



sMCDA Tool

An interactive tool for spatial Multi-Criteria Decision Analysis

User Manual

Version 1.0

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1. General Information

1.1. Introduction

The increased availability of spatial data, together with a deeper awareness about the importance of the spatial dimension to support decision-making have highlighted both the central role and the key directions for planning and management across many domains (e.g., Argyris et al., 2019). In this context, spatial Multi-Criteria Decision Analysis (sMCDA) has become a useful method that supports decision-making by leading the identification/creation of the alternatives, the selection of the evaluation criteria and the comprehensive comparison of these alternatives (with e.g., a ranking, a classification) to work out a decision recommendation (e.g., Ferretti and Montibeller, 2016). sMCDA combines Multi-Criteria Decision Analysis (MCDA) with Geographical Information System (GIS) and it is applicable to different topics (e.g., Demesouka et al., 2019; Spada et al., 2019; Xiao et al., 2018). The MCDA enables to consider a wide variety of aspects, e.g. environmental, socio-economic, etc., in a transparent manner (e.g., Volkart et al., 2017), while GIS accounts for the spatial variability of the problem (e.g., Yalcin and Kilic Gul, 2017).

This manual describes the sMCDA Tool, a R-Shiny (R-Studio Team, 2021) tool consisting of three main steps that guide the analyst in the assessment of MCDA at the spatial level starting from data loading, to criteria preparation and finally to sMCDA calculation. In particular, two main families of MCDA methods are considered and applied to the spatial problem in the tool (e.g., Greco et al., 2016):

- Composite indicators (CI), or indices, are single scores given by the aggregation of the performance of the alternatives and the preferences of the decision makers (e.g., Cinelli et al., 2020). In the sMCDA Tool the weighted sum method applied to the spatial case is considered for the construction of CI due to its simplicity and transparency (e.g., Hirschberg et al., 2015).
- Stochastic Multi-criteria Acceptability Analysis – ELECTRE-TRI (SMAA-TRI) is a stochastic approach applied to a classification method (ELECTRE-TRI) that does not allow compensation between criteria, and the weights are considered independent from the measurement scales (Tervonen et al., 2007). The SMAA-TRI assigns a class from 0 (worst) to 1 (best) to each alternative in probabilistic terms by comparing the score for each criteria with respect to class profiles, which distinguish between different classes. Since the SMAA-TRI assigned classes, in order to assess a score on a scale from 0 (Worst) to 1 (Best) for each alternative, the sMCDA tool makes use of a weighted sum of the probabilities, where the worst and best classes receive weights of 0 and 1, and weights for classes in between are linearly extrapolated.

The sMCDA tool aims to provide a practical and straightforward guide to assess MCDA at the spatial level, combining an intuitive Graphical User Interface (GUI) with advanced visualization capabilities and the possibility to export and print the results. The manual shows how to use this tool to conduct a spatial MCDA on the data under the user's interests.

1.2. Installation

The sMCDA Tool is a Shiny app downloadable/cloneable at the following GitHub link: https://github.com/mspada/sMCDA_Tool

To run the sMCDA Tool at the local level, R and R-Studio should be installed on the user machine by downloading them from:

- R: <https://stat.ethz.ch/CRAN/>

- R-Studio: <https://rstudio.com/products/rstudio/download/>

Once the user installed both R and R-Studio and downloaded/cloned the sMCDA Tool repository from GitHub, the process to run the tool can start. The user should follow these steps:

1. Unzip the repository of the sMCDA Tool to a folder (directory) most convenient to the user.
2. Open R-studio
3. Set the working directory, i.e., where the sMCDA Tool repository has been unzipped. This can be done by using the command line in R-studio as following:
 - a. Let us assume that the repository has been unzipped on the Desktop.
 - b. On the R-studio command line one should write `setwd("path to the sMCDA Tool folder")`, i.e., `setwd("~/Desktop/sMCDA_Tool")` on a Unix base system or `setwd("C:\\Users\\username\\Desktop\\sMCDA_Tool")` on a Windows system.
4. Since the sMCDA Tool is running within a R environment (Ushey, 2019), at the first run the user should follow these steps:
 - a. Once the working directory in the sMCDA Tool directory is set, the user should first run in the R-studio command line `source("renv/activate.R")`. This command will activate the R environment.
 - b. Afterwards the user needs to run the command `renv::restore()` on the R-Studio command line to download the packages used by the sMCDA Tool.
5. Next, the user can run the sMCDA Tool from inside the directory by using the command `shiny::runApp()`. **Important:** The first time the user runs the tool, it will take some additional time to start, since the tool needs to download phantomjs if not already installed in the machine.

Following the above mentioned steps, the user can run the sMCDA Tool locally. However, once steps one and four have been executed for the first time, they do not need to be repeated, except if the user is downloading/cloning a new version of the sMCDA Tool from GitHub.

Finally, to test the tool the user can make use of the sample in the **data_example** directory included in the sMCDA Tool GitHub repository.

1.3. The sMCDA Tool User Interface (UI) structure

The sMCDA Tool architecture is presented in Figure 1. In practical terms, the tool consists of three major modules, which are the **Input Data**, the **Criteria Selection** and the actual sMCDA analysis (**Run sMCDA**). Furthermore, the **Run sMCDA** block consists of two different submodules, the **Weighted Sum** and the **Outranking Approach**:

- **Input Data** here the user can select an ESRI shapefile that contains the dataset for the analysis and upload it for later processing. The structure and format of the shapefile is discussed in the section 2.1. Furthermore, the user can view the input dataset in a table form as well as map and histogram for each of the selected criteria in the dataset.
- **Criteria Selection** in this module the user can (1) select the criteria in the dataset for further process, (2) define for each criteria its polarity (i.e., the higher the criteria value is the better

or the other way around), (3) specify the nature of the criteria (i.e., uncertain or not), and (4) assign the distribution types for uncertain criteria. See section 2.2 for further explanations.

- **Run sMCDA** in this module the user can select between two possible approaches for sMCDA, the weighted sum and the outranking. For each of the submodules specific pages are opened when selected, since depending on the selected approach further inputs are needed. Further information is given in section 2.3.

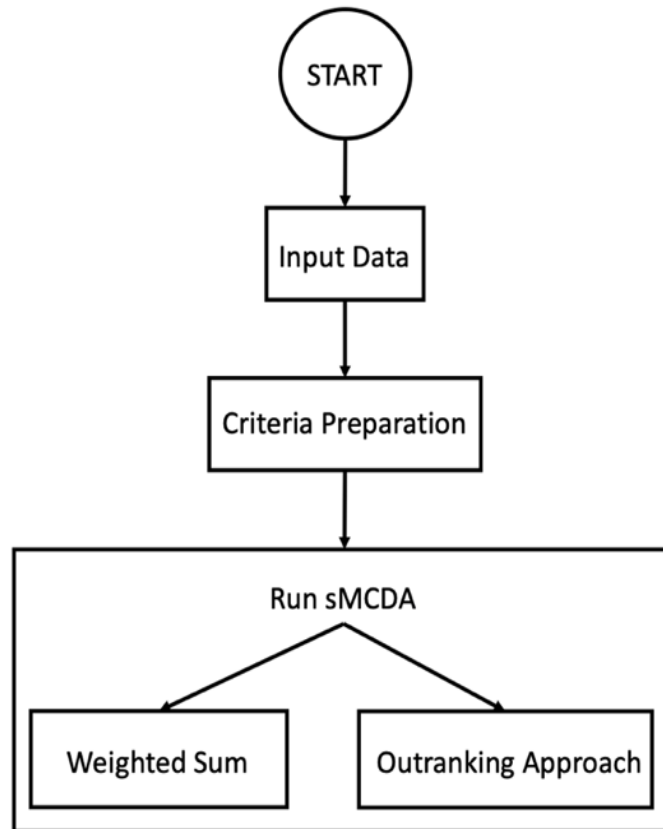


Figure 1 Structure of the User Interface (UI) of the sMCDA Tool

2. The sMCDA Tool

This section presents how to use the sMCDA Tool following the modules defined in Figure 1. In section 2.1 the **Input Data** block is discussed including all possible features in this page as well as how the input file should be structured. Furthermore, section 2.2 discusses how the criteria should be prepared for further analysis. Finally, in section 2.3 the actual sMCDA analysis is presented for both **Weighted Sum** (section 2.3.1) and **Outranking Approach** (section 2.3.2).

2.1. Input Data

Once the sMCDA Tool started, the user is redirected to the **Input Data** page (Figure 2). The page shows on top the name of the tool, a button to hide the sidebar, the Paul Scherrer Institute (PSI) logo, a mail icon linked to the e-mail address of the developer and a logout button (which will be implemented on a future version). The sidebar includes the three major modules of the tool as shown in Figure 1, and the active one is highlighted. In the **Input Data** page, the dataset to be analysed can be uploaded to the tool as an ESRI shapefile (e.g., ESRI, 1998).

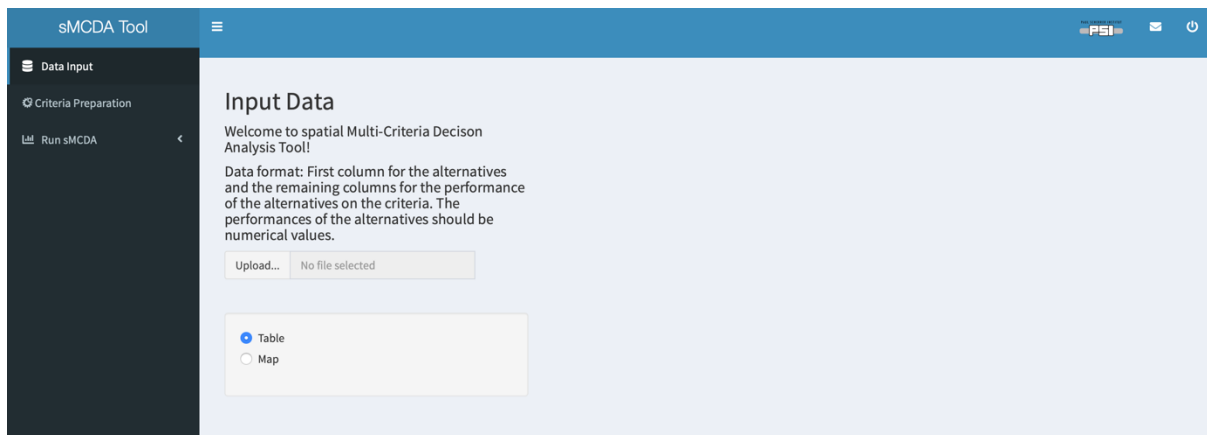


Figure 2 Input Data page as shows once the user runs the sMCDA Tool

The first column of the input dataset lists the alternatives, while the other columns contain the different criteria or their descriptive parameters defining an uncertain input as shown in Figure 3.

Alt	Crit1	Crit2min	Crit2max	Crit3min	Crit3max	Crit4min	Crit4max	Crit5min	Crit5max	Crit6min	Crit6max	Crit7
1 Alt1	2839.00000	0.072	0.168	0.0407	0.078	38.500	128.300	0.00152	0.00448	40.000	80.000	21.150
2 Alt2	8885.00000	0.038	0.077	0.0216	0.054	43.400	122.000	0.00178	0.00435	25.000	65.000	16.430
3 Alt3	4662.00000	0.075	0.154	0.0391	0.098	26.200	67.400	0.00147	0.00401	55.000	90.000	20.700
4 Alt4	4761.00000	0.067	0.125	0.0417	0.085	22.900	51.300	0.00151	0.00398	40.000	80.000	19.550
5 Alt5	4925.00000	0.03	0.1	0.0254	0.045	39.700	116.500	0.00167	0.0044	35.000	70.000	17.400

Figure 3 Format of the input dataset. The first column includes the sMCDA alternatives

To upload a dataset, the user needs to click on the **Upload** button in Figure 2. Then, a window will open, and the user can select the dataset to upload. **Important:** the user should upload not only the shapefile (.shp), but also the other files related to it (i.e., .dbf, .shx, .prj, etc.). In fact, the shapefile itself does not contain the entire set of information, but only some metadata (e.g., ESRI, 1998). The actual data are stored into the .dbf file, while the geographical projection is located on the .prj file, etc. Finally, the user clicks on **Choose for Upload** as shown in Figure 4.

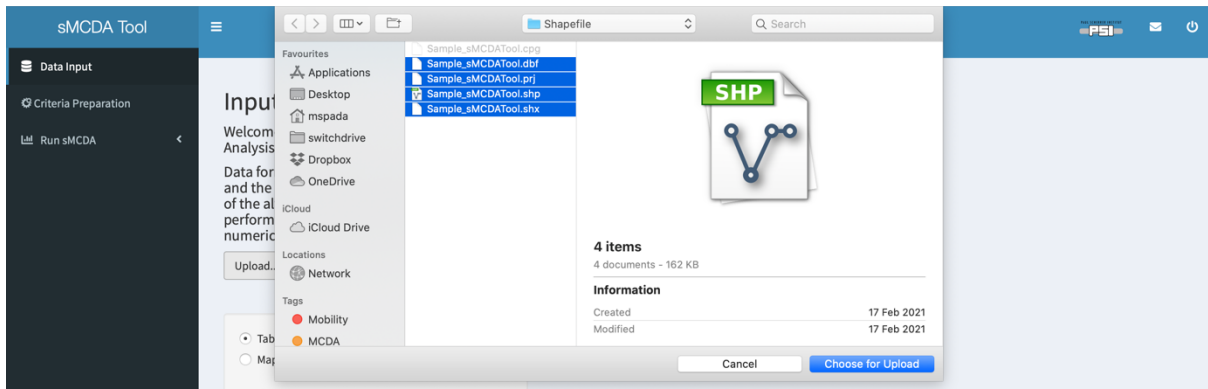


Figure 4 Selection of all the file needed to upload the dataset in the sMCDA Tool

Once the input dataset is uploaded, it is shown in the same page in a Table format (Figure 5). This allows the user to check the imported values.

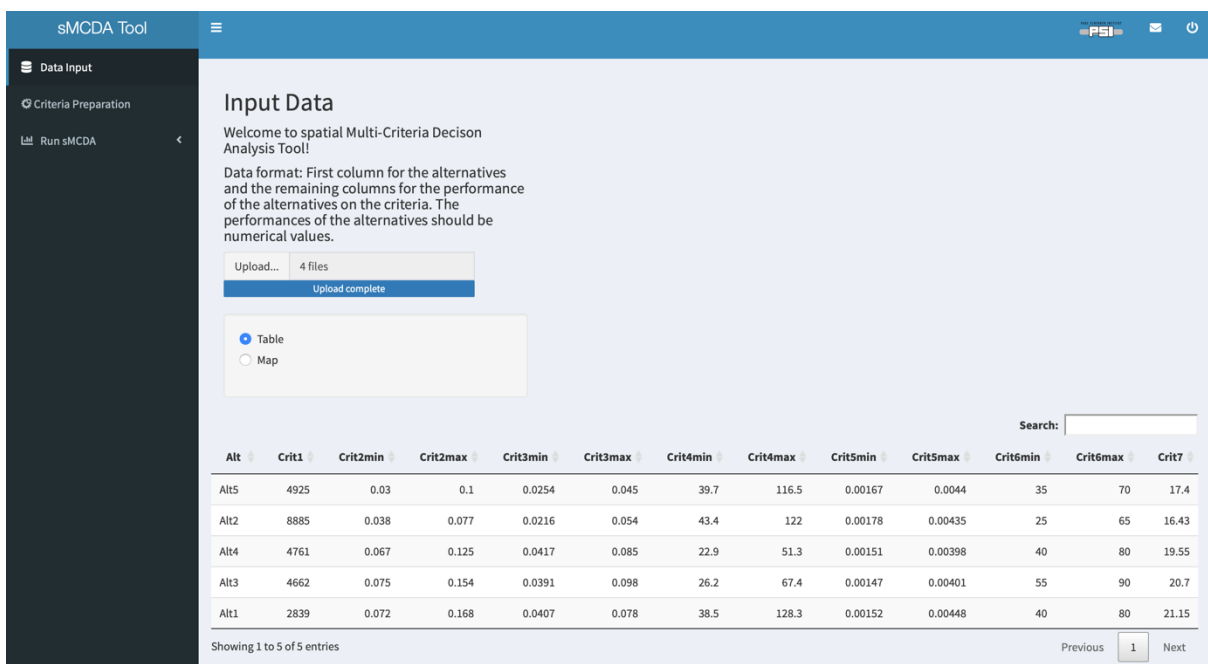


Figure 5 Uploaded Dataset shown as Table

In addition to the tabular format, the user can also plot the input dataset as maps. This can be done by select **Map** in the grayish box under the **Upload** button (Figure 5). Once selected, the table disappears, and on the top of the page a dropdown list containing the entire set of criteria names in the input dataset shows up. Here, the user can select what criteria map to plot as shown in Figure 6. In addition, the user can download the map as a .png file by clicking on **Download Image**.

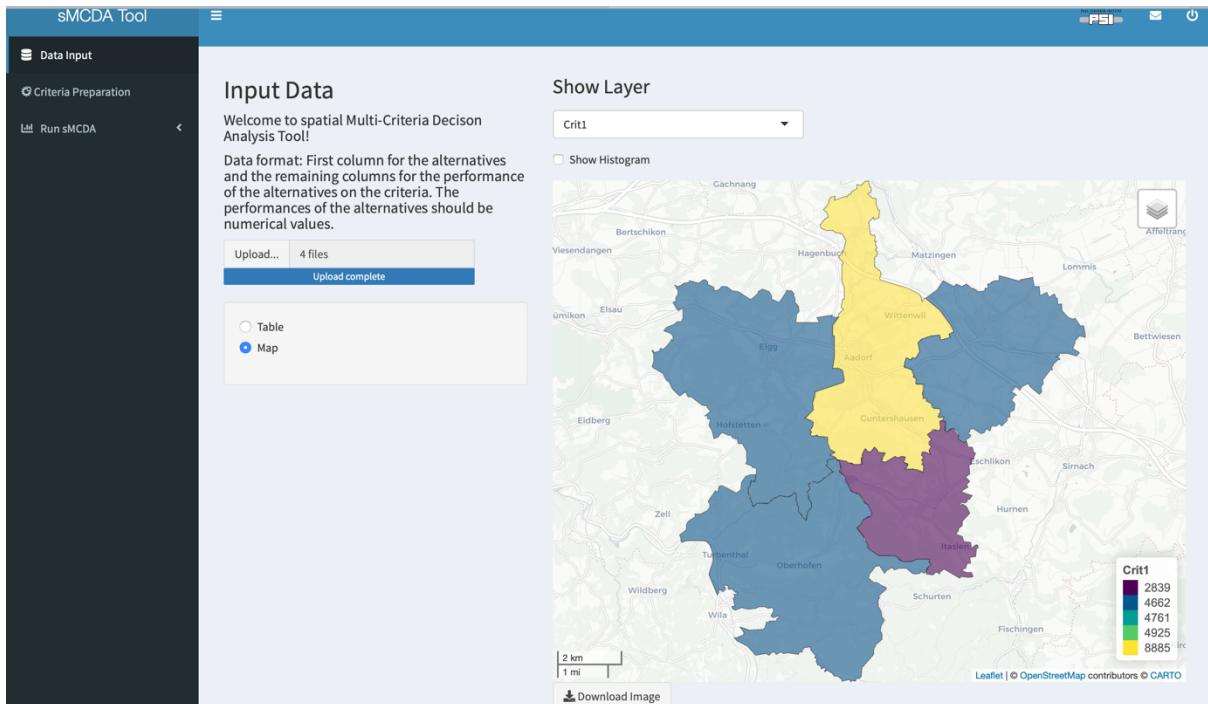


Figure 6 Example of the plot of a map for the selected indicator in the dropdown list

In addition to the map, the user can also plot the histogram of the selected criteria in the dropdown list by checking **Show Histogram**. Once this is done, the histogram appears below the map as shown in Figure 7.

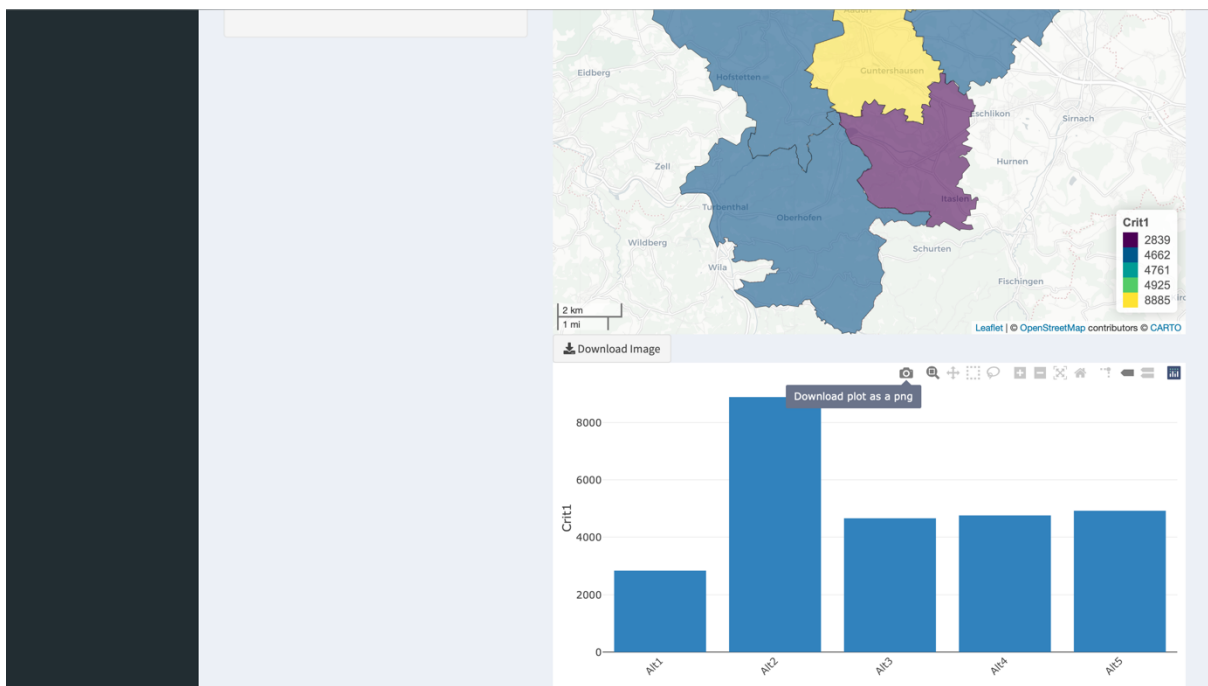


Figure 7 Example of the plot of a histogram for the selected indicator in the dropdown list

As for the map, the user can download the histogram as a .png file by clicking the camera logo that appears on the plot when moving over it with the mouse cursor (Figure 7).

2.2. Criteria Preparation

Given the input dataset uploaded in **Input Data**, in this module the user needs to prepare the criteria for the analysis. In particular, the user has to specify the polarity of each criteria, its nature (i.e. deterministic/exact or probabilistic), and finally assign the correct column heading from the input file. This procedure can be done either directly in the tool by selecting **Manual Input** or externally by importing a .csv file by selecting the **Input from File** in the grayish rectangular box as shown in Figure 8.

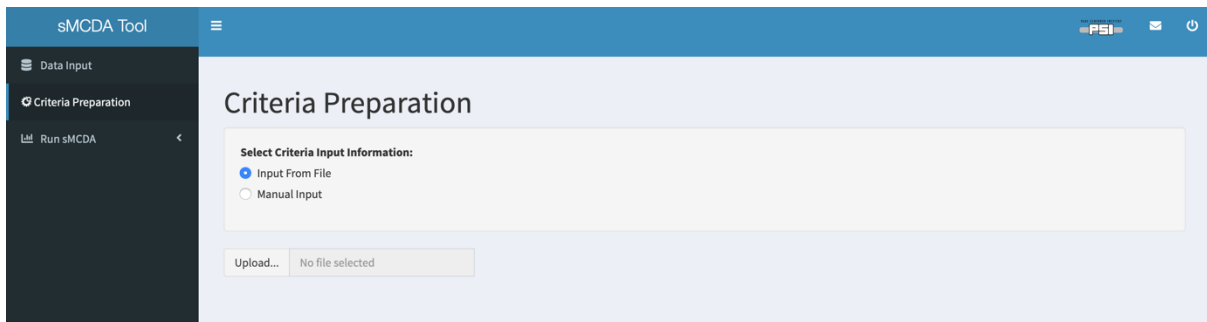


Figure 8 Criteria Preparation Page

2.2.1. Input From File

Once the user clicks on **Criteria Preparation**, the **Input from File** choice is selected as default. Here the user can upload the criteria information as .csv file by clicking on **Upload**. The .csv file should be comma-separated and thus the user needs to be sure that this is the default separation character for the operating system's (e.g., Windows, Mac OS, Linux, etc.) default language. In fact, for example, the separation character is the semi-colon (“;”) for a system with German as the default language, while for English it is comma (“,”). Therefore, in the German case, the system preferences need to be updated by the user. The uploaded .csv file should have the format shown in Figure 9.

Names	Polarity	Nature	Layers
Crit1	-	exact	Crit1
Crit2	-	unif	Crit2min Crit2max
Crit3	-	unif	Crit3min Crit3max
Crit4	+	unif	Crit4min Crit4max
Crit5	-	unif	Crit5min Crit5max
Crit6	-	unif	Crit6min Crit6max
Crit7	+	exact	Crit7

Figure 9 Format of the .csv file for Criteria Preparation

In the first column, the user has to insert the **Names** of the criteria. In the second column the **Polarity** of each criterion should be included in terms of + or -. The former indicates that the higher the criteria value is the better, while with - the lower the criteria value is the better. In the third column the **Nature** of the criteria should be specified. When **exact** the criteria is defined by a unique number for each alternative, while when the criteria are defined by a probabilistic distribution, i.e., as an uncertain input, the distribution name should be specified. In the sMCDA Tool, four different distributions are implemented: Uniform (**unif** in the file); Normal (**norm** in the file), Lognormal (**logno** in the file); Poisson (**pois** in the file). Finally, in the last column (**Layers**) the user should name the column in the

input dataset where the tool should look for the corresponding data. When the nature of a criterion is **exact**, then there is only one layer, while in case of the distributions there must be ≥ 1 layer associated with this criterion, depending on the number of parameters describing the distribution. In this context, the following parameters should be included:

- **Uniform distribution** is defined by the minimum and maximum parameters. Therefore, in **Layers** the first and second entries should indicate the column names in the input dataset where the minimum and maximum values of the criteria under interest are located, respectively (Figure 9).
- **Normal distribution** is defined by the mean and standard deviation parameters. Therefore, in **Layers** the first and second entries should indicate the column names in the input dataset where the mean and standard deviation of the criteria under interest are located, respectively.
- **Lognormal distribution** is defined by the log of the mean and the log of the standard deviation parameters. Therefore, in **Layers** the first and second entries should indicate the column names in the input dataset where the log of the mean and the log of the standard deviation of the criteria under interest are located, respectively.
- **Poisson distribution** is defined by the rate parameter only. Therefore, similar to the **exact** case, only one entry in **Layers** is needed.

Based on these premises, it is clear that whenever a criterion is described by a probabilistic distribution, the corresponding parameters should be included in the input dataset prior to import it in the tool. Furthermore, when a criteria is described by a distribution, the **Names**, **Polarity** and **Nature** inputs in the .csv file should be entered only once as shown in Figure 9. Finally, once the user uploads the .csv file including all the **Criteria Preparation** information a table shows up in the main page (Figure 10). In this way, the user can check the validity of the input information. **Important:** if the table does not show the format in Figure 10 based on the input file in Figure 9, it means that the user needs to revise the .csv file.

Criteria Preparation

Select Criteria Input Information:

Input From File
 Manual Input

Upload... Sample_Criteria.csv
 Upload complete

Search:

Names	Polarity	Nature	Layers
Crit1	-	exact	Crit1
Crit2	-	unif	Crit2min Crit2max
Crit3	-	unif	Crit3min Crit3max
Crit4	+	unif	Crit4min Crit4max
Crit5	-	unif	Crit5min Crit5max
Crit6	-	unif	Crit6min

Showing 1 to 10 of 12 entries

Previous 1 2 Next

Figure 10 Table showing the uploaded Criteria Preparation input file

2.2.2. Manual Input

The **Criteria Preparation** module can also be provided by using the **Manual Input** mode. In this context, the user once selected the **Manual Input** in the grayish box in **Criteria Preparation** is requested to input all the information about the criteria under interest by using different dropdown menus (Figure 11).

Criteria Preparation

Select Criteria Input Information:

Input From File
 Manual Input

Select Criteria

Crit1 Crit2min Crit3min Crit4min Crit5min
 Crit6min Crit7

Select Polarity of Crit1: Negative

Select nature of Crit1: Exact

Select Layer: Crit1

Select Polarity of Crit2min: Negative

Select nature of Crit2min: Uniform

Select Layer for Min Unif: Crit2min

Select Layer for Max Unif: Crit2max

Select Polarity of Crit3min: Negative

Select nature of Crit3min: [Dropdown menu open showing: Exact, Uniform, Normal, Lognormal, Poisson]

Select Polarity of Crit4min: Positive

Select Polarity of Crit5min: Negative

Select Polarity of Crit6min: Negative

Select Polarity of Crit7: Positive

Select nature of Crit6min: [Dropdown menu]

Select nature of Crit7: [Dropdown menu]

Figure 11 Manual Input for the Criteria Preparation

First, the user is requested to input the selected criteria from the input dataset by clicking in the white rectangular box under **Select Criteria** as shown in Figure 11. **Important:** when a criterion is described by an uncertain input, i.e. probabilistic distribution, the user should select only one of the two attributes describing the distribution in the **Select Criteria** box as shown, for example, for Crit2, Crit3, Crit4, Crit5 and Crit6 in Figure 11. For each selected criterion, the columns for Polarity and Nature show up. Here for each criterion, the user should use the dropdown menus to input the requested information. Furthermore, when **Exact** is selected for the nature of a criterion, a third column shows up requesting the **Layer**, which correspond to the column name where the tool has to look at for data in the input dataset. On the other hand, if a criterion has an uncertain input, the user should select the distribution defining this criterion (i.e., uniform, normal, etc.). In this case, depending on the selected distribution (see section 2.2.1), the **Layer** shows up with one or two possible entries to be populated with the column names in the input dataset corresponding to the parameters describing the distribution (see for example Figure 11 for Crit2). At the end of the manual **Criteria Preparation**, the user should have filled all entries for each selected criterion as shown, for example, in Figure 12.

Figure 12 Manually populated Criteria Preparation section

2.3. Run sMCDA

Once the **Criteria Preparation** module is finalized – either by using an input file or by doing it manually – the user can run the sMCDA under the **Run sMCDA** module. Here, the user can select between two methods: **Weighted Sum** and **Outranking Approach**. In the next sections, the two methods are presented.

2.3.1. Weighted Sum

When **Weighted Sum** is selected, the user makes use of a MIN-MAX normalization approach for the criteria under interest combined with a weighted sum aggregation method (e.g., Cinelli et al., 2020). The initial page looks like the one in Figure 13. On the left hand side of the main page the user can select to sample the weights of the criteria by using a SMAA approach (e.g., Pelissari et al., 2019), **Sample Weights**, or by input the weights of each criteria manually (e.g., Hirschberg et al., 2015), **Input Weights**. In either case, before running the sMCDA the user should select the number of Monte-Carlo

runs for the SMAA approach. The default value is 1 meaning no SMAA application. **Important:** If all input criteria are **exact**, i.e., defined by single numbers rather than probability distributions, and the weight profile is selected manually (**Input Weights**), the Monte-Carlo run should be kept to the default (1), i.e., no Monte-Carlo runs since no variability is present neither in the input criteria nor the weights. Once the number of runs is selected, the user should click on **Perform sMCDA** to calculate the results. **Important:** the calculation time is depending on the input number of runs, the architecture of the machine where the tool is running and the number of available CPUs, since the tool makes use of a parallel computation to calculate the results.

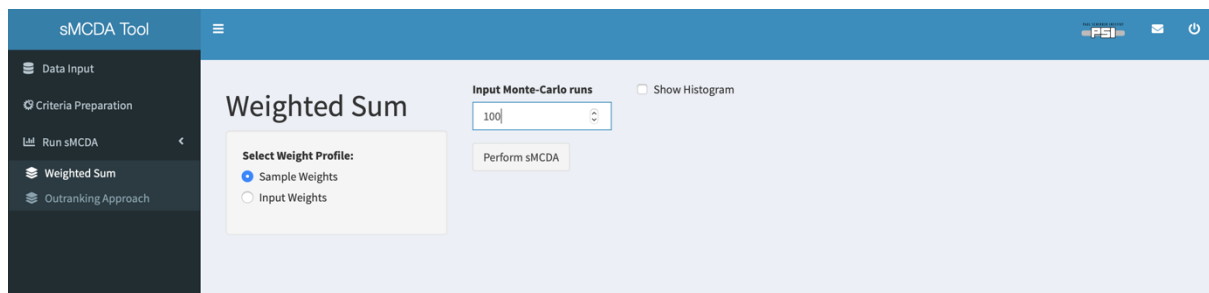


Figure 13 Main Page for the Weighted Sum sMCDA approach

Once the calculation finished, the resulting map is plotted on the right hand side of the main page (Figure 14). The map shows the **Mean sMCDA score** in case the number of Monte-Carlo runs > 1, while it just shows the final **sMCDA score** in case the number of Monte-Carlo runs = 1.

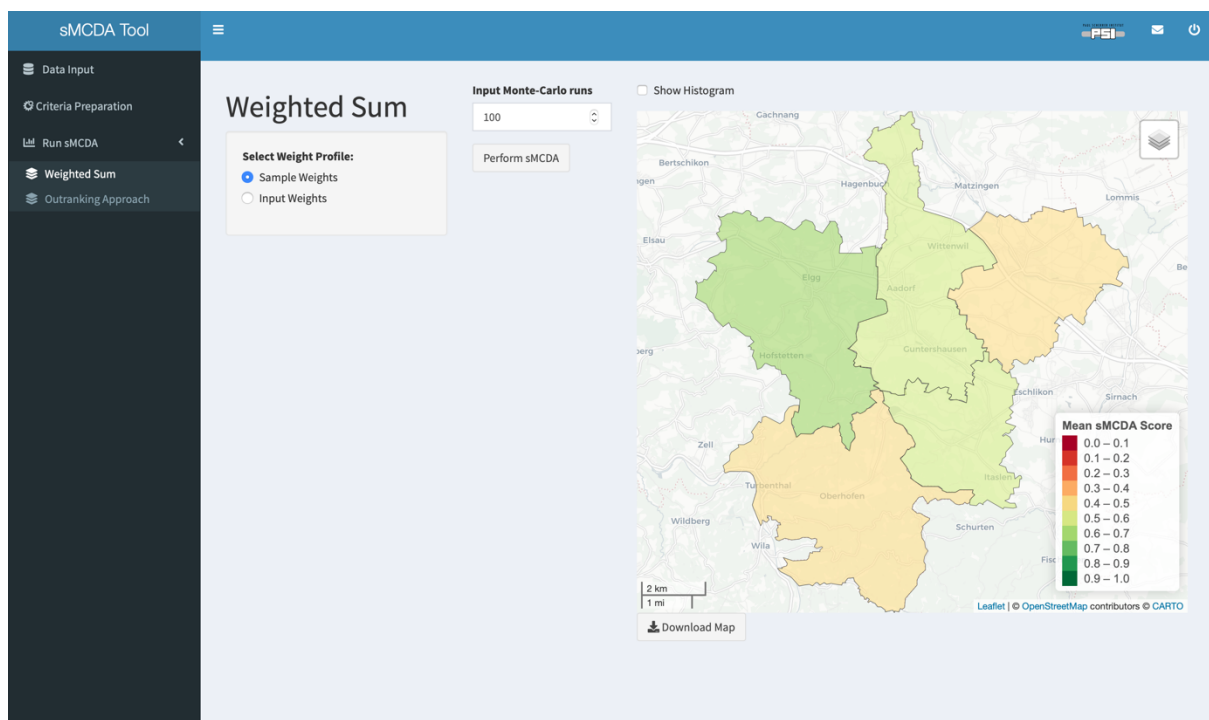


Figure 14 Example of a resulting Map (Mean sMCDA Score) after 100 Monte-Carlo samples using the input dataset described in 2.1, which combines uncertain and not exact criteria inputs, and a set of weights samples.

The user can download the map in different formats by clicking **Download Map** under the figure. Once clicked, a popup opens showing the different options for download that are implemented in the tool, which are .png, .jpg, .csv, .xlsx and ESRI shapefile (Figure 15). **Important:** Although the map shows only the mean of the sMCDA Score when running the sMCDA with Monte-Carlo samples > 1, in the .csv, .xlsx and shapefile downloadable file formats the standard deviation of the sMCDA score is also included.

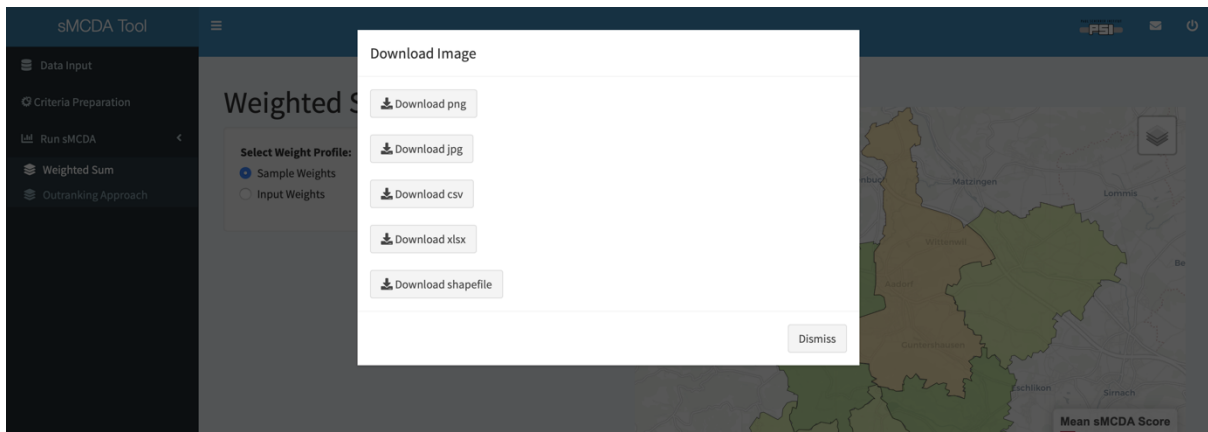


Figure 15 Resulting Map download options in the sMCDA Tool

As in section 2.1, the user can plot the histogram of the sMCDA score by checking the box **Show Histogram**. Once checked, the resulting histogram appears below the resulting map. If the results are based on a Monte-Carlo sample, i.e., runs > 1, the histogram shows the mean as well as the error bars based on the estimated standard deviation (Figure 16).

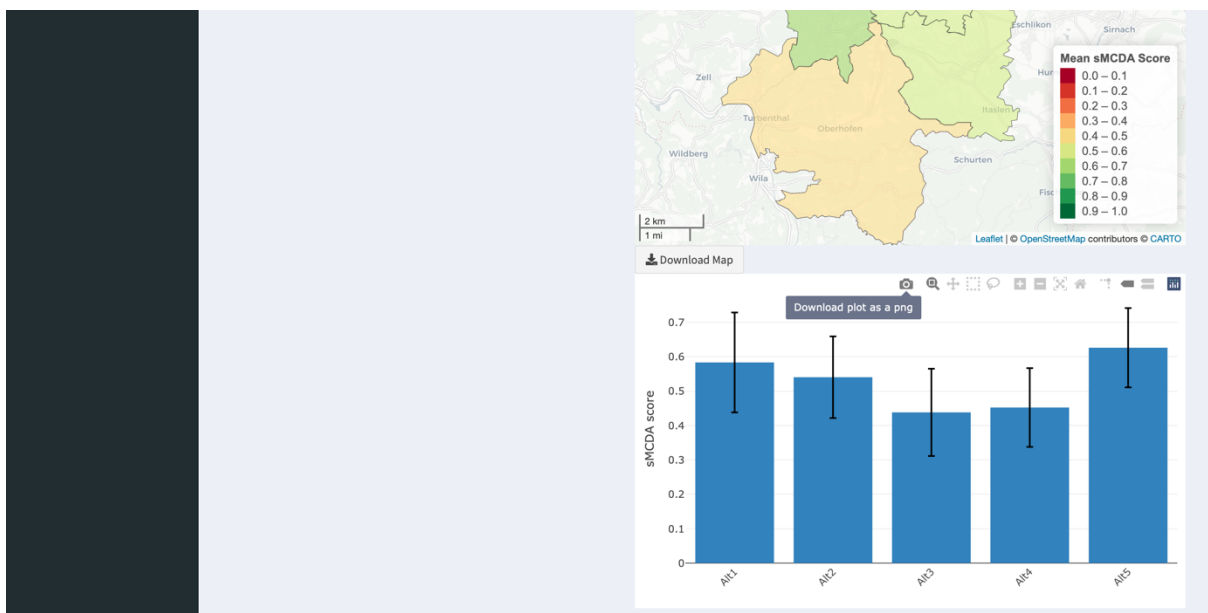


Figure 16 Example of a resulting histogram after 100 Monte-Carlo samples using the input dataset described in 2.1, which combines uncertain and not exact criteria inputs, and a set of weights samples.

Similar to the **Input Data** module (section 2.1), the histogram can be downloaded as .png by moving the mouse cursor on it and clicking on the camera logo.

Finally, instead of sampling the weights of each criterion, the user can manually input the criteria weights by selecting **Input Weights** in Figure 13. Once selected, weight bars for all criteria appear and the user can modify them according to his/her interest (Figure 17).

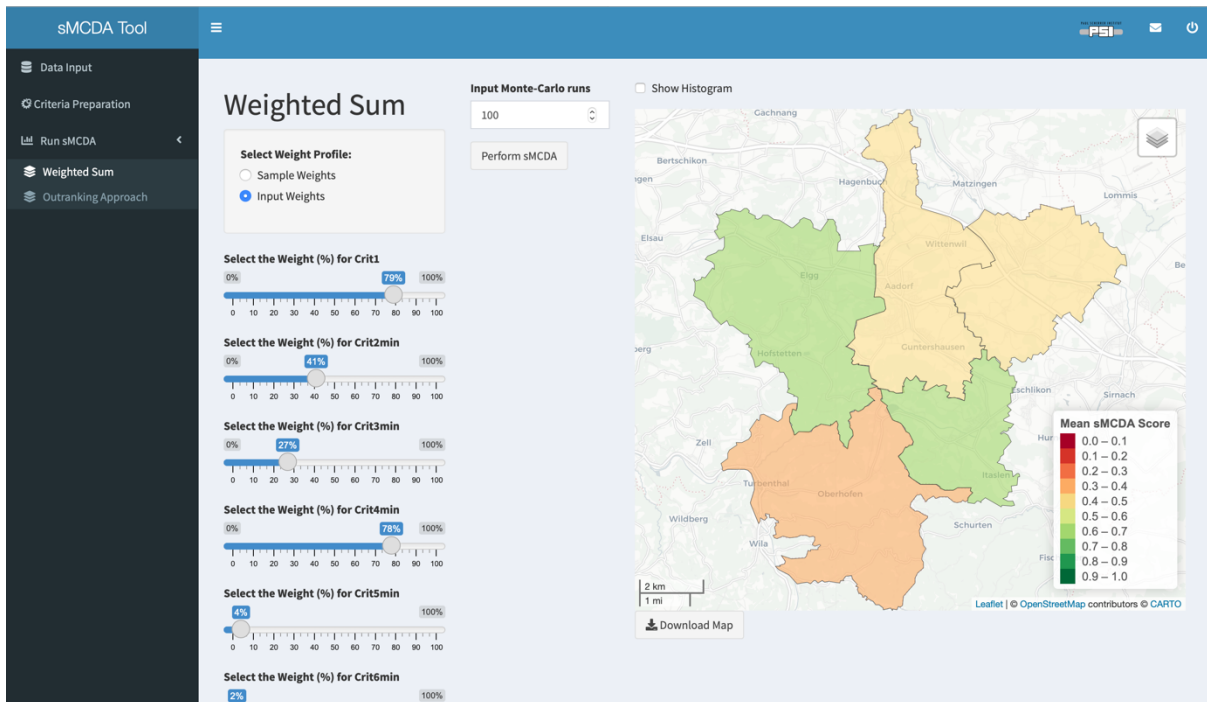


Figure 17 Weight bars to manually input the weights of each criteria under interest.

Once the weight of each criterion is selected, the user can follow the abovementioned steps from the selection of the number of Monte-Carlo runs on.

2.3.2. Outranking Approach

The outranking approach used in the sMCDA Tool is a Stochastic Multi-criteria Acceptability Analysis (SMAA-TRI) applied to the spatial problem. The SMAA-TRI algorithm is a classification method, which does not allow compensation between criteria, and the weights are considered independent from the measurement scales (e.g., Tervonen et al., 2007). Once clicked on the corresponding link of the sMCDA Tool sidebar, the user is redirected to the page where the SMAA-TRI approach can be used. To run the outranking approach additional information is needed, which concerns the classes and three additional thresholds: indifference, preference and veto (e.g., Greco et al., 2016). Therefore, the **Outranking Approach** page is developed to help the user adding this information step by step as discussed in the next sections.

2.3.2.1. Input Data Preparation

In the **Input Data Preparation** page, the user is requested to add the classes for the application of the outranking approach either by uploading a .csv file (**Input From File**) or by inserting them manually (**Manual Input**), see Figure 18.

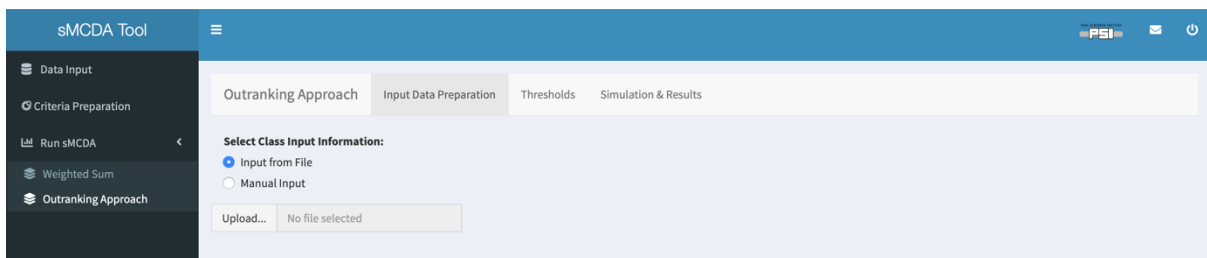


Figure 18 Input Data Preparation page for class definition

Input From File when the user selects this option, which is also the default one, a .csv file containing the class thresholds for each criterion needs to be uploaded by clicking on **Upload** in the main page (Figure 18). The .csv file should be comma-separated as discussed, for example, in section 2.2.1 and should have the format in Figure 19.

Crit1	Crit2	Crit3	Crit4	Crit5	Crit6	Crit7
100000	0.15	0.1	25	0.06	70	16
50000	0.03	0.02	50	0.01	50	21

Figure 19 Format of the .csv file containing the class thresholds used by the Outranking Approach

Each column of the .csv file refers to one of the criteria under interest. Furthermore, the numeric rows refer to the thresholds used to identify the classes by the outranking approach. For example, in Figure 19 two rows are populated by numbers, meaning that three classes are defined. In fact, by considering Crit1 in the figure, one class is defined for criteria values ≥ 100000 , one class for criteria values between 50000 and 100000 and one class for criteria values ≤ 50000 . **Important:** The threshold values order depends on the polarity of the criteria. If the polarity of the criteria is - the lower value should be in the last row (for example, Crit1 has a negative polarity, therefore, 50000 is written in the last row), while if the polarity is + the higher values should be written in the last row (for example, Crit4 has positive polarity, therefore, 50 is written in the last row).

Once the user uploads the .csv file including all class thresholds a table shows up in the main page. In this way, the user can check the validity of the input information. **Important:** if the table does not show the format in Figure 20 based on the input file in Figure 19, it means that the user needs to revise the .csv file.

Crit1	Crit2	Crit3	Crit4	Crit5	Crit6	Crit7
100000	0.15	0.1	25	0.06	70	16
50000	0.03	0.02	50	0.01	50	21

Figure 20 Table showing the uploaded class thresholds input file

Manual Input when the user selects this option, the main page is modified as shown for example in Figure 21. At first, only the **Insert the number of classes of interest** box is shown. Once the number of classes of interest are inserted, for each criterion a set of boxes appears depending on the number of selected classes. For example, if the user selects 3 classes, two boxes for each criterion appear; for 4 classes, three boxes for each criterion, etc.. The user needs then to fill the threshold values for each criterion, i.e. fill each appeared box. **Important:** Similar to the **Input From File** above, the threshold values order depends on the polarity of the criteria. If the polarity of the criteria is - the lower value should be written in the second box (for example, Crit1 has a negative polarity, therefore, 50000 is written in the second box), while if the polarity is + the higher values should be written in the second box (for example, Crit4 has positive polarity, therefore, 50 is written in the second box), see Figure 21.

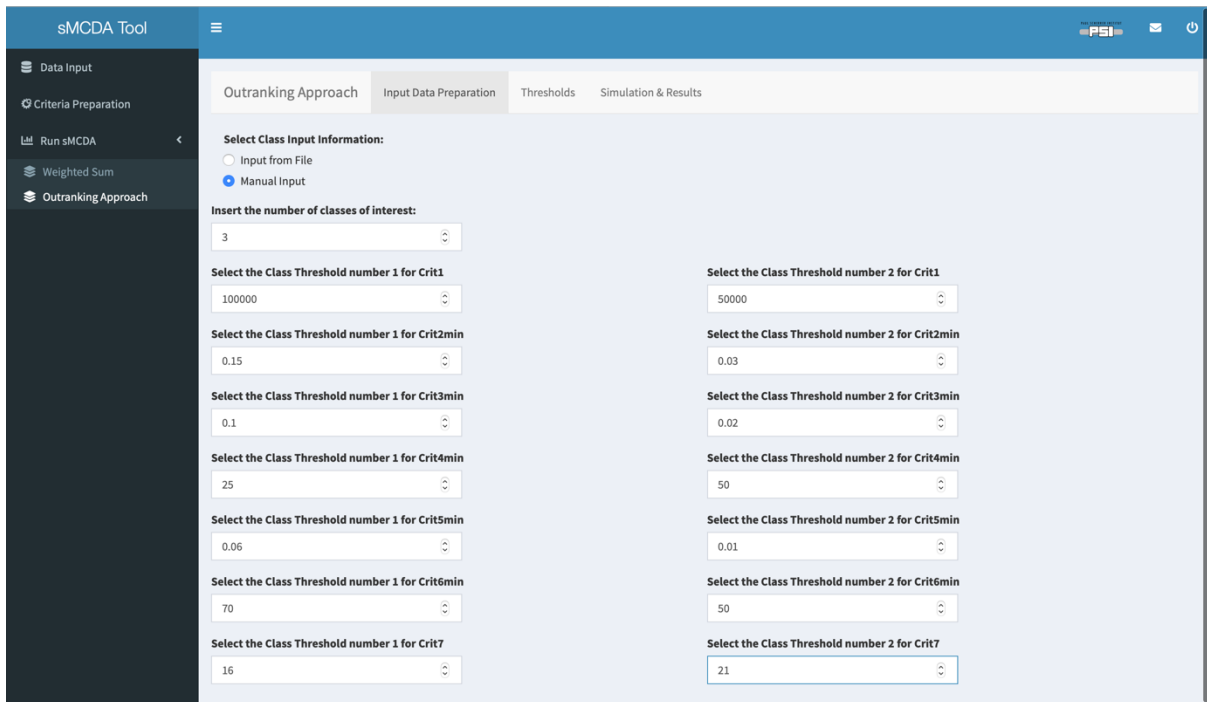


Figure 21 Manual Input for the class thresholds

Once the **Input Data Preparation** page is filled in either manually or by importing the .csv file, the user can click on **Thresholds** in the navigation bar of the **Outranking Approach** page.

2.3.2.2. Thresholds

Similar to the **Input Data Preparation** page, the user is requested to provide the additional thresholds commonly used in an ELECTRE-TRI model, which are indifference, preference and veto (e.g., Greco et al., 2016), by either uploading a .csv file (**Input From File**) or insert them manually (**Manual Input**), see Figure 22.

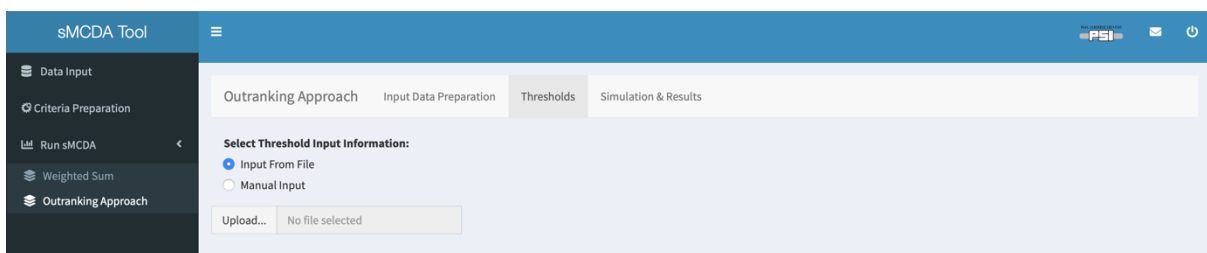


Figure 22 Thresholds page to input indifference, preference and veto thresholds

Input From File when the user select it, which is also the default one, it needs to upload a .csv file by clicking **Upload** in the main page (Figure 22). The .csv file should be comma-separated as discussed, for example, in section 2.2.1 and should have the format in Figure 23.

Names	Preference	Indifference	Veto
Crit1	500	250	1.00E+06
Crit2	0.01	0.005	1.00E+06
Crit3	0.01	0.005	1.00E+06
Crit4	5	1	1.00E+06
Crit5	0.01	0.005	1.00E+06
Crit6	5	2	1.00E+06
Crit7	0.5	0.1	1.00E+06

Figure 23 Format of the .csv file containing the indifference, preference and veto thresholds used by the Outranking Approach

In the first column, the .csv file should contain the criteria names, while in the second, third and fourth columns the preference, indifference and veto threshold values, respectively. **Important:** the user can also set the thresholds to have no effects in the calculation of the sMCDA, by putting 0 to the indifference and preference thresholds and a large number (relative to the criteria values) to the veto thresholds (as done in the example in Figure 23). Once the .csv file is uploaded in the tool, a table shows up in the main **Thresholds** page (Figure 24). **Important:** if the table does not show the format in Figure 24 based on the input file in Figure 23, it means that the user needs to revise the .csv file.

The screenshot shows the 'sMCDA Tool' interface with the 'Thresholds' tab selected. The 'Input From File' option is chosen. An upload button labeled 'Sample_Thresholds.csv' has been used, with a confirmation message 'Upload complete'. Below this is a table with the following data:

Names	Preference	Indifference	Veto
Crit1	500	250	1000000
Crit2	0.01	0.005	1000000
Crit3	0.01	0.005	1000000
Crit4	5	1	1000000
Crit5	0.01	0.005	1000000
Crit6	5	2	1000000
Crit7	0.5	0.1	1000000

At the bottom of the table, it says 'Showing 1 to 7 of 7 entries' and has 'Previous' and 'Next' navigation buttons.

Figure 24 Table showing the uploaded preference, indifference and veto thresholds

Manual Input when selected, the user needs to input the indifference, preference and veto thresholds for each criterion manually (Figure 25). **Important:** as for the **Input From File**, the user can set thresholds that do not affect the calculation by putting 0 to the indifference and preference thresholds and a large number (relative to the criteria values) veto threshold.

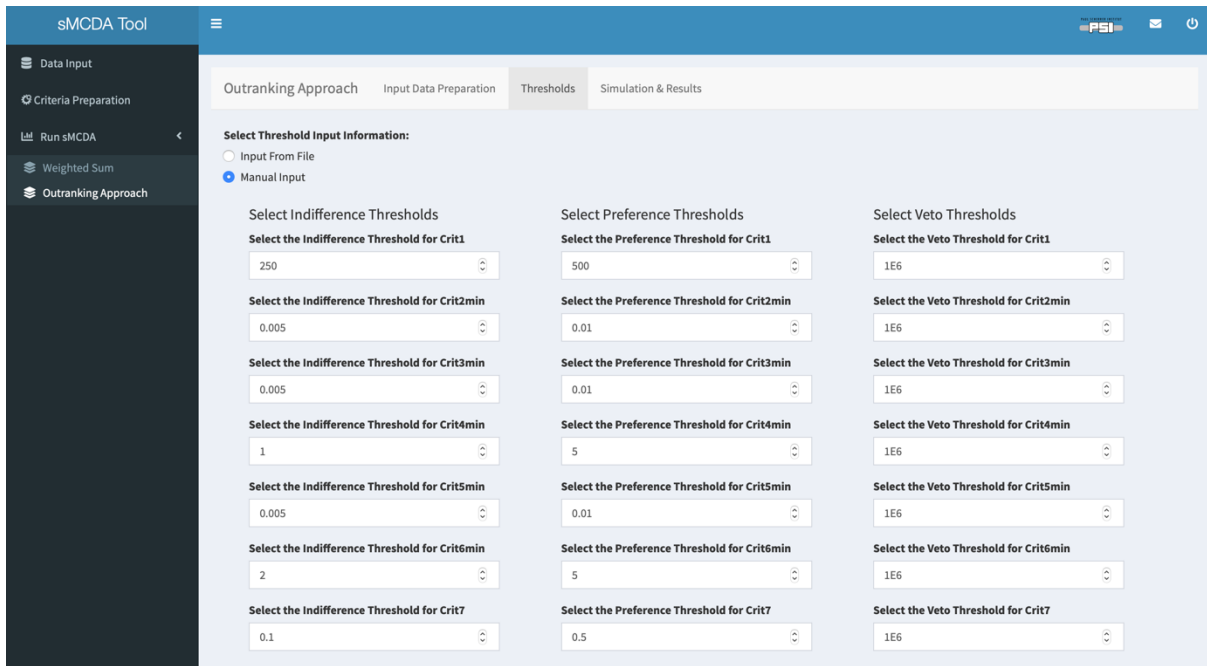


Figure 25 Manual Input for the indifference, preference and veto thresholds

Once the **Thresholds** page is completed either manually or by uploading the .csv file, the user can click on **Simulation & Results** in the navigation bar of the **Outranking Approach** page.

2.3.3. Simulation & Results

The **Simulation & Results** page in the **Outranking Approach** has the same functionalities as the **Weighted Sum** page described in section 2.3.1. Therefore, the user should refer to the former section for further explanations. However, with respect to the **Weighted Sum** page, in this page an additional input is needed, the **Input Decision Maker Strongness**, which refers to the level on how demanding the decision maker is (defined as λ , see Tervonen et al. (2007)).

As for the **Weighted Sum**, also in the **Simulation & Results** page the user can select to sample the weights (Figure 26a) or input the weights manually (Figure 26b). **Important:** In all cases, the sMCDA is running a SMAA-TRI method, since the **Input Decision Maker Strongness** is defined as a range and the values can be sampled from this range. However, the user can also run a common ELECTRE-TRI, i.e., by input 1 in the Monte-Carlo runs, if and only if no criteria are uncertain, i.e., all criteria are **exact**, the weights are set manually (**Input Weights**), and the **Input Decision Maker Strongness** is set to a unique value by overlapping the two values in the range bar.

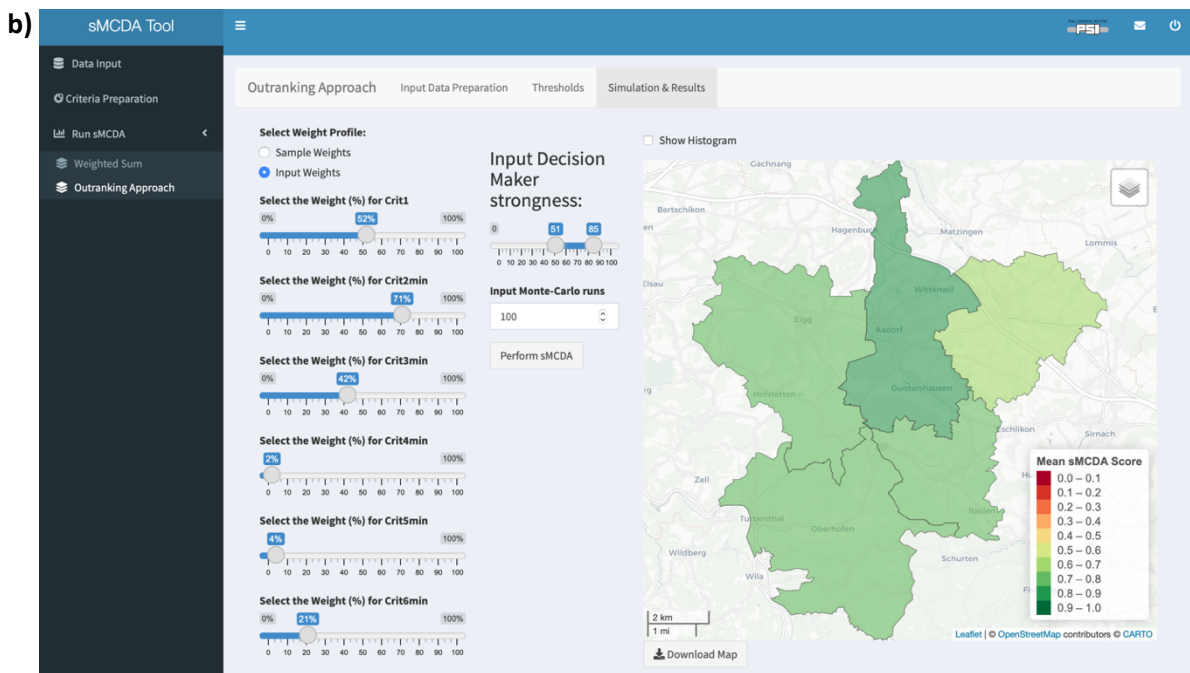
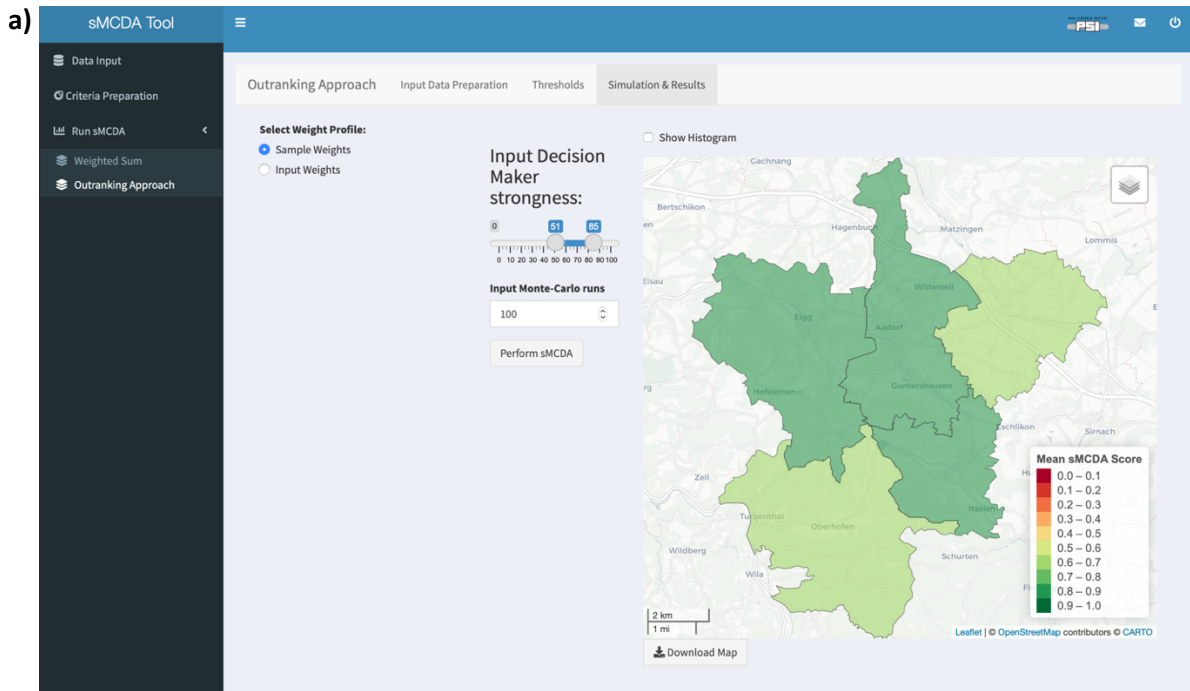


Figure 26 Simulation & Results page. a) Result for a 100 Monte-Carlo Samples of the weights, the λ in the range 0.51 (less demanding decision-maker) – 0.85 (demanding decision-maker) and the uncertain input criteria; b) Result for a 100 Monte-Carlo Samples of the λ in the range 0.51 (less demanding decision-maker) – 0.85 (demanding decision-maker) and the uncertain input criteria, while the weights are manually input by the user.

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