Hydrology-oriented forest management trade-offs. A modeling framework coupling field data, simulation results and Bayesian Networks

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Abstract

Hydrology-oriented forest management sets water as key factor of the forest management for adaptation due to water is the most limiting factor in the Mediterranean forest ecosystems. The aim of this study was to apply Bayesian Network modeling to assess potential indirect effects and trade-offs when hydrology-oriented forest management is applied to a real Mediterranean forest ecosystem. Water, carbon and nitrogen cycles, and forest fire risk were included in the modeling framework. Field data from experimental plots were employed to calibrate and validate the mechanistic Biome-BGCMuSo model that simulates the storage and flux of water, carbon, and nitrogen between the ecosystem and the atmosphere. Many other 50-year long scenarios with different conditions to the ones measured in the field experiment were simulated and the outcomes employed to build the Bayesian Network in a linked chain of models. Hydrology-oriented forest management was very positive insofar as more water was made available to the stand because of an interception reduction. This resource was made available to the stand, which increased the evapotranspiration and its components, the soil water content and a slightly increase of deep percolation. Conversely, Stemflow was drastically reduced. No effect was observed on Runof due to the thinning treatment. The soil organic carbon content was also increased which in turn caused a greater respiration. The long-term effect of the thinning treatment on the LAI was very positive. This was undoubtedly due to the increased vigor

generated by the greater availability of water and nutrients for the stand and the reduction of competence between trees. This greater activity resulted in an increase in GPP and vegetation carbon, and therefore, we would expect a higher carbon sequestration. Itis worth emphasizing that this extra amount of water and nutrients was taken up by the stand and did not entail any loss of nutrients.

Keywords: Hydrology-oriented forest management, Bayesian Network modeling, Biome-BGCMuSo model.

1. Introduction

One important objective of adaptive forest management is to reduce the climate-related vulnerabilities of forests (Fitzgerald et al., 2013), through tree and stand resilience against droughts, maintaining site productivity, reducing forest fire risk, enhancing soil water content and increasing the blue (water available for distribution to adjacent ecosystems, groundwater or surface water pathways, represented as runoff and deep percolation or groundwater recharge) /green water (evapotranspiration) ratio.

An in-depth review of the research effort carried out over the last 40 years aiming to assess the relationship between forests and water around the world (e.g. Levia et al., 2011 review) has demonstrated that forest management can modify water yields (Webb et al., 2012). In semi-arid areas water is the most limiting factor, and therefore, the water cycle is controlled by the canopy cover (Bargués Tobella et al., 2014). But it has been also demonstrated that forest and water interactions are very complex (Garcia-Prats et al., 2016). Related to this last effect, Molina and Del Campo (2012) coined the term *Hydrology-Oriented Silviculture* to bear on the particular case that forest management aims to quantify and manipulate the water cycle components in forests according to specific objectives. The effect of forest management on water issues in semi-arid regions like the Mediterranean basin has been emphasized elsewhere (Ungar et al., 2013). In these areas, adaptive management might be focused on addressing how the physical structure of the forest can be modified in order to optimize a particular water cycle component (rainfall interception, throughfall, transpiration, run-off, soil moisture and deep infiltration) (Ungar et al. 2013).

Villà-Cabrera et al. (2018) reviewed 239 case studies of forest management strategies for adaptation to climate change published in scientific papers until 2015. They built a theoretical framework based on 5 different strategies: i) Reduction of stand density, ii) Management of understory, iii) Promoting mixed forests, iv) Changing species, and v) Promoting spatial heterogeneity at the landscape scale. They pointed out that all those case studies demonstrated the validity of each strategy enhancing the capacity of adaptation, but at the same time, did not address other trade-offs or indirect effects that may reduce the ecosystem benefit of the management strategy.

Thus, although the targets and methods -management strategies- on the basis of the Hydrology-Oriented Silviculture in the Mediterranean area are well known (Molina and del Campo, 2012), it is no less true that could have indirect effects, both positive and negative ones, and then, trade-offs could arise. The maintenance of the chemical, biological and physical properties and processes of soils have to be accounted for in sustainable forest management (Wic Baena et al., 2013; Bastida et al., 2017). We might think that after the disturbance involved in a thinning treatment, soil organic carbon stock -usually high and in equilibrium in a natural forest ecosystems- could diminish because of the removal of certain amounts of biomass and timber (Jandl et al., 2007; Diochon et al., 2009; Nave et al., 2010). However, there are studies indicating that historic changes in forest management had not perceptible effects on forest soil organic carbon content (Wäldchen et al., 2013). On the other hand, the nitrogen cycle may be also affected —and enhanced— by forest management (Overby et al., 2015; Johnson et al., 2016; Hume et al., 2018). Because of these potential effects, hydrological-based forest management must target and address both soil and biogeochemical issues as well (Del Campo et al., 2017).

Changes in forest structure due to partial removal of the forest canopy are also a fire preventive silviculture inasmuch as it breaks the fuel continuity and reduces its availability. Thus, the reduction of fire risk through forest treatments should be quantified in order to provide a more comprehensive understanding of the effects of adaptive forest management on promoting enhanced resilience (Garcia-Prats et al., 2015).

With all those considerations in mind, we need a tool capable to cope with complex and uncertain relationships among variables involved in forest ecosystems management. A Bayesian Network (BN) is a probabilistic graphical model in which the nodes of the graph are random variables and the edges between the nodes represent probabilistic dependencies among them. Structured analysis of complex systems is the main scope of Bayesian Networks (BNs) (van Dam et al., 2013). BNs can be used to represent the uncertainty underlying the current understanding and variability in ecosystem response (Perez-Miñana, 2016). BNs are suitable to handle with problems that involve high levels of uncertainty and complexity due to its capacity to integrate different domains of knowledge (Perez-Miñana, 2016; Phan et al., 2016; Molina et al., 2013; Aguilera et al., 2011). Thus, BNs are well suited to include modelling results, expert knowledge and experimental field data into a single framework. This tool allows for investigating the impacts of management options through analysis of scenarios, assessing the consequences of management hypothesis or potential actions (Perez-Miñana, 2016). Many recent efforts can be found in the literature on solving complex problems in the field of ecohydrology (Woznicki et al., 2015), water resources (Xue et al., 2017), groundwater management (Martín de Santa Olalla et al., 2007), forestry (Nyberg et al., 2006), irrigation and farming (Wang et al., 2009), climate change (Molina et al., 2013), biosecurity (Lohr et al., 2017), public health (Beaudequin et al., 2016) -and many others-, using BNs. Of special interest some systematic reviews: Aguilera et al. (2011) classified 128 case studies by fields. Phan et al., (2016) analyzed 111 case studies in the field of water resources, and Perez-Miñana (2016) compared capacities of six BN existing tools.

The objective of this paper was to apply Bayesian network modeling to assess potential indirect effects and possible trade-offs when Hydrology-Oriented forest management is applied to a real Mediterranean forest ecosystem. Linking the intervention with those management strategies described in Vilà-Cabrera et al. (2018), in the experimental plots were reproduced both the first and second strategies in a single intervention: i) Reduction of stand density, and ii) management of understory (the most frequently silvicultural interventions employed according to the regional forest authority). In the future would be interesting to test the other strategies as well. Soil organic carbon and nitrogen cycles, forest fire risk and water cycle were included in the modeling framework to uncover hidden relationships or associations between factors. Field data from experimental plots where Hydrology-Oriented silvicultural operations were applied and effects on soil, water and nutrients were monitored and employed to calibrate and validate Biome-BGCMuSo (Hidy et al., 2016). Biome-BGCMuSo is a mechanistic biogeochemical model that simulates the storage and flux of water, carbon, and nitrogen between the ecosystem and the atmosphere. In order to generate enough variability, the validated and calibrated model was employed to simulate many other scenarios with different conditions to the ones measured in the field experiment. Outcomes of simulated scenarios were employed to build the Bayesian Network in a linked chain of models (Couture et al., 2018). This method allows us to analyze the aforementioned effects in the long run, and not only the immediate effect of the silvicultural intervention recorded in the experimental dataset.

2. Material and Methods

2.1 Site description and experimental plots

Experimental plots involved in this work were implemented in a marginal oak forest located in the southwest of Valencia Region (Spain), at latitude 39º04'-N, longitude 1º14'-W and elevation 1080-1100 m a.s.l. (Figure 1). The slope of the plots was 31% with NW aspect. According to the historic meteorological dataset (1960-2011) recorded in a nearby station (located at 900 m a.s.l.) the mean annual temperature is 12.8 °C, the mean annual rainfall is 466 mm, the mean annual potential evapotranspiration is 749 mm (Thornthwaite), and the reference evapotranspiration is 1200 mm (Hargreaves). Soil depth ranged from 10 to 40 cm, loam textured and basic pH (8.0±0.1) were encountered. Underneath the soil, the karstified Jurassic limestone parent rock give rise to rocky soils with a high stones and rocks fraction ranging from 48 to 69% according to the depth. According to the WRB the soils of the area are classified as

Rendzic Leptosol and Litic Leptosol with outcrop of Chromic Luvisols and Kastanozem Calcic, identifying the soil of the plots as Kastanozem Calcic. Eight boreholes up to four meters depth were drilled along the experimental plots which revealed a huge degree of rock fissuring providing important reservoirs of deep water. The water table was no encountered within the 4 meters of the boreholes.

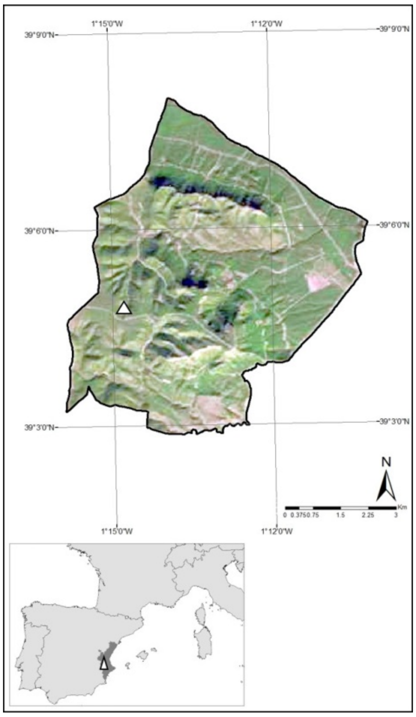


Figure 1. Experimental Site location

The stand was characterized as coppice oak forest with high stem densities consequence of the traditional fuelwood harvesting -abandoned in the seventies of the last century-, being the dominant species Holm oak (*Quercus ilex* subsp. ballota (Desf.) Samp.). Other species found were *Pinus halepensis, Juniperus phoenicea, Q. faginea, and J. oxycedrus.* Due to the fact that this stand play the role of marginal and protective forest, there has not been any silvicultural intervention since it was abandoned about 50 years ago.

In May 2012 a hydrology-oriented silvicultural intervention based on a thinning and scrub clearing took place with the following experimental design: two rectangular plots of 1800 m^2 each were delimited, the first one was treated and the second one acted out as control. Every plot was split into three replicates or blocks of similar size (no randomized layout). In the thinning treatment, about 2/3 of the initial standing trees with smaller diameter were removed besides most of the shrubs, being the final density about 317 trees·ha^{-1} and looking for the most homogeneous tree distribution and canopy cover. Initial canopy cover was about 63%, in the control plot, whilst the final canopy cover after the thinning treatment was reduced to about 40%. The thinning treatment was supervised by the forest service of the Valencia Region. Timber and coarse woody debris were removed outside the plots whereas fine woody debris was piled and grinded into mulch onto the plots.

With the aim of characterizing the stand structure, the following measures were taken within the six blocks: basal area (BA, in m^{2}·ha^{-1}), tree density (TD, in trees· ha^{-1}), diameter at basal and breast heights (DB, and DBH respectively, in cm) and its distribution by diametric classes, canopy cover (CC, in %) and leaf area index (LAI, in m^{2}·m^{-2}). The CC was measured by means a GRS densitometer with 50 readings per block. The LAI was seasonally measured in each block using a LI-COR LAI-2000 sensor. Further details about the methodology employed in the LAI measurement can be found in Molina and Del Campo, (2011). Table summarizes the characterization of the stand structure.

Table 1. Stand structure in control (C) and treated plot (T)

	DB (cm)	DBH (cm)	BA (m^{2}·ha^{-1})	TD (trees· ha^{-1})	CC (%)	LAI (m^{2}·m^{-2})
C	11.87±6.26	8.62±5.46	8.3	1020	62.7	1.1
T	18.09±8.51	14.18±7.14	5.22	317	39.3	0.6

Meteorological variables were registered on site using different instruments connected to a Campbell scientific CR1000 data-logger: Air temperature (Tmp, in ºC) and relative humidity (RH, in %) were recorded using a Decagon Devices Tmp/RH sensor located at 2 m abode ground. Precipitation (P, in mm) was continuously measured by means of a Davis tipping-bucket rain gauge with 0.2-mm resolution and located in an open area at 20 m apart from the experimental plots. Throughfall and Stemflow (Th, St, in mm) were measured using the methodology described in Molina and Del Campo (2012). Wind speed (V, in $m \cdot s^{-1}$) and wind direction were obtained from a Davis anemometer located in a mast above the canopy. Finally, shortwave radiation (Rs, in $MJ \cdot m^{-2} \cdot day^{-1}$) was measured using a Davis pyranometer. All meteorological variables were programmed to measure at 10-minute intervals and averaged on a daily basis.

Run-off was concentrated in a collecting trench at the lower boundary of the slope, piped and measured by means a Diehl Metering Altair v4 volumetric counter. Soil water content (SWC, in $m^3 \cdot m^{-3}$) was recorded using Decagon Devices EC-5 capacitance probes horizontally installed at 5, 15 and 30 cm depth. To deal with the heterogeneity usually involved in this type of measures, a total of 15 probes in the thinned plot a 15 probes in the control plot were installed. Gravimetric soil moisture was determined in different sampling dates ranging from field capacity (FC) to wilting point (WP) to carry out the calibration of the probes. The data-logger was programmed to measure at 10-minute intervals and records were averaged on a daily basis. With those daily values, the relative extractable water (REW) was computed after Chen et al. (2014) and Kumagai et al. (2004):

$$\mathrm{REW} = \frac{\mathrm{SWC} - \mathrm{SWC_{min}}}{\mathrm{SWC_{max}} - \mathrm{SWC_{min}}} \qquad (1)$$

Where SWC is the daily measure of soil water content and SWC_{min} and SWC_{max} are the minimum and maximum soil water content registered in the series.

Transpiration (T, in mm) was derived from measures of sap flow velocity. Sap flow velocity (Vs, in $cm \cdot h^{-1}$) was registered using the heat ratio method (Burguess et al., 2001) by means 14 ICT International sap flow sensors installed on the upslope side of the trunk, distributed proportionally within the different diameter classes. Sap flow was up-scaled by the density of trees to obtain the stand transpiration (T, mm) accounting for the tree diameter frequency distribution in both, thinned and control plots.

N mineralization was measured using the resin core method. Mineralization rates were determined by comparing concentrations in the resin cores after two-month field incubation to initial soil samples. Soil respiration was measured on a monthly basis using a PP System EGM-4 CO_2 gas analyzer.

Finally, aboveground biomass was obtained by means allometric models based on the stand characteristics previously described in Table 1. Wood samples were sent to the ionic laboratory for the carbon content test. They used a Leco SC-144DR for elemental analysis.

2.2 Biome-BGCMuSo calibration and validation using experimental data

The two-year period of experimental dataset (hydrological years 2012-2013 and 2013-2014) was employed to calibrate and validate the Biome-BGCMuSO model (Hidy et al., 2016). This model is an improved version of the previous Biome-BGC model (Thornton et al., 2002). The source code is publicly available on the Internet (NTSG 2001). The main model improvements especially relevant in this study are the soil layer sub-model, the drought effect on plant transpiration and functioning, and the management options where forest thinning is included. The model operates on a daily time step and describes the dynamics of energy, water, carbon and nitrogen in a defined terrestrial ecosystem. The model uses a scale of 1 m^2 and requires daily weather data, information about the general environment (soil, vegetation and site conditions) and parameters describing the eco-physiological characteristics of the vegetation understudy, such as specific leaf area, water interception coefficient or light extinction coefficient (see supplementary material).

Calibration was carried out using a two-stage procedure. First, automated model parameter estimation was conducted using PEST (model-independent parameter estimation program) (Doherty, 2007). PEST has implemented a variant of the Gauss-Marquardt-Levenberg method of nonlinear parameter estimation. PEST minimizes the weighted sum of squared residuals between observed and predicted values of the selected variables. In a second stage we repeatedly solved the forward problem with ad hoc adjustment of parameters until results match observations.

Calibration and validation periods were assessed separately. The model was first calibrated using the water year 2012-2013 field dataset from the not thinned plot (control), as it represents a mature and stable ecosystem. A set of eco-physiological parameters representative of such ecosystem were obtained. Subsequently, the thinned plot was simulated using the management options, particularly forest thinning, which was initiated over the calibrated model. Then, the model was validated by comparing simulated to observed field data, on the one hand the water year 2013-2014 for the control plot, and on the other hand, 2012-2014 for the thinned plot. The variables included in the calibration and validation procedure were: a) related to the water cycle, T and SWC; and b) related to the biochemical cycles (C and N), punctual field data of soil N mineralization, soil respiration and aboveground vegetation carbon.

A complete assessment of model performance should include at least one absolute error measure and one or several goodness-of-fit measurements (Legates and McCabe, 1999). For these reasons, the behaviour of the model was assessed using root mean square error (***RMSE)***, Index of agreement ***d*** (Willmott, 1981), Modified Index of agreement $\boldsymbol{d_1}$ (Willmott, 1984), $\boldsymbol{R^2}$ coefficient of determination, and the Nash-Sutcliffe modelling efficiency ***E*** (Nash and Sutcliffe, 1970).

2.3 Extended period Biome-BGCMuSo simulations

As we stated before, experimental data only cover a period of two years. This period is utterly insufficient to build a BN model directly from data, and only would include the experimental plots conditions. In order to generate enough variability for the overall variables included in the BN model, a sequence of 50 years for the all possible USDA-NRCS Hydrologic Soil Group (4 types) - Aspect (4 orientations) - Canopy Cover Treatment (1 original canopy cover + 5 thinning intensities) combinations described in Table 2 were simulated using the calibrated and validated Biome-BGCMuSo model. The final number of simulated scenarios was 4x4x5 = 80 for the thinning treatment experimental plot and 4x4x1=16 for the control plot. Due to the number of years within each simulation was 50, the total number of simulated years was 96x50 = 4800.

Table 2. USDA-NRCS Hydrologic Soil Group, Aspect and Canopy Cover simulated combinations.

EXPERIMENTAL PLOT	USDA-NRCS HYDROLOGIC SOIL GROUP	ASPECT	CANOPY COVER (%)
Control plot	A	NE	Original CC 63%
	B*	NW**	
	C	SE	
	D	SW	
Thinning treatment plot	A	NE	25% out 63% removed
	B*	NW**	35% out 63% removed
	C	SE	45% out 63% removed
	D	SW	55% out 63% removed
			65% out 63% removed

*Experimental plot soil group; **Experimental plot aspect

USDA-NRCS (1986, 2009) classified the overall textural classes into 4 Hydrologic Soil Groups (HSG) accounting for the potential run-off. The A group has the lower run-off potential and the higher infiltration rate, and the opposite properties for the D group. The original soil of the experimental plot was classified into the B group according to its texture. For the other three groups, an intermediate texture within each group was selected and employed in the simulations of Biome-BGCMuSo model. The hydraulic properties of each texture were derived from the pedotransfer functions of Saxton and Rawls (2006). Texture and hydraulic properties of each soil can be found in Table 3.

The way the plot is oriented really modify the amount of photosynthetically active radiation received, and therefore, both hydrological and biogeochemical cycle performances might be modified. That is why several aspects had to be simulated. Due to the fact that experimental plots were oriented to North West (NW), the other three perpendicular aspects were accounted for the simulations as well (NE = North East, SE = South East, SW = South West).

Table 3. Texture and hydraulic properties of each soil utilized in the simulations.

HYDROLOGIC SOIL GROUP	Textural Class	% Clay	% Sand	Wilting Point	Field Capacity	Saturation	Saturated Hydraulic Conductivity	Bulk Density ($g \cdot cm^{-3}$)
A	Loamy Sand	6	82	5.7	12.1	45.7	91.26	1.45
B*	Loam	23	44	15.4	28.5	45.4	12.50	1.44
C	Silty Clay Loam	34	10	21	37.9	51	5.93	1.30
D	Silty Clay	47	7	28.7	41.6	53.2	3.81	1.24

*Experimental plot soil group

2.4 Keetch and Byram Drought Index (KBDI)

There exists a wide variety of meteorological, drought and dryness indices employed as forest fire risk indices. The Keetch and Byram Drougth Index (Keetch and Byram, 1968) is an example of this. The importance and utility of those indices is proven insofar as they are integrated in the most important fire rating systems in the world (Canadian Forest Fire Danger Rating System, United States National Fire Danger Rating System, etc.). The KBDI calculates a daily simple water balance and accounts for cumulative soil water depletion due to the effects of evapotranspiration and precipitation on deep duff and upper soil layers. It ranges from 0 to 203.2 when rainfall is expressed in mm, (from 0 to 800 when is expressed in hundredths inches) from low to high fire risk or from no soil water depletion to very dry conditions.

García-Prats et al. (2015) demonstrated that the original version of the KBDI is not sensitive to forest management and is not capable to differentiate between managed and unmanaged forests. To avoid this trouble, they proposed to recalibrate the coefficients of the index specifically for each stand using series of measured soil moisture. This methodology was employed to obtain the forest fire risk on a daily basis in each Biome-BGCMuSo simulated scenario. Further details about the KBDI calculation can be found in García-Prats et al. (2015)

2.5 Bayesian Network Construction

All the steps of the BN construction and exploitation were developed using GeNIe Modeler v.2.2, available free of charge for academic research use from BayesFusion, LLC, under license from the University of Pittsburgh.

A Bayesian Network is a statistical graphic model with two components: i) A qualitative component -cause-effect diagram- defined by means of a directed acyclic graph (DAG). In this graph, each node represents one variable in the model, and each arc represents statistical dependence among linked variables. ii) A quantitative component defined by means the conditional probability tables –one per node- (CPT) quantifying the strength of the node dependency.

2.5.1 Data preprocessing

Quantitative data to apply the BN model was derived from the outputs of the aforementioned simulations using Biome-BGCMuSo. First of all, a qualitative statistical analysis including average, variance, standard deviation, maximum and minimum values, was developed in order to accept or reject the outputs of Biome-BGCMuSo. After that, 55% and 65% thinning treatment simulations were directly rejected for two reasons. On the one hand, the model outputs were no coherent (the forest directly died), and on the other hand, this silvicultural intervention intensity is far from what is usually done.

A few number of variables used in the BN construction were discrete variables (e.g. Aspect, HSG, Canopy Cover Treatment (CCT), etc.) However, most of the variables were continuous variables that had to be categorized. Continuous data were discretized in 5 states using a hierarchical procedure based on clustering. Table 3 summarized the list of variables included in the BN model, its states and units.

Table 3. List of variables, states, units and time-related information.

Name	States	Units	Observation
Aspect	NE, NW, SE, SW	-	-
Canopy Cover Treatment (CCT)	Control, Treatment25, 35, 45	-	Original Plot (Control) had a canopy cover of 63%. Each treatment indicate % of canopy removal out 63%.
Deep percolation	<48,48-143,143-234,234-396,>396	mm·year^{-1}	Daily values aggregated into 50 sum annual values
Evapotranspiration	<125,125-193,193-310,310-377,>377	mm·year^{-1}	Daily values aggregated into 50 sum annual values
Gross Primary Production (GPP)	<0.17,0.7-0.77,0.77-1.34,1.34-1.80,>1.80	kgC·m^{-2}·year^{-1}	Daily values aggregated into 50 sum annual values
Interception	<32,32-97,97-127,127-156,>156	mm·year^{-1}	Daily values aggregated into 50 sum annual values
KBDI	<167,167-330,330-488,488-629,629-715,>715	hundredths of Inch	Daily values aggregated into 50 maximum annual values
LAI	<0.22,0.22-1.46,1.46-2.25,2.25-3.13,>3.13	m^2·m^{-2}	Daily values aggregated into 50 average annual values
Minimum Soil Temperature	<1.15,1.15-2.68,2.68-3.88,3.88-4.89,>4.89	ºC	50 minimum annual values
N leaching	<0.02,0.02-0.05,0.05-0.09,0.09-0.15,>0.15	kgN·ha^{-1}·year^{-1}	Daily values aggregated into 50 average annual values
REW	<0.21,0.21-0.48,0.48-0.64,0.64-0.86,>0.86	-	Daily values aggregated into 50 average annual values
Rainfall	<321,321-366,366-433,433-473,>473	mm·year^{-1}	Daily values aggregated into 50 sum annual values
Runoff	<15,15-25,25-39,39-72,>72	mm·year^{-1}	Daily values aggregated into 50 sum annual values
Soil Organic Carbon	<1.91,1.91-2.54,2.54-3.21,3.21-3.63,>3.63	kgC·m^{-2}	Daily values aggregated into 50 average annual values
Soil Evaporation	<62,62-76,76-96,96-108,>108	mm·year^{-1}	Daily values aggregated into 50 sum annual values
Hydrologic Soil Group (HSG)	A,B,C,D	-	-
N Soil Mineralization	<1.95,1.95-5.61,5.61-7.53,7.53-10.22,>10.22	kgN·ha^{-1}·year^{-1}	Daily values aggregated into 50 average annual values
Soil Respiration	<0.19,0.19-0.56,0.56-0.75,0.75-1.02,>1.02	kgC·m^{-2}·year^{-1}	Daily values aggregated into 50 average annual values
Stemflow	<6,6-11,11-19,19-26,>26	mm·year^{-1}	Daily values aggregated into 50 sum annual values
Transpiration	<24,24-63,63-155,155-237,>237	mm·year^{-1}	Daily values aggregated into 50 sum annual values
Vegetation Carbon	<0.02,0.02-0.15,0.15-0.23,0.23-0.33,>0.33	kgC·m^{-2}	Daily values aggregated into 50 average annual values

2.5.2 Model Learning

The initial cause-effect DAG was derived from the aforementioned dataset using the *Essential Graph Search* structure learning algorithm, proposed by Dasch and Druzdzel (1999) implemented in GeNIe Modeler v2.2. It is a combination of the *Bayesian Search Approach* and the *Constraint-Based Search* (*PC* algorithm) algorithms. The *Bayesian Search Approach* was introduced by Cooper & Herkovitz, (1992) and refined by Heckerman et al. (1995). It follows essentially a hill climbing procedure, guided by a scoring heuristic, with random restarts. *PC* algorithm was introduced by Spirtes et al. (1993). *Essential Graph Search* performs a search for essential graphs using the *PC* algorithm and scores the various essential graphs using the Bayesian search approach (GeNIe Modeler User Manual, 2017). (https://www.bayesfusion.com/genie-modeler).

The initial DAG was reviewed by local experts in forest management. The assumptions underlying the diagram were discussed and evaluated. A very few number of relations were erased or modified.

The procedure of parameter learning and elicitation of the CPTs was based exclusively on the series of simulated data, previously discretized as explained before. The final cause-effect DAG can be found in Figure 2.

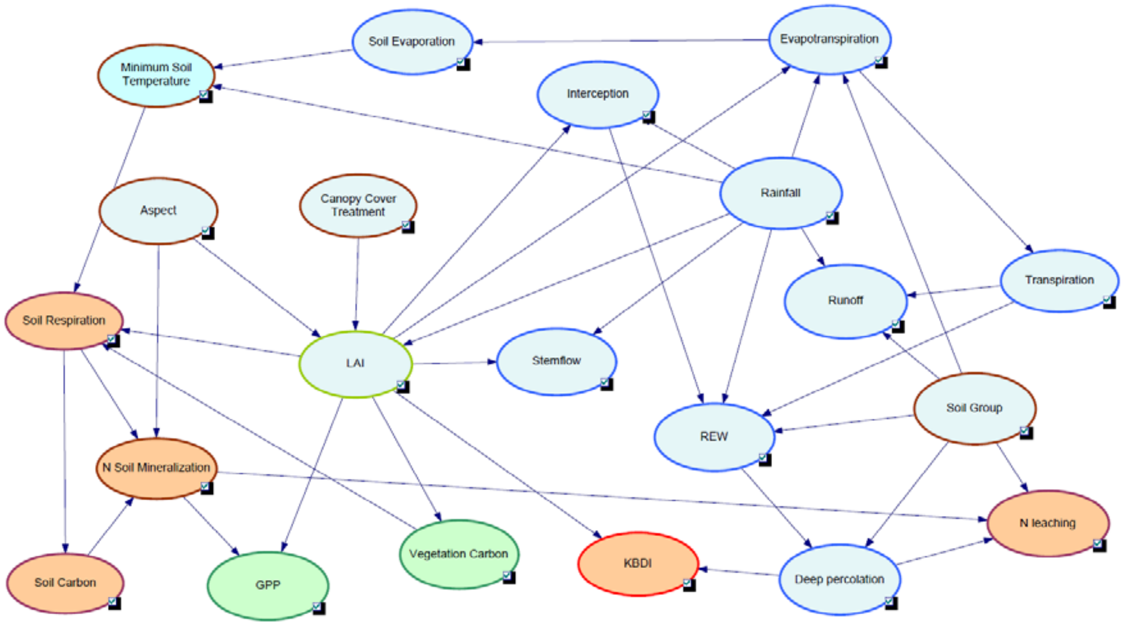


Figure 2. BN cause-effect structure. The color of the node aims to group variables in water-soil-atmosphere-vegetation-management related.

A crucial element of learning process is validation of the results. To do that, that dataset is divided into two subsets for training and testing. GeNIe Modeler v2.2. implements the *K-fold crossvalidation* method that allows to both learn and evaluate the model on the same dataset. In this method, the data set is divided into *K* parts of equal size, trains the network on *K-1* parts, and test it the results on the last *K*th part. The process is repeated *K* times on which a different part of the dataset is selected for testing.

Result of the validation process is the accuracy of predicting the selected variables. In our case, 16 outcomes of interest (nodes) were selected: N-leaching, Soil Organic Carbon, N-Soil Mineralization, Runoff, REW, LAI, Vegetation carbon, Deep percolation, Interception, GPP, KBDI, Transpiration, Soil Evaporation, Stemflow, Evapotranspiration and Soil Respiration. The average accuracy obtained was 73%. The final DAG with the probability distributions in its initial state can be seen in Figure 3.

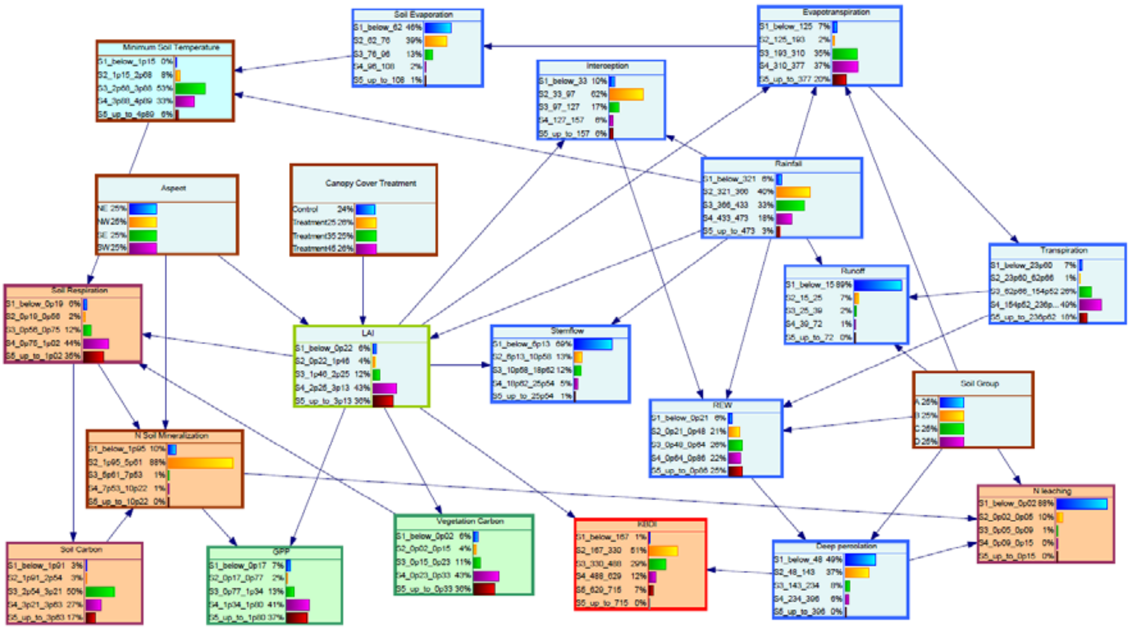


Figure 3. Hydrology oriented forest management BN model and elicited CPTs. The color of the node aims to group variables in water-soil-atmosphere-vegetation-management related.

3. Results and discussion

3.1 Calibration and validation of the Biome-BGCMuSo model

Calibration and validation periods were evaluated using ***RMSE, d,*** d_1, R^2 and ***E*** model performance statistics. Table 4 summarizes the obtained results of those statistics, which showed a good agreement between modeled and measured values of T and SWC in both calibration and validation periods. As was explained before, the model was first calibrated using the water year 2012-2013 field dataset from the control plot representing those conditions of an unmanaged forest. Subsequently, the thinned plot was simulated using the thinning management option of the model which was initiated over the calibrated model. Then, the model was validated by comparing simulated to observed field data, on the one hand the water year 2013-2014 for the control plot, and on the other hand, 2012-2014 for the thinned plot.

The validation under natural conditions -unmanaged forest- confirmed the good performance of the model in reproducing the natural hydrologic dynamics of a forest ecosystem, which leads to a E = 0.6 for SWC and 0.47 for T, or R^2 = 0.8 for SWC and 0.71 for T respectively. In the same way, the validation using field data from the managed plot stated the good performance of the model in simulating artificial forest thinning, where E ranged from 0.68 to 0.78 for SWC and from 0.46 to 0.53 for T, or R^2 ranging $0.71<R^2<0.72$ for SWC and $0.72<R^2<0.79$ for T respectively. The other goodness-of-fit statistics summarized in Table 4 showed similar results. RMSE –as usual- was lower in SWC than in T. For SWC ranged from 0.02 to 0.03 whilst ranged from 0.1 to 0.2 for T. The agreement between measured and modeled SWC and T can be seen graphically along the entire period in Figure 4, both in the control and treated plots. Nevertheless, despite the fact the model shows a satisfactory accuracy, its performance under high thinning intensities appears to be unrealistic as the forest is not capable of recovering after a 65 % treatment when it is NE or NW orientated. These results are probably due to the fact that the model does not consider resprouting, a very important strategy of the species under situations like high thinning intensities.

Table 4. Evaluation of model performance for soil water content (SWC) and transpiration (T) in the control (C & water year) and thinned (T & water year) experimental plot per water year, in calibration and validation phases.

Statistic	Calibration		Validation					
	T	SWC	T			SWC		
	C 12/13	C 12/13	C 13/14	T 12/13	T 13/14	C 13/14	T 12/13	T 13/14
RMSE	0.07	0.02	0.14	0.10	0.20	0.03	0.02	0.03
E	0.57	0.53	0.47	0.53	0.46	0.60	0.78	0.68
R^2	0.77	0.76	0.71	0.72	0.79	0.80	0.71	0.72
d	0.92	0.88	0.86	0.91	0.75	0.91	0.93	0.92
d_1	0.74	0.64	0.70	0.85	0.70	0.65	0.74	0.66

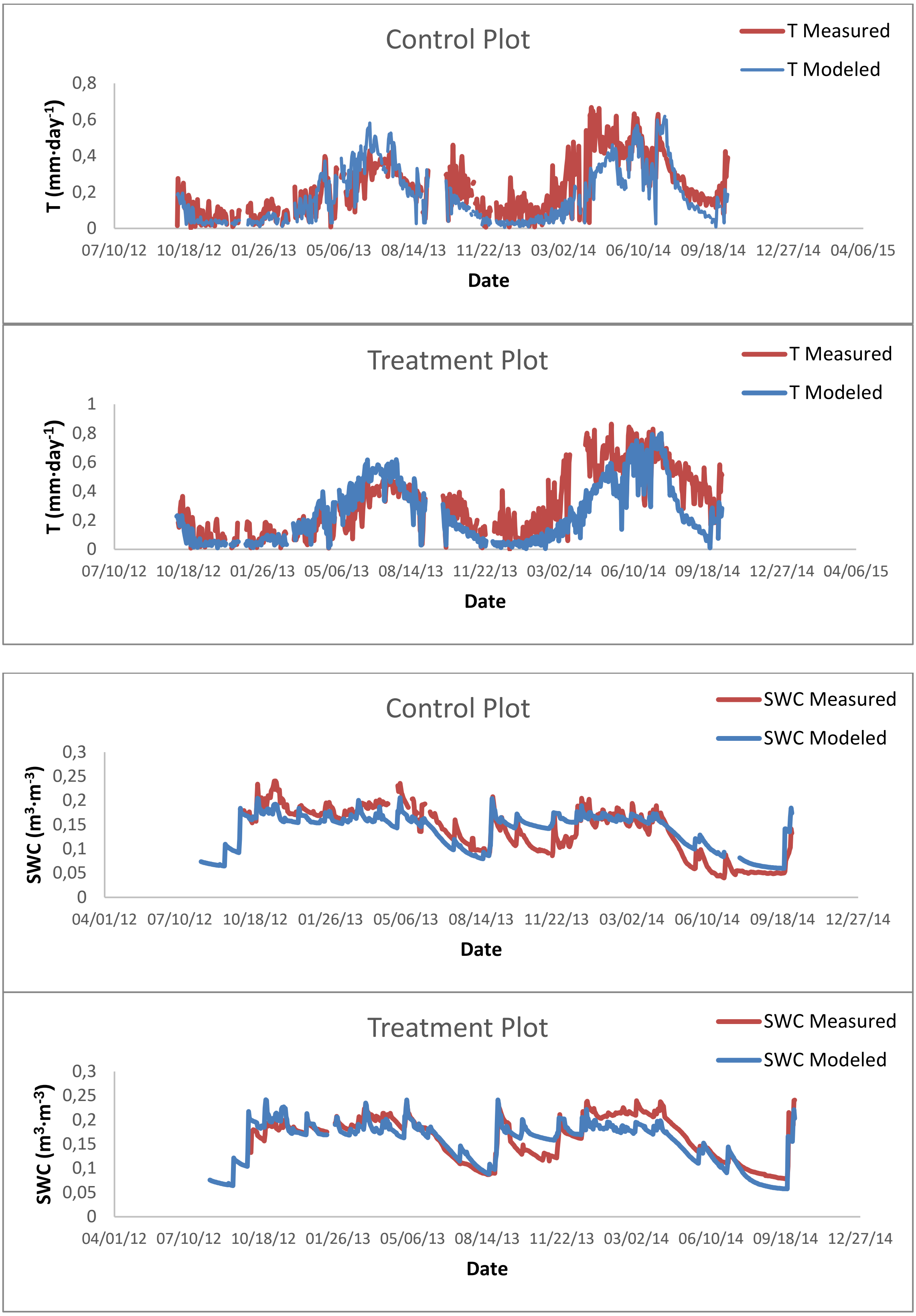


Figure 4. Time series comparing SWC and T between measured and modeled values in the control and treated plots.

The accuracy reached in this study when reproducing the dynamics of a forest ecosystem is comparable to that of the bibliography. Chiesi et al. (2002) used the FOREST-BGC (the former version of BIOME-BGC) to simulate two deciduous forest stands in Tuscany (central Italy), and reported a R^2 of 0.86 for *Quercus cerris* and 0.87 *Quercus pubescensduring* simulation of transpiration during the growing season. Pietsch et al. (2003) used the BIOME-BGC to simulate a floodplain deciduous forest stand at the northeastern edge of the Viennese Basin, and obtained an R^2 between 0.76 and 0.88 for the transpiration predictions. González-Sanchis et al (2015) obtained E of 0.35-0.74 when simulating transpiration and soil water content of a semi-arid Aleppo pine plantation under different management intensities. Likewise, other modeling approaches have resulted in a similar accuracy for daily transpiration and/or soil water content predictions. Keenan et al. (2009) have used the GOTILWA+ (Gracia et al., 1999) and the ORCHIDEE (Krinner et al., 2005) models to simulate evapotranspiration in four mono-specific stands of *Quercus ilex, Quercus cerris*, *Fagus sylvatica*, and *Pinus ponderosa* and reported an R^2 of 0.42–0.83 (GOTILWA+) and 0.47–0.78 (ORCHIDEE). Finally, Chen et al., (2014) reported a R^2 of 0.70 and 0.9 and a RMSE of 0.03 $m^3 \cdot m^{-3}$ and 1.07 $mm \cdot d^{-1}$ for SWC and T respectively using the WAVES model in an arid-zone of Acacia savanna woodland in Australia.

Regarding to the model performance in terms of biogeochemical cycling, it was evaluated by comparing punctual observations of N mineralization, soil respiration and vegetation carbon. The model showed satisfactory results in both plots, thinned and not thinned when simulating N mineralization and soil respiration (see Table 5). In the same way, the aboveground vegetation carbon, which in Biome-BGCMuSo corresponds to the C stored in leafs, fruits and soft stems, was compared to the measured value in the control plot. Both estimations were within the same order of magnitude, being the simulated 0.21 $KgC \cdot m^{-2}$ and the observed 0.28 $KgC \cdot m^{-2}$.

Hence, according to these results, the use of the model is considered reliable to reproduce the hydrological and biogeochemical dynamics of situations, natural conditions and forest thinning.

Table 5. Performance statistics between simulated and observed N mineralization and soil respiration at the thinned and not thinned plots.

	Control plot		Treatment plot	
Parameter	N mineralization $KgN \cdot m^{-2}$	Soil respiration $KgC \cdot m^{-2} \cdot day^{-1}$	N mineralization $KgN \cdot m^{-2}$	Soil respiration $KgC \cdot m^{-2} \cdot day^{-1}$
R^2	0.64	0.83	0.56	0.82
RMSE	9.80E-09	7.06E-06	8.77E-08	5.99E-06

3.2 BN Sensitivity analysis

Prior to analyze the effect of management alternatives a sensitive analysis was applied to identify network components that have the greatest influence on the outcomes of interest. For this task GeNIe implements the algorithm proposed by Kjaerulff and van der Gaag (2000). Given a target node, the derivative of the posterior probability distribution over each parameter is calculated. The larger the derivative is, the biggest the sensitivity of the output of interest - target- to this parameter. To illustrate this process, in Figure 5, following a color code, we can see that the output of interest “Deep percolation” is very sensitive to Hydrological Soil Group (HSG) and Rainfall, and less sensitive to Transpiration, Interception, REW and Evapotranspiration. Aspect, LAI and Canopy Cover Treatment (CCT) have a slight effect, whilst the other variables of the model were absolutely insensitive, i.e. big changes in the parameters have no effect on the Deep percolation. A sensitive analysis including the 16 outputs of interest was summarized in Figure 6.

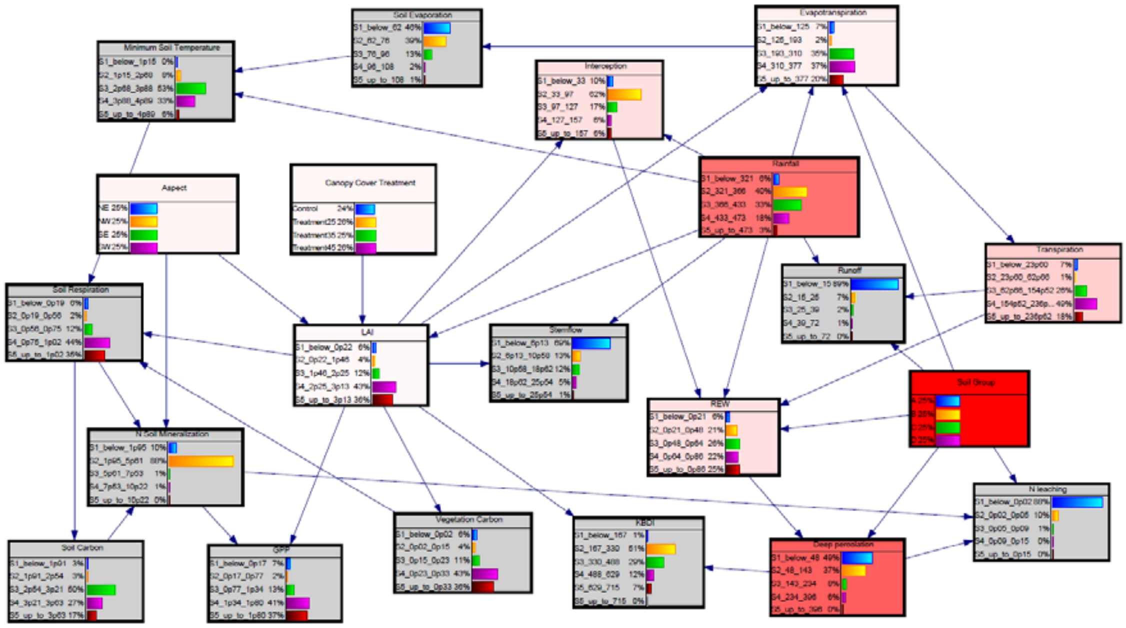
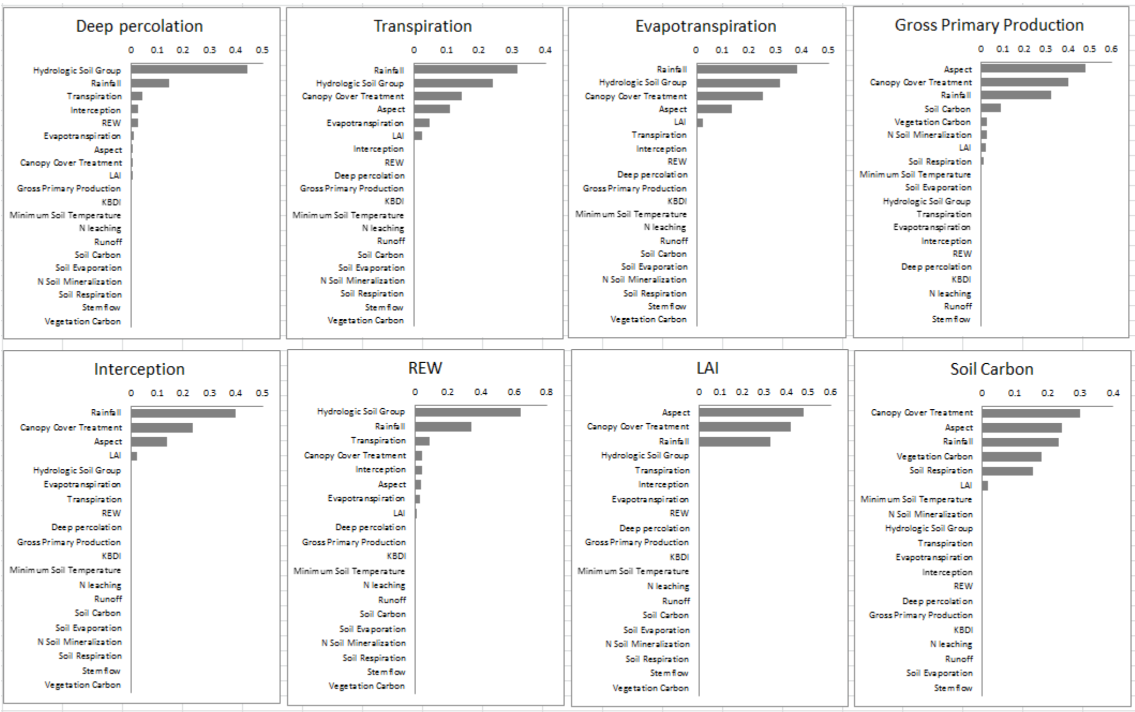


Figure 5. Example of sensitivity analysis. Case of "Deep percolation". Red colors indicate high sensitivity whilst grey color indicates insensitivity.



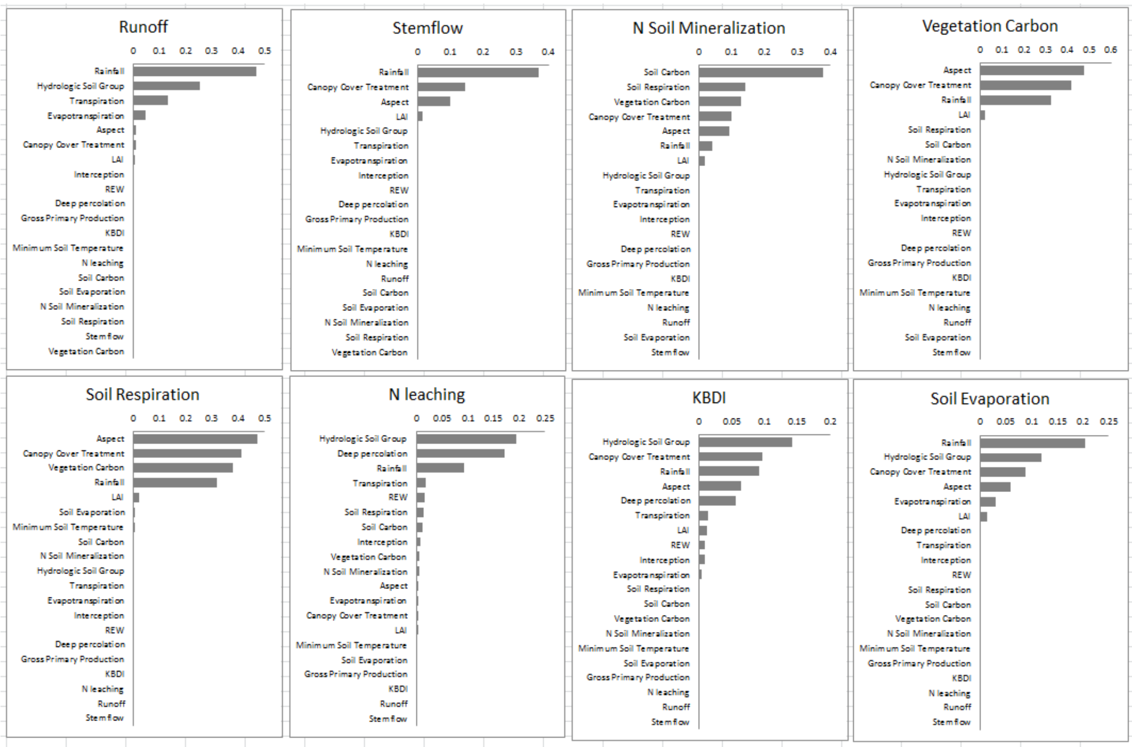


Figure 6. Sensitivity analysis for the outputs of interest.

The sensitivity analysis confirmed that water –rainfall- controls the main processes that occur in a Mediterranean forest system. Besides, note that there are two constant factors not modifiable at all, HSG (based on texture) and Aspect. Both have a deep influence on most of the outputs of interest. In the analysis of scenarios, the separated effect of HSG and Aspect was accounted for. On the other hand, a high or very high influence of CCT over the hydrologic cycle that implies more water for the plant (Evapotranspiration, Transpiration, Interception, Soil Evaporation, REW) was observed. However, the influence of CCT on export of water out of the soil-water-plant continuum by means Deepoff percolation or Runoff was relatively low.

Forest fire risk (KBDI) resulted sensitive to forest management (CCT), which means a positive effect.

Finally, carbon and nitrogen cycles were influenced by CCT, which means that might be plausible stablishing forest management strategies based on those effects, or at least account for them avoiding negative effects.

3.3 BN simulation analysis

The analyzed scenarios have been organized as follows: First of all, unmodifiable parameters were instantiated to the state that agrees with the experimental plots, i.e. Aspect = NW, HSG = B and CCT=Control or Treatment 25. In this “business as usual” scenario, outputs of interest were compared with the equivalent experimental registered data. It is worth emphasizing that the direct analysis of the experimental data allows assessing the short term effect of the silvicultural intervention. This short term effect it is pretty important and is being analyzed in other parallel work. However, this effect has to be addressed in the long run as well, in order to make decisions based on the overall benefit of the intervention. BN simulated scenarios aims at precisely asses this long run effect on which the transient’s effects produced by the treatment are stabilized. Thus, when experimental and BN modeled data were compared, the key factor was the sign of the effect (increase, decrease, without effect) instead of specific values.

Secondly, the influence of the unmodifiable parameters Aspect and HSG on the outputs of interest was evaluated in order to identify if different forest management strategies according to this parameters might be proposed. In this scenario one unmodifiable parameter was instantiated whilst the effect of CCT=Control and CCT= Treatment 25 was evaluated.

Finally the effect of the thinning intensity (CCT = Control, Treatment 25, Treatment 35, and Treatment 45) on the outputs of interest is assessed without instantiating any other parameter with the aim to detect positive or negative trade-offs.

3.3.1 Experimental plots scenario

In this “business as usual” scenario or Scenario 1, the effect of the canopy cover treatment was evaluated in the same conditions as the experimental plot. To do that, unmodifiable parameters were instantiated to the states that agrees with the experimental plots, i.e., Aspect = NW, HSG = B and changing from CCT = Control to CCT = Treatment 25.

Results can be seen in Table 6 and Figures 7 and 8. We can claim that all the variables have behaved in the same way as was observed in the experimental plots according to the sign of the effect (increase, decrease, without effect) produced on the outputs of interest. The hydrologic cycle was modified in such a way that more water was available to the stand because of an important reduction of the interception, which moves from the states S1=<33, S2=33-97, S3=97-127 and S4=127-157 mm·year^{-1} equally shared, to be mainly in S2=33-97 mm·year^{-1}. This resource was made available to the stand, which increased both Evapotranspiration (moves from a 74% likelihood of being in state S3=193-310 mm·year^{-1} to 57% likelihood of being in state S3=193-310 and 32% in state S4=310-377 mm·year^{-1}) and its components, Transpiration and Soil Evaporation. This effect can be seen as well in the increase of soil water content REW, which slightly increase the probability to be in states with higher REW. Conversely, Stemflow was drastically reduced –in agreement with the field observations- consequence of the reduction of both the number of trees per hectare and the Interception. Finally, no effect was observed on Runoff, unless Rainfall was instantiated in the highest state (>473 mm). It is worth pointing out that Runoff not only changed, but it was below 15 mm·year^{-1} (the lowest possible). However, Deep percolation was slightly increased because of the thinning treatment, reducing the probability of being in the first state, and increasing the S3 and S4 states associated to a highest amount of deep percolation. Note that the soil depth in the experimental plots ranged from 10 to 40 cm, beneath which there was a karstified Jurassic limestone parent rock with a huge degree of rock fissuring. In this work, deep percolation was considered the one that passes through the layer of 30 cm depth. This does not mean that all this water reach the aquifer, since within the rock there are roots uptaking water as well.

The long-term effect of the thinning treatment on the LAI was very positive, which moved from the state S3=1.46-2.25 to the state S4=2.25-3.13. This is undoubtedly due to the increased vigor generated by the greater availability of water for the stand. This in turn results in an increase in GPP, which passed from the state S3 = 0.77-1.34 kgC·m^{-2}·year^{-1} to the state S4=1.34-1.8 kgC·m^{-2}·year^{-1}, and the Vegetation Carbon that moved from the state S3=0.15-0.23 kgC·m^{-2} to the state S4 = S4=0.23-0.33 kgC·m^{-2}. Those values are within the order of magnitude of the ones encountered by Makineci et al., (2015) in a forest of similar characteristics.

The soil organic carbon content was also increased from the state S3=2.54-3.21 kgC·m^{-2} to the state S4= 3.21-3.63 kgC·m^{-2} which in turn caused a greater respiration, which moved from S3 = 0.56-0.75 kgC·m^{-2}·year^{-1} to S4 = 0.75-1.02 kgC·m^{-2}·year^{-1}. Increases in soil organic carbon content by increasing LAI agrees with other authors like Kumar et al. (2018). As far as the nitrogen is concerned, the mineralization from organic matter remained practically unchanged and the loss of N by leaching increased as it was associated with the deep percolation, but in very small quantity. The probability of being in the state S1 = <0.02 kgN·ha^{-1}·year^{-1} was reduced by 3% and the probability of being in the state S2 = 0.02-0.05 kgN·ha^{-1}·year^{-1} increased this same amount. These values are consistent with other studies such as Avila et al. (2002) who in a forest with similar characteristics found that the export of N outside the system was 0.05 kgN·ha^{-1}·year^{-1}.

Finally, the risk of fire was reduced with the thinning treatment. The probability of the state S5 = 629-715 (state with high risk) decreased at the cost of increasing the probability of being in other states with lesser fire risk.

Table 6. Treatment effects on the outputs of interest in the experimental plots scenario

Name	State	Units	Probability (%) Control	Probability (%) Treatment 25	Treatment effect	Match with Field Experiment
Deep percolation	S1 below 48	mm·year^{-1}	35	32	Increase	Yes
	S2 48-143		50	52		
	S3 143-234		9	9		
	S4 234-396		6	6		
	S5 up to 396		0	0		
Evapotranspiration	S1 below 125	mm·year^{-1}	20	11	Increase	yes
	S2 125-193		1	0		
	S3 193-310		74	57		
	S4 310-377		4	32		
	S5 up to 377		0	0		
Gross Primary Production	S1 below 0.17	kgC·m^{-2}·year^{-1}	20	11	Increase	Not measured
	S2 0.17-0.77		1	0		
	S3 0.77-1.34		74	7		
	S4 1.34-1.80		4	81		
	S5 up to 1.80		0	2		

Interception	S1 below 33	mm·year^{-1}	23	11	Descrease	yes
	S2 33-97		27	71		
	S3 97-127		22	3		
	S4 127-157		23	6		
	S5 up to 157		5	10		
KBDI	S1 below 167	hundredths of Inch	1	2	Descrease	yes
	S2 167-330		40	56		
	S3 330-488		40	31		
	S4 488-629		12	9		
	S5 629-715		6	3		
	S6 up to 715		0	0		
LAI	S1 below 0.22	-	20	1	Increase	yes
	S2 0.22-1.46		2	0		
	S3 1.46-2.25		77	6		
	S4 2.25-3.13		0	82		
	S5 up to 3.13		0	0		
N leaching	S1 below 0.02	kgN·ha^{-1}·year^{-1}	88	87	Increase	yes
	S2 0.02-0.05		12	12		
	S3 0.05-0.09		0	1		
	S4 0.09-0.15		0	0		
	S5 up to 0.15		0	0		
REW	S1 below 0.21	-	4	3	Increase	yes
	S2 0.21-0.48		9	4		
	S3 0.48-0.64		53	58		
	S4 0.64-0.86		22	21		
	S5 up to 0.86		13	14		
Runoff	S1 below 15	mm·year^{-1}	97	96	=	yes
	S2 15-25		2	3		
	S3 25-39		1	1		
	S4 39-72		0	0		
	S5 up to 72		0	0		
Soil Organic Carbon	S1 below 1.91	kgC·m^{-2}	10	5	Increase	yes
	S2 1.91-2.54		8	4		
	S3 2.54-3.21		80	64		

	S4 3.21-3.63		2	26		
	S5 up to 3.63		0	1		
Soil Evaporation	S1 below 62	mm·year^{-1}	53	52	Increase	yes
	S2 62-76		26	32		
	S3 76-96		14	11		
	S4 96-108		5	3		
	S5 up to 108		3	1		
Soil N Mineralization	S1 below 1.95	kgN·ha^{-1}·year^{-1}	2	3	=	yes
	S2 1.95-5.61		93	94		
	S3 5.61-7.53		3	1		
	S4 7.53-10.22		1	0		
	S5 up to 10.22		1	1		
Soil Respiration	S1 below 0.19	kgC·m^{-2}·year^{-1}	20	11	Increase	yes
	S2 0.19-0.56		2	1		
	S3 0.56-0.75		72	6		
	S4 0.75-1.02		6	82		
	S5 up to 1.02		0	0		
Stemflow	S1 below 6	mm·year^{-1}	46	76	Increase	yes
	S2 6-11		6	6		
	S3 11-19		38	9		
	S4 19-26		9	7		
	S5 up to 26		1	2		
Transpiration	S1 below 24	mm·year^{-1}	20	11	Increase	yes
	S2 24-63		1	1		
	S3 63-155		43	36		
	S4 155-237		36	50		
	S5 up to 237		0	2		
Vegetation Carbon	S1 below 0.02	kgC·m^{-2}	20	11	Increase	Not measured
	S2 0.02-0.15		2	0		
	S3 0.15-0.23		74	6		
	S4 0.23-0.33		4	83		
	S5 up to 0.33		0	0		

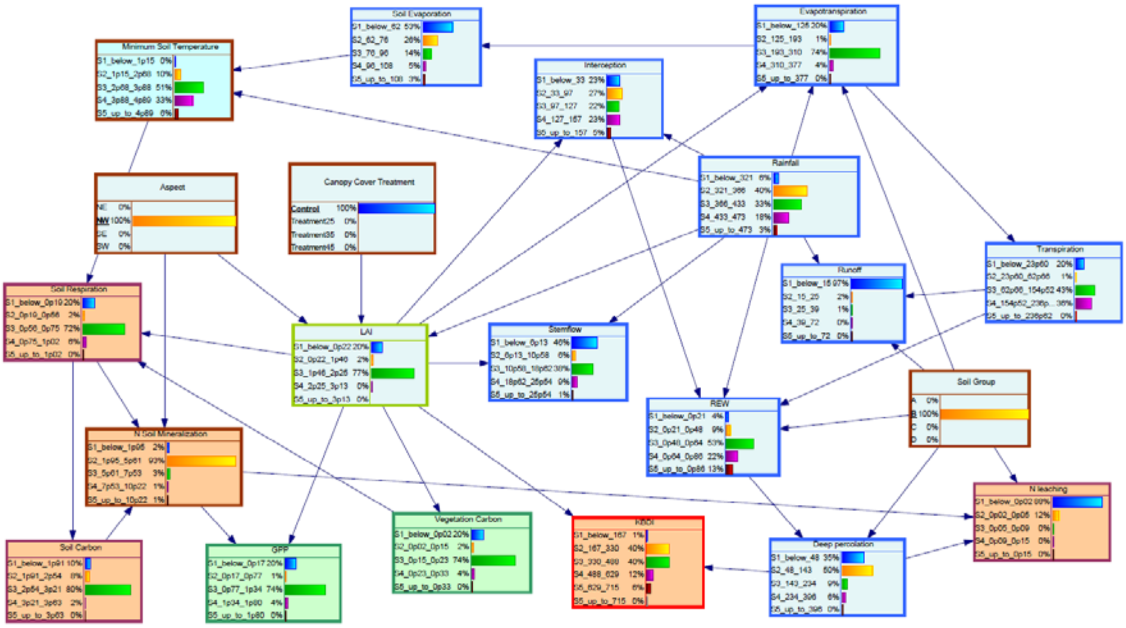


Figure 7. Effect of Control on the outputs of interest under experimental plots conditions. The color of the node aims to clasify variables in water-soil-atmosphere-vegetation-management related.

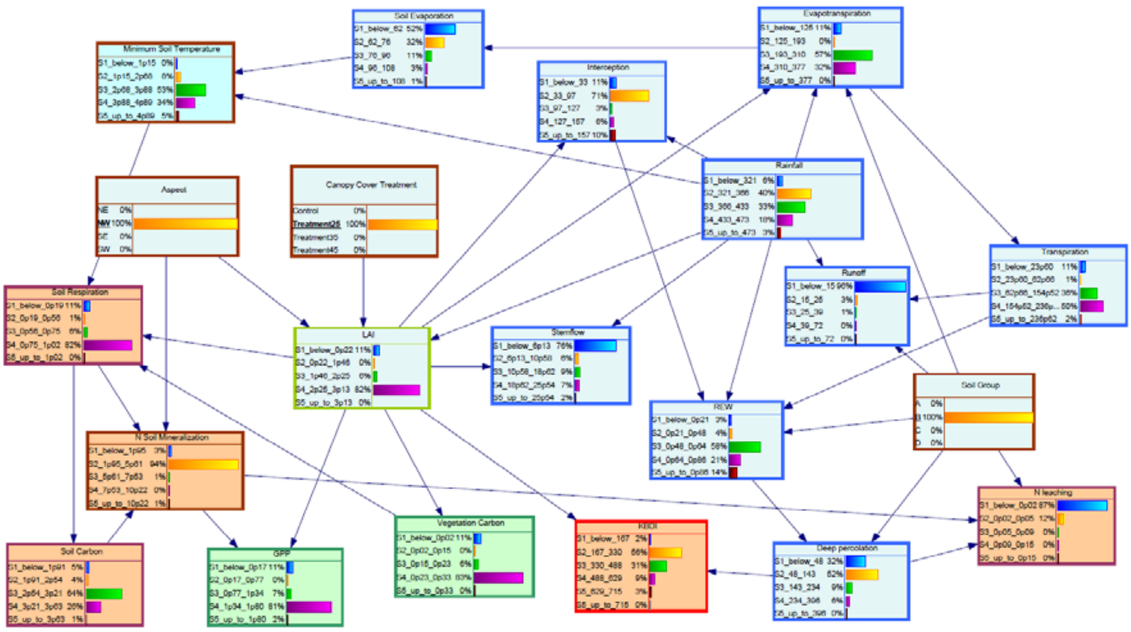


Figure 8. Effect of treatment 25 on the outputs of interest under experimental plots conditions. The color of the node aims to clasify variables in water-soil-atmosphere-vegetation-management related.

3.3.2 Aspect and Hydrologic Soil Group effects

In this scenario –Scenario 2 and 3-, unmodifiable parameters such as Aspect and HSG were sequentially instantiated to their possible states at the same time that CCT changed from CTT= Control to CTT= Treatment 25. In this way, the effect of forest management was evaluated in conditions different from those found in the experimental plots.

Regarding the Aspect effect (Scenario 2): Differences were found when compared the N orientations (NE-NW) to the S orientations (SE-SW), however no differences were found within each group (NE vs NW or SE vs SW). The thinning treatment produced the same general effects described in the previous section, but with greater intensity for the southern orientations consequence of the combination of more water available to the stand together with a greater received solar radiation. As a general rule, forest management effect (treatment) on LAI, Soil Respiration, Soil Organic Carbon, GPP and Vegetation Carbon increased from State 2 to State 3 when Aspect was N, and from State 3 to State 4 for southern orientations. The hydrological cycle was intensified in the southern orientations with respect to the northern ones, so there was more Evapotranspiration, Transpiration and Soil Evaporation, with a small reduction in REW and no perceptible effect in Runoff and Deep percolation. Soil organic carbon content increased, N mineralization was slightly reduced and no changes were observed in N leaching in the southern orientation compared to the north.

In conclusion, in the southern orientations, the adaptation treatment analyzed was equally beneficial, so it does not seem appropriate to prescribe specific actions according to the Aspect.

As regards the HSG effect (Scenario 3): It had a very important influence on Runoff production and Deep Percolation. Thus, when HSG was instantiated in the state HSG = D, the probability of being Runoff in the state S1 = <15 mm $\cdot$ year $^{-1}$ was 70% and 20% of being in the state S2 = 15-25 mm $\cdot$ year $^{-1}$, whilst instantiating HSG = B were 96% probability of being in state S1 and 3% in S2. In the same way, the type of soil also controls the Deep percolation and related to this, the N-Leaching, which is much higher in sandy soils (A) than in clay soils (D). When HSG was instantiated in state HSG = D, the probability of being Deep percolation in state S1= <48 mm $\cdot$ year^{-1} was 82% and 10% of being in state S2 = 48-143 mm $\cdot$ year^{-1}, whilst those probabilities change to 33% and 53% respectively when HSG was instantiated to HSG = B. However N-leaching increased only 8% the probability of being in state S2 = 0.02-0.05 $kgN \cdot ha^{-1} \cdot year^{-1}$ instead of the state S1 = <0.02 $kgN \cdot ha^{-1} \cdot year^{-1}$. As a general rule, it can be stated that forest management improved Deep percolation, but conditioned to the existence of soils with good infiltration capacity and without affecting the loss of nitrogen. Taking into account that a real case of forest management would normally be marked by the heterogeneity of its soils, it does not seem appropriate to propose specific actions by type of soil.

3.3.3 Hydrological Forest Management Scenario

In this scenario –Scenario 4- any variable was instantiated with the exception of CCT that was the effect analyzed. CCT was sequentially instantiated to its possible states CCT = Control, Treatment 25, Treatment 35, and Treatment 45. Results can be seen in Figure 9.

It is worth emphasizing that greater intensities than Treatment 25 did not produce changes in the behavior of the outputs of interest. The positive effects of the treatment (produced by the reduction of the interception that increased the amount of water available for uptake by plants) described in previous scenarios were achieved with the first intensity. No additional water reaches the soil when higher thinning intensities were applied. Note that in this scenario, only CTT was instantiated. Therefore, all those effects produced by Aspect, HSG or Rainfall were compensated with each other, and the final probabilities did not reflect substantial changes in the long run.

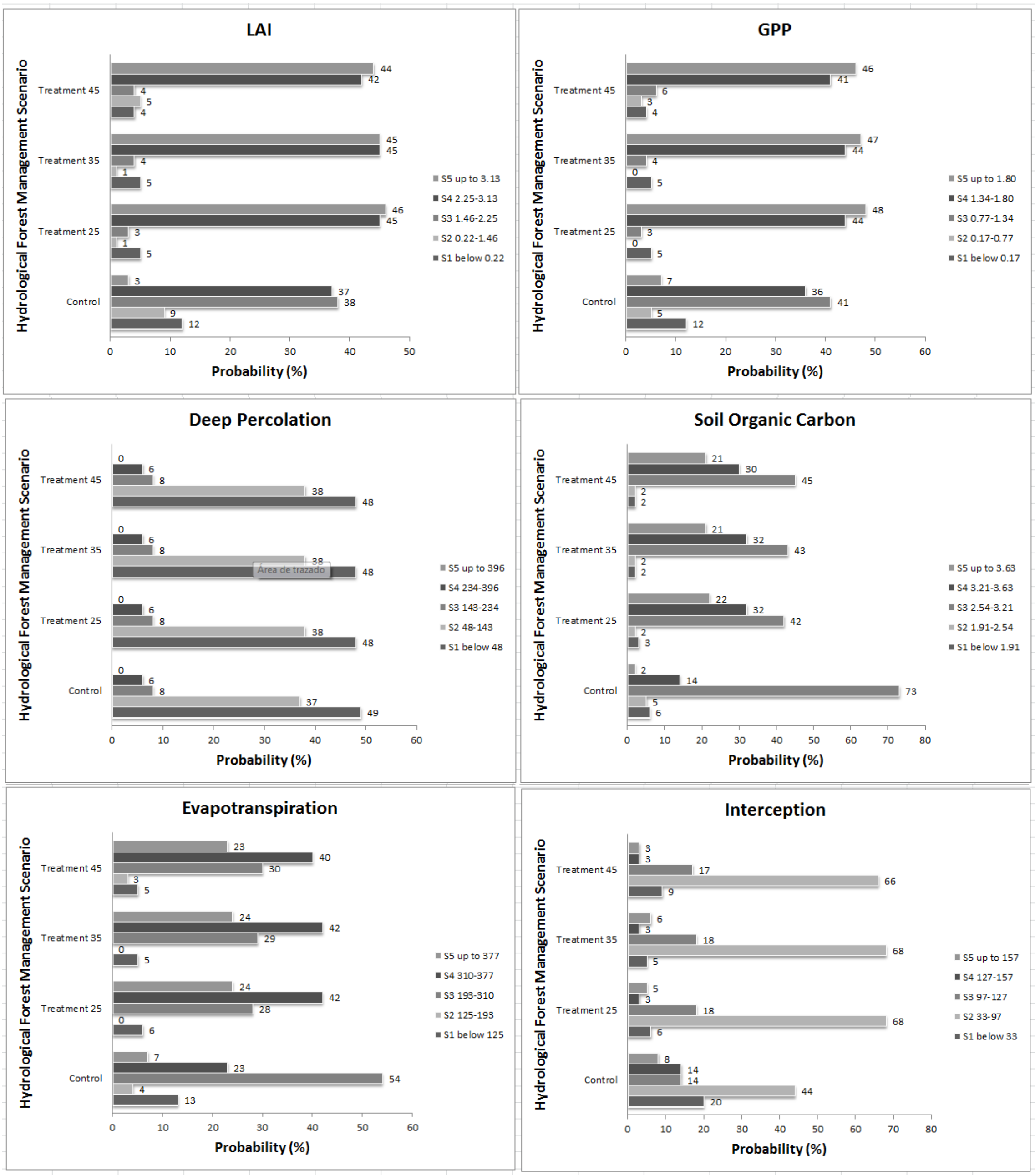


Figure 9. Evolution of the final probabilities of several outputs of interest in the simulated hydrological forest management scenarios.

Regarding the comparison between CCT = Control and CCT = Treatment 25, there were hardly any differences with respect to the analysis made in the previous section. The outputs of interest behaved in general terms as described in Table 6. The reduction of the Interception produced an increase in the water available for the stand with the consequent increase in vigor: LAI, GPP, Vegetation Carbon and Soil Organic Carbon increased. The Runoff and Deep percolation were hardly affected, and associated with it, there was a small increase in N-leaching, which in any case was negligible. The risk of fire was reduced and N mineralization and Respiration were activated.

In Figure 10 can be seen the evolution of the final probabilities of several outputs of interest along the described scenarios.

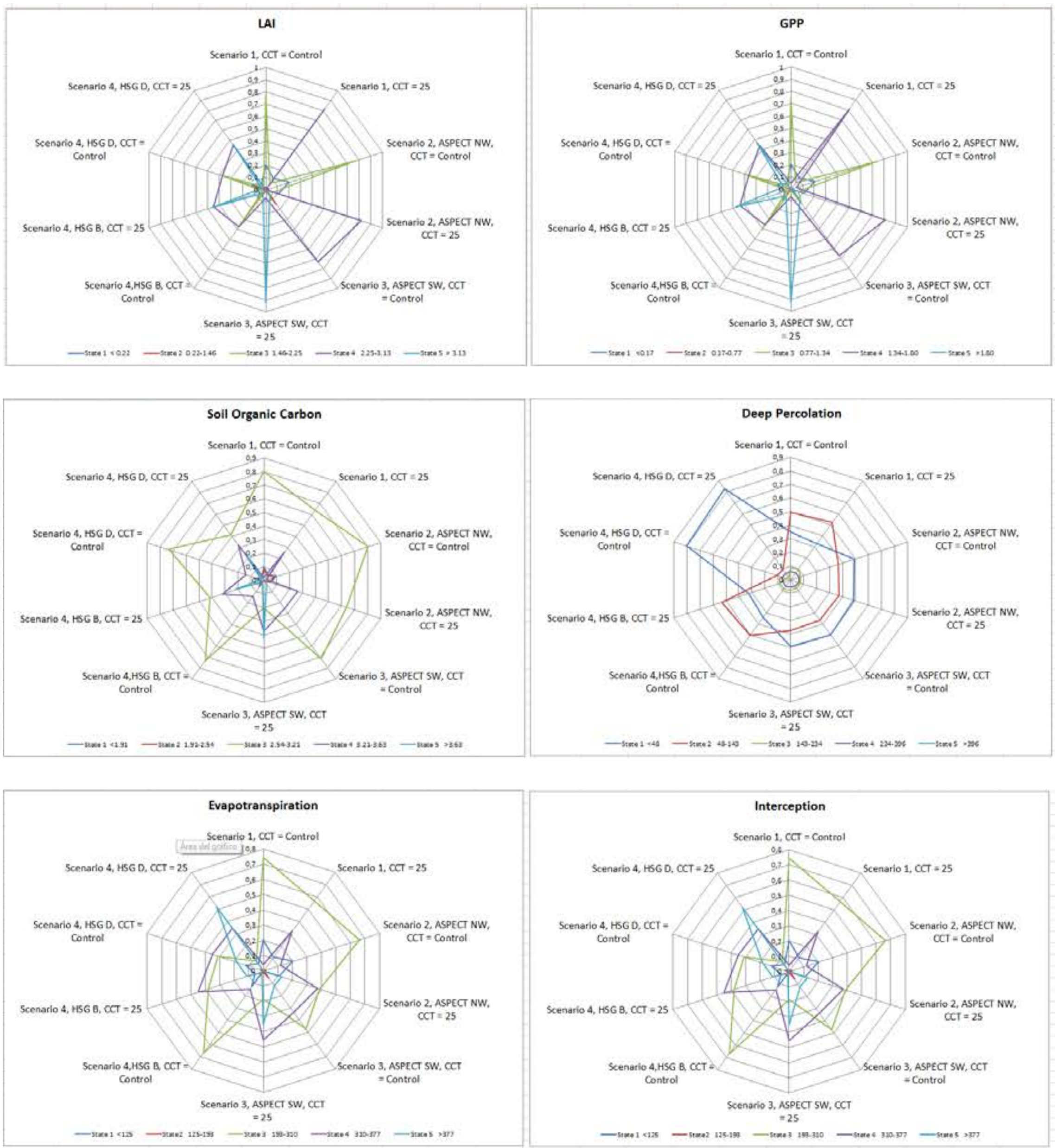


Figure 10. Evolution of the final probabilities of several outputs of interest along the BN simulated scenarios.

4. Conclusions

Many efforts can be found in the literature along the last 15 years addressing the broadly recognized need for adaptation of forest ecosystems in the Mediterranean basin. Hydrology-oriented forest management could respond to this need in those areas on which water is the most limiting factor. In those areas, adaptive management might be focused on forest and water relationships.

However, it should be recognize that research on forest management for adaptation has focused on demonstrating the short-term improvement in specific issues (reducing drought vulnerability, increasing resilience, decreasing forest fire risk, etc.) leaving aside other than those for which they were intended effects and leaving aside the long-term effects as well. To deal with both a broad range of variables involved and the long-term effects, biogeochemical models that simulate the storage and flux of water, carbon, and nitrogen between the ecosystem and the atmosphere, calibrated and validated using the short-term experimental datasets, proved to be a good solution. Nevertheless, outputs of models should be analyzed using a tool capable to cope with complex and uncertain relationships among variables involved in forest management. Structured analysis of complex systems is the main scope of Bayesian Networks. This tool allowed for investigating the impacts of management options through analysis of scenarios, assessing the consequences of management hypothesis and potential actions.

Specific results offered by the BN model showed that hydrology-oriented forest management was very positive insofar as more water was made available to the stand because of an important reduction of the interception. This resource was made available to the stand, which increased both Evapotranspiration and its components -Transpiration and Soil Evaporation-. This effect could be seen also in the increase of soil water content REW and a slightly increase of deep percolation. Conversely, Stemflow was drastically reduced consequence of the reduction of both the number of trees per hectare and the Interception. Finally, no effect was observed on Runof due to the thinning treatment.

As far as the nitrogen is concerned, the mineralization from organic matter remained practically unchanged and the loss of N by leaching increased as it was associated with the deep percolation, but in a negligible amount. The Soil organic carbon content was also increased which in turn caused a greater respiration. The long-term effect of the thinning treatment on the LAI was very positive. This was undoubtedly due to the increased vigor generated by the greater availability of water and nutrients for the stand and the reduction of competence between trees. This greater activity resulted in an increase in GPP and Vegetation Carbon, and therefore, we would expect a higher carbon sequestration. It is worth emphasizing that this extra amount of water and nutrients was taken up by the stand and did not entail any loss of nutrients. Finally, the risk of fire was also reduced with the thinning treatment.

Intensities of thinning with canopy cover removal greater than 25% in the 50–year unmanaged forest analyzed in this study did not offer any advantage compared to the lowest intensity.

Although the results obtained in the analysis of scenarios using the BN model showed differences between type of soil and aspect, the heterogeneity of those parameters in a real case discourage proposing different management strategies according to them.

Further studies including other issues and ecosystem services like pests resilience, biodiversity or economic treats should be done in the future.

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