Models Fitted

Loïc Pages

2025-02-26

Introduction

```
rm(list=ls())
library(knitr)
library(spaMM)
```

```
## Registered S3 methods overwritten by 'registry':
##   method               from
##   print.registry_field proxy
##   print.registry_entry proxy

## spaMM (Rousset & Ferdy, 2014, version 4.5.30) is loaded.
## Type 'help(spaMM)' for a short introduction,
## 'news(package='spaMM')' for news,
## and 'citation('spaMM')' for proper citation.
## Further infos, slides, etc. at https://gitlab.mbb.univ-montp2.fr/francois/spamm-ref.
```

```
library(tidyverse)
```

```
## -- Attaching core tidyverse packages ------------------------ tidyverse 2.0.0 --
## v dplyr     1.1.4     v readr     2.1.5
## v forcats   1.0.0     v stringr   1.5.1
## v ggplot2   3.5.1     v tibble    3.2.1
## v lubridate 1.9.4     v tidyr     1.3.1
## v purrr     1.0.2

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

```
library(splines)
library(patchwork)
library(SplinesUtils)

setwd("/media/loic/Commun/0Travail/Stage 2025 ISEM/Models")
```

```r
centauree_data <- read.csv("donnesIPM_short.csv")
centauree_data_complet <- read.csv("donnesIPM.csv")


#Supprimer plantes dont l'age est inconnu
centauree_data <- centauree_data[!is.na(centauree_data$age0), ]
centauree_data$age1 <- ifelse(centauree_data$Stage1=="V",centauree_data$age0+1,NA)

#Forcer l'age maximal à 8
length(centauree_data$age0[centauree_data$age0 >= 8])
```

```
## [1] 93
```

```r
centauree_data$age0[centauree_data$age0 > 8] <- 8

spaMM.options(separation_max=70)
```

```r
annees <- 1995:2022
populations <- c("Po","Au","Pe","E1","E2","Cr")
taille_range <- seq(0.5, 25, by = 0.5)
age_range <- 1:8

fake_data <- expand.grid(
  year = annees,
  Pop = populations,
  Size0Mars = taille_range,
  age0 = age_range
)

fake_data <- fake_data %>%
  mutate(Nrw = row_number())
```

BIC

```r
extractBIC <- function(fit, n){
  extractAIC(fit)[[2]]+(log(n)-2)*DoF(fit)[[3]]
}
```

Test Splines -> poly

```r
survdata <- centauree_data[centauree_data$Flowering0!=1,]
survdata <- survdata[!is.na(survdata$SurvieMars),]

library(nlme)
```

```
##
## Attaching package: 'nlme'

## The following object is masked from 'package:dplyr':
##
##     collapse
```

```r
library(SplinesUtils)
spline_model <- lme(SurvieMars ~ bs(age0, degree=3, knots=6.5)+bs(Size0Mars,df=5), data = survdata, ranc
    year = pdSymm(~ Size0Mars),
    Pop = pdSymm(~ age0)))

spl <- RegSplineAsPiecePoly(spline_model, "bs(Size0Mars, df = 5)")
spl2 <- RegSplineAsPiecePoly(spline_model, "bs(age0, degree = 3, knots = 6.5)")

spl$PiecePoly$coef
```

```
##               [,1]        [,2]          [,3]
## [1,] -1.040834e-17  0.06889436  0.1911940010
## [2,]  4.934356e-02  0.16645927  0.0961884958
## [3,]  2.964395e-01 -0.06220810 -0.0080626749
## [4,] -2.390984e-01  0.01804847  0.0002194813
```

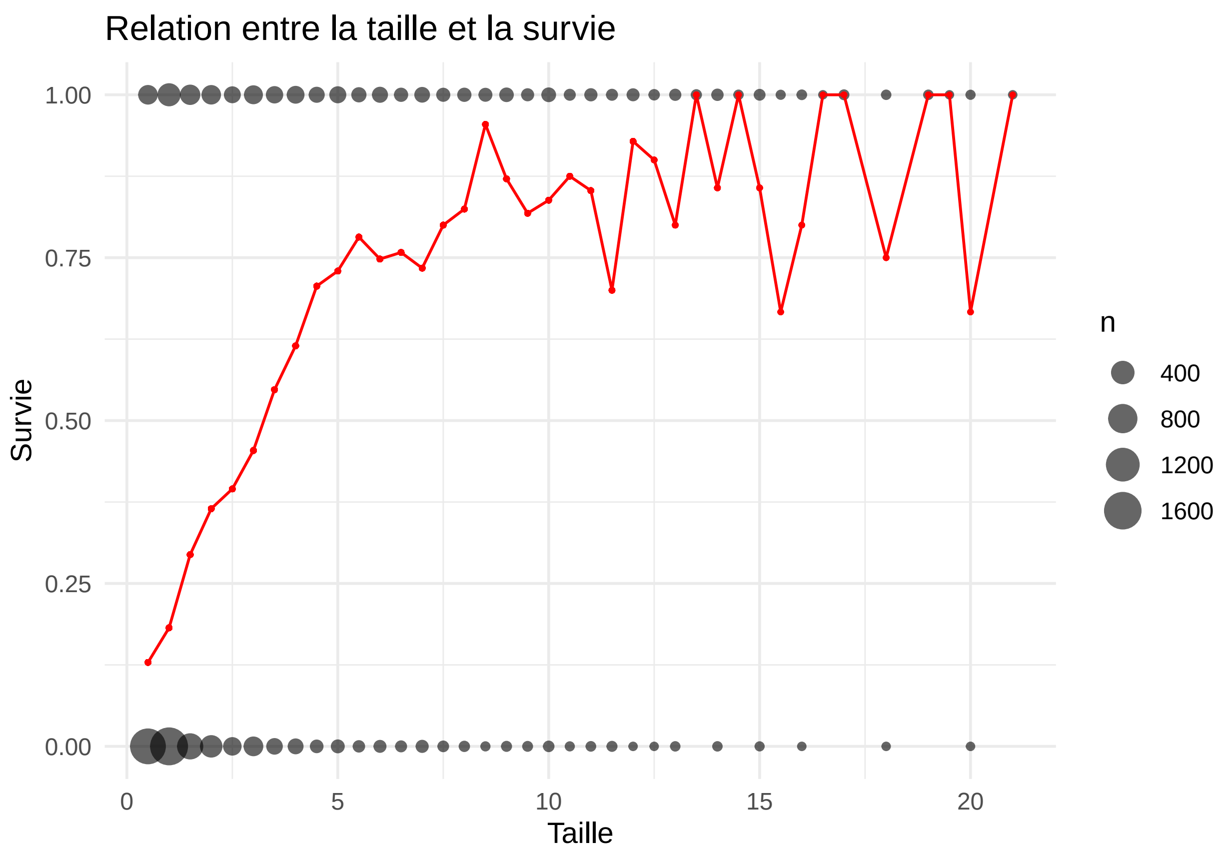
```r
spl
```

```
## 3 piecewise polynomials of degree 3 are constructed!
## Use 'summary' to export all of them.
## The first 3 are printed below.
## -1.04e-17 + 0.0493 * (x - 0.5) + 0.296 * (x - 0.5) ^ 2 - 0.239 * (x - 0.5) ^ 3
## 0.0689 + 0.166 * (x - 1) - 0.0622 * (x - 1) ^ 2 + 0.018 * (x - 1) ^ 3
## 0.191 + 0.0962 * (x - 2) - 0.00806 * (x - 2) ^ 2 + 0.000219 * (x - 2) ^ 3
```

Survival probability

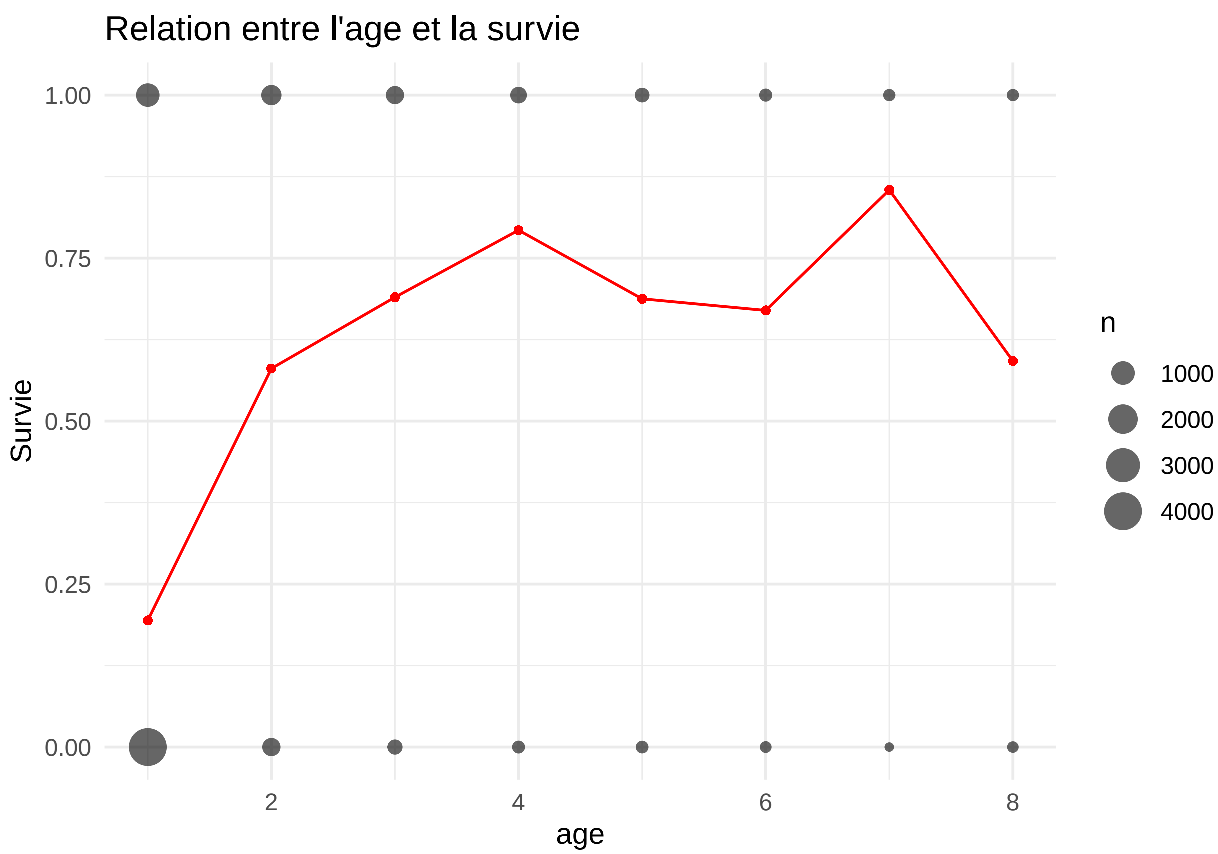
```r
survdata <- centauree_data[centauree_data$Flowering0!=1,]
# survdata$SurvieMars[survdata$age0==7][1:15] <- 0

survdata %>%
  group_by(Size0Mars) %>%
  mutate(survivalProba = sum(SurvieMars, na.rm = TRUE) / n()) %>%
  ggplot(aes(x = Size0Mars, y = SurvieMars)) +
  geom_count(alpha = 0.6) +  # Points dimensionnés selon la fréquence
  geom_point(aes(y = survivalProba), color = "red", size = 0.5) +
  geom_line(aes(y = survivalProba), color = "red") +
  labs(title = "Relation entre la taille et la survie",
    x = "Taille",
    y = "Survie") +
  ylim(0, 1) +
  theme_minimal()
```

```
## Warning: Removed 121 rows containing non-finite outside the scale range
## (`stat_sum()`).
```




```r
survdata %>%
  group_by(age0) %>%
  mutate(survivalProba = sum(SurvieMars, na.rm = TRUE) / n()) %>%
  ggplot(aes(x = age0, y = SurvieMars)) +
    geom_count(alpha = 0.6) +  # Points dimensionnés selon la fréquence
    geom_point(aes(x = age0, y = survivalProba), color = "red", size = 1) +
    geom_line(aes(x = age0, y = survivalProba), color = "red") +
    labs(title = "Relation entre l'age et la survie",
    x = "age",
    y = "Survie") +
  ylim(0, 1) +
  theme_minimal()
```

```
## Warning: Removed 121 rows containing non-finite outside the scale range
## (`stat_sum()`).
```



Avec splines

```
# Survglm1 <- fitme(SurvieMars ~ 1+ bs(Size0Mars,df=5,degree=3) + bs(age0,degree=3,knots = 6.5)+ (Size0
#                   family=binomial,
#                   data=survdata,
#                   method="PQL/L")
#
# Survglm2 <- fitme(SurvieMars ~ 1 + bs(Size0Mars,df=5,degree=3) + bs(age0,degree=3,knots = 6.5)
# + (Size0Mars + age0|year) + (age0|Pop) ,
#                   family=binomial,
#                   data=survdata,
#                   method="PQL/L")
#
# Survglm3 <- fitme(SurvieMars ~ 1 + bs(Size0Mars,df=5,degree=3) + bs(age0,degree=3,knots = c(1.5,6.5))
#                   family=binomial,
#                   data=survdata,
#                   method="PQL/L")
#
# Survglm4 <- fitme(SurvieMars ~ 1 + bs(Size0Mars,df=5,degree=3) + bs(age0,degree=3,knots = c(1.5,6.5))
# + (Size0Mars + age0|year) + (age0|Pop) ,
#                   family=binomial,
#                   data=survdata,
#                   method="PQL/L")
#
# Survglm5 <- fitme(SurvieMars ~ 1 + bs(Size0Mars,df=5,degree=3) + bs(age0,degree=3,knots = 6.5)
# + (Size0Mars|year) + (Size0Mars + age0|Pop) ,
```

```
#                    family=binomial,
#                    data=survdata,
#                    method="PQL/L")
```

Avec polynomes de degré 4 et effet aléatoire individus

```
Survglm1 <- fitme(SurvieMars ~ 1+ poly(Size0Mars,4) + poly(age0,4)+ (age0|year) + (age0|Pop) ,
                   family=binomial,
                   data=survdata,
                   method="PQL/L")

Survglm2 <- fitme(SurvieMars ~ 1+ poly(Size0Mars,3) + poly(age0,4)+ (age0|year) + (age0|Pop) ,
                   family=binomial,
                   data=survdata,
                   method="PQL/L")

Survglm3 <- fitme(SurvieMars ~ 1+ poly(Size0Mars,4) + poly(age0,4)+ (age0|year) + (age0|Pop) + (1|Nrw),
                   family=binomial,
                   data=survdata,
                   method="PQL/L")

Survglm4 <- fitme(SurvieMars ~ 1+ poly(Size0Mars,3) + poly(age0,4)+ (age0|year) + (age0|Pop) +(1|Nrw),
                   family=binomial,
                   data=survdata,
                   method="PQL/L")

Survglm5 <- fitme(SurvieMars ~ 1+ poly(Size0Mars,4) + poly(age0,4)+ (age0|year) + (Size0Mars + age0|Pop)
                   family=binomial,
                   data=survdata,
                   method="PQL/L")
```

Surv_poly <- RegBsplineAsPiecePoly(Survglm1,“bs(Size0Mars,df=5,degree=3)”)

```
n <- length(centauree_data$Nrw)
extractAIC(Survglm1) ; extractBIC(Survglm1, n)
```

```
##      edf      AIC
##    9.000 6715.552
```

```
## [1] 6778.017
```

```
extractAIC(Survglm2) ; extractBIC(Survglm2, n)
```

```
##      edf      AIC
##    8.000 6716.118
```

```
## [1] 6771.642
```

```
extractAIC(Survglm3) ; extractBIC(Survglm3, n)
```

```
##      edf      AIC
##    9.000 6716.191
```

```
## [1] 6778.656
```

```r
extractAIC(Survglm4) ; extractBIC(Survglm4, n)
```

```
##      edf      AIC
##    8.000 6716.653
```

```
## [1] 6772.177
```

```r
extractAIC(Survglm5) ; extractBIC(Survglm5, n)
```

```
##      edf      AIC
##    9.000 6718.384
```

```
## [1] 6780.848
```

```r
summary(Survglm1)
```

```
## formula: SurvieMars ~ 1 + poly(Size0Mars, 4) + poly(age0, 4) + (age0 |
##     year) + (age0 | Pop)
## Estimation of ranCoefs by ML (p_v approximation of logL).
## Estimation of fixed effects by h-likelihood approximation.
## family: binomial( link = logit )
##  ------------ Fixed effects (beta) ------------
##                      Estimate Cond. SE t-value
## (Intercept)           -0.8316   0.2089  -3.981
## poly(Size0Mars, 4)1   81.1109   4.2340  19.157
## poly(Size0Mars, 4)2  -28.7092   3.2348  -8.875
## poly(Size0Mars, 4)3   10.0305   2.9389   3.413
## poly(Size0Mars, 4)4   -4.8679   2.9373  -1.657
## poly(age0, 4)1        25.8434   8.5546   3.021
## poly(age0, 4)2       -25.2941   3.1175  -8.114
## poly(age0, 4)3        10.3349   2.7834   3.713
## poly(age0, 4)4        -7.7561   2.6666  -2.909
##  --------------- Random effects ---------------
## Family: gaussian( link = identity )
##          --- Random-coefficients Cov matrices:
##  Group        Term     Var.   Corr.
##   year (Intercept)    1.275
##   year        age0  0.05704  -0.723
##    Pop (Intercept)   0.1496
##    Pop        age0 0.009923 -0.7796
## # of obs: 7293; # of groups: year, 27; Pop, 6
##  ------------- Likelihood values  -------------
##                        logLik
##        h-likelihood: -3335.976
## logL       (p_v(h)): -3342.776
```

```r
summary(Survglm2)
```

```
## formula: SurvieMars ~ 1 + poly(Size0Mars, 3) + poly(age0, 4) + (age0 |
##     year) + (age0 | Pop)
## Estimation of ranCoefs by ML (p_v approximation of logL).
## Estimation of fixed effects by h-likelihood approximation.
## family: binomial( link = logit )
##  ------------ Fixed effects (beta) ------------
##                     Estimate Cond. SE t-value
## (Intercept)          -0.8266   0.2082  -3.971
## poly(Size0Mars, 3)1  80.7460   4.2179  19.144
## poly(Size0Mars, 3)2 -28.7984   3.4245  -8.410
## poly(Size0Mars, 3)3  10.6991   3.3016   3.241
## poly(age0, 4)1       25.8296   8.4834   3.045
## poly(age0, 4)2      -25.2809   3.1139  -8.119
## poly(age0, 4)3       10.5462   2.7810   3.792
## poly(age0, 4)4       -7.7687   2.6691  -2.911
##  --------------- Random effects ---------------
## Family: gaussian( link = identity )
##          --- Random-coefficients Cov matrices:
##  Group        Term     Var.   Corr.
##   year (Intercept)    1.268
##   year        age0  0.05551 -0.7228
##    Pop (Intercept)   0.1494
##    Pop        age0 0.009805 -0.7931
## # of obs: 7293; # of groups: year, 27; Pop, 6
##  ------------- Likelihood values  -------------
##                         logLik
##        h-likelihood: -3337.661
## logL       (p_v(h)): -3344.059
```

```r
summary(Survglm3)
```

```
## formula: SurvieMars ~ 1 + poly(Size0Mars, 4) + poly(age0, 4) + (age0 |
##     year) + (age0 | Pop) + (1 | Nrw)
## Estimation of lambda and ranCoefs by ML (p_v approximation of logL).
## Estimation of fixed effects by h-likelihood approximation.
## family: binomial( link = logit )
##  ------------ Fixed effects (beta) ------------
```

```
## [one-time computation of covariance matrix, which may be slow]
```

```
##                     Estimate Cond. SE t-value
## (Intercept)          -0.8677   0.2132  -4.069
## poly(Size0Mars, 4)1  82.1551   4.3039  19.088
## poly(Size0Mars, 4)2 -28.5717   3.2652  -8.750
## poly(Size0Mars, 4)3   9.7555   2.9692   3.286
## poly(Size0Mars, 4)4  -4.7928   2.9664  -1.616
## poly(age0, 4)1       20.2503   8.6429   2.343
## poly(age0, 4)2      -24.0855   3.1696  -7.599
## poly(age0, 4)3        9.7873   2.8056   3.488
## poly(age0, 4)4       -7.5383   2.6797  -2.813
```

```
##  --------------- Random effects ---------------
## Family: gaussian( link = identity )
##          --- Random-coefficients Cov matrices:
##  Group        Term     Var.   Corr.
##   year (Intercept)    1.321
##   year        age0  0.05831 -0.7256
##    Pop (Intercept)    0.154
##    Pop        age0 0.009912 -0.7696
##            --- Variance parameters ('lambda'):
## lambda = var(u) for u ~ Gaussian;
##    Nrw  :  0.1093
##              --- Coefficients for log(lambda):
##  Group        Term Estimate Cond.SE
##    Nrw (Intercept)   -2.213  0.1352
## # of obs: 7293; # of groups: year, 27; Pop, 6; Nrw, 5017
##  ------------- Likelihood values  -------------
##                         logLik
##       h-likelihood: -2336.431
## logL       (p_v(h)): -3342.096
## Estimates did not converge; increase control.HLfit's 'max.iter' above 200,
##  or try control.HLfit=list(LevenbergM=TRUE) (see help('control.HLfit') for details).
```

```
summary(Survglm4)
```

```
## formula: SurvieMars ~ 1 + poly(Size0Mars, 3) + poly(age0, 4) + (age0 |
##     year) + (age0 | Pop) + (1 | Nrw)
## Estimation of lambda and ranCoefs by ML (p_v approximation of logL).
## Estimation of fixed effects by h-likelihood approximation.
## family: binomial( link = logit )
##  ------------ Fixed effects (beta) ------------

## [one-time computation of covariance matrix, which may be slow]

##                     Estimate Cond. SE t-value
## (Intercept)          -0.8642   0.2127  -4.063
## poly(Size0Mars, 3)1  81.8385   4.2889  19.082
## poly(Size0Mars, 3)2 -28.6829   3.4416  -8.334
## poly(Size0Mars, 3)3  10.3754   3.3122   3.132
## poly(age0, 4)1       20.0306   8.5679   2.338
## poly(age0, 4)2      -24.0265   3.1671  -7.586
## poly(age0, 4)3        9.9703   2.8038   3.556
## poly(age0, 4)4       -7.5461   2.6822  -2.813
##  --------------- Random effects ---------------
## Family: gaussian( link = identity )
##          --- Random-coefficients Cov matrices:
##  Group        Term     Var.   Corr.
##   year (Intercept)    1.316
##   year        age0  0.05674 -0.7257
##    Pop (Intercept)    0.154
##    Pop        age0 0.009761  -0.783
##            --- Variance parameters ('lambda'):
## lambda = var(u) for u ~ Gaussian;
##    Nrw  :  0.1132
```

```
##              --- Coefficients for log(lambda):
##  Group        Term Estimate Cond.SE
##    Nrw (Intercept)   -2.179  0.1329
## # of obs: 7293; # of groups: year, 27; Pop, 6; Nrw, 5017
##  ------------- Likelihood values  -------------
##                          logLik
##        h-likelihood: -2423.785
## logL       (p_v(h)): -3343.327
## Estimates did not converge; increase control.HLfit's 'max.iter' above 200,
##  or try control.HLfit=list(LevenbergM=TRUE) (see help('control.HLfit') for details).
```

```
summary(Survglm5)
```

```
## formula: SurvieMars ~ 1 + poly(Size0Mars, 4) + poly(age0, 4) + (age0 |
##     year) + (Size0Mars + age0 | Pop)
## Estimation of ranCoefs by ML (p_v approximation of logL).
## Estimation of fixed effects by h-likelihood approximation.
## family: binomial( link = logit )
##  ------------ Fixed effects (beta) ------------
##                      Estimate Cond. SE t-value
## (Intercept)           -0.8135   0.2064  -3.942
## poly(Size0Mars, 4)1  81.4302   5.4094  15.053
## poly(Size0Mars, 4)2 -28.1166   3.2756  -8.584
## poly(Size0Mars, 4)3   9.8745   2.9351   3.364
## poly(Size0Mars, 4)4  -4.8495   2.8973  -1.674
## poly(age0, 4)1       26.6245   8.7001   3.060
## poly(age0, 4)2      -25.4679   3.1280  -8.142
## poly(age0, 4)3       10.4278   2.7882   3.740
## poly(age0, 4)4       -8.1169   2.6718  -3.038
##  --------------- Random effects ---------------
## Family: gaussian( link = identity )
##          --- Random-coefficients Cov matrices:
##  Group        Term     Var.   Corr. Corr..1
##   year (Intercept)    1.278
##   year        age0  0.05918 -0.7187
##    Pop (Intercept)   0.1376
##    Pop   Size0Mars 0.001237  0.5189
##    Pop        age0  0.01077 -0.9789 -0.3331
## # of obs: 7293; # of groups: year, 27; Pop, 6
##  ------------- Likelihood values  -------------
##                          logLik
##        h-likelihood: -3339.371
## logL       (p_v(h)): -3341.192
```

```
Survpredict1 <- predict(Survglm1, newdata = fake_data)[,1]
Survpredict2 <- predict(Survglm2, newdata = fake_data)[,1]
Survpredict3 <- predict(Survglm3, newdata = fake_data)[,1]
Survpredict4 <- predict(Survglm4, newdata = fake_data)[,1]
Survpredict5 <- predict(Survglm5, newdata = fake_data)[,1]
```

```
plot_survie <- function(data = fake_data, prediction, var, c1, valc1 = 1, c2, valc2 = "Au", fact, minda
  data %>%
    mutate(surv_predi = prediction) %>%
```

```
    filter(!!sym(c1) == valc1, !!sym(c2) == valc2) %>%
    ggplot(aes(x = .data[[var]], y = surv_predi)) +
    geom_vline(xintercept=maxdat, lty="dotted")+
    geom_vline(xintercept=mindat, lty="dotted")+
    geom_line(aes(color = as.factor(.data[[fact]]))) +
    theme_minimal() +
    ylim(0, 1)
}
```

Survie en fonction de la taille

En fixant la population : voir l'effet année

```
var <- "Size0Mars"
c1 <- "age0"
c2 <- "Pop"
valc2 <- "Au"
fact <- "year"
```

En fixant l'année : voir l'effet population

```
var <- "Size0Mars"
c1 <- "age0"
c2 <- "year"
valc2 <- 2000
fact <- "Pop"
```

Survie en fonction de l'age

En fixant la population : voir l'effet année

```
var <- "age0"
c1 <- "Size0Mars"
c2 <- "Pop"
valc2 <- "Au"
fact <- "year"
```

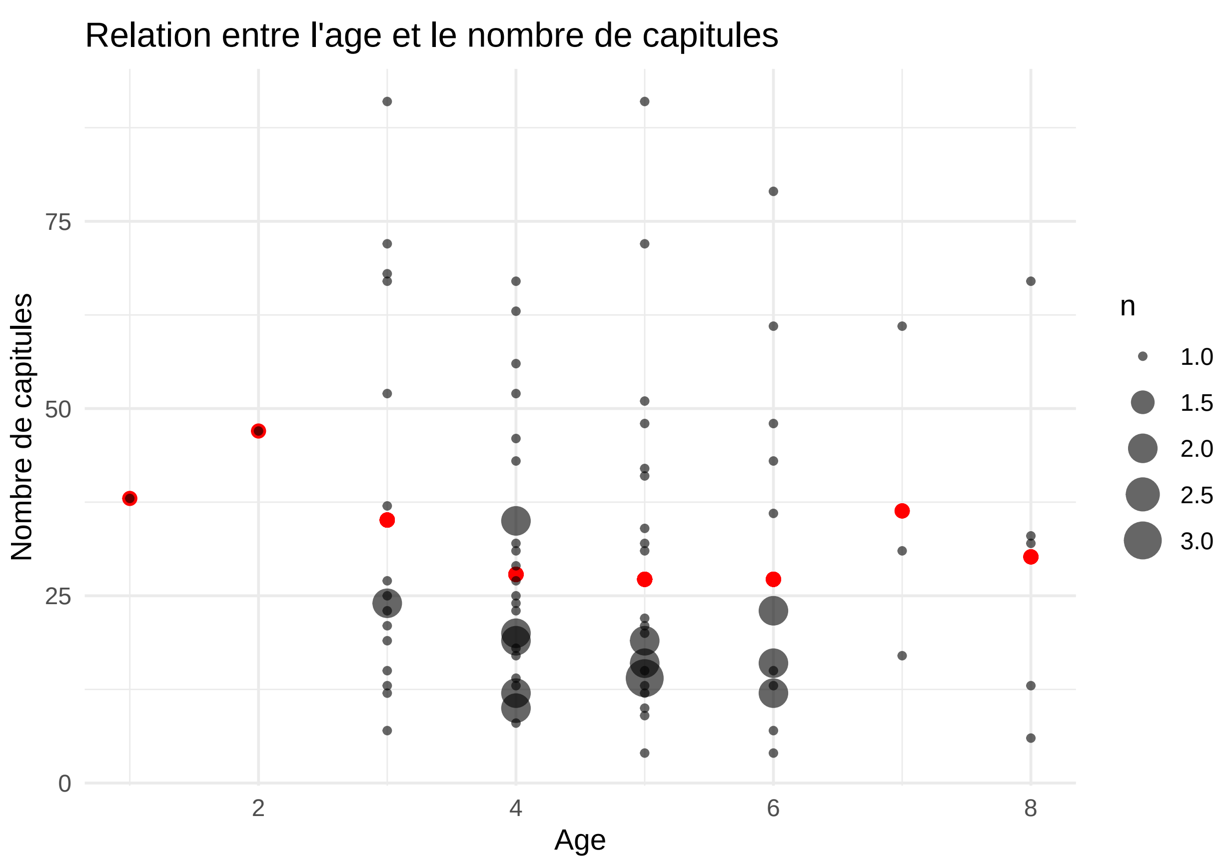
En fixant l'année : voir l'effet population

```
var <- "age0"
c1 <- "Size0Mars"
c2 <- "year"
valc2 <- 2000
fact <- "Pop"
```

Nombre de capitules

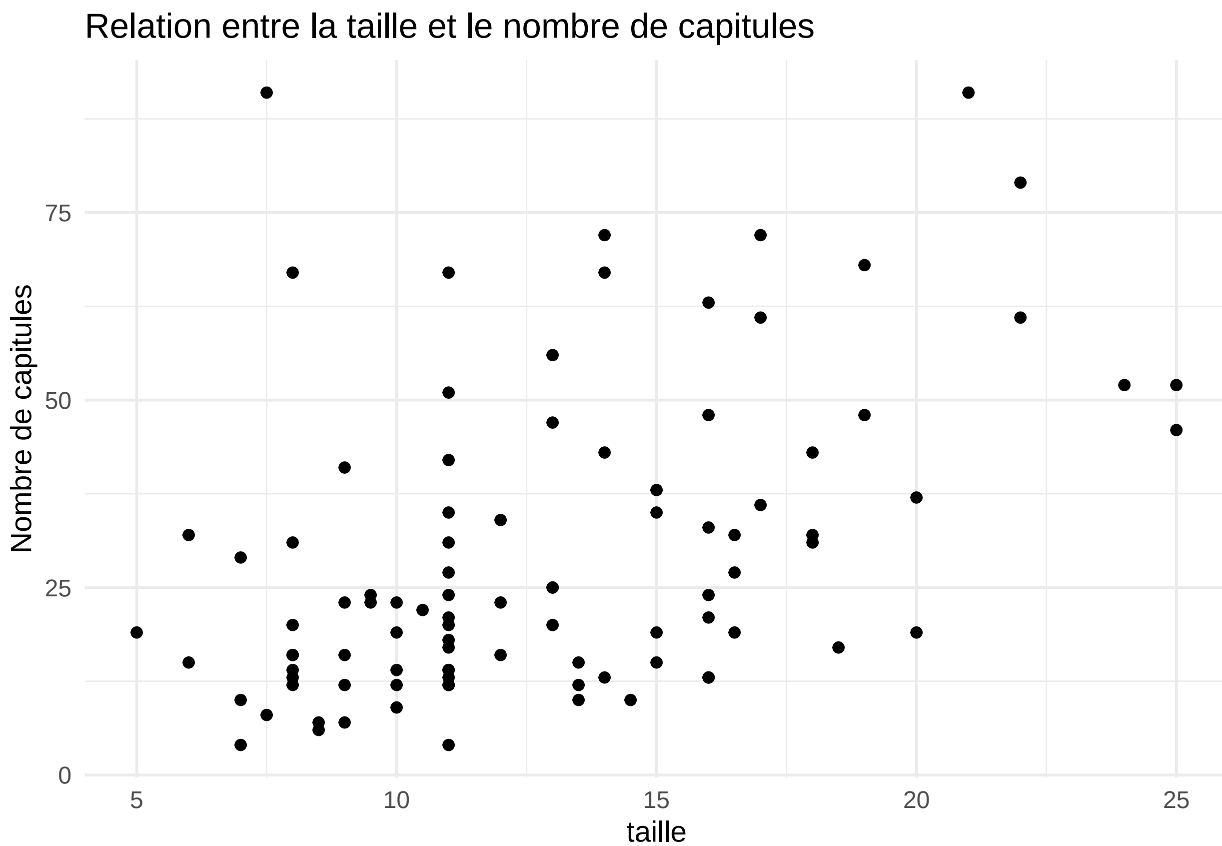
```
cptldata <- centauree_data[!is.na(centauree_data$Cptl0),]
cptldata <- cptldata[!cptldata$Flowering0==0,]
```

```
# Nombre de capitules moyen / age
capidata <- cptldata %>%
  group_by(age0) %>%
  mutate(meancptl=mean(Cptl0))

capidata%>%
ggplot(aes(x = age0, y = meancptl)) +
  geom_point(color = "red", size = 2) +
  geom_count(aes(y=Cptl0), alpha=0.6) +
  labs(title = "Relation entre l'age et le nombre de capitules",
    x = "Age",
    y = "Nombre de capitules") +
  theme_minimal()
```

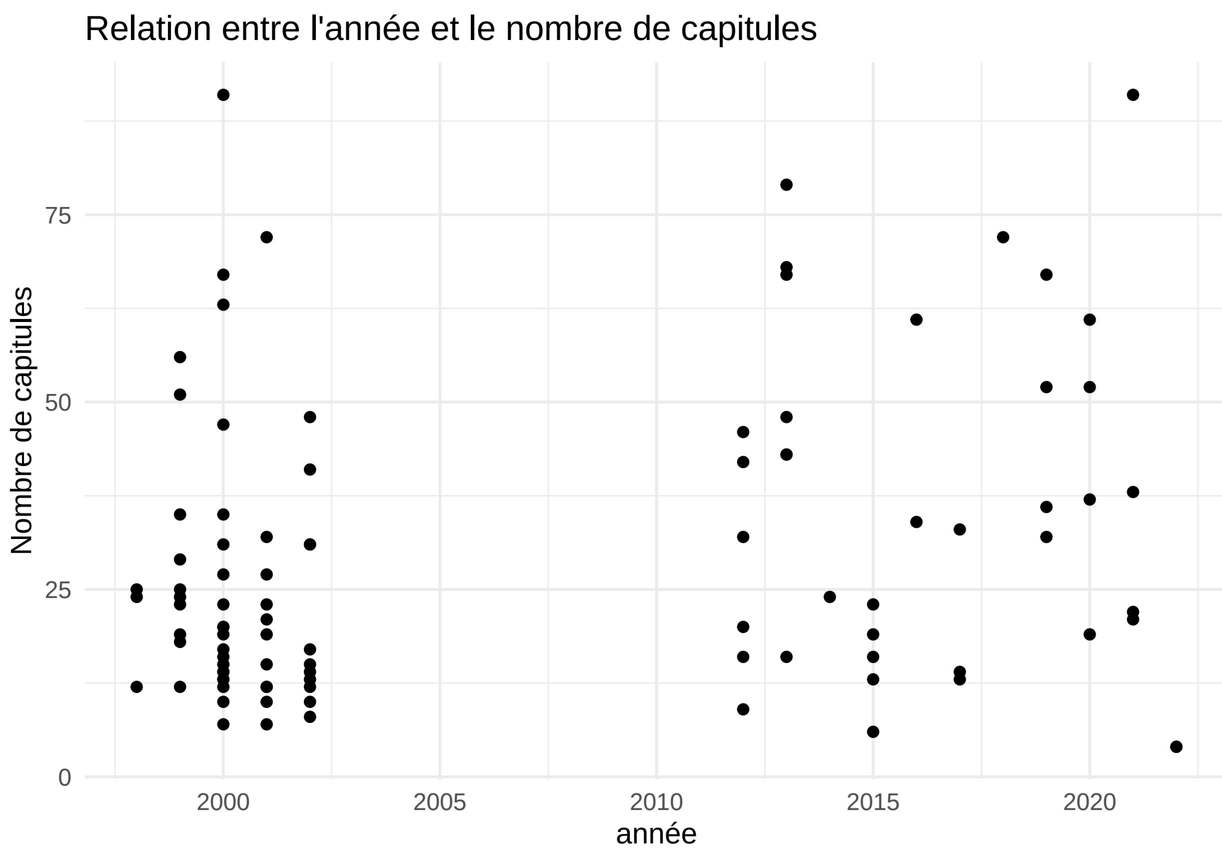



```
# Nombre de capitule / taille
cptldata %>%

  ggplot(aes(x=Size0Mars,y=Cptl0))+
    geom_point() +
```

```
labs(title = "Relation entre la taille et le nombre de capitules",
    x = "taille",
    y = "Nombre de capitules") +
    theme_minimal()
```




```
# Nombre de capitule / année
cptldata %>%

  ggplot(aes(x=year,y=Cptl0))+
    geom_point() +
labs(title = "Relation entre l'année et le nombre de capitules",
    x = "année",
    y = "Nombre de capitules") +
    theme_minimal()
```




```r
Cptlglm1 <- fitme(Cptl0 ~ 1 + Size0Mars,
              data=cptldata)

Cptlglm12 <- fitme(Cptl0 ~ 1 + Size0Mars,
              data=cptldata, resid.model = ~log(Size0Mars))

Cptlglm2 <- fitme(Cptl0 ~ 1 + poly(Size0Mars,2),
              data=cptldata)

Cptlglm3 <- fitme(Cptl0 ~ 1 + poly(Size0Mars,3),
              data=cptldata)

Cptlglm4 <- fitme(Cptl0 ~ 1 + Size0Mars +(1|year),
              data=cptldata)

Cptlglm5 <- fitme(Cptl0 ~ 1 + Size0Mars + age0,
              data=cptldata)
```

```r
n <- length(cptldata$Nrw)
extractAIC(Cptlglm1) ; extractBIC(Cptlglm1, n)
```

```
##      edf      AIC
##   2.0000 825.2362

## [1] 830.344
```

```r
extractAIC(Cptlglm2) ; extractBIC(Cptlglm2, n)
```

```
##      edf      AIC
##   3.0000 825.6888

## [1] 833.3505
```

```r
extractAIC(Cptlglm3) ; extractBIC(Cptlglm3, n)
```

```
##      edf      AIC
##   4.0000 826.4869

## [1] 836.7024
```

```r
extractAIC(Cptlglm4) ; extractBIC(Cptlglm4, n)
```

```
##      edf      AIC
##   2.0000 826.8208

## [1] 831.9286
```

```r
extractAIC(Cptlglm5) ; extractBIC(Cptlglm5, n)
```

```
##      edf      AIC
##   3.0000 827.2109

## [1] 834.8726
```

```r
summary(Cptlglm1)
```

```
## formula: Cptl0 ~ 1 + Size0Mars
## ML: Estimation of phi by ML.
##     Estimation of fixed effects by ML.
## family: gaussian( link = identity )
##  ------------ Fixed effects (beta) ------------
##             Estimate Cond. SE t-value
## (Intercept)    2.951   5.6590  0.5214
## Size0Mars      2.074   0.4166  4.9795
##  -------------- Residual variance  ------------
## Coefficients for log(phi)  ~ 1  :
##             Estimate Cond. SE
## (Intercept)    5.786   0.1451
## Estimate of phi=residual var:  325.6
##  ------------- Likelihood values  -------------
##                         logLik
## logL                : -409.6181
```

```r
summary(Cptlglm2)
```

```
## formula: Cptl0 ~ 1 + poly(Size0Mars, 2)
## ML: Estimation of phi by ML.
##     Estimation of fixed effects by ML.
## family: gaussian( link = identity )
##  ------------ Fixed effects (beta) ------------
##                      Estimate Cond. SE t-value
## (Intercept)             29.58    1.836  16.108
## poly(Size0Mars, 2)1    89.85   17.898   5.020
## poly(Size0Mars, 2)2    22.36   17.898   1.249
##  -------------- Residual variance  ------------
## Coefficients for log(phi)  ~ 1  :
##              Estimate Cond. SE
## (Intercept)    5.769   0.1451
## Estimate of phi=residual var:  320.3
##  ------------- Likelihood values  -------------
##                          logLik
## logL               : -408.8444
```

```r
summary(Cptlglm3)
```

```
## formula: Cptl0 ~ 1 + poly(Size0Mars, 3)
## ML: Estimation of phi by ML.
##     Estimation of fixed effects by ML.
## family: gaussian( link = identity )
##  ------------ Fixed effects (beta) ------------
##                      Estimate Cond. SE t-value
## (Intercept)             29.58    1.825  16.210
## poly(Size0Mars, 3)1    89.85   17.785   5.052
## poly(Size0Mars, 3)2    22.36   17.785   1.257
## poly(Size0Mars, 3)3   -19.56   17.785  -1.100
##  -------------- Residual variance  ------------
## Coefficients for log(phi)  ~ 1  :
##              Estimate Cond. SE
## (Intercept)    5.757   0.1451
## Estimate of phi=residual var:  316.3
##  ------------- Likelihood values  -------------
##                          logLik
## logL               : -408.2434
```

```r
summary(Cptlglm4)
```

```
## formula: Cptl0 ~ 1 + Size0Mars + (1 | year)
## Estimation of fixed effects by ML.
## Estimation of lambda and phi by 'outer' ML, maximizing logL.
## family: gaussian( link = identity )
##  ------------ Fixed effects (beta) ------------
##              Estimate Cond. SE t-value
## (Intercept)    4.198   5.9466  0.7059
## Size0Mars      2.010   0.4253  4.7263
```

```
## --------------- Random effects ---------------
## Family: gaussian( link = identity )
##           --- Variance parameters ('lambda'):
## lambda = var(u) for u ~ Gaussian;
##    year  :  19.26
## # of obs: 95; # of groups: year, 16
## -------------- Residual variance  ------------
## phi estimate was 308.566
## ------------- Likelihood values  -------------
##                         logLik
## logL       (p_v(h)): -409.4104
```

```
summary(Cptlglm5)
```

```
## formula: Cptl0 ~ 1 + Size0Mars + age0
## ML: Estimation of phi by ML.
##     Estimation of fixed effects by ML.
## family: gaussian( link = identity )
## ------------ Fixed effects (beta) ------------
##             Estimate Cond. SE t-value
## (Intercept)   1.7588   9.3904  0.1873
## Size0Mars     2.0883   0.4257  4.9059
## age0          0.2176   1.3685  0.1590
## -------------- Residual variance  ------------
## Coefficients for log(phi)  ~ 1  :
##             Estimate Cond. SE
## (Intercept)    5.785   0.1451
## Estimate of phi=residual var:  325.5
## ------------- Likelihood values  -------------
##                         logLik
## logL               : -409.6055
```

```
Cptlpredict1 <- predict(Cptlglm1, newdata = fake_data)[,1]
Cptlpredict2 <- predict(Cptlglm2, newdata = fake_data)[,1]
Cptlpredict3 <- predict(Cptlglm3, newdata = fake_data)[,1]
Cptlpredict4 <- predict(Cptlglm4, newdata = fake_data)[,1]
Cptlpredict5 <- predict(Cptlglm5, newdata = fake_data)[,1]
```

```
plot_capitule <- function(data = fake_data, prediction, var, c1, valc1 = 1, c2, valc2 = "Au", fact) {
  data %>%
    mutate(cptl_predi = prediction) %>%
    filter(!!sym(c1) == valc1, !!sym(c2) == valc2) %>%
    ggplot(aes(x = .data[[var]], y = cptl_predi)) +
    geom_point(data=cptldata, aes(y = Cptl0), alpha=0.6)+
    geom_line(aes(color = as.factor(.data[[fact]]))) +
    theme_minimal() +
    ylim(0,50)
}

plot_capitule2 <- function(data = fake_data, prediction, var, c1, valc1 = 1, c2, valc2 = "Au", fact) {
  data %>%
    mutate(cptl_predi = prediction) %>%
    filter(!!sym(c1) == valc1, !!sym(c2) == valc2) %>%
```

```
    ggplot(aes(x = .data[[var]], y = cptl_predi)) +
    geom_line(aes(color = as.factor(.data[[fact]]))) +
    theme_minimal() +
    ylim(0,50)
}
```

Nombre de capitules en fonction de la taille

En fixant la population : voir l'effet année

var <- "Size0Mars"; c1 <- "age0"; valc1 <- 1; c2 <- "Pop"; valc2 <- "Au"; fact <- "year"

Nombre de capitules en fonction de l'age

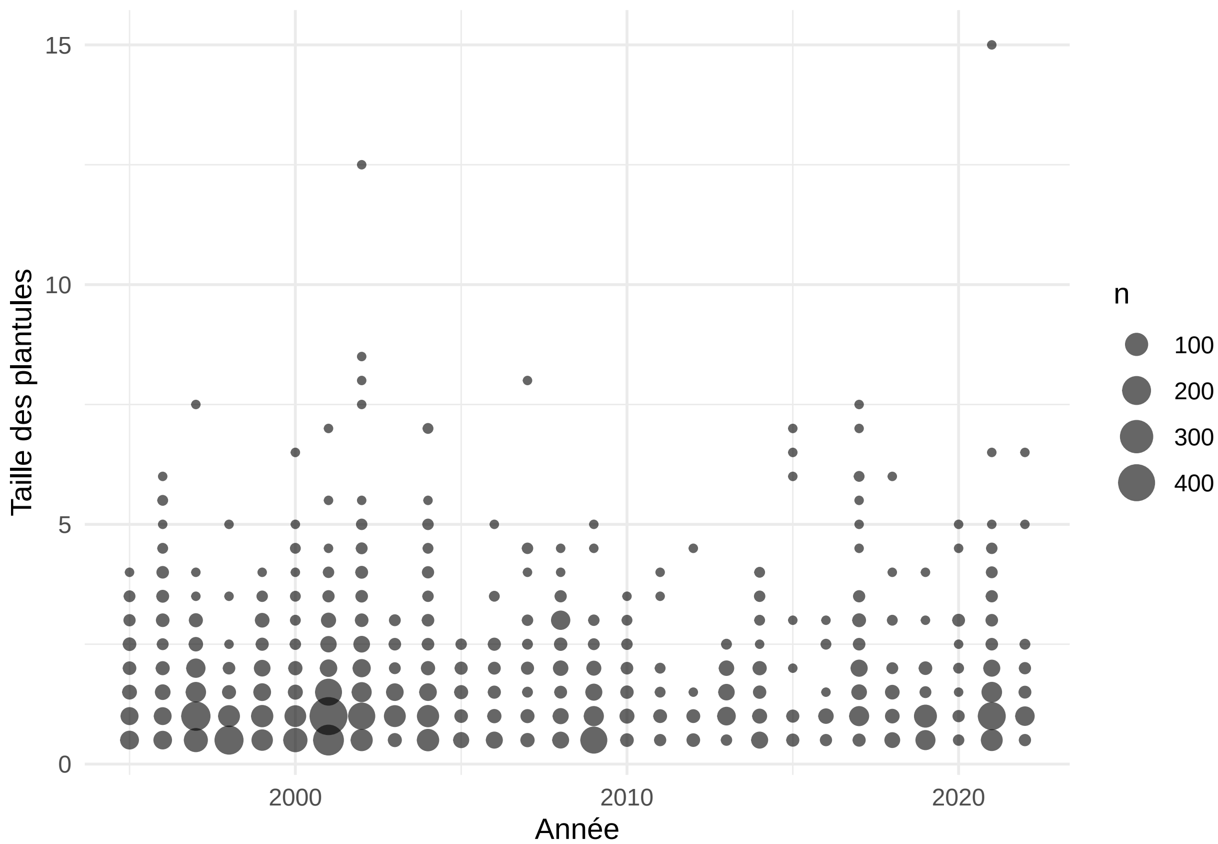
En fixant la population : voir l'effet année

var <- "age0"; c1 <- "Size0Mars"; valc1 <- 1; c2 <- "Pop"; valc2 <- "Au"; fact <- "year"

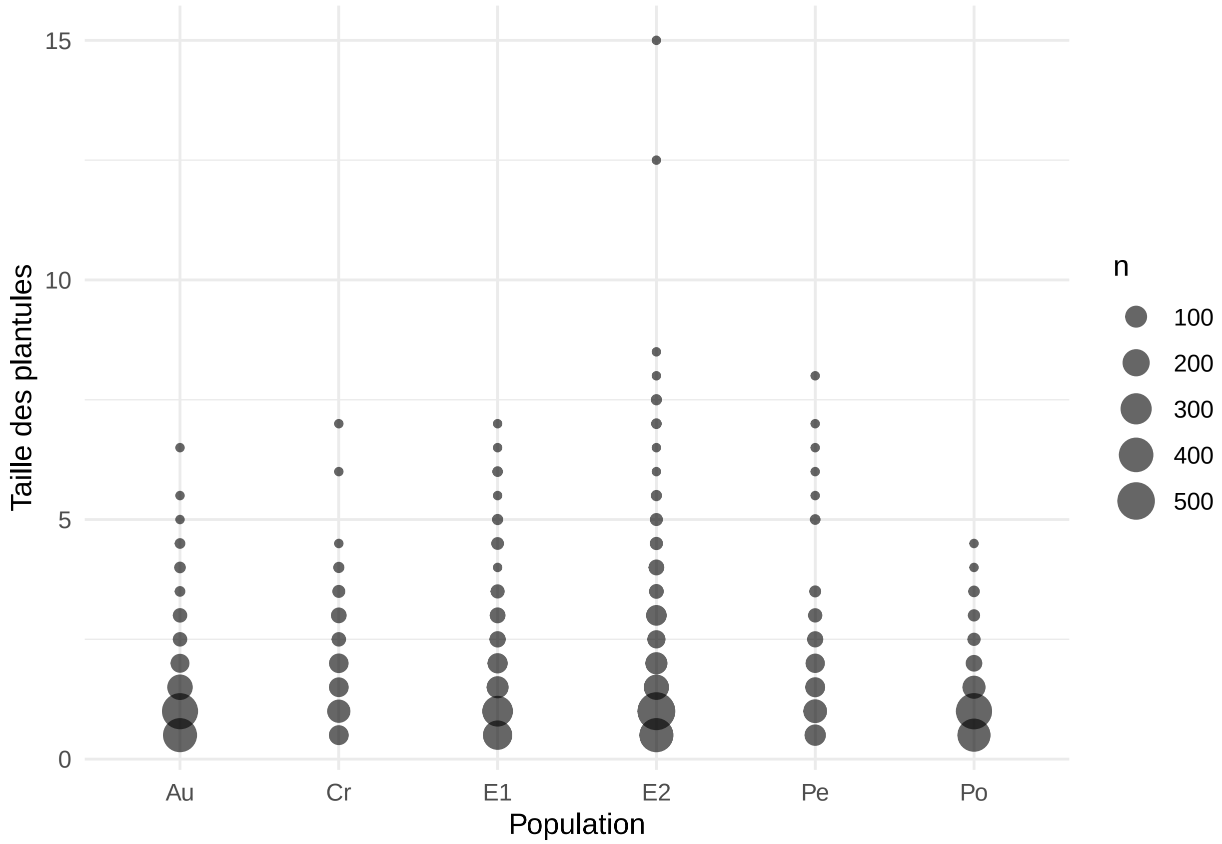
Taille des plantules

```
plantule_data <- centauree_data[centauree_data$age0==1,]
```

```
# Taille des plantules / année

plantule_data %>%
ggplot(aes(x = year, y = Size0Mars)) +
  geom_count(alpha=0.6) +
  labs(x = "Année",
    y = "Taille des plantules") +
  theme_minimal()
```




```r
# Taille des plantules / population

plantule_data %>%
ggplot(aes(x = Pop, y = Size0Mars)) +
  geom_count(alpha=0.6) +
  labs(x = "Population",
    y = "Taille des plantules") +
  theme_minimal()
```




```
Pltglm1 <- fitme(Size0Mars ~ 1 + (1|year) + (1|Pop) + (1|Pop:year),
              data=plantule_data,
               family = Gamma(log))

Pltglm2 <- fitme(Size0Mars ~ 1 + (1|Pop) + (1|Pop:year),
              data=plantule_data,
               family = Gamma(log))

Pltglm3 <- fitme(Size0Mars ~ 1 + (1|Pop:year),
              data=plantule_data,
               family = Gamma(log))

Pltglm4 <- fitme(Size0Mars ~ 1 + (1|year) + (1|Pop:year),
              data=plantule_data,
               family = Gamma(log))

Pltglm5 <- fitme(Size0Mars ~ 1 + (1|year) + (1|Pop),
              data=plantule_data,
               family = Gamma(log))
```

```
n <- length(plantule_data$Nrw)
extractAIC(Pltglm1) ; extractBIC(Pltglm1, n)
```

```
##      edf      AIC
##    1.000 8442.641
```

```
## [1] 8449.171
```

```r
extractAIC(Pltglm2) ; extractBIC(Pltglm2, n)
```

```
##      edf      AIC
##    1.000 8448.128

## [1] 8454.658
```

```r
extractAIC(Pltglm3) ; extractBIC(Pltglm3, n)
```

```
##      edf      AIC
##    1.000 8458.154

## [1] 8464.685
```

```r
extractAIC(Pltglm4) ; extractBIC(Pltglm4, n)
```

```
##      edf      AIC
##    1.000 8457.579

## [1] 8464.109
```

```r
extractAIC(Pltglm5) ; extractBIC(Pltglm5, n)
```

```
##      edf      AIC
##    1.000 8841.777

## [1] 8848.308
```

```r
summary(Pltglm1)
```

```
## formula: Size0Mars ~ 1 + (1 | year) + (1 | Pop) + (1 | Pop:year)
## Estimation of lambda and phi by ML (P_v approximation of logL).
## Estimation of fixed effects by ML (P_v approximation of logL).
## family: Gamma( link = log )
##  ------------ Fixed effects (beta) ------------
##             Estimate Cond. SE t-value
## (Intercept)   0.2132  0.07717   2.763
##  --------------- Random effects ---------------
## Family: gaussian( link = identity )
##            --- Variance parameters ('lambda'):
## lambda = var(u) for u ~ Gaussian;
##    year  :  0.02216
##    Pop  :  0.02626
##    Pop:year  :  0.07964
##              --- Coefficients for log(lambda):
##     Group        Term Estimate Cond.SE
##      year (Intercept)    -3.81  0.3809
```

```
##       Pop (Intercept)    -3.64  0.6351
##  Pop:year (Intercept)    -2.53  0.1444
## # of obs: 5065; # of groups: year, 28; Pop, 6; Pop:year, 147
##  --- Residual variation ( var = phi * mu^2 )  --
## Coefficients for log(phi)  ~ 1  :
##             Estimate Cond. SE
## (Intercept)    -1.34  0.01967
## Estimate of phi:  0.2619
##  ------------- Likelihood values  -------------
##                        logLik
## logL      (P_v(h)): -4216.321
```

```r
summary(Pltglm2)
```

```
## formula: Size0Mars ~ 1 + (1 | Pop) + (1 | Pop:year)
## Estimation of lambda and phi by ML (P_v approximation of logL).
## Estimation of fixed effects by ML (P_v approximation of logL).
## family: Gamma( link = log )
##  ------------ Fixed effects (beta) ------------
##             Estimate Cond. SE t-value
## (Intercept)   0.2024  0.06951   2.912
##  --------------- Random effects ---------------
## Family: gaussian( link = identity )
##            --- Variance parameters ('lambda'):
## lambda = var(u) for u ~ Gaussian;
##    Pop  :  0.02327
##    Pop:year  :  0.1083
##              --- Coefficients for log(lambda):
##     Group        Term Estimate Cond.SE
##       Pop (Intercept)   -3.761  0.6465
##  Pop:year (Intercept)   -2.223  0.1332
## # of obs: 5065; # of groups: Pop, 6; Pop:year, 147
##  --- Residual variation ( var = phi * mu^2 )  --
## Coefficients for log(phi)  ~ 1  :
##             Estimate Cond. SE
## (Intercept)   -1.341  0.01967
## Estimate of phi:  0.2616
##  ------------- Likelihood values  -------------
##                        logLik
## logL      (P_v(h)): -4220.064
```

```r
summary(Pltglm3)
```

```
## formula: Size0Mars ~ 1 + (1 | Pop:year)
## Estimation of lambda and phi by ML (P_v approximation of logL).
## Estimation of fixed effects by ML (P_v approximation of logL).
## family: Gamma( link = log )
##  ------------ Fixed effects (beta) ------------
##             Estimate Cond. SE t-value
## (Intercept)   0.1878  0.03325   5.648
##  --------------- Random effects ---------------
## Family: gaussian( link = identity )
##            --- Variance parameters ('lambda'):
```

```
## lambda = var(u) for u ~ Gaussian;
##    Pop:year  :  0.1333
##              --- Coefficients for log(lambda):
##     Group        Term Estimate Cond.SE
##  Pop:year (Intercept)   -2.015  0.1289
## # of obs: 5065; # of groups: Pop:year, 147
##  --- Residual variation ( var = phi * mu^2 )  --
## Coefficients for log(phi)  ~ 1  :
##             Estimate Cond. SE
## (Intercept)   -1.342  0.01968
## Estimate of phi:  0.2614
##  ------------- Likelihood values  -------------
##                         logLik
## logL      (P_v(h)): -4226.077
```

```r
summary(Pltglm4)
```

```
## formula: Size0Mars ~ 1 + (1 | year) + (1 | Pop:year)
## Estimation of lambda and phi by ML (P_v approximation of logL).
## Estimation of fixed effects by ML (P_v approximation of logL).
## family: Gamma( link = log )
##  ------------ Fixed effects (beta) ------------
##             Estimate Cond. SE t-value
## (Intercept)   0.1914  0.03913    4.89
##  --------------- Random effects ---------------
## Family: gaussian( link = identity )
##            --- Variance parameters ('lambda'):
## lambda = var(u) for u ~ Gaussian;
##    year  :  0.01472
##    Pop:year  :  0.1158
##              --- Coefficients for log(lambda):
##     Group        Term Estimate Cond.SE
##      year (Intercept)   -4.219  0.4567
##  Pop:year (Intercept)   -2.156  0.1348
## # of obs: 5065; # of groups: year, 28; Pop:year, 147
##  --- Residual variation ( var = phi * mu^2 )  --
## Coefficients for log(phi)  ~ 1  :
##             Estimate Cond. SE
## (Intercept)   -1.341  0.01968
## Estimate of phi:  0.2616
##  ------------- Likelihood values  -------------
##                        logLik
## logL      (P_v(h)): -4224.79
```

```r
summary(Pltglm5)
```

```
## formula: Size0Mars ~ 1 + (1 | year) + (1 | Pop)
## Estimation of lambda and phi by ML (P_v approximation of logL).
## Estimation of fixed effects by ML (P_v approximation of logL).
## family: Gamma( link = log )
##  ------------ Fixed effects (beta) ------------
##             Estimate Cond. SE t-value
## (Intercept)   0.2642   0.0892   2.962
```

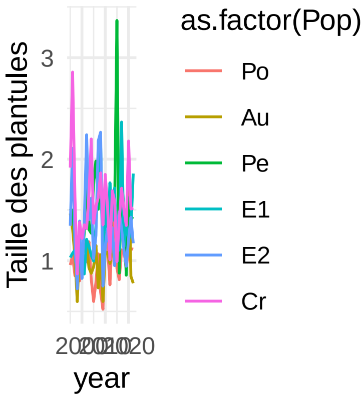
```
##  --------------- Random effects ---------------
## Family: gaussian( link = identity )
##            --- Variance parameters ('lambda'):
## lambda = var(u) for u ~ Gaussian;
##    year  :  0.05123
##    Pop  :  0.03582
##              --- Coefficients for log(lambda):
##  Group        Term Estimate Cond.SE
##   year (Intercept)   -2.971  0.2819
##    Pop (Intercept)   -3.329  0.5933
## # of obs: 5065; # of groups: year, 28; Pop, 6
##  --- Residual variation ( var = phi * mu^2 )  --
## Coefficients for log(phi)  ~ 1  :
##             Estimate Cond. SE
## (Intercept)   -1.231  0.01947
## Estimate of phi:  0.292
##  ------------- Likelihood values  -------------
##                          logLik
## logL      (P_v(h)): -4416.889
```

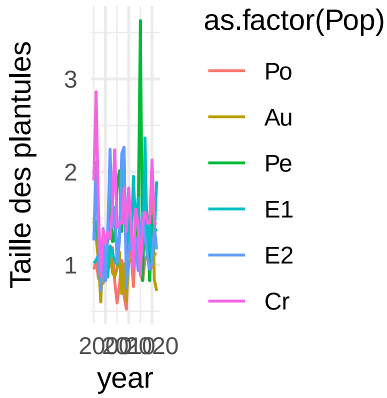
```
Pltpredict1 <- predict(Pltglm1, newdata = fake_data)[,1]
Pltpredict2 <- predict(Pltglm2, newdata = fake_data)[,1]
Pltpredict3 <- predict(Pltglm3, newdata = fake_data)[,1]
Pltpredict4 <- predict(Pltglm4, newdata = fake_data)[,1]
Pltpredict5 <- predict(Pltglm5, newdata = fake_data)[,1]
```

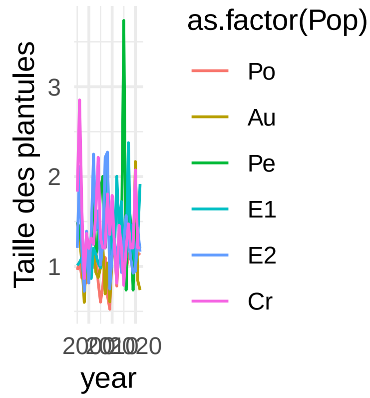
```
plot_plantule <- function(data = fake_data, prediction, var, fact) {
  data %>%
    mutate(plt_predi = prediction) %>%
    ggplot(aes(x = .data[[var]], y = plt_predi)) +
    geom_line(aes(color = as.factor(.data[[fact]]))) +
    labs(y="Taille des plantules")+
    theme_minimal()
}

plot_plantule1 <- function(data = fake_data, prediction, var, fact) {
  data %>%
    mutate(plt_predi = prediction) %>%
    ggplot(aes(x = .data[[var]], y = plt_predi)) +
    geom_point(aes(color = as.factor(.data[[fact]]))) +
    labs(y="Taille des plantules")+
    theme_minimal()
}

plot_plantule2 <- function(data = fake_data, prediction) {
  data %>%
    mutate(plt_predi = prediction) %>%
    ggplot(aes(x = plt_predi)) +
    geom_histogram() +
    labs(x="Taille des plantules")+
    theme_minimal()
}
```

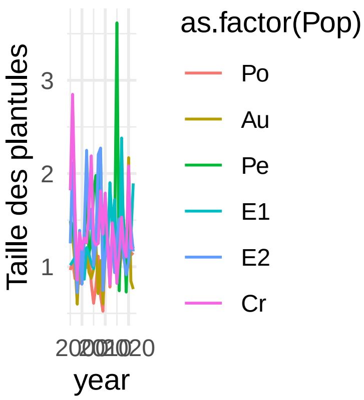
Taille des plantules en fonction de l'année

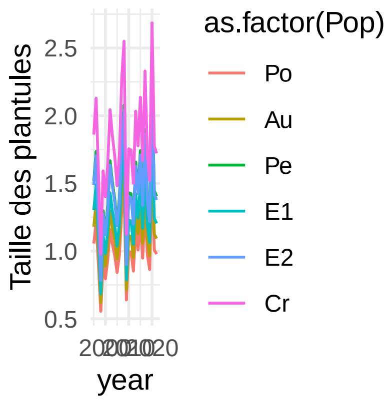
var <- "year" fact <- "Pop"





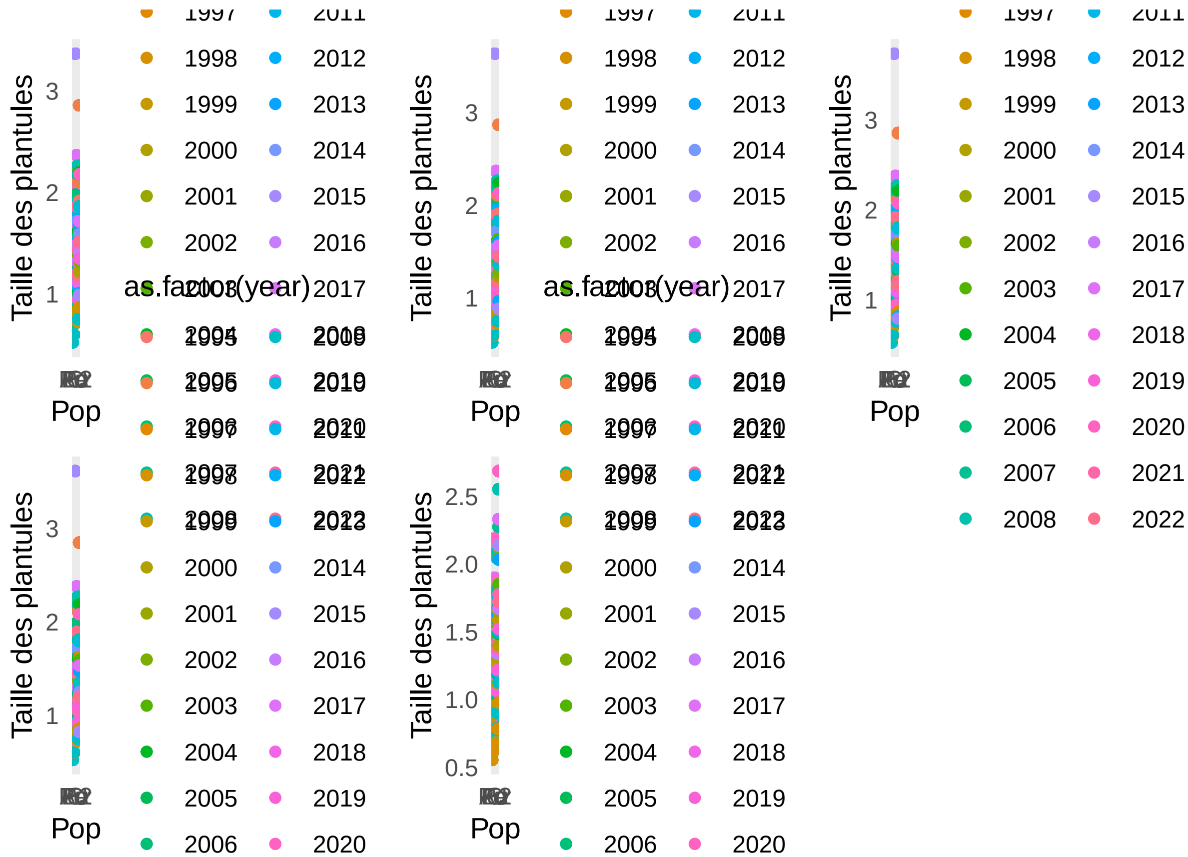






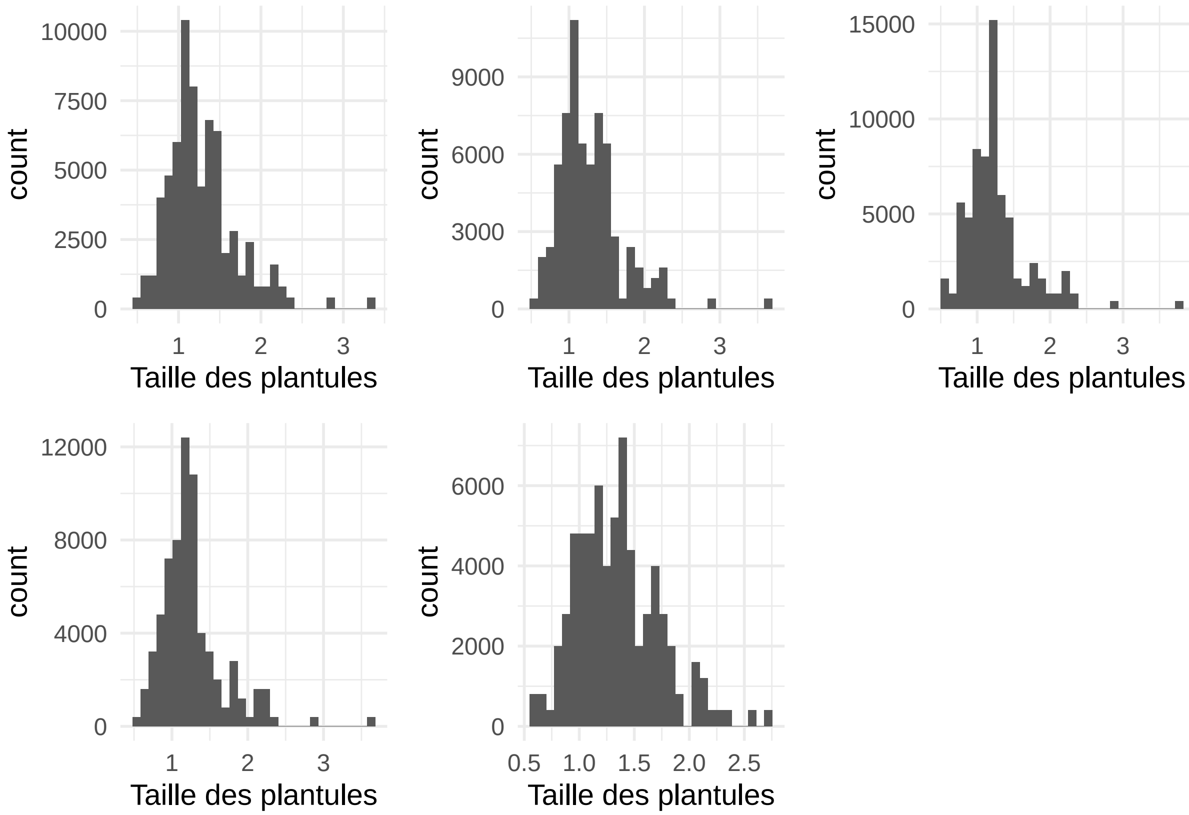
Taille des plantules en fonction de la population

var <- "Pop" fact <- "year"



Densité de taille de plantule

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```



Establishment rate

Remplir les données manquantes de nombres de capitules avec des prédictions.

```r
cptl_data <- centauree_data_complet[!centauree_data_complet$Flowering0==0,]
Cptlglm1 <- fitme(Cptl0 ~ 1 + Size0Mars,
              data=cptl_data)
# NbrCptl  = -3.769 + 2.683*Size0Mars

cptl_data_predi <- cptl_data %>%
  mutate(Cptl0 = ifelse(is.na(Cptl0), round(-3.769+2.683*Size0Mars), Cptl0))
```

```r
plt <- centauree_data_complet %>%
  filter(age0==1) %>%
  group_by(Quadrat,year,Pop) %>%
  summarize(NombrePlantules = sum(age0))
```

```
## 'summarise()' has grouped output by 'Quadrat', 'year'. You can override using
## the '.groups' argument.
```

```r
cptl <- cptl_data_predi %>%
  group_by(Quadrat,year,Pop) %>%
  summarize(NombresCapitules = sum(Cptl0))
```

```
## `summarise()` has grouped output by 'Quadrat', 'year'. You can override using
## the `.groups` argument.
```

```
Estb <- inner_join(plt,cptl, by=join_by(Quadrat,year,Pop))
summary(Estb)
```

```
##     Quadrat          year          Pop            NombrePlantules
##  Min.   : 1.0   Min.   :1995   Length:162         Min.   :  1.0
##  1st Qu.: 6.0   1st Qu.:1997   Class :character   1st Qu.:  2.0
##  Median :26.5   Median :2000   Mode  :character   Median :  8.0
##  Mean   :22.5   Mean   :2002                      Mean   : 17.7
##  3rd Qu.:34.0   3rd Qu.:2004                      3rd Qu.: 19.0
##  Max.   :80.0   Max.   :2021                      Max.   :203.0
##  NombresCapitules
##  Min.   :  1.00
##  1st Qu.: 20.25
##  Median : 34.50
##  Mean   : 50.10
##  3rd Qu.: 60.75
##  Max.   :214.00
```

```
Estb <- Estb %>% mutate(EstbRate=rep(NA)) %>%
  arrange(Quadrat)

for (i in 2:length(Estb$Quadrat)){
  if (Estb$Quadrat[i]!=Estb$Quadrat[i-1]){next}
  if (Estb$year[i]!=Estb$year[i-1]+1){next}
  Estb$EstbRate[i] <- Estb$NombrePlantules[i]/Estb$NombresCapitules[i-1]
}
```

```
Estbglm1 <- fitme(EstbRate ~ 1 + (1|Pop:year), data=Estb)
Estbglm2 <- fitme(EstbRate ~ 1 +(1|year), data=Estb)
Estbglm3 <- fitme(EstbRate ~ 1 + (1|year) + (1|Pop:year), data=Estb)
Estbglm4 <- fitme(EstbRate ~ 1, data=Estb)
Estbglm5 <- fitme(EstbRate ~ 1 + (1|Pop) + (1|Pop:year), data=Estb)

Estbglm1
```

```
## formula: EstbRate ~ 1 + (1 | Pop:year)
## Estimation of fixed effects by ML.
## Estimation of lambda and phi by 'outer' ML, maximizing logL.
## family: gaussian( link = identity )
##  ------------ Fixed effects (beta) ------------
##             Estimate Cond. SE t-value
## (Intercept)   0.4852  0.05292   9.169
##  --------------- Random effects ---------------
## Family: gaussian( link = identity )
##            --- Variance parameters ('lambda'):
## lambda = var(u) for u ~ Gaussian;
##    Pop:year  :  0.04924
## # of obs: 95; # of groups: Pop:year, 58
##  -------------- Residual variance  ------------
```

```
## phi estimate was 0.173107
##  ------------- Likelihood values  -------------
##                         logLik
## logL       (p_v(h)): -62.26091
```

```
Estbglm2
```

```
## formula: EstbRate ~ 1 + (1 | year)
## Estimation of fixed effects by ML.
## Estimation of lambda and phi by 'outer' ML, maximizing logL.
## family: gaussian( link = identity )
##  ------------ Fixed effects (beta) ------------
##             Estimate Cond. SE t-value
## (Intercept)    0.486  0.06047   8.036
##  --------------- Random effects ---------------
## Family: gaussian( link = identity )
##            --- Variance parameters ('lambda'):
## lambda = var(u) for u ~ Gaussian;
##    year  :  0.01659
## # of obs: 95; # of groups: year, 16
##  -------------- Residual variance  ------------
## phi estimate was 0.206833
##  ------------- Likelihood values  -------------
##                        logLik
## logL       (p_v(h)): -62.8351
```

```
Estbglm3
```

```
## formula: EstbRate ~ 1 + (1 | year) + (1 | Pop:year)
## Estimation of fixed effects by ML.
## Estimation of lambda and phi by 'outer' ML, maximizing logL.
## family: gaussian( link = identity )
##  ------------ Fixed effects (beta) ------------
##             Estimate Cond. SE t-value
## (Intercept)   0.4839  0.05963   8.116
##  --------------- Random effects ---------------
## Family: gaussian( link = identity )
##            --- Variance parameters ('lambda'):
## lambda = var(u) for u ~ Gaussian;
##    year  :  0.01134
##    Pop:year  :  0.03626
## # of obs: 95; # of groups: year, 16; Pop:year, 58
##  -------------- Residual variance  ------------
## phi estimate was 0.174002
##  ------------- Likelihood values  -------------
##                         logLik
## logL       (p_v(h)): -61.91014
```

```
Estbglm4
```

```
## formula: EstbRate ~ 1
## ML: Estimation of phi by ML.
```

```
##     Estimation of fixed effects by ML.
## family: gaussian( link = identity )
##  ------------ Fixed effects (beta) ------------
##              Estimate Cond. SE t-value
## (Intercept)   0.4912  0.04868   10.09
##  -------------- Residual variance  ------------
## Coefficients for log(phi)  ~ 1  :
##              Estimate Cond. SE
## (Intercept)   -1.491   0.1451
## Estimate of phi=residual var:  0.2251
##  ------------- Likelihood values  -------------
##                          logLik
## logL               : -63.96959
```

```
Estbglm5
```

```
## formula: EstbRate ~ 1 + (1 | Pop) + (1 | Pop:year)
## Estimation of fixed effects by ML.
## Estimation of lambda and phi by 'outer' ML, maximizing logL.
## family: gaussian( link = identity )
##  ------------ Fixed effects (beta) ------------
##              Estimate Cond. SE t-value
## (Intercept)   0.4852  0.05292   9.169
##  --------------- Random effects ---------------
## Family: gaussian( link = identity )
##             --- Variance parameters ('lambda'):
## lambda = var(u) for u ~ Gaussian;
##    Pop  :  1.98e-07
##    Pop:year  :  0.04924
## # of obs: 95; # of groups: Pop, 6; Pop:year, 58
##  -------------- Residual variance  ------------
## phi estimate was 0.173107
##  ------------- Likelihood values  -------------
##                          logLik
## logL       (p_v(h)): -62.26092
```

```r
n <- length(Estb$Quadrat)
extractAIC(Estbglm1) ; extractBIC(Estbglm1, n)
```

```
##      edf      AIC
##   1.0000 130.5218
```

```
## [1] 133.6094
```

```r
extractAIC(Estbglm2) ; extractBIC(Estbglm2, n)
```

```
##      edf      AIC
##   1.0000 131.6702
```

```
## [1] 134.7578
```

```r
extractAIC(Estbglm3) ; extractBIC(Estbglm3, n)
```

```
##      edf      AIC
##   1.0000 131.8203
```

```
## [1] 134.9079
```

```r
extractAIC(Estbglm4) ; extractBIC(Estbglm4, n)
```

```
##      edf      AIC
##   1.0000 131.9392
```

```
## [1] 135.0268
```

```r
extractAIC(Estbglm5) ; extractBIC(Estbglm5, n)
```

```
##      edf      AIC
##   1.0000 132.5218
```

```
## [1] 135.6094
```

```r
Estbpredict1 <- predict(Estbglm1, newdata = fake_data)[,1]
Estbpredict2 <- predict(Estbglm2, newdata = fake_data)[,1]
Estbpredict3 <- predict(Estbglm3, newdata = fake_data)[,1]
Estbpredict4 <- predict(Estbglm4, newdata = fake_data)[,1]
Estbpredict5 <- predict(Estbglm5, newdata = fake_data)[,1]
```

```r
plot_estb <- function(data = fake_data, prediction, var, fact) {
  data %>%
    mutate(plt_predi = prediction) %>%
    ggplot(aes(x = .data[[var]], y = plt_predi)) +
    geom_line(aes(color = as.factor(.data[[fact]]))) +
    labs(y="Establishment rate")+
    theme_minimal()
}

plot_estb2 <- function(data = fake_data, prediction, var, fact) {
  data %>%
    mutate(plt_predi = prediction) %>%
    ggplot(aes(x = .data[[var]], y = plt_predi)) +
    geom_point(aes(color = as.factor(.data[[fact]]))) +
    labs(y="Establishment rate")+
    theme_minimal()
}
```

Establishment rate en fonction de l'année

var <- "year"; fact <- "Pop"

Establishment rate en fonction de la population

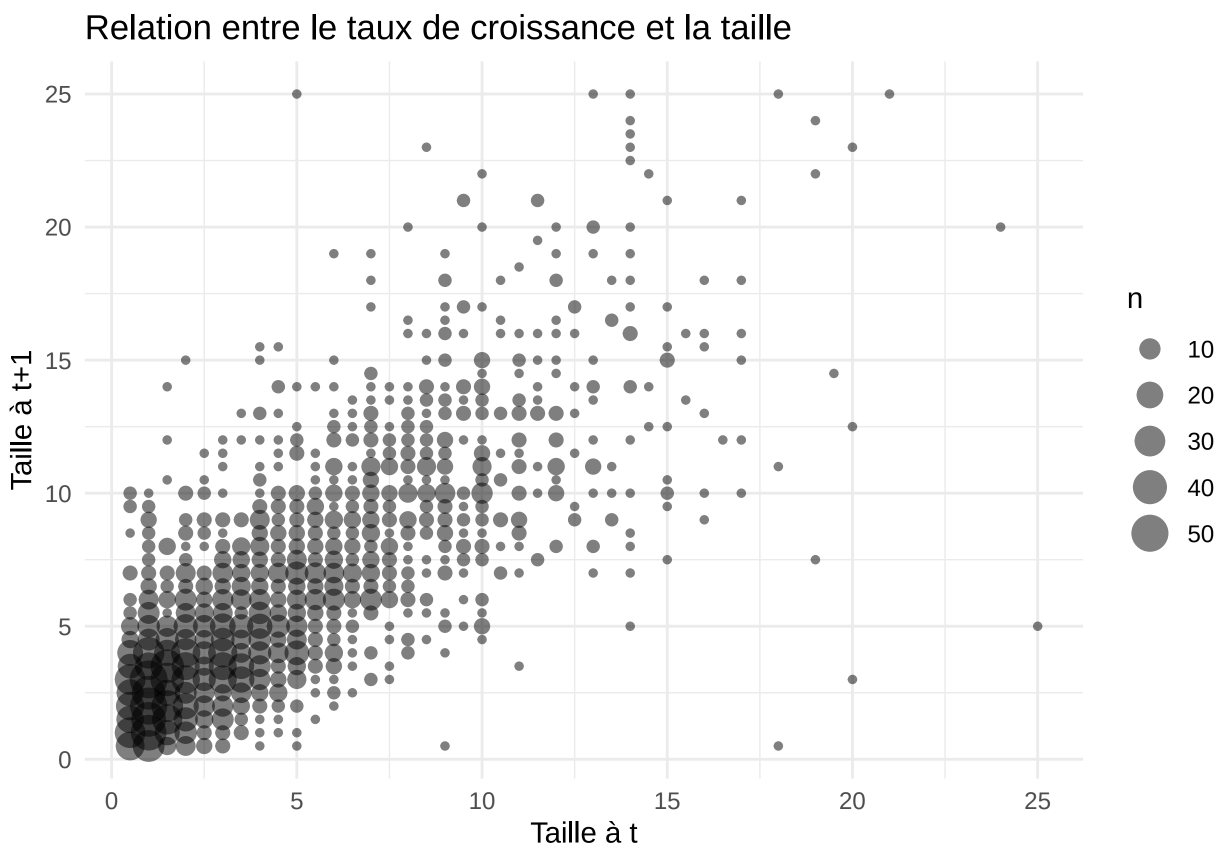
var <- "Pop"; fact <- "year"

Croissance

Variable : rapport taille t+1/ taille t

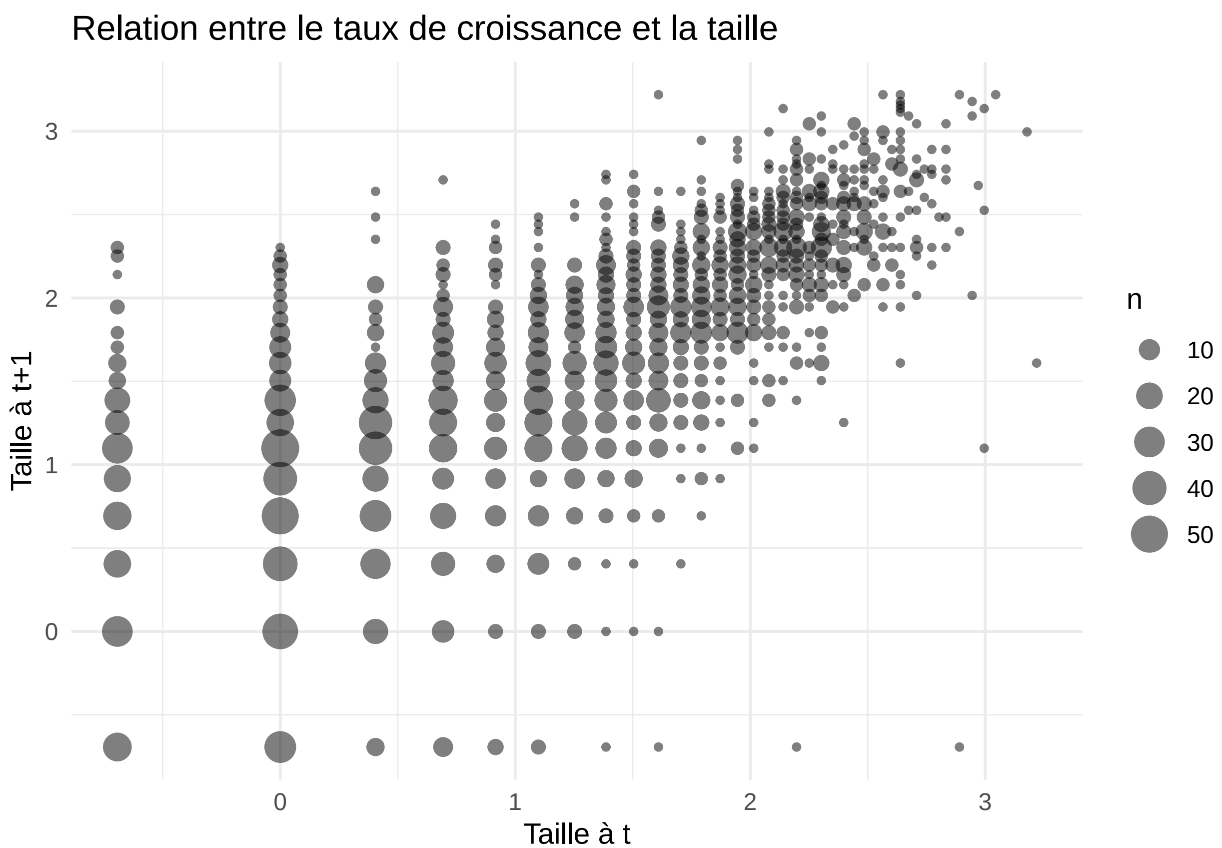
```
growthdata <- centauree_data[!is.na(centauree_data$Size1Mars), ]
growthdata <- growthdata[growthdata$Size1Mars != 0, ]
```

```
growthdata %>%
  ggplot(aes(y = Size1Mars, x = Size0Mars)) +
  geom_count(alpha=0.5) +
  labs(title = "Relation entre le taux de croissance et la taille",
    y = "Taille à t+1",
    x = "Taille à t") +
  theme_minimal()
```




```
growthdata %>%
  ggplot(aes(y = log(Size1Mars), x = log(Size0Mars))) +
  geom_count(alpha=0.5) +
```

```
  labs(title = "Relation entre le taux de croissance et la taille",
    y = "Taille à t+1",
    x = "Taille à t") +
  theme_minimal()
```




```
Growthglm1 <- fitme(log(Size1Mars) ~ 1 + poly(log(Size0Mars),4) + poly(age0,3) + (log(Size0Mars)|year) +
                    data=growthdata)

Growthglm2 <- fitme(log(Size1Mars) ~ 1 + bs(log(Size0Mars),df =5,degree=3) + poly(age0,3) + (log(Size0Ma
                   data=growthdata)

Growthglm3 <- fitme(log(Size1Mars) ~ 1 + poly(log(Size0Mars),4) + poly(age0,3) + (log(Size0Mars) + age0
                    data=growthdata)

Growthglm4 <- fitme(log(Size1Mars) ~ 1 + poly(log(Size0Mars),4) + poly(age0,4) + (log(Size0Mars)|year) +
                    data=growthdata)

Growthglm5 <- fitme(log(Size1Mars) ~ 1 + poly(log(Size0Mars),4) + poly(age0,3) + (log(Size0Mars)|year) +
                    data=growthdata)
```

```
n <- length(growthdata$Nrw)
extractAIC(Growthglm1) ; extractBIC(Growthglm1, n)
```

```
##      edf      AIC
##    8.000 4074.761
```

```
## [1] 4121.484
```

```
extractAIC(Growthglm2) ; extractBIC(Growthglm2, n)
```

```
##      edf      AIC
##    9.000 4076.138
```

```
## [1] 4128.701
```

```
extractAIC(Growthglm3) ; extractBIC(Growthglm3, n)
```

```
##      edf      AIC
##    8.000 4076.149
```

```
## [1] 4122.872
```

```
extractAIC(Growthglm4) ; extractBIC(Growthglm4, n)
```

```
##      edf      AIC
##    9.000 4076.238
```

```
## [1] 4128.801
```

```
extractAIC(Growthglm5) ; extractBIC(Growthglm5, n)
```

```
##      edf      AIC
##    8.000 4076.762
```

```
## [1] 4123.484
```

```
summary(Growthglm1)
```

```
## formula: log(Size1Mars) ~ 1 + poly(log(Size0Mars), 4) + poly(age0, 3) +
##     (log(Size0Mars) | year) + (log(Size0Mars) | Pop)
## ML: Estimation of ranCoefs and phi by ML.
##     Estimation of fixed effects by ML.
## Estimation of phi by 'outer' ML, maximizing logL.
## family: gaussian( link = identity )
##  ------------ Fixed effects (beta) ------------
##                          Estimate Cond. SE t-value
## (Intercept)                 1.533  0.06206  24.702
## poly(log(Size0Mars), 4)1   30.582  2.23174  13.703
## poly(log(Size0Mars), 4)2    6.167  0.56756  10.867
## poly(log(Size0Mars), 4)3   -3.618  0.57491  -6.293
## poly(log(Size0Mars), 4)4   -1.336  0.55018  -2.429
## poly(age0, 3)1             -5.407  0.80686  -6.701
## poly(age0, 3)2              2.845  0.65644   4.334
## poly(age0, 3)3             -2.153  0.58556  -3.677
##  --------------- Random effects ---------------
```

```
## Family: gaussian( link = identity )
##          --- Random-coefficients Cov matrices:
##  Group           Term     Var.   Corr.
##   year    (Intercept)  0.04364
##   year log(Size0Mars) 0.007463 -0.8427
##    Pop    (Intercept)  0.05301
##    Pop log(Size0Mars) 0.009215 -0.9945
## # of obs: 2541; # of groups: year, 27; Pop, 6
##  -------------- Residual variance  ------------
## phi estimate was 0.27795
##  ------------- Likelihood values  -------------
##                         logLik
## logL       (p_v(h)): -2022.381
```

```r
summary(Growthglm2)
```

```
## formula: log(Size1Mars) ~ 1 + bs(log(Size0Mars), df = 5, degree = 3) +
##     poly(age0, 3) + (log(Size0Mars) | year) + (log(Size0Mars) |
##     Pop)
## ML: Estimation of ranCoefs and phi by ML.
##     Estimation of fixed effects by ML.
## Estimation of phi by 'outer' ML, maximizing logL.
## family: gaussian( link = identity )
##  ------------ Fixed effects (beta) ------------
##                                         Estimate Cond. SE t-value
## (Intercept)                              0.74780  0.14074  5.3134
## bs(log(Size0Mars), df = 5, degree = 3)1 -0.06752  0.08756 -0.7711
## bs(log(Size0Mars), df = 5, degree = 3)2  0.21466  0.09504  2.2585
## bs(log(Size0Mars), df = 5, degree = 3)3  1.29997  0.14562  8.9269
## bs(log(Size0Mars), df = 5, degree = 3)4  2.27804  0.18985 11.9994
## bs(log(Size0Mars), df = 5, degree = 3)5  1.77441  0.27291  6.5019
## poly(age0, 3)1                          -5.35568  0.80958 -6.6154
## poly(age0, 3)2                           2.83234  0.65666  4.3132
## poly(age0, 3)3                          -2.15291  0.58574 -3.6755
##  --------------- Random effects ---------------
## Family: gaussian( link = identity )
##          --- Random-coefficients Cov matrices:
##  Group           Term     Var.   Corr.
##   year    (Intercept)  0.04314
##   year log(Size0Mars) 0.007267 -0.8394
##    Pop    (Intercept)  0.05268
##    Pop log(Size0Mars) 0.009181 -0.9934
## # of obs: 2541; # of groups: year, 27; Pop, 6
##  -------------- Residual variance  ------------
## phi estimate was 0.277889
##  ------------- Likelihood values  -------------
##                         logLik
## logL       (p_v(h)): -2022.069
```

```r
summary(Growthglm3)
```

```
## formula: log(Size1Mars) ~ 1 + poly(log(Size0Mars), 4) + poly(age0, 3) +
##     (log(Size0Mars) + age0 | year) + (log(Size0Mars) | Pop)
```

```
## ML: Estimation of ranCoefs and phi by ML.
##     Estimation of fixed effects by ML.
## Estimation of phi by 'outer' ML, maximizing logL.
## family: gaussian( link = identity )
##  ------------ Fixed effects (beta) ------------
##                           Estimate Cond. SE t-value
## (Intercept)                  1.533  0.06172  24.841
## poly(log(Size0Mars), 4)1   30.670  2.20015  13.940
## poly(log(Size0Mars), 4)2    6.211  0.56868  10.922
## poly(log(Size0Mars), 4)3   -3.587  0.57503  -6.238
## poly(log(Size0Mars), 4)4   -1.342  0.55069  -2.437
## poly(age0, 3)1             -5.682  0.89043  -6.381
## poly(age0, 3)2              2.680  0.65187   4.112
## poly(age0, 3)3             -2.183  0.58067  -3.759
##  --------------- Random effects ---------------
## Family: gaussian( link = identity )
##          --- Random-coefficients Cov matrices:
##  Group           Term      Var.   Corr.  Corr..1
##   year    (Intercept)   0.05418
##   year log(Size0Mars)  0.007555 -0.6099
##   year           age0 0.0005126 -0.7245 -0.08932
##    Pop    (Intercept)   0.05151
##    Pop log(Size0Mars)  0.008743 -0.9957
## # of obs: 2541; # of groups: year, 27; Pop, 6
##  -------------- Residual variance  ------------
## phi estimate was 0.277304
##  ------------- Likelihood values  -------------
##                          logLik
## logL       (p_v(h)): -2020.075
```

```
summary(Growthglm4)
```

```
## formula: log(Size1Mars) ~ 1 + poly(log(Size0Mars), 4) + poly(age0, 4) +
##     (log(Size0Mars) | year) + (log(Size0Mars) | Pop)
## ML: Estimation of ranCoefs and phi by ML.
##     Estimation of fixed effects by ML.
## Estimation of phi by 'outer' ML, maximizing logL.
## family: gaussian( link = identity )
##  ------------ Fixed effects (beta) ------------
##                           Estimate Cond. SE t-value
## (Intercept)                 1.5333  0.06206 24.7075
## poly(log(Size0Mars), 4)1  30.5015  2.25070 13.5520
## poly(log(Size0Mars), 4)2   6.2264  0.57217 10.8822
## poly(log(Size0Mars), 4)3  -3.5839  0.57644 -6.2174
## poly(log(Size0Mars), 4)4  -1.3578  0.55106 -2.4640
## poly(age0, 4)1            -5.3747  0.80791 -6.6526
## poly(age0, 4)2             2.8163  0.65746  4.2836
## poly(age0, 4)3            -2.1221  0.58693 -3.6156
## poly(age0, 4)4            -0.4037  0.55619 -0.7258
##  --------------- Random effects ---------------
## Family: gaussian( link = identity )
##          --- Random-coefficients Cov matrices:
##  Group           Term     Var.   Corr.
##   year    (Intercept)  0.04348
```

```
##   year log(Size0Mars) 0.007477  -0.842
##    Pop    (Intercept)  0.05359
##    Pop log(Size0Mars) 0.009416 -0.9951
## # of obs: 2541; # of groups: year, 27; Pop, 6
##  -------------- Residual variance  ------------
## phi estimate was 0.277899
##  ------------- Likelihood values  -------------
##                         logLik
## logL       (p_v(h)): -2022.119
```

```
summary(Growthglm5)
```

```
## formula: log(Size1Mars) ~ 1 + poly(log(Size0Mars), 4) + poly(age0, 3) +
##     (log(Size0Mars) | year) + (log(Size0Mars) | Pop) + (1 | Nrw)
## ML: Estimation of lambda, ranCoefs and phi by ML.
##     Estimation of fixed effects by ML.
## Estimation of phi by 'outer' ML, maximizing logL.
## family: gaussian( link = identity )
##  ------------ Fixed effects (beta) ------------
##                          Estimate Cond. SE t-value
## (Intercept)                 1.533  0.06206  24.702
## poly(log(Size0Mars), 4)1   30.582  2.23177  13.703
## poly(log(Size0Mars), 4)2    6.167  0.56756  10.867
## poly(log(Size0Mars), 4)3   -3.618  0.57491  -6.293
## poly(log(Size0Mars), 4)4   -1.336  0.55018  -2.429
## poly(age0, 3)1             -5.407  0.80687  -6.701
## poly(age0, 3)2              2.845  0.65645   4.333
## poly(age0, 3)3             -2.153  0.58556  -3.677
##  --------------- Random effects ---------------
## Family: gaussian( link = identity )
##          --- Random-coefficients Cov matrices:
##  Group           Term     Var.   Corr.
##   year    (Intercept)  0.04364
##   year log(Size0Mars) 0.007463 -0.8427
##    Pop    (Intercept)  0.05301
##    Pop log(Size0Mars) 0.009216 -0.9945
##            --- Variance parameters ('lambda'):
## lambda = var(u) for u ~ Gaussian;
##    Nrw  :  1.168e-06
##              --- Coefficients for log(lambda):
##  Group        Term Estimate Cond.SE
##    Nrw (Intercept)   -13.66    13.5
## # of obs: 2541; # of groups: year, 27; Pop, 6; Nrw, 1004
##  -------------- Residual variance  ------------
## phi estimate was 0.277948
##  ------------- Likelihood values  -------------
##                         logLik
## logL       (p_v(h)): -2022.381
```

```
Growthpredict1 <- predict(Growthglm1, newdata = fake_data)[,1]
Growthpredict2 <- predict(Growthglm2, newdata = fake_data)[,1]
```

```
## Warning in bs(log(Size0Mars), degree = 3L, knots = c(0.693147180559945, : some
```

```
## 'x' values beyond boundary knots may cause ill-conditioned bases
## Warning in bs(log(Size0Mars), degree = 3L, knots = c(0.693147180559945, : some
## 'x' values beyond boundary knots may cause ill-conditioned bases
## Warning in bs(log(Size0Mars), degree = 3L, knots = c(0.693147180559945, : some
## 'x' values beyond boundary knots may cause ill-conditioned bases
## Warning in bs(log(Size0Mars), degree = 3L, knots = c(0.693147180559945, : some
## 'x' values beyond boundary knots may cause ill-conditioned bases
## Warning in bs(log(Size0Mars), degree = 3L, knots = c(0.693147180559945, : some
## 'x' values beyond boundary knots may cause ill-conditioned bases
## Warning in bs(log(Size0Mars), degree = 3L, knots = c(0.693147180559945, : some
## 'x' values beyond boundary knots may cause ill-conditioned bases
## Warning in bs(log(Size0Mars), degree = 3L, knots = c(0.693147180559945, : some
## 'x' values beyond boundary knots may cause ill-conditioned bases
## Warning in bs(log(Size0Mars), degree = 3L, knots = c(0.693147180559945, : some
## 'x' values beyond boundary knots may cause ill-conditioned bases
## Warning in bs(log(Size0Mars), degree = 3L, knots = c(0.693147180559945, : some
## 'x' values beyond boundary knots may cause ill-conditioned bases
## Warning in bs(log(Size0Mars), degree = 3L, knots = c(0.693147180559945, : some
## 'x' values beyond boundary knots may cause ill-conditioned bases
```

```
Growthpredict3 <- predict(Growthglm3, newdata = fake_data)[,1]
Growthpredict4 <- predict(Growthglm4, newdata = fake_data)[,1]
Growthpredict5 <- predict(Growthglm5, newdata = fake_data)[,1]
```

```
plot_growth <- function(data = fake_data, prediction, var, c1, valc1 = 1, c2, valc2 = "Au", fact, minda
  data %>%
    mutate(logsize1predi = prediction) %>%
    filter(!!sym(c1) == valc1, !!sym(c2) == valc2) %>%
    ggplot(aes(x = log(.data[[var]]), y = logsize1predi)) +
    geom_vline(xintercept=maxdat, lty="dotted")+
    geom_vline(xintercept=mindat, lty="dotted")+
    geom_line(aes(color = as.factor(.data[[fact]]))) +
    theme_minimal()
}

plot_growth2 <- function(data = fake_data, prediction, var, c1, valc1 = 1, c2, valc2 = "Au", fact, minda
  data %>%
    mutate(logsize1predi = prediction) %>%
    filter(!!sym(c1) == valc1, !!sym(c2) == valc2) %>%
    ggplot(aes(x = .data[[var]], y = logsize1predi)) +
    geom_vline(xintercept=maxdat, lty="dotted")+
    geom_vline(xintercept=mindat, lty="dotted")+
    geom_line(aes(color = as.factor(.data[[fact]]))) +
    theme_minimal()
}
```

Croissance en fonction de la taille

En fixant la population : voir l'effet année

var <- "Size0Mars"; c1 <- "age0"; valc1 <- 1; c2 <- "Pop"; valc2 <- "Au"; fact <- "year"

En fixant l'année : voir l'effet population

var <- "Size0Mars"; c1 <- "age0"; valc1 <- 1; c2 <- "year"; valc2 <- 2000; fact <- "Pop"

size à t+1 en fonction de l'age

En fixant la population : voir l'effet année

var <- "age0"; c1 <- "Size0Mars"; valc1 <- 1; c2 <- "Pop"; valc2 <- "Au"; fact <- "year"

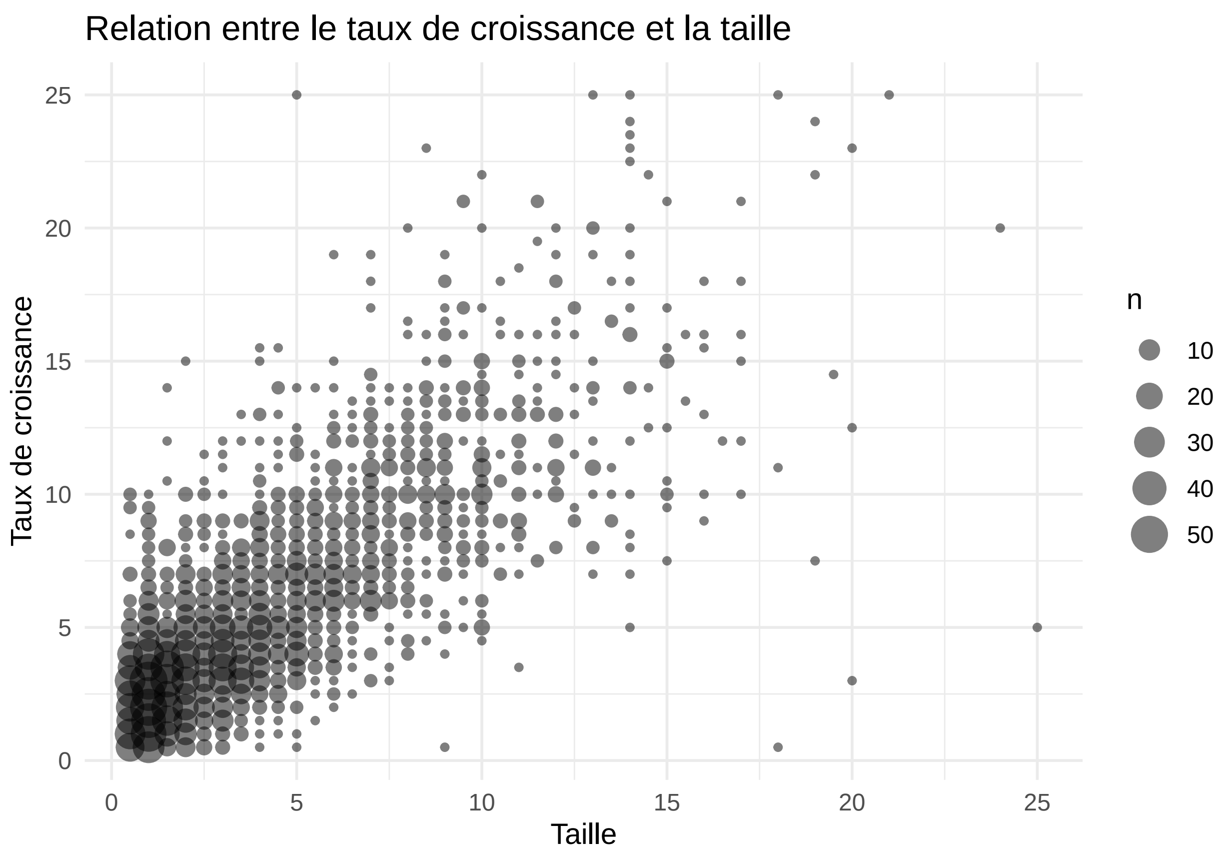
En fixant l'année : voir l'effet population

var <- "age0"; c1 <- "Size0Mars"; valc1 <- 1; c2 <- "year"; valc2 <- 2000; fact <- "Pop"

Variable : rapport taille t+1/ taille t

```r
growthdata <- centauree_data[!is.na(centauree_data$Size1Mars), ]
growthdata <- growthdata[growthdata$Size1Mars != 0, ]

growthdata <- growthdata %>%
  mutate(growthrate=Size1Mars/Size0Mars)
```

```r
growthdata %>%
  ggplot(aes(y = Size1Mars, x = Size0Mars)) +
  geom_count(alpha=0.5) +
  labs(title = "Relation entre le taux de croissance et la taille",
    y = "Taux de croissance",
    x = "Taille") +
  theme_minimal()
```




```r
Growthglm1 <- fitme(growthrate ~ 1 + bs(Size0Mars,df =5,degree=3) + bs(age0,df=3,degree=3) + (Size0Mars
                    data=growthdata,
                    resid.model = ~ 1)

Growthglm2 <- fitme(growthrate ~ 1 + bs(Size0Mars,df =5,degree=3) + bs(age0,df=3,degree=3) + (Size0Mars
                    data=growthdata,
                    resid.model = ~ log(Size0Mars) + log(age0))

Growthglm3 <- fitme(growthrate ~ 1 + bs(Size0Mars,df =5,degree=3) + bs(age0,degree=3,knots=6.5) + (Size0
                    data=growthdata,
                    resid.model = ~ 1)

Growthglm4 <- fitme(growthrate ~ 1 + bs(Size0Mars,df =5,degree=3) + bs(age0,degree=3,df=3) + (Size0Mars
                    data=growthdata,
                    resid.model = ~ 1)

Growthglm5 <- fitme(growthrate ~ 1 + bs(Size0Mars,df =5,degree=3) + bs(age0,degree=3,knots=6.5) + (Size0
                    data=growthdata,
                    resid.model = ~ log(Size0Mars) + log(age0))
```

```r
n <- length(growthdata$Nrw)
extractAIC(Growthglm1) ; extractBIC(Growthglm1, n)
```

```
##      edf      AIC
##    9.000 8741.212
```

```
## [1] 8793.774
```

```r
extractAIC(Growthglm2) ; extractBIC(Growthglm2, n)
```

```
##      edf      AIC
##    9.000 6163.692
```

```
## [1] 6216.255
```

```r
extractAIC(Growthglm3) ; extractBIC(Growthglm3, n)
```

```
##     edf     AIC
##   10.00 8743.17
```

```
## [1] 8801.573
```

```r
extractAIC(Growthglm4) ; extractBIC(Growthglm4, n)
```

```
##      edf      AIC
##    9.000 8745.224
```

```
## [1] 8797.786
```

```r
extractAIC(Growthglm5) ; extractBIC(Growthglm5, n)
```

```
##      edf      AIC
##   10.000 6165.547
```

```
## [1] 6223.95
```

```r
summary(Growthglm1)
```

```
## formula: growthrate ~ 1 + bs(Size0Mars, df = 5, degree = 3) + bs(age0,
##     df = 3, degree = 3) + (Size0Mars + age0 | year) + (Size0Mars |
##     Pop)
## ML: Estimation of ranCoefs and phi by ML.
##     Estimation of fixed effects by ML.
## Estimation of phi by 'outer' ML, maximizing logL.
## family: gaussian( link = identity )
##  ------------ Fixed effects (beta) ------------
##                                   Estimate Cond. SE  t-value
## (Intercept)                        5.40363   0.2728  19.8064
## bs(Size0Mars, df = 5, degree = 3)1 -3.05913   0.1540 -19.8594
## bs(Size0Mars, df = 5, degree = 3)2 -3.49529   0.1504 -23.2457
## bs(Size0Mars, df = 5, degree = 3)3 -4.03183   0.4199  -9.6010
## bs(Size0Mars, df = 5, degree = 3)4 -4.25474   0.7530  -5.6502
## bs(Size0Mars, df = 5, degree = 3)5 -3.82522   1.1190  -3.4184
## bs(age0, df = 3, degree = 3)1      -0.88737   0.2551  -3.4783
## bs(age0, df = 3, degree = 3)2       0.06978   0.2853   0.2446
```

```
## bs(age0, df = 3, degree = 3)3      -0.56861   0.2190  -2.5962
##  --------------- Random effects ---------------
## Family: gaussian( link = identity )
##          --- Random-coefficients Cov matrices:
##  Group        Term     Var. Corr. Corr..1
##   year (Intercept)   0.4068
##   year   Size0Mars 0.001918    -1
##   year        age0  0.00296    -1       1
##    Pop (Intercept)    0.344
##    Pop   Size0Mars 0.003338    -1
## # of obs: 2541; # of groups: year, 27; Pop, 6
##  -------------- Residual variance  ------------
## phi estimate was 1.75016
##  ------------- Likelihood values  -------------
##                         logLik
## logL       (p_v(h)): -4351.606
```

```r
summary(Growthglm2)
```

```
## formula: growthrate ~ 1 + bs(Size0Mars, df = 5, degree = 3) + bs(age0,
##     df = 3, degree = 3) + (Size0Mars + age0 | year) + (Size0Mars |
##     Pop)
## ML: Estimation of ranCoefs, rdisPars and phi by ML.
##     Estimation of fixed effects by ML.
## Estimation of phi by 'outer' ML, maximizing logL.
## family: gaussian( link = identity )
##  ------------ Fixed effects (beta) ------------
##                                   Estimate Cond. SE t-value
## (Intercept)                         5.0943  0.20871  24.409
## bs(Size0Mars, df = 5, degree = 3)1  -2.8407  0.23459 -12.110
## bs(Size0Mars, df = 5, degree = 3)2  -3.2300  0.18621 -17.345
## bs(Size0Mars, df = 5, degree = 3)3  -3.5132  0.23041 -15.248
## bs(Size0Mars, df = 5, degree = 3)4  -3.5808  0.26623 -13.450
## bs(Size0Mars, df = 5, degree = 3)5  -4.4551  0.32380 -13.759
## bs(age0, df = 3, degree = 3)1       -1.0228  0.12873  -7.945
## bs(age0, df = 3, degree = 3)2       -0.1641  0.10207  -1.607
## bs(age0, df = 3, degree = 3)3       -0.6014  0.09804  -6.135
##  --------------- Random effects ---------------
## Family: gaussian( link = identity )
##          --- Random-coefficients Cov matrices:
##  Group        Term      Var.   Corr. Corr..1
##   year (Intercept)    0.1335
##   year   Size0Mars 0.0006606 -0.6499
##   year        age0  0.001854 -0.5012 -0.2602
##    Pop (Intercept)   0.03475
##    Pop   Size0Mars 0.0001957 -0.9244
## # of obs: 2541; # of groups: year, 27; Pop, 6
##  -------------- Residual variance  ------------
## Estimates for log(phi) ~log(Size0Mars) + log(age0):
##    (Intercept) log(Size0Mars)      log(age0)
##      1.1421138     -1.4861186     -0.1021334
##  ------------- Likelihood values  -------------
##                         logLik
## logL       (p_v(h)): -3060.846
```

```r
summary(Growthglm3)
```

```
## formula: growthrate ~ 1 + bs(Size0Mars, df = 5, degree = 3) + bs(age0,
##     degree = 3, knots = 6.5) + (Size0Mars + age0 | year) + (Size0Mars |
##     Pop)
## ML: Estimation of ranCoefs and phi by ML.
##     Estimation of fixed effects by ML.
## Estimation of phi by 'outer' ML, maximizing logL.
## family: gaussian( link = identity )
##  ------------ Fixed effects (beta) ------------
##                                    Estimate Cond. SE  t-value
## (Intercept)                          5.4035   0.2719  19.8718
## bs(Size0Mars, df = 5, degree = 3)1  -3.0593   0.1540 -19.8594
## bs(Size0Mars, df = 5, degree = 3)2  -3.4980   0.1509 -23.1798
## bs(Size0Mars, df = 5, degree = 3)3  -4.0347   0.4196  -9.6147
## bs(Size0Mars, df = 5, degree = 3)4  -4.2528   0.7521  -5.6548
## bs(Size0Mars, df = 5, degree = 3)5  -3.8284   1.1181  -3.4241
## bs(age0, degree = 3, knots = 6.5)1  -0.6746   0.2288  -2.9482
## bs(age0, degree = 3, knots = 6.5)2  -0.1827   0.3078  -0.5936
## bs(age0, degree = 3, knots = 6.5)3  -0.3775   0.3132  -1.2054
## bs(age0, degree = 3, knots = 6.5)4  -0.5837   0.2302  -2.5355
##  --------------- Random effects ---------------
## Family: gaussian( link = identity )
##          --- Random-coefficients Cov matrices:
##  Group        Term     Var. Corr. Corr..1
##   year (Intercept)   0.4106
##   year   Size0Mars 0.001929    -1
##   year        age0 0.003008    -1       1
##    Pop (Intercept)     0.34
##    Pop   Size0Mars 0.003307    -1
## # of obs: 2541; # of groups: year, 27; Pop, 6
##  -------------- Residual variance  ------------
## phi estimate was 1.75005
##  ------------- Likelihood values  -------------
##                        logLik
## logL       (p_v(h)): -4351.585
```

```r
summary(Growthglm4)
```

```
## formula: growthrate ~ 1 + bs(Size0Mars, df = 5, degree = 3) + bs(age0,
##     degree = 3, df = 3) + (Size0Mars + age0 | year) + (Size0Mars +
##     age0 | Pop)
## ML: Estimation of ranCoefs and phi by ML.
##     Estimation of fixed effects by ML.
## Estimation of phi by 'outer' ML, maximizing logL.
## family: gaussian( link = identity )
##  ------------ Fixed effects (beta) ------------
##                                     Estimate Cond. SE    t-value
## (Intercept)                         5.407774   0.2732  19.797236
## bs(Size0Mars, df = 5, degree = 3)1 -3.064227   0.1538 -19.917473
## bs(Size0Mars, df = 5, degree = 3)2 -3.491257   0.1475 -23.668232
## bs(Size0Mars, df = 5, degree = 3)3 -4.030970   0.3930 -10.256702
```

```
## bs(Size0Mars, df = 5, degree = 3)4 -4.120266   0.7059  -5.836839
## bs(Size0Mars, df = 5, degree = 3)5 -3.851350   1.0578  -3.640913
## bs(age0, degree = 3, df = 3)1      -0.918810   0.2585  -3.554759
## bs(age0, degree = 3, df = 3)2      -0.001408   0.2976  -0.004732
## bs(age0, degree = 3, df = 3)3      -0.688966   0.2528  -2.725702
##  --------------- Random effects ---------------
## Family: gaussian( link = identity )
##          --- Random-coefficients Cov matrices:
##  Group        Term     Var. Corr. Corr..1
##   year (Intercept)   0.4034
##   year   Size0Mars 0.001782    -1
##   year        age0 0.003211    -1       1
##    Pop (Intercept)   0.3927
##    Pop   Size0Mars 0.002117    -1
##    Pop        age0 0.001943    -1       1
## # of obs: 2541; # of groups: year, 27; Pop, 6
##  -------------- Residual variance  ------------
## phi estimate was 1.74933
##  ------------- Likelihood values  -------------
##                        logLik
## logL       (p_v(h)): -4350.612
```

```
summary(Growthglm5)
```

```
## formula: growthrate ~ 1 + bs(Size0Mars, df = 5, degree = 3) + bs(age0,
##     degree = 3, knots = 6.5) + (Size0Mars + age0 | year) + (Size0Mars |
##     Pop)
## ML: Estimation of ranCoefs, rdisPars and phi by ML.
##     Estimation of fixed effects by ML.
## Estimation of phi by 'outer' ML, maximizing logL.
## family: gaussian( link = identity )
##  ------------ Fixed effects (beta) ------------
##                                    Estimate Cond. SE t-value
## (Intercept)                          5.0947  0.20866  24.416
## bs(Size0Mars, df = 5, degree = 3)1  -2.8407  0.23458 -12.110
## bs(Size0Mars, df = 5, degree = 3)2  -3.2246  0.18672 -17.270
## bs(Size0Mars, df = 5, degree = 3)3  -3.5081  0.23082 -15.199
## bs(Size0Mars, df = 5, degree = 3)4  -3.5751  0.26659 -13.411
## bs(Size0Mars, df = 5, degree = 3)5  -4.4522  0.32419 -13.733
## bs(age0, degree = 3, knots = 6.5)1  -0.8276  0.11884  -6.964
## bs(age0, degree = 3, knots = 6.5)2  -0.3208  0.10724  -2.992
## bs(age0, degree = 3, knots = 6.5)3  -0.5430  0.12365  -4.391
## bs(age0, degree = 3, knots = 6.5)4  -0.5998  0.09858  -6.084
##  --------------- Random effects ---------------
## Family: gaussian( link = identity )
##          --- Random-coefficients Cov matrices:
##  Group        Term      Var.   Corr. Corr..1
##   year (Intercept)    0.1341
##   year   Size0Mars 0.0006696 -0.6491
##   year        age0  0.001898 -0.4969 -0.2676
##    Pop (Intercept)   0.03449
##    Pop   Size0Mars 0.0001937 -0.9222
## # of obs: 2541; # of groups: year, 27; Pop, 6
##  -------------- Residual variance  ------------
```

```
## Estimates for log(phi) ~log(Size0Mars) + log(age0):
##    (Intercept) log(Size0Mars)      log(age0)
##      1.1422173     -1.4859774     -0.1027729
##  ------------- Likelihood values  -------------
##                          logLik
## logL       (p_v(h)): -3060.774
```

```
Growthpredict1 <- predict(Growthglm1, newdata = fake_data)[,1]
Growthpredict2 <- predict(Growthglm2, newdata = fake_data)[,1]
Growthpredict3 <- predict(Growthglm3, newdata = fake_data)[,1]
Growthpredict4 <- predict(Growthglm4, newdata = fake_data)[,1]
Growthpredict5 <- predict(Growthglm5, newdata = fake_data)[,1]
```

```
plot_growth <- function(data = fake_data, prediction, var, c1, valc1 = 1, c2, valc2 = "Au", fact, minda
  data %>%
    mutate(growth_predi = prediction) %>%
    filter(!!sym(c1) == valc1, !!sym(c2) == valc2) %>%
    ggplot(aes(x = .data[[var]], y = growth_predi)) +
    geom_vline(xintercept=maxdat, lty="dotted")+
    geom_vline(xintercept=mindat, lty="dotted")+
    geom_line(aes(color = as.factor(.data[[fact]]))) +
    theme_minimal()
}
```

Croissance en fonction de la taille

En fixant la population : voir l'effet année

En fixant l'année : voir l'effet population

growth en fonction de l'age

En fixant la population : voir l'effet année

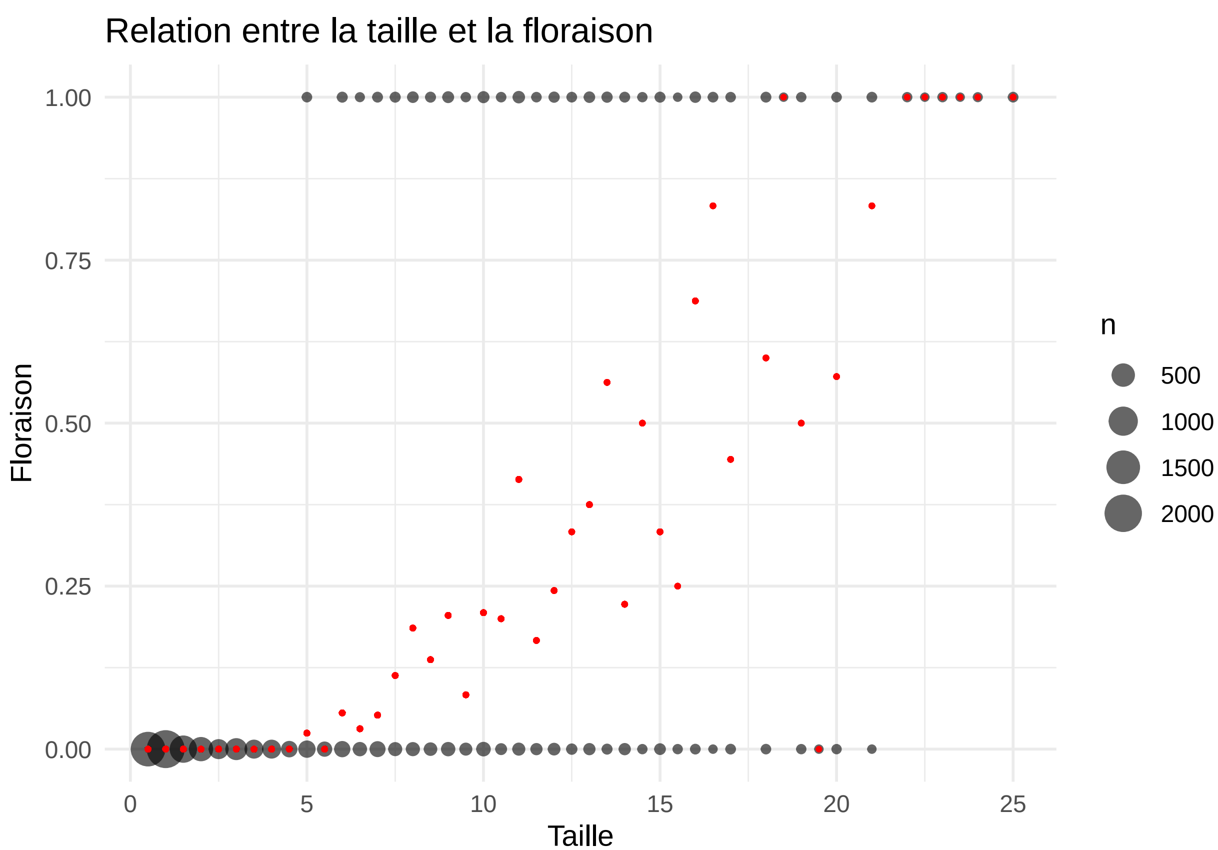
```
var <- "age0"
c1 <- "Size0Mars"
c2 <- "Pop"
valc2 <- "Au"
fact <- "year"
```

En fixant l'année : voir l'effet population

```
var <- "age0"
c1 <- "Size0Mars"
c2 <- "year"
valc2 <- 2000
fact <- "Pop"
```

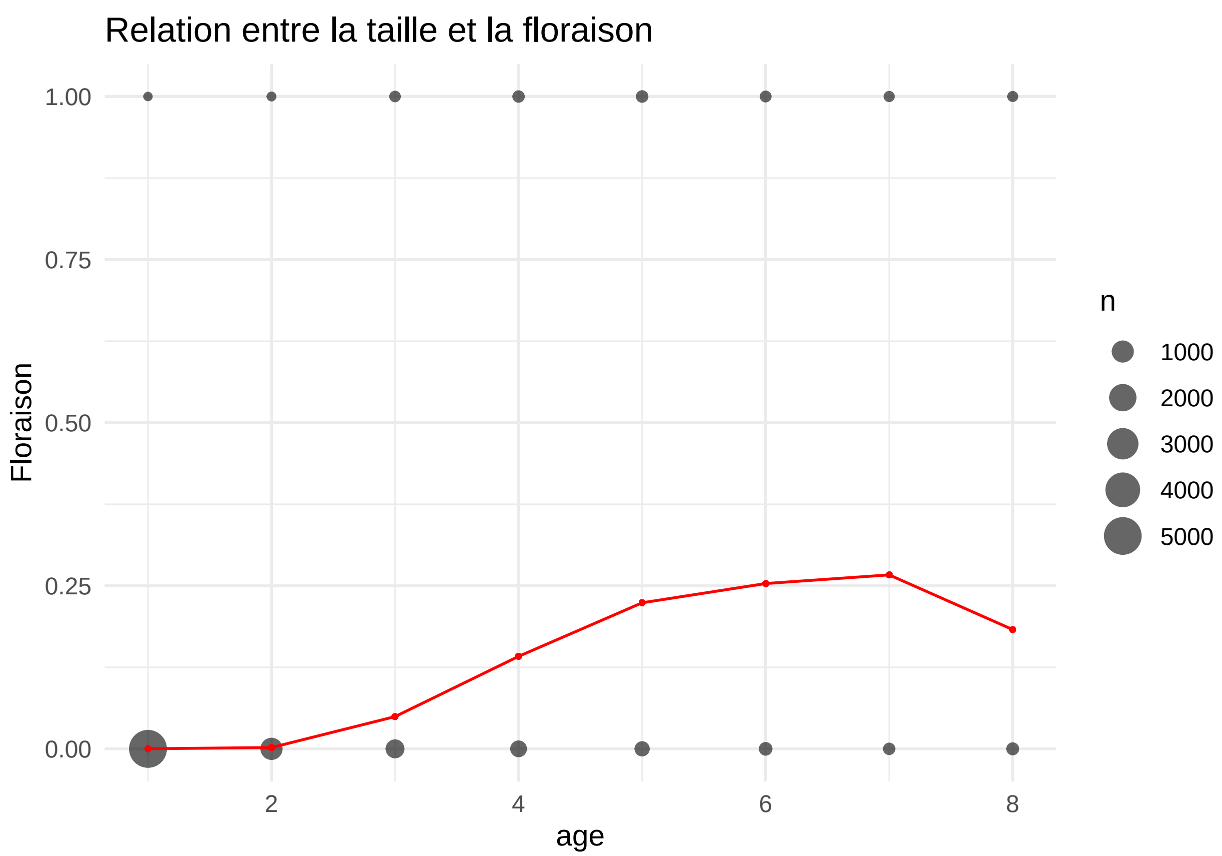
Flowering probability

```
centauree_data %>%
  group_by(Size0Mars) %>%
  mutate(floweringProba = sum(Flowering0, na.rm = TRUE) / n()) %>%
  ggplot(aes(x = Size0Mars, y = Flowering0)) +
  geom_count(alpha = 0.6) +
  geom_point(aes(y = floweringProba), color = "red", size = 0.5) +
  labs(title = "Relation entre la taille et la floraison",
    x = "Taille",
    y = "Floraison") +
  ylim(0, 1) +
  theme_minimal()
```




```
centauree_data %>%
  group_by(age0) %>%
  mutate(floweringProba = sum(Flowering0, na.rm = TRUE) / n()) %>%
  ggplot(aes(x = age0, y = Flowering0)) +
  geom_count(alpha = 0.6) +
  geom_point(aes(y = floweringProba), color = "red", size = 0.5) +
  geom_line(aes(y = floweringProba), color = "red") +
  labs(title = "Relation entre la taille et la floraison",
    x = "age",
    y = "Floraison") +
```

```r
  ylim(0, 1) +
  theme_minimal()
```




```r
Flowglm1 <- fitme(Flowering0 ~  1 + poly(Size0Mars,3) + poly(age0,2) + (age0|Pop),
                  family=binomial,
                  data=centauree_data, method="PQL/L")

Flowglm2 <- fitme(Flowering0 ~  1 + poly(Size0Mars,3) + bs(age0,degree=2,knots=6.5) + (age0|Pop),
                  family=binomial,
                  data=centauree_data, method="PQL/L")

Flowglm3 <- fitme(Flowering0 ~  1 + poly(Size0Mars,3) + poly(age0,3) + (age0|Pop),
                  family=binomial,
                  data=centauree_data, method="PQL/L")

Flowglm4 <- fitme(Flowering0 ~  1 + poly(Size0Mars,3) + poly(age0,2) + (age0|Pop) + (1|year),
                  family=binomial,
                  data=centauree_data, method="PQL/L")

Flowglm5 <- fitme(Flowering0 ~  1 + poly(Size0Mars,3) + bs(age0,degree=3,knots=c(1.5,6.5)) + (age0|Pop)
                  family=binomial,
                  data=centauree_data, method="PQL/L")
```

```
## Warning in (function (formula, resid.formula = NULL, data, prior.weights, :
## 'c(' detected in formula: did you mean cbind() for binomial response or for
```

```
## poly()?
```

```r
summary(Flowglm1)
```

```
## formula: Flowering0 ~ 1 + poly(Size0Mars, 3) + poly(age0, 2) + (age0 |
##     Pop)
## Estimation of ranCoefs by ML (p_v approximation of logL).
## Estimation of fixed effects by h-likelihood approximation.
## family: binomial( link = logit )
##  ------------ Fixed effects (beta) ------------
##                     Estimate Cond. SE t-value
## (Intercept)           -11.49    1.136 -10.120
## poly(Size0Mars, 3)1   258.56   39.050   6.621
## poly(Size0Mars, 3)2   -86.88   18.999  -4.573
## poly(Size0Mars, 3)3    42.73   12.085   3.536
## poly(age0, 2)1        148.26   24.504   6.051
## poly(age0, 2)2        -57.46    9.260  -6.206
##  --------------- Random effects ---------------
## Family: gaussian( link = identity )
##          --- Random-coefficients Cov matrices:
##  Group        Term    Var.   Corr.
##    Pop (Intercept)   2.175
##    Pop        age0 0.09044 -0.9806
## # of obs: 7635; # of groups: Pop, 6
##  ------------- Likelihood values  -------------
##                         logLik
##       h-likelihood: -416.1972
## logL       (p_v(h)): -412.9545
```

```r
summary(Flowglm2)
```

```
## formula: Flowering0 ~ 1 + poly(Size0Mars, 3) + bs(age0, degree = 2, knots = 6.5) +
##     (age0 | Pop)
## Estimation of ranCoefs by ML (p_v approximation of logL).
## Estimation of fixed effects by h-likelihood approximation.
## family: binomial( link = logit )
##  ------------ Fixed effects (beta) ------------
##                                    Estimate Cond. SE t-value
## (Intercept)                         -12.895    1.320  -9.771
## poly(Size0Mars, 3)1                 258.456   39.149   6.602
## poly(Size0Mars, 3)2                 -86.875   19.030  -4.565
## poly(Size0Mars, 3)3                  42.872   12.145   3.530
## bs(age0, degree = 2, knots = 6.5)1    6.565    1.232   5.328
## bs(age0, degree = 2, knots = 6.5)2    5.304    1.017   5.215
## bs(age0, degree = 2, knots = 6.5)3    4.859    1.197   4.058
##  --------------- Random effects ---------------
## Family: gaussian( link = identity )
##          --- Random-coefficients Cov matrices:
##  Group        Term    Var.   Corr.
##    Pop (Intercept)   2.244
##    Pop        age0 0.09294 -0.9812
## # of obs: 7635; # of groups: Pop, 6
##  ------------- Likelihood values  -------------
```

```
##                          logLik
##        h-likelihood: -415.9942
## logL       (p_v(h)): -412.8128
```

```r
summary(Flowglm3)
```

```
## formula: Flowering0 ~ 1 + poly(Size0Mars, 3) + poly(age0, 3) + (age0 |
##     Pop)
## Estimation of ranCoefs by ML (p_v approximation of logL).
## Estimation of fixed effects by h-likelihood approximation.
## family: binomial( link = logit )
##  ------------ Fixed effects (beta) ------------
##                       Estimate Cond. SE   t-value
## (Intercept)          -11.48993    1.300 -8.838688
## poly(Size0Mars, 3)1 258.56487   39.065  6.618867
## poly(Size0Mars, 3)2 -86.87835   19.000 -4.572558
## poly(Size0Mars, 3)3  42.72946   12.086  3.535589
## poly(age0, 3)1      148.17357   39.018  3.797538
## poly(age0, 3)2      -57.41183   19.585 -2.931398
## poly(age0, 3)3       -0.02751    9.031 -0.003046
##  --------------- Random effects ---------------
## Family: gaussian( link = identity )
##         --- Random-coefficients Cov matrices:
##  Group        Term    Var.   Corr.
##    Pop (Intercept)   2.175
##    Pop        age0 0.09045 -0.9806
## # of obs: 7635; # of groups: Pop, 6
##  ------------- Likelihood values  -------------
##                          logLik
##        h-likelihood: -416.1970
## logL       (p_v(h)): -412.9545
```

```r
summary(Flowglm4)
```

```
## formula: Flowering0 ~ 1 + poly(Size0Mars, 3) + poly(age0, 2) + (age0 |
##     Pop) + (1 | year)
## Estimation of lambda and ranCoefs by ML (p_v approximation of logL).
## Estimation of fixed effects by h-likelihood approximation.
## family: binomial( link = logit )
##  ------------ Fixed effects (beta) ------------
##                     Estimate Cond. SE t-value
## (Intercept)           -11.49    1.136 -10.120
## poly(Size0Mars, 3)1   258.56   39.050   6.621
## poly(Size0Mars, 3)2   -86.88   18.999  -4.573
## poly(Size0Mars, 3)3    42.73   12.085   3.536
## poly(age0, 2)1        148.26   24.504   6.051
## poly(age0, 2)2        -57.46    9.260  -6.206
##  --------------- Random effects ---------------
## Family: gaussian( link = identity )
##         --- Random-coefficients Cov matrices:
##  Group        Term    Var.   Corr.
##    Pop (Intercept)   2.175
##    Pop        age0 0.09044 -0.9806
```

```
##           --- Variance parameters ('lambda'):
## lambda = var(u) for u ~ Gaussian;
##    year  :  9.682e-07
##             --- Coefficients for log(lambda):
##  Group        Term Estimate Cond.SE
##   year (Intercept)   -13.85   129.6
## # of obs: 7635; # of groups: Pop, 6; year, 28
##  ------------- Likelihood values  -------------
##                         logLik
##       h-likelihood: -248.0580
## logL       (p_v(h)): -412.9545
```

```r
summary(Flowglm5)
```

```
## formula: Flowering0 ~ 1 + poly(Size0Mars, 3) + bs(age0, degree = 3, knots = c(1.5,
##     6.5)) + (age0 | Pop)
## Estimation of ranCoefs by ML (p_v approximation of logL).
## Estimation of fixed effects by h-likelihood approximation.
## family: binomial( link = logit )
##  ------------ Fixed effects (beta) ------------
##                                           Estimate Cond. SE t-value
## (Intercept)                                -10.363    1.417  -7.314
## poly(Size0Mars, 3)1                        265.304   39.010   6.801
## poly(Size0Mars, 3)2                        -89.882   18.908  -4.754
## poly(Size0Mars, 3)3                         44.773   12.179   3.676
## bs(age0, degree = 3, knots = c(1.5, 6.5))1   -3.186    1.741  -1.830
## bs(age0, degree = 3, knots = c(1.5, 6.5))2    2.266    1.567   1.447
## bs(age0, degree = 3, knots = c(1.5, 6.5))3    3.739    1.532   2.441
## bs(age0, degree = 3, knots = c(1.5, 6.5))4    2.365    1.491   1.587
## bs(age0, degree = 3, knots = c(1.5, 6.5))5    2.148    1.449   1.482
##  --------------- Random effects ---------------
## Family: gaussian( link = identity )
##         --- Random-coefficients Cov matrices:
##  Group        Term    Var.   Corr.
##    Pop (Intercept)   2.349
##    Pop        age0 0.09775 -0.9816
## # of obs: 7635; # of groups: Pop, 6
##  ------------- Likelihood values  -------------
##                         logLik
##       h-likelihood: -413.8448
## logL       (p_v(h)): -410.8147
```

```r
Flowpredict1 <- predict(Flowglm1, newdata = fake_data)[,1]
Flowpredict2 <- predict(Flowglm2, newdata = fake_data)[,1]
Flowpredict3 <- predict(Flowglm3, newdata = fake_data)[,1]
Flowpredict4 <- predict(Flowglm4, newdata = fake_data)[,1]
Flowpredict5 <- predict(Flowglm5, newdata = fake_data)[,1]
```

```r
plot_flow <- function(data = fake_data, prediction, var, c1, valc1 = 1, c2, valc2 = "Au", fact, mindat,
  data %>%
    mutate(flow_predi = prediction) %>%
    filter(!!sym(c1) == valc1, !!sym(c2) == valc2) %>%
    ggplot(aes(x = .data[[var]], y = flow_predi)) +
```

```
    geom_vline(xintercept=maxdat, lty="dotted")+
    geom_vline(xintercept=mindat, lty="dotted")+
    geom_line(aes(color = as.factor(.data[[fact]]))) +
    theme_minimal() +
    ylim(0, 1)
}
```

Floraison en fonction de la taille

En fixant la population : voir l'effet année

```
var <- "Size0Mars"
c1 <- "age0"
c2 <- "Pop"
valc2 <- "Au"
fact <- "year"
```

En fixant l'année : voir l'effet population

```
var <- "Size0Mars"
c1 <- "age0"
c2 <- "year"
valc2 <- 2000
fact <- "Pop"
```

Floraison en fonction de l'age

En fixant la population : voir l'effet année

```
var <- "age0"
c1 <- "Size0Mars"
c2 <- "Pop"
valc2 <- "Au"
fact <- "year"
```

En fixant l'année : voir l'effet population

```
var <- "age0"
c1 <- "Size0Mars"
c2 <- "year"
valc2 <- 2000
fact <- "Pop"
```