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C.A.F.E: A Multi-Objective Decision Support System for eco-hydrological forest management that quantifies and optimizes different ecosystem services.

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Abstract

Sustainable forest management is a powerful nature-based solution for climate-change adaptation and mitigation. In this sense, knowledge of the ecosystem services (ES) generated by forests is essential to plan and implement efficient management alternatives, especially when resources are threatened by climate change. Even more so in forests with low timber productivity, such as semi-arid Mediterranean ecosystems, where forest management based exclusively on timber products, which is the most easily monetizable service and therefore the most attractive for companies and individuals, is not profitable. C.A.F.E. (Carbon, Aqua, Fire & Eco-resilience) is a Multi-Objective Decision Support System for forest management that quantifies and optimizes ES derived from forest management, thus paving the way to payment for ES schemes. It is based on the combination of multiple pyro-eco-hydrological processes simulated by process-based models and multi-criteria optimization with genetic evolutionary algorithms. This tool allows managers to plan the silvicultural operations oriented towards thinning or planting necessary for multi-criteria forest management, answering the following 4 fundamental questions: How much, where, when or how do I have to act? In addition, it allows to see how climate change scenarios influence silvicultural actions and the production of goods and ES. The provided results are a list of possible silvicultural actions (Pareto front), each of one, associated with the quantification of the targeted ES and compared to the base line situation. As Pareto front, all solutions provided are equally valid and none is better than the other. To select a final solution, users must establish their priorities in terms of ES by filtering the solutions with the help of an iterative visualization interface.

Keywords: Sustainable forest management, Climate change, Knowledge management, Landscape management, Innovation.

Introduction, scope and main objectives

Forest ecosystems provide ecological, economic and social services, including sustaining biodiversity, supplying food biodiversity, provision of food, medicines and forest products, regulation of the hydrological cycle, soil protection or recreational uses (Bonan, 2008). However, to be multifunctional, appropriate management of their natural resources is necessary to ensure their sustainability. In addition, forest management enables forests to perform better and make them more resilient to disturbances. Historically, European forest ecosystems have had mainly a productive role and have therefore been managed accordingly. Over time, this approach has evolved to the present day, which recognizes the multifunctionality of forests, combining the provision of multiple ecological, economic and social goods and services. Such approach, while increasing the complexity of forest management, increases the sustainability of forest management and highlights its role as a regulator of the provision of goods and services. Moreover, if we consider climate forecasts here, the application of this type of management becomes even more necessary (Bravo et al., 2017).

Decision support systems (DSS) are essential tools that enable forest managers to consider the offsetting among different Ecosystem Services (ES) and its economic and legal implications that interfere with forest planning (Segura et al., 2014). They can be defined and take many different forms, but over the years they have evolved into interactive and flexible software that allows managers to make sound management and planning decisions when faced with an ill-structured or unstructured problem through direct interaction with data and analysis models (Rauscher et al., 2000).

These tools appeared after the second half of the 20th century, in the business sector, where mainly companies developed and applied the use of DSS to realize management and administration strategies. In the 1980s, they started to be used in the forestry sector and have continued to be used to this day. Its use has been changing throughout time, due to the multi-functionality of forests (Vacik and Lexer, 2014). Since the development of the first DSSs for forest management, multi-objective forest management was already being carried out, this is why these tools were so well received by managers. A multitude of complex processes occur in natural ecosystems, which make decision-making difficult for the manager. Furthermore, in order to achieve sustainable ecosystem management, the socio-ecological aspects involved in ecosystem processes must be understood (Ananda and Herath, 2009). Thus, the uses of these management tools are all the more necessary to achieve this goal.

Due to the large number of complex processes occurring in ecosystems, the importance of these tools in forest management has led to their wide and varied use in the sector. This is why numerous DSSs have been developed for forest management that consider a diverse range of goods, services and aspects related to environmental management, such as wildlife (Garcia and Armbruster, 1997), fire or disturbance risk (Noble and Paveglio, 2020), landscape management (Jahani and Rayegani, 2020), consideration of climate change constraints (Cristal et al., 2019) or uncertainties in logistics operation (Maldonado et al., 2019). In addition, there are multi-objective DSSs that allow understanding how these multiple objectives are interacting and which solutions are the most optimal Given the multifunctionality and complexity of forest ecosystems, this approach is necessary to manage a forest in a sustainable way by managing forests in a way that maximizes and quantifies ecosystem services.

This work stems from the European LIFE project program "Life Resilient Forests" (https://www.resilientforest.eu/), which promotes a forest management approach at the watershed scale that improves forests resilience to wildfires, water scarcity, environmental degradation and other effects induced by climate change. The main aim of this work is to show the creation of a multi-objective DSS (CAFE, (Carbon, Aqua, Fire & Eco-resilience)) that combines simulation of process-based eco-hydrological models and optimization with multi-objective evolutionary algorithms to help managers to plan and carry out optimal and multi-objective forest management (Thinning or Planting), considering the 4 fundamental questions of forestry (How much do I act? Where do I act? When do I act? and How do I act?).

Methodology/Approach

1- DSS structure

CAFE is a Multi-Objective DSS (MODSS) for forest management. This tool determines the optimum silvicultural activities (thinning or planting) to manage multiple goods and services such as biomass production, carbon sequestration, fire risk, water provisioning, climatic resilience or biodiversity, which are simultaneously quantified in time and space for a selected solution. To that end, CAFE. combines eco-hydrological simulation and multi-objectives optimization with evolutionary algorithms. Finishing the execution with an iterative visualization of the results that allows the user to understand and select the most appropriate option. Therefore, the three modules on which this DSS is structured are: simulation, optimization and visualization (Fig. 1). The combination and communication of these modules make it a multipurpose and useful tool for decision making by forest managers.

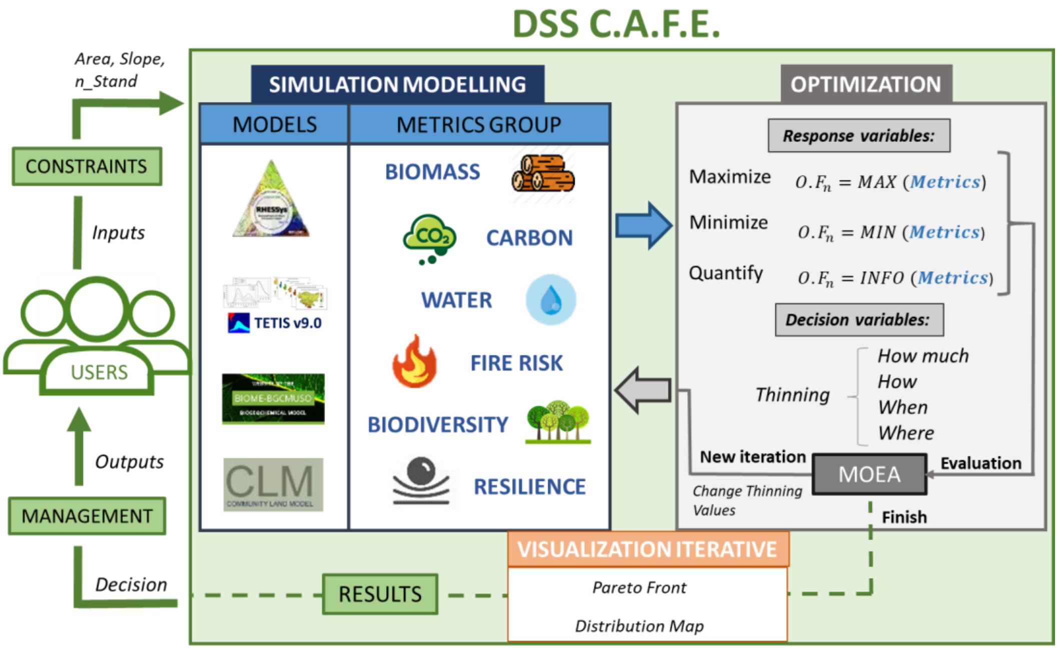

Fig. 1: Scheme of the Decision Support System (DSS), CAFE.

Simulation: Process-based models

Process-based models (PBM), also known as mechanical or ecosystem models, are the mathematical representation of the functioning of a well-defined biological system (Tanevski et al., 2017). These models represent and simulate physiological and biogeochemical processes and their interactions with the environment. Such models usually consist of a set of ordinary or partial differential equations that define the essence of each process (temporal patterns of key parameters), as well as its inputs and outputs, based on the first principles (generic PBM) or, otherwise, empirical knowledge (descriptive PBM) (Jorgensen, 2011; Wiegert, 1975).

PBM can be distributed and non-distributed, the difference being the spatial component. Distributed models discretise the simulation domain, being therefore able to differentiate the processes occurring in a given area by terrain or vegetation characteristics. On the contrary, non-distributed models do not discretise the simulation domain, and represent its characteristics and processes averaged into a single area. Within this module, the tool has 4 simulation PBM. Being 2 distributed models (Rhessys and Tetis-Veg) and 2 non-distributed (Biome-Bgc and CLM). Both types have been implemented to meet the different needs of managers. They can simulate a whole forest or just a single stand. Distributed models can be interesting when the simulation domain is heterogeneous or the user just wants to spatially differentiate the domain. ON the contrary, if the user works with contemporary stand (productive or not), the non-distributed models can be used.

The metrics that this tool provides are (Table 1): Biomass extracted, carbon sequestered, water increased, fire risk reduction, structural biodiversity and forest resilience. To obtain these metrics, the water and carbon cycle provided by the models must be evaluated. Since the tool development is not closed, new metrics are being included and the behaviour of the calculated values is being evaluated with field data.

RHESSys is a hydro-ecological model designed to simulate integrated water, carbon, and nutrient cycling and transport over spatially variable terrain. The model is structured as a spatially nested hierarchical representation of the landscape with a range of hydrological, microclimate, and ecosystem processes that it has been applied in a variety of ecosystem types, including deciduous conifer forested and grassland regions, alpine and Mediterrain-type ecosystems and urban areas (Tague and Band, 2004).

Tetis-Veg is composed of two main modules: the TETIS hydrological module and the HORAS vegetation module. It is a conceptual distributed model that represents the catchment as a grid of interconnected cells according to the topographic configuration derived from a digital elevation model (DEM). The model adequately incorporates the spatial variability of hydrological cycles and vegetation growth. Its conceptual basis is based on the current state of the art and complies with the principle of parsimony (Francés et al., 2007).

Biome-BGC-MuSo is a noon-distributed biogeochemical model that simulates the storage and flux of water, carbon, and nitrogen between the ecosystem and the atmosphere, and within the components of the terrestrial ecosystem. It was developed from the widely used Biome-BGC model (Hidy et al., 2016).

CLM (Community Land Model) is a model that formalizes and quantifies concepts of ecological climatology. It examines the physical, chemical, and biological processes by which terrestrial ecosystems affect and are affected by climate across a variety of spatial and temporal scales. The central theme is that terrestrial ecosystems, through their cycling of energy, water, chemical elements, and trace gases, are important determinants of climate (Lawrence et al., 2019).

Table 1: Calculated metrics to quantify and optimize.

Metric	Description	Units
Biomass Extraction	It is the sum of all the stands to which the carbon difference between the day before the thinning and after the thinning is applied and repeated as interventions throughout the simulation.	Kg/m^2
Carbon Sequestration	Metric calculated by the models which is averaged over the simulation period.	Kg/m^2
Soil respiration	Metric calculated by the models which is averaged over the simulation period.	Kg/m^2
Percolation	Metric calculated by the models to which the total sum is added for the simulation period and divided by the simulation years.	Hm^3
Baseflow	Metric calculated by the models to which the total sum is added for the simulation period and divided by the simulation years.	Hm^3
Streamflow	Metric calculated by the models to which the total sum is added for the simulation period and divided by the simulation years.	Hm^3
KBDI	This is the average KBDI value for the simulation period.	-
FWI	This is the average FWI value for the simulation period.	-
Biodiversity Structure	It is the sum of different structural values of the stand such as density, number of strata, diameters, dead wood on the ground and in flight and finally gap in the stand.	-
Resilience	The average value of the annual mean values of the ratio between water used by the plant and wood growth, compared to the baseline situation.	-
Improve baseline	It is the sum of the categorical value provided to each of the metrics that exceed the values with forestry performance at baseline.	-

Optimization: Multi-Objectives Evolutionary Algorithm

A multiobjectives optimization problem (MOP) involves a number of objective functions that are to be either minimized or maximized, subjected to a number of constraints and variable bounds. The objectives often conflict with each other, where the improvement of one objective may lead to the deterioration of another. Thus, a single solution, which can optimize all objectives simultaneously, does not exist. Instead, the best trade-off solutions, called the Pareto optimal solutions, are important to a decision maker (DM). These solutions are the points lying on the non-domination front, where by definition, do not become dominated by any other point in the objective space; hence they are Pareto-optimal Front (PF). It is characteristic that no unique solution exists but a set of mathematically equally good solutions can be identified. Due to their population-based nature, Multi-Objectives evolutionary algorithms (MOEAs) are able to approximate the whole PF of an MOP in a single run and is one of the most widely used heuristic optimization methods in research over the last 20 years (Deb, 2015; Zhou et al., 2011).

To create the optimization module with MOEA in CAFE, the open source python library Rhodium has been used, which allows for robust decision making (RDM), many-objective robust decision making (MORDM), and exploratory modelling. These decision-support frameworks enable the identification of robust strategies for the management of complex environmental systems, by evaluating the trade-offs among candidate strategies, and characterizing their vulnerabilities. Robust strategies refer to management options that perform sufficiently well or acceptably under a range of potential system conditions, rather than optimally in a single, nominal state of the world. Exploratory modelling allows for the simulation of the system under an ensemble of states of the world, so as to discover the ones with consequential effects on the system. Rhodium facilitates rapid application of the RDM and MORDM frameworks by providing a suite of optimization, visualization, scenario discovery, and sensitivity analysis functions. Rhodium is written in Python and can interface with models written in Python, C and C++, Fortran, R, and Excel (Hadjimichael et al., 2020).

The first difference is given by the type of algorithm used; there are many different types of algorithms. Since in recent decades, multi-objective evolutionary algorithms have developed rapidly and are roughly divided into four phases, they are divided into four phases. Phase 3 and 4 are included in the optimisation block (NSGAII, EpsMOEA, GDE3, SPEA2, NSGAIII, MOPSO, SMPSO, CMAES, IBEA, PAES, PESA2, EpsNSGAII). The next part of MOEAs like any optimisation is the objective functions (OF). These are the formulation of the variables (metrics) that you want to optimise or quantify if they do not come into play in the optimisation. In this case, the MODSS has with OF all the metrics that the simulation models generate in the operations (Table 1). The selected algorithm must be told whether each of these is to be maximised, minimised or info. Another important section of these algorithms are the decision variables. These are the variables that the optimisation has to provide their appropriate values to maximise the OF. In CAFE there are up to 4 decision variables (Where? When? How? or How much?). All or only some of them can be used. Finally, there are the constraints, which are the limits that the optimisation has on the decision variables or the OFs. In this case the tool has implemented for the moment the maximum slope constraint, where a high thinning is not applied.

Visualization: Iterative Results

The last module implemented in CAFE is the iterative visualization part. It is divided into three parts, console, iterative graphics and thinning maps. The first one is where the values of each iteration are shown (Metrics-Actuations), and where the optimization proposes the values of the decision variables ("Where? When? How much? How?", being able to be any combination of the four of them, according to the user's needs), the proposed changes are applied, and the simulation is launched. At the end of the simulation, the metrics to be quantified or optimized are calculated, according to the user's selection for each one (each one can be selected as Maximize, Minimize or Info). The value obtained in each metric (Objective Functions) is evaluated by the algorithm, and decides whether to store the solution or to discard it and go to the next iteration making changes in the decision variables to repeat the process. This is repeated until the optimization algorithm finds the PF. This is when the optimization is finished and the results generated are shown in a more detailed and interactive way, where the user can filter and select among all the possible solutions using the equalizer of Java J3 application. J3 allows the iterative visualization of the PF**,** thanks to this free desktop application for producing and sharing high-dimensional, interactive scientific visualizations (https://github.com/Project-Platypus/J3). Thus, with J3, if at the time of choosing one metric is more important than another, it is only necessary to limit the range of that metric to the appropriate values for the user. For example, prioritizing higher values for biodiversity over biomass or prioritizing lower values for fire risk over carbon sequestration.

When selecting the final solution, the user can see the quantification of all the metrics and the forestry actions needed to achieve them. When the case study uses distributed models, several stands come into play and therefore each stand has its own planting or thinning values. To see these spatial values, the thinning distribution map is displayed for the solution chosen by the user, giving as a result the thinning intensity (answering: How much?) and the location of those (answering: Where?) where it is necessary to act, being all or a limited number of them according to the user's criteria. If in addition, the user has selected more than one intervention, there will be a thinning map per intervention. Being the years in which the optimization has said that it is necessary to intervene for the chosen solution (answering: When?). All this is easily understandable thanks to an iterative visualization of the map, with a slider that allows to visualize the different performances in the appropriate years. The Plotly library (https://plotly.com/graphing-libraries/) in Python has been used to realize this, as it is an open source charting library that allows you to create interactive charts and maps that can be saved in Html format.

2- Workflow

The workflow performed for CAFE (Fig. 1) starts with the data to be entered by the user. On the one hand, the input data for the eco-hydrological simulation which will be different (format and required variables) according to the selected model. In addition, the tool must be provided with the directory of the executable of the case study, which for each model has an extension and internal parameters that it must contain. From this file, the tool obtains the simulation period and all the information of the study area.

On the other hand, there is the optimisation part, where the user can choose the optimisation algorithm among the 6 available, where the default option is the best known (NSGA-II). Subsequently, the user must select the metrics to optimize (OF), if minimising or maximising each of them and which ones are only quantified (Info "Example: Carbon Sequestration"). Then to the user chooses the decision variables, which are the forestry questions that the user would like to answer (Where? When? How? or How much?). If “Where” is selected, the user must choose whether to act in all stands or in a limited number n to be selected by the algorithm (this only comes into play if the eco-hydrological model used is distributed). When selecting the decision variable “When”, the user must indicate the number of interventions to be performed, and the optimisation will calculate the time that must elapse between them to be applied. If “How” is selected, the user must indicate whether he/she wants to work at stand or stratum scale. The last decision variable, “How much”, always comes into play and the user must mark the maximum and minimum thinning values.

Finally, if constrains have to be applied, the user must select them, such as maximum slope and maximum thinning value so that in those stands that have too much slope no high thinning is applied and thus no erosion damage is caused.

Once all the above steps have been completed by the user, it is time to run CAFE, where it first simulates the base line (starting point) in order to evaluate if the management improves the desired metrics with respect to the baseline. After this, the iterations between simulation-optimisation start, and the process can take more or less time depending on the selected model and the area to be applied. This can range from a few minutes to a couple of days. Once the execution is finished, the results of the most optimal solutions are obtained. This is when all these options are visualised with the iterative graphs and where the user can go back to edit and customise the interface to understand and filter with the equaliser the most appropriate solutions according to their criteria of preference. This reduces the number of solutions and makes it easier to choose the option that will be the final one. When this is reached, the next step is to see the silvicultural management selected by means of the thinning distribution map, which makes the solution more visual and easier to understand.

Results

CAFE provides users with two main outputs: (1) Pareto Front charts and (2) Thinning distribution maps. The first one allows the user to know the relationship between metrics and which solution is more adequate among all the possibilities. The second one, once the first one has been decided, is to see what, where and when the forestry actions should be done. Therefore, the result that the manager would have is the quantification with optimisation of multiple goods and services, and the spatial-temporal planning of the forest management that produces them.

1- Pareto Front with Equalizers

As an examplewe have run a case study, which is a Mediterranean forest with 205 stands, where only 190 can be managed. The optimization goal of the user were: maximising the extracted biomass, biodiversity, percolation and minimising the fire risk, while the rest of the variables were only quantified. The eco-hydrologial model used was RHESSys. The time period was 25 years, and the number of interventions was 3. In addition, a slope constrain was included with a maximum thinning of 40% when the slope exceeded 30%. For this case study the optimisation provided 69 possible solutions. The graph that is generated is fully customisable and the user can provide more or less elements for its interpretation, this example has the PF, the cube, the table of values and the equaliser (Fig. 5).

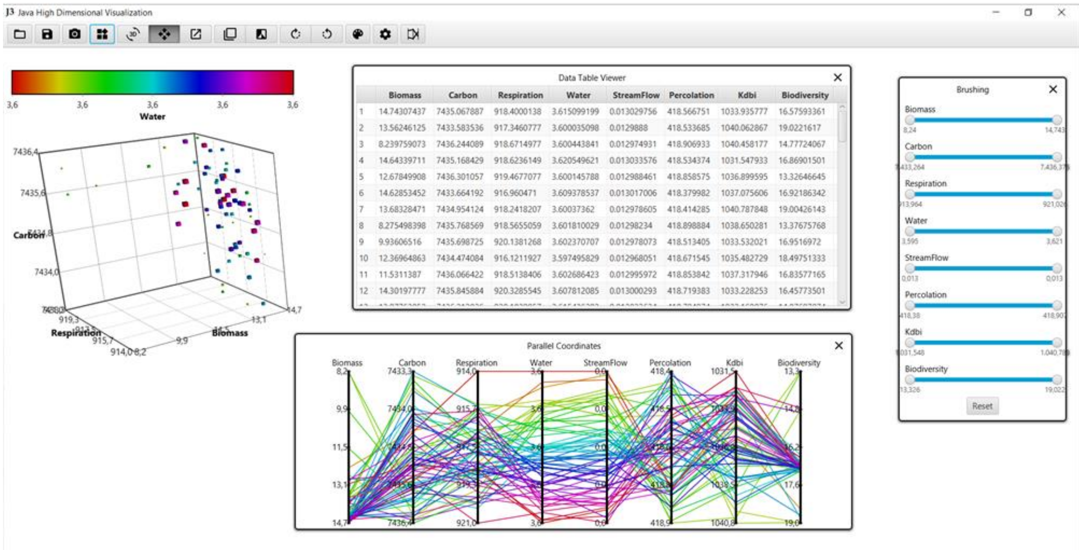

Fig. 5: Scheme of the Decision Support System (DSS), CAFE

All solutions are equally valid and none is better than the other, where the user can select one. The user can prioritise the higher or lower value of one metric over another. As an example, a filtering is done with the equaliser, where first the highest values of extracted biomass and carbon sequestration will be prioritised, while the lowest values of KBDI are desired. Thus, the most suitable solution for the manager is the one that meets these criteria (Fig 6.a).

If, on the other hand, the metrics prioritised by the manager were the highest values of biomass removal and structural biodiversity, the most appropriate solution would be number 7 (Fig. 6b).

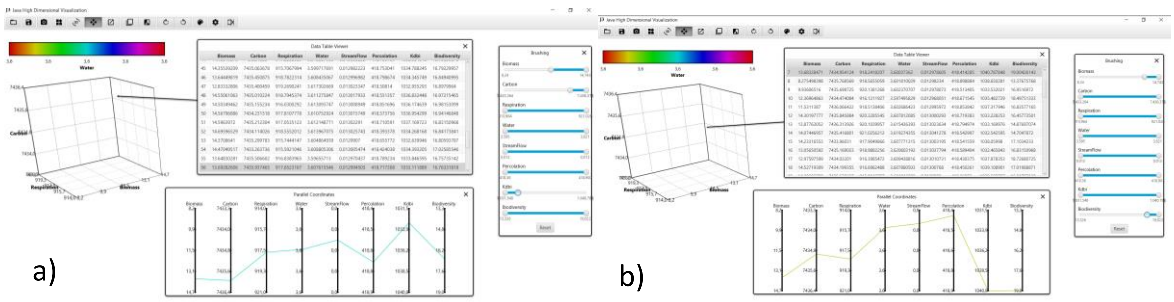

Fig. 6: Filtering of solutions with the equalizer according to user criteria (a)Solution 56, b) solution 7).

Each of these solutions has of course a specific silvicultural management associated to it.

2- Thinning Distribution Map

The maps provided by this tool are those resulting from a solution chosen by the user. They are displayed when the user determines the most appropriate solution for his work. This is because it is a DSS and does not make the decision for the user but helps the user to decide. Hence the need for the results to be iterative and easy to interpret. To visualise these results, the two solutions filtered in the previous point are shown. Solutions 56 and 7 will have the thinning distribution mapping (Fig. 7). A slider can be seen to move the following actions and the values of thinning of each stand in the legend that allows to click and activate or deactivate the stands of that value, so the user can see the stands that have more and less percentage of thinning.

Fig. 7: Thinning distribution maps for the solutions selected by the user (a) Solution 56, b) Solution 7).

Discussion

CAFE is a tool that combines two main modules: ecohydrological simulation and multi-objective optimisation with evolutionary algorithms. It provides quantitative information on the processes occurring in ecosystems as they fluctuate when one forest management or another is carried out. Provided the complexity of each module, synthetic cases are required to understand how the changes in the solutions fluctuate when the simulation interacts with the optimisation depending on a multitude of factors such as: which model is used, which optimisation algorithm is used, which metrics are optimised and which are quantified, which questions (decision variables) come into play and applied constrains. All these questions need to be covered and realised in order for the application of this tool to be solid.

The fact that the results can be edited by the user, makes the tool practical and interactive. It may seem complex at first glance, but given the amount of information that the tool provides, these measures are necessary for a correct interpretation of the results.

Conclusions

The combination of simulation models and optimization with multi-objective evolutionary algorithms makes this DSS offer the user a generalized view of all possible optimal combinations for a multi-criteria forest management, allowing to get the maximum ecosystemic benefit from the forest to be managed. Moreover, this is easy to handle and interpret thanks to the iterative visualization that provides plasticity and customization by the user who has to work with the results obtained.

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