Introduction to SpaDES

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Contents

1 Spatial Discrete Event Simulation (SpaDES)

Requirements This packages makes heavy use of the `raster` and `sp` packages, so familiarity with these packages and their classes and methods is recommended.

2 Discrete event simulation

Lorem ipsum ...

3 SpaDES modules

3.1 Module overview

`SpaDES` modules are event-based, meaning that different actions are performed on data objects based on the order of scheduled events. Basically, a module consists of a collection of events which are scehduled depending on the rules of your simulation. Each event may evaluate or modify a simulation data object, or perform other operations such as saving and loading data objects.

3.2 Events

Simulation event list Lorem ipsum ...

Module events Lorem ipsum ...

Module event dependencies Typically, each module schedules its own events (e.g., a "fire" module may schedule "burn" events) and only uses its own data objects. Modules that behave in this way are indepedent of each other, and this is generally the prefered way to design and implement modules. A module that schedules events from another module is said to depend on that module. Module event dependencies compilcate the construction of simulation models, and hinder the ability to develop and deploy models with modularity. If two modules are actually depedent on each others' events, then you should consider whether they really are separate modules or should be merged into a single module.

3.3 Objects

As you build your modules for your simulation, you can use any of R's data types to store your objects and data. In particular, matrices (including vectors) and lists work well for this purpose because as of R version 3.1 they are more efficient and reduce your model's memory footprint and speeds up your codes execution. Other useful datatypes include `Raster*` and `SpatialPoints*` objects.

Global objects Use the superassignment operator (`<<-`) to assign global objects to reduce copying large objects (such as maps), which slows model execution.

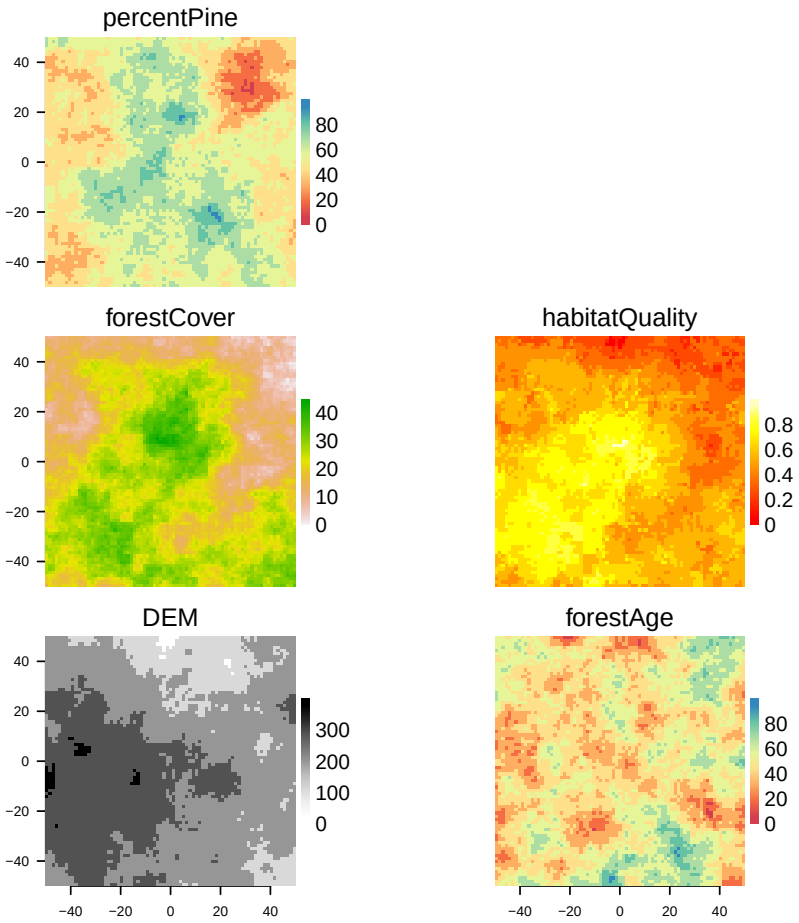
Module object dependencies As noted above, modules can depend on one another for event scheduling. Modules can also be design to rely on outputs (data objects) from other modules. A module that relies on a global simulation data object that previously used by another module is said to be dependent on that other module. It is often useful to develop collections of modules that interact indirectly and are dependent in this way. Note that modules need not be inter-dependent on one another: module B may depend on module A (for example to initialize a data object), without module A depending on module B.

4 Working with maps

A raster map Sample map of habitat quality.

Plotting maps

```
> # Give dimensions of dummy raster
> nx <- 1e2
> ny <- 1e2
> template <- raster(nrows=ny, ncols=nx, xmn=-nx/2, xmx=nx/2, ymn =-ny/2, ymx=ny/2)
> # Make dummy maps for testing of models:
> # - digital elevation model (DEM)
> # - forest age
> # - forset cover
> # - percent pine
> DEM <- round(GaussMap(template, scale=300, var=0.03, speedup=1), 1)*1000
> forestAge <- round(GaussMap(template, scale=10, var=0.1, speedup=1), 1)*20
> forestCover <- round(GaussMap(template, scale=50, var=1, speedup=1),2)*10
> percentPine <- round(GaussMap(template, scale=50, var=1, speedup=1),1)
> # Scale them as needed
> forestAge <- forestAge/maxValue(forestAge)*100
> percentPine <- percentPine/maxValue(percentPine)*100
> # Make layers that are derived from other layers
> habitatQuality <- (DEM+10 + (forestCover+5)*10)/100
> habitatQuality <- habitatQuality/maxValue(habitatQuality)
> # Stack them into a single stack for plotting
> habitat <- stack(list(DEM, forestAge, forestCover, habitatQuality, percentPine))
> names(habitat) <- c("DEM","forestAge", "forestCover", "habitatQuality", "percentPine")
> library(RColorBrewer)
> cols <- list(
+   transparent.greys <- c("#00000000",paste(brewer.pal(8,"Greys"),"66",sep="")[8:1]),
+   grey <- brewer.pal(9,"Greys"),
+   spectral <- brewer.pal(8,"Spectral"),
+   terrain <- rev(terrain.colors(100)),
+   heat <- heat.colors(10),
+   topo <- topo.colors(10)
+ )
> simPlot(habitat, col=cols[c(2:5,3)])
```


percentPine
80
60
40
20
0
forestCover
40
30
20
10
0
habitatQuality
0.8
0.6
0.4
0.2
0
DEM
300
200
100
0
forestAge
80
60
40
20
0
40
20
0
−20
−40
−40
−20
0
20
40

5 Simulating "agents"

Lorem ipsum ...

5.1 Spatial agents

5.1.1 Point agents

agents represented by a single set of coordinates indicating their current position.

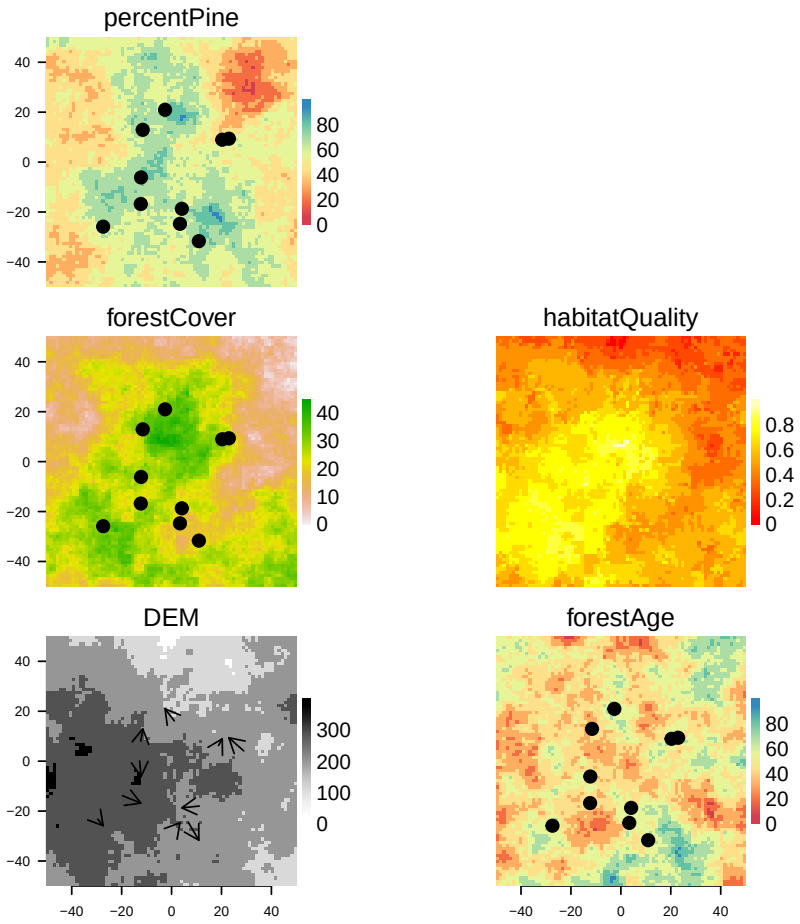
Use a `SpatialPointsDataFrame` with additional columns as needed.

Non-mobile point agents e.g., plants

Mobile point agents e.g., animals use a `SpatialPointsDataFrame`, with additonal columns for agents' previous `n` positions, and any other columns such as age, sex, group membership, etc.

```
> N <- 1e1 # number of agents
> # caribou data vectors
> IDs <- c("Alice", "Bob", "Clark", "Daisy", "Eric",
+          "Franz", "Gabby", "Hayley", "Igor", "Jane")
> sex <- c("female", "male", "male", "female", "male",
+          "male", "female", "female", "male", "female")
> age <- round(rnorm(N, mean=8, sd=3))
> prevX <- runif(N, xmin(habitat)+(ncol(habitat)*0.2), xmax(habitat)-(ncol(habitat)*0.2)) # previous X l
> prevY <- runif(N, ymin(habitat)+(nrow(habitat)*0.2), ymax(habitat)-(nrow(habitat)*0.2)) # previous Y l
> # create the caribou agent object
> caribou <- SpatialPointsDataFrame(coords=cbind(x=rnorm(N, prevX, ncol(habitat)/20),
+                                                y=rnorm(N, prevY, ncol(habitat)/20)),
+                                   data=data.frame(prevX, prevY, sex, age))
> row.names(caribou) <- IDs # alternatively, add IDs as column in data.frame above
> heading(SpatialPoints(cbind(x=prevX,y=prevY)),caribou)

     Alice        Bob      Clark      Daisy       Eric      Franz      Gabby
140.446399  39.913894 174.958905 264.076498 322.294982   8.959608 111.902569
    Hayley       Igor       Jane
149.453927  29.167036 311.408063

> coordinates(caribou)

                x          y
Alice  -27.398455 -25.858994
Bob      3.361798 -24.731074
Clark  -12.234190  -6.151791
Daisy    4.118903 -18.705284
Eric    -2.610590  20.954445
Franz  -11.545520  12.933164
Gabby  -12.321908 -16.792921
Hayley  10.939232 -31.669876
Igor    20.304826   8.956786
Jane    22.960244   9.372123

> ## conventional plotting method - agents don't plot properly when it is a raster stack
> #plot(habitat)
> #plot(caribou, add=TRUE)
```

```
>
> # convenient plotting using simPlot
> simPlot(habitat, col=cols[c(2:5,3)])
> simPlot(caribou, on.which.to.plot=c(2,3,5), pch=19, size=unit(0.1,"inches"))
> drawArrows(from=SpatialPoints(cbind(x=prevX, y=prevY)),
+            to=caribou,
+            on.which.to.plot="DEM")
```



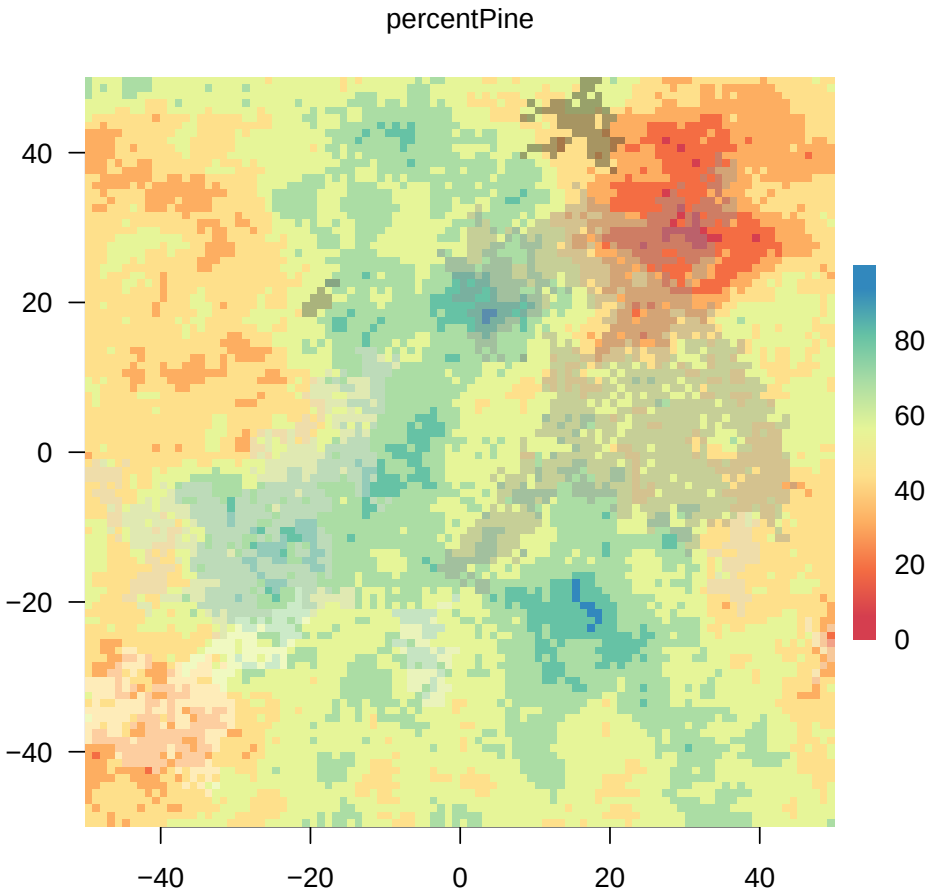
6 A simple fire model

Burn some of the forest Using the spread function, we can simulate fires, and subsequent changes to the various map layers. Here, spreadProb can be a single probability or a raster map where each pixel has a probability. In the example below, each cell's probability is taken from the Percent Pine map layer.

```
> nFires <- 10 # number of agents
> habitat[["Fires"]] <- spread(habitat[[1]],
+                              loci=as.integer(sample(1:ncell(habitat), nFires)),
+                              spreadProb=0.225,
+                              #spreadProb=habitat[["percentPine"]]/(maxValue(habitat[["percentPine"]])+
+                              persistance=0,
+                              mapFireID=TRUE,
```

```
+                                 mask=NULL,
+                                 maxSize=1e8,
+                                 directions=8,
+                                 iterations=1e6,
+                                 plot.it=FALSE,
+                                 mapID=TRUE)
> simPlot(habitat[["Fires"]])
```

```
> # Show the burning more strongly over abundant pine
> simPlot(habitat[["percentPine"]], col=cols[[3]])
> simPlot(habitat[["Fires"]], add=TRUE, delete.previous=FALSE, col=cols[[1]])
```



We can see that the fires tend to be in the Pines because we made it that way, using an arbitrary weighting with pine abundance

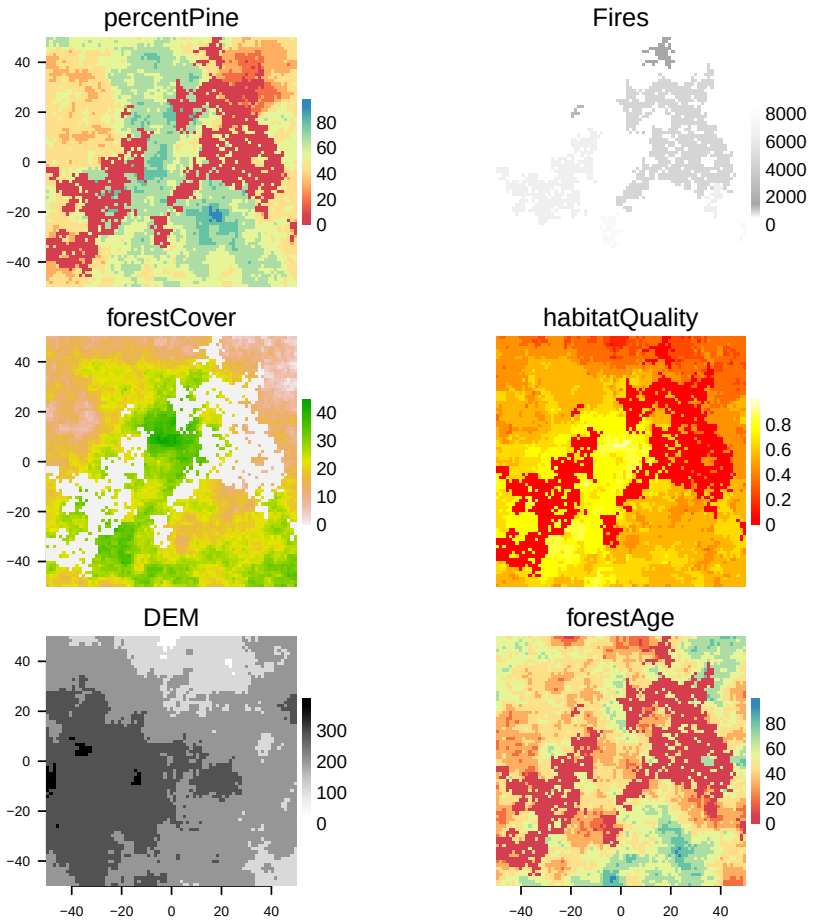
```
> # Show the burning more strongly over abundant pine
> fire <- reclassify(habitat[["Fires"]],rcl= cbind(0:1,c(0,ncell(habitat)),0:1))
> pine <- reclassify(habitat[["percentPine"]],rcl= cbind(0:9*10, 1:10*10, 0:9))
> PineByFire <- crosstab(fire, pine, long=TRUE)
> colnames(PineByFire) <- c("fire", "pine", "freq")
```

```
> PineByFire$pine <- as.numeric(as.character(PineByFire$pine))
> summary(glm(freq ~ fire*pine, data=PineByFire, family="poisson"))

Call:
glm(formula = freq ~ fire * pine, family = "poisson", data = PineByFire)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-41.223  -18.171   -2.712   10.667   32.786

Coefficients:
             Estimate Std. Error z value Pr(>|z|)
(Intercept)  6.390328   0.022770 280.648   <2e-16 ***
fire1       -1.166615   0.047359 -24.633   <2e-16 ***
pine         0.056146   0.003980  14.107   <2e-16 ***
fire1:pine  -0.017168   0.008409  -2.042   0.0412 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for poisson family taken to be 1)

    Null deviance: 11800  on 19  degrees of freedom
Residual deviance:  8312  on 16  degrees of freedom
AIC: 8464.8

Number of Fisher Scoring iterations: 5
```

Sure enough, there are more fires as the abundance of pine goes up, as seen by the positive interaction term (the negative `fire1` term means that there are more pixels without fires than with fires).

Impact some of the forest

```
> habitat[["forestAge"]][habitat[["Fires"]]>0] <- 0
> habitat[["forestCover"]][habitat[["Fires"]]>0] <- 0
> habitat[["habitatQuality"]][habitat[["Fires"]]>0] <- 0.1
> habitat[["percentPine"]][habitat[["Fires"]]>0] <- 0
> simPlot(habitat, col=cols[c(2:5,3,1)])
```

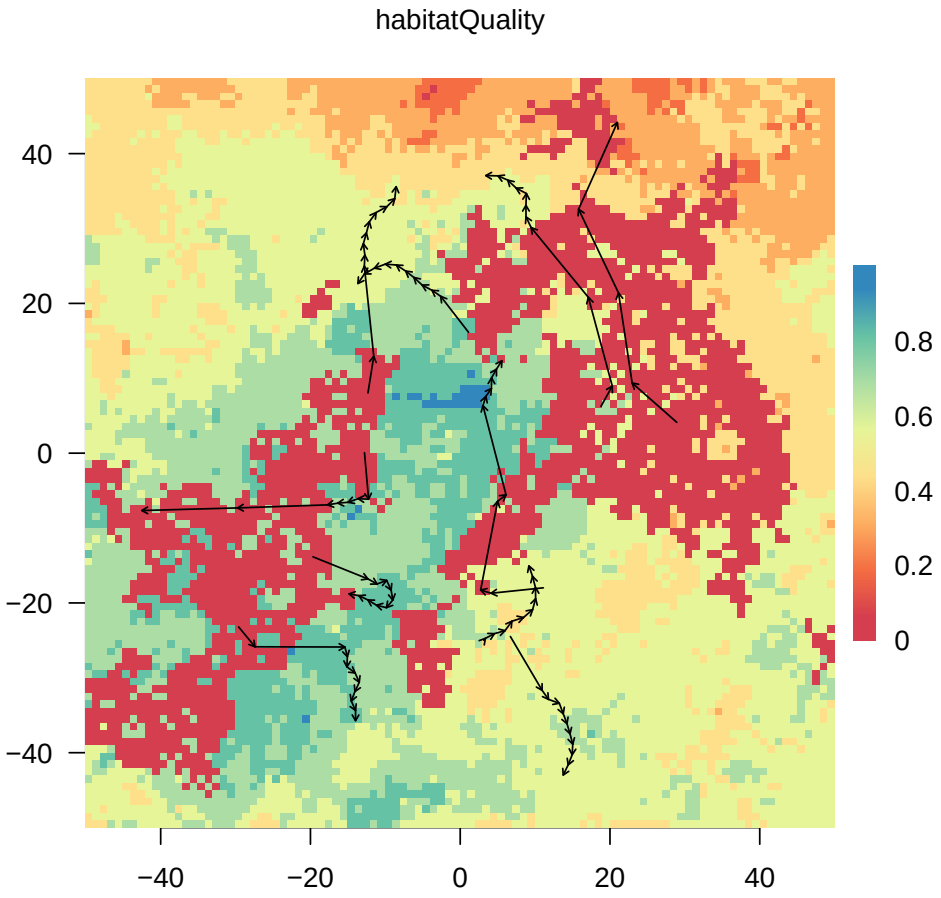


7 A simple individual based model (IBM)

Move some agents Using a simple habitat-depedent correlated random walk, simulate the movement of caribou across a heterogeneous landscape. Because we had just had fires, and we assume that fires have a detrimental effect on animal movement, we can see the long steps taken in the new, low quality, post-burn sections of the landscape.

```
> simPlot(habitat[["habitatQuality"]], col=cols[[3]])
> for (i in 1:10) {
+   #crop any caribou that went off maps
+   caribou <<- crop(caribou,habitat)
+   drawArrows(from=SpatialPoints(cbind(x=caribou$prevX, y=caribou$prevY)),
+              to=caribou,length=0.04,
+              on.which.to.plot=1)
+
+   # find out what pixels the individuals are on now
+   ex <- habitat[["habitatQuality"]][caribou]
+
+   #step length is a function of current cell's habitat quality
+   sl <- 0.25/ex
+
```

```
+   ln <- rlnorm(length(ex), sl, 0.02) # log normal step length
+   sd <- 30 # could be specified globally in params
+
+   caribou <<- crw(caribou, stepLength=ln, stddev=sd, lonlat=FALSE)
+ }
```



8 Further reading

8.1 Other SpaDES vignettes:

- `modules`: Building modules in `SpaDES`
- `plotting`: Plotting with `simPlot` in `SpaDES`