Simulating the cost effectiveness of controlled burning with the decisionSupport R package

Illustrative example by Cory Whitney and Eike Luedeling, University of Bonn, Germany

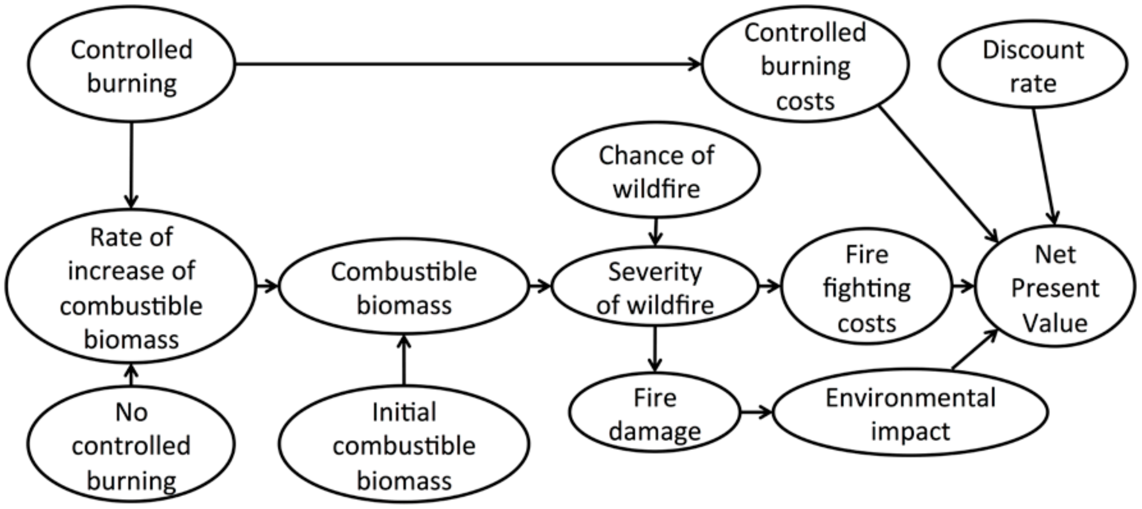
The decisionSupport package

Decision-makers often wish to have a quantitative basis for their decisions, but many variables they have to consider cannot be precisely quantified, at least not without unreasonable effort. The major objective of (prescriptive) decision analysis is to support decision-making processes faced with this problem (Luedeling and Shepherd, 2016). Decision analysis can make forecasts of decision outcomes without precise numbers, as long as probability distributions describing the possible values for all variables can be estimated. The decisionSupport package (Luedeling and Göhring, 2017) implements this as a Monte Carlo simulation, which generates a large number of plausible system outcomes, based on random numbers for each input variable that are drawn from user-specified probability distributions. It also conducts a sensitivity analysis (based on Projection-to-Latent-Structures regression) to highlight uncertain variables that have large impacts on model outputs (Luedeling and Gassner, 2012; Wold et al., 2001). If the distribution of predicted system outcomes doesn't imply a clearly preferable decision option, these variables can then be targeted by decision-supporting research (Luedeling et al., 2015).

Example – Controlled burning for ecological conservation in forests of the American West

The ecology of the conifer forests of the American west is largely shaped by wildfires. Many ecologists recommend regular and low-intensity burns to manage the build-up of combustible understory materials (shrubs, fallen branches). Not all municipalities or regions implement these practices. Failure to follow recommended controlled burning may lead to the build-up of fire stock and increase the frequency and severity of large wildfires. Such fires have destroyed many western ecosystems in the recent past.

The code provided simulates the decision of forest managers to use controlled fires in conifer forests vs. running the risk of severe fire. This is done through the use of a Monte Carlo analysis with 10,000 model runs based on probability distributions for all uncertain variables. These distributions aim to represent the full range of possible values for each component of the model. For example, the cost of controlled burning may vary greatly with remoteness and topography of forests. Also the frequency at which these controlled fires are necessary may vary with weather events such as storms and droughts. There is often no 'hard data' for many such variables, which can paralyze the decision-making processes or lead decision-makers to conclude that large research efforts are needed, before a decision can be made. The decisionSupport package allows simulation of the costs and benefits of complex decisions based on the full range of values deemed plausible for all variables. This is useful for determining whether a clearly preferable course of action can already be delineated based on the present state of knowledge. It also allows identifying key uncertainties that should be reduced by decision-supporting research.



Graphic illustrating the decision to apply controlled burning management or not.

The decisionSupport function in the package requires two inputs:

1) a data table (.csv format) specifying the names and distributions for all uncertain variables
2) an R function that predicts decision outcomes based on the variables named in the data table

For this example, both inputs are provided to illustrate the process. Usually, data table and model have to be customized to fit the particulars of a specific decision.

The data table

The data table (wildfire_input_table.csv) contains all variables used in the model. Their distributions are described by a 90% confidence interval, which is specified by lower (5% quantile) and upper (95% quantile) bounds, as well as the shape of the distribution. This example uses four different distributions:

1) const – a constant value (not really a distribution)
2) norm – a normal distribution

3) tnorm_0_1 – a truncated normal distribution that can only have values between 0 and 1 (useful for probabilities; note that 0 and 1, as well as numbers outside this interval are not permitted as inputs)
4) posnorm – a normal distribution truncated at 0 (only positive values allowed)

For a full list of possible distributions, type '`?random.estimate1d`' in R. When specifying confidence intervals for truncated distributions, note that approximately 5% of the random values should 'fit' within the truncation interval on either side. If there isn't enough space, the function will generate a warning (usually it will still work, but the inputs may not look like you intended them to).

Default distributions are provided for all variables, but feel free to make adjustments by editing the .csv file in a spreadsheet program.

The decision model

Before you start developing the decision model, open R and download and load the decisionSupport package (version >1.102).

```
install.packages("decisionSupport")
library(decisionSupport)
```

You could simply start developing the decision model now, but since the model function will be designed to make use of variables provided to it externally (random numbers drawn according to the information in the data table), you'll need to define sample values for all variables, if you want to test pieces of the code during the development process. This can be done manually, but it is more easily accomplished with the following helper function '`make_variables`':

```
make_variables<-function(est,n=1)
{ x<-random(rho=est, n=n)
    for(i in colnames(x)) assign(i,
     as.numeric(x[1,i]),envir=.GlobalEnv)
}
```

(This function isn't included in the decisionSupport package, because it places the desired variables in the global environment. This isn't allowed for functions included in packages on R's download servers.)

Applying `make_variables` to the data table (with default setting `n=1`) generates one random number for each variable, which then allows you to easily test code you're developing:

```
filepath<-[folder, where the 'wildfire_input_table.csv' file is saved]
```

```
make_variables(estimate_read_csv(paste(filepath,
  "wildfire_input_table.csv",sep="")))
```

You can now start developing the model, which has to be designed as a function for R, with the two arguments `x` and `varnames`, as well as a (named or unnamed) list of numbers as output:

```
[YOUR_MODEL]<-function(x,varnames)
{
[freely programmable content, relying only on inputs specified in the
data table]
return(list([OUTPUTS]))
}
```

Below is an example model to calculate the Net Present Value (NPV) for the decision to manage forests with controlled burns:

```
controlled_burning<-function(x, varnames)
{
 #simulate occurrence of fire (random event)
  fire<-chance_event(fire_risk,value_if=1,n=n_years)
 #set up time series vectors with one value for each simulation year
  severe_fire_contr_burn<-rep(0,n_years)
  severe_fire_no_burn<-rep(0,n_years)
  env_imp_contr_burn<-rep(0,n_years)
  env_imp_no_burn<-rep(0,n_years)
  fire_fighting_cost_contr_burn<-rep(0,n_years)
  fire_fighting_cost_no_burn<-rep(0,n_years)

 #simulate occurrence of controlled burns (random event)
  controlled_burns<-chance_event(controlled_burning_frequency,
    value_if=1,n=n_years)

 #calculate the change in the initial combustible biomass (Mg/ha)
  biomass_contr_burn<-initial_biomass
  biomass_no_burn<-initial_biomass

  for(y in 2:n_years) #for all years but year one
   {
    if(controlled_burns[y])
     biomass_contr_burn[y]<-biomass_after_burning*(1+
      biomass_accumulation_rate_with_controlled_burning/100) else
       biomass_contr_burn[y]<-biomass_contr_burn[y-1]*
        (1+biomass_accumulation_rate_with_controlled_burning/100)
    biomass_no_burn[y]<-biomass_no_burn[y-1]*
     (1+biomass_accumulation_rate_without_controlled_burning/100)

 #calculate the severity and impact of fire
    if(fire[y])
```

```
       {
#calculate when the accumulated combustible biomass (Mg/ha) that leads
# to severe fire is surpassed
         if(biomass_contr_burn[y]>severity_threshold)
           severe_fire_contr_burn[y]<-1
         if(biomass_no_burn[y]>severity_threshold)
           severe_fire_no_burn[y]<-1

#calculate the combustible biomass (Mg/ha) after a fire in a forest
# with controlled burning
         if(severe_fire_contr_burn[y])
          biomass_contr_burn[y]<-biomass_after_severe_fire else
           biomass_contr_burn[y]<-biomass_after_mild_fire

#calculate the combustible biomass (Mg/ha) after a fire in a forest
# without controlled burning
         if(severe_fire_no_burn[y])
          biomass_no_burn[y]<-biomass_after_severe_fire else
           biomass_no_burn[y]<-biomass_after_mild_fire

#calculate the environmental impact (USD) after a fire in a forest
# with controlled burning
         if(severe_fire_contr_burn[y])
          env_imp_contr_burn[y]<-env_imp_severe_fire else
           env_imp_contr_burn[y]<-env_imp_mild_fire

#calculate the cost of wildfire (USD) in a forest with controlled
# burning
         if(severe_fire_contr_burn[y])
          fire_fighting_cost_contr_burn[y]<-
            fire_fighting_cost_severe_fire else
          fire_fighting_cost_contr_burn[y]<-
            fire_fighting_cost_mild_fire

#calculate the environmental impact (USD) after a fire in a forest
# without controlled burning
         if(severe_fire_no_burn[y])
          env_imp_no_burn[y]<-env_imp_severe_fire else
           env_imp_no_burn[y]<-env_imp_mild_fire

#calculate the cost of wildfire (USD) in a forest without controlled
# burning
         if(severe_fire_no_burn[y])
          fire_fighting_cost_no_burn[y]<-
            fire_fighting_cost_severe_fire else
          fire_fighting_cost_no_burn[y]<-
            fire_fighting_cost_mild_fire

       } #end of simulating severity and cost of fire
 } #end of year loop
```

```
#calculate the cost (USD) of forest management through
# controlled burning and without controlled burning
 costs_contr_burn<-
   cost_of_controlled_burning*controlled_burns+
     fire_fighting_cost_contr_burn
 costs_no_burn<-fire_fighting_cost_no_burn

#calculate the bottom-line (USD) for forest management
# through controlled burning and without controlled burning
 bottomline_contr_burn<-(-costs_contr_burn-env_imp_contr_burn)
 bottomline_no_burn<-(-costs_no_burn-env_imp_no_burn)

#calculate the benefit of controlled burning over no
# controlled burning
 benefit_of_controlled_burning<-
   bottomline_contr_burn-bottomline_no_burn

#calculate the Net Present Value (NPV) for forest management
# with controlled burning
 NPV_controlled_burning<-
  discount(benefit_of_controlled_burning,discount_rate=discount_rate,
    calculate_NPV=TRUE)

 return(list(NPV_controlled_burning=NPV_controlled_burning))

}
```

Note that this model uses two ‘helper functions’ included in the decisionSupport package:

1) `chance_event` for determining whether an event occurs or not based on a specified probability
2) `discount` for adjusting net benefits for time preference (a standard economic practice). With the attribute `calculate_NPV`, the function automatically calculates the Net Present Value (the sum of discounted values)

Perform the Monte Carlo simulation with 10,000 model runs:

```
decisionSupport(
  inputFilePath=paste(filepath,"wildfire_input_table.csv",
   sep=""),
  outputPath=paste(filepath,"MCResults",sep=""),
  write_table=TRUE,
  welfareFunction=controlled_burning,
  numberOfModelRuns=10000,
  functionSyntax="plainNames"
)
```

```
#the arguments are the following:
# inputFilePath = input file with estimates
# outputPath = output folder
# write_table = specifies whether all outputs should be saved as
a table
# welfareFunction = the decision model function
# numberOfModelRuns = the number of model runs for the Monte
#   Carlo simulation
# functionSyntax = technical parameter that allows specifying
#   variables simply by the names given in the data table
#   (otherwise a notation like x$[variable_name] would be needed)
```

This function produces a table of all inputs and outputs of the 10,000 model runs (`mcSimulationResults.csv`; only if `write_table=TRUE`), as well as two outputs for each model output variable:

1) a histogram showing all 10,000 output values
2) a variable-importance-plot that illustrates the sensitivity of model outputs to variation in each input variable (this is derived by statistically relating outputs to inputs using Projection-to-Latent-Structures (PLS) regression; results are also saved in a table)

All results are stored in the folder specified by `outputPath`. The two summary tables '`mcSummary.csv`' and '`welfareDecisionSummary.csv`' provide summaries of the results shown in the histogram.

References

Luedeling, E. and Gassner, A., 2012. Partial Least Squares regression for analyzing walnut phenology in California. Agricultural and Forest Meteorology, 158: 43-52.

Luedeling, E. and Göhring, L., 2017. decisionSupport: Quantitative Support of Decision Making under Uncertainty, CRAN archive; https://cran.r-project.org/web/packages/decisionSupport/.

Luedeling, E. et al., 2015. Fresh groundwater for Wajir – ex-ante assessment of uncertain benefits for multiple stakeholders in a water supply project in Northern Kenya. Frontiers in Environmental Science, 3: Article 16, 1-18.

Luedeling, E. and Shepherd, K., 2016. Decision-focused agricultural research. Solutions, 7(5): 46-54.

Wold, S., Sjostrom, M. and Eriksson, L., 2001. PLS-regression: a basic tool of chemometrics. Chemom. Intell. Lab. Syst., 58(2): 109-130.