Landscape- and regional-scale simulations (practice)

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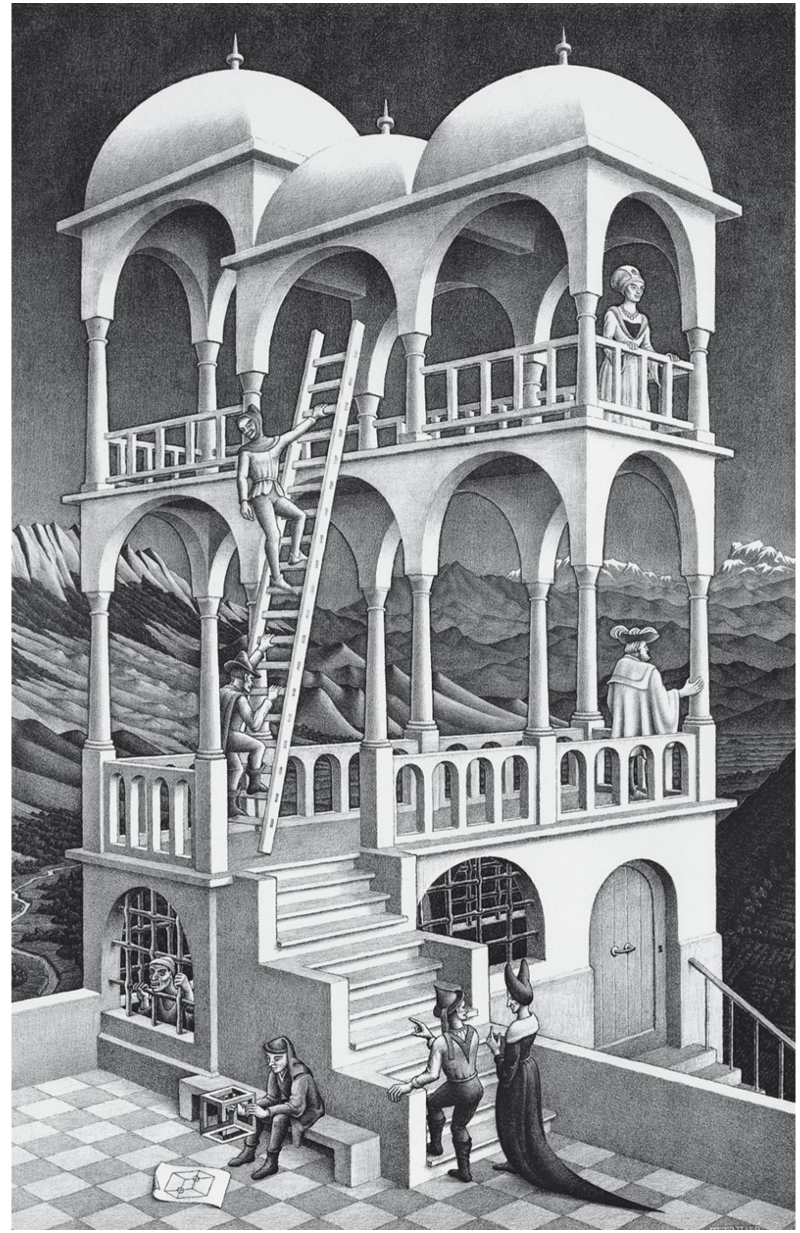
Outline

1. **Data structures in medfateland**
2. **Spatially-uncoupled simulations**
3. **Regional management scenarios**
4. **Watershed-level simulations**
5. **Creating spatial inputs I: forest inventory plots**
6. **Creating spatial inputs II: continuous landscapes**

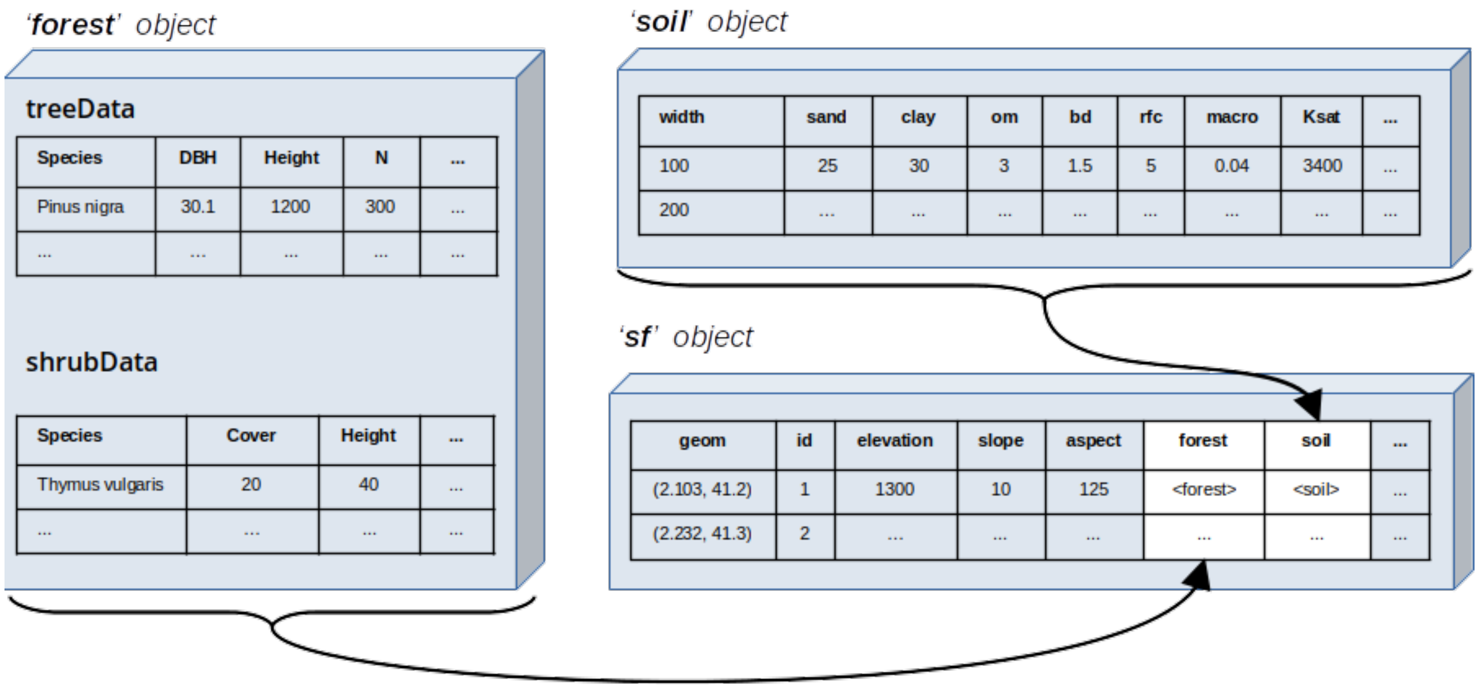
M.C. Escher - Belvedere, 1958



1. Data structures in medfateland

Spatial structures (1)

- Current versions of medfateland (ver. > 2.0.0) extensively use package **sf** (simple features) to represent spatial structures, where rows correspond to spatial units (normally point geometries) and columns include either *model inputs* (topography, forest, soil, weather forcing, etc.) or *model outputs*.
- Essentially, an `sf` object is a data frame with spatial (geometry) information and a coordinate reference system.
- Both `forest` and `soil` objects are nested in the corresponding columns of the `sf` object:



Spatial structures (2)

If we load the package we can inspect the structure of an example dataset with 100 forest inventory plots:

```
example_ifn
```

```
Simple feature collection with 100 features and 7 fields
Geometry type: POINT
Dimension:     XY
Bounding box:  xmin: 1.817095 ymin: 41.93301 xmax: 2.142956 ymax: 41.99881
Geodetic CRS:  WGS 84
# A tibble: 100 × 8
                  geom id        elevation slope aspect land_cover_type soil
 *         <POINT [°]> <chr>         <dbl> <dbl>  <dbl> <chr>           <list>
 1 (2.130641 41.99872) 081015_A1       680  7.73  281.  wildland        <df>
 2 (2.142714 41.99881) 081016_A1       736 15.6   212.  wildland        <df>
 3 (1.828998 41.98704) 081018_A1       532 17.6   291.  wildland        <df>
 4 (1.841068 41.98716) 081019_A1       581  4.79  174.  wildland        <df>
 5 (1.853138 41.98728) 081020_A1       613  4.76   36.9 wildland        <df>
 6 (1.901418 41.98775) 081021_A1       617 10.6   253.  wildland        <df>
 7 (1.937629 41.98809) 081022_A1       622 20.6   360   wildland        <df>
 8  (1.949699 41.9882) 081023_A1       687 14.4   324.  wildland        <df>
 9  (1.96177 41.98831) 081024_A1       597 11.8    16.3 wildland        <df>
10  (1.97384 41.98842) 081025_A1       577 14.6   348.  wildland        <df>
# ℹ 90 more rows
# ℹ 1 more variable: forest <list>
```

Accessing a given position of the `sf` object we can inspect `forest` or `soil` objects:

```
example_ifn$soil[[3]]
```

```
  widths     clay  sand   om       bd      rfc
1    300 25.76667 37.90 2.73 1.406667 23.84454
2    700 27.30000 36.35 0.98 1.535000 31.63389
3   1000 27.70000 36.00 0.64 1.560000 53.90746
4   2000 27.70000 36.00 0.64 1.560000 97.50000
```

Spatial structures (3)

To perform simulations on a gridded landscape we require both an `sf` object and an object `SpatRaster` from package **terra**, which defines the raster topology. For example, the following `sf` describes 65 cells in a small watershed:

```
example_watershed
```

```
Simple feature collection with 66 features and 14 fields
Geometry type: POINT
Dimension:     XY
Bounding box:  xmin: 401430 ymin: 4671870 xmax: 402830 ymax: 4672570
Projected CRS: WGS 84 / UTM zone 31N
# A tibble: 66 × 15
           geometry    id elevation slope aspect land_cover_type
 *      <POINT [m]> <int>     <dbl> <dbl>  <dbl> <chr>
 1 (402630 4672570)     1      1162 11.3   79.2  wildland
 2 (402330 4672470)     2      1214 12.4   98.7  agriculture
 3 (402430 4672470)     3      1197 10.4  102.   wildland
 4 (402530 4672470)     4      1180  8.12  83.3  wildland
 5 (402630 4672470)     5      1164 13.9   96.8  wildland
 6 (402730 4672470)     6      1146 11.2    8.47 agriculture
 7 (402830 4672470)     7      1153  9.26 356.   agriculture
 8 (402230 4672370)     8      1237 14.5   75.1  wildland
 9 (402330 4672370)     9      1213 13.2   78.7  wildland
10 (402430 4672370)    10      1198  8.56  75.6  agriculture
# ℹ 56 more rows
# ℹ 9 more variables: forest <list>, soil <list>, state <list>,
#   depth_to_bedrock <dbl>, bedrock_conductivity <dbl>, bedrock_porosity <dbl>,
#   snowpack <dbl>, aquifer <dbl>, crop_factor <dbl>
```

The following code defines a 100-m raster topology with the same CRS as the watershed:

```
r <-terra::rast(xmin = 401380, ymin = 4671820, xmax = 402880, ymax = 4672620,
                nrow = 8, ncol = 15, crs = "epsg:32631")
r
```

```
class       : SpatRaster
dimensions  : 8, 15, 1  (nrow, ncol, nlyr)
resolution  : 100, 100  (x, y)
extent      : 401380, 402880, 4671820, 4672620  (xmin, xmax, ymin, ymax)
coord. ref. : WGS 84 / UTM zone 31N (EPSG:32631)
```

Weather forcing in medfateland

There are three ways of supplying weather forcing to simulation functions in **medfateland**, each with its own advantages/ disadvantages:

Supply method	Advantages	Disadvantages
A data frame as parameter `meteo`	Efficient both computationally and memory-wise	Assumes weather is spatially constant
A column `meteo` in `sf` objects	Allows a different weather forcing for each spatial unit	The resulting `sf` is often huge in memory requirements
An interpolator object of class `stars` (or a list of them) as issued from package **meteoland**	More efficient in terms of memory usage	Weather interpolation is performed during simulations, which entails some computational burden

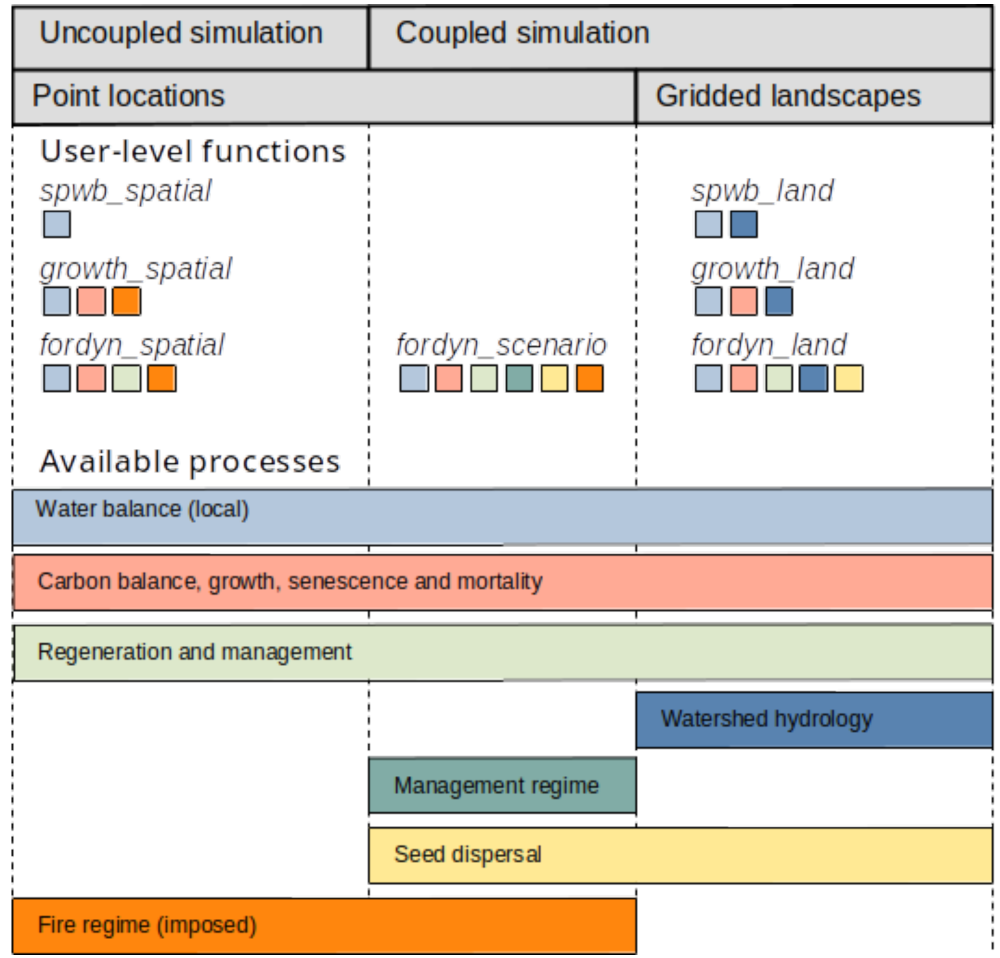
Tip

- If a list of interpolator objects is supplied, each of the interpolators should correspond to a different, consecutive, non-overlapping time period (e.g. 5-year periods).
- Taken together, the interpolators should cover the simulated target period.
- The simulation function will use the correct interpolator for each target date.

2. Spatially-uncoupled simulations

Spatially-uncoupled simulations

- Spatially-uncoupled simulations are those where simulations in different stands are completely independent.
- This situation is where *parallelization* is more advantageous.
- Following the nested models of **medfate**, **medfateland** offers functions `spwb_spatial()`, `growth_spatial()` and `fordyn_spatial()` for uncoupled simulations [1].



1. Three different kinds of scenarios are allowed in `create_management_scenario()`, two of them being demand-based

Running spatially-uncoupled simulations

Since it builds on **medfate**, simulations using **medfateland** require *species parameters* and *control parameters* for local simulations:

```r
data("SpParamsMED")
local_control <- defaultControl()
```

We can specify the target simulation period as a vector of `Date` or subset the target plots:

```r
dates <- seq(as.Date("2001-01-01"), as.Date("2001-01-31"), by="day")
example_subset <- example_ifn[1:5, ]
```

If we are interested in water (or energy) balance, we can use function `spwb_spatial()` as follows:

```r
res <- spwb_spatial(example_subset, SpParamsMED, examplemeteo,
                    dates = dates, local_control = local_control)
```

The output is an `sf` object as well, where column `result` contains the results of calling `spwb()` and column `state` contains the final status of `spwbInput` objects:

```
Simple feature collection with 5 features and 3 fields
Geometry type: POINT
Dimension:     XY
Bounding box:  xmin: 1.828998 ymin: 41.98704 xmax: 2.142714 ymax: 41.99881
Geodetic CRS:  WGS 84
# A tibble: 5 × 4
             geometry id        state           result
          <POINT [°]> <chr>     <list>          <list>
1 (2.130641 41.99872) 081015_A1 <spwbInpt [19]> <spwb [10]>
2 (2.142714 41.99881) 081016_A1 <spwbInpt [19]> <spwb [10]>
3 (1.828998 41.98704) 081018_A1 <spwbInpt [19]> <spwb [10]>
4 (1.841068 41.98716) 081019_A1 <spwbInpt [19]> <spwb [10]>
5 (1.853138 41.98728) 081020_A1 <spwbInpt [19]> <spwb [10]>
```

Using summary functions (1)

Simulations with **medfate** can generate a lot of output. This can be reduced using `control` parameter, but simulation output with **medfateland** can require a lot of memory.

To save memory, it is possible to generate temporal summaries automatically after the simulation of each target forest stand, and avoid storing the full output of the simulation function (using `keep_results = FALSE`).

The key element here is the **summary function** (and possibly, its parameters), which needs to be defined and supplied.

In the following call to `spwb_spatial()` we provide the summary function for `spwb` objects available in **medfate**:

```
res_2 <- spwb_spatial(example_subset, SpParamsMED, examplemeteo,
                      dates = dates, local_control = local_control,
                      keep_results = FALSE,
                      summary_function = summary.spwb, summary_arguments = list(freq="months"))
res_2
```

```
Simple feature collection with 5 features and 4 fields
Geometry type: POINT
Dimension:     XY
Bounding box:  xmin: 1.828998 ymin: 41.98704 xmax: 2.142714 ymax: 41.99881
Geodetic CRS:  WGS 84
# A tibble: 5 × 5
             geometry id        state           result summary
          <POINT [°]> <chr>     <list>          <list> <list>
1 (2.130641 41.99872) 081015_A1 <spwbInpt [19]> <NULL> <dbl [1 × 19]>
2 (2.142714 41.99881) 081016_A1 <spwbInpt [19]> <NULL> <dbl [1 × 19]>
3 (1.828998 41.98704) 081018_A1 <spwbInpt [19]> <NULL> <dbl [1 × 19]>
4 (1.841068 41.98716) 081019_A1 <spwbInpt [19]> <NULL> <dbl [1 × 19]>
5 (1.853138 41.98728) 081020_A1 <spwbInpt [19]> <NULL> <dbl [1 × 19]>
```

Using summary functions (2)

We can access the simulation summary for the first stand using:

```
res_2$summary[[1]]
```

```
                PET Precipitation     Rain     Snow  NetRain Snowmelt
2001-01-01 31.14173      74.74949 58.09884 16.65065 40.91681 13.09301
           Infiltration InfiltrationExcess SaturationExcess Runoff DeepDrainage
2001-01-01     54.00981                  0                0      0     32.61347
           CapillarityRise Evapotranspiration Interception SoilEvaporation
2001-01-01               0           30.34032     17.18203        5.405063
           HerbTranspiration PlantExtraction Transpiration
2001-01-01                 0        7.753223      7.753223
           HydraulicRedistribution
2001-01-01              0.01133329
```

Summaries can be generated *a posteriori* for a given simulation, using function `simulation_summary()`, e.g.:

```
simulation_summary(res, summary_function = summary.spwb, freq="months")
```

```
Simple feature collection with 5 features and 2 fields
Geometry type: POINT
Dimension:     XY
Bounding box:  xmin: 1.828998 ymin: 41.98704 xmax: 2.142714 ymax: 41.99881
Geodetic CRS:  WGS 84
# A tibble: 5 × 3
             geometry id         summary
          <POINT [°]> <chr>      <list>
1 (2.130641 41.99872) 081015_A1 <dbl [1 × 19]>
2 (2.142714 41.99881) 081016_A1 <dbl [1 × 19]>
3 (1.828998 41.98704) 081018_A1 <dbl [1 × 19]>
4 (1.841068 41.98716) 081019_A1 <dbl [1 × 19]>
5 (1.853138 41.98728) 081020_A1 <dbl [1 × 19]>
```

Tip

Learning how to define summary functions is a good investment when using **medfateland**.

Continuing a previous simulation

The result of a simulation includes an element `state`, which stores the state of soil and stand variables at the end of the simulation. This information can be used to perform a new simulation from the point where the first one ended.

In order to do so, we need to update the state variables in spatial object with their values at the end of the simulation, using function `update_landscape()`:

```r
example_mod <- update_landscape(example_subset, res)
example_mod
```

```
Simple feature collection with 5 features and 8 fields
Geometry type: POINT
Dimension:     XY
Bounding box:  xmin: 1.828998 ymin: 41.98704 xmax: 2.142714 ymax: 41.99881
Geodetic CRS:  WGS 84
# A tibble: 5 × 9
                 geom id        elevation slope aspect land_cover_type soil
          <POINT [°]> <chr>         <dbl> <dbl>  <dbl> <chr>           <list>
1 (2.130641 41.99872) 081015_A1       680  7.73  281.  wildland        <soil>
2 (2.142714 41.99881) 081016_A1       736 15.6   212.  wildland        <soil>
3 (1.828998 41.98704) 081018_A1       532 17.6   291.  wildland        <soil>
4 (1.841068 41.98716) 081019_A1       581  4.79  174.  wildland        <soil>
5 (1.853138 41.98728) 081020_A1       613  4.76   36.9 wildland        <soil>
# ℹ 2 more variables: forest <list>, state <list>
```

Note that `example_mod` contains a new column `state` with initialized inputs.

Finally, we can call again the simulation function for a new consecutive time period:

```r
dates <- seq(as.Date("2001-02-01"), as.Date("2001-02-28"), by="day")
res_3 <- spwb_spatial(example_mod, SpParamsMED, examplemeteo,
                      dates = dates, local_control = local_control)
```

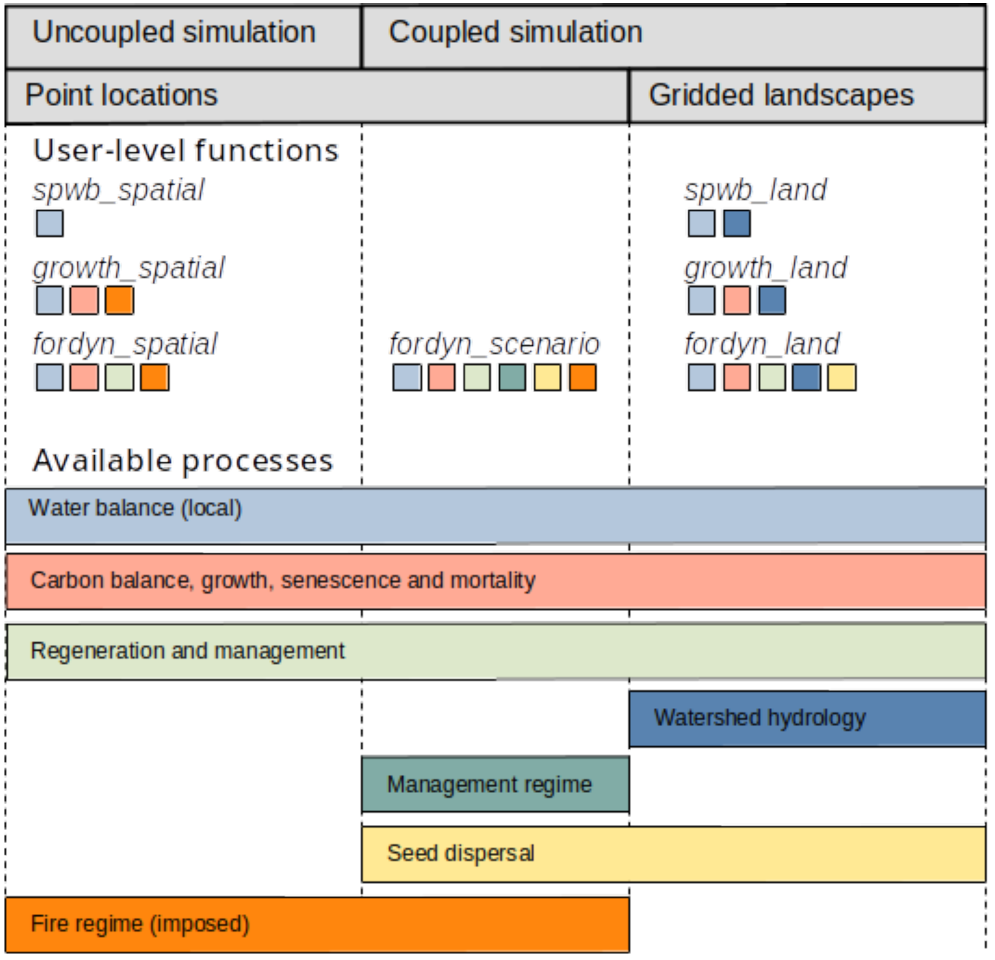
Important

Function `update_landscape()` will also modify column `soil`.

3. Regional management scenarios

`fordyn_spatial()` *vs* `fordyn_scenario()`

- Function `fordyn_spatial()` allows running simulations of forest dynamics for a set of forest stands, possibly including forest management and stand-specific silviculture prescriptions.
- However, in `fordyn_spatial()` simulated stand dynamics are **uncoupled**.
- Function `fordyn_scenario()` allows simulating forest dynamics on a set of forest stands while evaluating a demand-based **management scenario**.
- Considering the management scenario leads to a relationship in the management actions on forest stands, hence **coupling simulations**.
- Running management scenarios is a complex task, we will cover all details in this tutorial.



Management units and prescriptions (1)

Management scenarios require classifying forest stands into **management units**. Each management unit can be interpreted as a set of stands that are managed following the same prescriptions.

Management units can be arbitrarily defined, but here we will define them on the basis of **dominant tree species**.

The following code allows determining the dominant tree species in each of the 5 forest stands:

```
example_subset$dominant_tree_species <- sapply(example_subset$forest,
                                               stand_dominantTreeSpecies, SpParamsMED)
example_subset$dominant_tree_species
```

```
[1] "Pinus sylvestris"  "Pinus sylvestris"  "Quercus pubescens"
[4] "Quercus ilex"      "Quercus faginea"
```

The package includes a table with **default prescription parameters** for a set of species, whose columns are management parameters:

```
names(defaultPrescriptionsBySpecies)
```

```
 [1] "Name"                 "SpIndex"              "type"
 [4] "targetTreeSpecies"    "thinning"             "thinningMetric"
 [7] "thinningThreshold"    "thinningPerc"         "minThinningInterval"
[10] "yearsSinceThinning"   "finalMeanDBH"         "finalPerc"
[13] "finalPreviousStage"   "finalYearsBetweenCuts" "finalYearsToCut"
[16] "plantingSpecies"      "plantingDBH"          "plantingHeight"
[19] "plantingDensity"      "understoryMaximumCover"
```

whereas the rows correspond to species or species groups, whose names are:

```
head(defaultPrescriptionsBySpecies$Name)
```

```
[1] "Abies/Picea/Pseudotsuga spp." "Betula/Acer spp."
[3] "Castanea sativa"              "Eucalyptus spp."
[5] "Fagus sylvatica"              "Fraxinus spp."
```

Management units and prescriptions (2)

To specify the management unit for stands, we first define a column management_unit with missing values:

```
example_subset$management_unit <- NA
```

and then assign the corresponding row number of `defaultPrescriptionsBySpecies` for stands dominated by each species where management is to be conducted:

```
example_subset$management_unit[example_subset$dominant_tree_species=="Pinus sylvestris"] <- 14
example_subset$management_unit[example_subset$dominant_tree_species=="Quercus ilex"] <- 19
example_subset$management_unit[example_subset$dominant_tree_species=="Quercus pubescens"] <- 23
example_subset[,c("id", "dominant_tree_species", "management_unit")]
```

```
Simple feature collection with 5 features and 3 fields
Geometry type: POINT
Dimension:     XY
Bounding box:  xmin: 1.828998 ymin: 41.98704 xmax: 2.142714 ymax: 41.99881
Geodetic CRS:  WGS 84
# A tibble: 5 × 4
  id        dominant_tree_species management_unit                geom
  <chr>     <chr>                           <dbl>         <POINT [°]>
1 081015_A1 Pinus sylvestris                   14 (2.130641 41.99872)
2 081016_A1 Pinus sylvestris                   14 (2.142714 41.99881)
3 081018_A1 Quercus pubescens                  23 (1.828998 41.98704)
4 081019_A1 Quercus ilex                       19 (1.841068 41.98716)
5 081020_A1 Quercus faginea                    NA (1.853138 41.98728)
```

In this example stands dominated by *Quercus faginea* are not harvested.

Management scenarios and represented area

Management scenarios

Management scenarios are defined using function `create_management_scenario()` [1].

Demand-based management scenarios require specifying the demand in annual volume [2].

```
scen <- create_management_scenario(units = defaultPrescriptionsBySpecies,
                                   annual_demand_by_species = c("Quercus ilex/Quercus pubescens" = 1300,
                                                                "Pinus sylvestris" = 500))
```

Note that in this case the timber obtained from *Q. ilex* or *Q. pubescens* will be subtracted from the same annual demand.

We can check the kind of management scenario using:

```
scen$scenario_type
```

```
[1] "input_demand"
```

Represented area

Finally, it is necessary to specify the area (in ha) that each forest stand represents, because all timber volumes are defined at the stand level in units of **m3/ha**, whereas the demand is in units of **m3/yr**.

In our example, we will assume a constant area of 100 ha for all stands:

```
example_subset$represented_area_ha <- 100
```

1. Three different kinds of scenarios are allowed in `create_management_scenario()`, two of them being demand-based.
2. The fact that demand is specified in volume entails that simulations need to be able to estimate timber volume for any given tree. In practice, this requ
specifying a **volume_function**. See `fordyn_scenario` for details.

Launching simulations

We are now ready to launch the simulation of the management scenario using a call to function `fordyn_scenario()`.

```
fs <- fordyn_scenario(example_subset, SpParamsMED, meteo = examplemeteo,
                      management_scenario = scen,
                      parallelize = TRUE)
```

Tip

We will often set `parallelize = TRUE` to speed-up calculations (`fordyn_scenario()` makes internall calls to `fordyn_spatial()` for each simulated year).

Function `fordyn_scenario()` returns a list whose elements are:

```
names(fs)
```

```
[1] "result_sf"               "result_volumes"          "result_volumes_spp"
[4] "result_volumes_demand" "next_demand"             "next_sf"
```

Stand-level results are available in element `result_sf`, whose columns should be easy to interpret if you have experience with `fordyn()`:

```
fs$result_sf
```

```
Simple feature collection with 5 features and 8 fields
Geometry type: POINT
Dimension:     XY
Bounding box:  xmin: 1.828998 ymin: 41.98704 xmax: 2.142714 ymax: 41.99881
Geodetic CRS:  WGS 84
# A tibble: 5 × 9
             geometry id        tree_table          shrub_table dead_tree_table
          <POINT [°]> <chr>     <list>              <list>      <list>
1 (2.130641 41.99872) 081015_A1 <tibble [48 × 11]> <tibble>    <tibble>
2 (2.142714 41.99881) 081016_A1 <tibble [30 × 11]> <tibble>    <tibble>
3 (1.828998 41.98704) 081018_A1 <tibble [2 × 11]>  <tibble>    <tibble [1 × 14]>
4 (1.841068 41.98716) 081019_A1 <tibble [2 × 11]>  <tibble>    <tibble [1 × 14]>
5 (1.853138 41.98728) 081020_A1 <tibble [4 × 11]>  <tibble>    <tibble [2 × 14]>
# ℹ 4 more variables: dead_shrub_table <list>, cut_tree_table <list>,
#   cut_shrub_table <list>, summary <list>
```

4. Watershed-level simulations

SS

M.C. Escher - Belvedere, 1958