Growth Models Fitted

Loïc Pages

2025-06-20

Introduction

```r
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 4.5.35) 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.
```

```r
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
```

```r
library(splines)
library(foreach)
```

```
##
## Attaching package: 'foreach'
##
## The following objects are masked from 'package:purrr':
##
##     accumulate, when
```

```r
library(doParallel)
```

```
## Loading required package: iterators
## Loading required package: parallel
```

```r
library(patchwork)

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

IPM_data <- read.csv("newdata.csv")

centauree_data <- IPM_data[!is.na(IPM_data$Size0Mars) & !is.na(IPM_data$Age),]
centauree_data$Age[centauree_data$Age > 8] <- 8

spaMM.options(separation_max=70)
```

```r
annees <- 1995:2022
populations <- c("E2","E1","Au","Po","Pe","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,
  Age = age_range
)

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

BIC

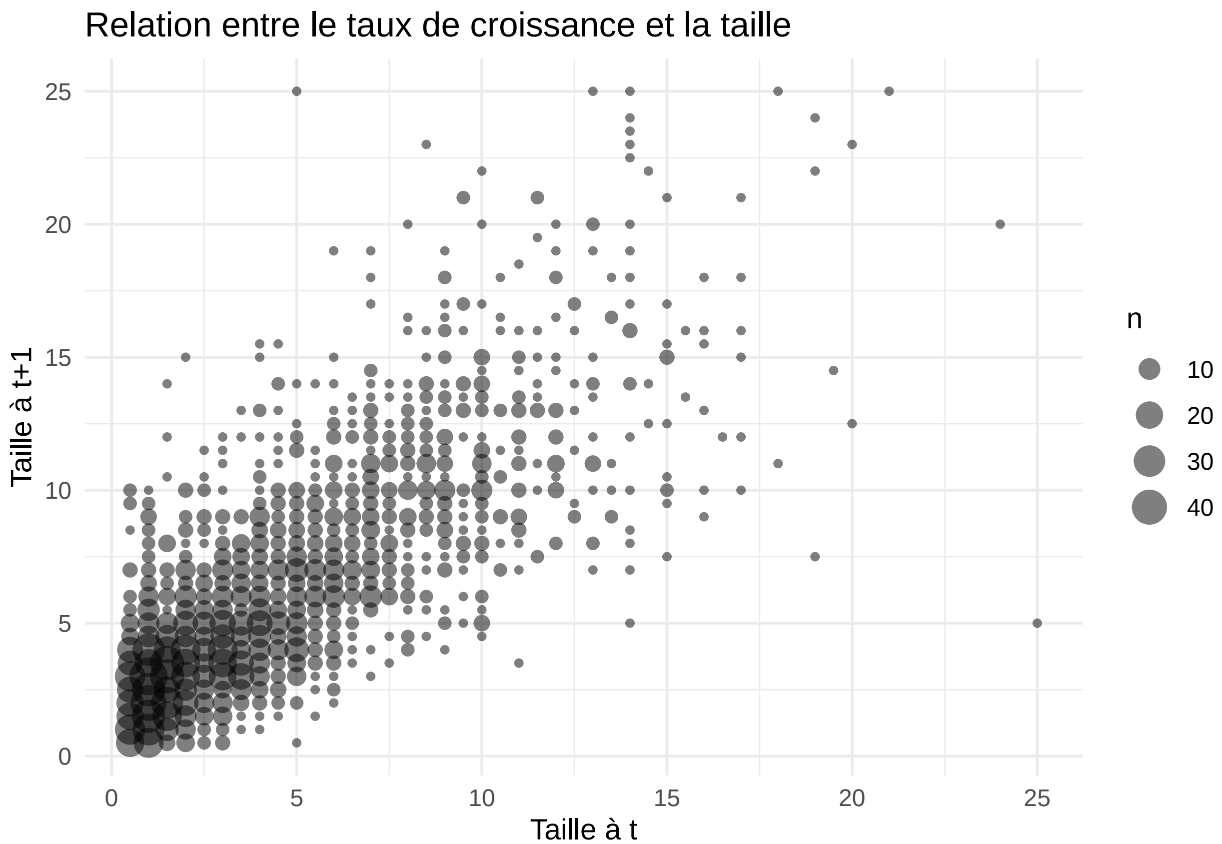
```r
# N the number of subjects
# ntot the total number of observations
extractBIC <- function(fit, ntot, N){
  extractAIC(fit)[[2]] +(log(ntot)-2)*DoF(fit)[[3]] + log(N)*DoF(fit)[[1]]
}
```

Croissance

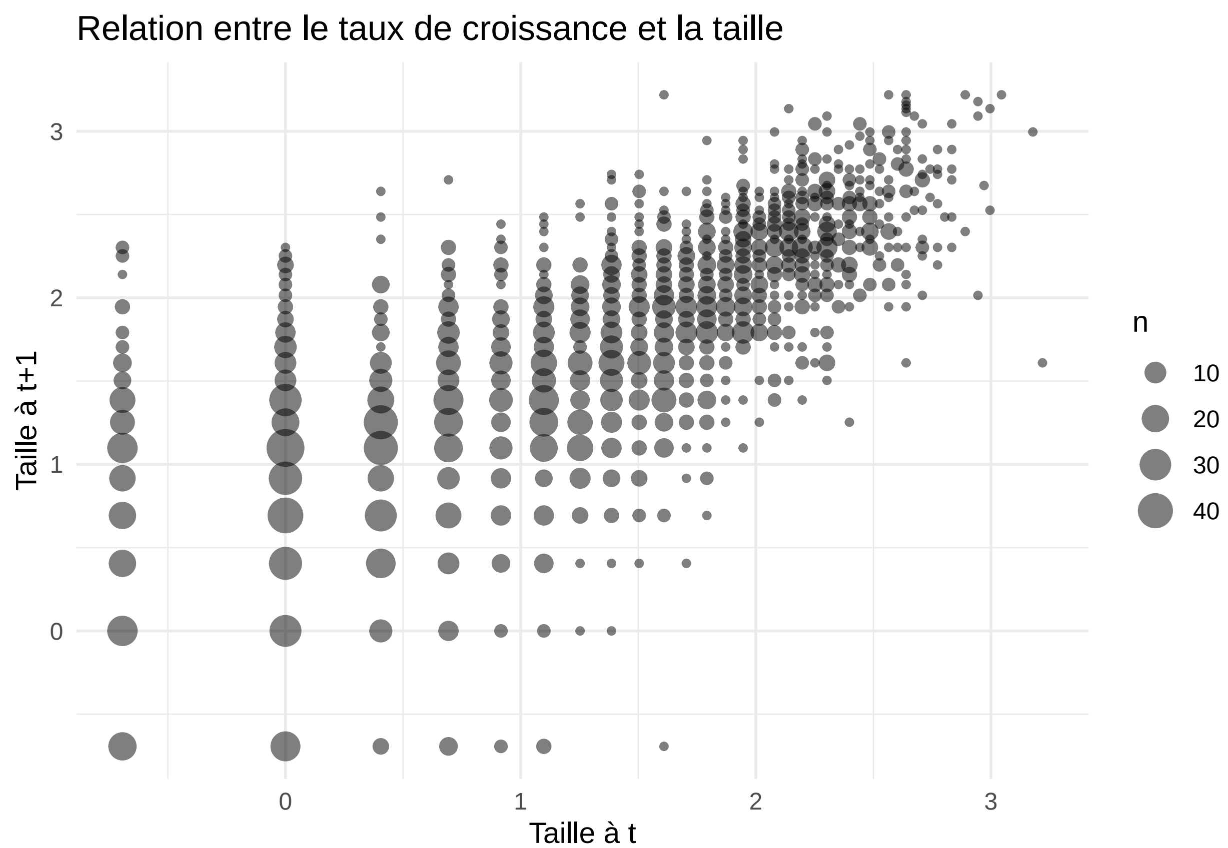
```r
growthdata <- centauree_data[!is.na(centauree_data$Size1Mars), ]
growthdata <- growthdata[growthdata$Size1Mars != 0, ]
```

```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 = "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()
```



Variable : taille à t+1

AIC

```
AGrowthglm1 <- fitme(Size1Mars ~ 1 + poly(Size0Mars,3) + bs(Age,degree=2,knots=6.5) + (Size0Mars+Age|yea
                     resid.model = ~ log(Size0Mars)+log(Age),
                     data=growthdata)

AGrowthglm2 <- fitme(Size1Mars ~ 1 + poly(Size0Mars,3) + bs(Age,degree=2,knots=6.5) + (Size0Mars+Age|yea
                     resid.model = ~ log(Size0Mars)+log(Age),
                     data=growthdata)

AGrowthglm3 <- fitme(Size1Mars ~ 1 + poly(Size0Mars,3) + bs(Age,degree=2,knots=6.5) + (Size0Mars+Age|yea
                     resid.model = ~ log(Size0Mars)+log(Age),
                     data=growthdata)

AGrowthglm4 <- fitme(Size1Mars ~ 1 + bs(Size0Mars,df=5,degree=3) + bs(Age,degree=2,knots=6.5) + (Size0Ma
                     resid.model = ~ log(Size0Mars)+log(Age),
                     data=growthdata)

AGrowthglm5 <- fitme(Size1Mars ~ 1 + bs(Size0Mars,df=5,degree=3)+ bs(Age,degree=2,knots=6.5) + (Size0Mar
                     resid.model = ~ log(Size0Mars)+log(Age),
                     data=growthdata)
```

BIC

```r
BGrowthglm1 <- fitme(Size1Mars ~ 1 + poly(Size0Mars,3) + poly(Age,2) + (Size0Mars+Age|year) + (1|Pop),
                    resid.model = ~ log(Size0Mars)+log(Age),
                    data=growthdata)

BGrowthglm2 <- fitme(Size1Mars ~ 1 + poly(Size0Mars,3) + poly(Age,2) + (Size0Mars+Age|year) + (Size0Mar
                    resid.model = ~ log(Size0Mars)+log(Age),
                    data=growthdata)

BGrowthglm3 <- fitme(Size1Mars ~ 1 + bs(Size0Mars,df=3,degree=2) + poly(Age,2) + (Size0Mars+Age|year) +
                    resid.model = ~ log(Size0Mars)+log(Age),
                    data=growthdata)

BGrowthglm4 <- fitme(Size1Mars ~ 1 + bs(Size0Mars,df=3,degree=2) + poly(Age,2) + (Size0Mars+Age|year) +
                    resid.model = ~ log(Size0Mars)+log(Age),
                    data=growthdata)

BGrowthglm5 <- fitme(Size1Mars ~ 1 + bs(Size0Mars,df=3,degree=2) + poly(Age,2) + (Size0Mars+Age|year) +
                    resid.model = ~ log(Size0Mars)+log(Age),
                    data=growthdata)
```

```r
summary(AGrowthglm1)
```

```
## formula: Size1Mars ~ 1 + poly(Size0Mars, 3) + bs(Age, degree = 2, knots = 6.5) +
##     (Size0Mars + Age | year) + (1 | Pop)
## ML: Estimation of lambda, 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)                          6.8681   0.3254  21.107
## poly(Size0Mars, 3)1                175.3943   7.9729  21.999
## poly(Size0Mars, 3)2                -27.1381   3.6562  -7.422
## poly(Size0Mars, 3)3                -14.0231   3.2240  -4.350
## bs(Age, degree = 2, knots = 6.5)1  -2.1796   0.3670  -5.939
## bs(Age, degree = 2, knots = 6.5)2  -0.7758   0.5123  -1.514
## bs(Age, degree = 2, knots = 6.5)3  -1.6608   0.5824  -2.851
##  --------------- Random effects ---------------
## Family: gaussian( link = identity )
##          --- Random-coefficients Cov matrices:
##  Group        Term    Var.   Corr. Corr..1
##   year (Intercept)  0.3225
##   year   Size0Mars 0.03617  0.4012
##   year         Age  0.0579 -0.5788 -0.6466
##            --- Variance parameters ('lambda'):
## lambda = var(u) for u ~ Gaussian;
##    Pop  :  0.3307
##              --- Coefficients for log(lambda):
##  Group        Term Estimate Cond.SE
##    Pop (Intercept)   -1.106     0.6
## # of obs: 2389; # of groups: year, 27; Pop, 6
##  -------------- Residual variance  ------------
## Estimates for log(phi) ~log(Size0Mars) + log(Age):
```

```
##    (Intercept) log(Size0Mars)       log(Age)
##      1.1013346      0.5553254     -0.1231723
##  ------------- Likelihood values  -------------
##                        logLik
## logL       (p_v(h)): -5373.672
```

```r
summary(AGrowthglm2)
```

```
## formula: Size1Mars ~ 1 + poly(Size0Mars, 3) + bs(Age, degree = 2, knots = 6.5) +
##     (Size0Mars + Age | 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)                          6.8557   0.3269  20.970
## poly(Size0Mars, 3)1                173.4030   8.8739  19.541
## poly(Size0Mars, 3)2                -27.5269   3.7105  -7.419
## poly(Size0Mars, 3)3                -14.5190   3.2482  -4.470
## bs(Age, degree = 2, knots = 6.5)1  -2.1614   0.3681  -5.873
## bs(Age, degree = 2, knots = 6.5)2  -0.7182   0.5163  -1.391
## bs(Age, degree = 2, knots = 6.5)3  -1.6535   0.5854  -2.825
##  --------------- Random effects ---------------
## Family: gaussian( link = identity )
##          --- Random-coefficients Cov matrices:
##  Group        Term     Var.   Corr. Corr..1
##   year (Intercept)   0.3111
##   year   Size0Mars  0.03749  0.3567
##   year         Age  0.05897 -0.5292 -0.6511
##    Pop (Intercept)   0.4227
##    Pop   Size0Mars 0.002421 -0.4581
## # of obs: 2389; # of groups: year, 27; Pop, 6
##  -------------- Residual variance  ------------
## Estimates for log(phi) ~log(Size0Mars) + log(Age):
##    (Intercept) log(Size0Mars)       log(Age)
##      1.1002590      0.5487968     -0.1177191
##  ------------- Likelihood values  -------------
##                        logLik
## logL       (p_v(h)): -5371.931
```

```r
summary(AGrowthglm3)
```

```
## formula: Size1Mars ~ 1 + poly(Size0Mars, 3) + bs(Age, degree = 2, knots = 6.5) +
##     (Size0Mars + Age | year) + (Size0Mars + Age | 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)                          6.7909   0.3216 21.1182
## poly(Size0Mars, 3)1                169.8463  10.3203 16.4576
```

```
## poly(Size0Mars, 3)2               -27.0214   3.7069 -7.2895
## poly(Size0Mars, 3)3               -14.1233   3.2407 -4.3581
## bs(Age, degree = 2, knots = 6.5)1  -2.0146   0.4071 -4.9492
## bs(Age, degree = 2, knots = 6.5)2  -0.3801   0.6493 -0.5853
## bs(Age, degree = 2, knots = 6.5)3  -1.1438   0.7335 -1.5594
##  --------------- Random effects ---------------
## Family: gaussian( link = identity )
##          --- Random-coefficients Cov matrices:
##  Group        Term     Var.   Corr. Corr..1
##   year (Intercept)   0.3044
##   year   Size0Mars  0.03769  0.3497
##   year         Age  0.06018 -0.4798 -0.6621
##    Pop (Intercept)   0.3457
##    Pop   Size0Mars 0.007327 -0.3799
##    Pop         Age  0.02162  0.4513 -0.8924
## # of obs: 2389; # of groups: year, 27; Pop, 6
##  -------------- Residual variance  ------------
## Estimates for log(phi) ~log(Size0Mars) + log(Age):
##    (Intercept) log(Size0Mars)       log(Age)
##      1.1018776      0.5529610     -0.1335205
##  ------------- Likelihood values  -------------
##                         logLik
## logL       (p_v(h)): -5368.948
```

```r
summary(AGrowthglm4)
```

```
## formula: Size1Mars ~ 1 + bs(Size0Mars, df = 5, degree = 3) + bs(Age, degree = 2,
##     knots = 6.5) + (Size0Mars + Age | year) + (1 | Pop)
## ML: Estimation of lambda, 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)                          2.9951   0.2817 10.6304
## bs(Size0Mars, df = 5, degree = 3)1   0.1898   0.2021  0.9393
## bs(Size0Mars, df = 5, degree = 3)2   2.0137   0.2319  8.6838
## bs(Size0Mars, df = 5, degree = 3)3  11.5301   0.7767 14.8446
## bs(Size0Mars, df = 5, degree = 3)4  18.4791   1.6136 11.4519
## bs(Size0Mars, df = 5, degree = 3)5   9.6559   2.8508  3.3871
## bs(Age, degree = 2, knots = 6.5)1   -2.2395   0.3726 -6.0110
## bs(Age, degree = 2, knots = 6.5)2   -0.8167   0.5127 -1.5929
## bs(Age, degree = 2, knots = 6.5)3   -1.6982   0.5823 -2.9165
##  --------------- Random effects ---------------
## Family: gaussian( link = identity )
##          --- Random-coefficients Cov matrices:
##  Group        Term    Var.  Corr. Corr..1
##   year (Intercept)  0.3157
##   year   Size0Mars 0.03521 0.4125
##   year         Age 0.05676 -0.587 -0.6374
##            --- Variance parameters ('lambda'):
## lambda = var(u) for u ~ Gaussian;
##    Pop  :  0.3325
##              --- Coefficients for log(lambda):
```

```
##  Group        Term Estimate Cond.SE
##    Pop (Intercept)   -1.101  0.5997
## # of obs: 2389; # of groups: year, 27; Pop, 6
##  -------------- Residual variance  ------------
## Estimates for log(phi) ~log(Size0Mars) + log(Age):
##    (Intercept) log(Size0Mars)       log(Age)
##      1.0977436      0.5530660     -0.1162531
##  ------------- Likelihood values  -------------
##                           logLik
## logL       (p_v(h)): -5371.908
```

```r
summary(AGrowthglm5)
```

```
## formula: Size1Mars ~ 1 + bs(Size0Mars, df = 5, degree = 3) + bs(Age, degree = 2,
##     knots = 6.5) + (Size0Mars + Age | 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)                          3.0394   0.3072  9.8945
## bs(Size0Mars, df = 5, degree = 3)1   0.1631   0.2029  0.8039
## bs(Size0Mars, df = 5, degree = 3)2   1.9682   0.2372  8.2966
## bs(Size0Mars, df = 5, degree = 3)3  11.4357   0.8095 14.1274
## bs(Size0Mars, df = 5, degree = 3)4  18.2805   1.6658 10.9740
## bs(Size0Mars, df = 5, degree = 3)5   9.0784   2.9213  3.1077
## bs(Age, degree = 2, knots = 6.5)1   -2.2218   0.3736 -5.9466
## bs(Age, degree = 2, knots = 6.5)2   -0.7635   0.5170 -1.4768
## bs(Age, degree = 2, knots = 6.5)3   -1.6931   0.5854 -2.8923
##  --------------- Random effects ---------------
## Family: gaussian( link = identity )
##          --- Random-coefficients Cov matrices:
##  Group        Term     Var.   Corr. Corr..1
##   year (Intercept)   0.3026
##   year   Size0Mars  0.03646    0.37
##   year         Age  0.05783 -0.5384 -0.6414
##    Pop (Intercept)   0.4342
##    Pop   Size0Mars 0.002599 -0.4807
## # of obs: 2389; # of groups: year, 27; Pop, 6
##  -------------- Residual variance  ------------
## Estimates for log(phi) ~log(Size0Mars) + log(Age):
##    (Intercept) log(Size0Mars)       log(Age)
##      1.0961953      0.5459654     -0.1096202
##  ------------- Likelihood values  -------------
##                           logLik
## logL       (p_v(h)): -5369.948
```

```r
summary(BGrowthglm1)
```

```
## formula: Size1Mars ~ 1 + poly(Size0Mars, 3) + poly(Age, 2) + (Size0Mars +
##     Age | year) + (1 | Pop)
## ML: Estimation of lambda, 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)             6.204   0.2943  21.081
## poly(Size0Mars, 3)1  175.238   8.0186  21.854
## poly(Size0Mars, 3)2  -26.783   3.6566  -7.324
## poly(Size0Mars, 3)3  -14.597   3.2153  -4.540
## poly(Age, 2)1        -24.454   5.8905  -4.151
## poly(Age, 2)2         13.247   3.1211   4.244
##  --------------- Random effects ---------------
## Family: gaussian( link = identity )
##          --- Random-coefficients Cov matrices:
##  Group        Term    Var.   Corr. Corr..1
##   year (Intercept)  0.3258
##   year   Size0Mars  0.0366  0.4169
##   year         Age 0.06767 -0.5861 -0.6402
##            --- Variance parameters ('lambda'):
## lambda = var(u) for u ~ Gaussian;
##    Pop  :  0.3333
##              --- Coefficients for log(lambda):
##  Group        Term Estimate Cond.SE
##    Pop (Intercept)   -1.099  0.5998
## # of obs: 2389; # of groups: year, 27; Pop, 6
##  -------------- Residual variance  ------------
## Estimates for log(phi) ~log(Size0Mars) + log(Age):
##    (Intercept) log(Size0Mars)       log(Age)
##      1.1005961      0.5550940     -0.1207695
##  ------------- Likelihood values  -------------
##                          logLik
## logL       (p_v(h)): -5375.646
```

```r
summary(BGrowthglm2)
```

```
## formula: Size1Mars ~ 1 + poly(Size0Mars, 3) + poly(Age, 2) + (Size0Mars +
##     Age | year) + (Size0Mars + Age | 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)             6.222   0.3161  19.684
## poly(Size0Mars, 3)1  169.652  10.3213  16.437
## poly(Size0Mars, 3)2  -26.512   3.7000  -7.165
## poly(Size0Mars, 3)3  -14.585   3.2316  -4.513
## poly(Age, 2)1        -18.885   8.1322  -2.322
## poly(Age, 2)2         13.616   3.1115   4.376
##  --------------- Random effects ---------------
## Family: gaussian( link = identity )
##          --- Random-coefficients Cov matrices:
##  Group        Term     Var.   Corr. Corr..1
##   year (Intercept)    0.306
```

```
##   year   Size0Mars  0.03791  0.3702
##   year         Age  0.06945 -0.5009  -0.652
##    Pop (Intercept)   0.3445
##    Pop   Size0Mars 0.007243  -0.397
##    Pop         Age  0.02488   0.445 -0.8937
## # of obs: 2389; # of groups: year, 27; Pop, 6
##  -------------- Residual variance  ------------
## Estimates for log(phi) ~log(Size0Mars) + log(Age):
##    (Intercept) log(Size0Mars)       log(Age)
##      1.1013469      0.5536565     -0.1329799
##  ------------- Likelihood values  -------------
##                          logLik
## logL       (p_v(h)): -5370.716
```

```r
summary(BGrowthglm3)
```

```
## formula: Size1Mars ~ 1 + bs(Size0Mars, df = 3, degree = 2) + poly(Age,
##     2) + (Size0Mars + Age | year) + (1 | Pop)
## ML: Estimation of lambda, 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)                          2.3035   0.2962   7.776
## bs(Size0Mars, df = 3, degree = 2)1   0.8622   0.1814   4.754
## bs(Size0Mars, df = 3, degree = 2)2  16.9987   0.7567  22.465
## bs(Size0Mars, df = 3, degree = 2)3  14.1734   1.6955   8.359
## poly(Age, 2)1                      -25.6615   5.8234  -4.407
## poly(Age, 2)2                       13.7731   3.1191   4.416
##  --------------- Random effects ---------------
## Family: gaussian( link = identity )
##         --- Random-coefficients Cov matrices:
##  Group        Term    Var.   Corr. Corr..1
##   year (Intercept)  0.3226
##   year   Size0Mars 0.03285  0.4383
##   year         Age 0.06484 -0.5954 -0.6164
##           --- Variance parameters ('lambda'):
## lambda = var(u) for u ~ Gaussian;
##    Pop  :  0.3352
##             --- Coefficients for log(lambda):
##  Group        Term Estimate Cond.SE
##    Pop (Intercept)   -1.093  0.5996
## # of obs: 2389; # of groups: year, 27; Pop, 6
##  -------------- Residual variance  ------------
## Estimates for log(phi) ~log(Size0Mars) + log(Age):
##    (Intercept) log(Size0Mars)       log(Age)
##      1.0939827      0.5525519     -0.1057685
##  ------------- Likelihood values  -------------
##                          logLik
## logL       (p_v(h)): -5376.037
```

```r
summary(BGrowthglm4)
```

```
## formula: Size1Mars ~ 1 + bs(Size0Mars, df = 3, degree = 2) + poly(Age,
##     2) + (Size0Mars + Age | 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)                           2.3587   0.3262   7.230
## bs(Size0Mars, df = 3, degree = 2)1    0.8198   0.1844   4.446
## bs(Size0Mars, df = 3, degree = 2)2   16.8865   0.8111  20.820
## bs(Size0Mars, df = 3, degree = 2)3   13.8051   1.7810   7.752
## poly(Age, 2)1                       -25.2920   5.8676  -4.310
## poly(Age, 2)2                        13.5650   3.1255   4.340
##  --------------- Random effects ---------------
## Family: gaussian( link = identity )
##          --- Random-coefficients Cov matrices:
##  Group        Term     Var.   Corr. Corr..1
##   year (Intercept)   0.3089
##   year   Size0Mars  0.03393  0.4029
##   year         Age  0.06602 -0.5576 -0.6184
##    Pop (Intercept)   0.4541
##    Pop   Size0Mars 0.002262  -0.559
## # of obs: 2389; # of groups: year, 27; Pop, 6
##  -------------- Residual variance  ------------
## Estimates for log(phi) ~log(Size0Mars) + log(Age):
##    (Intercept) log(Size0Mars)       log(Age)
##      1.0919372      0.5463953     -0.0990932
##  ------------- Likelihood values  -------------
##                         logLik
## logL       (p_v(h)): -5374.325
```

```r
summary(BGrowthglm5)
```

```
## formula: Size1Mars ~ 1 + bs(Size0Mars, df = 3, degree = 2) + poly(Age,
##     2) + (Size0Mars + Age | year) + (Size0Mars + Age | 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)                           2.4441   0.3896   6.274
## bs(Size0Mars, df = 3, degree = 2)1    0.8288   0.1875   4.420
## bs(Size0Mars, df = 3, degree = 2)2   16.5176   0.9027  18.298
## bs(Size0Mars, df = 3, degree = 2)3   13.6225   1.9119   7.125
## poly(Age, 2)1                       -20.2866   8.0725  -2.513
## poly(Age, 2)2                        14.1127   3.1105   4.537
##  --------------- Random effects ---------------
## Family: gaussian( link = identity )
```

```
##          --- Random-coefficients Cov matrices:
##   Group        Term     Var.   Corr. Corr..1
##    year (Intercept)   0.3031
##    year   Size0Mars  0.03404  0.3906
##    year         Age  0.06608 -0.5158 -0.6268
##     Pop (Intercept)   0.3599
##     Pop   Size0Mars 0.007014 -0.4838
##     Pop         Age  0.02489  0.4903  -0.898
## # of obs: 2389; # of groups: year, 27; Pop, 6
##  -------------- Residual variance  ------------
## Estimates for log(phi) ~log(Size0Mars) + log(Age):
##    (Intercept) log(Size0Mars)       log(Age)
##      1.0946807      0.5512137     -0.1174473
##  ------------- Likelihood values  -------------
##                           logLik
## logL       (p_v(h)): -5371.355
```

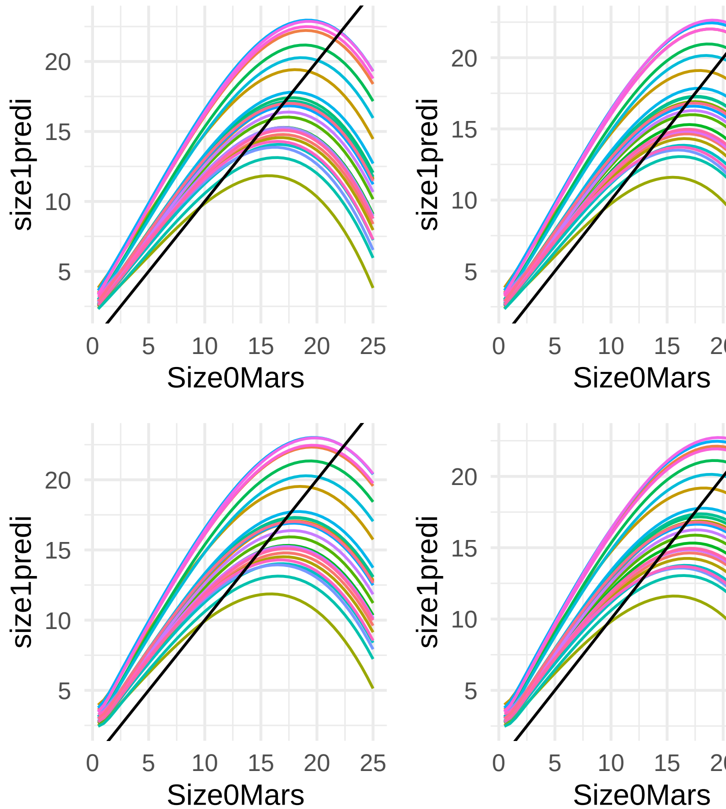
```
AGrowthpredict1 <- predict(AGrowthglm1, newdata = fake_data)[,1]
AGrowthpredict2 <- predict(AGrowthglm2, newdata = fake_data)[,1]
AGrowthpredict3 <- predict(AGrowthglm3, newdata = fake_data)[,1]
AGrowthpredict4 <- predict(AGrowthglm4, newdata = fake_data)[,1]
AGrowthpredict5 <- predict(AGrowthglm5, newdata = fake_data)[,1]

BGrowthpredict1 <- predict(BGrowthglm1, newdata = fake_data)[,1]
BGrowthpredict2 <- predict(BGrowthglm2, newdata = fake_data)[,1]
BGrowthpredict3 <- predict(BGrowthglm3, newdata = fake_data)[,1]
BGrowthpredict4 <- predict(BGrowthglm4, newdata = fake_data)[,1]
BGrowthpredict5 <- predict(BGrowthglm5, newdata = fake_data)[,1]
```

```
plot_growth1 <- function(data = fake_data, prediction, var, c1, c2, valc1=1, fact) {
  data %>%
    mutate(size1predi = prediction) %>%
    group_by(!!sym(var),!!sym(fact)) %>%
    filter(!!sym(c1) == valc1) %>%
    summarise(size1predi = mean(size1predi),
            .groups = "drop") %>%
    ggplot(aes(x = .data[[var]], y = size1predi)) +
    geom_line(aes(color = as.factor(.data[[fact]])),show.legend = FALSE) +
    geom_abline()+
    theme_minimal()
}

plot_growth2 <- function(data = fake_data, prediction, var, c1, c2, valc1=1, fact) {
  data %>%
    mutate(size1predi = prediction) %>%
    group_by(!!sym(var),!!sym(fact)) %>%
    filter(!!sym(c1) == valc1) %>%
    summarise(size1predi = mean(size1predi),
            .groups = "drop") %>%
    ggplot(aes(x = .data[[var]], y = size1predi)) +
    geom_line(aes(color = as.factor(.data[[fact]])),show.legend = FALSE) +
    geom_abline()+
    theme_minimal()+
    scale_color_viridis_d(option = "plasma")
```

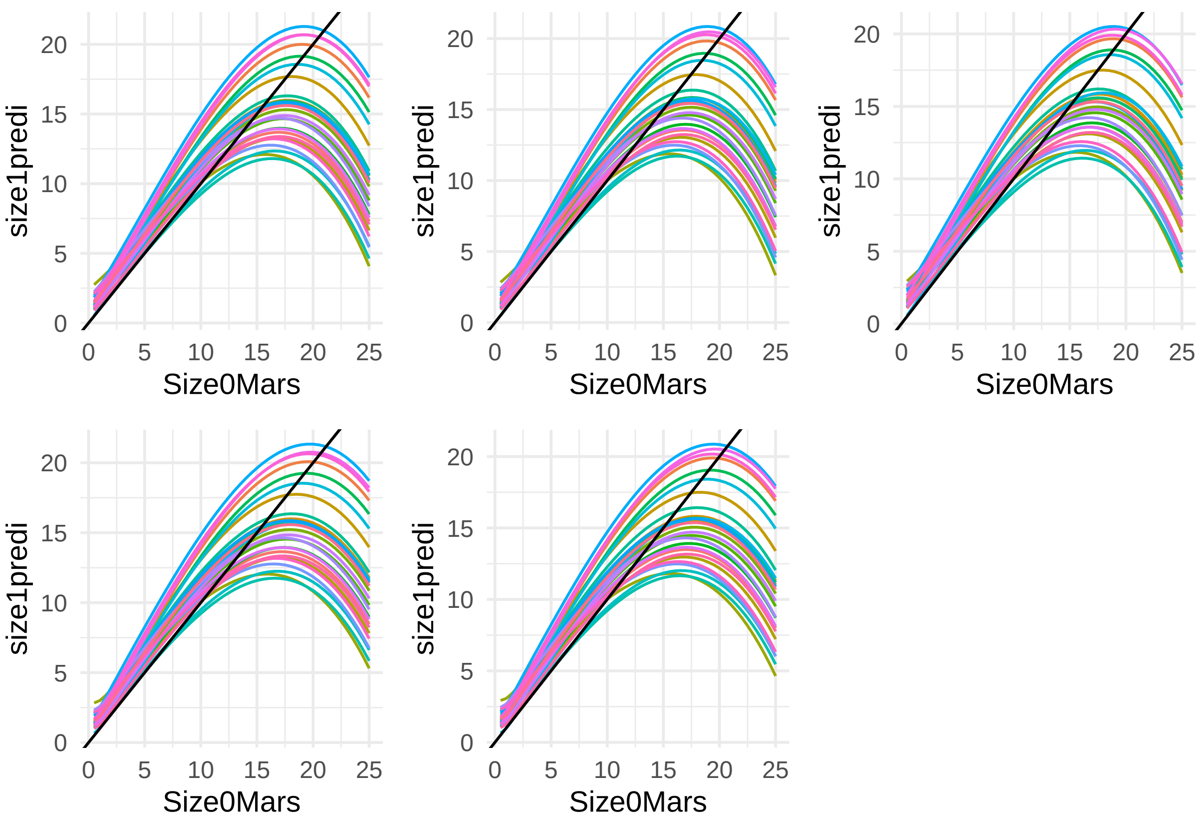
```r
}

plot_growth3 <- function(data = fake_data, prediction, var, c1, c2, valc1=1, fact) {
  data %>% mutate(sdgrow = prediction) %>%
  group_by(Size0Mars, Age) %>%
  summarise(sd_predi = mean(sdgrow),
            .groups = "drop") %>%
  ggplot(aes(x = Size0Mars, y = sd_predi)) +
  geom_line(aes(color = as.factor(Age))) +
  theme_bw()+
  labs(x = "Size(t)",
      y = "Growth residual variance",
      fill = "Age",
      color = "Age")+
    scale_color_brewer(palette = "Spectral", direction = -1)
}
```

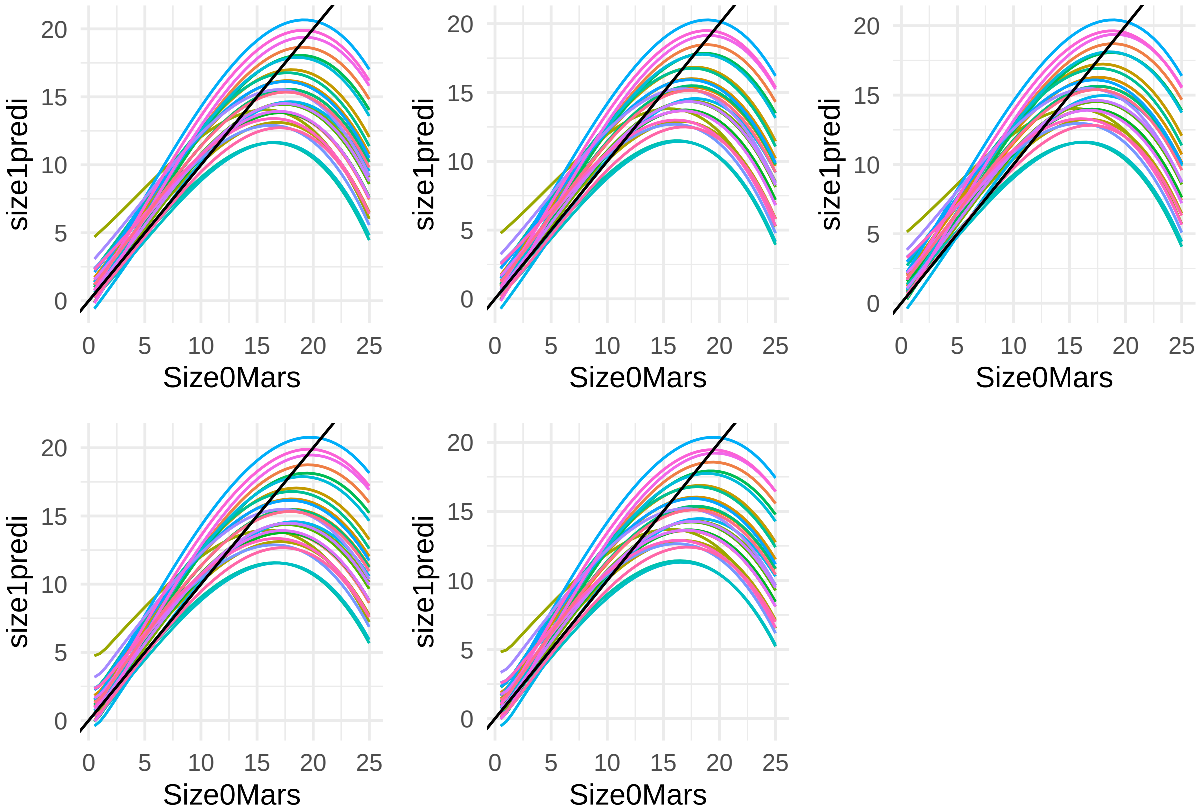
Taille à t+1 en fonction de taille à t

```r
var <- "Size0Mars"
c1 <- "Age"
c2 <- "Pop"
fact <- "year"
```

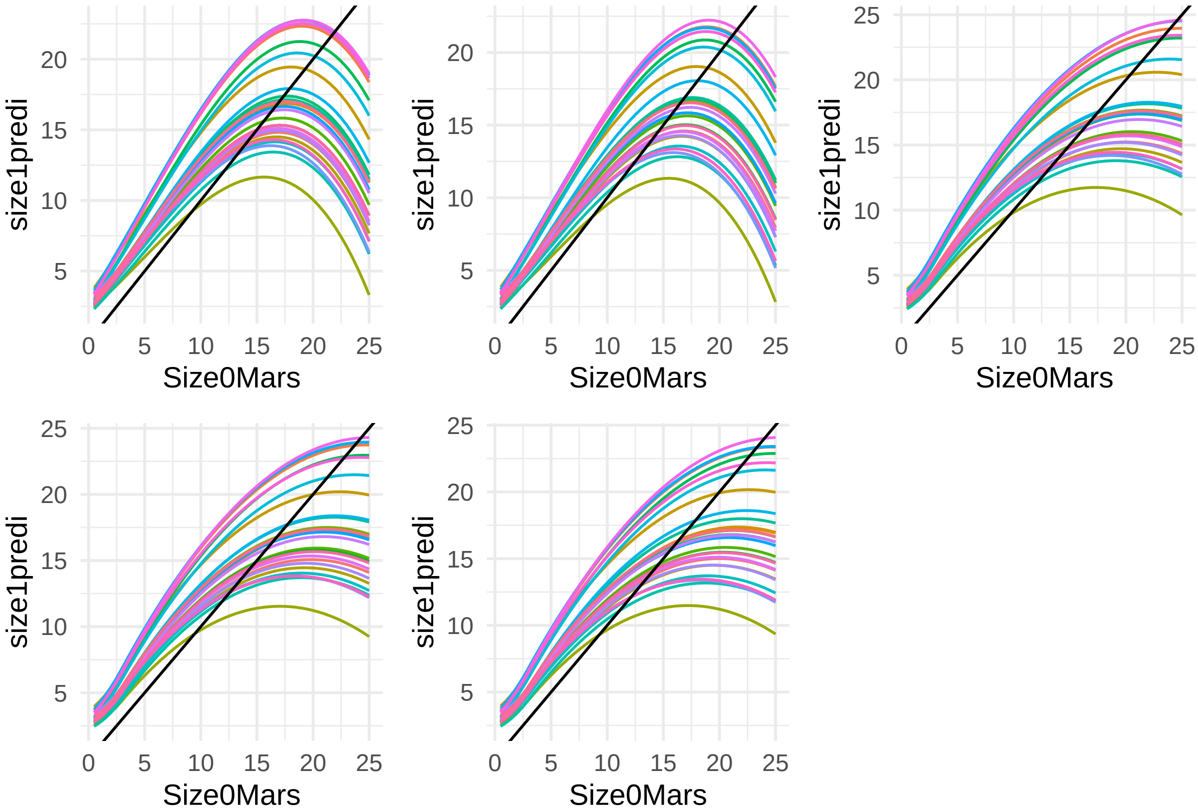


En fixant la population : voir l'effet année Age 1, 4, 8

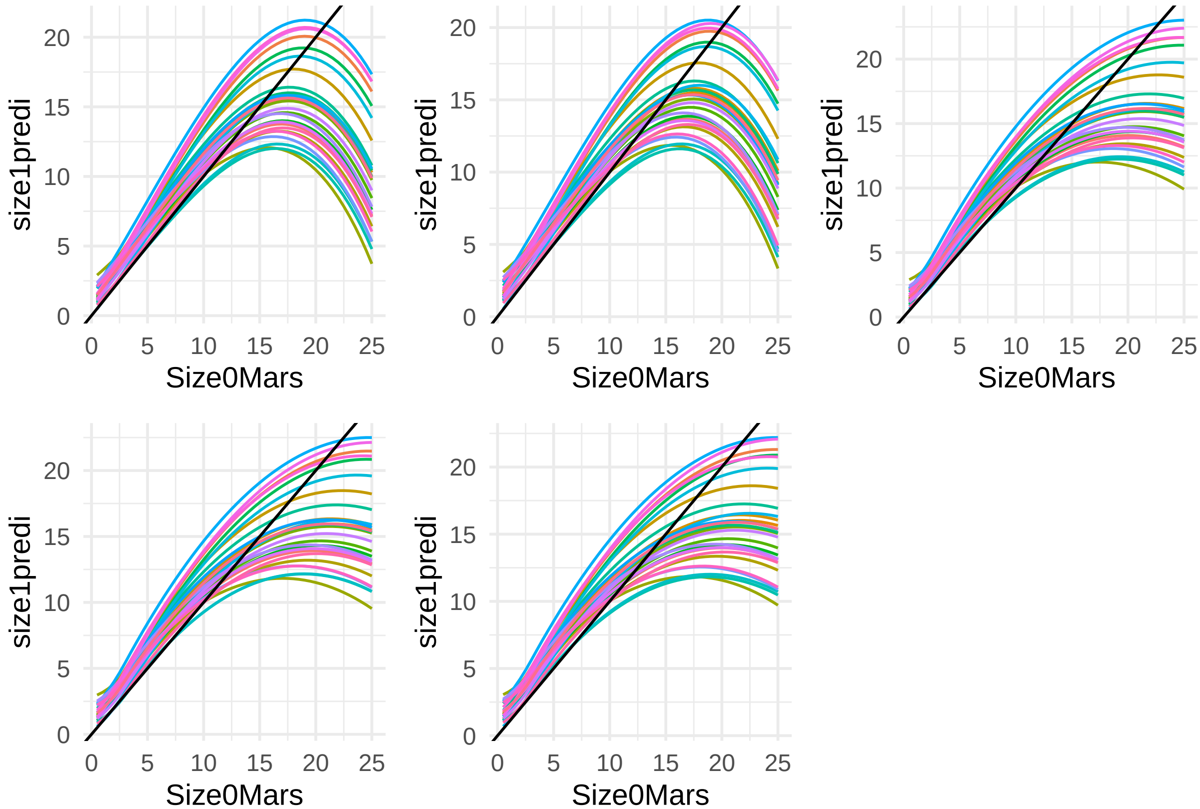


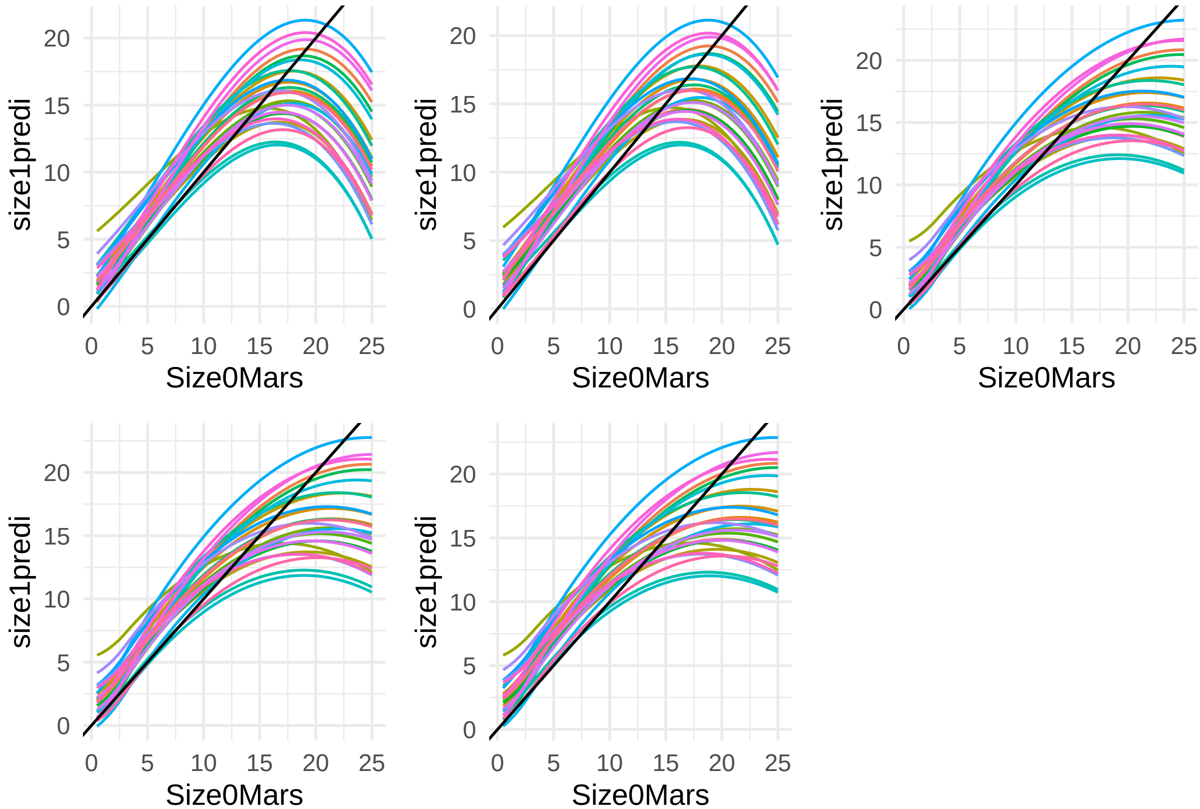


Age 1, 4, 8



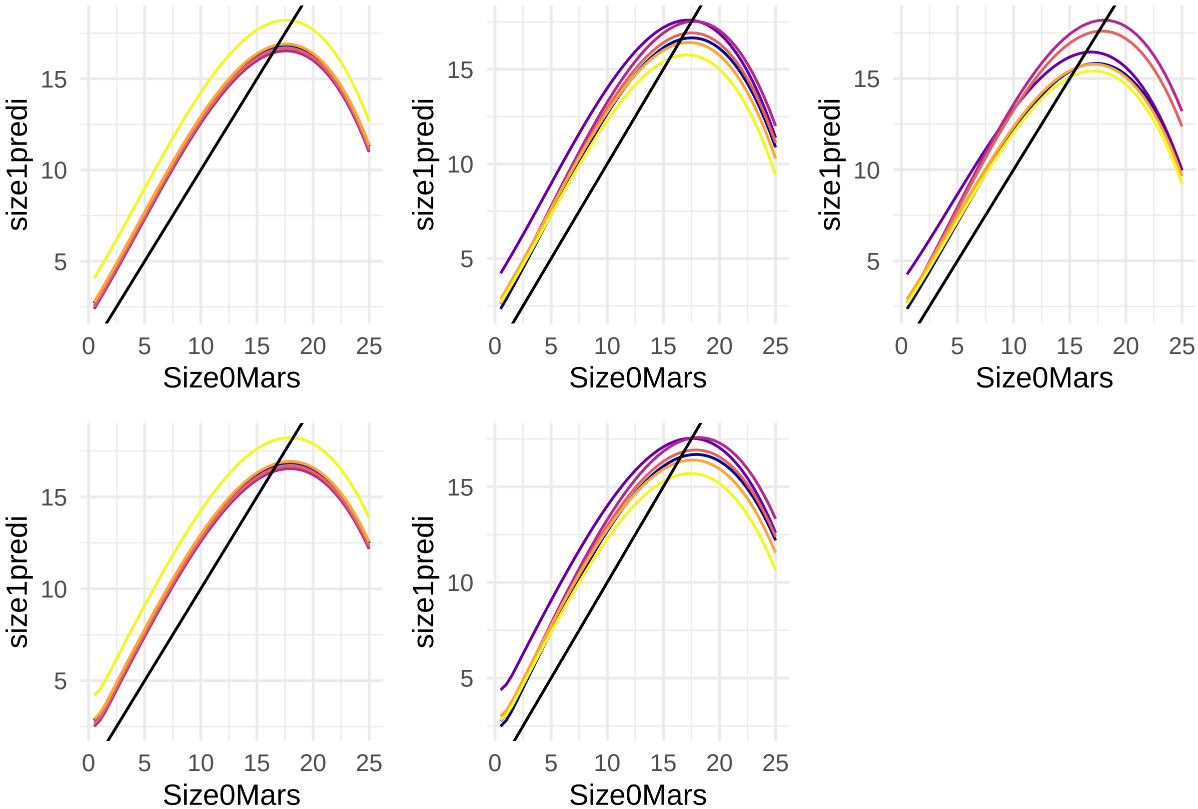
size1predi
Size0Mars
0
5
10
15
20
25

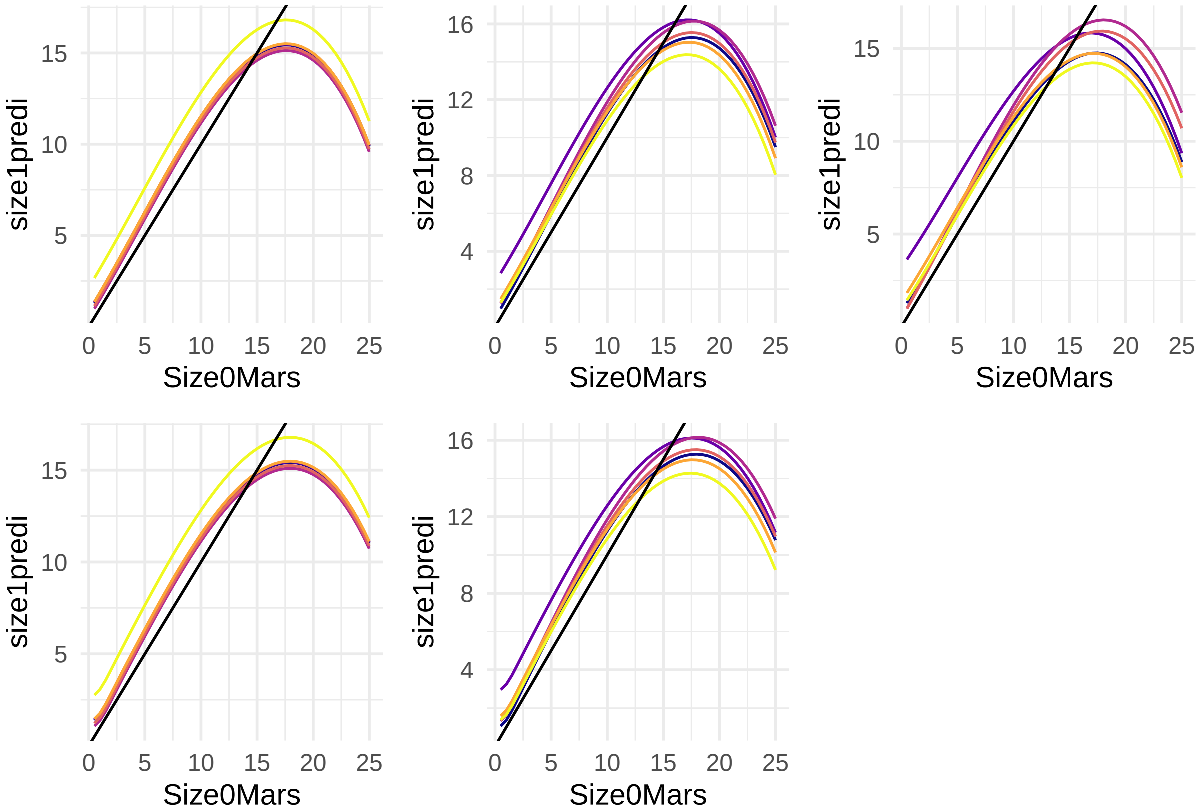

size1predi
Size0Mars
0
5
10
15
20
25

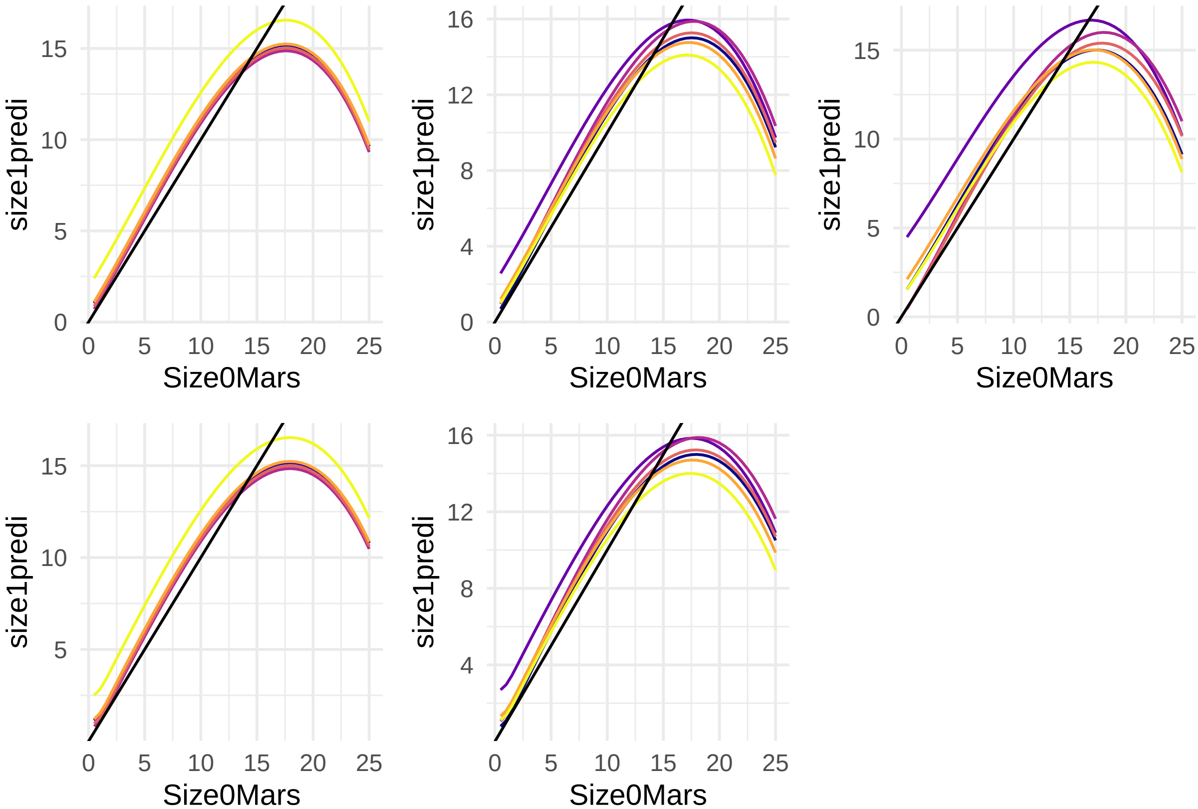



```
var <- "Size0Mars";
c1 <- "Age";
c2 <- "year";
fact <- "Pop"
```

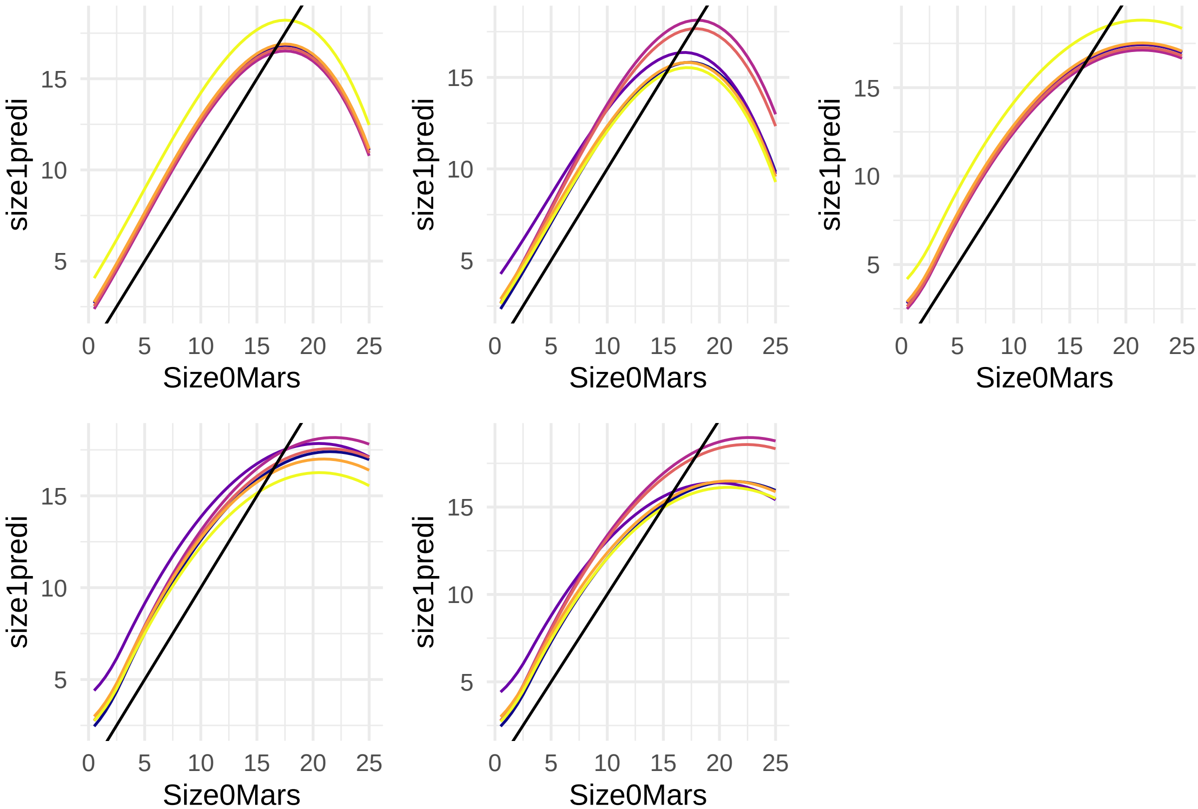
En fixant l'année : voir l'effet population Age 1, 4, 8

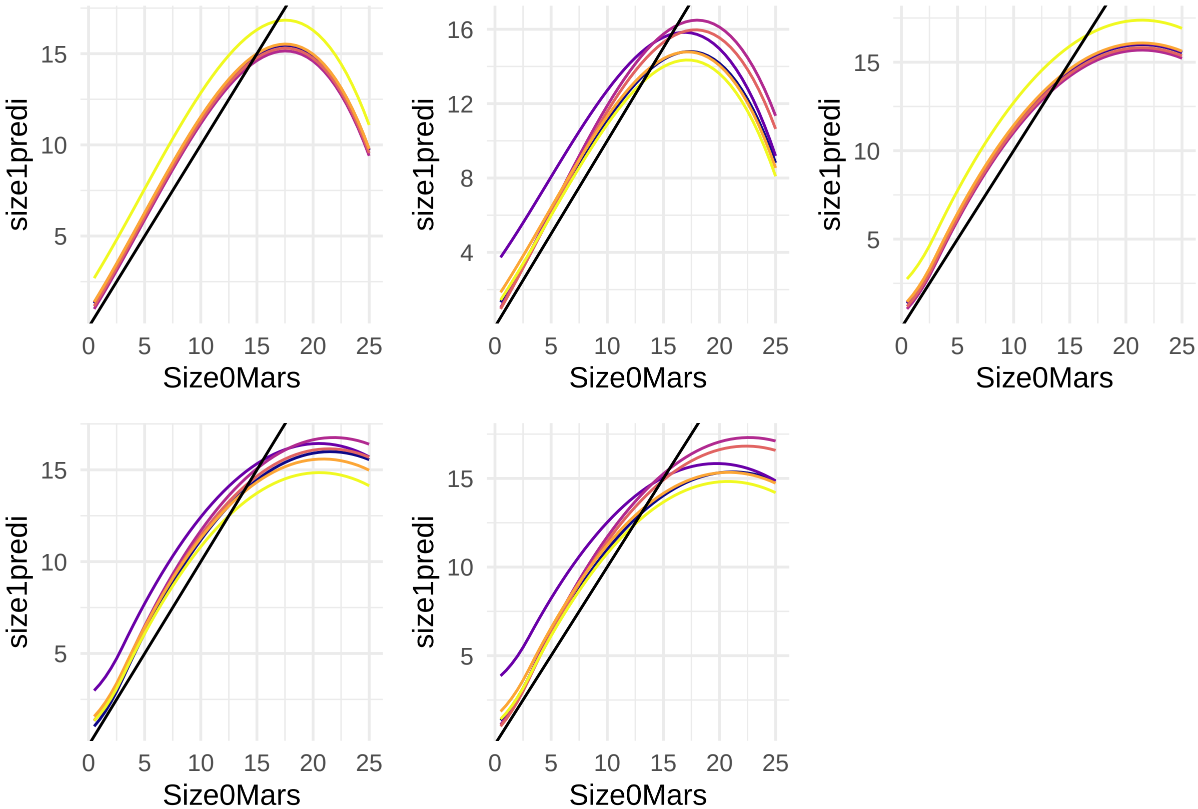

size1predi
Size0Mars
size1predi
Size0Mars
size1predi
Size0Mars
size1predi
Size0Mars
size1predi
Size0Mars

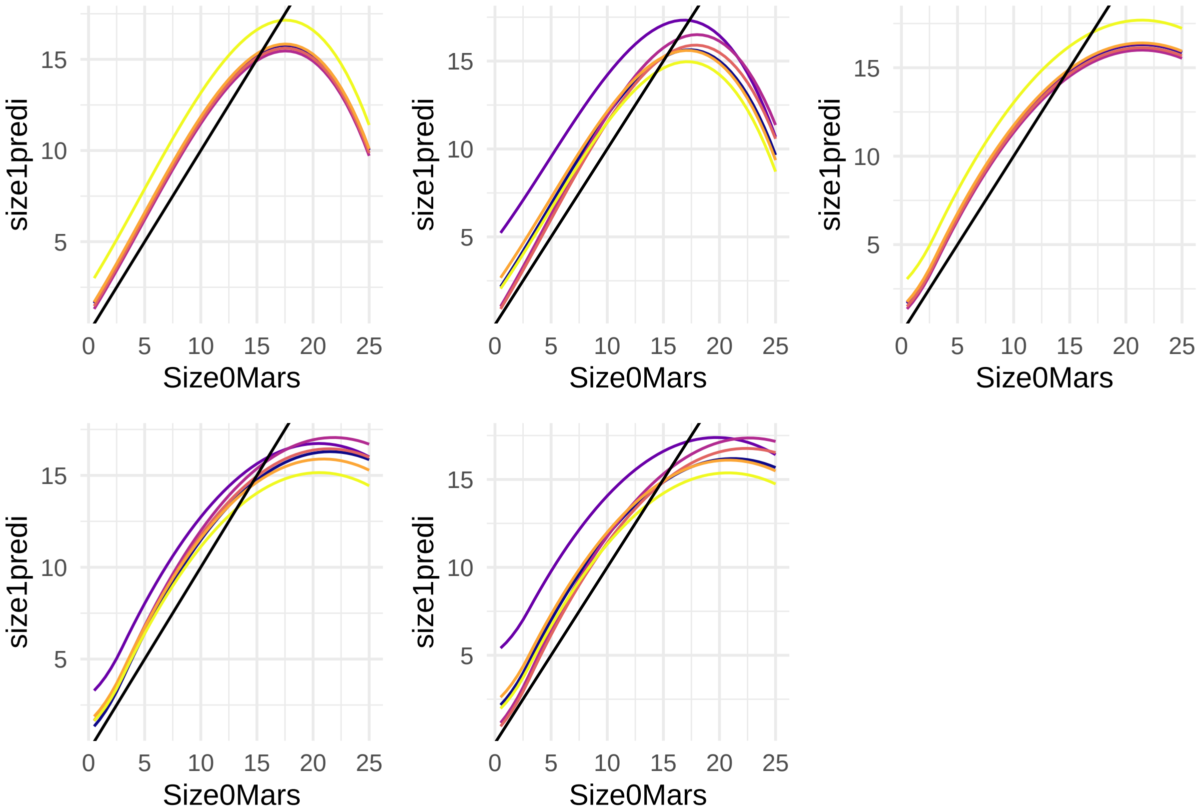

15
10
5
size1predi
0 5 10 15 20 25
Size0Mars
16
12
8
4
size1predi
0 5 10 15 20 25
Size0Mars
15
10
5
size1predi
0 5 10 15 20 25
Size0Mars
15
10
5
size1predi
0 5 10 15 20 25
Size0Mars
16
12
8
4
size1predi
0 5 10 15 20 25
Size0Mars



Age 1, 4, 8

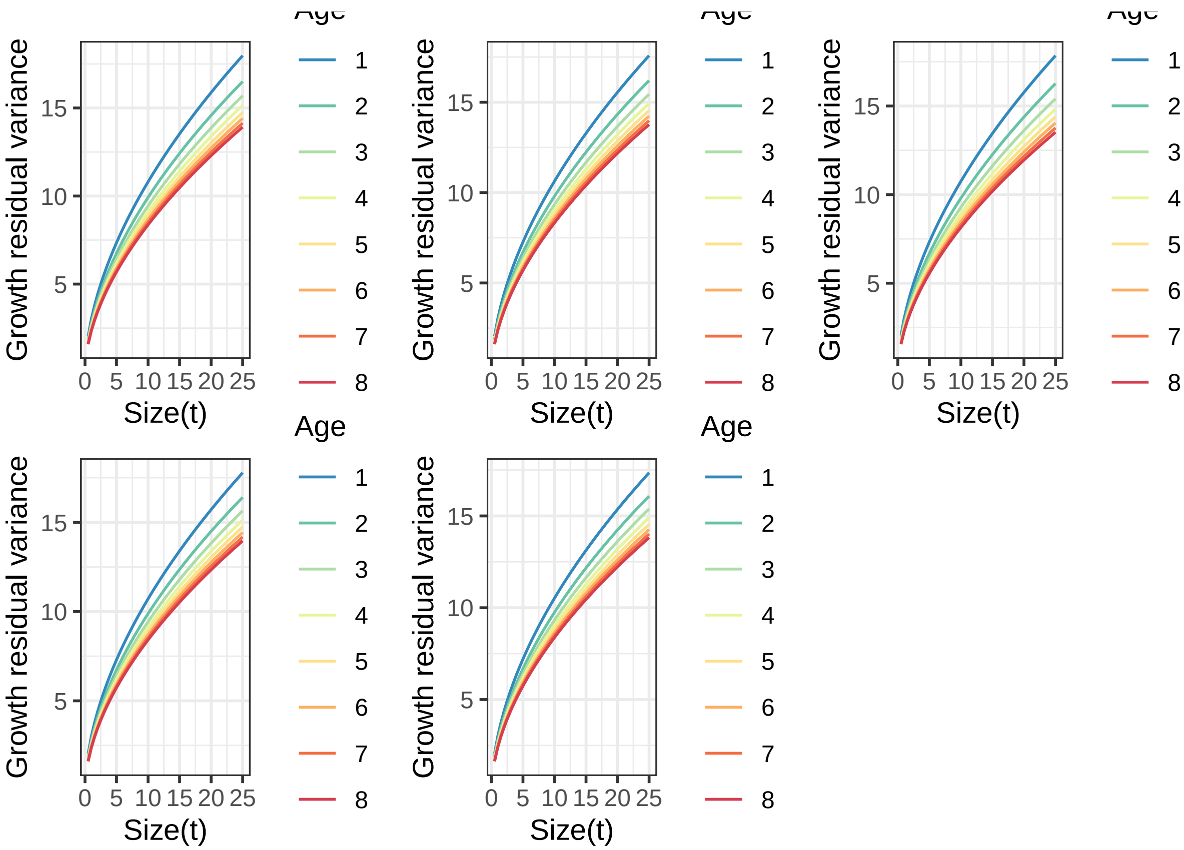

size1predi
Size0Mars
0
5
10
15
20
25
5
10
15

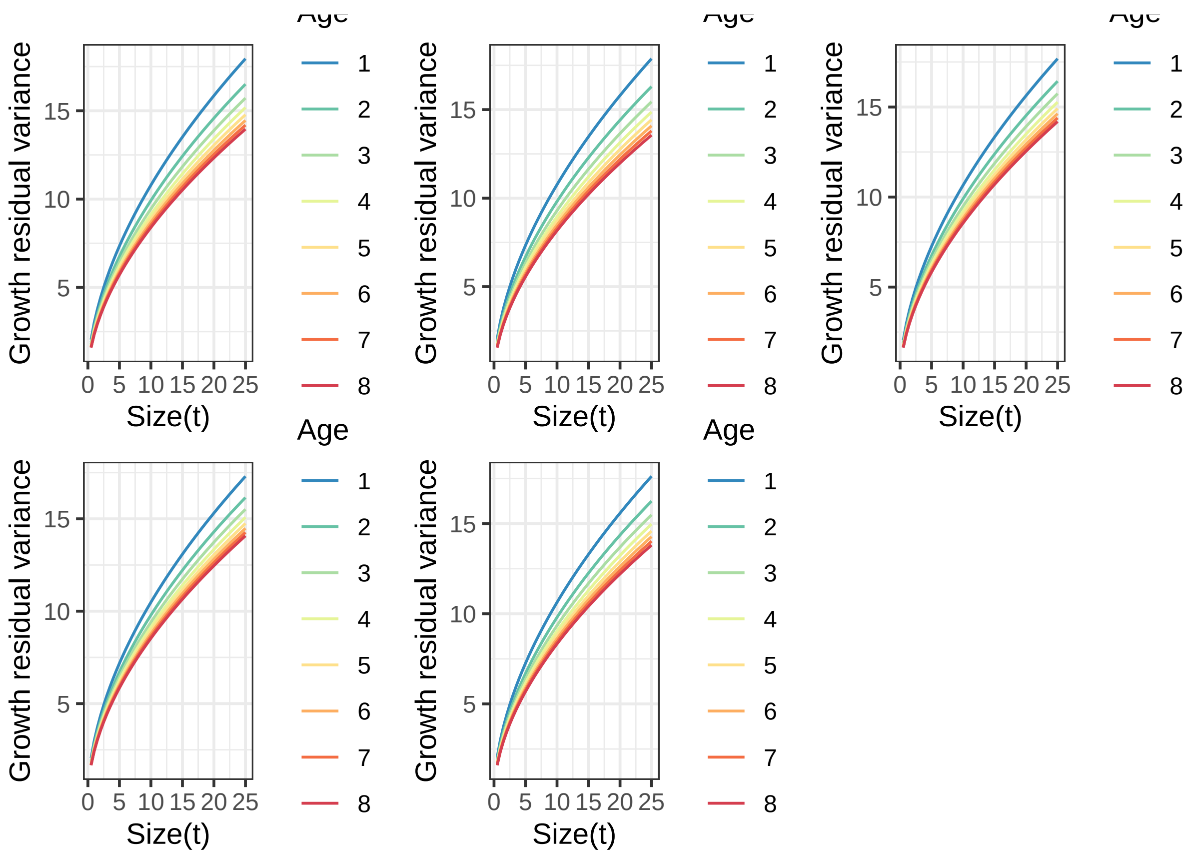

size1predi
Size0Mars
0
5
10
15
20
25
4
8
12
16



###Residual variance

```
Arespred1 <- get_residVar(AGrowthglm1,newdata=fake_data)
Arespred2 <- get_residVar(AGrowthglm2,newdata=fake_data)
Arespred3 <- get_residVar(AGrowthglm3,newdata=fake_data)
Arespred4 <- get_residVar(AGrowthglm4,newdata=fake_data)
Arespred5 <- get_residVar(AGrowthglm5,newdata=fake_data)

Brespred1 <- get_residVar(BGrowthglm1,newdata=fake_data)
Brespred2 <- get_residVar(BGrowthglm2,newdata=fake_data)
Brespred3 <- get_residVar(BGrowthglm3,newdata=fake_data)
Brespred4 <- get_residVar(BGrowthglm4,newdata=fake_data)
Brespred5 <- get_residVar(BGrowthglm5,newdata=fake_data)
```


Age
Growth residual variance
5
10
15
0 5 10 15 20 25
Size(t)
1
2
3
4
5
6
7
8
Age
Growth residual variance
5
10
15
0 5 10 15 20 25
Size(t)
1
2
3
4
5
6
7
8
Age
Growth residual variance
5
10
15
0 5 10 15 20 25
Size(t)
1
2
3
4
5
6
7
8
Age
Growth residual variance
5
10
15
0 5 10 15 20 25
Size(t)
1
2
3
4
5
6
7
8
Age
Growth residual variance
5
10
15
0 5 10 15 20 25
Size(t)
1
2
3
4
5
6
7
8


Growth residual variance
Size(t)
Age
1
2
3
4
5
6
7
8
0 5 10 15 20 25
5 10 15