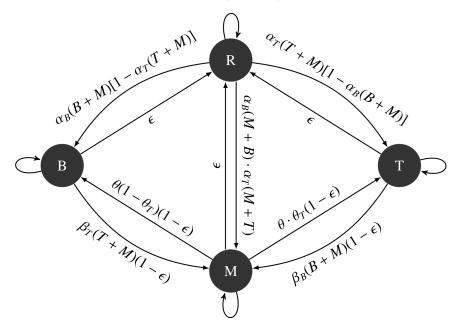
Linking SDMs and forest management

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Introduction

Here I am using a four states transition model (STM) to understand how forest management can increase forest resilience. The model has four process-parameters that defines the transition rate between the four states: Regeneration, Boreal, Temperate and Mixed (Figure 1).



Each parameter represents a different process: α is the colonisation rate (R -> B, T, M), β the succession (B, T -> M), θ the exclusion extintion (M -> B, T) and ϵ the pertubation (B, T, M -> R).

Example of model running

```
# call the model
source("vissault_model.R")
```

Running the model to equilibrium

```
# parameters
params = read.table("pars.txt", row.names = 1)

# Wrapper to collect parameters for a given set of environmental conditions
pars = get_pars(ENV1 = 0, ENV2 = 0, params, int = 3)
pars
```

```
##
        alphab
                    alphat
                                 betab
                                              betat
                                                          theta
## 0.999991086 0.998278766 0.269252962 0.442427327 0.159791566 0.973086903
## 0.009397677
# Get the transition matrix
transition_matrix = get_matrix(ENV1 = 0, ENV2 = 0, params, int = 3)
transition_matrix$MAT
##
                R
                             В
                                                      Τ
## R 9.906906e-01 0.0000598863 0.003873647 0.005375876
## B 3.885079e-05 0.9354824254 0.064478724 0.000000000
## M 3.896877e-03 0.0017832562 0.929843330 0.064476536
## T 5.373681e-03 0.0000000000 0.001804291 0.992822028
# Equilibrium of the model for the specific parameters (pars)
eq = get_eq(pars)
eq
## $eq
##
## 0.004134084 0.571809507 0.414663890
##
## $ev
## [1] -0.1122421
```

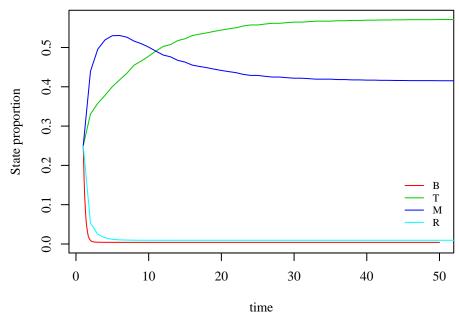
See the model behavior graphically

\$eq is the proportion of each state at equilibrium and \$ev the eigenvalue

Starting with 25% of the proportion for each state, we can graphically see the behavior of the model until reaching the equilibrium.

```
#data frame
time <- seq(1, 50, by = 0.1)
dm2 <- data.frame(matrix(NA, nrow = length(time), ncol = 4))</pre>
#Initial condition
y = c(B = 0.25, T = 0.25, M = 0.25)
dm2[1,] = c(y, 0.25)
#loop
for(i in 2:length(time)) {
  eq = runsteady(y = y, func = model, parms = pars, times = c(0, i))[[1]]
  eq[4] \leftarrow 1 - eq[1] - eq[2] - eq[3]
  dm2[i,] \leftarrow eq
}
#plot
par(family = 'serif', cex = 0.8)
plot(time, dm2[, 1],
     type = "1",
     ylim = c(0, max(dm2)),
     col = 2,
     ylab = "State proportion")
lines(dm2[, 2], col = 3)
```

```
lines(dm2[, 3], col = 4)
lines(dm2[, 4], col = 5)
legend(44, 0.18, c("B", "T", "M", "R"), col = 2:5, lty = 1, bty = "n", cex = 0.8)
```



Add hypothesized disturbance

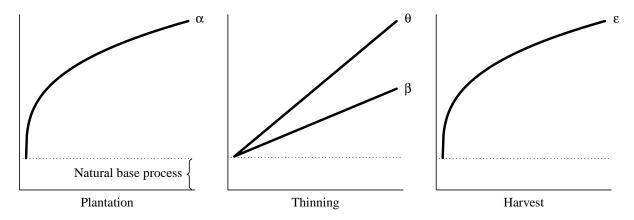
Setting up a data frame with two different environmental conditions is a way to see the behavior of the model after a disturbance. In this case, the model will start with 25% of the proportion for each state and after reaching equilibrium, the environmental patters will change.

```
#Function to produce the data frame with the equilibrium proportion of
#each state based on the environmnetal variation.
behavior <- function(envComb1, envComb2) {</pre>
    xx < - seq(1, 40, by = 1)
    dat <- data.frame(matrix(NA, nrow = length(xx), ncol = 6))</pre>
    names(dat) <- c("ENV1", "ENV2", "B", "T", "M", "R")</pre>
    dat[c(1:20), c(1,2)] \leftarrow envComb1 \#environmnetal 1
    dat[c(21: dim(dat)[1]), c(1,2)] \leftarrow envComb2 \#environmnetal 2
    #initial condition
    dat[1, c(3:6)] = c(B = 0.25, T = 0.25, M = 0.25, R = 0.25)
    #behavior
    for(i in 2:length(xx)) {
        pars = get_pars(ENV1 = dat[i, 1], ENV2 = dat[i, 2], params, int = 3)
        y = c(B = dat[(i - 1), 3], T = dat[(i - 1), 4], M = dat[(i - 1), 5])
        eq = runsteady(y = y, func = model, parms = pars, times = c(0, i))[[1]]
      eq[4] \leftarrow 1 - eq[1] - eq[2] - eq[3]
      dat[i, c(3:6)] \leftarrow eq
    }
    return(dat)
```

```
#run function
dat <- behavior(envComb1 = c(-.05, -.05), envComb2= c(0.05, 0.05))
#plot
par(family = 'serif', cex = 0.8)
plot(0,
     xlim = c(0, dim(dat)[1]),
     ylim = c(0, max(dat[,c(3:6)]) + 0.1),
     xlab = "time",
     ylab = "state proportion"
lines(dat$B, col = 2)
lines(dat$T, col = 3)
lines(dat$M, col = 4)
lines(dat$R, col = 5)
legend(34, 0.25, c("B", "T", "M", "R"), col = 2:5, bty = "n", lty = 1)
    0.7
    9.0
    0.5
state proportion
    0.4
    0.3
    0.2
                                                                  В
                                                                  Т
    0.1
                                                                  M
                                                                  R
    0.0
            0
           0
                        10
                                      20
                                                    30
                                                                  40
                                     time
```

Effect of forest management on resilience

Using a numerical approach, I will take forest management into the model by changing the parameters related to each management process. For example, **plantation** can enhance colonization (α) , pre-commercial **thinning** can enhance both competitive exclusion (θ) and succession (β) , and **cutting** can enhance disturbance $(\epsilon;$ Figure 2). Dotted line is the base natural process that occur without intervention.



By simply increasing the value of each parameter related to management, we can simulate the inclusion of management in the model processes (see Figure 2). The **recovery resilience**, or time rate in which a system returns to equilibrium after a disturbance, is measured by the largest real part of the **eigenvalue**. The eigenvalue is optained by the Jacobian matrix and a nice example can be found in this vignette of the rootSolve package.

As the choice of parameters is delicate in this kind of "sensitivity analysis", I chose to do 2 different tests in the parametric variation to simulate the response of resilience to the increasing in forest management.

Test1 varies a specific parameter (the tested one) from 0 to 1.7, and the other parameters remains with the original values (fitted with field data). Test2 varies a specific parameter from 0 to 1.7, and the other parameters remains with a fixed value fixPar.

TEST 1

```
#Fixed value for main parameters from 0 to 1.7 and original value for the other parameters
int <- 2
parSeq \leftarrow seq(0, 1.7, 0.1)
#running eigenvalue to each parameter
pars = get_pars(ENV1 = 0, ENV2 = 0, params, int = int)
eql <- as.list("NA")
df <- data.frame()</pre>
for(k in 1: length(pars)) {
    pars = get_pars(ENV1 = 0, ENV2 = 0, params, int = int)
    for(j in 1: length(parSeq)) {
        pars[k] = parSeq[j]
                    <- parSeq[j]</pre>
        df[j, 1]
        df[j, 2] <- get_eq(pars)$ev</pre>
eql[[k]] \leftarrow df
}
#plot
Pars <- c(expression(alpha), expression(alpha), expression(beta),
          expression(beta), expression(theta), expression(theta),
          expression(epsilon))
par(family = 'serif', cex = 0.8, mfrow = c(3,3), mai = c(0.3, .5, .2, .2))
for(i in 1:7) {
    plot(eql[[i]], type = "l", lwd = 1.7, xlab = "", ylab = "", ylim = c(-.35,0))
```

```
if(i == 4) mtext(side = 2, "largest real part", line = 2.1, cex = 0.9)
   legend("bottomleft", Pars[i], bty = "n")
}
     -0.05
                                                    -0.05
                                                                                                   -0.05
     -0.20
                                                    -0.20
                                                    -0.35
                                                                                                   -0.35
          0.0
                  0.5
                           1.0
                                    1.5
                                                         0.0
                                                                 0.5
                                                                          1.0
                                                                                   1.5
                                                                                                        0.0
                                                                                                                 0.5
                                                                                                                          1.0
                                                                                                                                   1.5
                                                                                                   -0.05
 largest real part
                                                                                                   -0.20
     -0.20
                                                    -0.20
                                                                                                   -0.35
                                                    -0.35
          0.0
                  0.5
                           1.0
                                    1.5
                                                         0.0
                                                                 0.5
                                                                          1.0
                                                                                   1.5
                                                                                                        0.0
                                                                                                                 0.5
                                                                                                                          1.0
                                                                                                                                   1.5
     -0.20
     -0.35
          0.0
                  0.5
                           1.0
                                    1.5
```

TEST 2

```
#Fixed value for all parameters from 0 to 1.7
int <- 2
parSeq < - seq(0, 1.7, 0.1)
fixPar <- c(0.2, 0.5, 0.8, 1.2) #fixed value of all other parameters
#running eigenvalue to each parameter
pars = get_pars(ENV1 = 0, ENV2 = 0, params, int = int)
eql <- as.list("NA")
df <- data.frame()</pre>
for(k in 1: length(pars)) {
    pars = get_pars(ENV1 = 0, ENV2 = 0, params, int = int)
  for(l in 1: length(fixPar)) {
    pars[-k] <- fixPar[1]</pre>
    for(j in 1: length(parSeq)) {
        pars[k] = parSeq[j]
        df[j, 1]
                     <- parSeq[j]</pre>
        df[j, 1 + 1] <- get_eq(pars)$ev</pre>
     }
  }
eql[[k]] \leftarrow df
```

```
}
#plot
Pars <- c(expression(alpha), expression(alpha), expression(beta),</pre>
           expression(beta), expression(theta), expression(theta),
           expression(epsilon))
par(family = 'serif', cex = 0.8, mfrow = c(3,3), mai = c(0.3, .5, .2, .2))
for(i in 1:7) {
    plot(0, type = "n", lwd = 1.7, xlab = "", ylab = "", xlim = c(0, 1.7), ylim = c(-0.4, 0.01))
  if(i == 4) mtext(side = 2, "largest real part", line = 2.1, cex = 0.9)
  legend("bottomleft", Pars[i], bty = "n")
      points(eql[[i]]$V1, eql[[i]]$V2, type = "l", lwd = 1.5)
      points(eql[[i]]$V1, eql[[i]]$V3, type = "l", lwd = 1.5, col = 2)
      points(eql[[i]]$V1, eql[[i]]$V4, type = "l", lwd = 1.5, col = 3)
      points(eql[[i]]$V1, eql[[i]]$V5, type = "l", lwd = 1.5, col = 4)
plot(c(-1, 1), c(-1, 1), ann = FALSE, axes = FALSE, type = "n")
legend(-1, 1, fixPar, lty = 1, col = c(1:4), bty = "n", cex = 0.95)
   0.0
                                                                      0.0
                                     -0.2
                                     4.0-
       0.0
             0.5
                   1.0
                         1.5
                                        0.0
                                              0.5
                                                    1.0
                                                          1.5
                                                                         0.0
                                                                               0.5
                                                                                      1.0
                                                                                            1.5
                                     0.0
                                                                      0.0
 largest real part
                                     -0.2
                                     4.0-
       0.0
             0.5
                   1.0
                         1.5
                                        0.0
                                              0.5
                                                    1.0
                                                          1.5
                                                                         0.0
                                                                               0.5
                                                                                      1.0
                                                                                            1.5
                                               0.2
                                               0.5
                                               0.8
                                              1.2
       0.0
             0.5
                   1.0
                         1.5
```

Using expand.grid to test all parameters combination

Now we saw the variation of each parameter, we want to see every parameter changing with each other to test all combinations of parameters. Here I will test the parameters variation from 0.09 to 0.99.

```
#parameters
parm <- seq(0.09, 0.99, 0.15)
```

```
\#expand\ grid\ function
sim <- expand.grid(alphab = parm,</pre>
                    alphat = parm,
                    betab = parm,
                    betat = parm,
                    theta = parm,
                    thetat = parm,
                    eps = parm)
dim(sim)
## [1] 823543
                    7
#get eigenvalue for each variation (time ~ 36 hrs in one core):
\#system.time(for(i in 1: dim(sim)[1]) \{
\# \ sim[i,\ 8] \leftarrow get\_eq(sim[i,]) \$ ev
# cat(100*i/dim(sim)[1], "%", "\r")
#})
#save the output
#save(sim, file = "data/ev.RData")
#load the output
#load("data/ev.RData")
```

Analysing the results

TODO

• Solve differntial equantion to equilibrium