# 7. Supplementary Materials

## 7.1 Active period of fire spread

Fire radiative energy (FRE) was estimated from Fire Radiative Power (FRP) data from the Spinning Enhanced Visible and Infrared Imager (SEVIRI) sensor on board the Meteosat Second Generation (MSG) geostationary satellite. For a set of 81 large wildfires, contained in the Portuguese Large Wildfire Spread Database (PT-FireSprd; Benali et al., 2023), the average hourly FRE was calculated, covering the entire diurnal cycle.

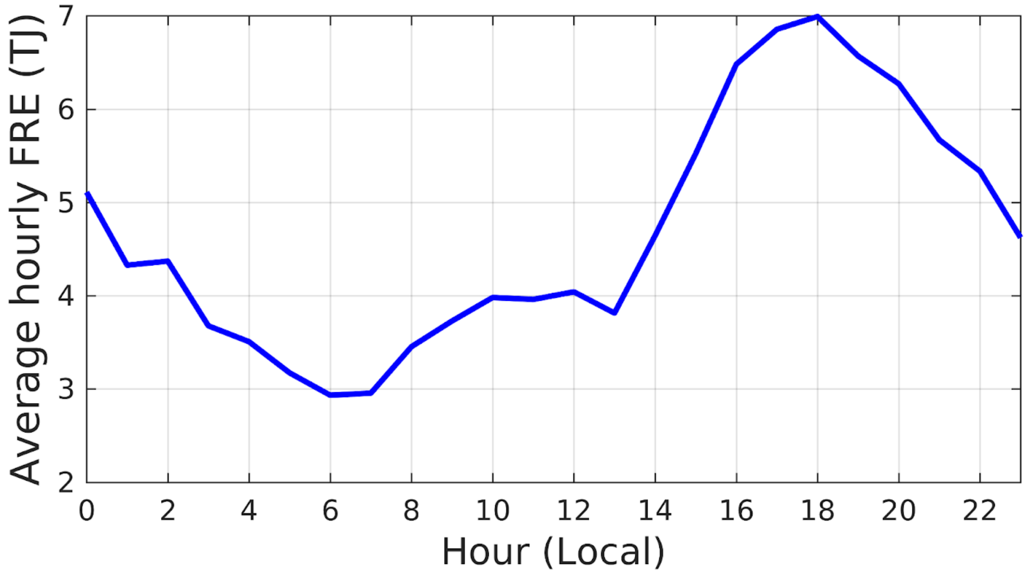



Figure S1 - Diurnal distribution of Fire Radiative Energy (TJ)

## 7.2 Example of the required format for the meteorological conditions text file

Table S1 – Example of the text file (csv) generated after using the functions *get_fire_weather* and *fire_weather_nc*. If the user wants to use other meteorological data than ERA5-Land, then they need to provide a similar table in build_report function. The ID represents the id of the fire perimeter in the shapefile used as input in the function *get_fire_weather* or *fire_weather_nc*; the row and col represent the row number and the column number (respectively) where the information regarding the weather conditions is stored in the netcdf file for the fire event specified in the column ID; lon and lat represent the longitude and latitude (respectively) of the ERA5-Land point that is either contained by the fire perimeter or the closest to the fire perimeter; day_files represent the date and time of the specified weather conditions (format yyyymmddhh) in UTC+0; day_UTC_corrected represent the date and time of the specified weather conditions (format yyyymmddhh) in the UTC specified by the user (here UTC+1); temperature represents the temperature in degrees Celsius in the specified point at the specified time; RH represents the relative humidity in percentage in the specified point at the specified time; WS represents the wind speed in km/h in the specified point at the specified time; and WD represents the wind direction in degrees in the specified point at the specified time.

| *ID* | *row* | *col* | *lon* | *lat* | *day_files* | *day_UTC_corrected* | *T* | *RH* | *WS* | *WD* |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | 1986071711 | 1986071712 | 31.86 | 29.33 | 4.78 | 346.13 |
| *12929* | 10 | 10 | -8.1 | 40.1 | 1986071712 | 1986071713 | 32.8 | 27.54 | 6.51 | 325.84 |
| | | | | | 1986071713 | 1986071714 | 33.41 | 26.99 | 8.83 | 320.26 |

## 7.2 Comprehensive example of the distribution of ignitions within the scenarios

Table S2 – Example of the final matrix used to generate the ignitions. The number of ignitions in each scenario results from the combined relative frequencies and weights from all factors considered (relative frequency of the cluster or percentile x relative frequency of the wind direction x relative frequency of the duration class x weight of the year of fuel model map). WD represents wind direction; W represents the weight. The number of ignitions is shown between parenthesis.

| *cluster* | *WD* | *duration_1* | *duration_2* | *duration_3* | *duration_4* | *Year of fuel map (W)* |
|---|---|---|---|---|---|---|
| *1* | N | 0.085 (254) | 0.010 (31) | 0.020 (61) | 0.004 (13) | 2003 (0.6) |
| | E | 0.006 (18) | 0.001 (2) | 0.001 (4) | 0.000 (1) | |
| | SE | 0.060 (181) | 0.007 (22) | 0.015 (44) | 0.003 (9) | |
| | S | 0.022 (66) | 0.003 (8) | 0.005 (16) | 0.001 (3) | |
| | SW | 0.010 (30) | 0.001 (4) | 0.002 (7) | 0.001 (2) | |
| | W | 0.048 (145) | 0.006 (18) | 0.012 (35) | 0.003 (8) | |
| | NW | 0.185 (556) | 0.022 (67) | 0.045 (134) | 0.010 (29) | |
| *2* | N | 0.016 (48) | 0.002 (6) | 0.004 (12) | 0.001 (3) | |
| | E | 0.004 (12) | 0.000 (1) | 0.001 (3) | 0.000 (1) | |
| | SE | 0.087 (260) | 0.010 (31) | 0.021 (63) | 0.004 (13) | |
| | S | 0.002 (6) | 0.000 (1) | 0.000 (1) | 0.000 (0) | |
| | SW | 0.006 (18) | 0.001 (2) | 0.001 (4) | 0.000 (1) | |
| | W | 0.006 (18) | 0.001 (2) | 0.001 (4) | 0.000 (1) | |
| | NW | 0.169 (508) | 0.020 (61) | 0.041 (123) | 0.009 (26) | |
| *1* | N | 0.085 (169) | 0.010 (20) | 0.020 (41) | 0.004 (9) | 2018 (0.4) |
| | E | 0.006 (12) | 0.001 (1) | 0.001 (3) | 0.000 (1) | |
| | SE | 0.060 (121) | 0.007 (15) | 0.015 (29) | 0.003 (6) | |
| | S | 0.022 (44) | 0.003 (5) | 0.005 (11) | 0.001 (2) | |
| | SW | 0.010 (20) | 0.001 (2) | 0.002 (5) | 0.001 (1) | |
| | W | 0.048 (97) | 0.006 (12) | 0.012 (23) | 0.003 (5) | |
| | NW | 0.185 (371) | 0.022 (45) | 0.045 (90) | 0.010 (19) | |
| *2* | N | 0.016 (32) | 0.002 (4) | 0.004 (8) | 0.001 (2) | |
| | E | 0.004 (8) | 0.000 (1) | 0.001 (2) | 0.000 (0) | |
| | SE | 0.087 (173) | 0.010 (21) | 0.021 (42) | 0.004 (9) | |
| | S | 0.002 (4) | 0.000 (0) | 0.000 (1) | 0.000 (0) | |
| | SW | 0.006 (12) | 0.001 (1) | 0.001 (3) | 0.000 (1) | |
| | W | 0.006 (12) | 0.001 (1) | 0.001 (3) | 0.000 (1) | |
| | NW | 0.169 (339) | 0.020 (41) | 0.041 (82) | 0.009 (18) | |

## 7.3 Influence of landscape files used in the MTT simulations

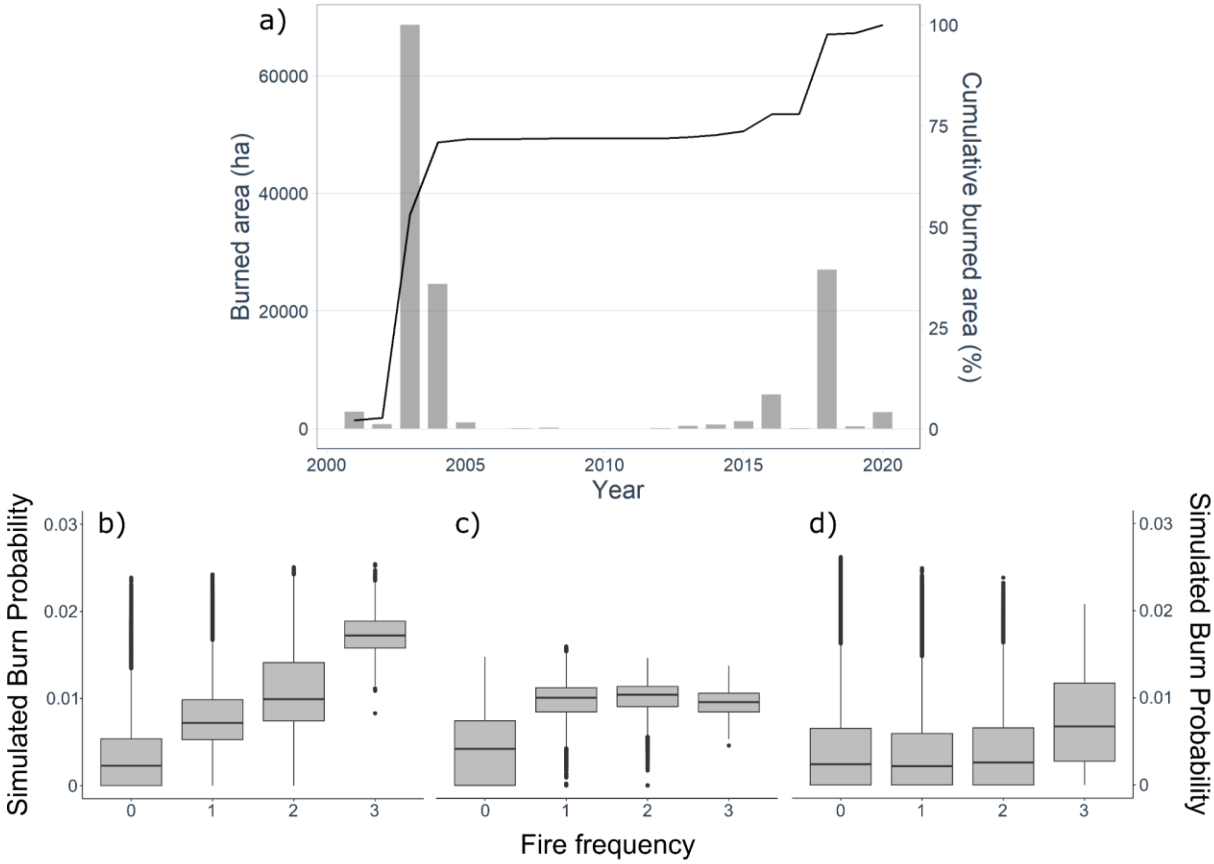



Figure S2 – The upper panel shows the distribution of burned area (in ha) for the period 2000-2020 in the Barlavento Algarvio study area (a). Similar figure is exported using the function build_report. The lower panel shows the correlation between the simulated burn probability and the historical fire frequency in the period 2000-2020. The simulated burn probability was calculated using b) two historical fuel models corresponding to the years with the greatest contribution to the burned area (2003 and 2018) and ignitions randomly sampled following the historical probability of ignition; c) the same historical fuel models (2003 and 2018) and ignitions randomly sampled; and d) only one historical fuel models corresponding to the year of 2022 and ignitions randomly sampled following the historical probability of ignition.

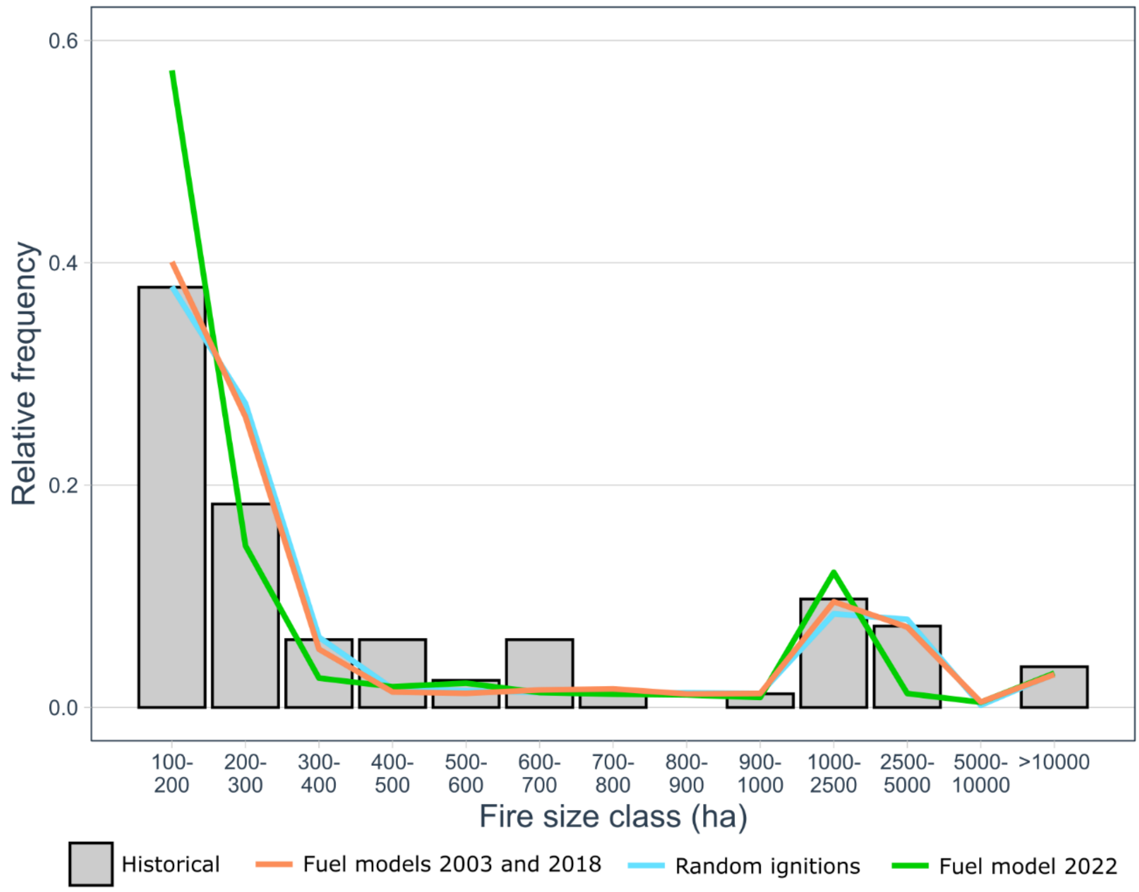



Figure S3 – Historical and simulated fire size distribution generated using two historical fuel models corresponding to the years with the greatest contribution to the burned area (2003 and 2018) and ignitions sampled following the historical probability of ignition (identified in the legend as scenario "Fuel models 2003 and 2018", which corresponds to panel b in Figure SM2); the same historical fuel models (2003 and 2018) and ignitions randomly sampled (identified in the legend as scenario "Random ignitions", which corresponds to panel c in Figure SM2); and only one historical fuel models corresponding to the year of 2022 and ignitions sampled following the historical probability of ignition (identified in the legend as scenario "Fuel model 2022", which corresponds to panel d in Figure SM2). The historical fire size distribution is represented by a histogram.

## 7.4 Minimum simulations required for a trustworthy calibration

### 7.4.1 Fire size distribution

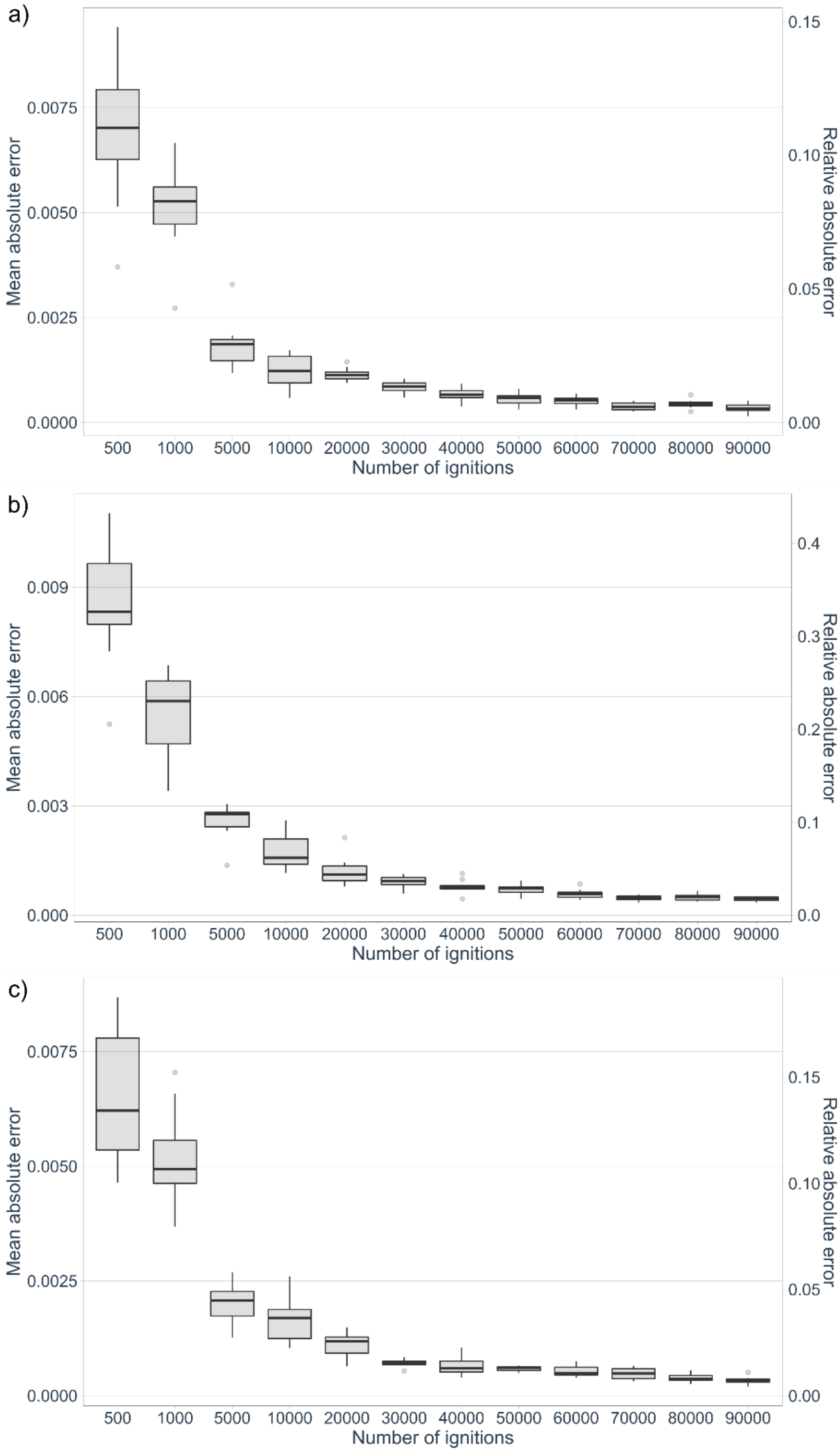



Figure S4 – Mean absolute error (MAE) and relative absolute error (RAE) calculated from the fire size distribution obtained from 200,000 fire runs and from 500, 1000, 5000, 10000, 20000, 30000, 40000, 50000, 60000, 70000, 80000, 90000 fire runs for AM Porto (a), Médio Tejo (b), and Barlavento Algarvio (c).

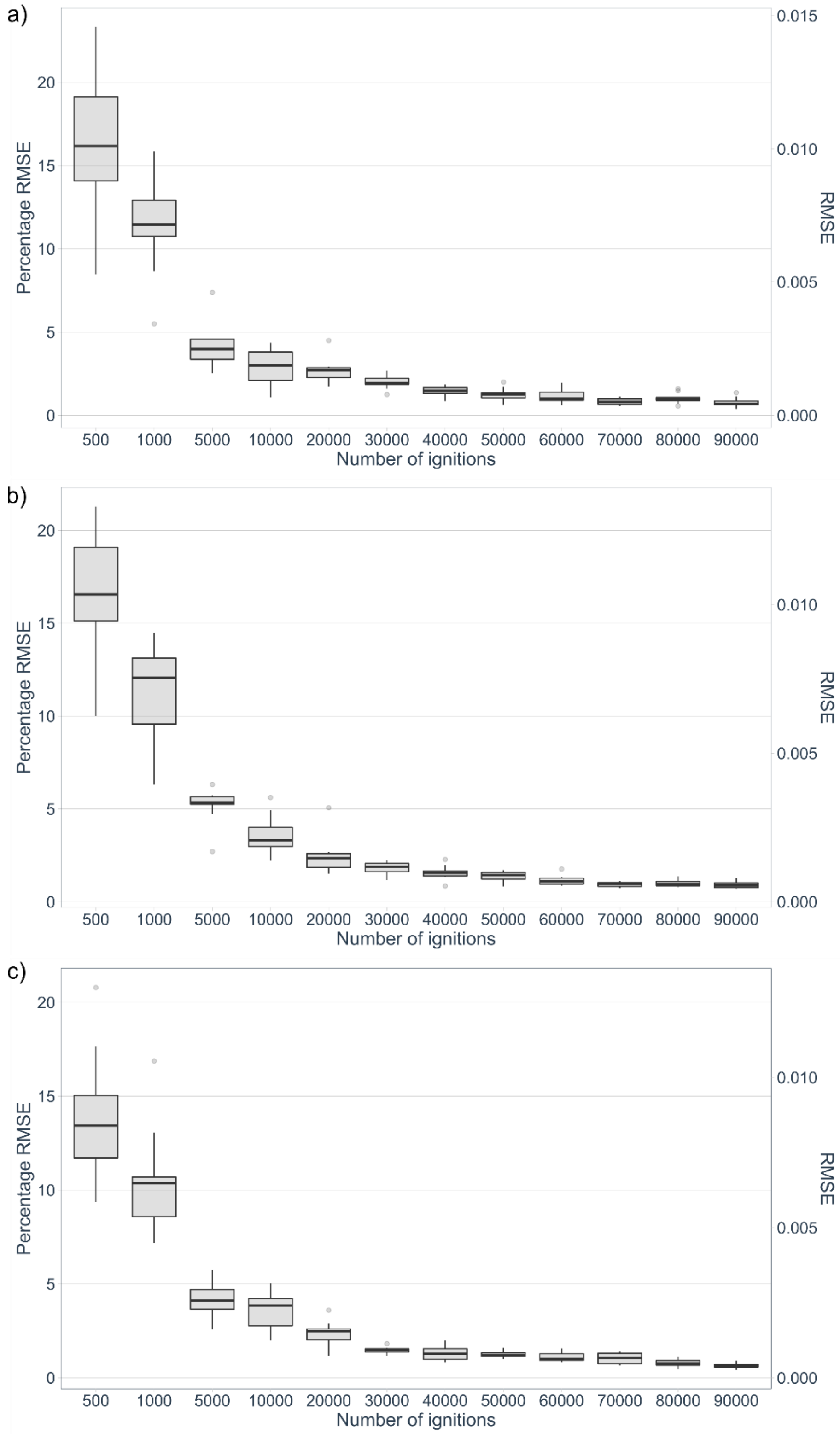



Figure S5 – Root Mean Square Error (RMSE) and percentage NRMSE calculated for the fire size distribution obtained from 200,000 fire runs and from 500, 1000, 5000, 10000, 20000, 30000, 40000, 50000, 60000, 70000, 80000, 90000 fire runs for AM Porto (a), Médio Tejo (b), and Barlavento Algarvio (c).

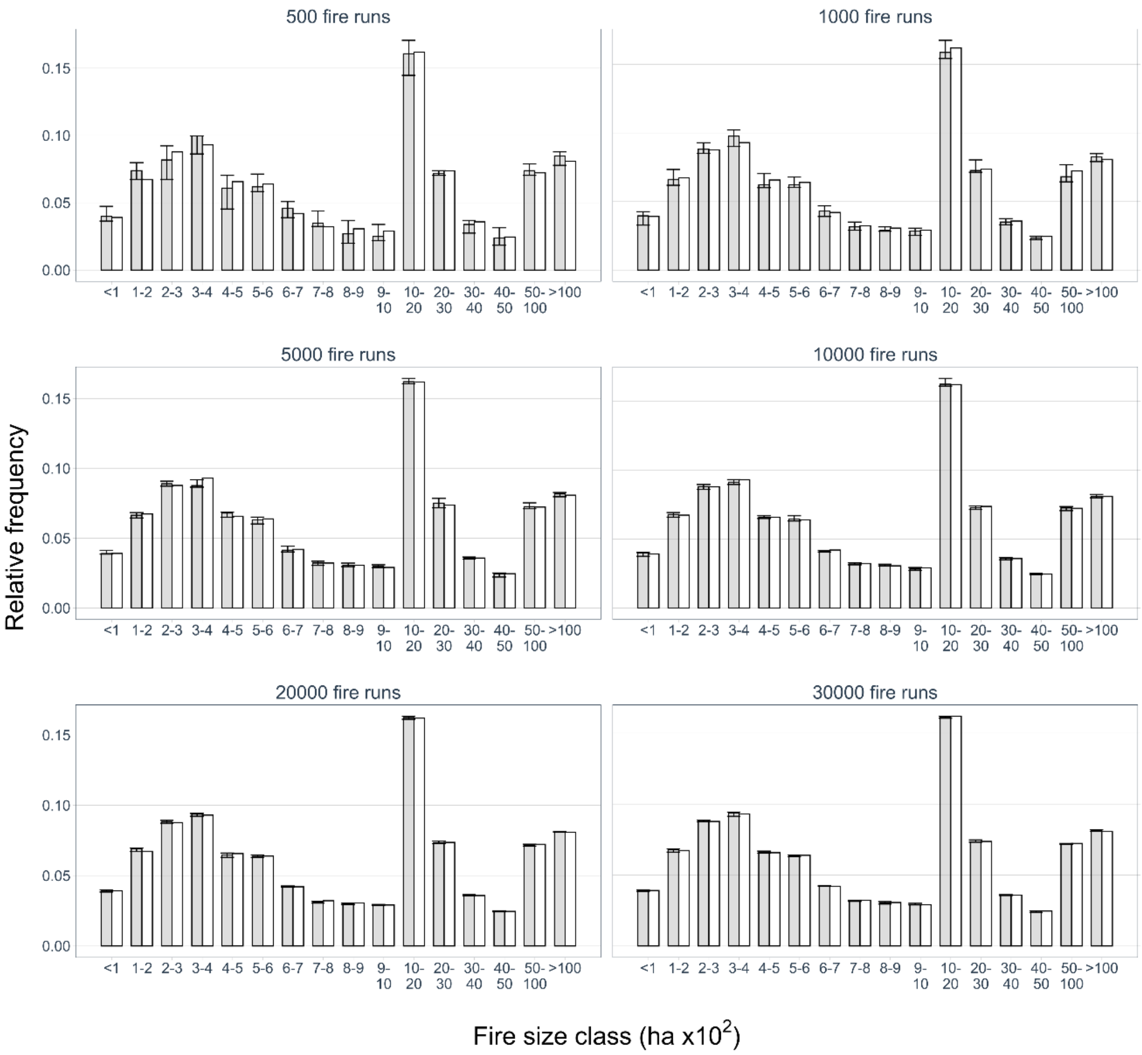



Figure S6 - Fire size distribution for the baseline scenario calculated from 200,000 fire runs (white) and for the scenarios calculated from N fire runs (grey) for the Médio Tejo study area. The error bar on top of the grey barplot represents the variability in the 10 replicates considered in each scenario. The grey bar represents the median value of the 10 replicates.

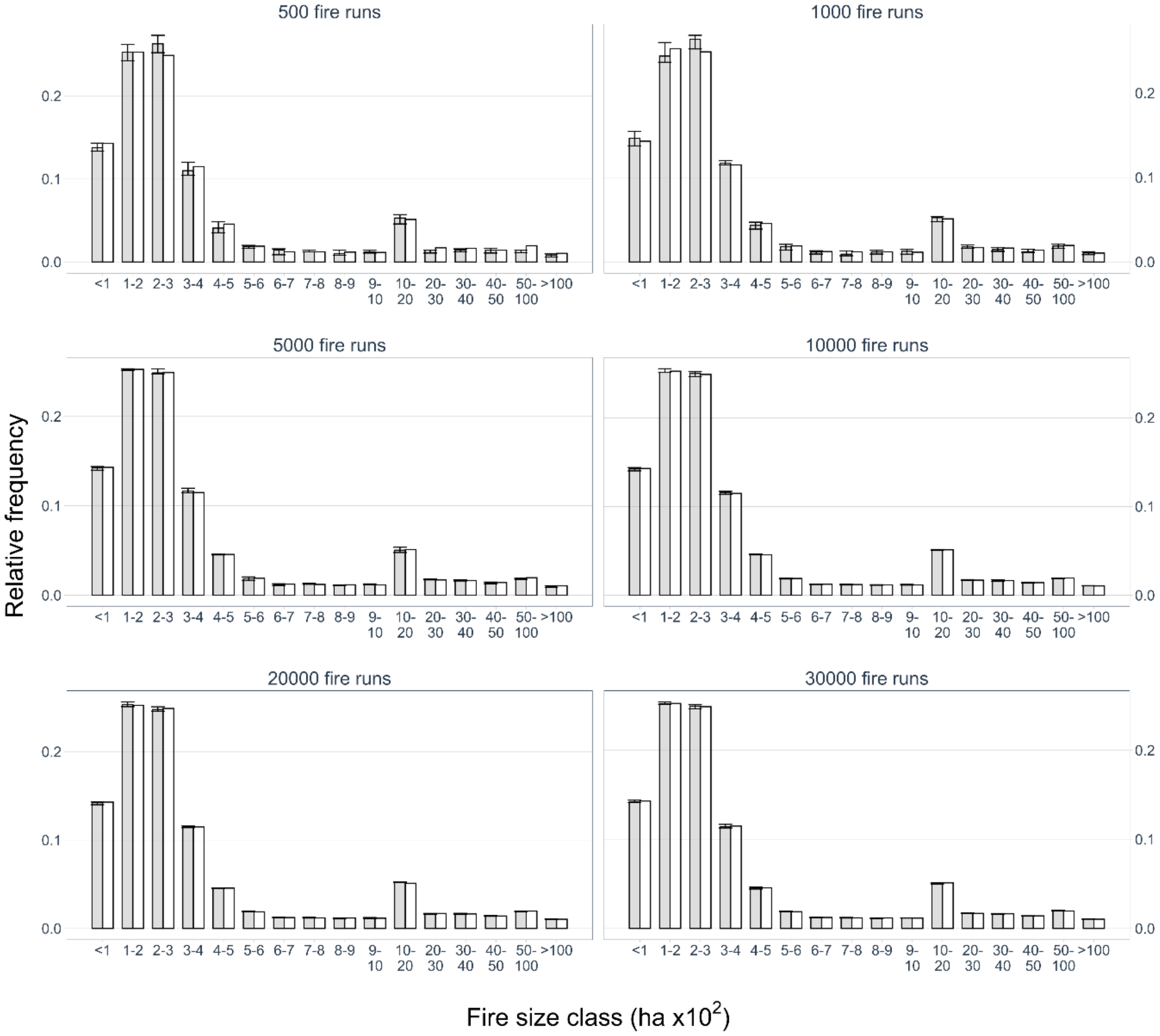



Figure S7 - Fire size distribution for the baseline scenario calculated from 200,000 fire runs (white) and for the scenarios calculated from N fire runs (grey) for the AM Porto study area. The error bar on top of the grey barplot represents the variability in the 10 replicates considered in each scenario. The grey bar represents the median value of the 10 replicates.

## 7.4.2 Correlation between Burn Probabilities

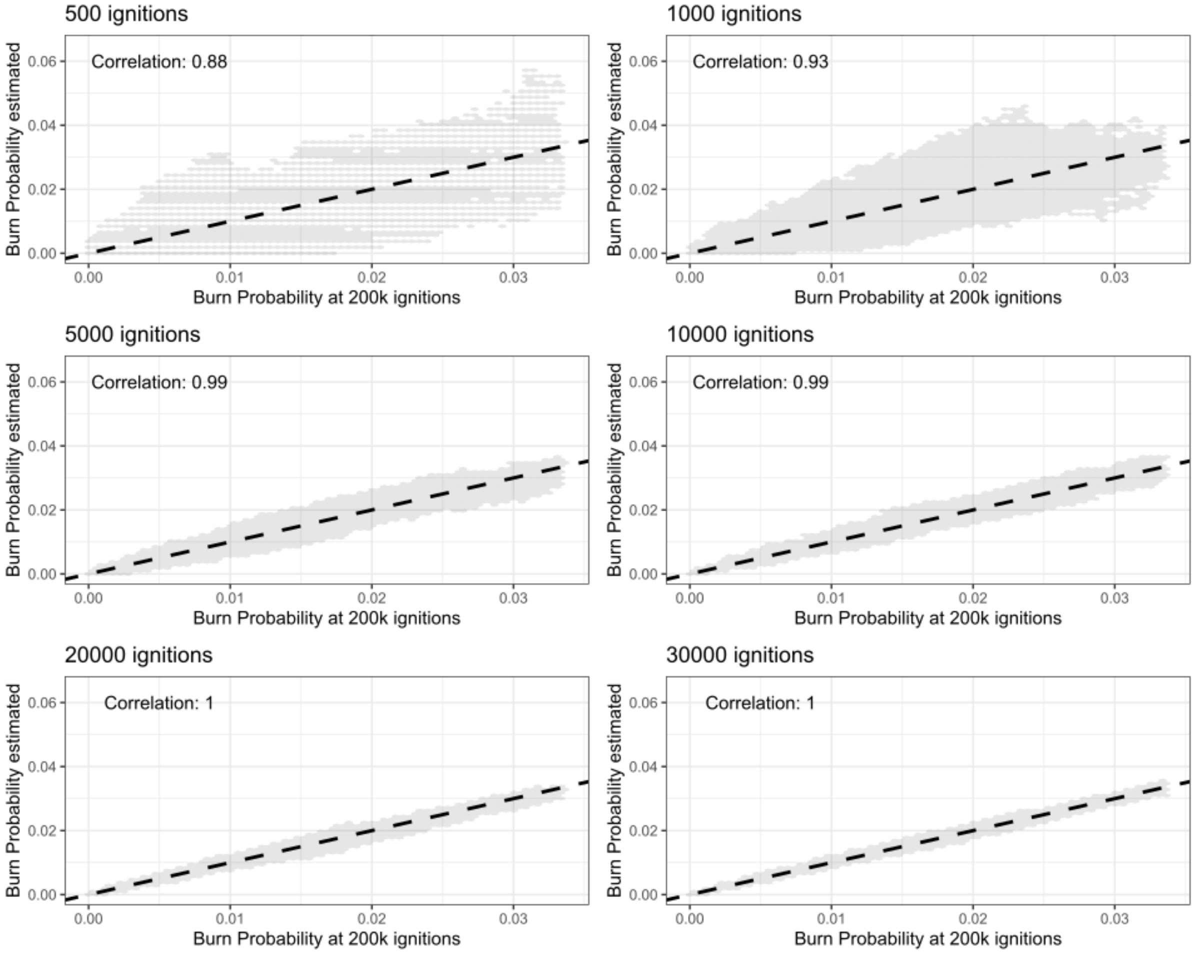



Figure S8 – Correlation between the estimated burn probability calculated with 200,000 fire runs and the estimated burn probability calculated using 500, 1000, 5000, 10000, 20000 and 30000 fire runs for the AM Porto. Each scenario (except the 200,000 fire runs) has 10 replicates. The dashed line represents the 1:1 line. The top-left of each panel shows the Pearson correlation coefficient between the two variables.

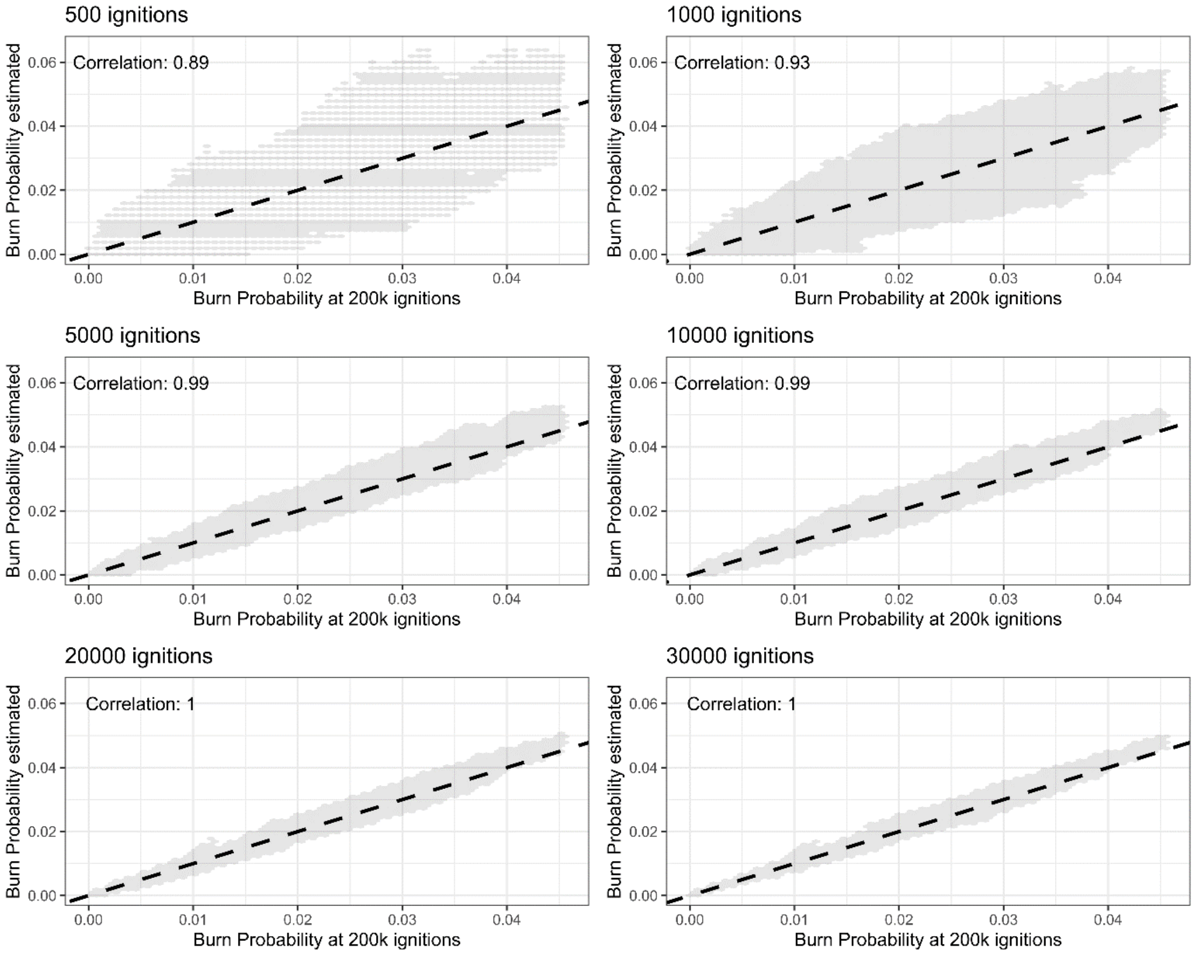



Figure S9 – Correlation between the estimated burn probability calculated with 200,000 fire runs and the estimated burn probability calculated using 500, 1000, 5000, 10000, 20000 and 30000 fire runs for the Médio Tejo. Each scenario (except the 200,000 fire runs) has 10 replicates. The dashed line represents the 1:1 line. The top-left of each panel shows the Pearson correlation coefficient between the two variables.

### 7.4.3 Normalized the minimum number of fire runs required for calibration

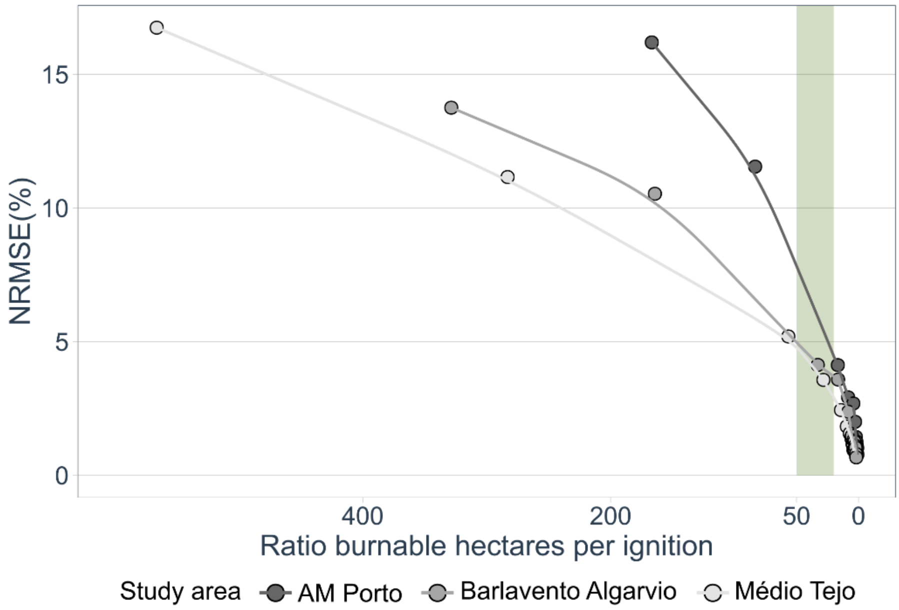



Figure S10 – Change in the NRMSE (%) following the decrease in the ratio of area burnable (in hectares). The green area identifies the interval recommended for the ratio of burnable hectares per ignition. Ratio values higher than the recommended interval may not provide a trustworthy calibration, and ratio values smaller than the recommended interval will need more computational time than required to calibrate the MTT model. The circles represent the average NRMSE (%) for each ratio and study area. The lines were generated by using the X-spline in the ggalt R package (Rudis et al., 2017).

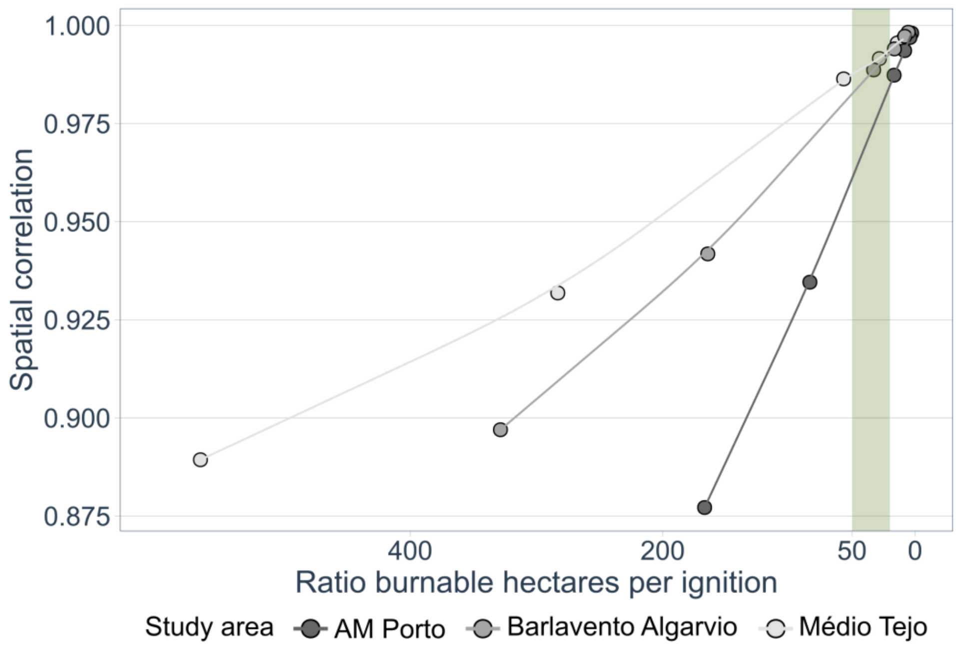



Figure S11 – Change in the spatial correlation following the decrease in the ratio of area burnable (in hectares). The green area identifies the interval recommended for the ratio of burnable hectares per ignition. Ratio values higher than the recommended interval may not provide a trustworthy calibration, and ratio values smaller than the recommended interval will need more computational time than required to calibrate the MTT model. The circles represent the average spatial correlation for each ratio and study area. The lines were generated by using the X-spline in the ggalt R package (Rudis et al., 2017).

Table S3 – Minimum number of ignitions to use in the calibration. Nign represents the calculated minimum number of ignitions to achieve a 30 burnable hectare per ignition ratio.

| **Study area** | **Burnable area (ha)** | **Nign** |
|---|---|---|
| AM Porto | 83,395 | 2780 |
| Médio Tejo | 283,133 | 9438 |
| Barlavento Algarvio | 164,288 | 5476 |

## 7.5 Duration intervals used in the validation

Table S4 – Combinations tested in the MTTfireCAL during the calibration for AM Porto

| | Duration class | | | | |
|---|---|---|---|---|---|
| | **1** | **2** | **3** | **4** | **5** |
| ***Minimum*** | 240 | 450 | 800 | 1400 | 2450 |
| ***Maximum*** | 440 | 800 | 1200 | 2500 | 3050 |
| ***Step*** | 20 | 50 | 100 | 100 | 100 |

Table S5 – Combinations tested in the MTTfireCAL during the calibration for Médio Tejo

| | Duration class | | | | |
|---|---|---|---|---|---|
| | **1** | **2** | **3** | **4** | **5** |
| ***Minimum*** | 340 | 600 | 900 | 1500 | 2750 |
| ***Maximum*** | 500 | 850 | 1300 | 2500 | 3250 |
| ***Step*** | 20 | 25 | 100 | 250 | 250 |

## 7.6 Performance metrics

Table S6 – Full Performance metrics for the calibrated MTT algorithm in the three study areas using MTTfireCAL (grey rows) and manual calibration (white rows). The performance metrics for the Barlavento Algarvio study area correspond to the combination 1 showed in Figure 4. The performance metrics were calculated using 5,000 fire runs for the MTTfireCAL and 200,000 fire runs for manual calibration.

| ***Study area*** | ***NRMSE (%)*** | ***RMSE*** | ***Pearson Correlation*** | ***MAE*** | ***RAE*** | ***NSE*** | ***Spatial correlation*** |
|---|---|---|---|---|---|---|---|
| *AM Porto* | 68 | 0.036 | 0.95 | 0.020 | 0.33 | 0.87 | 0.4 |
| | 102 | 0.054 | 0.86 | 0.026 | 0.43 | 0.70 | 0.41 |
| *Médio Tejo* | 6 | 0.023 | 1 | 0.010 | 0.092 | 0.99 | 0.44 |
| | 15 | 0.029 | 0.99 | 0.017 | 0.15 | 0.95 | 0.38 |
| *Barlavento Algarvio* | 38 | 0.029 | 0.97 | 0.019 | 0.281 | 0.91 | 0.59 |

## 7.7 Influence of the fire size distribution bins in the performance metrics

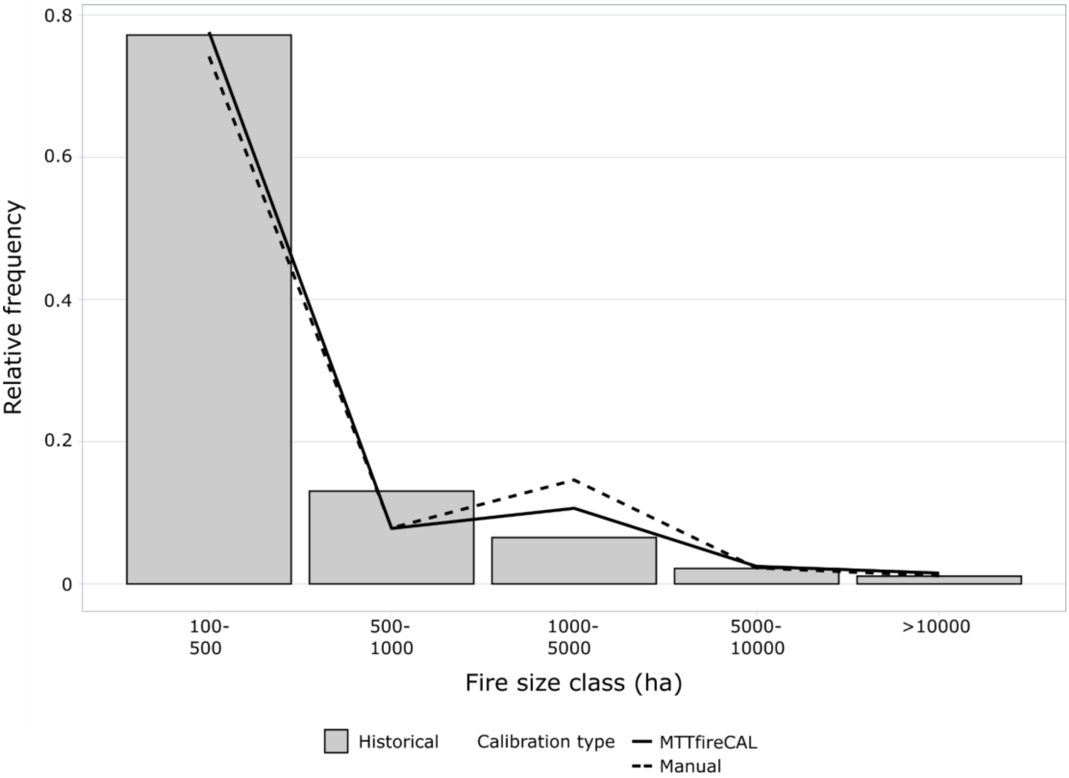



Figure S12 – Comparison between the historical (barplots) and the simulated fire size distribution using the MTTfireCAL (solid line) and the manual calibration process (dashed line) for the study areas of AM Porto. The classes of fire size distribution were changed to the same as applied in Médio Tejo (see Figure 7).

Table S7 – Performance metrics for the calibrated MTT algorithm in AM Porto using MTTfireCAL (grey rows) and manual calibration (white rows). The rows identified with N bins = 20 refer to the Figure 8a, while N bins = 5 refer to the Figure SM12.

| ***Study area*** | ***N bins*** | ***NRMSE (%)*** | ***RMSE*** | ***Pearson Correlation*** | ***MAE*** | ***RAE*** | ***NSE*** |
|---|---|---|---|---|---|---|---|
| *AM Porto* | 20 | 68 | 0.036 | 0.95 | 0.020 | 0.33 | 0.87 |
| | 20 | 102 | 0.054 | 0.86 | 0.026 | 0.43 | 0.70 |
| | 5 | 15 | 0.03 | 1 | 0.021 | 0.09 | 0.99 |
| | 5 | 23 | 0.045 | 0.99 | 0.033 | 0.14 | 0.98 |

7.8 Equations

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(O_i - S_i)^2}{N}} \qquad \text{eq.1}$$

$$NRMSE\ (\%) = \frac{RMSE}{\bar{\mathrm{O}}} \times 100 \qquad \text{eq.2}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|O_i - S_i| \qquad \text{eq.3}$$

$$RAE = \frac{\sum_{i=1}^{N}|O_i - S_i|}{\sum_{i=1}^{N}|O_i - \bar{\mathrm{O}}|} \qquad \text{eq.4}$$

$$NSE = 1 - \frac{\Sigma_{i=1}^{N}(S_i - O_i)^2}{\Sigma_{i=1}^{N}(O_i - \bar{\mathrm{O}})^2} \qquad \text{eq.5}$$

Where S is the simulated value, O is the observed value, $\bar{\mathrm{O}}$ is the mean of the observed data, N represents the number of observations. When assessing the minimum number of fire runs required for calibration, O represents the simulated value after 200,000 fire runs and $\bar{\mathrm{O}}$ represents the mean of the simulated value after 200,000 fire runs.

### 7.9 Automatic Report

The following section represents the automatic report generated in word format by the function *build_report*. The automatic report is shown without any modification.

## Conditions of the analysis

The following report was generated automatically by the 'MTTfireCAL' package. The results should be critically analyzed. For questions and comments please contact Bruno Aparicio (bruno.a.aparicio@gmail.com)

This report was generated using the following settings:
Active period was defined by the average energy released during fire spread, which peaks from 12h to 20h (for more information contact Akli Benali: aklibenali@gmail.com)

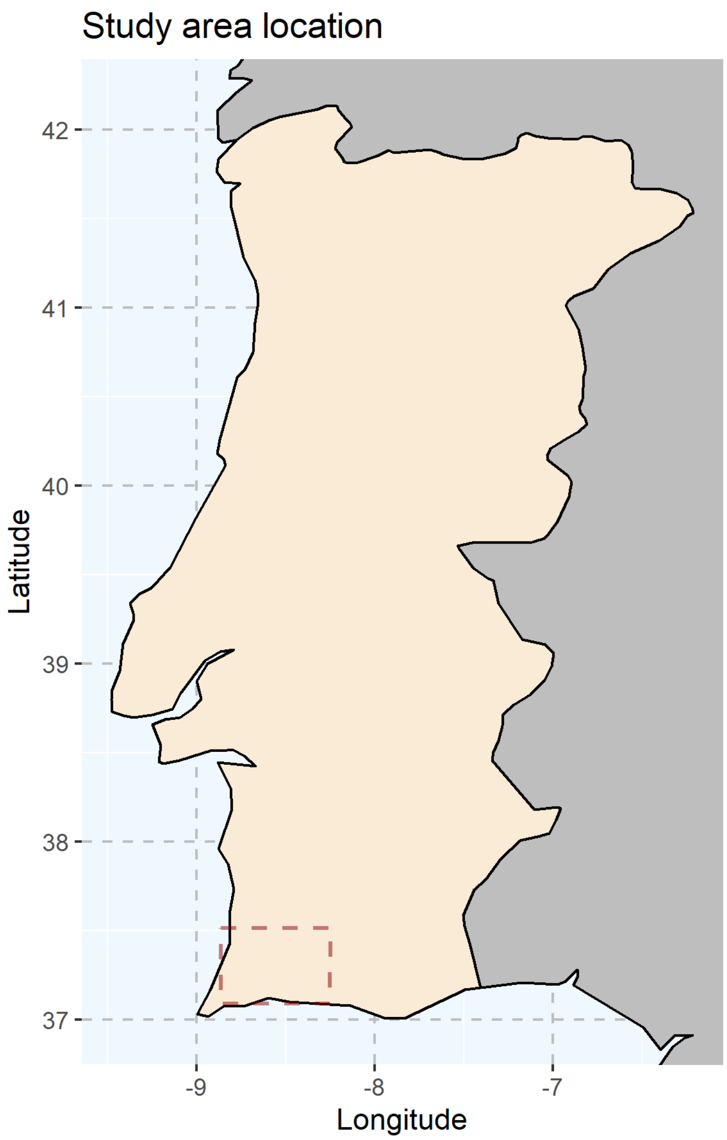
The analysis considered a minimum fire size of 100 ha

The analysis considered only fire perimeters with at least 50% of their area inside the limits of the study area. The period considered was the entire dataset

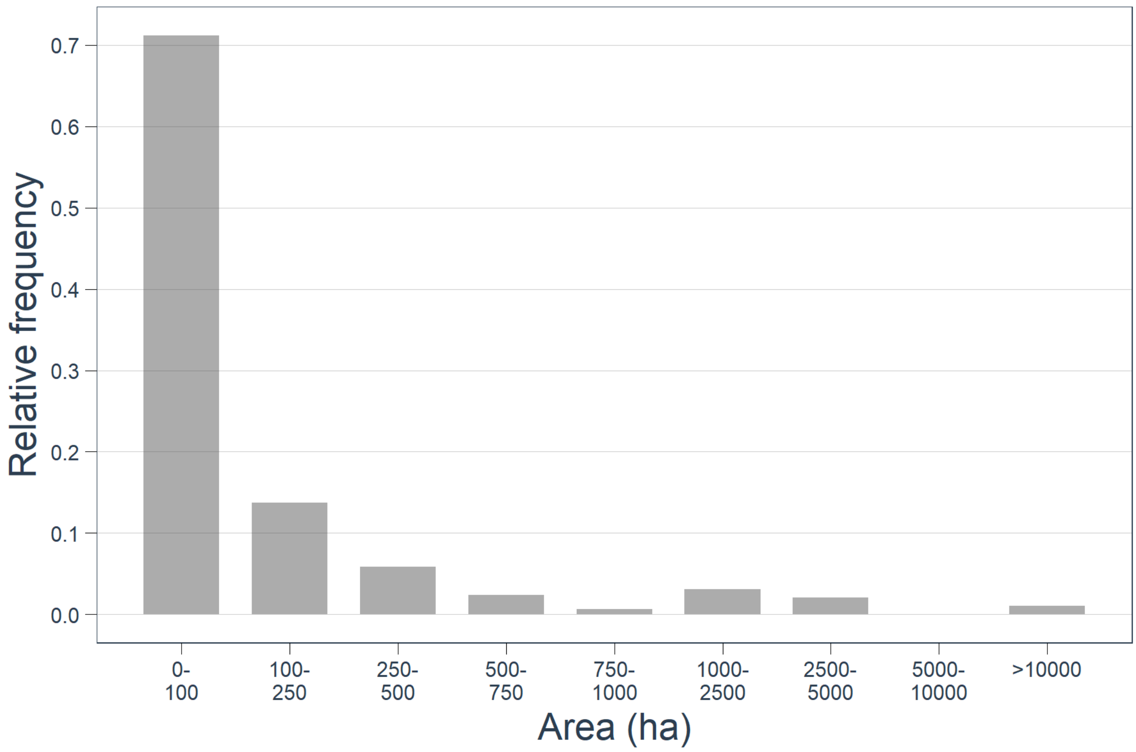
## Fire regime analysis

For the selected study area and using the settings above, the total number of fire events used for the characterization of fire size distribution was 83. From these, 39 fires are dated and were used to extract the meteorological conditions during fire spread. Because the user defined the fire.aggregation as WS and the meteorological aggregation as max.min the total number of meteorological data used for the meteorological clustering process is 39.

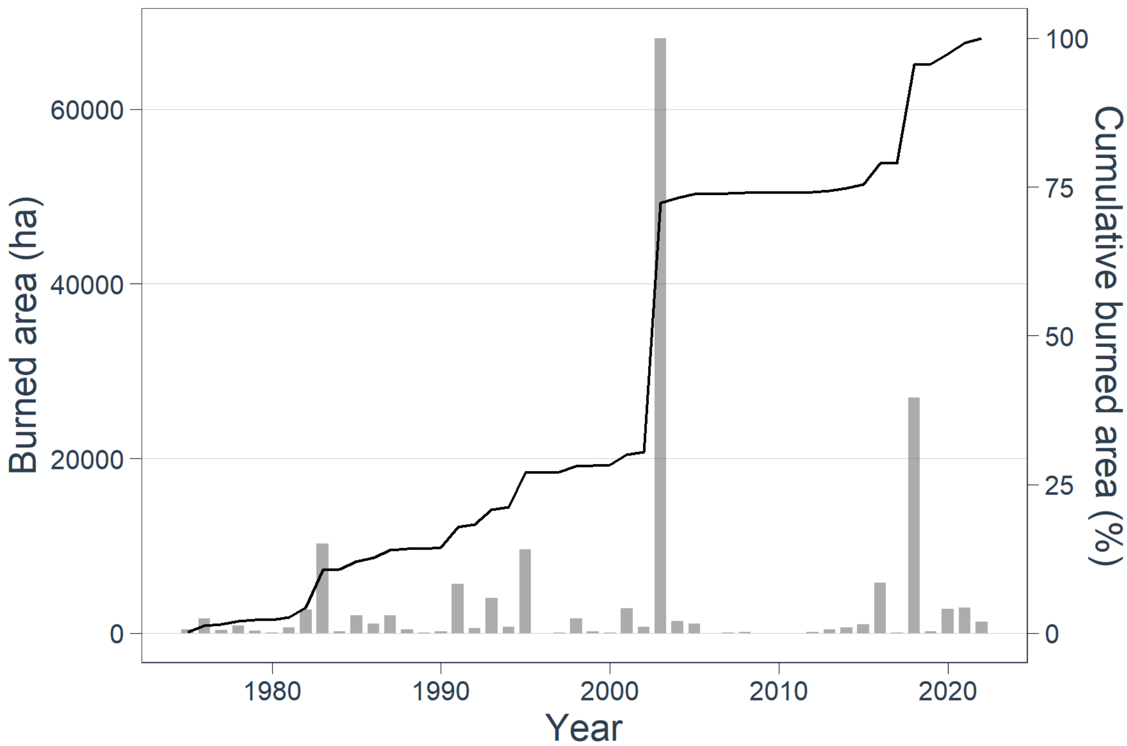
The figure below illustrates the location of the study area in Portugal (in black)




The figure below illustrates the fire size distribution for the considered period (the entire dataset) in the study area

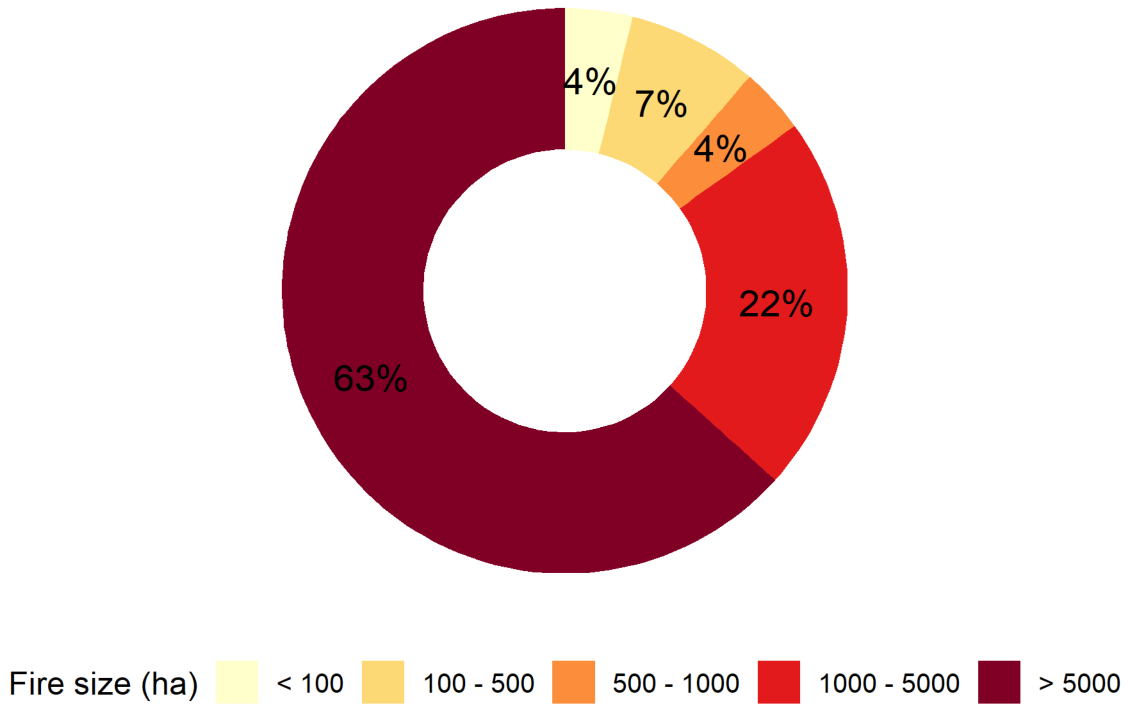



The figure below illustrates the burned area per year in hectares (barplot) and the cumulative burned area as percentage (line) for the considered period (the entire dataset) in the study area

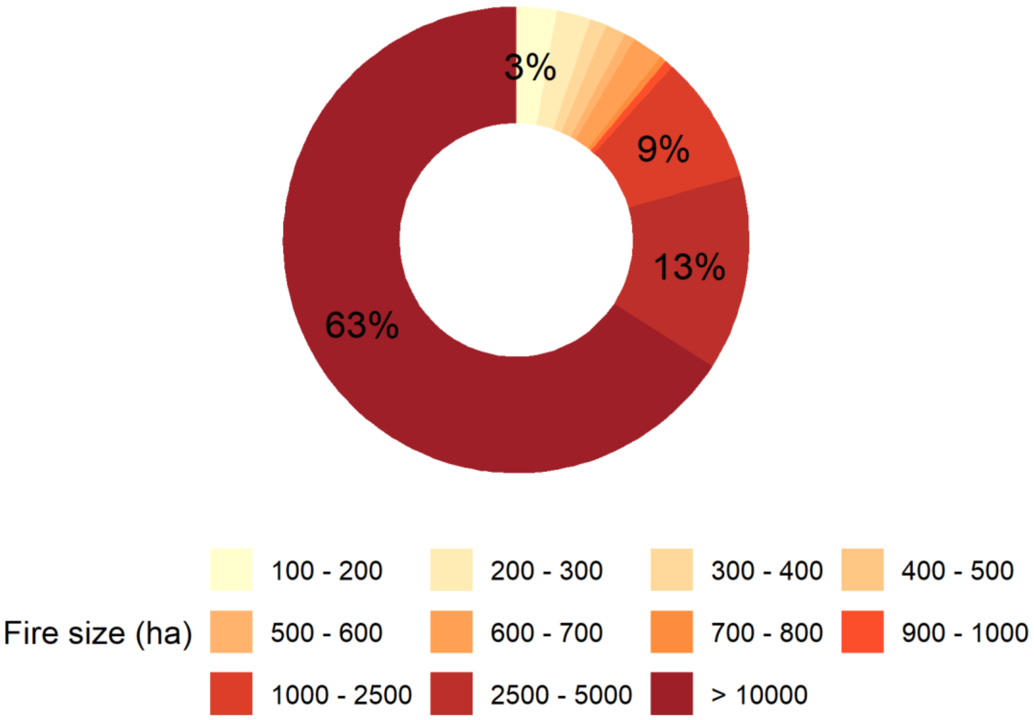



The figure below illustrates the contribution of burned area in each fire size class to the overall burned area. For instance, fires that burned less than 100 ha contributed with

4% to the total burned area; fires that burned between 100 and 500 ha contributed with 7% to the total burned area, etc. The fire size classes are in hectares. Labels are only shown for fire size classes that represent at least 3% of the total burned area




The figure below illustrates the same as the figure above, but considering the intervals defined by the user. Labels are only shown for fire size classes that represent at least 3% of the total burned area.

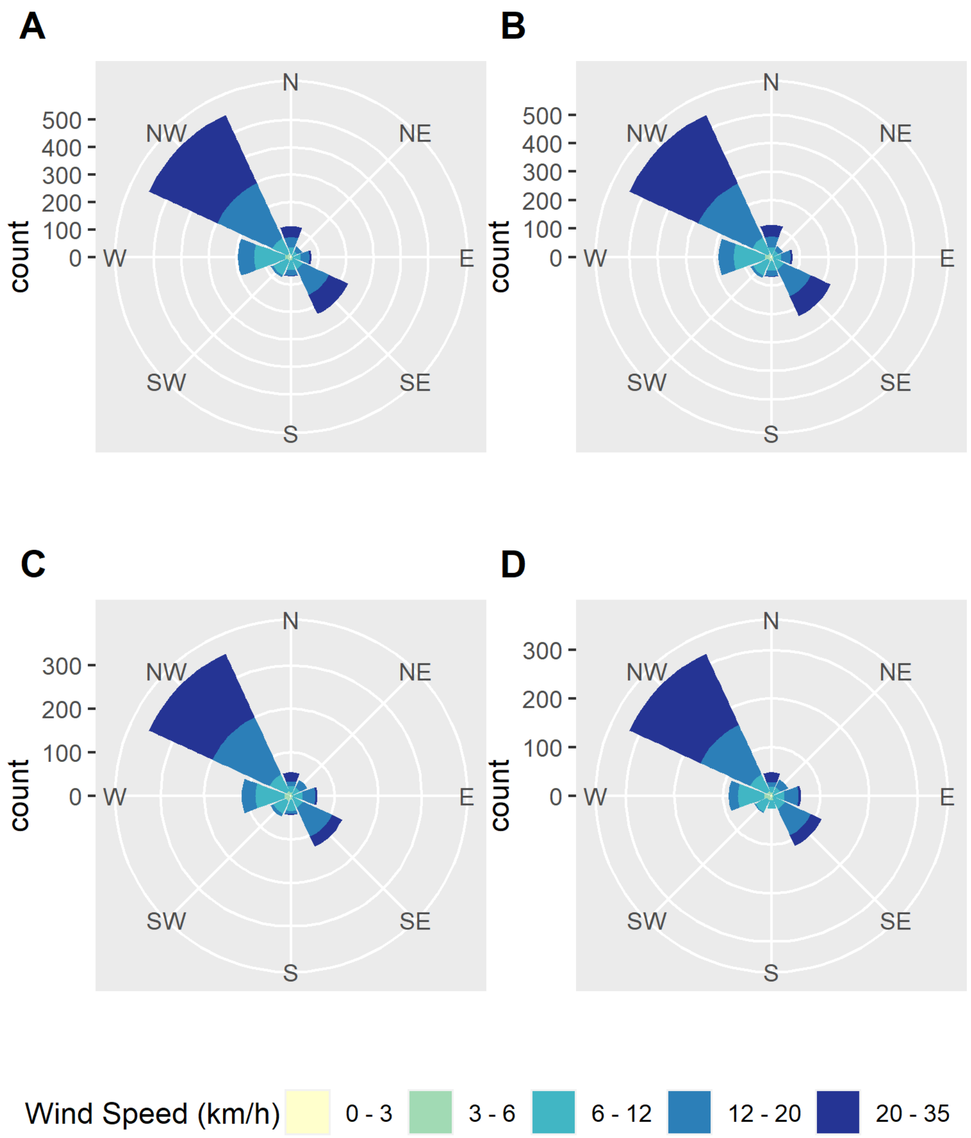



## Fire weather analysis

The table below statistically characterizes the fire size in the study area. Min, Max and Mean represent the minimum, maximum and mean fire size, respectively; SD represents the standard deviation of fire size; P25, Median, P75 and P90 represent the percentile 25, median, percentile 75 and percentile 90 of the fire size, respectively. Fires used represent the fires that were used for the statitical analysis: All fires indicate that all fires in the dataset were used, regardless of being dated; Dated fires indicate that only dated fires were used.

| Min | Max | Mean | SD | P25 | Median | P75 | P90 | Fires used |
|---|---|---|---|---|---|---|---|---|
| 5 | 66014 | 559 | 4236 | 13 | 38 | 126 | 448 | All fires |
| 100 | 26865 | 2914 | 6954 | 200 | 437 | 1272 | 5506 | Dated fires |

The figure below illustrates the wind roses considering the days with fire occurrence

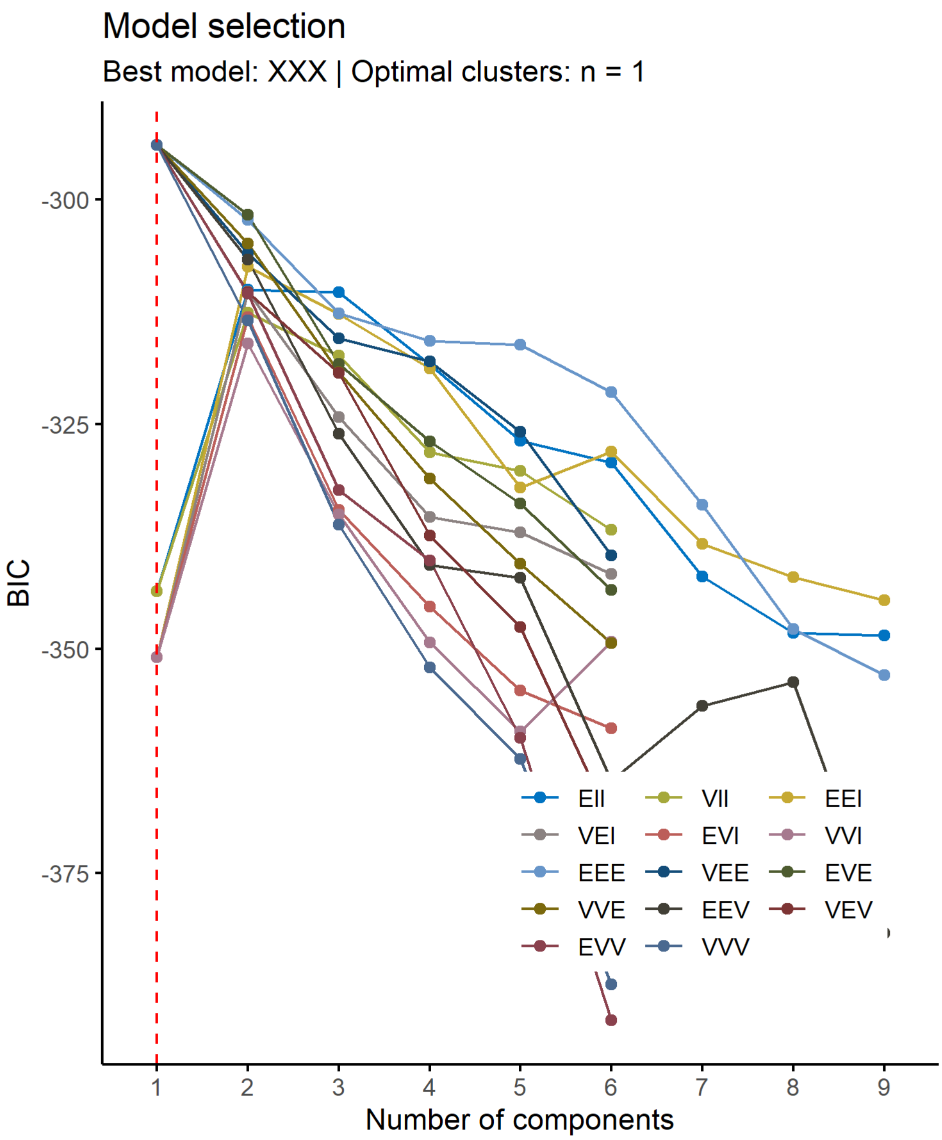



A - Considering fire size > 0 ha; B - Considering fire size > 100 ha; C - Considering fire size > 500 ha; D - Considering fire size > 1000 ha

### Cluster analysis

Model-based cluster analysis (MBCA) was created to automatize the demanding model-selection procedure of traditional explorative clustering methods (e. g., hierarchical and k-means clustering). For a proper understanding of the outputs interpretation please see Stahl and Sallis, 2012 (https://doi.org/10.1002/wics.1204).

The figure below illustrates the Bayesian Information Criterion (BIC) to evaluate model appropriateness regarding the optimal number of clusters. In this particular case, model-based clustering indicates 1 as the optimal number of clusters
Note that a warning message of too few points to calculate an ellipse might be generated when running the function. This does not represent an error and the clustering analysis was not compromised. The warning message only indicates that at least one cluster has few points (observations) and will not be displayed in the figure below.



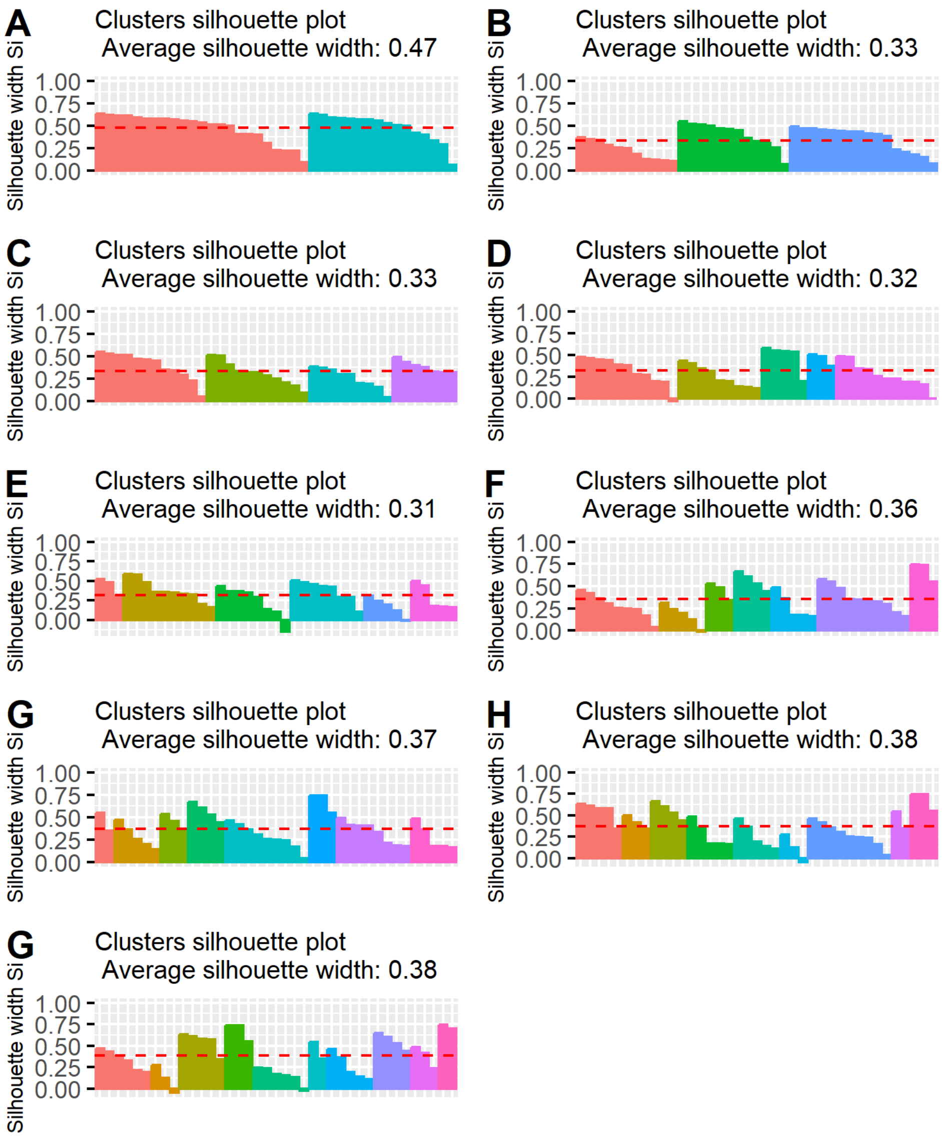

**Mean value (centroid) per meteorological cluster**

| cluster | T | RH | WS | Cluster size | Cluster RF |
|---|---|---|---|---|---|
| 1 | 31 | 31 | 23 | 39 | 1 |

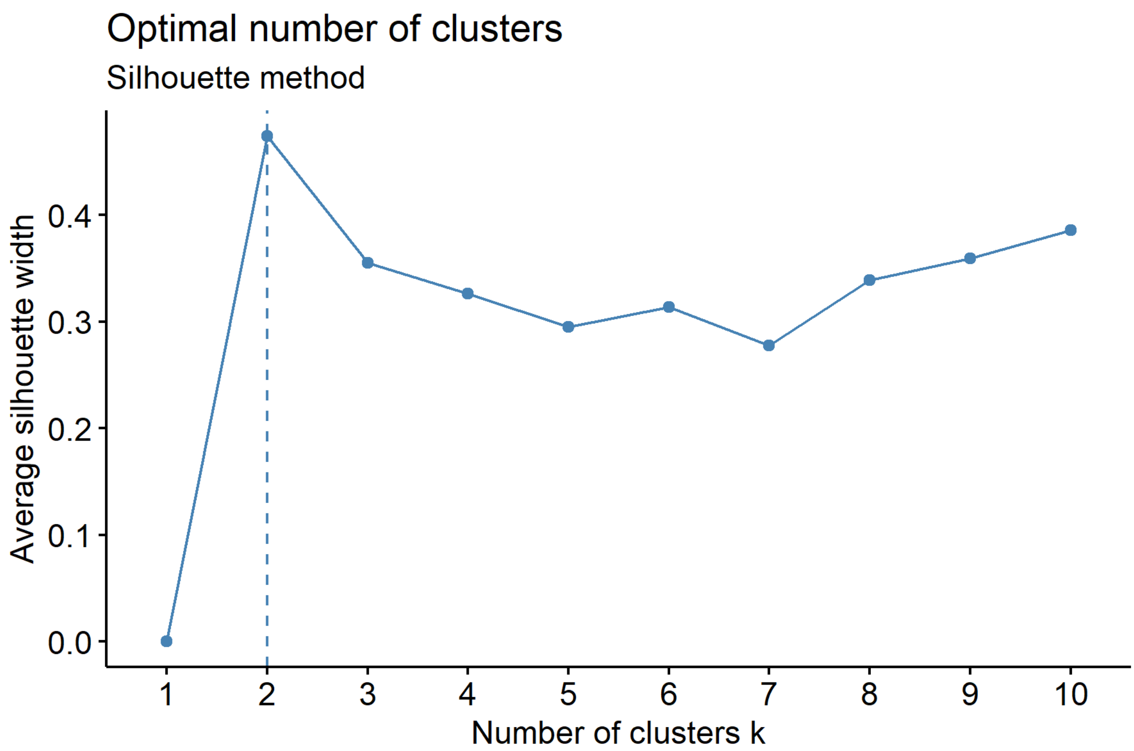
T represents the average temperature in each cluster; RH represents the average relative humidity in each cluster; WS represents average wind speed in each cluster; and Cluster RF represents the relative frequency of each cluster.

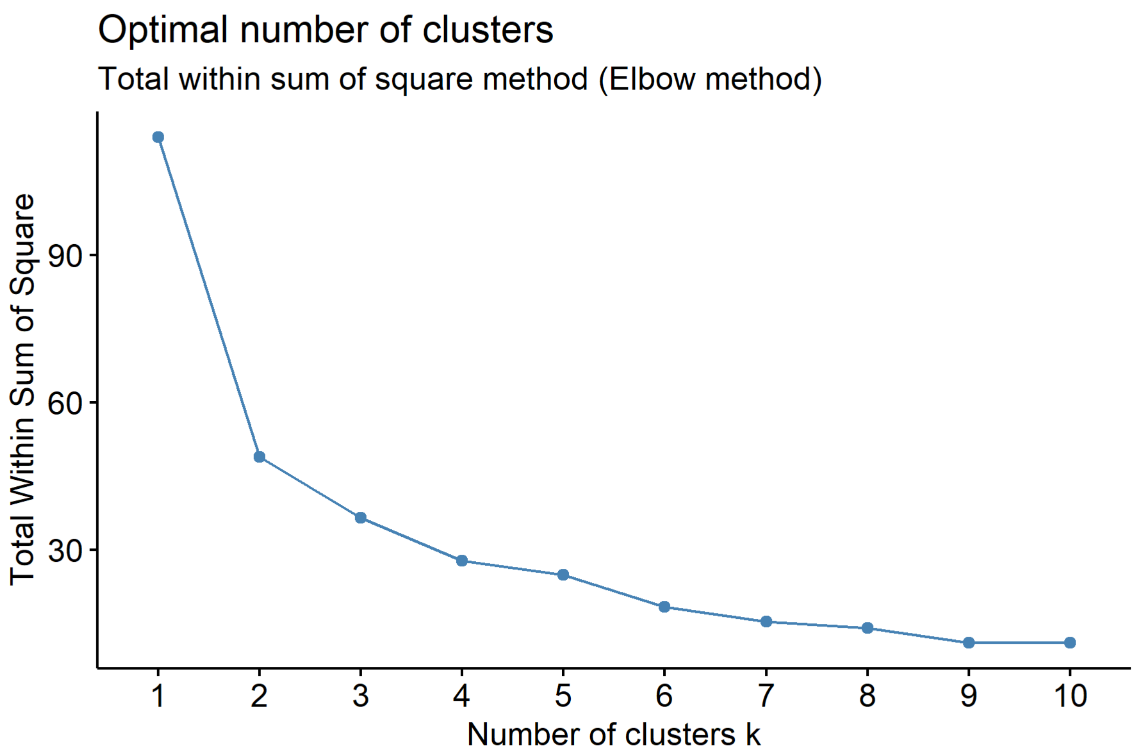
## K-means classification

Kmeans algorithm is an iterative algorithm that tries to partition the dataset into K pre-defined distinct non-overlapping clusters. It assigns data points to a cluster such that it minimizes the sum of the squared distance between the data points and the cluster's centroid (arithmetic mean). A lower variation represents a more homogeneous cluster. For more details on k-means clustering algorithm please refer to Likas et al. 2003 (https://doi.org/10.1016/S0031-3203(02)00060-2) and to Kodinariya and Makwana (2013). Review on determining number of Cluster in K-Means Clustering




The silhouette value is a measure of how similar an object is to its own cluster (cohesion) compared to other clusters (separation). The silhouette ranges from -1 to +1, where a high value indicates that the object is well matched to its own cluster and poorly matched to neighboring clusters. If most objects have a high value, then the clustering configuration is appropriate. If many points have a low or negative value, then the clustering configuration may have too many or too few clusters.




The elbow method calculates the Within-Cluster-Sum of Squared Errors (WSS) for different values of k, and choose the k for which WSS first starts to diminish at a lower rate (smaller slope). The optimal number of clusters is found at the elbow, i.e. the point after which the total within sum of square starts to decrease in a linear way

**Mean value (centroid) of each meteorological cluster**

| cluster | T | RH | WS | Cluster size | Cluster RF |
|---|---|---|---|---|---|
| 1 | 34 | 24 | 20 | 23 | 0.59 |
| 2 | 27 | 40 | 27 | 16 | 0.41 |

| cluster | T | RH | WS | Cluster size | Cluster RF |
|---|---|---|---|---|---|
| 1 | 30 | 33 | 21 | 11 | 0.28 |
| 2 | 26 | 41 | 29 | 12 | 0.31 |
| 3 | 35 | 21 | 20 | 16 | 0.41 |

| cluster | T | RH | WS | Cluster size | Cluster RF |
|---|---|---|---|---|---|
| 1 | 26 | 41 | 29 | 12 | 0.31 |
| 2 | 35 | 22 | 18 | 11 | 0.28 |
| 3 | 30 | 34 | 20 | 9 | 0.23 |
| 4 | 36 | 22 | 26 | 7 | 0.18 |

| cluster | T | RH | WS | Cluster size | Cluster RF |
|---|---|---|---|---|---|
| 1 | 26 | 42 | 30 | 11 | 0.28 |
| 2 | 30 | 32 | 24 | 9 | 0.23 |
| 3 | 37 | 20 | 25 | 5 | 0.13 |
| 4 | 29 | 38 | 15 | 3 | 0.08 |
| 5 | 35 | 22 | 18 | 11 | 0.28 |

| cluster | T | RH | WS | Cluster size | Cluster RF |
|---|---|---|---|---|---|
| 1 | 29 | 38 | 15 | 3 | 0.08 |
| 2 | 27 | 38 | 26 | 10 | 0.26 |
| 3 | 36 | 23 | 25 | 8 | 0.21 |
| 4 | 33 | 25 | 20 | 8 | 0.21 |
| 5 | 27 | 45 | 33 | 5 | 0.13 |
| 6 | 36 | 20 | 15 | 5 | 0.13 |

| cluster | T | RH | WS | Cluster size | Cluster RF |
|---|---|---|---|---|---|
| 1 | 33 | 25 | 20 | 9 | 0.23 |
| 2 | 27 | 45 | 33 | 5 | 0.13 |
| 3 | 29 | 38 | 15 | 3 | 0.08 |
| 4 | 37 | 18 | 25 | 4 | 0.10 |
| 5 | 36 | 20 | 15 | 5 | 0.13 |
| 6 | 27 | 38 | 26 | 10 | 0.26 |
| 7 | 33 | 28 | 27 | 3 | 0.08 |

| cluster | T | RH | WS | Cluster size | Cluster RF |
|---|---|---|---|---|---|
| 1 | 25 | 52 | 32 | 2 | 0.05 |
| 2 | 28 | 40 | 31 | 5 | 0.13 |
| 3 | 29 | 38 | 15 | 3 | 0.08 |
| 4 | 37 | 18 | 25 | 4 | 0.10 |

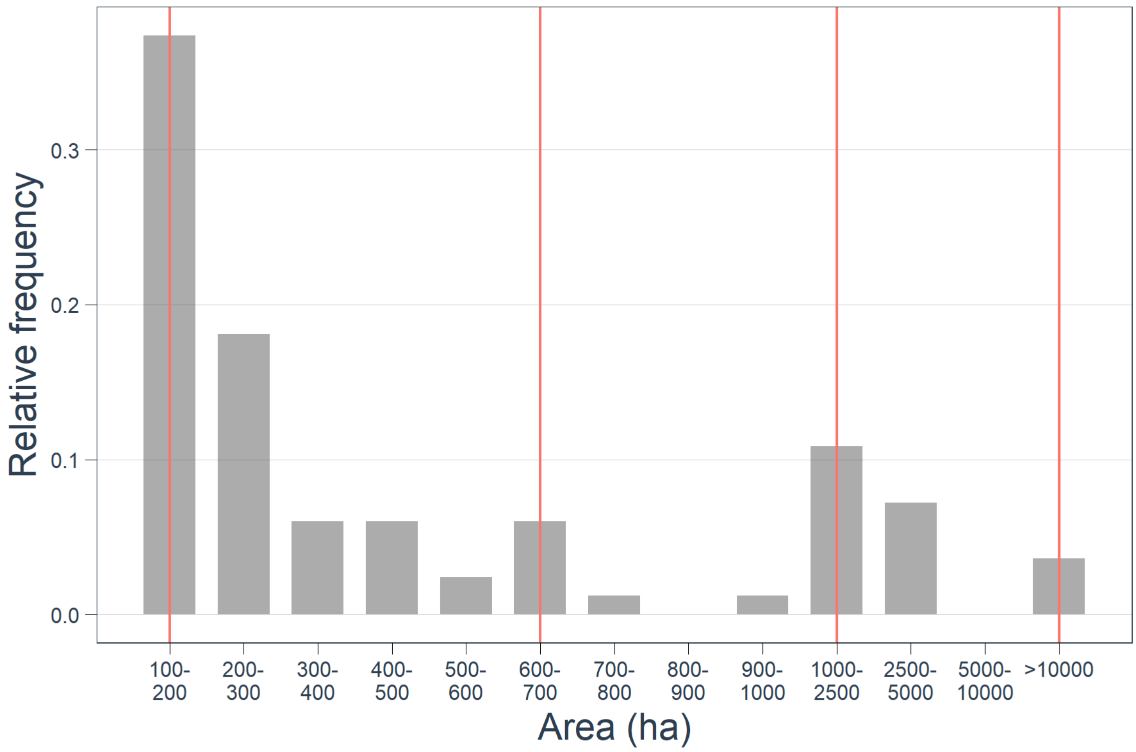
| cluster | T | RH | WS | Cluster size | Cluster RF |
|---|---|---|---|---|---|
| 5 | 33 | 25 | 20 | 9 | 0.23 |
| 6 | 33 | 28 | 27 | 3 | 0.08 |
| 7 | 27 | 38 | 25 | 8 | 0.21 |
| 8 | 36 | 20 | 15 | 5 | 0.13 |

| cluster | T | RH | WS | Cluster size | Cluster RF |
|---|---|---|---|---|---|
| 1 | 28 | 36 | 24 | 5 | 0.13 |
| 2 | 29 | 38 | 15 | 3 | 0.08 |
| 3 | 37 | 18 | 25 | 4 | 0.10 |
| 4 | 36 | 20 | 15 | 5 | 0.13 |
| 5 | 28 | 40 | 31 | 5 | 0.13 |
| 6 | 24 | 40 | 26 | 3 | 0.08 |
| 7 | 33 | 25 | 20 | 9 | 0.23 |
| 8 | 25 | 52 | 32 | 2 | 0.05 |
| 9 | 33 | 28 | 27 | 3 | 0.08 |

| cluster | T | RH | WS | Cluster size | Cluster RF |
|---|---|---|---|---|---|
| 1 | 32 | 26 | 20 | 6 | 0.15 |
| 2 | 24 | 40 | 26 | 3 | 0.08 |
| 3 | 28 | 36 | 24 | 5 | 0.13 |
| 4 | 33 | 28 | 27 | 3 | 0.08 |
| 5 | 35 | 23 | 18 | 6 | 0.15 |
| 6 | 25 | 52 | 32 | 2 | 0.05 |
| 7 | 28 | 40 | 31 | 5 | 0.13 |
| 8 | 37 | 18 | 25 | 4 | 0.10 |
| 9 | 29 | 38 | 15 | 3 | 0.08 |
| 10 | 39 | 16 | 15 | 2 | 0.05 |

## Number of durations to consider

The figure below represents the identification of peaks in the distribution of fire size (vertical red lines). There are 4 recommended to use in the calibration to better reproduce the historical pattern of fire size distribution. For example, the first duration should represent fires with size between 100 and 600 hectares.




Note that each duration class is meant to represent a reasonable interval of fire sizes. For example, consider that the figure above returns one duration class for the fire size interval 10 hectares to 1000 hectares (i.e. it displays one red line at the 10 hectares and another one in the 1000 hectares), it is highly unlikely that a single value for fire duration will accurately represent this interval of fire size distribution. If this is the case, the user should consider use the manual.dur option and set the duration classes to be used. More information about this topic can be found in the MTTfireCAL tutorial, available at https://github.com/bmaparicio/MTTfireCAL