 8 8 12 17 18 10 9 12
+ 9 9 9 14 18 21 11 12 11
+ 8 10 10 15 16 22 9 9 9 "
+ )
> block <-gl (4, 9)
> clone <-rep (gl (3, 3, labels = c ("c1", "c2", "c3")), 4)
> nitrogen <-rep (gl (3, 1, labels = c ("n1", "n2", "n3")), 12)
> A <-data.frame (block, clone, nitrogen, yield)
> head (A)
```

	block	clone	nitrogen	yield
1	1	c1	n1	6
2	1	c1	n2	7
3	1	c1	n3	9
4	1	c2	n1	13
5	1	c2	n2	16
6	1	c2	n3	20

```
> outAOV <-aov (yield ~ block + clone * nitrogen, data = A)
```

```
> anova (outAOV)
```

Analysis of Variance Table

Response: yield

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
block	3	21	6.9	5.82	0.00387 **
clone	2	498	248.9	209.57	6.4e-16 ***
nitrogen	2	54	27.0	22.76	2.9e-06 ***
clone:nitrogen	4	43	10.8	9.11	0.00013 ***
Residuals	24	29	1.2		

Signif. codes:

0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```
> outFactorial <-LSD.test (outAOV, c("clone", "nitrogen"),
+ main = "Yield ~ block + nitrogen + clone + clone:nitrogen",console=TRUE)
```

Study: Yield ~ block + nitrogen + clone + clone:nitrogen

LSD t Test for yield

Mean Square Error: 1.2

clone:nitrogen, means and individual (95 %) CI

	yield	std	r	LCL	UCL	Min	Max
c1:n1	7.5	1.29	4	6.4	8.6	6	9
c1:n2	8.5	1.29	4	7.4	9.6	7	10
c1:n3	9.0	0.82	4	7.9	10.1	8	10
c2:n1	13.5	1.29	4	12.4	14.6	12	15
c2:n2	16.8	0.96	4	15.6	17.9	16	18
c2:n3	20.2	1.71	4	19.1	21.4	18	22
c3:n1	9.5	1.29	4	8.4	10.6	8	11
c3:n2	9.5	1.73	4	8.4	10.6	8	12
c3:n3	10.2	1.50	4	9.1	11.4	9	12

Alpha: 0.05 ; DF Error: 24

Critical Value of t: 2.1

least Significant Difference: 1.6

Treatments with the same letter are not significantly different.

	yield	groups
c2:n3	20.2	a
c2:n2	16.8	b
c2:n1	13.5	c
c3:n3	10.2	d
c3:n1	9.5	de
c3:n2	9.5	de
c1:n3	9.0	def
c1:n2	8.5	ef
c1:n1	7.5	f

```
> par(mar=c(3,3,2,0))
> pic1<-bar.err(outFactorial$means,variation="range",ylim=c(5,25), bar=FALSE,col=0,las=1)
> points(pic1$index,pic1$means,pch=18,cex=1.5,col="blue")
> axis(1,pic1$index,labels=FALSE)
> title(main="average and range\nclone:nitrogen")
```

4.10 Analysis of Balanced Incomplete Blocks

This analysis can come from balanced or partially balanced designs. The function *BIB.test* is for balanced designs, and *BIB.test*, for partially balanced designs. In the following example, the **agricolae** data will be used, [Joshi \(1987\)](#).

```
> # Example linear estimation and design of experiments. (Joshi)
> # Institute of Social Sciences Agra, India
> # 6 varieties of wheat in 10 blocks of 3 plots each.
> block<-gl(10,3)
> variety<-c(1,2,3,1,2,4,1,3,5,1,4,6,1,5,6,2,3,6,2,4,5,2,5,6,3,4,5,3, 4,6)
```

```
> Y<-c(69,54,50,77,65,38,72,45,54,63,60,39,70,65,54,65,68,67,57,60,62,
+ 59,65,63,75,62,61,59,55,56)
> head(cbind(block,variety,Y))
```

```
      block variety  Y
[1,]      1      1 69
[2,]      1      2 54
[3,]      1      3 50
[4,]      2      1 77
[5,]      2      2 65
[6,]      2      4 38
```

```
> BIB.test(block, variety, Y,console=TRUE)
```

ANALYSIS BIB: Y

Class level information

```
Block:  1 2 3 4 5 6 7 8 9 10
Trt   :  1 2 3 4 5 6
```

Number of observations: 30

Analysis of Variance Table

Response: Y

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
block.unadj	9	467	51.9	0.90	0.547
trt.adj	5	1156	231.3	4.02	0.016 *
Residuals	15	863	57.5		

Signif. codes:

0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

coefficient of variation: 13 %

Y Means: 60

variety, statistics

	Y mean.adj	SE	r	std	Min	Max
1	70	75	3.7	5	5.1	63 77
2	60	59	3.7	5	4.9	54 65
3	59	59	3.7	5	12.4	45 75
4	55	55	3.7	5	9.8	38 62
5	61	60	3.7	5	4.5	54 65
6	56	54	3.7	5	10.8	39 67

LSD test

Std.diff : 5.4

Alpha : 0.05

LSD : 11

Parameters BIB

```

Lambda      : 2
treatmeans  : 6
Block size  : 3
Blocks      : 10
Replication: 5

```

Efficiency factor 0.8

<<< Book >>>

Comparison between treatments means

	Difference	pvalue	sig.
1 - 2	16.42	0.0080	**
1 - 3	16.58	0.0074	**
1 - 4	20.17	0.0018	**
1 - 5	15.08	0.0132	*
1 - 6	20.75	0.0016	**
2 - 3	0.17	0.9756	
2 - 4	3.75	0.4952	
2 - 5	-1.33	0.8070	
2 - 6	4.33	0.4318	
3 - 4	3.58	0.5142	
3 - 5	-1.50	0.7836	
3 - 6	4.17	0.4492	
4 - 5	-5.08	0.3582	
4 - 6	0.58	0.9148	
5 - 6	5.67	0.3074	

Treatments with the same letter are not significantly different.

	Y groups
1 75	a
5 60	b
2 59	b
3 59	b
4 55	b
6 54	b

function (block, trt, Y, test = c("lsd", "tukey", "duncan", "waller", "snk"), alpha = 0.05, **group** = **TRUE**) LSD, Tukey Duncan, Waller-Duncan and SNK, can be used. The probabilities of the comparison can also be obtained. It should only be indicated: group=FALSE, thus:

```
> out <-BIB.test(block, trt=variety, Y, test="tukey", group=FALSE, console=TRUE)
```

ANALYSIS BIB: Y

Class level information

```

Block:  1 2 3 4 5 6 7 8 9 10
Trt   :  1 2 3 4 5 6

```

Number of observations: 30

Analysis of Variance Table

Response: Y

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
block.unadj	9	467	51.9	0.90	0.547
trt.adj	5	1156	231.3	4.02	0.016 *
Residuals	15	863	57.5		

Signif. codes:

0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

coefficient of variation: 13 %

Y Means: 60

variety, statistics

	Y mean.adj	SE	r	std	Min	Max
1 70	75	3.7	5	5.1	63	77
2 60	59	3.7	5	4.9	54	65
3 59	59	3.7	5	12.4	45	75
4 55	55	3.7	5	9.8	38	62
5 61	60	3.7	5	4.5	54	65
6 56	54	3.7	5	10.8	39	67

Tukey

Alpha : 0.05

Std.err : 3.8

HSD : 17

Parameters BIB

Lambda : 2

treatmeans : 6

Block size : 3

Blocks : 10

Replication: 5

Efficiency factor 0.8

<<< Book >>>

Comparison between treatments means

	Difference	pvalue	sig.
1 - 2	16.42	0.070	.
1 - 3	16.58	0.067	.
1 - 4	20.17	0.019	*
1 - 5	15.08	0.110	
1 - 6	20.75	0.015	*
2 - 3	0.17	1.000	
2 - 4	3.75	0.979	
2 - 5	-1.33	1.000	
2 - 6	4.33	0.962	

```

3 - 4      3.58  0.983
3 - 5     -1.50  1.000
3 - 6      4.17  0.967
4 - 5     -5.08  0.927
4 - 6      0.58  1.000
5 - 6      5.67  0.891

```

```
> names(out)
```

```

[1] "parameters" "statistics" "comparison" "means"
[5] "groups"

```

```
> rm(block, variety)
```

```
bar.group: out$groups
```

```
bar.err: out$means
```

4.11 Partially Balanced Incomplete Blocks

The function *PBIB.test* [Joshi \(1987\)](#), can be used for the lattice and alpha designs.

Consider the following case: Construct the alpha design with 30 treatments, 2 repetitions, and a block size equal to 3.

```

> # alpha design
> Genotype<-paste("geno",1:30,sep="")
> r<-2
> k<-3
> plan<-design.alpha(Genotype,k,r,seed=5)

```

```
Alpha Design (0,1) - Serie I
```

```
Parameters Alpha Design
```

```
=====
```

```
Treatmeans : 30
```

```
Block size : 3
```

```
Blocks      : 10
```

```
Replication: 2
```

```
Efficiency factor
```

```
(E ) 0.62
```

```
<<< Book >>>
```

The generated plan is plan\$book. Suppose that the corresponding observation to each experimental unit is:

```

> yield <-c(5,2,7,6,4,9,7,6,7,9,6,2,1,1,3,2,4,6,7,9,8,7,6,4,3,2,2,1,1,
+           2,1,1,2,4,5,6,7,8,6,5,4,3,1,1,2,5,4,2,7,6,6,5,6,4,5,7,6,5,5,4)

```


The data table is constructed for the analysis. In theory, it is presumed that a design is applied and the experiment is carried out; subsequently, the study variables are observed from each experimental unit.

```
> data<-data.frame(plan$book,yield)
> # The analysis:
> modelPBIB <- with(data,PBIB.test(block, Genotype, replication, yield, k=3, group=TRUE, console=TRUE
```

ANALYSIS PBIB: yield

Class level information

block : 20

Genotype : 30

Number of observations: 60

Estimation Method: Residual (restricted) maximum likelihood

Parameter Estimates

	Variance
block:replication	2.8e+00
replication	8.0e-09
Residual	2.0e+00

Fit Statistics

AIC	214
BIC	260
-2 Res Log Likelihood	-74

Analysis of Variance Table

Response: yield

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
Genotype	29	71.9	2.48	1.24	0.37
Residuals	11	22.0	2.00		

Coefficient of variation: 31 %

yield Means: 4.5

Parameters PBIB

Genotype	30
block size	3
block/replication	10
replication	2

Efficiency factor 0.62

Comparison test lsd

Treatments with the same letter are not significantly different.

	yield.adj	groups
geno27	7.7	a
geno20	6.7	ab
geno1	6.5	ab
geno16	6.2	abc
geno30	6.0	abcd
geno3	5.7	abcd
geno18	5.5	abcd
geno23	5.5	abcd
geno28	5.1	abcd
geno29	5.1	abcd
geno12	4.9	abcd
geno11	4.8	abcd
geno21	4.7	abcd
geno22	4.6	abcd
geno6	4.6	abcd
geno15	4.4	abcd
geno13	4.3	abcd
geno26	4.2	abcd
geno14	4.2	abcd
geno4	4.0	abcd
geno24	3.9	abcd
geno10	3.6	bcd
geno7	3.5	bcd
geno19	3.4	bcd
geno5	3.3	bcd
geno17	3.1	bcd
geno9	3.0	bcd
geno2	2.9	bcd
geno8	2.4	cd
geno25	2.2	d

```
<<< to see the objects: means, comparison and groups. >>>
```

The adjusted averages can be extracted from the modelPBIB.

```
head(modelPBIB$means)
```

The comparisons:

```
head(modelPBIB$comparison)
```

The data on the adjusted averages and their variation can be illustrated with the functions `plot.group` and `bar.err`. Since the created object is very similar to the objects generated by the multiple comparisons.

Analysis of balanced lattice 3x3, 9 treatments, 4 repetitions.

Create the data in a text file: `lattice3x3.txt` and read with R:

sqr block trt yield											
1	1	1	48.76	1	1	4	14.46	1	1	3	19.68
1	2	8	10.83	1	2	6	30.69	1	2	7	31.00
1	3	5	12.54	1	3	9	42.01	1	3	2	23.00
2	4	5	11.07	2	4	8	22.00	2	4	1	41.00
2	5	2	22.00	2	5	7	42.80	2	5	3	12.90
2	6	9	47.43	2	6	6	28.28	2	6	4	49.95
3	7	2	27.67	3	7	1	50.00	3	7	6	25.00
3	8	7	30.00	3	8	5	24.00	3	8	4	45.57
3	9	3	13.78	3	9	8	24.00	3	9	9	30.00
4	10	6	37.00	4	10	3	15.42	4	10	5	20.00
4	11	4	42.37	4	11	2	30.00	4	11	8	18.00
4	12	9	39.00	4	12	7	23.80	4	12	1	43.81

```
> trt<-c(1,8,5,5,2,9,2,7,3,6,4,9,4,6,9,8,7,6,1,5,8,3,2,7,3,7,2,1,3,4,6,4,9,5,8,1)
> yield<-c(48.76,10.83,12.54,11.07,22,47.43,27.67,30,13.78,37,42.37,39,14.46,30.69,42.01,
+ 22,42.8,28.28,50,24,24,15.42,30,23.8,19.68,31,23,41,12.9,49.95,25,45.57,30,20,18,43.81)
> sqr<-rep(gl(4,3),3)
> block<-rep(1:12,3)
> modelLattice<-PBIB.test(block,trt,sqr,yield,k=3,console=TRUE, method="VC")
```

ANALYSIS PBIB: yield

Class level information

block : 12

trt : 9

Number of observations: 36

Estimation Method: Variances component model

Fit Statistics

AIC 265

BIC 298

Analysis of Variance Table

Response: yield

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
sqr	3	133	44	0.69	0.57361
trt.unadj	8	3749	469	7.24	0.00042 ***
block/sqr	8	368	46	0.71	0.67917
Residual	16	1036	65		

Signif. codes:

0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Coefficient of variation: 28 %

yield Means: 29

Parameters PBIB

```

      .
trt      9
block size 3
block/sqr 3
sqr      4

```

Efficiency factor 0.75

Comparison test lsd

Treatments with the same letter are not significantly different.

```

      yield.adj groups
1      44      a
9      39     ab
4      39     ab
7      32     bc
6      31     bc
2      26     cd
8      18      d
5      17      d
3      15      d

```

<<< to see the objects: means, comparison and groups. >>>

The adjusted averages can be extracted from the modelLattice.

```
print(modelLattice$means)
```

The comparisons:

```
head(modelLattice$comparison)
```

4.12 Augmented Blocks

The function *DAU.test* can be used for the analysis of the augmented block design. The data should be organized in a table, containing the blocks, treatments, and the response.

```

> block<-c(rep("I",7),rep("II",6),rep("III",7))
> trt<-c("A","B","C","D","g","k","l","A","B","C","D","e","i","A","B","C",
+ "D","f","h","j")
> yield<-c(83,77,78,78,70,75,74,79,81,81,91,79,78,92,79,87,81,89,96, 82)
> head(data.frame(block, trt, yield))

```

```

      block trt yield
1      I    A    83
2      I    B    77
3      I    C    78
4      I    D    78
5      I    g    70
6      I    k    75

```

The treatments are in each block:

```
> by(trt,block,as.character)
```

```
block: I
```

```
[1] "A" "B" "C" "D" "g" "k" "l"
```

```
block: II
```

```
[1] "A" "B" "C" "D" "e" "i"
```

```
block: III
```

```
[1] "A" "B" "C" "D" "f" "h" "j"
```

With their respective responses:

```
> by(yield,block,as.character)
```

```
block: I
```

```
[1] "83" "77" "78" "78" "70" "75" "74"
```

```
block: II
```

```
[1] "79" "81" "81" "91" "79" "78"
```

```
block: III
```

```
[1] "92" "79" "87" "81" "89" "96" "82"
```

Analysis:

```
> modelDAU<- DAU.test(block,trt,yield,method="lsd",console=TRUE)
```

```
ANALYSIS DAU: yield
```

```
Class level information
```

```
Block: I II III
```

```
Trt : A B C D e f g h i j k l
```

```
Number of observations: 20
```

```
ANOVA, Treatment Adjusted
```

```
Analysis of Variance Table
```

```
Response: yield
```

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
block.unadj	2	360	180.0		
trt.adj	11	285	25.9	0.96	0.55
Control	3	53	17.6	0.65	0.61
Control + control.VS.aug.	8	232	29.0	1.08	0.48
Residuals	6	162	27.0		

```
ANOVA, Block Adjusted
```

```
Analysis of Variance Table
```

Response: yield

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
trt.unadj	11	576	52.3		
block.adj	2	70	34.8	1.29	0.34
Control	3	53	17.6	0.65	0.61
Augmented	7	506	72.3	2.68	0.13
Control vs augmented	1	17	16.9	0.63	0.46
Residuals	6	162	27.0		

coefficient of variation: 6.4 %

yield Means: 82

Critical Differences (Between)

	Std Error Diff.
Two Control Treatments	4.2
Two Augmented Treatments (Same Block)	7.3
Two Augmented Treatments(Different Blocks)	8.2
A Augmented Treatment and A Control Treatment	6.4

Treatments with the same letter are not significantly different.

yield groups		
h	94	a
f	86	ab
A	85	ab
D	83	ab
C	82	ab
j	80	ab
B	79	ab
e	78	ab
k	78	ab
i	77	ab
l	77	ab
g	73	b

Comparison between treatments means

<<< to see the objects: comparison and means >>>

```
> options(digits = 2)
> modelDAU$means
```

	yield	std	r	Min	Max	Q25	Q50	Q75	mean.adj	SE	block
A	85	6.7	3	79	92	81	83	88	85	3.0	
B	79	2.0	3	77	81	78	79	80	79	3.0	
C	82	4.6	3	78	87	80	81	84	82	3.0	
D	83	6.8	3	78	91	80	81	86	83	3.0	
e	79	NA	1	79	79	79	79	79	78	5.2	II
f	89	NA	1	89	89	89	89	89	86	5.2	III
g	70	NA	1	70	70	70	70	70	73	5.2	I

```

h    96 NA 1  96 96 96 96 96      94 5.2   III
i    78 NA 1  78 78 78 78 78      77 5.2    II
j    82 NA 1  82 82 82 82 82      80 5.2   III
k    75 NA 1  75 75 75 75 75      78 5.2    I
l    74 NA 1  74 74 74 74 74      77 5.2    I

> modelDAU<- DAU.test(block,trt,yield,method="lsd",group=FALSE,console=FALSE)
> head(modelDAU$comparison,8)

```

```

      Difference pvalue sig.
A - B          5.7   0.23
A - C          2.7   0.55
A - D          1.3   0.76
A - e          6.4   0.35
A - f         -1.8   0.78
A - g         11.4   0.12
A - h         -8.8   0.21
A - i          7.4   0.29

```

5 Non-parametric comparisons

The functions for non-parametric multiple comparisons included in **agricolae** are: *kruskal*, *waerden.test*, *friedman* and *durbin.test*, [Conover \(1999\)](#).

The post hoc nonparametrics tests (*kruskal*, *friedman*, *durbin* and *waerden*) are using the criterium Fisher's least significant difference (LSD).

The function *kruskal* is used for N samples (N>2), populations or data coming from a completely random experiment (populations = treatments).

The function *waerden.test*, similar to *kruskal-wallis*, uses a normal score instead of ranges as *kruskal* does.

The function *friedman* is used for organoleptic evaluations of different products, made by judges (every judge evaluates all the products). It can also be used for the analysis of treatments of the randomized complete block design, where the response cannot be treated through the analysis of variance.

The function *durbin.test* for the analysis of balanced incomplete block designs is very used for sampling tests, where the judges only evaluate a part of the treatments.

The function *Median.test* for the analysis the distribution is approximate with chi-squared ditribution with degree free number of groups minus one. In each comparison a table of 2x2 (pair of groups) and the criterion of greater or lesser value than the median of both are formed, the chi-square test is applied for the calculation of the probability of error that both are independent. This value is compared to the alpha level for group formation.

Montgomery book data, [Montgomery \(2002\)](#). Included in the **agricolae** package

```

> data(corn)
> str(corn)

'data.frame':      34 obs. of  3 variables:
 $ method      : int  1 1 1 1 1 1 1 1 1 2 ...
 $ observation: int  83 91 94 89 89 96 91 92 90 91 ...
 $ rx          : num  11 23 28.5 17 17 31.5 23 26 19.5 23 ...

```

For the examples, the agricolae package data will be used

5.1 Kruskal-Wallis

It makes the multiple comparison with Kruskal-Wallis. The parameters by default are $\alpha = 0.05$.

```
> str(kruskal)
```

```
function (y, trt, alpha = 0.05, p.adj = c("none", "holm",  
      "hommel", "hochberg", "bonferroni", "BH", "BY",  
      "fdr"), group = TRUE, main = NULL, console = FALSE)
```

Analysis

```
> outKruskal<-with(corn,kruskal(observation,method,group=TRUE, main="corn", console=TRUE))
```

Study: corn

Kruskal-Wallis test's

Ties or no Ties

Critical Value: 26

Degrees of freedom: 3

Pvalue Chisq : 1.1e-05

method, means of the ranks

	observation	r
1	21.8	9
2	15.3	10
3	29.6	7
4	4.8	8

Post Hoc Analysis

t-Student: 2

Alpha : 0.05

Groups according to probability of treatment differences and alpha level.

Treatments with the same letter are not significantly different.

	observation	groups
3	29.6	a
1	21.8	b
2	15.3	c
4	4.8	d

The object output has the same structure of the comparisons see the functions `plot.group(agricolae)`, `bar.err(agricolae)` and `bar.group(agricolae)`.

5.2 Kruskal-Wallis: adjust P-values

To see `p.adjust.methods()`

```
> out<-with(corn,kruskal(observation,method,group=TRUE, main="corn", p.adj="holm"))
> print(out$group)
```

```
observation groups
3          29.6    a
1          21.8    b
2          15.3    c
4           4.8    d
```

```
> out<-with(corn,kruskal(observation,method,group=FALSE, main="corn", p.adj="holm"))
> print(out$comparison)
```

```
      Difference pvalue Signif.
1 - 2          6.5 0.0079      **
1 - 3         -7.7 0.0079      **
1 - 4         17.0 0.0000     ***
2 - 3        -14.3 0.0000     ***
2 - 4         10.5 0.0003     ***
3 - 4         24.8 0.0000     ***
```

5.3 Friedman

The data consist of b mutually independent k -variate random variables called b blocks. The random variable is in a block and is associated with treatment. It makes the multiple comparison of the Friedman test with or without ties. A first result is obtained by `friedman.test` of R.

```
> str(friedman)
```

```
function (judge, trt, evaluation, alpha = 0.05, group = TRUE,
  main = NULL, console = FALSE)
```

Analysis

```
> data(grass)
> out<-with(grass,friedman(judge,trt, evaluation,alpha=0.05, group=FALSE,
+ main="Data of the book of Conover",console=TRUE))
```

Study: Data of the book of Conover

trt, Sum of the ranks

```
evaluation r
t1          38 12
t2          24 12
t3          24 12
t4          34 12
```

```

Friedman's Test
=====
Adjusted for ties
Critical Value: 8.1
P.Value Chisq: 0.044
F Value: 3.2
P.Value F: 0.036

```

Post Hoc Analysis

Comparison between treatments
Sum of the ranks

	difference	pvalue	signif.	LCL	UCL
t1 - t2	14.5	0.015	*	3.0	25.98
t1 - t3	13.5	0.023	*	2.0	24.98
t1 - t4	4.0	0.483		-7.5	15.48
t2 - t3	-1.0	0.860		-12.5	10.48
t2 - t4	-10.5	0.072	.	-22.0	0.98
t3 - t4	-9.5	0.102		-21.0	1.98

5.4 Waerden

A nonparametric test for several independent samples. Example applied with the sweet potato data in the **agricolae** basis.

```
> str(waerden.test)
```

```
function (y, trt, alpha = 0.05, group = TRUE, main = NULL,
  console = FALSE)
```

Analysis

```
> data(sweetpotato)
> outWaerden<-with(sweetpotato,waerden.test(yield,virus,alpha=0.01,group=TRUE,console=TRUE))
```

Study: yield ~ virus
Van der Waerden (Normal Scores) test's

```
Value : 8.4
Pvalue: 0.038
Degrees of Freedom: 3
```

virus, means of the normal score

	yield	std	r
cc	-0.23	0.30	3
fc	-1.06	0.35	3
ff	0.69	0.76	3

oo 0.60 0.37 3

Post Hoc Analysis

Alpha: 0.01 ; DF Error: 8

Minimum Significant Difference: 1.3

Treatments with the same letter are not significantly different.

Means of the normal score

	score	groups
ff	0.69	a
oo	0.60	a
cc	-0.23	ab
fc	-1.06	b

The comparison probabilities are obtained with the parameter group = **FALSE**

```
> names(outWaerden)
```

```
[1] "statistics" "parameters" "means"      "comparison"
[5] "groups"
```

To see outWaerden\$comparison

```
> out<-with(sweetpotato,waerden.test(yield,virus,group=FALSE,console=TRUE))
```

Study: yield ~ virus

Van der Waerden (Normal Scores) test's

Value : 8.4

Pvalue: 0.038

Degrees of Freedom: 3

virus, means of the normal score

	yield	std	r
cc	-0.23	0.30	3
fc	-1.06	0.35	3
ff	0.69	0.76	3
oo	0.60	0.37	3

Post Hoc Analysis

Comparison between treatments

mean of the normal score

	difference	pvalue	signif.	LCL	UCL
cc - fc	0.827	0.0690	.	-0.082	1.736

cc - ff	-0.921	0.0476	*	-1.830	-0.013
cc - oo	-0.837	0.0664	.	-1.746	0.072
fc - ff	-1.749	0.0022	**	-2.658	-0.840
fc - oo	-1.665	0.0029	**	-2.574	-0.756
ff - oo	0.084	0.8363		-0.825	0.993

5.5 Median test

A nonparametric test for several independent samples. The median test is designed to examine whether several samples came from populations having the same median, [Conover \(1999\)](#). See also Figure 4.

In each comparison a table of 2x2 (pair of groups) and the criterion of greater or lesser value than the median of both are formed, the chi-square test is applied for the calculation of the probability of error that both are independent. This value is compared to the alpha level for group formation.

```
> str(Median.test)

function (y, trt, alpha = 0.05, correct = TRUE, simulate.p.value = FALSE,
  group = TRUE, main = NULL, console = TRUE)

> str(Median.test)

function (y, trt, alpha = 0.05, correct = TRUE, simulate.p.value = FALSE,
  group = TRUE, main = NULL, console = TRUE)
```

Analysis

```
> data(sweetpotato)
> outMedian<-with(sweetpotato,Median.test(yield,virus,console=TRUE))
```

The Median Test for yield ~ virus

Chi Square = 6.7 DF = 3 P.Value 0.083
Median = 28

	Median	r	Min	Max	Q25	Q75
cc	23	3	22	28	22	26
fc	13	3	11	15	12	14
ff	39	3	28	42	34	40
oo	38	3	32	40	35	39

Post Hoc Analysis

Groups according to probability of treatment differences and alpha level.

Treatments with the same letter are not significantly different.

	yield	groups
ff	39	a
oo	38	a
cc	23	a
fc	13	b

```

> par(mfrow=c(2,2),mar=c(3,3,1,1),cex=0.8)
> # Graphics
> bar.group(outMedian$groups,ylim=c(0,50))
> bar.group(outMedian$groups,xlim=c(0,50),horiz = TRUE)
> plot(outMedian)
> plot(outMedian,variation="IQR",horiz = TRUE)

```

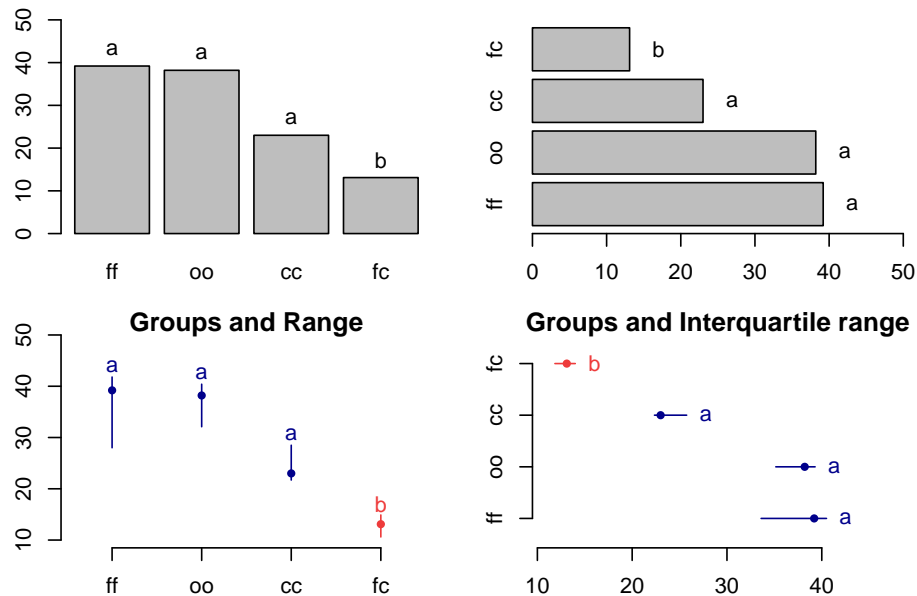


Figure 4: Grouping of treatments and its variation, Median method

```

> names(outMedian)

[1] "statistics" "parameters" "medians"      "comparison"
[5] "groups"

> outMedian$statistics

Chisq Df p.chisq Median
6.7 3 0.083 28

> outMedian$medians

Median r Min Max Q25 Q75
cc 23 3 22 28 22 26
fc 13 3 11 15 12 14
ff 39 3 28 42 34 40
oo 38 3 32 40 35 39

```

5.6 Durbin

durbin.test; example: Myles Hollander (p. 311) Source: W. Moore and C.I. Bliss. (1942) A multiple comparison of the Durbin test for the balanced incomplete blocks for sensorial or categorical evaluation. It forms groups according to the demanded ones for level of significance (alpha); by default, 0.05.

```
> str(durbin.test)
```

```
function (judge, trt, evaluation, alpha = 0.05, group = TRUE,
  main = NULL, console = FALSE)
```

Analysis

```
> days <-gl(7,3)
> chemical<-c("A","B","D","A","C","E","C","D","G","A","F","G", "B","C","F",
+ "B","E","G","D","E","F")
> toxic<-c(0.465,0.343,0.396,0.602,0.873,0.634,0.875,0.325,0.330, 0.423,0.987,0.426,
+ 0.652,1.142,0.989,0.536,0.409,0.309, 0.609,0.417,0.931)
> head(data.frame(days,chemical,toxic))
```

	days	chemical	toxic
1	1	A	0.46
2	1	B	0.34
3	1	D	0.40
4	2	A	0.60
5	2	C	0.87
6	2	E	0.63

```
> out<-durbin.test(days,chemical,toxic,group=FALSE,console=TRUE,
+ main="Logarithm of the toxic dose")
```

Study: Logarithm of the toxic dose
chemical, Sum of ranks

	sum
A	5
B	5
C	9
D	5
E	5
F	8
G	5

Durbin Test

```
=====
Value      : 7.7
DF 1       : 6
P-value    : 0.26
Alpha      : 0.05
DF 2       : 8
```

t-Student : 2.3

Least Significant Difference
between the sum of ranks: 5

Parameters BIB

Lambda : 1

Treatmeans : 7

Block size : 3

Blocks : 7

Replication: 3

Comparison between treatments

Sum of the ranks

	difference	pvalue	signif.
A - B	0	1.00	
A - C	-4	0.10	
A - D	0	1.00	
A - E	0	1.00	
A - F	-3	0.20	
A - G	0	1.00	
B - C	-4	0.10	
B - D	0	1.00	
B - E	0	1.00	
B - F	-3	0.20	
B - G	0	1.00	
C - D	4	0.10	
C - E	4	0.10	
C - F	1	0.66	
C - G	4	0.10	
D - E	0	1.00	
D - F	-3	0.20	
D - G	0	1.00	
E - F	-3	0.20	
E - G	0	1.00	
F - G	3	0.20	

> names(out)

```
[1] "statistics" "parameters" "means"      "rank"
[5] "comparison" "groups"
```

> out\$statistics

chisq.value	p.value	t.value	LSD
7.7	0.26	2.3	5

6 Graphics of the multiple comparison

The results of a comparison can be graphically seen with the functions *bar.group*, *bar.err* and *diffograph*.

6.1 bar.group

A function to plot horizontal or vertical bar, where the letters of groups of treatments is expressed. The function applies to all functions comparison treatments. Each object must use the group object previously generated by comparative function in indicating that group = TRUE.

example:

```
> # model <-aov (yield ~ fertilizer, data = field)
> # out <-LSD.test (model, "fertilizer", group = TRUE)
> # bar.group (out $ group)
> str(bar.group)
```

```
function (x, horiz = FALSE, ...)
```

See Figure 4. The Median test with option group=TRUE (default) is used in the exercise.

6.2 bar.err

A function to plot horizontal or vertical bar, where the variation of the error is expressed in every treatments. The function applies to all functions comparison treatments. Each object must use the means object previously generated by the comparison function, see Figure 5

```
> # model <-aov (yield ~ fertilizer, data = field)
> # out <-LSD.test (model, "fertilizer", group = TRUE)
> # bar.err(out$means)
> str(bar.err)
```

```
function (x, variation = c("SE", "SD", "range", "IQR"),
        horiz = FALSE, bar = TRUE, ...)
```

variation

SE: Standard error

SD: standard deviation

range: max-min

```
> par(mfrow=c(2,2),cex=0.7,mar=c(3.5,1.5,3,1))
> C1<-bar.err(modelPBIB$means[1:7, ], ylim=c(0,9), col=0, main="C1",
+ variation="range",border=3,las=2)
> C2<-bar.err(modelPBIB$means[8:15,], ylim=c(0,9), col=0, main="C2",
+ variation="range", border =4,las=2)
> # Others graphic
> C3<-bar.err(modelPBIB$means[16:22,], ylim=c(0,9), col=0, main="C3",
+ variation="range",border =2,las=2)
> C4<-bar.err(modelPBIB$means[23:30,], ylim=c(0,9), col=0, main="C4",
```



```

> par(mfrow=c(2,2),mar=c(3,3,2,1),cex=0.7)
> c1<-colors()[480]; c2=colors()[65]
> bar.err(outhSD$means, variation="range",ylim=c(0,50),col=c1,las=1)
> bar.err(outhSD$means, variation="IQR",horiz=TRUE, xlim=c(0,50),col=c2,las=1)
> plot(outhSD, variation="range",las=1)
> plot(outhSD, horiz=TRUE, variation="SD",las=1)

```

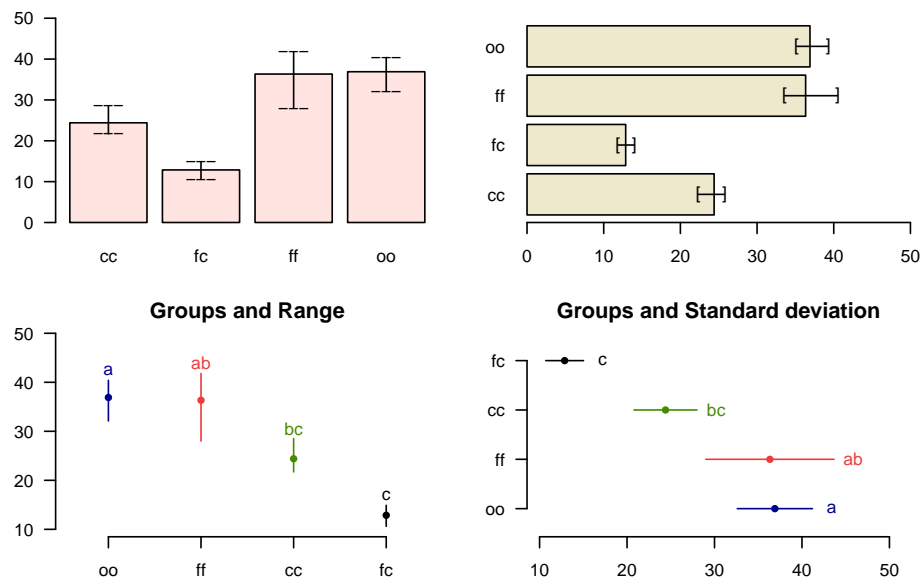


Figure 5: Comparison between treatments

```

> # model : yield ~ virus
> # Important group=TRUE
> par(mfrow=c(1,2),mar=c(3,3,1,1),cex=0.8)
> x<-duncan.test(model, "virus", group=TRUE)
> plot(x,las=1)
> plot(x,variation="IQR",horiz=TRUE,las=1)

```

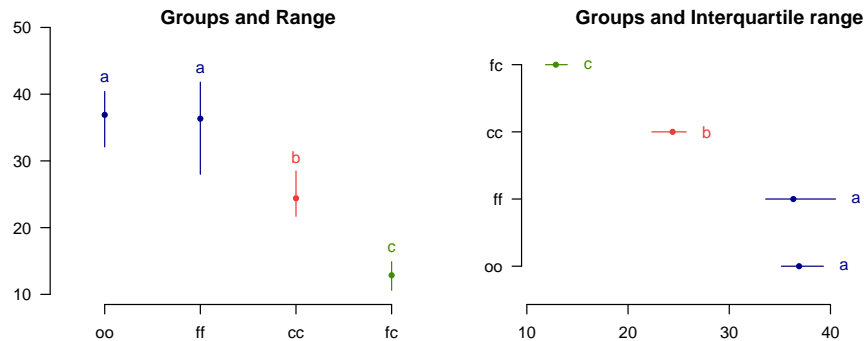


Figure 6: Grouping of treatments and its variation, Duncan method

```

+ variation="range", border =6,las=2)
> # Lattice graphics
> par(mar=c(2.5,2.5,1,0),cex=0.6)
> bar.group(modelLattice$group,ylim=c(0,55),density=10,las=1)

```

6.3 plot.group

It plot groups and variation of the treatments to compare. It uses the objects generated by a procedure of comparison like LSD (Fisher), duncan, Tukey (HSD), Student Newman Keul (SNK), Scheffe, Waller-Duncan, Ryan, Einot and Gabriel and Welsch (REGW), Kruskal Wallis, Friedman, Median, Waerden and other tests like Durbin, DAU, BIB, PBIB. The variation types are range (maximum and minimum), IQR (interquartile range), SD (standard deviation) and SE (standard error), see Figure 6.

The function: `plot.group()` and their arguments are `x` (output of test), `variation = c("range", "IQR", "SE", "SD")`, `horiz` (TRUE or FALSE), `xlim`, `ylim` and `main` are optional `plot()` parameters and others plot parameters.

6.4 diffograph

It plots bars of the averages of treatments to compare. It uses the objects generated by a procedure of comparison like LSD (Fisher), duncan, Tukey (HSD), Student Newman Keul (SNK), Scheffe, Ryan, Einot and Gabriel and Welsch (REGW), Kruskal Wallis, Friedman and Waerden, [Hsu \(1996\)](#), see Figure 7

```

> # function (x, main = NULL, color1 = "red", color2 = "blue",
> #   color3 = "black", cex.axis = 0.8, las = 1, pch = 20,
> #   bty = "l", cex = 0.8, lwd = 1, xlab = "", ylab = "",
> #   ...)
> # model : yield ~ virus
> # Important group=FALSE
> x<-HSD.test(model, "virus", group=FALSE)
> diffograph(x,cex.axis=0.9,xlab="Yield",ylab="Yield",cex=0.9)

```

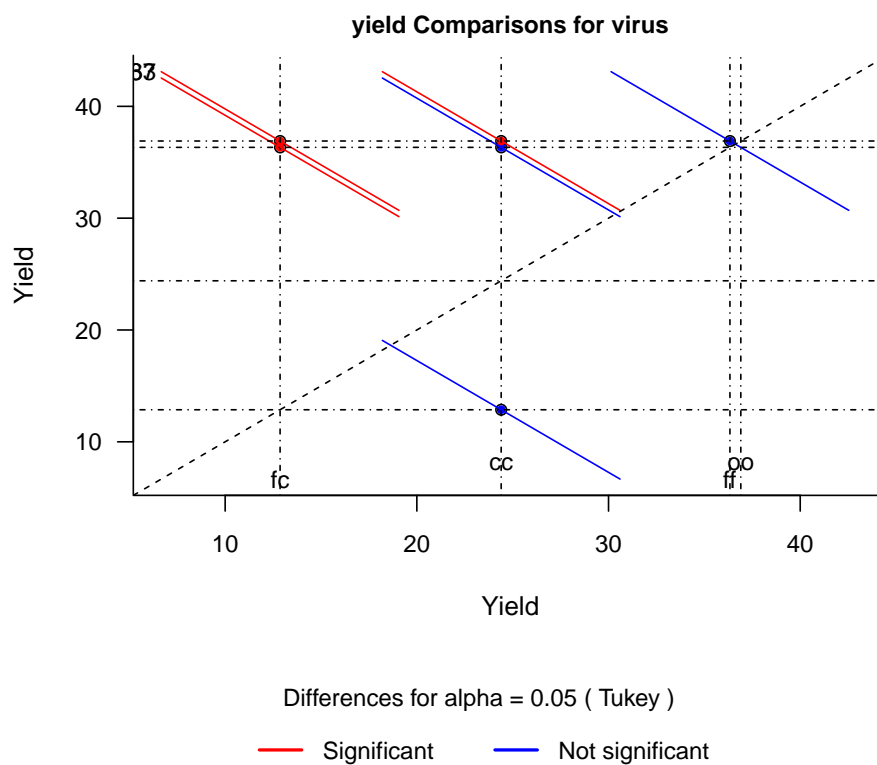


Figure 7: Mean-Mean scatter plot representation of the Tukey method

7 Stability Analysis

In **agricolae** there are two methods for the study of stability and the AMMI model. These are: a parametric model for a simultaneous selection in yield and stability "SHUKLA'S STABILITY VARIANCE AND KANG'S", Kang (1993) and a non-parametric method of Haynes, based on the data range.

7.1 Parametric Stability

Use the parametric model, function *stability.par*.

Prepare a data table where the rows and the columns are the genotypes and the environments, respectively. The data should correspond to yield averages or to another measured variable. Determine the variance of the common error for all the environments and the number of repetitions that was evaluated for every genotype. If the repetitions are different, find a harmonious average that will represent the set. Finally, assign a name to each row that will represent the genotype, Kang (1993). We will consider five environments in the following example:

```
> options(digit=2)
> f <- system.file("external/dataStb.csv", package="agricolae")
> dataStb<-read.csv(f)
> stability.par(dataStb, rep=4, MSError=1.8, alpha=0.1, main="Genotype",console=TRUE)
```

```
INTERACTIVE PROGRAM FOR CALCULATING SHUKLA'S STABILITY VARIANCE AND KANG'S
YIELD - STABILITY (YSi) STATISTICS
```

```
Genotype
```

```
Environmental index - covariate
```

```
Analysis of Variance
```

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
Total	203	2964.1716			
Genotypes	16	186.9082	11.6818	4.17	<0.001
Environments	11	2284.0116	207.6374	115.35	<0.001
Interaction	176	493.2518	2.8026	1.56	<0.001
Heterogeneity	16	44.8576	2.8036	1	0.459
Residual	160	448.3942	2.8025	1.56	<0.001
Pooled Error	576		1.8		

```
Genotype. Stability statistics
```

	Mean	Sigma-square	. s-square	. Ecovalence
A	7.4	2.47 ns	2.45 ns	25.8
B	6.8	1.60 ns	1.43 ns	17.4
C	7.2	0.57 ns	0.63 ns	7.3
D	6.8	2.61 ns	2.13 ns	27.2
E	7.1	1.86 ns	2.05 ns	19.9
F	6.9	3.58 *	3.95 *	36.5
G	7.8	3.58 *	3.96 *	36.6
H	7.9	2.72 ns	2.12 ns	28.2
I	7.3	4.25 **	3.94 *	43.0
J	7.1	2.27 ns	2.51 ns	23.9

K	6.4	2.56 ns	2.55 ns	26.7
L	6.9	1.56 ns	1.73 ns	16.9
M	6.8	3.48 *	3.28 ns	35.6
N	7.5	5.16 **	4.88 **	51.9
O	7.7	2.38 ns	2.64 ns	24.9
P	6.4	3.45 *	3.71 *	35.3
Q	6.2	3.53 *	3.69 *	36.1

Signif. codes: 0 '***' 0.01 '**' 0.05 'ns' 1

Simultaneous selection for yield and stability (++)

	Yield	Rank	Adj.rank	Adjusted	Stab.var	Stab.rating	YSi	...
A	7.4	13	1	14	2.47	0	14	+
B	6.8	4	-1	3	1.60	0	3	
C	7.2	11	1	12	0.57	0	12	+
D	6.8	4	-1	3	2.61	0	3	
E	7.1	9	1	10	1.86	0	10	+
F	6.9	8	-1	7	3.58	-4	3	
G	7.8	16	2	18	3.58	-4	14	+
H	7.9	17	2	19	2.72	0	19	+
I	7.3	12	1	13	4.25	-8	5	
J	7.1	10	1	11	2.27	0	11	+
K	6.4	3	-2	1	2.56	0	1	
L	6.9	7	-1	6	1.56	0	6	
M	6.8	6	-1	5	3.48	-4	1	
N	7.5	14	1	15	5.16	-8	7	+
O	7.7	15	2	17	2.38	0	17	+
P	6.4	2	-2	0	3.45	-4	-4	
Q	6.2	1	-3	-2	3.53	-4	-6	

Yield Mean: 7.1

YS Mean: 6.8

LSD (0.05): 0.45

- - - - -

+ selected genotype

++ Reference: Kang, M. S. 1993. Simultaneous selection for yield and stability: Consequences for growers. Agron. J. 85:754-757.

For 17 genotypes, the identification is made by letters. An error variance of 2 and 4 repetitions is assumed.

Analysis

```
> output <- stability.par(dataStb, rep=4, MSerror=2)
```

```
> names(output)
```

```
[1] "analysis" "statistics" "stability"
```

```
> print(output$stability)
```

	Yield	Rank	Adj.rank	Adjusted	Stab.var	Stab.rating	YSi	...
A	7.4	13	1	14	2.47	0	14	+
B	6.8	4	-1	3	1.60	0	3	
C	7.2	11	1	12	0.57	0	12	+
D	6.8	4	-1	3	2.61	0	3	
E	7.1	9	1	10	1.86	0	10	+
F	6.9	8	-1	7	3.58	-2	5	
G	7.8	16	2	18	3.58	-2	16	+
H	7.9	17	2	19	2.72	0	19	+
I	7.3	12	1	13	4.25	-4	9	+
J	7.1	10	1	11	2.27	0	11	+
K	6.4	3	-2	1	2.56	0	1	
L	6.9	7	-1	6	1.56	0	6	
M	6.8	6	-1	5	3.48	-2	3	
N	7.5	14	1	15	5.16	-8	7	
O	7.7	15	2	17	2.38	0	17	+
P	6.4	2	-2	0	3.45	-2	-2	
Q	6.2	1	-2	-1	3.53	-2	-3	

The selected genotypes are: A, C, E, G, H, I, J and O. These genotypes have a higher yield and a lower variation. to see `output$analysis`, the interaction is significant.

If for example there is an environmental index, it can be added as a covariate In the first five locations. For this case, the altitude of the localities is included.

```
> data5<-dataStb[,1:5]
> altitude<-c(1200, 1300, 800, 1600, 2400)
> stability <- stability.par(data5,rep=4,MSerror=2, cova=TRUE, name.cov= "altitude",
+ file.cov=altitude)
```

7.2 Non-parametric Stability

For non-parametric stability, the function in 'agricolae' is `stability.nonpar()`. The names of the genotypes should be included in the first column, and in the other columns, the response by environments, [Haynes and Lambert](#) and [Christ and Weingartner](#) and [Douches and Backlund](#) and [Secor and Fry](#) and [Stevenson \(1998\)](#).

Analysis

```
> data <- data.frame(name=row.names(dataStb), dataStb)
> output<-stability.nonpar(data, "YIELD", ranking=TRUE)
> names(output)
```

```
[1] "ranking"      "statistics"
```

```
> output$statistics
```

```
MEAN es1 es2 vs1 vs2 chi.ind chi.sum
1 7.1 5.6 24 0.72 47 8.8 28
```

7.3 AMMI

The model AMMI uses the biplot constructed through the principal components generated by the interaction environment-genotype. If there is such interaction, the percentage of the two principal components would explain more than the 50% of the total variation; in such case, the biplot would be a good alternative to study the interaction environment-genotype, [Crossa \(1990\)](#).

The data for AMMI should come from similar experiments conducted in different environments. Homogeneity of variance of the experimental error, produced in the different environments, is required. The analysis is done by combining the experiments.

The data can be organized in columns, thus: environment, genotype, repetition, and variable.

The data can also be the averages of the genotypes in each environment, but it is necessary to consider a harmonious average for the repetitions and a common variance of the error. The data should be organized in columns: environment, genotype, and variable.

When performing AMMI, this generates the Biplot, Triplot and Influence graphics, see [Figure 8](#).

For the application, we consider the data used in the example of parametric stability (study):

AMMI structure

```
> str(AMMI)
```

```
function (ENV, GEN, REP, Y, MSE = 0, console = FALSE,  
         PC = FALSE)
```

plot.AMMI structure, plot()

```
> str(plot.AMMI)
```

```
function (x, first = 1, second = 2, third = 3, type = 1,  
         number = FALSE, gcol = NULL, ecol = NULL, icol = NULL,  
         angle = 25, lwd = 1.8, length = 0.1, xlab = NULL,  
         ylab = NULL, xlim = NULL, ylim = NULL, ...)
```

type: 1=biplot, 2= triplot 3=influence genotype

```
> data(plrv)  
> model<-with(plrv,AMMI(Locality, Genotype, Rep, Yield, console=FALSE))  
> names(model)
```

```
[1] "ANOVA"      "genXenv"    "analysis"   "means"      "biplot"  
[6] "PC"
```

```
> model$ANOVA
```

Analysis of Variance Table

Response: Y

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
ENV	5	122284	24457	257.04	9.1e-12 ***
REP(ENV)	12	1142	95	2.57	0.0029 **

```
> par(cex=0.4,mar=c(4,4,1,2))
> plot(model,type=1,las=1,xlim=c(-5,6))
```

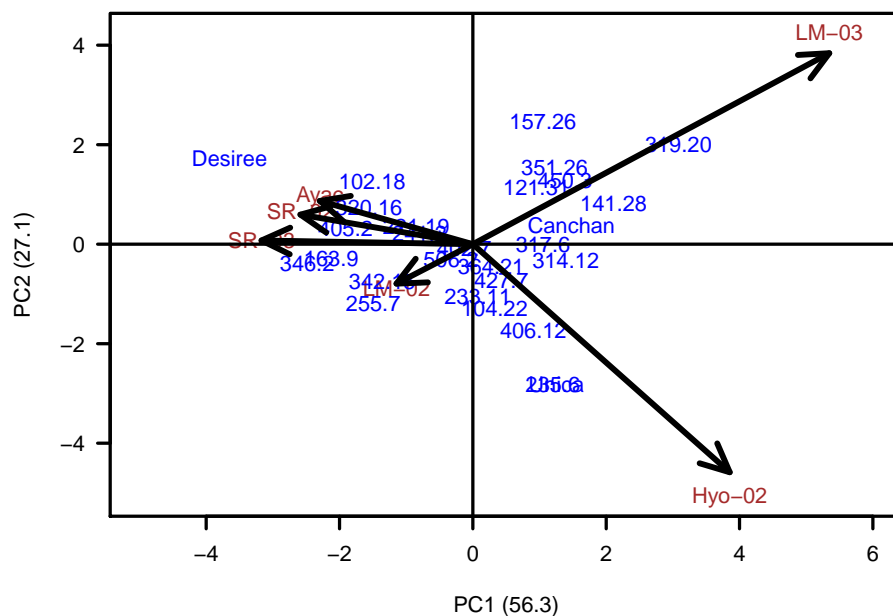


Figure 8: Biplot

```
GEN      27  17533      649  17.54 < 2e-16 ***
ENV:GEN  135  23762      176   4.75 < 2e-16 ***
Residuals 324  11998       37
```

Signif. codes:

0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```
> model$analysis
```

	percent	acum	Df	Sum.Sq	Mean.Sq	F.value	Pr.F
PC1	56.3	56	31	13369	431	11.65	0.0000
PC2	27.1	83	29	6428	222	5.99	0.0000
PC3	9.4	93	27	2242	83	2.24	0.0005
PC4	4.3	97	25	1028	41	1.11	0.3286
PC5	2.9	100	23	696	30	0.82	0.7059

```
> pc <- model$analysis[, 1]
> pc12<-sum(pc[1:2])
> pc123<-sum(pc[1:3])
```

In this case, the interaction is significant. The first two components explain 83.4 %; then the biplot can provide information about the interaction genotype-environment. With the triplot, 92.8% would be explained.


```
> par(mar=c(4,4,1,2),cex=0.5)
> plot(model,type=3,number=TRUE,las=1,xlim=c(-5,6),bty="l")
```

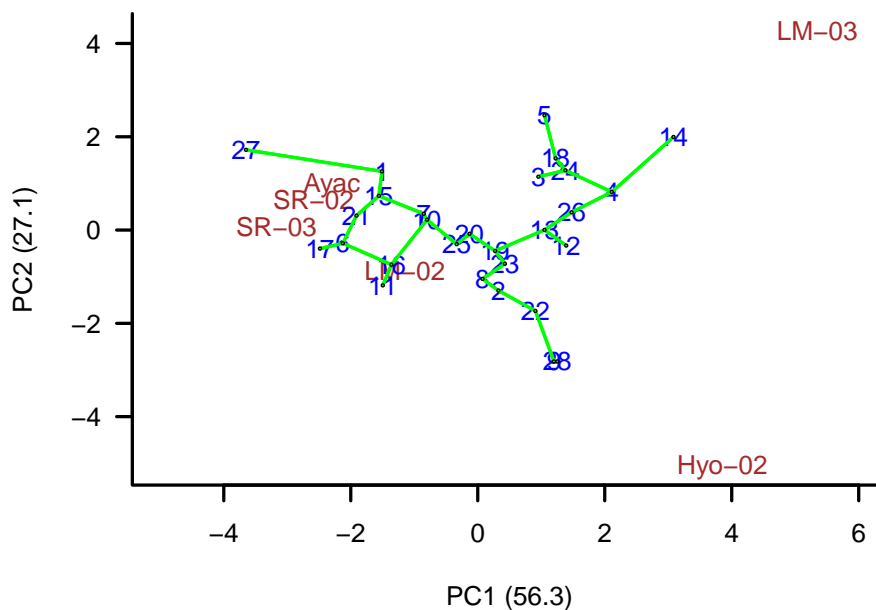


Figure 9: Influence genotype

To triplot require klaR package. in R execute:

```
plot(model,type=2,las=1)
```

To Influence graphics genotype require spdep package, in R execute:

```
plot(model,type=3). See Figure 9.
```

7.4 AMMI index and yield stability

Calculate AMMI stability value (ASV) and Yield stability index (YSI), [Sabaghnia and Sabaghpour and Dehghani \(2008\)](#); [Purchase \(1997\)](#).

```
> data(plrv)
> model<- with(plrv,AMMI(Locality, Genotype, Rep, Yield, console=FALSE))
> index<-index.AMMI(model)
> # Crops with improved stability according AMMI.
> print(index[order(index[,3]),])
```

	ASV	YSI	rASV	rYSI	means
402.7	0.20	20	1	19	27
506.2	0.56	13	2	11	33
364.21	0.60	13	3	10	34
427.7	0.95	11	4	7	36
233.11	1.05	22	5	17	29

241.2	1.17	28	6	22	26
221.19	1.27	33	7	26	23
104.22	1.38	21	8	13	31
317.6	1.52	18	9	9	35
121.31	1.79	25	10	15	30
314.12	2.04	29	11	18	28
342.15	2.10	36	12	24	26
Canchan	2.17	33	13	20	27
406.12	2.17	26	14	12	33
351.26	2.34	23	15	8	36
320.16	2.36	37	16	21	26
450.3	2.37	23	17	6	36
255.7	2.46	32	18	14	31
102.18	2.51	42	19	23	26
405.2	2.77	36	20	16	29
157.26	2.89	26	21	5	37
163.9	3.08	49	22	27	21
141.28	3.15	24	23	1	40
235.6	3.31	28	24	4	39
Unica	3.35	27	25	2	39
346.2	3.61	51	26	25	24
319.20	4.87	30	27	3	39
Desiree	5.54	56	28	28	16

```
> # Crops with better response and improved stability according AMMI.
> print(index[order(index[,4]),])
```

	ASV	YSI	rASV	rYSI	means
141.28	3.15	24	23	1	40
Unica	3.35	27	25	2	39
319.20	4.87	30	27	3	39
235.6	3.31	28	24	4	39
157.26	2.89	26	21	5	37
450.3	2.37	23	17	6	36
427.7	0.95	11	4	7	36
351.26	2.34	23	15	8	36
317.6	1.52	18	9	9	35
364.21	0.60	13	3	10	34
506.2	0.56	13	2	11	33
406.12	2.17	26	14	12	33
104.22	1.38	21	8	13	31
255.7	2.46	32	18	14	31
121.31	1.79	25	10	15	30
405.2	2.77	36	20	16	29
233.11	1.05	22	5	17	29
314.12	2.04	29	11	18	28
402.7	0.20	20	1	19	27
Canchan	2.17	33	13	20	27
320.16	2.36	37	16	21	26
241.2	1.17	28	6	22	26
102.18	2.51	42	19	23	26

```

> par(cex=0.6,mar=c(3,3,2,1))
> data(pamCIP)
> rownames(pamCIP)<-substr(rownames(pamCIP),1,6)
> output<-consensus(pamCIP,distance="binary", method="complete", nboot=5)

```

Duplicates: 18

New data : 25 Records

Consensus hclust

Method distance: binary

Method cluster : complete

rows and cols : 25 107

n-bootstrap : 5

Run time : 1.9 secs

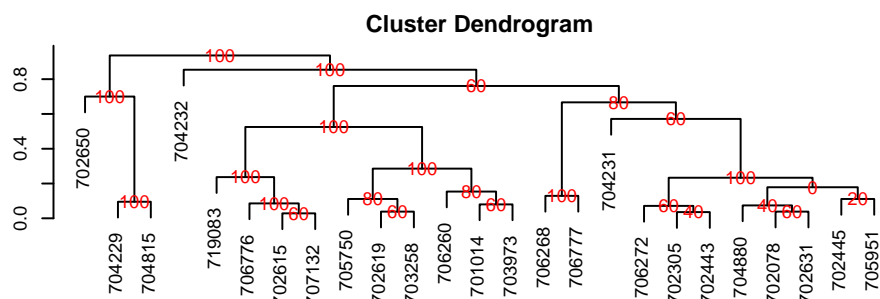


Figure 10: Dendrogram, production by consensus

342.15	2.10	36	12	24	26
346.2	3.61	51	26	25	24
221.19	1.27	33	7	26	23
163.9	3.08	49	22	27	21
Desiree	5.54	56	28	28	16

8 Special functions

8.1 Consensus of dendrogram

Consensus is the degree or similarity of the vertexes of a tree regarding its branches of the constructed dendrogram. The function to apply is `consensus()`.

The data correspond to a table, with the name of the individuals and the variables in the rows and columns respectively. For the demonstration, we will use the "pamCIP" data of 'agricolae', which correspond to molecular markers of 43 entries of a germplasm bank (rows) and 107 markers (columns).

The program identifies duplicates in the rows and can operate in both cases. The result is a dendrogram, in which the consensus percentage is included, see Figure 10.

```
> par(cex=0.6,mar=c(3,3,1.5,1))
> out1<- hcut(output,h=0.4,group=8,type="t",edgePar = list(lty=1:2, col=colors()[c(42,84)]),
+ main="group 8" ,col.text="blue",cex.text=1,las=1)
```

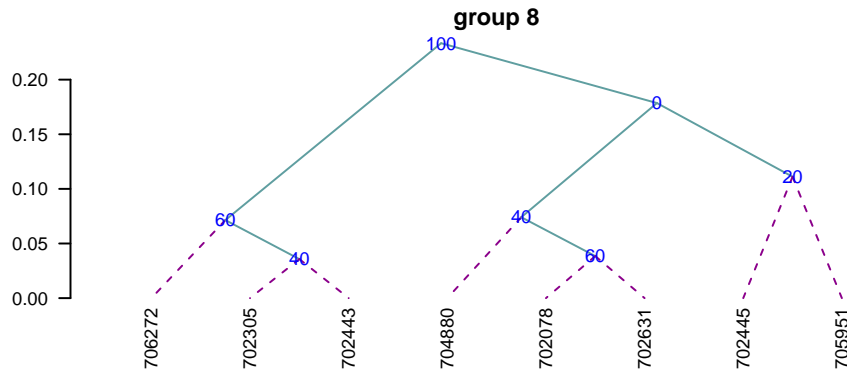


Figure 11: Dendrogram, production by hcut()

When the dendrogram is complex, it is convenient to extract part of it with the function `hcut()`, see Figure 11.

The obtained object "output" contains information about the process:

```
> names(output)

[1] "table.dend" "dendrogram" "duplicates"
```

Construct a classic dendrogram, execute procedure in R

use the previous result 'output'

```
> dend <- as.dendrogram(output$dendrogram)
> data <- output$table.dend
> head(output$table.dend)
```

	X1	X2	xaxis	height	percentage	groups
1	-6	-24	7.5	0.029	60	6-24
2	-3	-4	19.5	0.036	40	3-4
3	-2	-8	22.5	0.038	60	2-8
4	-7	-10	10.5	0.038	60	7-10
5	-21	2	18.8	0.071	60	3-4-21
6	-16	3	21.8	0.074	40	2-8-16

```
> par(mar=c(3,3,1,1),cex=0.6)
> plot(dend,type="r",edgePar = list(lty=1:2, col=colors()[c(42,84)]),las=1)
> text(data[,3],data[,4],data[,5],col="blue",cex=1)
```

8.2 Montecarlo

It is a method for generating random numbers of an unknown distribution. It uses a data set and, through the cumulative behavior of its relative frequency, generates the possible random values that

```
> par(mar=c(2,0,2,1),cex=0.6)
> plot(density(soil$pH),axes=FALSE,main="pH density of the soil\ncon Ralstonia",xlab="",lwd=4)
> lines(density(simulated), col="blue", lty=4,lwd=4)
> axis(1,0:12)
> legend("topright",c("Original", "Simulated"),lty=c(1,4),col=c("black", "blue"), lwd=4)
```

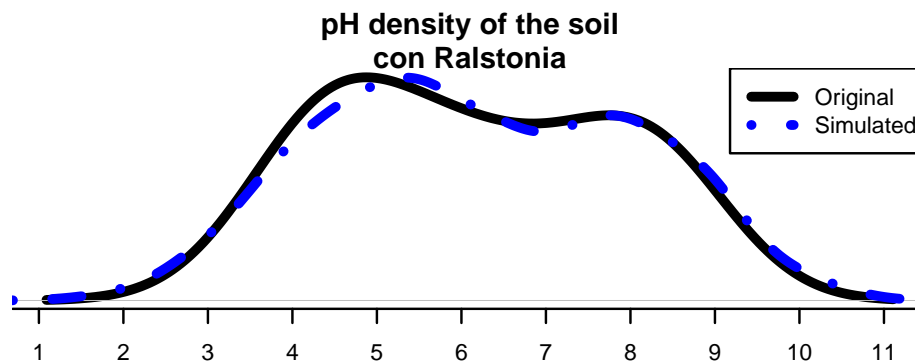


Figure 12: Distribution of the simulated and the original data

follow the data distribution. These new numbers are used in some simulation process.

The probability density of the original and simulated data can be compared, see Figure 12.

```
> data(soil)
> # set.seed(9473)
> simulated <- montecarlo(soil$pH,1000)
> h<-graph.freq(simulated,nclass=7,plot=FALSE)
```

1000 data was simulated, being the frequency table:

```
> round(table.freq(h),2)
```

	Lower	Upper	Main	Frequency	Percentage	CF	CPF
1	1.5	2.8	2.2	20	2.0	20	2
2	2.8	4.1	3.5	120	12.0	140	14
3	4.1	5.4	4.8	238	23.8	378	38
4	5.4	6.7	6.1	225	22.5	603	60
5	6.7	8.1	7.4	198	19.8	801	80
6	8.1	9.4	8.7	168	16.8	969	97
7	9.4	10.7	10.0	31	3.1	1000	100

Some statistics, original data:

```
> summary(soil$pH)
```

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
3.8	4.7	6.1	6.2	7.6	8.4

Some statistics, montecarlo simulate data:

```
> summary(simulated)
```

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
1.6	4.8	6.1	6.2	7.7	10.7

8.3 Re-Sampling in linear model

It uses the permutation method for the calculation of the probabilities of the sources of variation of ANOVA according to the linear regression model or the design used. The principle is that the Y response does not depend on the averages proposed in the model; hence, the Y values can be permuted and many model estimates can be constructed. On the basis of the patterns of the random variables of the elements under study, the probability is calculated in order to measure the significance.

For a variance analysis, the data should be prepared similarly. The function to use is: `resampling.model()`

```
> data(potato)
> potato[,1]<-as.factor(potato[,1])
> potato[,2]<-as.factor(potato[,2])
> model<-"cutting~variety + date + variety:date"
> analysis<-resampling.model(model, potato, k=100)
> Xsol<-as.matrix(round(analysis$solution,2))
> print(Xsol,na.print = "")
```

	Df	Sum Sq	Mean Sq	F value	Pr(>F)	Resampling
variety	1	25.1	25.1	7.3	0.02	0.01
date	2	13.9	7.0	2.0	0.18	0.16
variety:date	2	4.8	2.4	0.7	0.51	0.61
Residuals	12	41.5	3.5			

The function `resampling.model()` can be used when the errors have a different distribution from normal

8.4 Simulation in linear model

Under the assumption of normality, the function generates pseudo experimental errors under the proposed model, and determines the proportion of valid results according to the analysis of variance found.

The function is: `simulation.model()`. The data are prepared in a table, similarly to an analysis of variance.

Considering the example proposed in the previous procedure:

```
> simModel <- simulation.model(model, potato, k=100,console=TRUE)
```

Simulation of experiments

Under the normality assumption

- - - - -

Proposed model: cutting~variety + date + variety:date

Analysis of Variance Table

```

Response: cutting
      Df Sum Sq Mean Sq F value Pr(>F)
variety  1  25.1   25.09    7.26  0.02 *
date     2  13.9    6.95    2.01  0.18
variety:date  2   4.9    2.43    0.70  0.51
Residuals 12  41.5    3.46
---
Signif. codes:
0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
---
Validation of the analysis of variancia for the proposed model
Simulations: 100

```

```

      Df F value % Acceptance % Rejection
variety  1    7.3         49         51
date     2    2.0         60         40
variety:date  2    0.7         61         39
      Criterion
variety    nonacceptable
date        acceptable
variety:date acceptable
---

```

The validation is referred to the percentage of decision results equal to the result of the ANOVA decision. Thus, 61% of the results simulated on the interaction variety*date gave the same result of acceptance or rejection obtained in the ANOVA.

8.5 Path Analysis

It corresponds to the "path analysis" method. The data correspond to correlation matrices of the independent ones with the dependent matrix (XY) and between the independent ones (XX).

It is necessary to assign names to the rows and columns in order to identify the direct and indirect effects.

```

> corr.x<- matrix(c(1,0.5,0.5,1),c(2,2))
> corr.y<- rbind(0.6,0.7)
> names<-c("X1", "X2")
> dimnames(corr.x)<-list(names,names)
> dimnames(corr.y)<-list(names,"Y")
> output<-path.analysis(corr.x,corr.y)

```

Direct(Diagonal) and indirect effect path coefficients

```

=====
      X1  X2
X1 0.33 0.27
X2 0.17 0.53

```

Residual Effect^2 = 0.43

```

> output

```

```
$Coeff
      X1   X2
X1 0.33 0.27
X2 0.17 0.53

$Residual
[1] 0.43
```

8.6 Line X Tester

It corresponds to a crossbreeding analysis of a genetic design. The data should be organized in a table. Only four columns are required: repetition, females, males, and response. In case it corresponds to progenitors, the females or males field will only be filled with the corresponding one. See the heterosis data, [Singh and Chaudhary \(1979\)](#).

Example with the heterosis data, locality 2.

	Replication	Female	Male	v2
109	1	LT-8	TS-15	2.65
110	1	LT-8	TPS-13	2.26
...				
131	1	Achirana	TPS-13	3.55
132	1	Achirana	TPS-67	3.05
...				
140	1	Achirana	<NA>	3.35
...				
215	3	<NA>	TPS-67	2.91

where <NA> is empty.

If it is a progeny, it comes from a "Female" and a "Male." If it is a progenitor, it will only be "Female" or "Male."

The following example corresponds to data of the locality 2:

24 progenies 8 females 3 males 3 repetitions

They are 35 treatments (24, 8, 3) applied to three blocks.

```
> rm(list=ls())
> options(digits = 2)
> data(heterosis)
> str(heterosis)

'data.frame':      324 obs. of  11 variables:
 $ Place      : num  1 1 1 1 1 1 1 1 1 1 ...
 $ Replication: num  1 1 1 1 1 1 1 1 1 1 ...
 $ Treatment  : num  1 2 3 4 5 6 7 8 9 10 ...
 $ Factor     : Factor w/ 3 levels "Control","progenie",...: 2 2 2 2 2 2 2 2 2 2 ...
 $ Female     : Factor w/ 8 levels "Achirana","LT-8",...: 2 2 2 6 6 6 7 7 7 8 ...
 $ Male       : Factor w/ 3 levels "TPS-13","TPS-67",...: 3 1 2 3 1 2 3 1 2 3 ...
 $ v1         : num  0.948 1.052 1.05 1.058 1.123 ...
 $ v2         : num  1.65 2.2 1.88 2 2.45 2.63 2.75 3 2.51 1.93 ...
```



```

$ v3      : num  17.2 17.8 15.6 16 16.5 ...
$ v4      : num   9.93 12.45 9.3 12.77 14.13 ...
$ v5      : num  102.6 107.4 120.5 83.8 90.4 ...

> site2<-subset(heterosis,heterosis[,1]==2)
> site2<-subset(site2[,c(2,5,6,8)],site2[,4]!="Control")
> output1<-with(site2,lineXtester(Replication, Female, Male, v2))

```

ANALYSIS LINE x TESTER: v2

ANOVA with parents and crosses

=====

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
Replications	2	0.5192	0.2596	9.80	0.0002
Treatments	34	16.1016	0.4736	17.88	0.0000
Parents	10	7.7315	0.7731	29.19	0.0000
Parents vs. Crosses	1	0.0051	0.0051	0.19	0.6626
Crosses	23	8.3650	0.3637	13.73	0.0000
Error	68	1.8011	0.0265		
Total	104	18.4219			

ANOVA for line X tester analysis

=====

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
Lines	7	4.98	0.711	3.6	0.019
Testers	2	0.65	0.325	1.7	0.226
Lines X Testers	14	2.74	0.196	7.4	0.000
Error	68	1.80	0.026		

ANOVA for line X tester analysis including parents

=====

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
Replications	2	0.5192	0.2596	9.80	0.0002
Treatments	34	16.1016	0.4736	17.88	0.0000
Parents	10	7.7315	0.7731	29.19	0.0000
Parents vs. Crosses	1	0.0051	0.0051	0.19	0.6626
Crosses	23	8.3650	0.3637	13.73	0.0000
Lines	7	4.9755	0.7108	3.63	0.0191
Testers	2	0.6494	0.3247	1.66	0.2256
Lines X Testers	14	2.7401	0.1957	7.39	0.0000
Error	68	1.8011	0.0265		
Total	104	18.4219			

GCA Effects:

=====

Lines Effects:

Achirana	LT-8	MF-I	MF-II	Serrana	TPS-2
0.022	-0.338	0.199	-0.449	0.058	-0.047
TPS-25	TPS-7				
0.414	0.141				

Testers Effects:

TPS-13	TPS-67	TS-15
0.087	0.046	-0.132

SCA Effects:

=====

Lines	Testers		
	TPS-13	TPS-67	TS-15
Achirana	0.061	0.059	-0.120
LT-8	-0.435	0.519	-0.083
MF-I	-0.122	-0.065	0.187
MF-II	-0.194	0.047	0.148
Serrana	0.032	-0.113	0.081
TPS-2	0.197	-0.072	-0.124
TPS-25	0.126	-0.200	0.074
TPS-7	0.336	-0.173	-0.162

Standard Errors for Combining Ability Effects:

=====

S.E. (gca for line) : 0.054
S.E. (gca for tester) : 0.033
S.E. (sca effect) : 0.094
S.E. (gi - gj)line : 0.077
S.E. (gi - gj)tester : 0.047
S.E. (sij - skl)tester: 0.13

Genetic Components:

=====

Cov H.S. (line) : 0.057
Cov H.S. (tester) : 0.0054
Cov H.S. (average): 0.0039
Cov F.S. (average): 0.13
F = 0, Additive genetic variance: 0.015
F = 1, Additive genetic variance: 0.0077
F = 0, Variance due to Dominance: 0.11
F = 1, Variance due to Dominance: 0.056

Proportional contribution of lines, testers
and their interactions to total variance

=====

Contributions of lines : 59
Contributions of testers: 7.8
Contributions of lxt : 33

> options(digits = 7)

8.7 Soil Uniformity

The Smith index is an indicator of the uniformity, used to determine the parcel size for research purposes. The data correspond to a matrix or table that contains the response per basic unit, a

```
> par(mar=c(3,3,4,1),cex=0.7)
> data(rice)
> table<-index.smith(rice, col="blue",
+ main="Interaction between the CV and the plot size",type="l",xlab="Size")
```

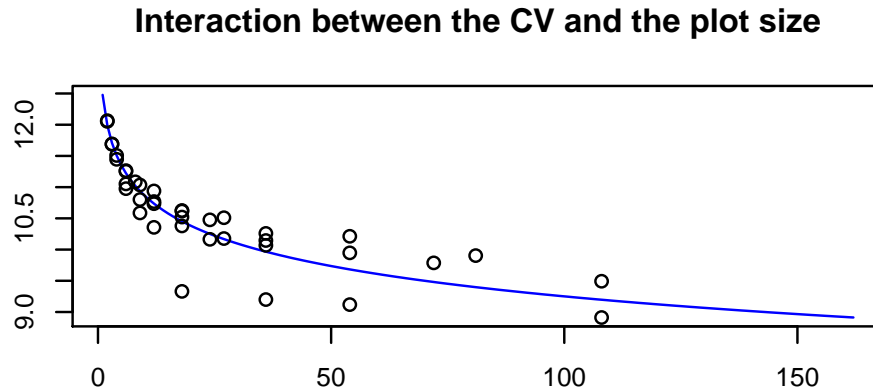


Figure 13: Adjustment curve for the optimal size of plot

number of n rows \times m columns, and a total of $n \times m$ basic units.

For the test, we will use the rice file. The graphic is a result with the adjustment of a model for the plot size and the coefficient of variation, see Figure 13.

```
> uniformity <- data.frame(table$uniformity)
> head(uniformity)
```

	Size	Width	Length	plots	Vx	CV
1	1	1	1	648	9044.539	13.0
2	2	1	2	324	7816.068	12.1
3	2	2	1	324	7831.232	12.1
4	3	1	3	216	7347.975	11.7
5	3	3	1	216	7355.216	11.7
6	4	1	4	162	7047.717	11.4

8.8 Confidence Limits In Biodiversity Indices

The biodiversity indices are widely used for measuring the presence of living things in an ecological area. Many programs indicate their value. The function of 'agricolae' is also to show the confidence intervals, which can be used for a statistical comparison. Use the bootstrap procedure. The data are organized in a table; the species are placed in a column; and in another one, the number of individuals. The indices that can be calculated with the function `index.bio()` of 'agricolae' are: "Margalef", "Simpson.Dom", "Simpson.Div", "Berger.Parker", "McIntosh", and "Shannon."

In the example below, we will use the data obtained in the locality of Paracsho, district of Huasahuasi, province of Tarma in the department of Junin.

The evaluation was carried out in the parcels on 17 November 2005, without insecticide application. The counted specimens were the following:

```
> data(paracsho)
> species <- paracsho[79:87,4:6]
> species
```

	Orden	Family	Number.of.specimens
79	DIPTERA	TIPULIDAE	3
80	LEPIDOPTERA	NOCTUIDAE	1
81	NOCTUIDAE	PYRALIDAE	3
82	HEMIPTERA	ANTHOCORIDAE	1
83	DIPTERA	TACHINIDAE	16
84	DIPTERA	ANTHOCORIDAE	3
85	DIPTERA	SCATOPHAGIDAE	5
86	DIPTERA	SYRPHIDAE	1
87	DIPTERA	MUSCIDAE	3

The Shannon index is:

```
> output <- index.bio(species[,3],method="Shannon",level=95,nboot=200)
```

Method: Shannon

The index: 3.52304

95 percent confidence interval:
3.180131 ; 4.260501

8.9 Correlation

The function `correlation()` of 'agricolae' makes the correlations through the methods of Pearson, Spearman and Kendall for vectors and/or matrices. If they are two vectors, the test is carried out for one or two lines; if it is a matrix one, it determines the probabilities for a difference, whether it is greater or smaller.

For its application, consider the soil data: `data(soil)`

```
> data(soil)
> correlation(soil[,2:4],method="pearson")
```

```
$correlation
      pH    EC CaCO3
pH    1.00 0.55  0.73
EC    0.55 1.00  0.32
CaCO3 0.73 0.32  1.00
```

```
$pvalue
      pH          EC          CaCO3
pH    1.000000000 0.0525330 0.004797027
EC    0.052532997 1.0000000 0.294159813
```

```
CaCO3 0.004797027 0.2941598 1.000000000
```

```
$n.obs
[1] 13
```

```
> with(soil,correlation(pH,soil[,3:4],method="pearson"))
```

```
$correlation
      EC CaCO3
pH 0.55  0.73
```

```
$pvalue
      EC CaCO3
pH 0.0525 0.0048
```

```
$n.obs
[1] 13
```

8.10 tapply.stat()

Gets a functional calculation of variables grouped by study factors.

Application with 'agricolae' data:

max(yield)-min(yield) by farmer

```
> data(RioChillon)
> with(RioChillon$babies,tapply.stat(yield,farmer,function(x) max(x)-min(x)))
```

	farmer	yield
1	AugustoZambrano	7.5
2	Caballero	13.4
3	ChocasAlto	14.1
4	FelixAndia	19.4
5	Huarangal-1	9.8
6	Huarangal-2	9.1
7	Huarangal-3	9.4
8	Huatocay	19.4
9	IgnacioPolinario	13.1

It corresponds to the range of variation in the farmers' yield.

The function "tapply" can be used directly or with function.

If A is a table with columns 1,2 and 3 as category, and 5,6 and 7 as variables, then the following procedures are valid:

```
tapply.stat(A[,5:7], A[,1:3],mean)
```

```
tapply.stat(A[,5:7], A[,1:3],function(x) mean(x,na.rm=TRUE))
```

```
tapply.stat(A[,c(7,6)], A[,1:2],function(x) sd(x)*100/mean(x))
```

8.11 Coefficient of variation of an experiment

If "model" is the object resulting from an analysis of variance of the function `aov()` or `lm()` of R, then the function `cv.model()` calculates the coefficient of variation.

```
> data(sweetpotato)
> model <- aov(yield ~ virus, data=sweetpotato)
> cv.model(model)
```

```
[1] 17.1666
```

8.12 Skewness and kurtosis

The skewness and kurtosis results, obtained by 'agricolae', are equal to the ones obtained by SAS, MiniTab, SPSS, InfoStat, and Excel.

If x represents a data set:

```
> x<-c(3,4,5,2,3,4,5,6,4,NA,7)
```

skewness is calculated with:

```
> skewness(x)
```

```
[1] 0.3595431
```

and kurtosis with:

```
> kurtosis(x)
```

```
[1] -0.1517996
```

8.13 Tabular value of Waller-Duncan

The function `Waller` determines the tabular value of Waller-Duncan. For the calculation, value F is necessary, calculated from the analysis of variance of the study factor, with its freedom degrees and the estimate of the variance of the experimental error. Value K, parameter of the function is the ratio between the two types of errors (I and II). To use it, a value associated with the alpha level is assigned. When the alpha level is 0.10, 50 is assigned to K; for 0.05, K=100; and for 0.01, K=500. K can take any value.

```
> q<-5
> f<-15
> K<-seq(10,1000,100)
> n<-length(K)
> y<-rep(0,3*n)
> dim(y)<-c(n,3)
> for(i in 1:n) y[i,1]<-waller(K[i],q,f,Fc=2)
> for(i in 1:n) y[i,2]<-waller(K[i],q,f,Fc=4)
> for(i in 1:n) y[i,3]<-waller(K[i],q,f,Fc=8)
```

Function of Waller to different value of parameters K and Fc The next procedure illustrates the function for different values of K with freedom degrees of 5 for the numerator and 15 for the denominator, and values of calculated F, equal to 2, 4, and 8.

```
> par(mar=c(3,3,4,1),cex=0.7)
> plot(K,y[,1],type="l",col="blue",ylab="waller",bty="l")
> lines(K,y[,2],type="l",col="brown",lty=2,lwd=2)
> lines(K,y[,3],type="l",col="green",lty=4,lwd=2)
> legend("topleft",c("2","4","8"),col=c("blue","brown","green"),lty=c(1,8,20),
+ lwd=2,title="Fc")
> title(main="Waller in function of K")
```

Generating table Waller-Duncan

```
> K<-100
> Fc<-1.2
> q<-c(seq(6,20,1),30,40,100)
> f<-c(seq(4,20,2),24,30)
> n<-length(q)
> m<-length(f)
> W.D <-rep(0,n*m)
> dim(W.D)<-c(n,m)
> for (i in 1:n) {
+ for (j in 1:m) {
+ W.D[i,j]<-waller(K, q[i], f[j], Fc)
+ }}
> W.D<-round(W.D,2)
> dimnames(W.D)<-list(q,f)
> cat("table: Waller Duncan k=100, F=1.2")
```

table: Waller Duncan k=100, F=1.2

```
> print(W.D)
```

	4	6	8	10	12	14	16	18	20	24	30
6	2.85	2.87	2.88	2.89	2.89	2.89	2.89	2.88	2.88	2.88	2.88
7	2.85	2.89	2.92	2.93	2.94	2.94	2.94	2.94	2.94	2.94	2.94
8	2.85	2.91	2.94	2.96	2.97	2.98	2.99	2.99	2.99	3.00	3.00
9	2.85	2.92	2.96	2.99	3.01	3.02	3.03	3.03	3.04	3.04	3.05
10	2.85	2.93	2.98	3.01	3.04	3.05	3.06	3.07	3.08	3.09	3.10
11	2.85	2.94	3.00	3.04	3.06	3.08	3.09	3.10	3.11	3.12	3.14
12	2.85	2.95	3.01	3.05	3.08	3.10	3.12	3.13	3.14	3.16	3.17
13	2.85	2.96	3.02	3.07	3.10	3.12	3.14	3.16	3.17	3.19	3.20
14	2.85	2.96	3.03	3.08	3.12	3.14	3.16	3.18	3.19	3.21	3.23
15	2.85	2.97	3.04	3.10	3.13	3.16	3.18	3.20	3.21	3.24	3.26
16	2.85	2.97	3.05	3.11	3.15	3.18	3.20	3.22	3.24	3.26	3.29
17	2.85	2.98	3.06	3.12	3.16	3.19	3.22	3.24	3.25	3.28	3.31
18	2.85	2.98	3.07	3.13	3.17	3.21	3.23	3.25	3.27	3.30	3.33
19	2.85	2.98	3.07	3.13	3.18	3.22	3.25	3.27	3.29	3.32	3.35
20	2.85	2.99	3.08	3.14	3.19	3.23	3.26	3.28	3.30	3.33	3.37
30	2.85	3.01	3.11	3.19	3.26	3.31	3.35	3.38	3.41	3.45	3.50

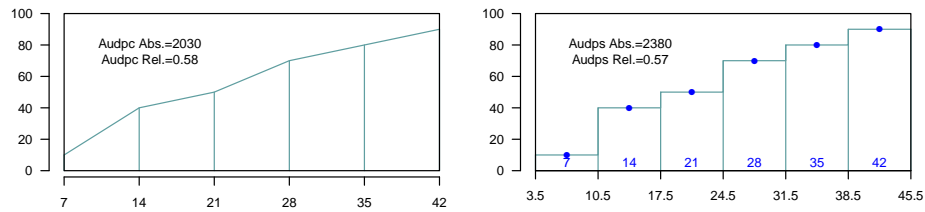


Figure 14: Area under the curve (AUDPC) and Area under the Stairs (AUDPS)

```
40  2.85 3.02 3.13 3.22 3.29 3.35 3.39 3.43 3.47 3.52 3.58
100 2.85 3.04 3.17 3.28 3.36 3.44 3.50 3.55 3.59 3.67 3.76
```

8.14 AUDPC

The area under the disease progress curve (AUDPC), see Figure 14 calculates the absolute and relative progress of the disease. It is required to measure the disease in percentage terms during several dates, preferably equidistantly.

```
> days<-c(7,14,21,28,35,42)
> evaluation<-data.frame(E1=10,E2=40,E3=50,E4=70,E5=80,E6=90)
> print(evaluation)

  E1 E2 E3 E4 E5 E6
1 10 40 50 70 80 90

> absolute1 <-audpc(evaluation,days)
> relative1 <-round(audpc(evaluation,days,"relative"),2)
```

8.15 AUDPS

The Area Under the Disease Progress Stairs (AUDPS), see Figure 14. A better estimate of disease progress is the area under the disease progress stairs (AUDPS). The AUDPS approach improves the estimation of disease progress by giving a weight closer to optimal to the first and last observations..

```
> absolute2 <-audps(evaluation,days)
> relative2 <-round(audps(evaluation,days,"relative"),2)
```

8.16 Non-Additivity

Tukey's test for non-additivity is used when there are doubts about the additivity veracity of a model. This test confirms such assumption and it is expected to accept the null hypothesis of the non-additive effect of the model.

For this test, all the experimental data used in the estimation of the linear additive model are required.

Use the function `nonadditivity()` of 'agricolae'. For its demonstration, the experimental data "potato", of the package 'agricolae', will be used. In this case, the model corresponds to the randomized complete block design, where the treatments are the varieties.


```

> data(potato)
> potato[,1]<-as.factor(potato[,1])
> model<-lm(cutting ~ date + variety,potato)
> df<-df.residual(model)
> MSerror<-deviance(model)/df
> analysis<-with(potato,nonadditivity(cutting, date, variety, df, MSerror))

```

Tukey's test of nonadditivity
cutting

P : 15.37166

Q : 77.44441

Analysis of Variance Table

Response: residual

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
Nonadditivity	1	3.051	3.0511	0.922	0.3532
Residuals	14	46.330	3.3093		

According to the results, the model is additive because the p.value 0.35 is greater than 0.05.

8.17 LATEBLIGHT

LATEBLIGHT is a mathematical model that simulates the effect of weather, host growth and resistance, and fungicide use on asexual development and growth of *Phytophthora infestans* on potato foliage, see Figure 15

LATEBLIGHT Version LB2004 was created in October 2004 (Andrade-Piedra et al., 2005a, b and c), based on the C-version written by B.E. Ticknor ('BET 21191 modification of cbm8d29.c'), reported by Doster et al. (1990) and described in detail by Fry et al. (1991) (This version is referred as LB1990 by Andrade-Piedra et al. [2005a]). The first version of LATEBLIGHT was developed by Bruhn and Fry (1981) and described in detail by Bruhn et al. (1980).

```

> options(digits=2)
> f <- system.file("external/weather.csv", package="agricolae")
> weather <- read.csv(f,header=FALSE)
> f <- system.file("external/severity.csv", package="agricolae")
> severity <- read.csv(f)
> weather[,1]<-as.Date(weather[,1],format = "%m/%d/%Y")
> # Parameters dates
> dates<-c("2000-03-25", "2000-04-09", "2000-04-12", "2000-04-16", "2000-04-22")
> dates<-as.Date(dates)
> EmergDate <- as.Date("2000/01/19")
> EndEpidDate <- as.Date("2000-04-22")
> dates<-as.Date(dates)
> NoReadingsH<- 1
> RHthreshold <- 90
> WS<-weatherSeverity(weather,severity,dates,EmergDate,EndEpidDate,
+ NoReadingsH,RHthreshold)
> # Parameters to Lateblight function

```

```

> par(mar=c(3,3,4,1),cex=0.7)
> #-----
> model<-lateblight(WS, Cultivar,ApplSys, InocDate, LGR,IniSpor,SR,IE,
+ LP,MatTime='LATESEASON',InMicCol,main=main,type="l",xlim=c(65,95),lwd=1.5,
+ xlab="Time (days after emergence)", ylab="Severity (Percentage)")

```

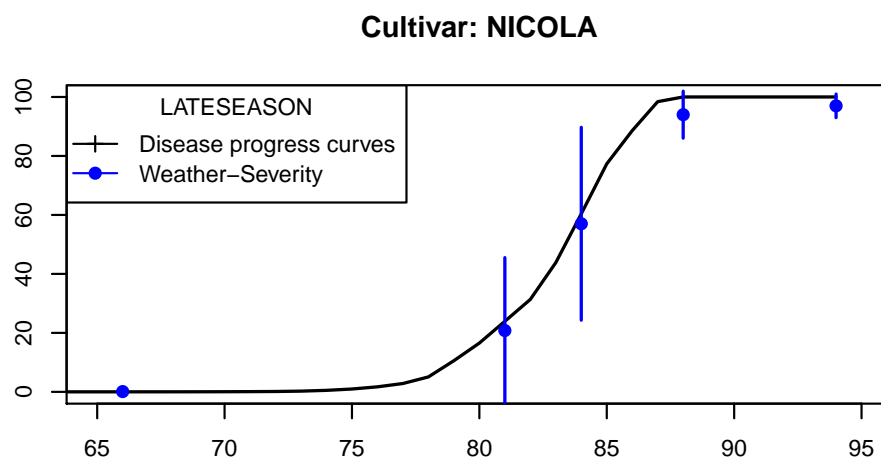


Figure 15: lateblight: LATESEASON

```

> InocDate<-"2000-03-18"
> LGR <- 0.00410
> IniSpor <- 0
> SR <- 292000000
> IE <- 1.0
> LP <- 2.82
> InMicCol <- 9
> Cultivar <- "NICOLA"
> ApplSys <- "NOFUNGICIDE"
> main<-"Cultivar: NICOLA"

```

```
> head(model$Gfile)
```

	dates	nday	MeanSeverity	StDevSeverity	MinObs
Eval1	2000-03-25	66	0.1	0	0.1
Eval2	2000-04-09	81	20.8	25	-3.9
Eval3	2000-04-12	84	57.0	33	24.3
Eval4	2000-04-16	88	94.0	8	86.0
Eval5	2000-04-22	94	97.0	4	93.0

	MaxObs
Eval1	0.1
Eval2	45.5
Eval3	89.7
Eval4	102.0
Eval5	101.0

```
> str(model$Ofile)
```

```
'data.frame':      94 obs. of  13 variables:
 $ Date      : Date, format: "2000-01-20" ...
 $ nday      : num  1 2 3 4 5 6 7 8 9 10 ...
 $ MicCol    : num  0 0 0 0 0 0 0 0 0 0 ...
 $ SimSeverity: num  0 0 0 0 0 0 0 0 0 0 ...
 $ LAI       : num  0.01 0.0276 0.0384 0.0492 0.06 0.086 0.112 0.138 0.164 0.19 ...
 $ LatPer    : num  0 2 2 2 2 2 2 2 2 2 ...
 $ LesExInc  : num  0 0 0 0 0 0 0 0 0 0 ...
 $ AttchSp   : num  0 0 0 0 0 0 0 0 0 0 ...
 $ AUDPC     : num  0 0 0 0 0 0 0 0 0 0 ...
 $ rLP       : num  0 0 0 0 0 0 0 0 0 0 ...
 $ InvrLP    : num  0 0 0 0 0 0 0 0 0 0 ...
 $ BlPr      : num  0 0 0 0 0 0 0 0 0 0 ...
 $ Defol     : num  0 0 0 0 0 0 0 0 0 0 ...
```

```
> head(model$Ofile[,1:7])
```

	Date	nday	MicCol	SimSeverity	LAI	LatPer	LesExInc
1	2000-01-20	1	0	0	0.010	0	0
2	2000-01-21	2	0	0	0.028	2	0
3	2000-01-22	3	0	0	0.038	2	0
4	2000-01-23	4	0	0	0.049	2	0
5	2000-01-24	5	0	0	0.060	2	0
6	2000-01-25	6	0	0	0.086	2	0

Repeating graphic

```
> x<- model$Ofile$nday
> y<- model$Ofile$SimSeverity
> w<- model$Gfile$nday
> z<- model$Gfile$MeanSeverity
> Min<-model$Gfile$MinObs
> Max<-model$Gfile$MaxObs
```

```

> par(mar=c(3,2.5,1,1),cex=0.7)
> plot(x,y,type="l",xlim=c(65,95),lwd=1.5,xlab="Time (days after emergence)",
+ ylab="Severity (Percentage)")
> points(w,z,col="red",cex=1,pch=19); npoints <- length(w)
> for ( i in 1:npoints)segments(w[i],Min[i],w[i],Max[i],lwd=1.5,col="red")
> legend("topleft",c("Disease progress curves","Weather-Severity"),
+ title="Description",lty=1,pch=c(3,19),col=c("black","red"))

```

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