

multi-Risk sciEnce for resilienT commUnities undeR a changiNg climate

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2. ABSTRACT

Activities in this task are mostly connected to the goals and outcomes of the Spokes 4 and 8, where most of the climate change effects are envisaged. New instances of hazard mapping are proposed for the increasing climate risks, as those related to windstorms and wildfires.

This deliverable describes the products that were developed within the RETURN project to address these goals, which can be summarized in:

- remote sensing-based datasets of the wind hazard along critical infrastructures (Section 3.3.a);
- a national-scale evaluation of the impact of extreme rainfall events on the residual risk assessment for hydraulic infrastructures, complemented with some general guidelines (Section 3.3.b);
- dynamic maps of the pluvial flooding under current and future climatic conditions (Section 3.3.b);
- a methodology for improving rainfall monitoring in urban areas by integrating crowdsourced personal weather stations into official networks (Section 3.3.b);
- national-scale evaluation of temporal trends in short-duration rainfall extremes (Section 3.3.b);
- probabilistic risk assessment for isolated areas in connection to forest fires (Section 3.3.c);
- new method for wildfire hazard mapping and consequent hydrological risk management (Section 3.3.c);
- reservoir and water supply management under drought conditions, including analysis of future scenarios of water availability and user demand (Sections 3.3.d.1 and 3.3.d.2);
- assessment of water shortage hazard on urban water distribution users (Section 3.3.d.3).

The methodologies developed in the task are described in the first part of the deliverable (*DV 6.3.3 - Climate-related service interruption threats over critical infrastructures - Methodology Report*). This second part is instead focused on the implementation process and the key results obtained.

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3.3 Reports on climate-related service interruption threats over critical infrastructures

3.3.a Enhanced methodology for wind hazard mapping over network CI - Remote sensing-based mapping of the wind hazard along CI

3.3.a.1 Performance assessment of reanalysis model

In the following, the performances of REA models are assessed by comparing simulation results to statistical measurements. The ability of the REA models to capture individual, real-world, phenomenologically distinct wind events is critically discussed, first with reference to their temporal and spatial scales. For purely illustrative purposes, two stations 300 km apart in Northern Italy, i.e., Venezia and Milano Malpensa, are selected for the year 2018. Both stats offer high-quality measurements during that time, i.e., a low percentage of calms and missing data, and constant exposure. Wind speed resulting from stat measurements, ERA5, ERA5L, and VHR modelling approaches are compared in Figure 1. The whole time series of wind speed daily averages V_d are plotted in Figure 1a,b, while hourly speed V close-up views in correspondence of significant and well-documented mesoscale events are plotted in Figure 1c–j.

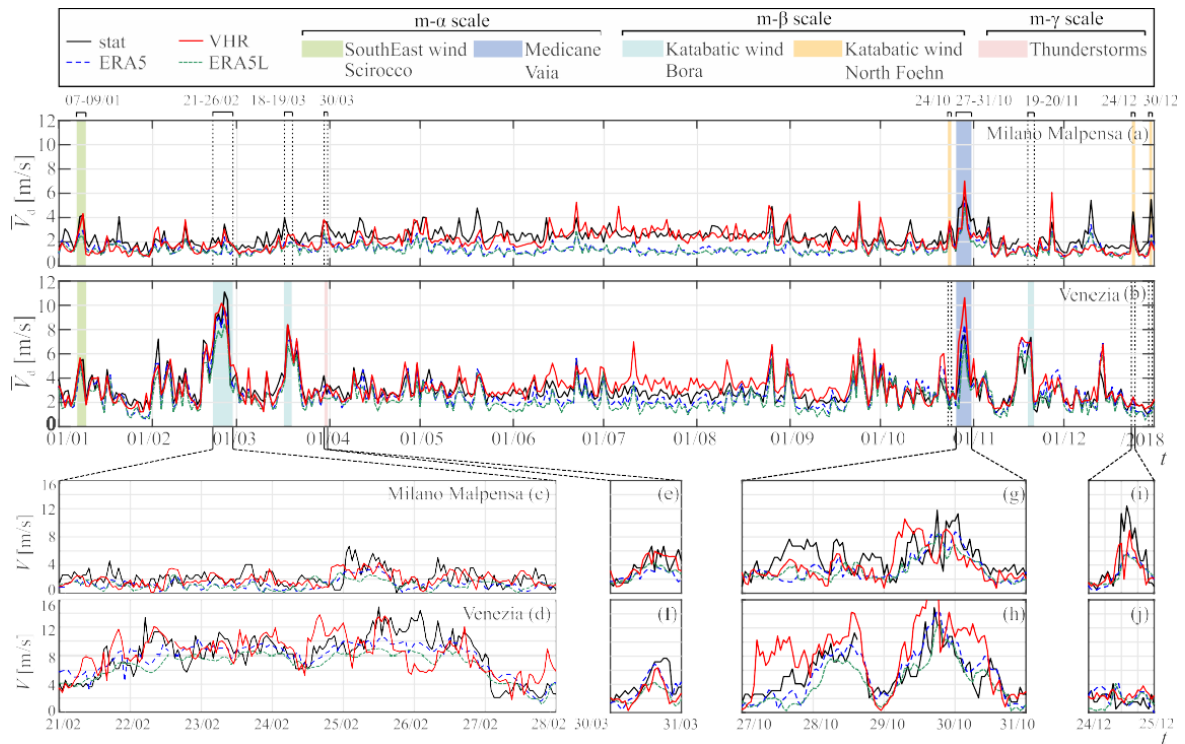


Figure 1. Comparison among station, ERA5, ERA5L and VHR time series for Milano M. and Venezia during the year 2018: time series of daily average wind speeds V_d (a,b) and hourly wind speeds V in correspondence of individual wind events (c–j).

Overall, REA datasets confirm their capability in simulating mesoscale phenomena. In general, VHR model provides the best estimate of the wind speed while ERA5/ERA5L systematically underestimate the measurements, namely during the summer, i.e. in the absence of severe weather events. Individual meso- α meteorological phenomena can be clearly recognized in both time series, among them a strong Scirocco wind event (Figure 1g,h), since the distance between the two stations is in the meso- α range. Meso- β meteorological events induced by katabatic winds remain localized on the single time series, e.g. Bora wind

in February (a 6-day event, Nimbus Web, 2018b, Figure 1d) and March in Venezia, and North Foehn in October and December (Fig. 1i; Nimbus Web, 2018a) in Milano. Nevertheless, REA models inevitably lead to different quantitative estimations of the wind speed magnitude. A very short-duration, meso- γ thunderstorm induced by convective phenomena was reported in the evening of March the 30th in Milano Malpensa, inducing multiple cancelled flights (Figure 1e; Italiavola, 2018). It appears that VHR models seem to better capture the large wind speeds induced by such kind of events. Discrepancies between VHR and the other ERA-type models result from their different horizontal resolution and modelling approaches.

In order to synthetically compare measurements and REA models over the whole considered time window T for the same two stations, the time series of wind speed yearly maxima $\hat{V}_y$ and averages V_y are plotted in Figure 2a,b for Milano Malpensa, and Figure 2c,d for Venezia. Overall, ERA5 and VHR yearly maxima and averages follow the same weakly increasing trend even if they settle on two different levels, being VHR magnitudes about 1.3–1.5 times larger than ERA5 ones. However, Figure 2a,b highlights that the trend of stats and REA yearly statistics can be in strong contrast. This is also reflected in more general terms by Figure 2e,f where the linear regression angular coefficients a resulting from measurements, ERA5 and VHR data obtained in correspondence of all 21 selected stations are collected. Striking differences emerge in terms of both V_y and $\bar{V}_y$. The trends of the yearly average speed V_y (Figure 2f) are fully stationary in REA models, while time series measured at stats are always weakly decreasing non stationary ($-0.04 < a < 0$). Whilst V_y stat time series are mainly ranked as stationary and weakly non-stationary with decreasing trend (i.e. $-0.1 < a < 0$), ERA5 time series are ranked as stationary ($-0.05 < a < +0.05$), and VHR ones are mostly stationary with a few weakly increasing non-stationary ($+0.05 < a < +0.1$). Such discrepancies between measurements and REA models should be attributed to the variation over time of the terrain characteristics around anemometric stations, the presence of disturbing bodies, the shifting of the anemometer, as well as replacements of the anemometer sensor. Conversely, REA models do not account for variations in exposure conditions since z_0 is mainly a time-constant parameter. In summary, stat measurements are indirectly indicative of the actual condition of the specific site exposure and its changes in time, while REA models are able to rule out such changes and to point out climatic changes, if any.

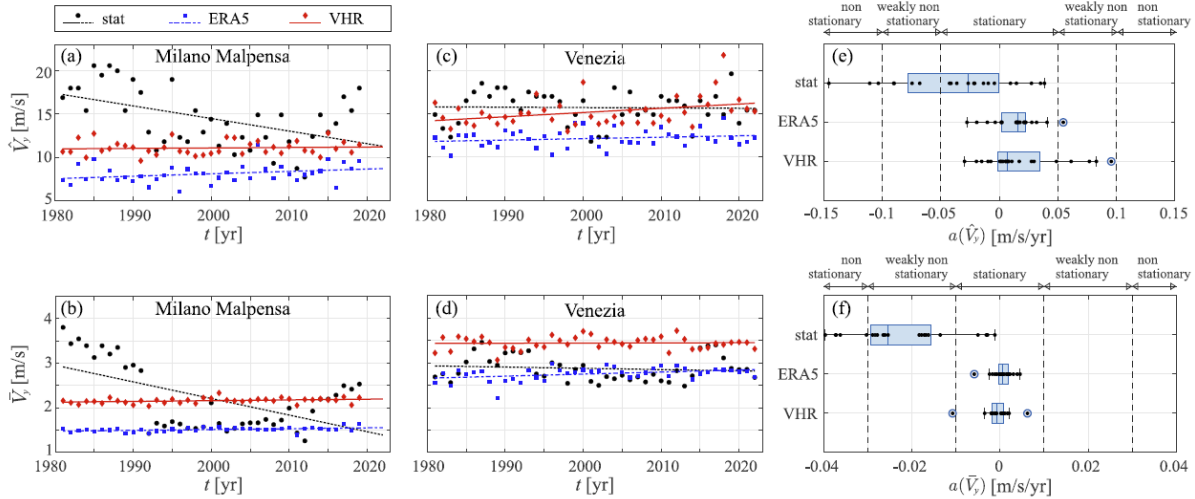


Figure 2. Time series of yearly average $\bar{V}$ and extreme $\hat{V}$ wind speeds for Milano Malpensa (a, b) and Venezia (c, d) stations. Box plots of angular coefficients a resulting from the linear regression of $\bar{V}$ and $\hat{V}$ for measurements, ERA5 and VHR at all the selected anemometric stations (e, f).

The concise overall comparison between REA models and stat measurements is provided in Figure 3. In particular, the scatter plots of mean ($\bar{V}$, Figure 3a–c) and extreme wind speeds with 2-year (V_2 , Figure 3e–g), 50-year (V_{50} , Figure 3i–k), 100-year (V_{100} , Figure 3m–o), and 200-year (V_{200} , Figure 3q–s) return periods are given.

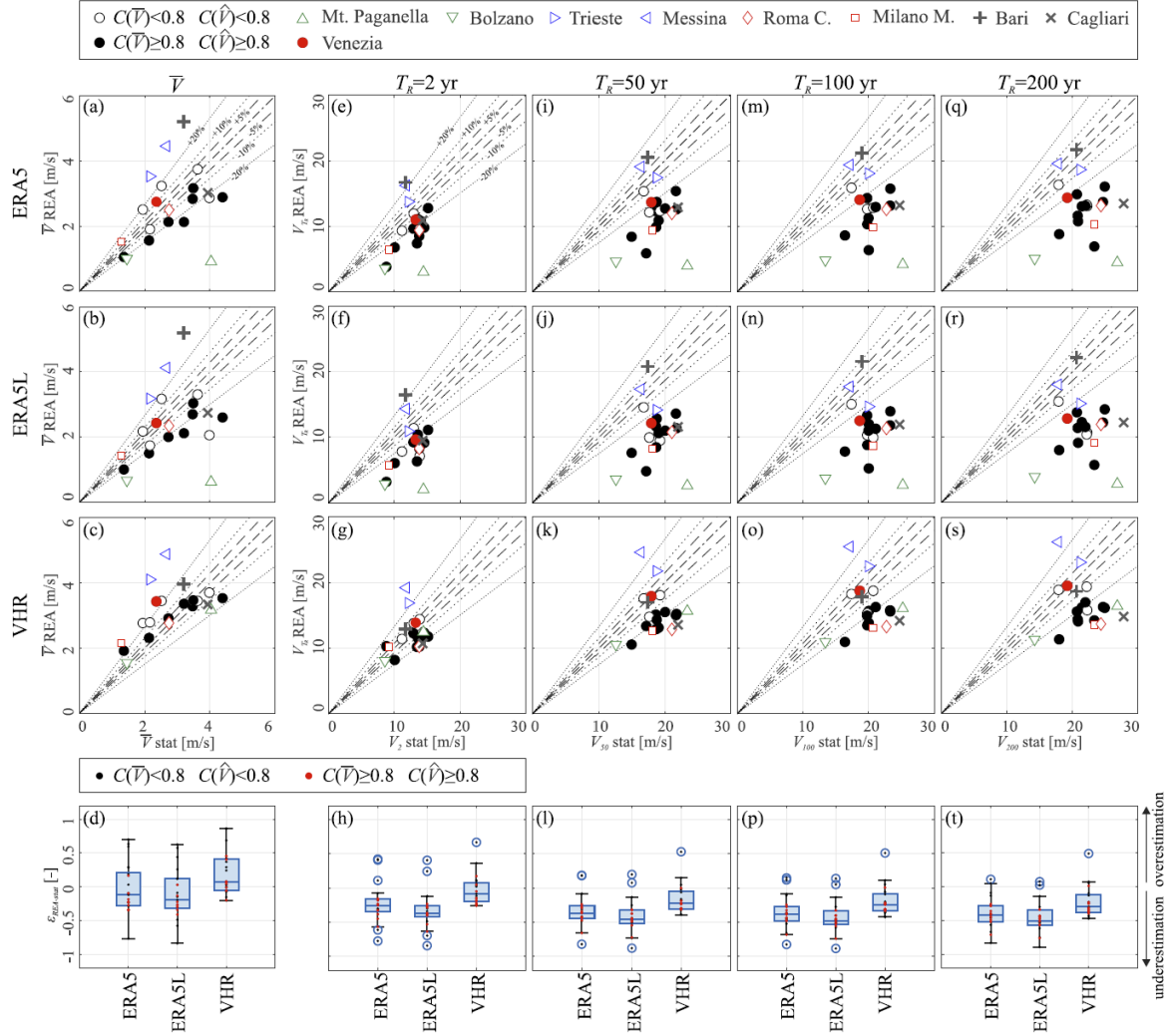


Figure 3. Scatter plot of mean $\bar{V}$ (a–c) and extreme V_{TR} (e–g, i–k, m–o, q–s) wind speeds resulting from REA models and stat measurements, and resulting box plots of the relative error $\epsilon_{REA-stat}$ of REA models with respect to measurements (d, h, l, p, t).

EVA POT approach is adopted to assess extreme wind speeds on both stat and REA time series to filter out uncertainty induced by statistical analysis (Torrielli et al., 2013). The POT approach fits a GPD to the exceedances over a chosen threshold. In this study, the threshold of each time series is set equal to the lowest annual maxima detected along the same time series, in agreement with Outten and Sobolowski (2021). Then, independence of extreme events is ensured by filtering extremes from consecutive events occurring within two days. In such a way, the exceedances constitute an independent identically distributed sample. From the fitted GPD, V_{TR} corresponds to the percentile which on average is only exceeded once within T_R . Filled and empty markers refer to WMO-compliant stations ($C(\bar{V}) \geq 0.8$ or $C(\hat{V}) \geq 0.8$) and non-compliant ones, respectively. In particular, red filling colour highlights the most compliant station (Venezia), while the green, blue, and red outline colours refer to examples of non-compliant stats affected by orographic changes, uneven roughness, and unsteady time series of the annual speed maxima, respectively. The REA-stat resulting relative error is expressed as:

$$\epsilon_{REA-stat} = \frac{\phi_{REA} - \phi_{stat}}{\phi_{stat}} \quad (3.3.1)$$

where ϕ is the generic speed statics, i.e. V and V_{TR} . The statistics of the relative error at every selected station for each REA model are given in Figure 3(d, h, l, p, t), in terms of box plots together with red filled

and empty markers for each single compliant and non-compliant station, respectively. Two very general remarks follow with reference to the whole 21 stations. First, REA models systematically predict extreme wind speeds lower than the ones measured at stats. Second, such an underestimation increases as the return period increases. With specific reference to the REA models, scatter plots resulting from ERA5 and ERA5L look qualitatively analogous, even if ERA5L errors look in average absolute value systematically slightly higher than the ones resulting from ERA5. We can conclude that the mere refined horizontal resolution obtained by interpolation in ERA5L does not improve the accuracy of the parent ERA5 wind dataset. Conversely, VHR model on the whole predicts extreme speeds closer to stat measurements, and mean speed even slightly higher than the measured ones. Convection permitting RCMs capability to more accurately simulate severe winds is also highlighted by Belušić Vozila et al. (2023) for Bora and Scirocco winds. The error is in average very small for $\bar{V}$ (Figure 3d) and V_2 (Figure 3h). However, the above general remarks about the stations as a whole must be enriched in more detail with specific reference to the stat degree of WMO-compliance, and related inconsistencies. First, reference to WMO-compliant station only rules out microscale effects at stations, significantly reduces the dispersion of the data, and allows to clarify the trends depicted above. For the sake of brevity, let us comment on VHR only: the mean speed is very well simulated, except for the high value in Venezia due to the very low summer wind speed $V \approx 3$ m/s (see e.g. Figure 1b); extreme wind speed are nearly matching in Venezia, and underestimated with an error ranging from 10% to -25% for increasing T_R at the other WMO-compliant stats. Secondly, outliers and related errors up to $\pm 90\%$ can be discussed and interpreted in the light of specific stat inconsistencies. Let us bring attention to a few examples. The speedup at Mt. Paganella is systematically and inevitably underestimated by VHR, because of the very local orographic variation occurring at a scale smaller than the VHR horizontal resolution L . Conversely, the channelling induced by the Adige Valley at Bolzano is much better simulated by VHR than by ERA5, because L is smaller than the valley width. VHR overestimates mean and extreme speeds at stations with very uneven roughness along the wind prevailing direction(s) such as Trieste and Messina. VHR simulates wind speed during the whole T with reference to present-day roughness length obtained by recent satellite imagery, usually higher than roughness at eighties in Italy: it follows that the VHR extreme speed are lower than the ones at stations that include old measurements obtained at low z_0 among non-stationary time series, e.g. Milano Malpensa, Roma Ciampino. However, it is worth highlighting that the proposed compliance index has some limitations probably induced by REA model approximations, e.g. extreme wind speeds are nearly matching in Bari despite the poor compliance $C(\hat{V}_y) = 0.61$ induced by non-stationary time series, while estimates are very poor for Cagliari despite the overall fair compliance $C(\hat{V}_y) = 0.76$. In summary, ERA5 looks suitable for the estimate of the mean wind speed, despite the large dispersion of ε towards both positive and negative values. Conversely, VHR scores the lowest error in the estimation of extreme wind speeds, and it is usually associated with a shorter dispersion of ε with respect to other analysed REA models.

The VHR-based meso- γ scale Italian wind map of the extreme wind speeds is shown in Figure 4 in terms of V_{50} filled isocontours. The other Italian maps of the mean wind speed $\bar{V}$, and extreme wind speeds V_2 , V_{100} , V_{200} are provided in Raffaele et al. (2025) for the sake of brevity. As such, the drafting of each map involved the processing of about 163.5 billion wind speed data at 444,000 cells, i.e. about 160,000 times the data available 33 year ago by Ballio et al. (1991).

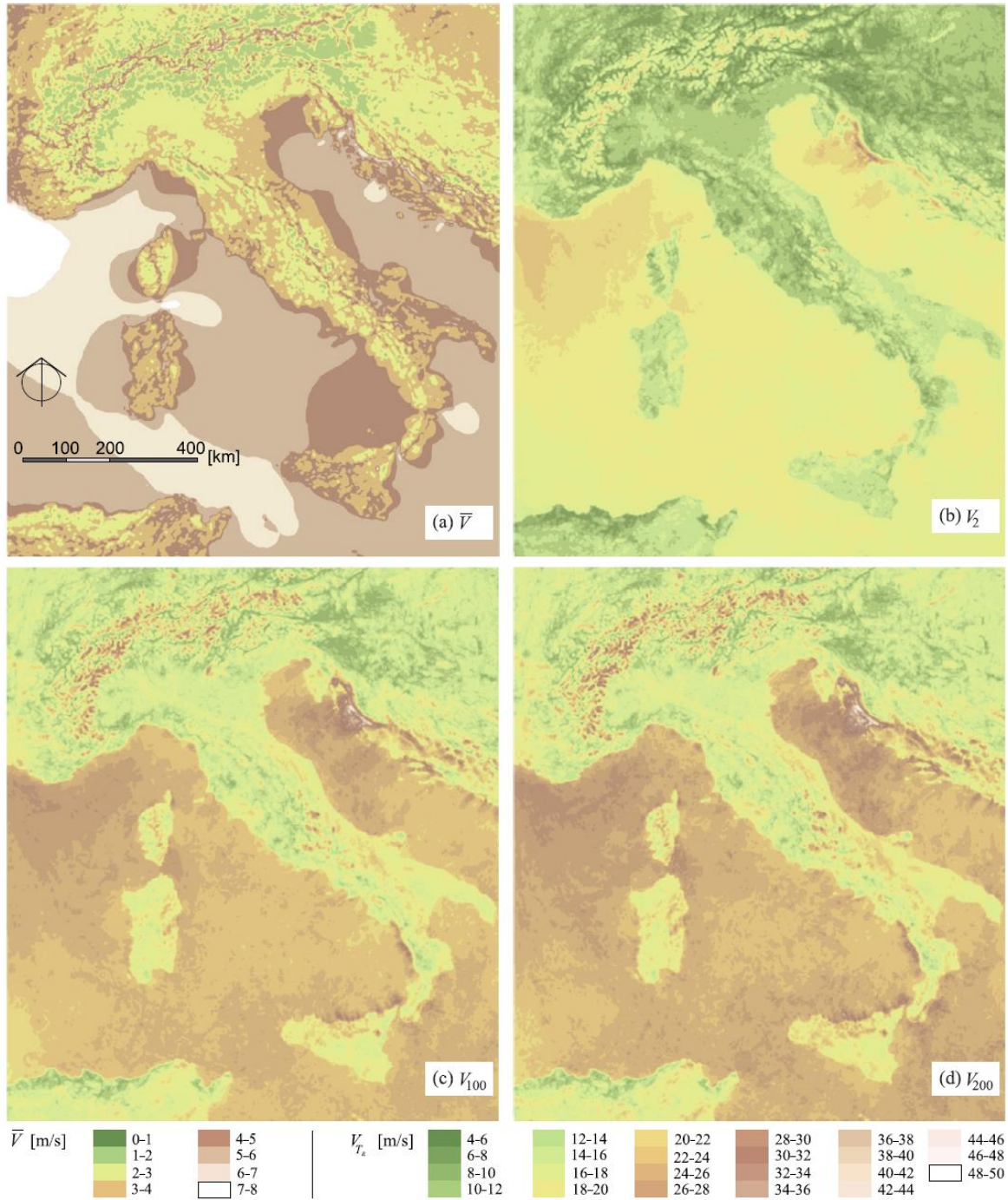


Figure 4. Map of the average value of the current wind speed (a), maps of the extreme wind speed with return period $TR = 2$ (b), $TR = 100$ (c), $TR = 200$ (d) yr.

To better appreciate the horizontal resolution of the Italian map and its mesoscale features, a closeup isocontour view of the zone surrounding the Adige and Sarca valleys, from Bolzano to the Garda lake is shown in Figure 5b. The following main considerations confirming the key features of VHR-based wind maps can be outlined:

- the spatial resolution of VHR massively enriches the description of the extreme wind speeds with respect to the current design wind speed zoning provided in the Italian standard (DM 17-01-2018, 2018, CNR-DT 207 R1/2018, 2018);

- the highest wind speed magnitudes take place over (i) water bodies, i.e. sea and lakes, due to the low roughness; and (ii) mountain ridges, due to the strong orographic effects directly accounted for. In absolute terms, the largest V_{50} in the analysed domain occurs along the Croatian coast around the Velebit mountain. Such a region has been widely recognized in the literature as an area giving rise to particularly strong Bora winds (Alpers et al., 2009; Belušić Vozila et al., 2023). Along the Italian coast, strong windy areas are recognized at the mouth of the strait of Bonifacio due to channelling effect induced by north Sardegna and south Corsica, and along the Tyrrhenian coast of Sicilia and Calabria, because of the complex orography behind the shoreline;
- the effects induced by orography and low roughness are exemplified in the closeup view in Figure 5b. $V_{50} \approx 10$ m/s in proximity of Bolzano, also consistently to stat measurements. It slightly increases along the Sarca valley due to its narrowing. The microscale features of the wind speed-up at the top of Mt. Paganella are not caught, consistently with the VHR meso- γ resolution. At the mouth of Sarca valley and over the Garda lake wind speed dramatically increases, confirming the 'wind machine' reputation of the lake. Such a mesoscale speed-up is due to (i) the contribution of strong meso- β Foehn winds blowing from NorthEast and directed along the major axis of the lake (Amadori et al., 2018; Piccolroaz et al., 2019), (ii) the steep surrounding orography, and (iii) the low local roughness of the stretch of water.

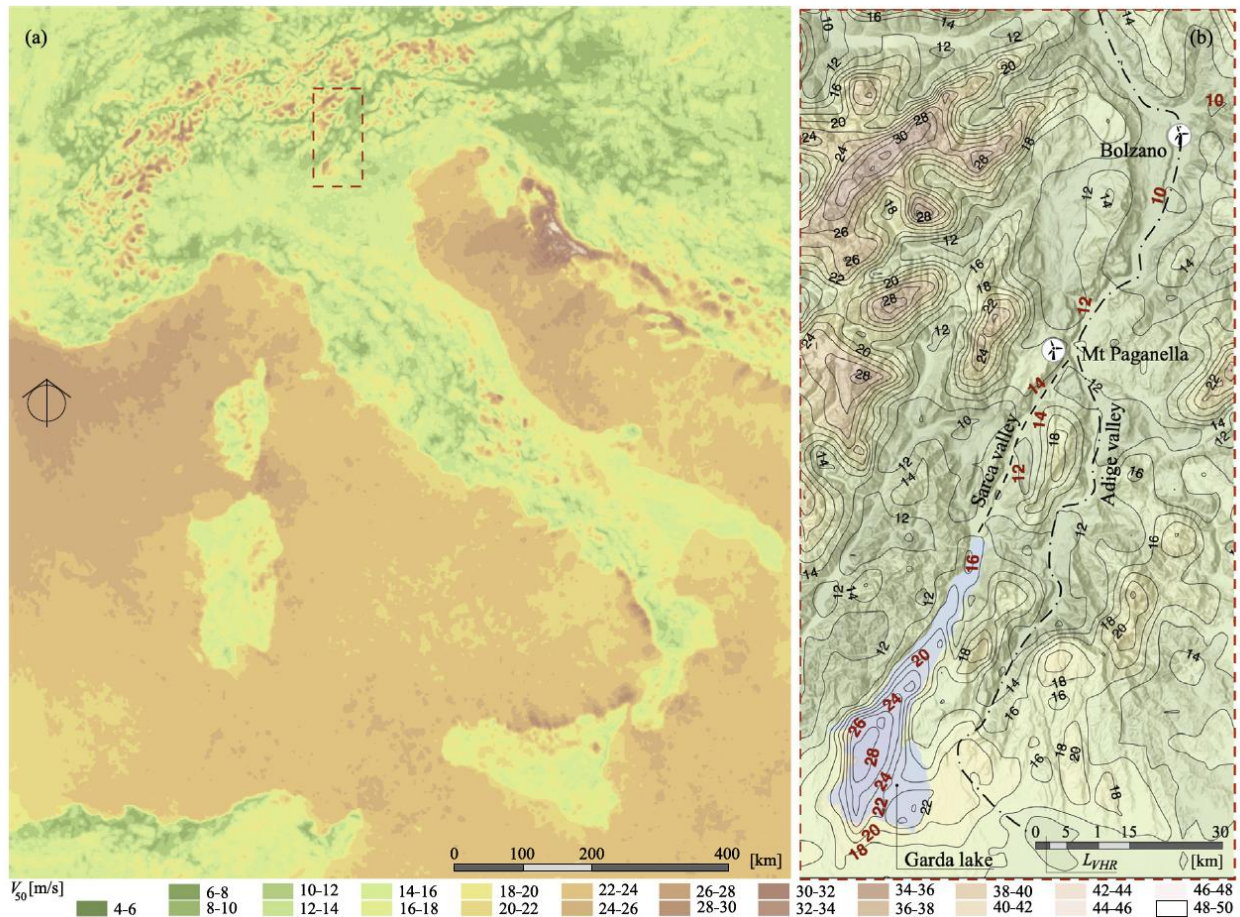


Figure 5. Map of the extreme wind speed V_{50} with return period $TR = 50$ in reference system ETRS89-extended/LCC Europe (a). Closeup view of the map around the zone surrounding the Adige and Sarca valleys, from Bolzano to the Garda lake (b).

3.3.a.2 A novel a reanalysis-based approach

In light of Section 3.3.a.2.3 of Deliverable 6.3.3 (Reports on climate-related service interruption threats over critical infrastructures – Methodology Report), and based on the previous paragraph, REA-based, REA-

based extreme wind speed estimates shall be adjusted by means of a suitably tuned model correction factor. As a result, the design wind speed $V_m(h_d)$ is expressed in REA-HA as

$$V_m(h_d) = \gamma_m \cdot V_{REA} \cdot \frac{\ln \frac{h_d}{z_0}}{\ln \frac{h_{ref}}{z_0}}, \quad (3.3.2)$$

where γ_m is the model correction factor, $V_{REA}(x_d, y_d)$ and $z_0(x_d, y_d)$ are the wind speed and aerodynamic roughness at the design site position (x_d, y_d) as mapped in the REA stage (e.g. in Figure 5), h_d is the reference design height relevant to the structure under consideration, $h_{ref} = 10$ m is the reference height at which V_{REA} is mapped. In other words, the designer is only called upon to select the return period relevant to design, apply the related model correction factor γ_m and adjust the height. In the following, a first exploratory step towards the estimate of γ_m is proposed. As such, γ_m is obtained from the comparison of REA models with WMO-compliant stat measurements and results equal to:

$$\gamma_m = \frac{V_{REA}}{V_{stat}} = \frac{1}{1 + Q_2(\varepsilon_{REA-stat})} \quad (3.3.3)$$

where $Q_2(\varepsilon_{REA-stat})$ stands for the median value of the relative error $\varepsilon_{REA-stat}$ (see Figure 3d,h,l,p,t). γ_m shall be considered as a bulk factor accounting for REA-H approach approximations, i.e. (i) dishomogeneity of wind speed averaging periods between REA models and stat measurements (Kasperski, 2002; Picozzi et al., 2022), (ii) discrepancies in roughness length definition and values among REA models and in force standards (Yu et al., 2023), and (iii) assumption of in-equilibrium wind speed log profile (Foken, 2006) adopted in the height adjust stage in correspondence of mesoscale orographic and roughness transitions. Figure 6 quantifies REA modelling errors by referring only to compliant stations in order to secure the representativeness of the measurements at the meso- and macro-scales, and filter out local microscale effects on wind speed.

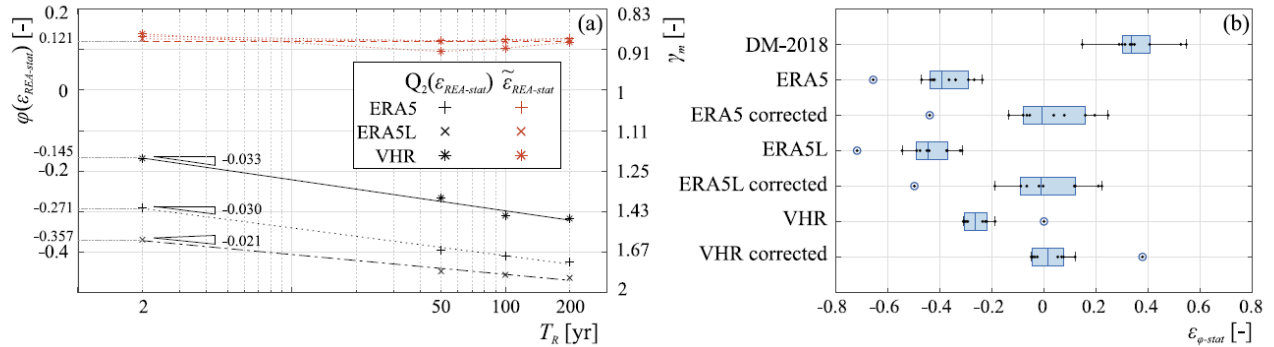


Figure 6. Median and standard deviation of $\varepsilon_{REA-stat}$ for each model and return period at compliant stations, together with corresponding model correction factor γ_m (a). Relative errors with respect to stat measurements made on V50 by DM 17-01-2018 and REA models without and with model correction factor (b).

Figure 6a plots the standard deviation $\tilde{\varepsilon}_{REA-stat}$ and median value $Q_2(\varepsilon_{REA-stat})$ of the relative error for each return period. The average constant trend of $\tilde{\varepsilon}_{REA-stat}$ highlights how the return period does not sensibly affect the dispersion of the relative error. The exponential decreasing trend of $Q_2(\varepsilon_{REA-stat})$ confirms the pattern qualitatively observed in Fig.3, i.e. the systematic underestimation of the REA-based extreme wind speed with respect to station measurements for increasing return periods, with VHR and ERA5L resulting in the closest and farthest estimates to station measurements, respectively. The related values of γ_m are still provided in Figure 6a. As an example, when $TR = 50$ years it results $\gamma_m = \{1.38, 1.63, 1.79\}$ for VHR, ERA5 and ERA5L, respectively. REA model deviations with respect to the codified approach (DM 17-01-2018) are shown by box plots in Figure 6b particularly by referring to V50 estimates at compliant stations. V50 estimates based on DM 17-01-2018 are evaluated according to the roughness classes provided in Ballio et al. (1999). According to Figure 6b, DM 17-01-2018 approach results in non-negligible overestimation

ranging from about 0.15 to 0.55 times station measurements. VHR-based extreme speeds result the closest ones to measurements in average terms and the least scattered, ranging from about -0.2 to -0.3 times station measurements. In light of the errors highlighted above, REA-based estimations can be corrected by means of γ_m to decrease $\varepsilon_{REA-stat}$. However, it is worth stressing that the proposed values of γ_m only take into account the modelling approximations above, while they have limited value since they neglect the uncertainties related to EVA statistical approach; they are estimated based on local observations referring to 10 stations, unevenly distributed over the Italian territory; they obviously depend on the considered REA model and have uniquely been estimated for the REA models considered in the present study; they compensate REA-based estimations in median terms only. In other words, the tuning and generalization of γ_m still deserves extensive modelling effort.

3.3.a.3 Conclusion

The present study is the first effort to map the extreme wind speeds at the lower bound of the meso- γ scale resolution over the whole Italian territory. Three different reanalysis-based models are adopted, described and discussed in the light of their strengths and weaknesses face to Wind Engineering problems. 21 anemometric stations over the Italian territory are selected for comparison, and their compliance to WMO specification quantitatively assessed by means of a novel synthetic index. The performances of REA models are critically compared with measurements. Mesoscale maps of mean and extreme wind speeds with 2, 50, 100, and 200-year return periods are given. Finally, a new engineering REA-HA approach to the definition of the design wind speed is proposed. This study suggests that mesoscale wind maps are a promising tool for engineers and designers, provided that a correction factor covering modelling approximations is applied.

The proposal of a novel reanalysis-based approach to mesoscale wind maps opens the door to a number of research and applications perspectives. Research perspectives are intended to improve the proposed approach for design and assessment engineering purposes. Among them, we mention:

- the critical comparison of the performances of different global and regional models in drafting extreme wind maps in general, and in simulating meso- γ scale winds such as thunderstorms in particular;
- the correction of the ‘reanalysis-and-height adjust’ approach current approximations by accounting for the different averaging period in VHR (Picozzi et al., 2022), and wind speed transition profile in correspondence of mesoscale orographic and roughness transitions;
- the improvement of the proposed model correction factor to account for further modelling uncertainties.

Application perspectives are intended to directly exploit the proposed approach and obtained results. Some of them are mentioned in the following, necessarily not exhaustive list:

- the same approach would allow to draw a unified European map of extreme winds to overcome the inconsistencies among the national maps at their administrative borders, as pointed out by Miller (2003) and Ricciardelli (2023). The ongoing Euro-CORDEX dynamical downscaling at European region wide level (Jacob et al., 2020) offers a real prospect (Outten and Sobolowski, 2021) towards such an ambitious project;
- mesoscale wind maps considering the effect of climate change can be drawn to predict extreme wind scenarios and their impact on both built and natural environment (e.g. Raffa et al., 2023);
- specific mesoscale maps can be drawn for line-like infrastructures such as railways (Burlando et al., 2010; Freda and Solari, 2010; Gageik et al., 2024), highways, power lines (Yang et al., 2022);
- coupling the mesoscale maps with microscale CWE simulations (see e.g. Bruno et al., 2023) or wind tunnel tests at point-wise locations to account for local effects of orography, roughness transition, large man-built obstacles, if deemed useful by the designer in the light of the specific features of the construction site and of the structure.

3.3.a.4 Data availability

The wind maps in Figure 4 and Figure 5 are browsable and zoomable over the whole Italian Country in Open Access at <https://arcg.is/1jzizj1> and <https://geowindy.polito.it/projects/>.

Databases: European Centre for Medium-Range Weather Forecasts (ECMWF), the Copernicus European programme, and the Euro-Mediterranean Centre on Climate Change (CMCC), and without the datasets ERA5 (<https://doi.org/10.24381/cds.adbb2d47>), ERA5-Land (<https://doi.org/10.24381/cds.e2161bac>), VHR-REA_IT (https://doi.org/10.25424/cmcc/era5-2km_italy) and CORINE Land Cover 2018 (<https://doi.org/10.2909/71c95a07-e296-44fc-b22b-415f42acfd0>) made available in Open Access.

3.3.b Enhanced methodology for defining pluvial flood hazard and risk over network CI, under CC

3.3.b.1 Updating Residual Risk Assessment for Hydraulic Infrastructures: Evaluating the Impact of Extreme Rainfall Events in Italy

3.3.b.1.1 Dataset and case study

In this work, we use Italian rainfall records from the National System for the Collection, Elaboration and Diffusion of Climatological Data (SCIA; Desiato et al., 2007), an open-access system provided by the Italian National Institute for Environmental Protection and Research (ISPRA). Specifically, we focus on daily time series recorded by the 2282 rain gauges spread over the Italian territory that fulfilled the following criteria: (i) yearly missing data less than 10%; (ii) at least 40 years of records. The location of the selected rain gauges together with some statistics are depicted in Figure 7.

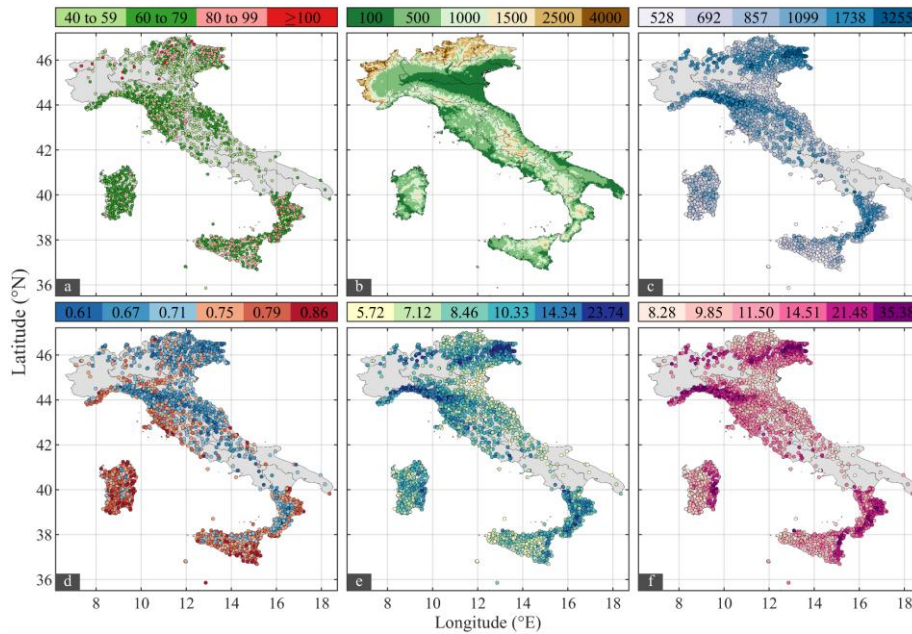


Figure 7. (a) location of the 2282 selected rain gauges colored based on the number of recording years; (b) Italy altitude map; (c) mean annual rainfall; (d) probability of failure; (e) mean daily rainfall; and (f) standard deviation. In panels c-f statistics are grouped based on 5th, 25th, 50th, 75th and 95th percentiles and maximum values.

3.3.b.1.2 Results

In Figure 8 we provide the spatial representation of the best fitting distribution. As expected, 78% of the analysed annual-maxima samples are best-fitted by a heavy-tail distribution (48% Fréchet and 30% Lognormal).

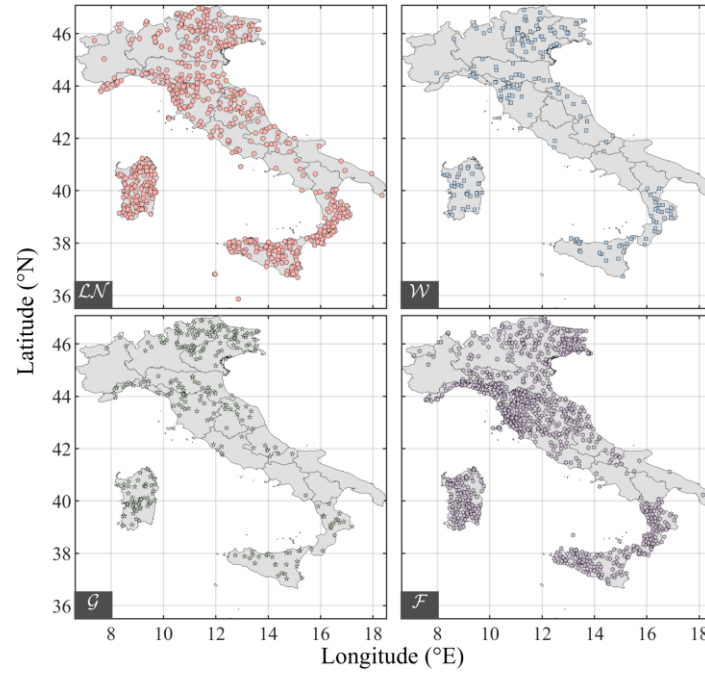


Figure 8. Spatial representation of the best fitting distributions. Each panel is representative of one probability distribution, namely, Lognormal (LN), Weibull (W), Gumbel (G) and Fréchet (F).

In this study, the first 30-years of observation at each station are assumed to represent the historical records used for the hydraulic design (hereinafter referred to as design time). Although each 30-years has the same duration, their time windows differ according to the station's period of observation. At the design time, we define all the design variables: the return period T_d , the corresponding rainfall quantile $h_d(T_d)$, the design life l and the probability of failure R_d . Here, both T_d and l are set to 100-years, resulting in an initial probability of failure of 0.63. In this analysis we do not include the natural degradation of the structure's performance, focusing solely on statistical variations in the probability of failure over time.

Figure 9 illustrates three representative and limiting cases. The dark red line shows the evolution of the probability of failure without updating, while the dashed blue line represents the updated probability estimated using the revised return period (dotted blue line). Bars highlight the difference ΔR between the two probabilities of failure, where positive values indicate a higher updated probability of failure. In Figure 9, the updated probability of failure decreases more rapidly than the original one, implying improved safety, with the probability of failure dropping from 53% to 38% after 25-years from its design. Conversely, Figure 9b shows a critical increase of more than 34%, suggesting that the design variable may occur more frequently than initially expected. Figure 9c, represents an intermediate case, with a moderate difference of about 8% after 24-years.

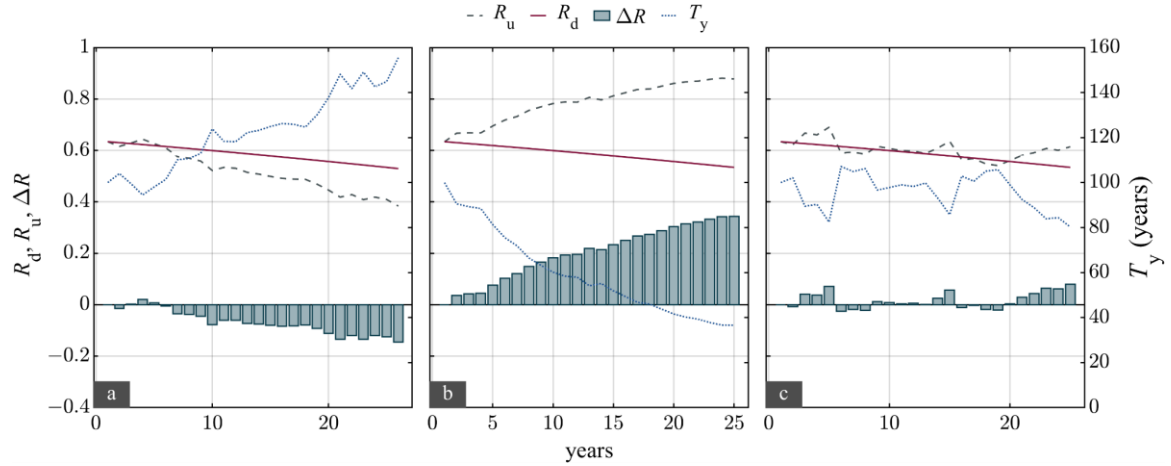


Figure 9. Probability of failure monitoring procedure for three different stations: (a) AGNONE (Molise), 55-years of observation, (b) Antonimina – Canolo Nuovo (Calabria), 54-years of observation, and (c) ALCANTARA (Sicily), 54-years of observation. On the y-left axis are represented all the probability of failures (design, updated and difference); while on the y-right axis is provided the updated return period of the design variable estimated at the design time (30-years subsample).

The same procedure can be extended to all the 2282 stations. Figure 10a–c presents histograms of: (a) the differences ΔR between expected and updated probabilities of failure after $N - 30$ years of monitoring; (b) the cumulative sum of these differences over time; and (c) changes in the design rainfall. The negatively skewed behaviour of ΔR indicates that 64% of the analysed samples show an increase in the probability of failure after the monitoring period, implying more frequent exceedances of the design event. Larger $\Sigma \Delta R$ values suggest persistent deviations over time. Changes in design rainfall are consistent with these results, as lower rainfall quantiles correspond to shorter return periods and higher failure probabilities. Because stations have different record lengths (40–146 years), Figure 10d–e provides a comparable analysis limited to the first 10 years of monitoring. Results confirm that 67% of the stations (1527 out of 2282) exhibit an increased probability of failure during this period.

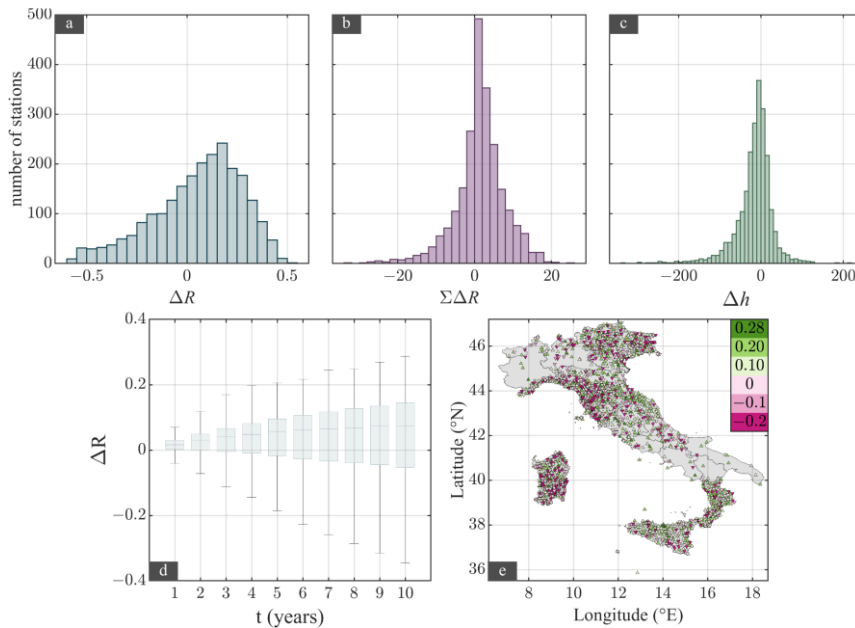


Figure 10. Histograms representing: a ΔR after $N - 30$ years of monitoring; b the total sum of the differences ΔR during the monitoring period; and c the differences Δh of the design rainfall estimated with the 30-years subsamples and after $N - 30$ years. For the first 10-years monitoring procedure: d boxplots representing the variability of ΔR during the first 10-years after the design time, e spatial variability of ΔR related to the 10th year of observation.

3.3.b.1.3 Discussion

The proposed updating procedure provides a dynamic view of the reliability of hydraulic works by quantifying how the probability of failure evolves as new data become available. Results show that assuming stationary design conditions may lead to a progressive underestimation of risk, as the return period associated with the design rainfall can significantly change over time. The analysis of 2282 stations highlights that about 64% of the samples experience an increase in the probability of failure after the monitoring period, indicating that design events tend to occur more frequently than expected. This behaviour is particularly critical when the updated return period becomes shorter than the design one, implying that rainfall intensities originally associated with rare events may now be reached several times within the design life.

These findings suggest that the periodic updating of design variables represents an essential tool for risk assessment and infrastructure management. The proposed procedure allows decision-makers to identify structures or infrastructure whose failure probability deviates most from the design condition and to prioritise inspections, maintenance, or reinforcement accordingly. Moreover, by aggregating local results, it becomes possible to develop dynamic risk maps that track the spatial and temporal evolution of hydraulic risk.

For more details on this work, please refer to Moccia et al. (2024).

3.3.b.2 Dynamic maps of pluvial flooding under current and future climatic conditions

3.3.b.2.1 Study Area and Data

We selected the Milvian Bridge district, located in the northern sector of Rome (Figure 11), as our case study due to its recurrent pluvial flooding issues, which are well documented in climate observatory reports (Legambiente, 2025) and previous research (Di Salvo et al., 2017). We also selected this site because high-quality rainfall observations and a high-resolution Digital Surface Model (DSM) were already available for this area, providing the necessary input data for rain-on-grid hydraulic simulations.



Figure 11. Progressive zoom from the national (Italy) to the urban (Rome) scale, showing the location of the Milvian Bridge district and the nearby reference rain gauge stations.

The Milvian Bridge district covers an area of approximately 3.36 km² and features a heterogeneous urban fabric composed of residential quarters, commercial establishments, and recreational facilities. The district holds strategic importance for the city, as it hosts several major facilities, including the Foro Italico sports complex, the Olympic Stadium and the Auditorium Parco della Musica, one of the city's principal concert venues. Furthermore, the area is intersected by major transportation arteries such as Via Flaminia and Via Cassia (Archeoroma, 2025). Topographically, the Milvian Bridge area is predominantly flat, with an average slope of 0.064, towards the Tiber River.

To develop the pluvial flood model, we combine multiple geospatial and hydrometeorological datasets representing the physical characteristics of the area. Specifically, we use: (i) a 1 m-resolution Digital Surface Model (DSM) derived from Mobile Light Detection and Ranging (LiDAR; Gargoum & El-Basyouny, 2017) surveys provided by the Italian Ministry of the Environment via the National Geoportal, which we preprocessed to correct distortions and improve the representation of building features; (ii) land cover and soil information from the Copernicus Urban Atlas 2018 (Buchhorn et al., 2020), which we employed to parameterize surface roughness and infiltration through curve number (CN) values; (iii) rainfall data from the Hydrographic Service of the Lazio Region, including hourly records and annual maxima from four regional gauges, that are, Roma Flaminio, Monte Mario, Acqua Acetosa, and Cassiodoro, spanning 24-44 years of observation in the period 1951-2024. Rainfall inputs were spatially interpolated over the study area using the Thiessen Polygon method, which ensures an appropriate representation of rainfall distribution within small and relatively homogeneous urban catchments (Olawoyin & Acheampong, 2017; Guo et al., 2022).

3.3.b.2.2 Results

In this section we present the results of our study based on the distinct assessment of hazard, vulnerability, dynamic exposure and dynamic pluvial flood risk.

3.3.b.2.2.1 Flood Hazard

We simulate synthetic rainfall events corresponding to a 50-year return period with durations of 10-min, 30-min and 1-hour to reproduce the conditions of intense urban storms typically responsible for pluvial flooding (Houston et al., 2011; Lompi et al., 2022; Mediero et al., 2022). Using the HEC-RAS rain-on-grid framework, we produce flood hazard maps that depict the spatial distribution of water depth, which we adopt as the main indicator of flood hazard levels.

We conducted a preliminary sensitivity analysis to evaluate the influence of Manning's roughness coefficient across three land use categories: buildings, green areas, and roads. Variations in the roughness of buildings and vegetated areas show limited impact on water depth and flood extent, whereas modifications to road roughness markedly alter overland flow pathways. Since roads act as the primary drainage corridors, we focus the next analyses on this variable. We specifically test the effect of increased road roughness (from $n = 0.02$ to $n = 0.05$) to represent urban flood drifters (such as parked vehicles, debris, or other temporary obstructions) (Bayón et al., 2024; Valero et al., 2024). We then classify flood depth results into four hazard categories: low (<0.1 m), moderate (0.1-0.3 m), high (0.3-0.5 m), and very high (>0.5 m), following Bhola et al. (2020). Among the tested configurations, the 1-hour rainfall event combined with $n = 0.05$ produced the greatest inundation depths and the largest fraction of high-hazard zones (Figure 12). This outcome reflects the capacity of longer storms to sustain surface runoff accumulation, particularly along low-lying streets and topographic depressions.

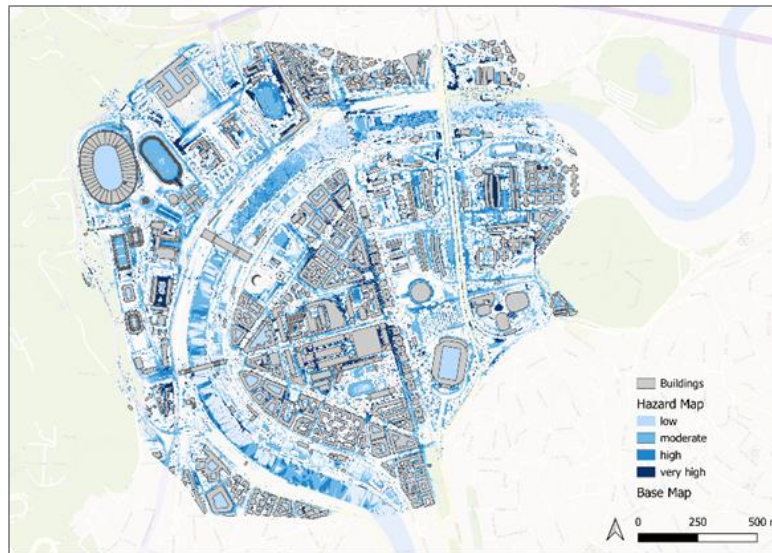


Figure 12. Flood hazard map corresponding to a 50-year return period rainfall event with 1-hour durations and Manning's $n = 0.05$.

To better understand the influence of road roughness, we compare results between the two n values, generating a differential depth map (Δ -map). We observe local variations up to ± 0.1 m (Figure 13), mainly along major intersections where higher friction reduced flow conveyance and promoted ponding. Even small changes in depth caused reclassification across hazard thresholds, underscoring the sensitivity of flood hazard mapping to local surface conditions.

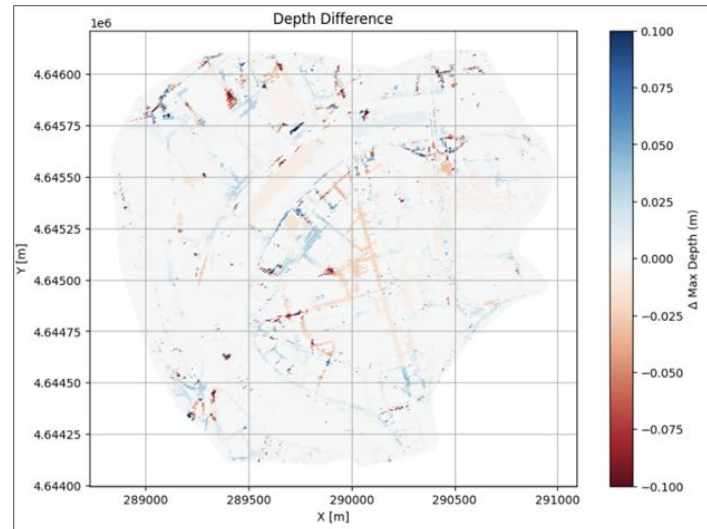


Figure 13. Differences in water depth (Δ -map) resulting from two Manning's n values.

3.3.b.2.2.2 Vulnerability

We assess structural vulnerability through a multi-criteria evaluation of building attributes, including age, material, height, and condition. The dominant building typology in the district consists of concrete residential structures built between 1919 and 1945, typically 5–10 m tall and in good structural condition. The resulting composite score is 11 which corresponds to the “high vulnerability” class according to the classification proposed by Taramelli et al. (2022).

3.3.b.2.2.3 Exposure

To evaluate exposure, we compile a detailed inventory of buildings and associated population estimates, categorizing them into nine functional types (residential, offices, schools, sports centers, recreational facilities, restaurants, hospitals, the Olympic Stadium, and others; Figure 14). Residential buildings represent the majority of the built-up area and accommodate most of the population. However, specific facilities such as the Olympic Stadium and sports or recreational complexes exhibit very high occupancy densities, generating localized exposure peaks within limited spaces.

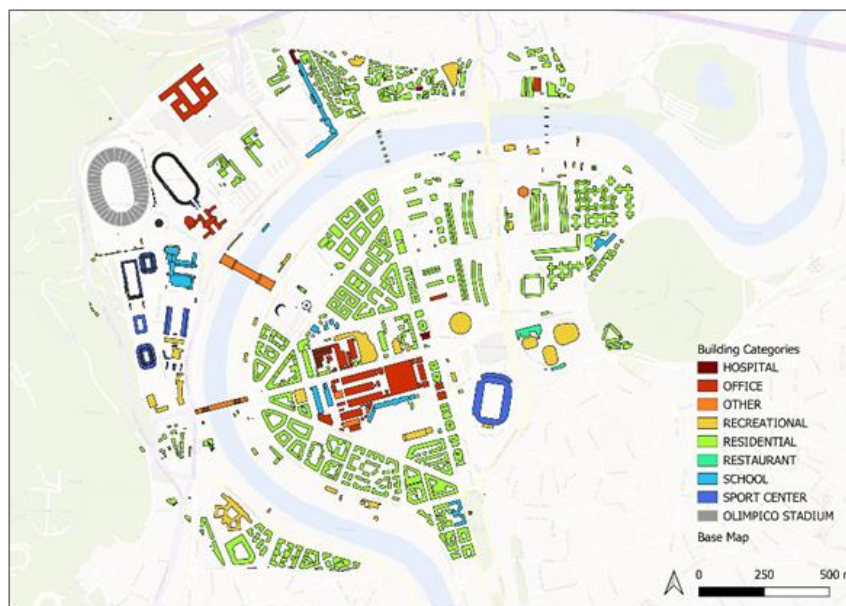


Figure 14. Map showing the buildings classification in the study area.

3.3.b.2.2.4 Dynamic Pluvial Flood Risk

Historical climate conditions

With the intersection of the results for hazard, vulnerability and exposure, we quantify dynamic pluvial flood risk by mapping the population exposed under the most critical hazard scenario (1-hour rainfall, $n = 0.05$). Figure 15 illustrates the temporal distribution of affected populations at five representative hours of the day (6 a.m., 9 a.m., 1 p.m., 6 p.m., and 12 a.m.). Results show distinct temporal patterns:

- 6 a.m.: low exposure levels dominate, as most inhabitants remain indoors;
- 9 a.m.: exposure increases near schools and offices as daily activities begin;
- 1 p.m.: the highest impact levels occur, driven by peak occupancy of recreational and cultural facilities situated in flood-prone areas;
- 6 p.m.: activity shifts to sports infrastructures (Foro Italico, Olympic Stadium), though impacts remain moderate due to low local water depths;
- 12 a.m.: exposure decreases again, returning to levels similar to early morning conditions.

These temporal variations highlight how daily population dynamics significantly influence pluvial flood risk distribution within urban districts.

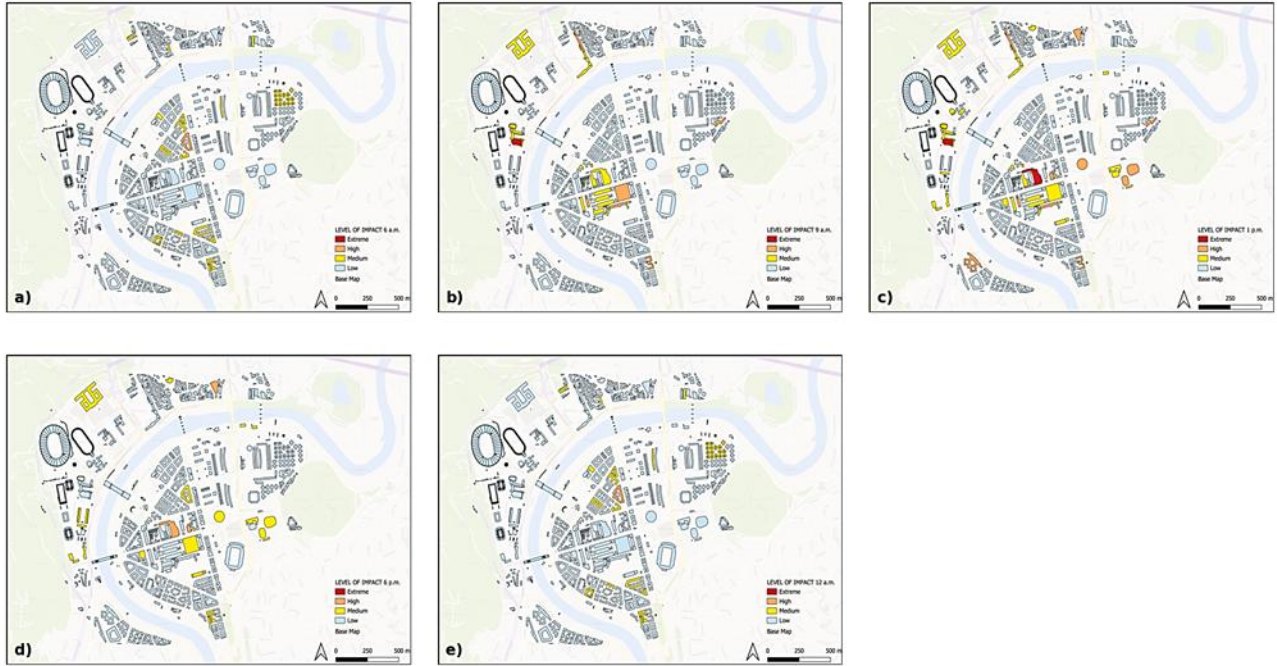


Figure 15. Spatial representation of the affected population at different times of the day. (a) 6 a.m., (b) 9 a.m., (c) 1 p.m., (d) 6 p.m., (e) 12 a.m. under the extreme hazard scenario

Climate change conditions

To explore potential future changes in the dynamic pluvial flood risk, we adjust rainfall intensity based on the trend analysis proposed by Avino et al. (2024). By using the Mann–Kendall test and the Sen’s slope estimator (Gocic & Trajkovic, 2013), we quantify monotonic trends in annual maxima rainfall recorded at the four rain gauge stations. The resulting slope values are then applied to derive climate-adjusted rainfall intensities (i_{cc}), summarized in Table 1. Particularly, both the historical and the climate change rainfall intensity reported in Table 1 are associated with a 50-year return period and a duration of 1-hour.

Table 1. Comparison of rainfall intensities for historical and climate change conditions.

Rain Gauge	i_{HIST} (mm/h)	i_{CC} (mm/h)
Acqua Acetosa	88	80
Cassiodoro	74	77
Monte Mario	67	72
Roma Flaminio	67	66

We then re-ran the HEC-RAS simulations using i_{CC} values under the same worst-case configuration (1-hour, $n = 0.05$). The updated maps indicate an expansion of the flooded area from 37% to 54% of the district. The proportion of zones classified as high and very high hazard increased from 6.0% to 9.5% and from 4.7% to 35.5%, respectively (

Table 2 and

Table 3).

Table 2. Percentage of normalized area for each hazard class under historical conditions.

Hazard Class	Area (km ²)	% Total Area
Low	0.38	11.3%
Moderate	0.49	14.6%
High	0.2	6.0%
Very High	0.16	4.7%
	1.23	37%

Table 3. Percentage of normalized area for each hazard class under climate change conditions.

Hazard Class	Area (km ²)	% Total Area
Low	0.05	1.4%
Moderate	0.25	7.6%
High	0.32	9.5%
Very High	1.19	35.5%
	1.82	54%

Although our purpose was not to propose a new climate adjustment method, our findings demonstrate that even moderate increases in rainfall intensity can substantially amplify pluvial flood hazard in dense urban environments such as the Milvian Bridge district.

3.3.b.2.3 Discussion

Our findings show that rainfall duration strongly influences pluvial flood dynamics in the Milvian Bridge district. Short events (10- and 30-min) produced only localized flooding, while the 1-hour storm generated more continuous flooding, with a larger area exceeding moderate and high hazard thresholds. Flood patterns were mainly controlled by local topography and land use: shallow depths occurred along streets and courtyards, whereas deeper inundation concentrated in low-lying impervious zones such as parking lots and recreational facilities. These hotspots are critical, as they often coincide with pedestrian or vehicle movements during emergencies, posing safety risks.

The sensitivity analysis confirmed that surface conditions markedly affect flow propagation. Small variations in road roughness led to changes in water depth of about ± 0.1 m, sufficient to shift hazard classes and reveal the strong influence of temporary urban obstructions on flood dynamics.

The vulnerability assessment indicated that many early 20th-century reinforced-concrete buildings fall within the high vulnerability class due to their age and lack of flood resilient design. This underlines the relevance of considering historical construction practices when assessing urban vulnerability in European cities.

Exposure and dynamic risk analyses highlighted strong spatial and temporal variability. Nighttime exposure was dominated by residential areas, while daytime peaks occurred around workplaces and services, with the highest overall risk observed at 1 p.m., when recreational buildings reached maximum occupancy in flood-prone areas. Evening peaks were mainly linked to sports facilities, demonstrating how event-driven activities can significantly alter the district's risk profile.

Some limitations remain, particularly regarding building use and occupancy assumptions, which may overestimate exposure. Future studies should incorporate real-time mobility data, refined land-use information, and loss estimation to improve dynamic risk modeling and support more effective flood preparedness strategies. Moreover, the climate change scenario indicated a marked increase in flooded area and hazard intensity, confirming that even moderate intensification of rainfall could substantially amplify pluvial flood risk in the district.

This work is currently under review in the *Journal of Flood Risk Management*.

3.3.b.3 Enhancing rainfall monitoring in urban areas by integrating crowdsourced personal weather stations into official networks

3.3.b.3.1 Study Area and Data

In this study, we selected 11 major Italian cities as case studies and retrieved both official meteorological networks (OMN) data and Netatmo Personal Weather Station (PWS) observations at hourly resolution. The selected cities represent a wide range of climatic and topographical conditions across the national territory, which can significantly influence rainfall patterns. The selection was driven by the aim of ensuring an adequate geographical representation of the Italian regions, as well as by the availability of freely accessible hourly (or sub-hourly) observations from the OMN. In Figure 16a we show the 11 selected cities, which are Ancona, Bologna, Catania, Catanzaro, Firenze, Genova, Milano, Padova, Potenza, Roma, and Torino and the spatial distribution of both Netatmo and OMN rain gauges.

We defined the analysis period based on the availability and activity of 432 PWSs. As shown in Figure 16b, the number of active PWSs over time for the selected cities presents an increasing trend, rising from fewer than 50 stations before 2018 to more than 250 after 2021. For these reasons, we selected the year 2022 which ensures the highest number of working PWSs.

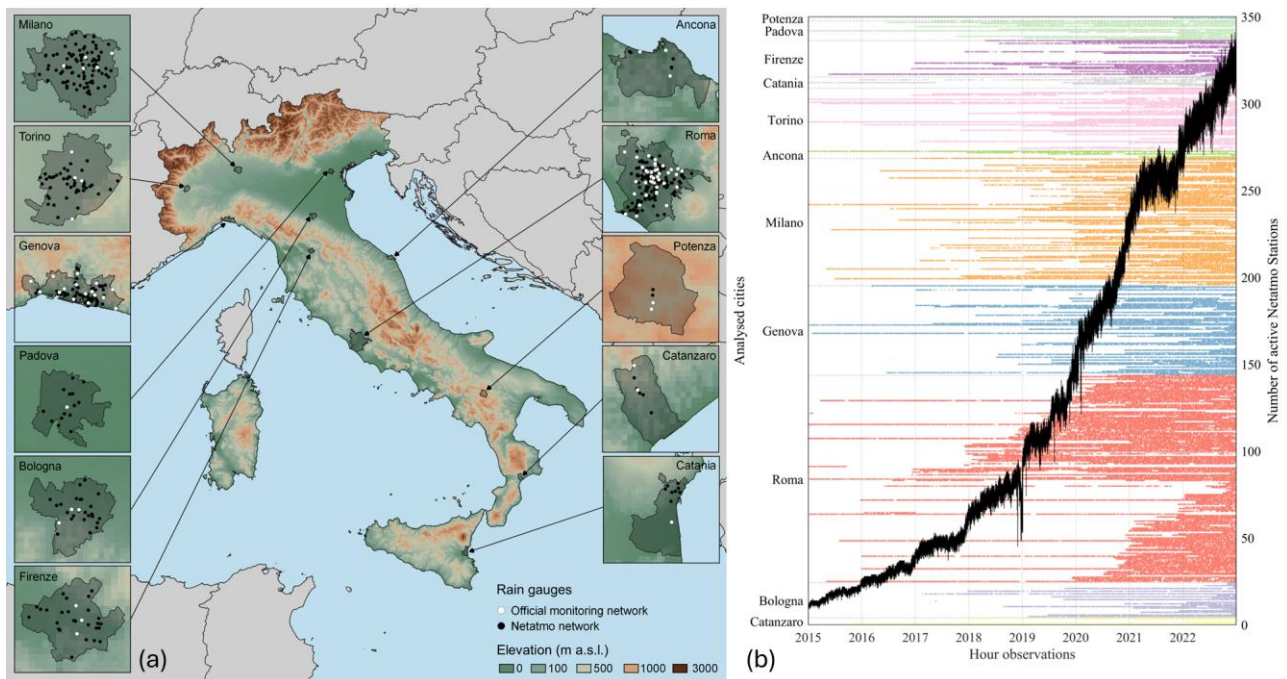


Figure 16. The 11 Italian cities selected for the analysis with the Netatmo and Official Meteorological rain gauge networks (a). Number of active Netatmo stations in the 2015-2022 period (b).

The number of available PWSs strongly depends on the download period as data are collected via API and cannot be retrieved from devices that are temporarily offline (e.g., due to network or battery issues). Such data may become accessible once the device reconnects.

3.3.b.3.2 Results

3.3.b.3.2.1. PWSs hourly records performance

In this study we investigate the reliability of PWSs in recording rainfall in 11 Italian cities, without applying any quality control procedures. Specifically, we compared raw rainfall data from 391 PWSs with

observations from 78 gauges of the OMN to assess correlations and deviations in precipitation measurements during 2022.

Each PWS was paired with the nearest OMN station based on minimum Euclidean distance. The resulting distances ranged from approximately 900 m to 10 km, which we consider reasonable for rainfall comparison, given the high spatial and temporal variability of precipitation.

After pairing, only the time steps with simultaneous records at both gauges were considered for the performance evaluation. Thus, all results refer to the year 2022, although the effective comparison periods may vary among the pairs. In Figure 17 we show the completeness of the analyzed time series, indicating that about 73% of the stations have more than 50% of available data.

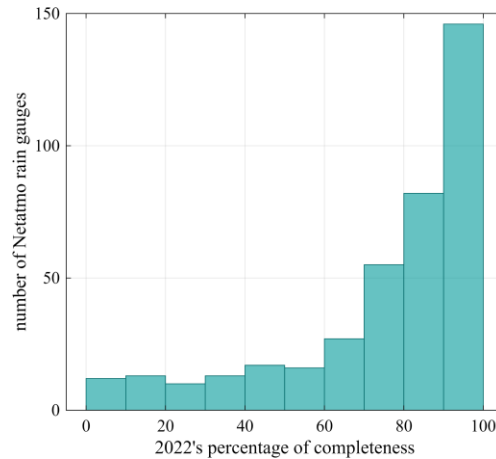


Figure 17. Time series percentage of completeness for the 2022 year.

For each gauge pair, we computed the probability of dry, the total annual rainfall, and the average and maximum 1-hour rainfall values (Figure 18).

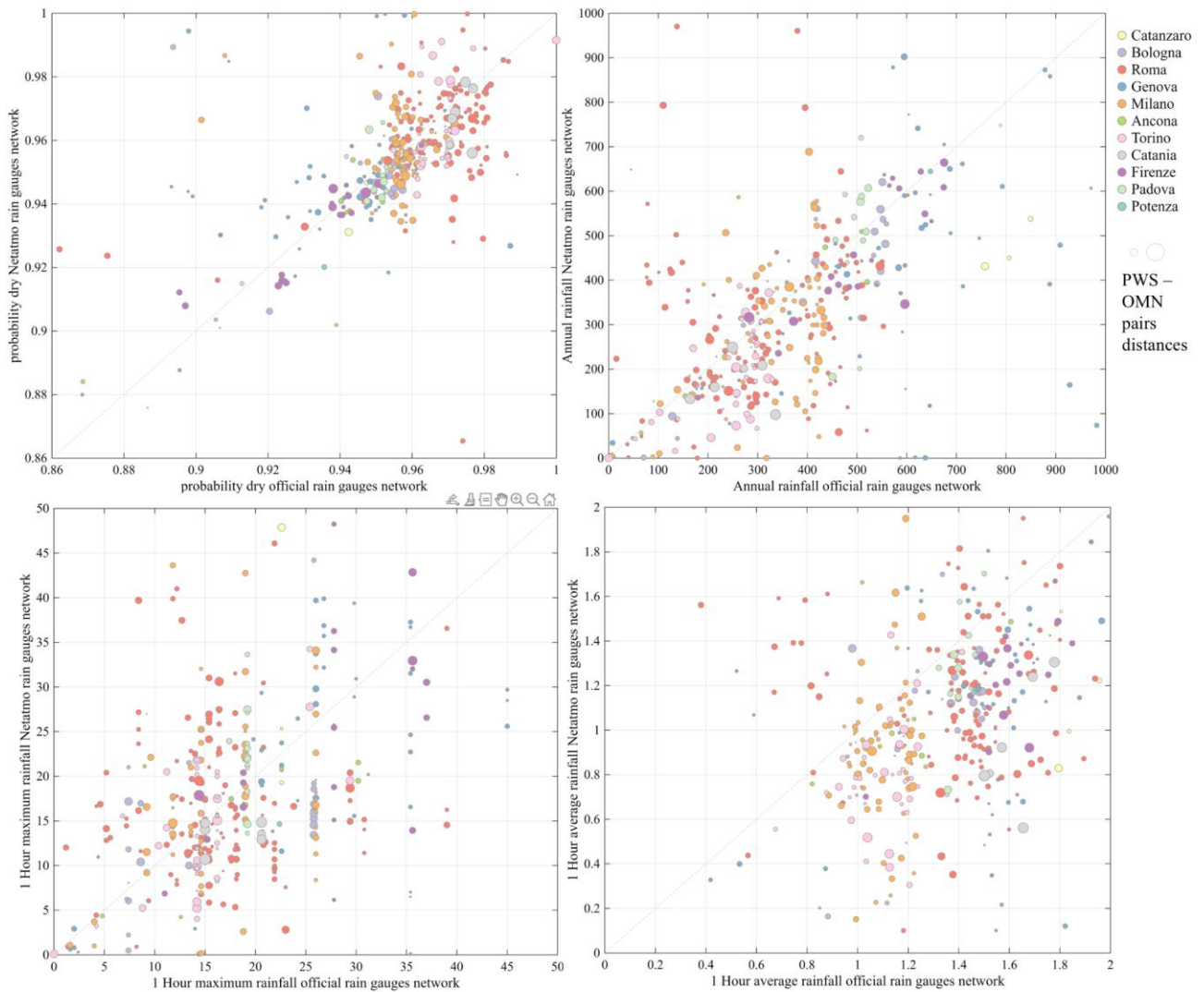


Figure 18. Gauges pair comparison of raw rainfall data in terms of probability dry, annual rainfall, and 1-hour maximum and average rainfall. Different colors identify the cities, while the marker size represents the distance between the Netatmo and the coupled OMN gauges.

Probability dry and annual rainfall show a good consistency between the two datasets. As expected, larger deviations occur in the 1-hour average and maximum rainfall, with PWSs generally underestimating hourly rainfall compared to the corresponding OMN gauges. These differences can be partly attributed to the high spatial variability of precipitation events. Overall, these preliminary results suggest that, even without quality control, PWS data provide a reasonable representation of local rainfall behaviour.

Based on this preliminary analysis, we then computed additional metrics to further evaluate PWS performance. For each station pair, we calculated the Pearson correlation coefficient (ρ) and the BIAS of the raw hourly time series. These metrics, combined with the inter-station distance, were used to identify the most reliable pairs. By applying a minimum correlation threshold of 0.4 and a maximum distance of 6 km, the number of pairs considered for further analysis decreased to 283. These thresholds can be adjusted according to specific requirements.

For the filtered pairs, we calculated the cumulative rainfall and the 20% confidence intervals (CIs) of the corresponding OMN gauge. This approach quantified the temporal agreement between PWS and OMN cumulative rainfall. We then identified the pairs where PWS cumulative rainfall fell within the OMN CIs. Among the 283 analysed pairs, 73 met this criterion, indicating that 25% of the selected PWSs produced

rainfall estimates statistically consistent with the reference network. These pairs show an average bias of 0.96, confirming the overall robustness of the comparison.

To evaluate the effectiveness of the applied filters, we calculate again the same rainfall characteristics previously derived from the raw data (Figure 17). In Figure 19 we show the results for the filtered pairs. Compared to the raw data, the dispersion of the analysed characteristics (i.e. probability dry, annual rainfall, 1-hour maximum and average rainfall) is significantly reduced, with values lying closer to the bisector. This result highlights the improved coherence and consistency of the filtered dataset.

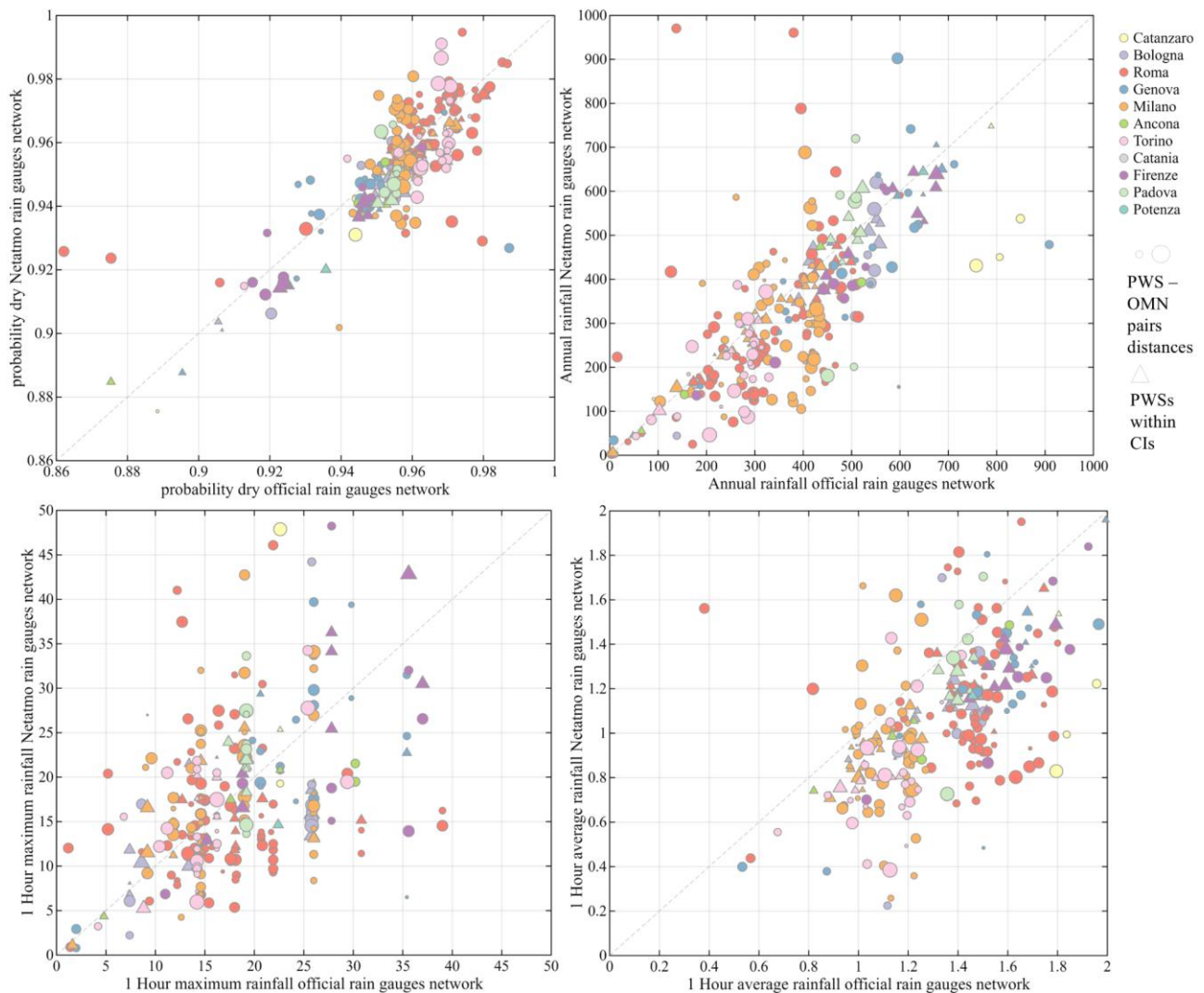


Figure 19. Gauges couples comparison of rainfall data after the filter application in terms of probability dry, annual rainfall, and 1-hour maximum and average rainfall. Different colors identify the cities, while the marker size represents the distance between the Netatmo and the coupled OMN gauges. Triangle markers are associated with gauge pairs whose PWS cumulative observations fall within the confidence intervals of their corresponding OMN stations.

3.3.b.3.2.1. PWSs applications: hazard pluvial flood maps

Netatmo PWSs rainfall observations can be used as input for several hydrological applications. Here we employ hourly PWSs rainfall data to enhance the spatial resolution of a critical event that occurred in the Milvian Bridge district (Rome) and simulate an event-based pluvial flood hazard map. As previously discussed in section 3.3.b.2, the OMN managed by the Hydrographic Service of the Lazio Region includes four rain gauge stations within and around the Milvian Bridge district, while 23 PWSs are located in the same area (Figure 20a).

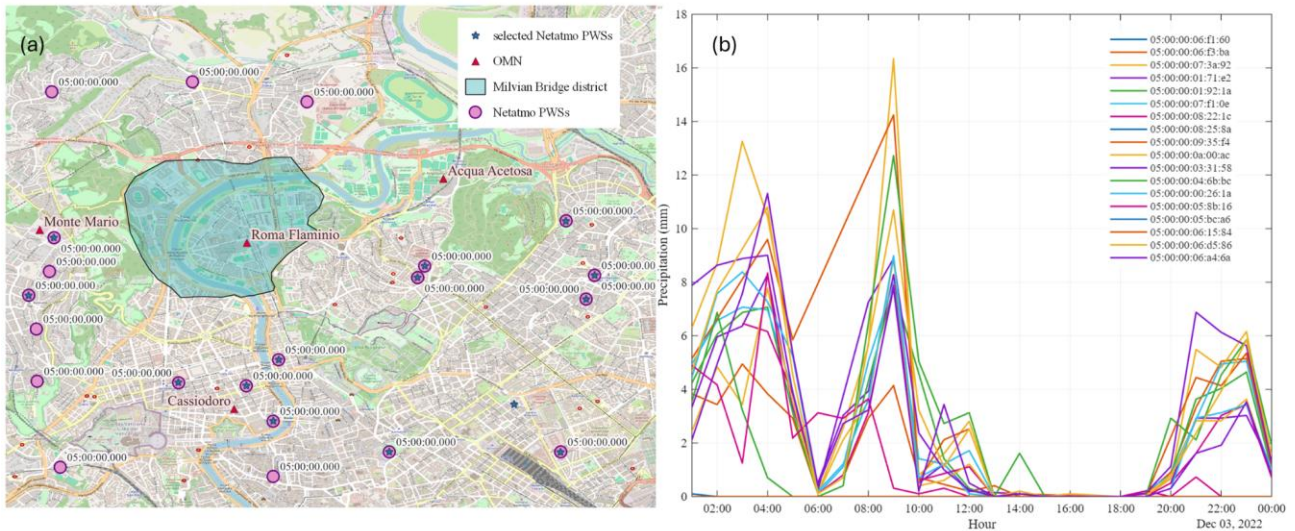


Figure 20. (a) Milvian Bridge district neighborhood area with the spatial location of Netatmo PWSs and OMN gauges; (b) 3rd December 2022 critical event hyetographs recorded by PWSs.

Since the length of the PWSs time series does not yet allow a robust statistical analysis to determine synthetic hyetographs for specific return periods, in this application we selected a representative critical event recorded by the PWS network. In a preliminary analysis over the period 2015–2022, we identified the 3rd December 2022 as the event with the highest number of active PWSs and daily rainfall exceeding 40 mm. During this event, 13 PWSs recorded over 40 mm of rain (Figure 20b), while the only active OMN rain gauge (i.e. Acqua Acetosa) measured 4.6 mm. Using Acqua Acetosa alone as rainfall input produced no flooded areas. On the contrary, the simulation based on the 13 PWS hyetographs (Figure 20b) resulted in a detailed pluvial flood hazard map that highlights the added value of PWS for local-scale flood assessment (Figure 21).

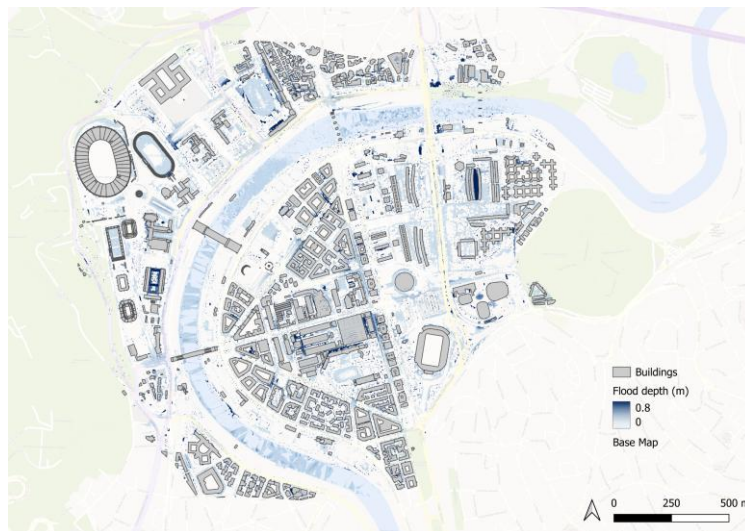


Figure 21. Pluvial Flood Hazard map for the 3rd December 2022 critical event.

3.3.b.3.3 Discussion

The preliminary analysis presented in this section highlights the promising potential of crowdsourced Personal Weather Station (PWS) data for urban rainfall monitoring. Despite the absence of a dedicated quality control procedure, simple filters based solely on correlation and distance already improved the consistency between PWS and official network observation, with 25% of the filtered pairs showing statistically

comparable cumulative rainfall in 2022. This demonstrates that even basic selection criteria can effectively identify reliable PWSs and enhance data integration with institutional networks.

Future developments will focus on implementing quality control procedures from the literature and designing an ad hoc methodology tailored to our case studies. These improvements are expected to further enhance the reliability and usability of PWS data for hydrological applications.

A review article on this topic is currently under revision in *Frontiers in Built Environment – Urban Science*.

3.3.b.4 Evaluation of temporal trends in short-duration rainfall extremes

3.3.b.4.1 Results of the application of the Mann-Kendall test

The Mann-Kendall test has been applied to the 1614 time series with at least 30 years of data. On a total of 1614 time series considered, 279 of them (17%) present a statistically significant trend (either positive or negative) at the 5% level for the 1h duration (Table 4), confirming that over a large portion of the nation the trend is not statistically significant. This is consistent with previous findings reported in the literature over Italy (Crisci et al., 2002; Bonaccorso et al., 2005; Arnone et al., 2013; Libertino et al., 2019; Persiano et al., 2020; Avino et al., 2021; Treppiedi et al., 2021; Mazzoglio et al., 2022; Roseto et al., 2023; Avino et al., 2024) or in the Mediterranean region (Sun et al., 2021). In our analysis, however, the percentage of stations with significant trend is higher than in the before-mentioned studies, indicating that by including the most recent years the signal of change is becoming stronger. In Libertino et al., 2019, as an example, only 163 time series out of more than 1300 presented a statistically-significant trend at the 5% level. The number of locations with a statistically significant trend decreases to 214 (13%) when considering the 24h interval. In Libertino et al. (2019) the number of statistically-significant trends at the 5% level was 150. From Table 4 we can see that the percentage of stations with a statistically significant trend decreases with increasing rainfall duration. A similar decrease is also evident when considering the subset of stations with a positive statistically significant trend. The highest number of stations with a negative statistically significant trend is present in the 1 and 24h durations, while intermediate durations are characterized by lower numbers. However, we cannot detect a clear positive or negative variation with the duration, since the numbers are quite similar.

Table 4. Number of stations with a statistically significant trend at the 5% level for the 5 different durations, with the distinction between stations with positive and negative trends.

Duration (h)	Time series with a statistically significant trend (-)	Positive trends (-)	Negative trends (-)
1	279	211	68
3	252	202	50
6	256	199	57
12	236	182	54
24	214	144	70

In Figure 22, panels a and b show the results obtained by considering the 1h duration, while panels c and d show the results obtained by processing the 24h annual maxima. Panels a and c show the trend significance from the application of the Mann-Kendall test, while panels b and d show the Sen's slope estimate. The triangles in Figure 22a,c indicate the position of the time series with a statistically significant variation detected by the Mann-Kendall test (the size of the triangle is proportional to the entity of the Mann-Kendall test statistic Z). The background map is obtained by spatially interpolating with ordinary kriging all the at-site Z statistics without considering the significance of the trend. In Figure 22b,d the triangles indicate the position of the time series with a statistically significant trend, while the size is proportional to the entity of the Sen's slope. The background map is, again, obtained by spatially interpolating with ordinary kriging all the at-site Sen's slope estimator without considering the significance of the trend.

Considering the sign of change, we can see that short-duration rainfall extremes are not increasing uniformly over Italy (Figure 22) but a certain degree of spatial consistency exists. Opposite tendencies in the variation of 1h extremes emerge in different geographic sectors of Italy: positive trends prevail in North-East and in Central Italy, while negative trends prevail in the North-West (Figure 22a,b). For the 1h duration, some areas show a clear reduction of the extremes over time, such as in most of Piedmont and in parts of Toscana, Sardegna, and Calabria, while in other regions the decreasing trends lose spatial coherence, as in the case of Emilia-Romagna (Figure 22a,b). For longer durations (24h), positive trends are visible in some areas, such as in the North-East, in Liguria, and in Campania (Figure 22c,d). However, in most of the territory, the spatial variability is larger than for short duration extremes, and the extent of areas with equal sign is smaller. The lack of spatial coherence of the trends in precipitation extremes is in line with the findings already reported in global-scale studies (see e.g. Alexander et al., 2006, and Sun et al., 2021).

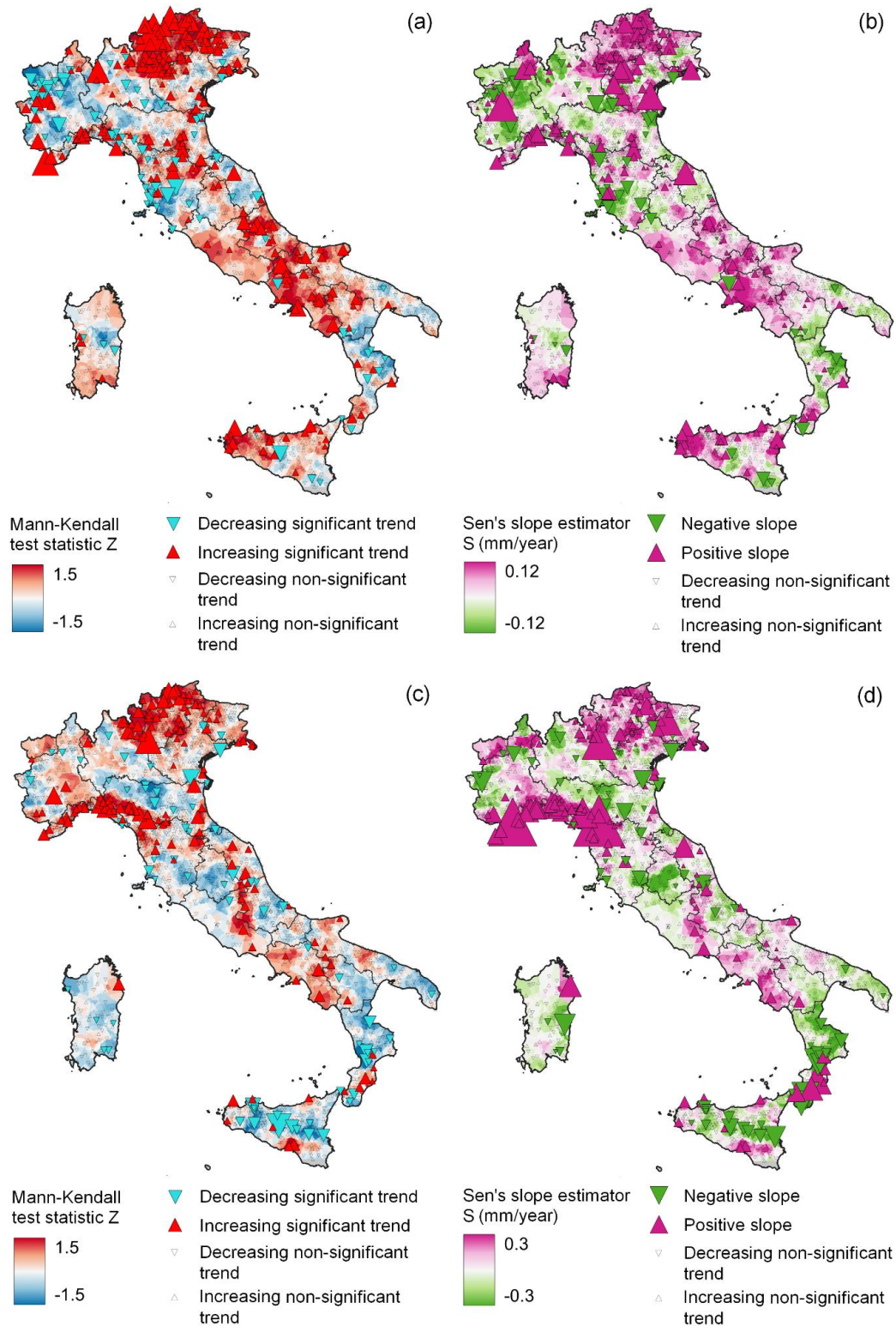


Figure 22. Mann-Kendall test statistic for the 1h (a) and 24h (c) time intervals. Sen's slope estimator for the 1h (b) and 24h (d) time intervals. The background maps are obtained by spatially interpolating with an ordinary kriging the MK test statistics (a, c) and the Sen's slope estimators (b, d) obtained in all the stations, without considering the significance of the trend. The size of the triangle is inversely proportional to the significance level in panels (a, c) and proportional to the Sen's slope estimator in panels (b, d).

The application presented simultaneously investigates all the time series, not considering which specific period is covered by each of them. To better understand the period considered in each gauged location, Figure 23

illustrates the spatial distribution of rain gauges with statistically significant trends, categorized by the ending year of their time series. Panels a and b are related to the 1h duration, while Panels c and d refer to the 24 h data. For each row, the left panel shows the location of the series with negative trends (the lightest blue represents the time series ending before 1970, and the darker blue indicates the series ending in more recent years). The right panel shows the position of the time series with positive trends.

From Figure 23a,c emerges that most of the stations with negative trends are characterized by time series that end more than 20 years ago, especially for the 1 hour duration. More specifically, for the 1h duration, among all the 68 time series with negative statistically significant trend, only 17 end in 2010 or later. Conversely, Figure 23b,d shows that most of the stations with a positive trend end in 2010 or later. With this check, we understand that Figure 22 compares trends related to different periods, which does not allow a consistent investigation over Italy. The problem becomes relevant in regions such as Piemonte and Campania, where most of the new stations were installed quite far from the old ones.

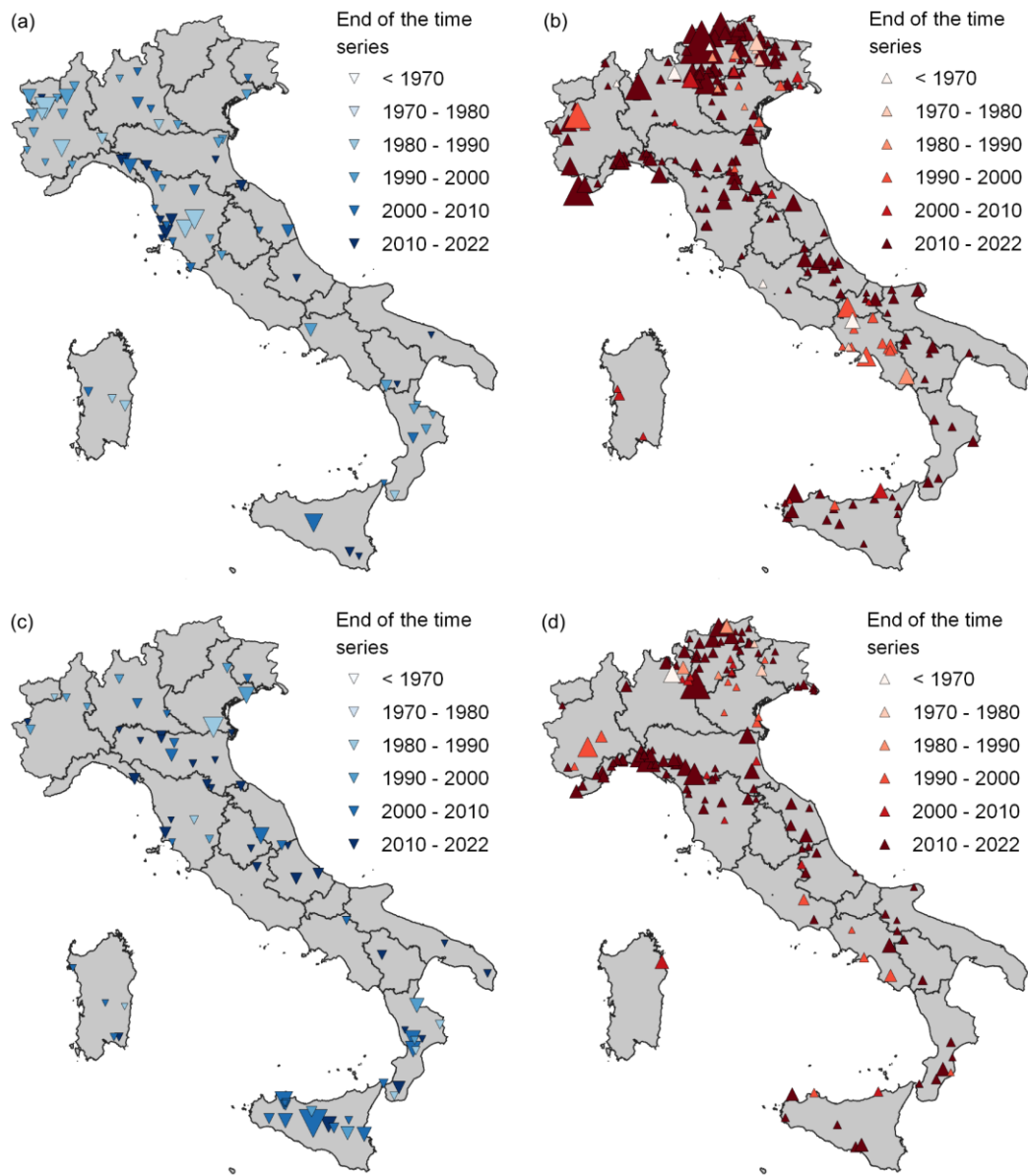


Figure 23. End of the time series used in this work for the 1h (a, b) and 24h (c, d) durations. The left (right) column shows the end of the time series with decreasing (increasing) variations.

3.3.b.4.2 Results of the application of the quantile regression

The systematic application of the quantile regressions all over Italy allows us to build maps with observed variations in rainfall extremes. The new approach is no longer representative of very local variations of the extremes, but it is more robust and allows a national-scale comparison of the results. In this section, we focus on the results obtained using a grid size of $s = 20$ km and a search radius of $r = 60$ km.

Figure 24 shows the slopes of the quantile regressions obtained for 1h (first row) and 24h (second row) durations, expressed in mm/year. The first, second, and third column show the results related to $q = 0.5$, 0.95, and 0.99, respectively. The base color indicates the slope (red is positive, blue is negative). The dots overlapping the base map indicate the entity of the p-value: small white points indicate p-values lower than 0.05 (i.e., a statistically significant regression), while grey dots represent cells where the quantile regression is not statistically significant at a 5% level (the size of the dots is proportional to the entity of the p-value).

More in detail, Figure 24a shows that the median values of 1h rainfall extremes ($q = 0.5$) slightly increase all over Italy, except for two small areas in Valle d'Aosta (North-West of Italy) and Puglia (South of Italy). The latter area, Puglia, however, presents variations that are not statistically significant at a 5% level. For almost all the other areas, the increase is statistically significant. The situation becomes more variable when considering longer durations, such as the 24h one (Figure 24d): in this case, for $q = 0.5$, the number and the extent of locations with negative trends increase. Also, the spatial distribution of the p-values, and their entity, presents some differences: for 24h, the number of not statistically significant areas increases. The decrease in the number of areas with a statistically significant variation in the 24h case is consistent with previous findings reported in the literature and the at-site analysis.

Another important piece of evidence that emerges when comparing these maps is the different rates of increase of ordinary ($q = 0.5$) and extraordinary ($q = 0.95$ and higher) extremes in places where both quantiles present positive variations. For the 1h interval, over large areas of North and Central Italy, we observe more steep positive slopes when considering higher quantiles (Figure 24b,c). These slope coefficients are all statistically significant. Figure 24c also shows that in other areas, extraordinary rainfall extremes decrease, while ordinary ones show a slight increase (Figure 24a). These areas, however, show high p-values (non-significant trends at the 5% significance level).

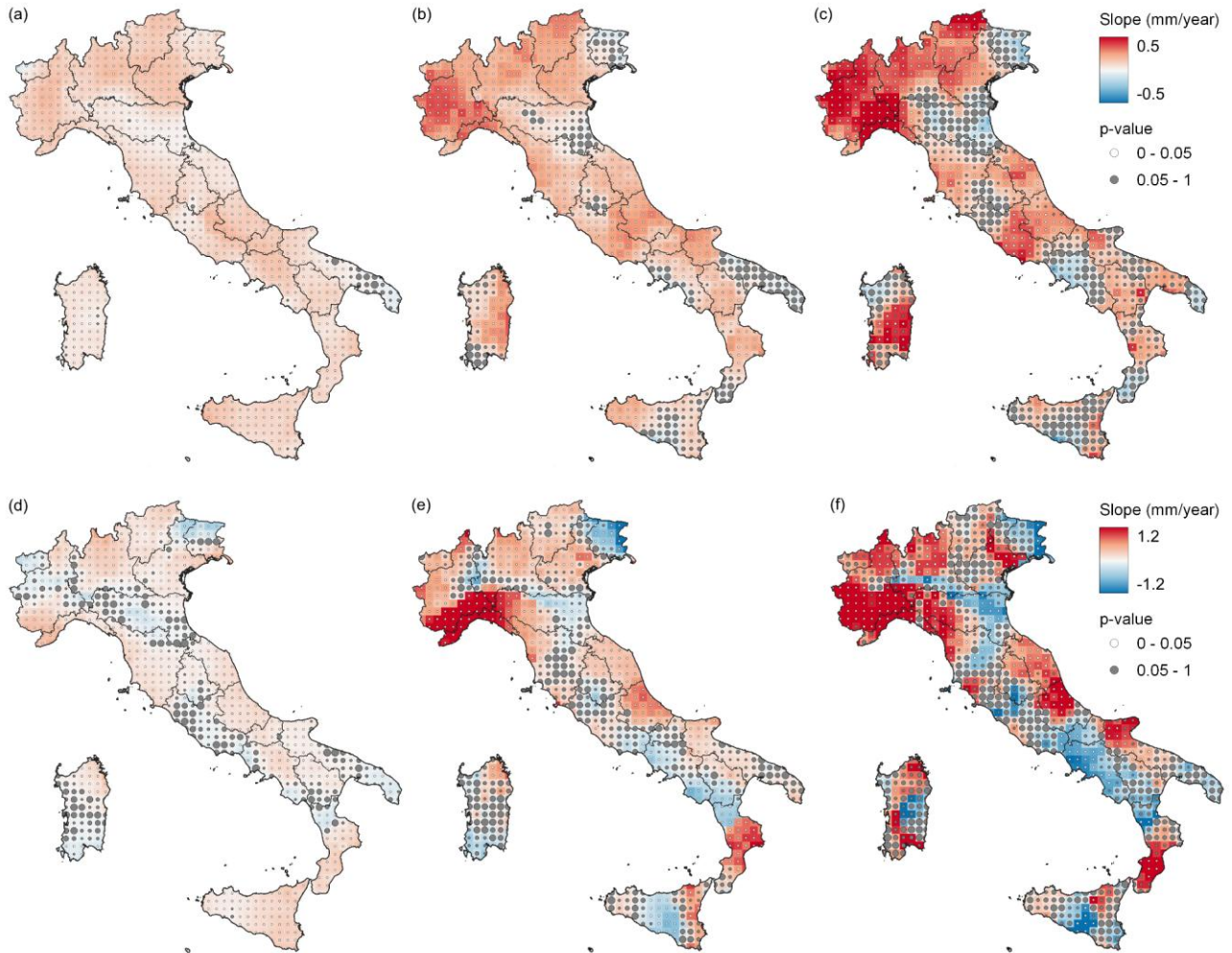


Figure 24. Slopes of the quantile regressions obtained for: $d = 1h$ and $q = 0.5$ (a), $d = 1h$ and $q = 0.95$ (b), $d = 1h$ and $q = 0.99$ (c), $d = 24h$ and $q = 0.5$ (d), $d = 24h$ and $q = 0.95$ (e), $d = 24h$ and $q = 0.99$ (f). The basemap shows the slope of the quantile regression. Circles represent the p-value of the regression: white indicates a statistically significant regression (p-value lower than 0.05) while grey indicates not statistically significant regressions (p-value higher than 0.05). The size of the dot is proportional to the p-value.

When comparing the results obtained with a quantile regression able to cover the entire period under investigation (Figure 24) with those obtained with the at-site analysis (Figure 22) we can observe quite different behavior in terms of the sign of the trend when the time period covered by the record is limited. Marked positive trends that emerge in Trentino Alto-Adige (North-East of Italy) and at the border between Liguria, Toscana and Emilia Romagna visible in Figure 22 are, in fact, still present in Figure 24. This result was expected, since, as visible in Figure 23, most of the time series of these areas reach recent years. The same is not true when comparing, e.g., the results obtained over Piemonte (North-West of Italy). In this case, the data pooling that we used in the quantile regression enables us to cover the entire time window, thus investigating the real entity of the change that is emerging as of today. The former at-site analysis shown in Figure 22 was instead based on single time series that do not guarantee a complete temporal coverage in each site. By comparing the two analyses, however, we can see a similar behavior in the significance of the trends. For the at-site analysis, the 1h duration is characterized by a higher percentage of series with statistically significant variations with respect to the 24h case (the percentage decreases with increasing duration). The same is true when considering the quantile regression: even in this case, we can see, for all the quantiles, a higher percentage of pixels with a statistically significant regression in the 1h duration with respect to the 24h.

The results discussed so far are related to observed variations (expressed in mm/years). However, Italy presents significant spatial differences in rainfall regimes. Comparing the variations in relative terms (i.e., after a

normalization) it is thus a valuable addition to the previous analyses. Figure 25 shows the percentage of variation of rainfall extremes over 10 years, that is evaluated as the slope of the quantile regression computed over the 1960-2022 period divided by the mean of the rainfall extremes of the pixel in the 1960-2022 period, multiplied by 10. In this figure, orange indicates a positive variation, while violet a negative one. Also in this case, the dots overlapping the base map indicate the p-value of the quantile regression. As expected, these maps present patterns similar to the ones visible in Figure 24. However, in this case, the relative variations are comparable at the national scale since they provided information related to a variation in relative terms, with respect to the mean value, rather than a variation in mm/years, that is not informative since the range of observed rainfall extremes is quite large in the Italian context.

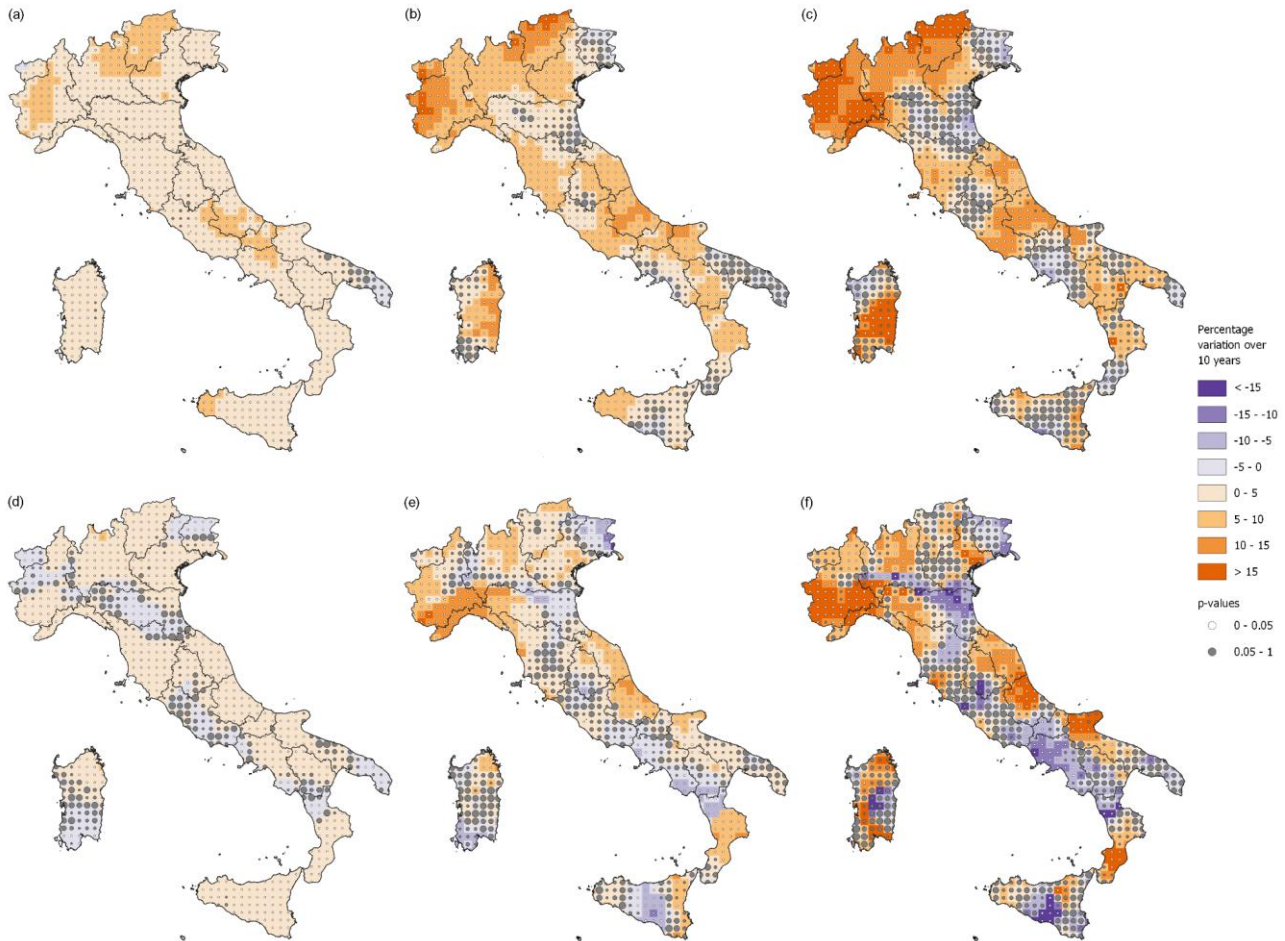


Figure 25. Percentage variation obtained for: $d = 1h$ and $q = 0.5$ (a), $d = 1h$ and $q = 0.95$ (b), $d = 1h$ and $q = 0.99$ (c), $d = 24h$ and $q = 0.5$ (d), $d = 24h$ and $q = 0.95$ (e), $d = 24h$ and $q = 0.99$ (f).

Ordinary extremes (i.e., the median values) have an observed rate of change lower than 5%, both for short and long durations. When considering higher quantiles, the entity of the variation increases in many areas. For the 1 hour duration and $q = 0.99$, variations are higher than 15% for selected areas in the North of Italy and in Sardegna. When considering the same quantile but the 24 hour duration, similar variations are observed in the Southern part of Piedmont, Liguria, few coastal areas in Central Italy, part of Sardegna and the southern part of Calabria.

Both for the entity of the slope of the quantile regression and for the percentage of variations it could be interesting to briefly discuss the influence of the spatial resolution and the research radius. If we keep constant the resolution (20 km) and reduce the search radius (30 km in place of 60 km) we notice that the trend patterns remain quite similar. However, the number of pixels with non-statistically significant relationships increases, both for short and longer durations. For the 24h, we notice that the trends of the

higher quantiles are not statistically significant over almost the entire country, except for a few pixels. Results obtained with a 10 or 25 km resolution are quite similar to the ones obtained at 20 km. Also in this case, shorter research radius produces a lower number of pixels with statistically significant trends. Thus, changing the spatial aggregation does not have significant consequences on the overall results. While some local variations are observed when modifying the resolution, the overall quantile regression patterns remain consistent. Specifically, clusters of pixels that exhibit uniformly positive or uniformly negative trends continue to be evident, even when the resolution is altered. This consistency is particularly noticeable in regions where the trends are pronounced.

3.3.b.4.3 Discussion

In this work, two different methodologies are applied to evaluate the possible presence of trends in the time series of short-duration rainfall extremes in Italy. The first method is an at-site application of the Mann-Kendall test, combined with the computation of the Sen's slope estimator. This first approach produces useful results at the local scale, but is not suited to providing an overview of trends on large areas. As Italy presents very fragmented time series, the results cannot be easily compared among them, even at close distances. To overcome this limitation and try to obtain wide-area trend information we used a distributed quantile regression approach, that allows to analyze data covering the entire 1960 – 2022 period and provides information valid for areas that coincide with the extent of the cells of a grid covering the country.

The results obtained suggest that the distributed approach should be preferred to the at-site one when the dataset is extremely fragmented both in space and in time, as in the case of Italy. The quantile regression approach is also able to investigate variations in extremes with different exceedance probabilities. Its application over Italy points out that extraordinary extremes appear to change more than ordinary ones, both in terms of the entity of the trend and in terms of spatial variability. Ordinary (low quantile) extremes are characterized by positive variations for the 1h duration, while both positive and negative variations characterize the 24h ones. Extraordinary extremes, instead, show both a positive and a negative variation, depending on the region and on the duration under investigation.

The findings presented in this study offer valuable insights into the magnitude of observed variations in rainfall extremes across Italy and of its spatial variability. These results are particularly relevant for the planning and design of new infrastructure, as they highlight both the increasing intensity of extreme rainfall events and the increasing number of stations with statistically-significant trends with respect to previous studies. Moreover, these results can be used as a baseline for testing trends in climate model output over the historical period.

It is worth underlying that all the results discussed here are obtained from observations and describe the trends observed on data recorded from 1916 (in the case of the at-site analysis) or 1960 (in the case of the quantile regression) up to now. Thus, it's important to acknowledge that while these observations offer valuable insights into historical trends, they may not entirely encapsulate the potential variations that could unfold in the future. As such, caution must be exercised in extrapolating these trends to predict future scenarios, as observed trends could potentially diverge from their current trajectories in the coming years.

More details on this work are available in Mazzoglio et al. (2025).

3.3.c Enhanced methodology for analyzing forest fires impacts on network CI and on slope instability

3.3.c.1 Probabilistic risk assessment for isolated areas in connection to forest fires

3.3.c.1.1 Introduction

In this study, we aim to assess the risk of isolation in a probabilistic framework. To ensure a scientifically robust analysis, it is essential to generate a set of scenarios that are collectively exhaustive and mutually exclusive. The objective of the forest fire scenario generation process is to simulate all possible events that could affect different areas of the region or country with varying intensities.

The generation of synthetic wildfire event scenarios is performed through a stochastic modelling framework designed to reproduce both the statistical properties and spatial coherence of observed extreme events. This framework enables the simulation of realistic yet unobserved wildfire conditions, essential for probabilistic risk assessment.

3.3.c.1.2 Methodological adjustments

The methodology follows the main steps described in the first part of the deliverable (*DV 6.3.3 - Reports on climate-related service interruption threats over critical infrastructures – Methodology Report*). However, some details were adjusted during the case-study process. In particular, the scenario generation process consisted on:

1. **Event Definition and Selection:** to identify independent wildfire events, several tests were conducted to determine the most appropriate selection criteria. The final selection is primarily driven by relative humidity, recognized as the main controlling factor for fire occurrence. Specifically, when relative humidity in a given cell on a given day falls below the 5-year return period threshold, a potential event is triggered. Each identified event is then characterized by:
 - the minimum relative humidity on that same day and location
 - the maximum wind speed observed on that same day and location, and
 - the number of hours during which relative humidity and wind speed remain beyond critical thresholds (e.g., 6 or 8 hours).
2. **Probabilistic Event Generation:** a Gaussian copula distribution is employed as the probabilistic framework, taking as input the set of selected independent events. As outcome a comprehensive event catalogue representing thousands of years of potential wildfire conditions is obtained, each simulated event characterized by meteorological conditions and an ignition, which is treated as a random process: if meteorological conditions meet the criteria for fire occurrence, an event is realized only when a stochastic ignition parameter exceeds a defined threshold. This threshold can be calibrated using historical records of burned areas, ensuring realistic representation of ignition likelihood.

The analysis focuses on the impacts of wildfire events on the road network employing a simplified vulnerability function to estimate potential damage, assuming that if, at a given location, the meteorological conditions, the fire ignition, and the hazard level surpasses their thresholds the critical infrastructure located within that area is considered affected. Thus, each event contained in the fire event catalogue can be associated with a corresponding level of direct physical impact, expressed for instance in terms of the length of road segments (km) affected. These estimates allow the quantification of direct losses, which can subsequently be used to compute classical probabilistic risk metrics, such as the Average Annual Loss (AAL) and the Probable Maximum Loss (PML).

However, direct physical damage represents only one component of the overall system impact. The ultimate goal of this activity is to extend the analysis from direct impacts on road infrastructure to functional impacts on the road network performance, accounting for potential disruptions to connectivity, accessibility, and service continuity. To achieve this, we treated our exposed elements following a modified k-shortest path approach. Thus, we evaluated direct impacts to a given set of road links belonging to the k-shortest path

between origin o and destination d , localized within a pertinence area x . This can be represented as $(\bar{P}_{o,d}^{k,x})_e$ where the set of road links is P , belonging to the k -shortest path between origin o and destination d , localized within pertinence area x is non-negligibly damaged by the event e . From this, the overall length of road links belonging to this sub-set can be indicated as $(\bar{L}_{o,d}^{k,x})_e$.

In line with what is described in activity D.3.1.1, the application of the classical Dijkstra algorithm, to identify shortest paths, produced misleading results. A high degree of path overlap was observed among the derived shortest paths, which could introduce significant bias in the subsequent probabilistic risk modeling, particularly by overemphasizing frequently used network segments. To address this limitation, the standard methodological approach was modified. For each origin–destination pair, a modified version of Yen's algorithm (Yen, 1971) was implemented. The revised procedure incorporates three key features: i) Bidirectionality, whereby for every traversed edge, both the $u-v$ and $v-u$ directions are considered when updating usage statistics and during path selection; ii) Incremental path removal, which forms the basis of Yen's algorithm and enables the extraction of successive shortest paths; and iii) a penalty-based edge weighting system. The penalty mechanism discourages excessive reuse of the same segments by increasing the traversal cost of an edge proportionally to the number of times it has already been included in previously identified paths.

So, under this consideration, the isolation index associated with a generic origin O , as a function of the effects of an event e over the shortest paths that connect this O with all d , within a given homogeneous hazard area x , can be defined as:

$$II_o^e = \begin{cases} \frac{\sum_{x=1}^X \sum_{k=1}^K \sum_{d \in D} \gamma_{o,d}^{k,x,e} \cdot (\bar{L}_{o,d}^{k,x})_e}{\sum_{x=1}^X \sum_{k=1}^K \sum_{d \in D} \mu_{o,d}^{k,x,e} \cdot L_{o,d}^{k,x}} & \text{if } \sum_{x=1}^X \sum_{k=1}^K \sum_{d \in D} \mu_{o,d}^{k,x,e} > 0 \\ 0 & \text{otherwise} \end{cases} \quad (3.3.4)$$

The connection between o and d will be reduced according to the isolation index ratio, up to the extreme case where 100% of the k -shortest paths connecting o and d are no longer functional. Thus, the fraction of functional paths serves as an index of potential reachability (indirect impacts).

3.3.c.1.3 Case Study - An application to the Marche region

The methodology for assessing isolation due to forest fires in probabilistic terms, developed during the project, was applied to a case study in the Marche region.

The meteorological information on relative humidity and wind speed used in this case study were derived from the ERA5 Downscaling @2.2 km over Italy (Raffa et al., 2021, Adinolfi et al., 2023). This dataset provides high-resolution meteorological fields over the Italian domain, derived via dynamical downscaling of the global reanalysis ERA5 (produced by ECMWF) to a convection-permitting scale (~2.2 km horizontal grid spacing). The downscaling was performed using the non-hydrostatic regional climate model COSMO-CLM (in combination with the TERRA-URB urban scheme) for the spatial domain covering the Italian peninsula and surrounding areas (approximate bounds: Lon 5° W–20° E; Lat 36° N–48° N) for a multi-decadal run.

Temporal resolution is hourly, aligning with the parent ERA5 product, and the dataset spans, for the version used in this application, from January 1981 to December 2023. The fine horizontal resolution (~2.2 km) allows better representation of orographic features, coastal gradients, local scale processes (e.g., convective precipitation, urban heat islands) than the parent ~31 km ERA5 grid and it is intended to improve use case like local-scale climate assessment, hydrological modelling, extreme event investigation, urban climate studies, decision-support services. It preserves large-scale atmospheric forcing from ERA5 while enabling higher spatial detail and temporal fidelity (hourly) for applied-scale studies. Validation studies indicate that the downscaled dataset improves spatial pattern realism for mean precipitation (an example of average total precipitation per year is shown in Figure 26) and temperature relative to coarser reanalysis, though with caveats.

This dataset has some limitations: although the model is convection-permitting, some parameterizations (especially for deep convection) are disabled or altered; this means that extreme convective processes may still be imperfectly represented. In complex terrain (particularly alpine regions) and for certain extreme

precipitation metrics, the model shows biases (for example, a tendency to over-estimate daily precipitation in Alpine areas). The dataset is identified with DOI 10.25424/cmcc/era5-2km_italy.

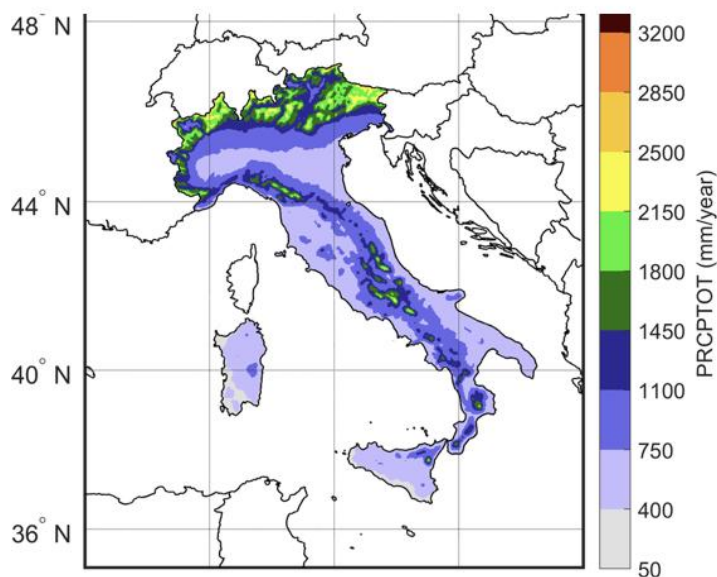


Figure 26. Average total precipitation per year over the Italian territory.

The dataset, extracted over the Marche regional domain, was analyzed to identify independent forest fire events using relative humidity (RH) as a proxy indicator. For each day and each Homogeneous Hazard Area (HHA), the minimum relative humidity was computed to construct a temporal series used to assess the return period of specific humidity thresholds. An event was defined to occur when the daily minimum relative humidity fell below the threshold corresponding to a 5-year return period. If this condition was met in at least one HHA, a fire-favorable event was recorded.

For each identified event and location, several key meteorological descriptors were also considered:

- the minimum relative humidity,
- the maximum wind velocity, and
- the cumulative number of hours during which $RH < 30\%$ and wind speed > 6 m/s.

Based on this definition, an event catalogue covering the period 1981–2023 was established, comprising 375 events in which the minimum relative humidity exceeded the 5-year return period threshold. Among these, 28 events exhibited meteorological conditions (i.e., $RH < 30\%$ and wind velocity > 6 m/s sustained for at least 6 consecutive hours) favorable for wildfire development. Some of these events were spatially localized, while others were widespread, involving, for example, more than 70 HHAs simultaneously exceeding critical thresholds.

It is important to note that not all events characterized by critical meteorological conditions lead to the ignition or propagation of wildfires. To represent this variability, a simplified probabilistic fire ignition module was incorporated. This module accounts for the stochastic nature of the ignition-to-wildfire transition, recognizing that multiple biophysical and anthropogenic factors—such as fuel type and moisture, topographic heterogeneity, and fire suppression capacity—govern the probability that an ignition develops into a sustained fire.

The probabilistic component is implemented through a random draw from a uniform distribution, where ignition occurs if the random value exceeds a predefined threshold. For the Marche region, based on local environmental characteristics and the analysis of historical fire data, this ignition threshold was set to 0.8.

The resulting event catalogue serves as the input dataset for the scenario generation process. As described in the previous chapter, scenarios are generated using a multivariate Gaussian copula, which allows for a

flexible representation of the dependence structure among variables while maintaining the empirical characteristics of each marginal distribution. To enhance both the fitting of the marginal distributions and the estimation of inter-variable correlations, the entire set of 375 identified events was retained in the analysis. Two examples of synthetically generated events using this approach are shown in Figure 27. The highlighted areas indicate regions where meteorological conditions are favorable for fire occurrence. The simulated event catalogue covers 3000 years of possible forest fires.

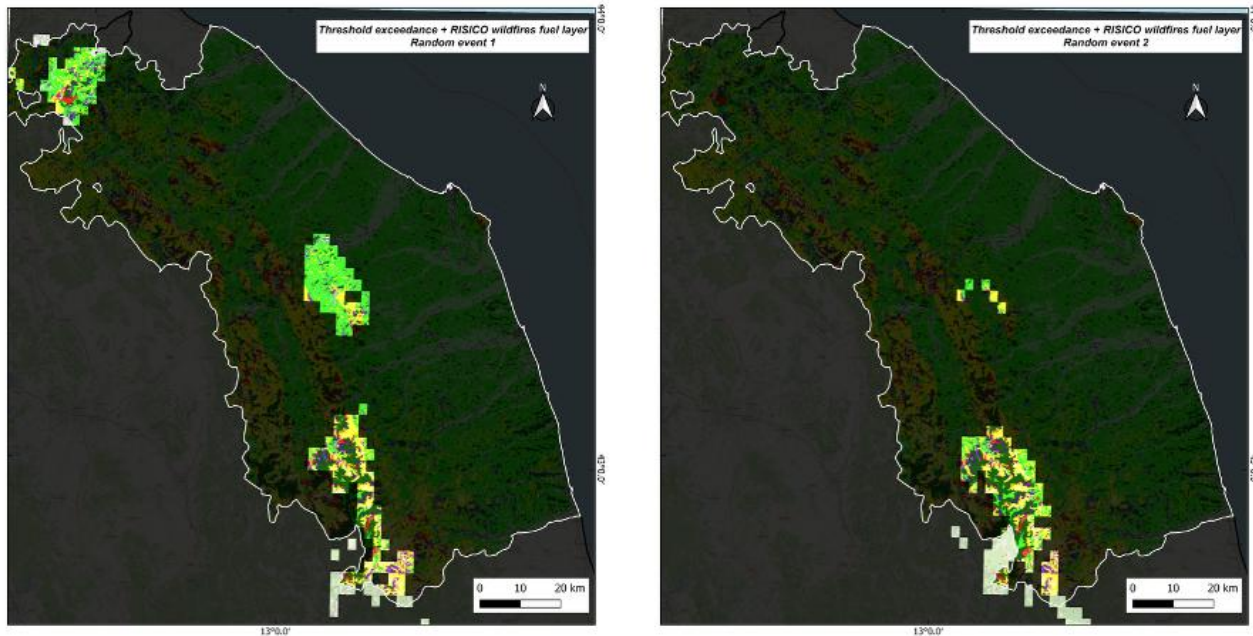


Figure 27. Two examples of synthetic events: the highlighted areas have meteorological conditions favorable for fire occurrence.

Once having the meteorological and ignition input data, and the event catalogue produced, they are merged with the forest fire hazard map, i.e., the static component. As explained before, this element combines the static probability of experiencing wildfires in a certain area, and fuel information. For the Marche region, we use the RISICO fuel type classification layer, clipped to the AOI (Perello et al., 2025). This layer has a 100 m horizontal spatial resolution containing four vegetation classes (grassland and croplands, broadleaves, shrubs and conifers) based on CORINE 2018 IV level landcover map (SNPA, 2024). Each one of these classes has three types of wildfires susceptibility, intended as the probability that fire occurs in a specific area without considering a temporal scale, thus, related to terrain's intrinsic characteristics (Leuenberger et al., 2018; Tonini et al., 2020). As a result, 12 classes of fuels are identified (Figure 28), from which we only considered relevant to road network disruption the classes of medium and high likelihood of vegetation types of broadleaves, bushfires or shrubs, and conifers.

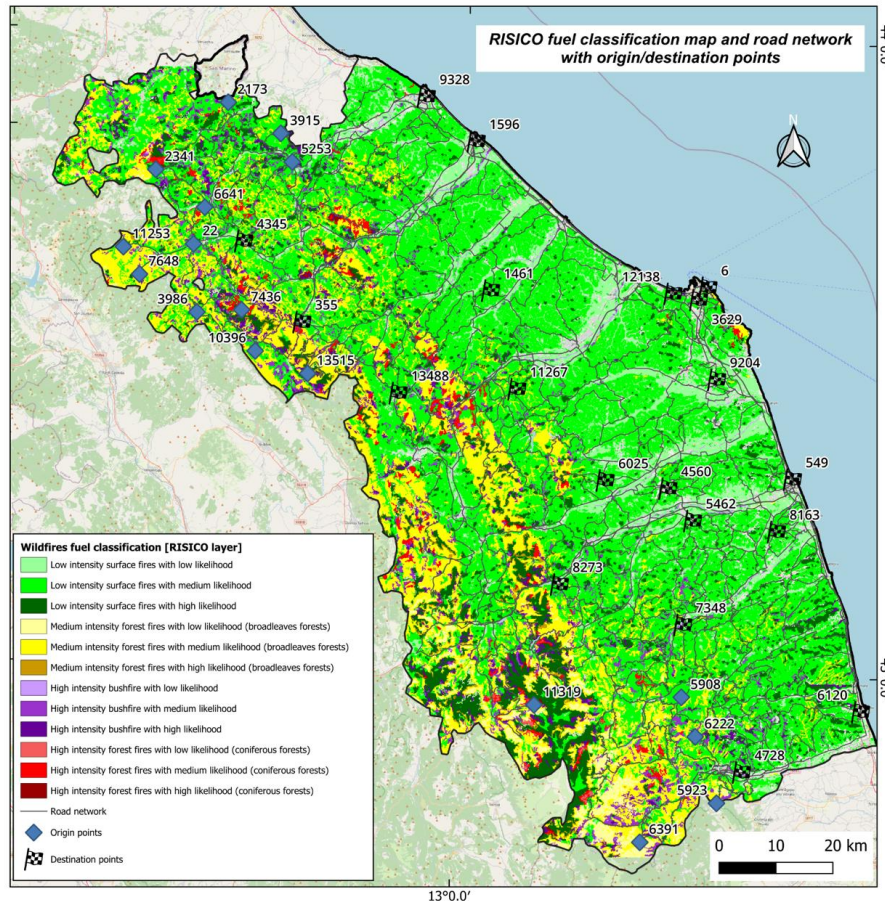


Figure 28. Fuel type Classification from RISICO model and RISICO map for Marche region.

For each simulated event, the spatial distribution of favorable meteorological conditions—including critical thresholds of relative humidity, wind velocity, and their duration—is evaluated to determine potential zones of fire propagation. When ignition occurs according to the probabilistic ignition framework, the resulting map is overlaid with the hazard map previously defined to identify burned areas (areas characterized by medium to high fuel availability): if a road segment is located in a burned area, for the purpose of this analysis, it is affected by the fire event.

3.3.c.1.4 Road Network

The regional road network used in this activity is the one described in detail in Deliverable D.6.3.1. We provide here only the main information: the road network was modeled as a graph, where each edge represents a road segment and each node a junction, enabling spatially detailed forest fire impact simulations.

Data was obtained from OpenStreetMap via the OSMnx Python library, including over 20,000 road segments, 13,000 nodes, and 8,500 km of total road length. The model incorporates motorway, trunk, primary, secondary, and tertiary roads (including link variants).

The graph was treated as undirected, reflecting emergency conditions where roads are assumed usable in both directions. Parallel segments were retained to preserve the differentiation in physical vulnerability. Bridges and tunnels were treated as standard segments due to the study's regional scale.

A connectivity analysis identified:

- 16 origin nodes: isolated, low-population areas ($\leq 5,000$ inhabitants within a 2 km buffer);
- 20 destination nodes: hospitals acting as critical service centers.

Routing between origins and destinations was computed using a modified Yen's algorithm, which builds on Dijkstra's algorithm to calculate multiple (k)-shortest paths while minimizing overlap. The subset of the network relevant for forest fire risk analysis was extracted by intersecting k-shortest paths with the RISICO fuel categories mentioned in the previous section, resulting in 2,418 road segments (Figure 29) used for Probabilistic Flood Risk Assessment (PRA). A mapping table links each segment to the origin–destination pairs and paths traversing it, supporting detailed isolation analysis.

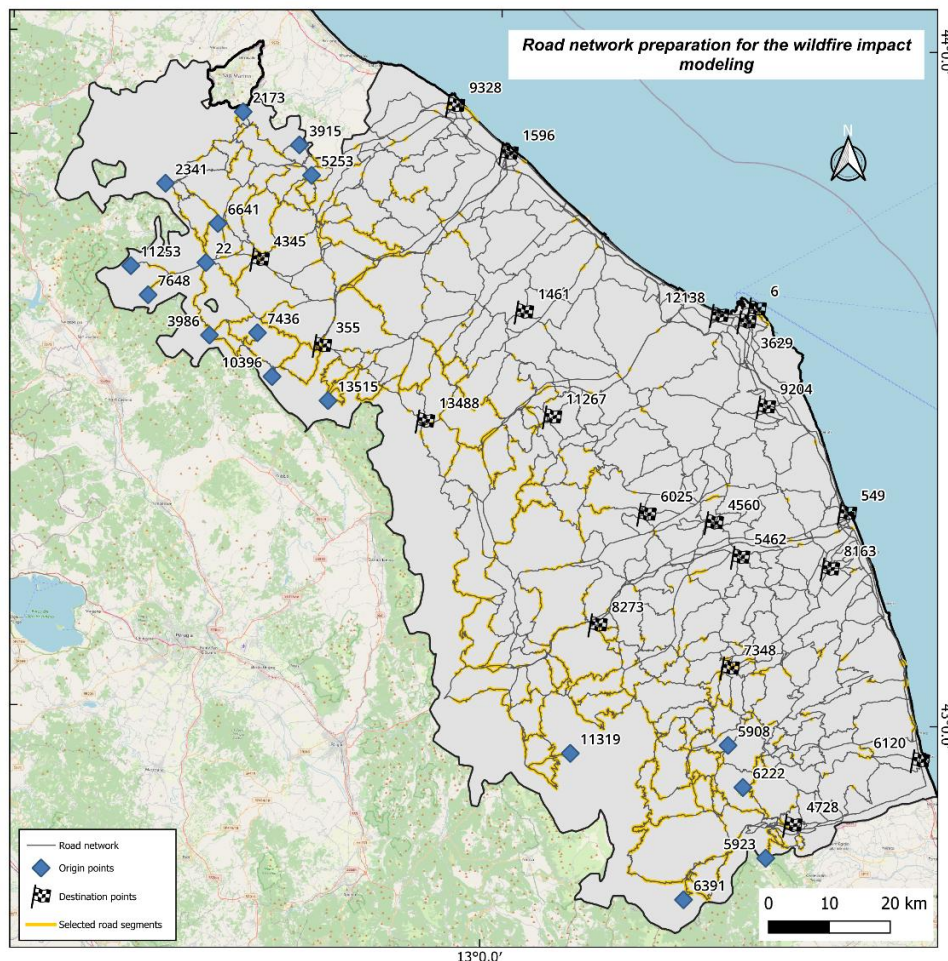


Figure 29. Selected road segments for wildfires PRA analysis with origins and destinations.

3.3.c.1.5 Results

Each forest fire event identifies burned areas at 100 m resolution, by overlaying these event maps with the road network it is possible to identify road segments affected by fire events: the risk calculation engine provides, as direct output, the number of pixels in each road feature affected by a fire event. During the post-processing stage, using the pre-compiled mapping table described earlier, it is possible to determine which shortest paths are disrupted due to direct impacts on specific road segments. For each origin point and each simulated event, the total length of affected roads within all shortest paths, as well as the overall length of those paths, are calculated to derive the Isolation Index.

During the post-processing stage, the Isolation Index values are used to compute conventional risk metrics, specifically the Annual Average Loss (AAL) and Probable Maximum Loss (PML) for each origin (Figure 30). Finally, tables and maps are generated to visualize the impacts of forest fire on the road network.

The results of the probabilistic analysis show low isolation index, in terms of annual average numbers, in particular in the northern part of the region: these estimates increase significantly if, instead of the annual average, we take into considerations isolation index for high return period (e.g. 100 years): in this case a hotspot in terms of isolation can be identified in the southern part of the region.

The main reason for this result can be explained by looking at the map reported in Figure 31, which shows the frequency of wildfire hazard threshold exceedances map across the Marche region, derived from the stochastic event simulation, covering 3 '000 years of potential events. The colour scale represents the number of times a given location exceeds the defined hazard threshold (relative humidity below 30% and wind velocity above 6m/s sustained for at least 6 consecutive hours) in the simulated catalog: areas in yellow and red show high recurrence, indicating frequent wildfire occurrence; dark blue to purple zones low recurrence, indicating areas seldom or never exceeding the threshold. This spatial pattern confirms that southern areas frequently experience meteorological conditions conducive to forest fires. Such conditions substantially increase the isolation index of the origins located in these areas, indicating a higher vulnerability of local communities to disrupted accessibility during fire events.

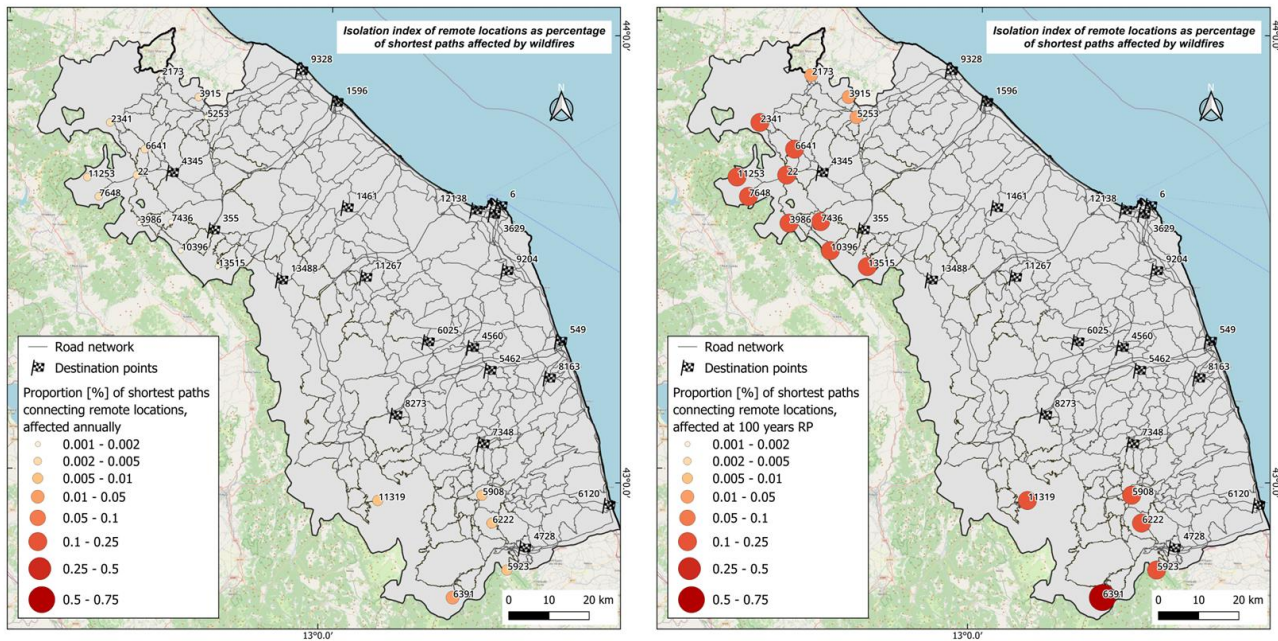


Figure 30. AAL and 100-years RP Probable Maximum Losses, expressed in terms of proportion of shortest paths connecting remote locations affected by wildfire events (isolation index).

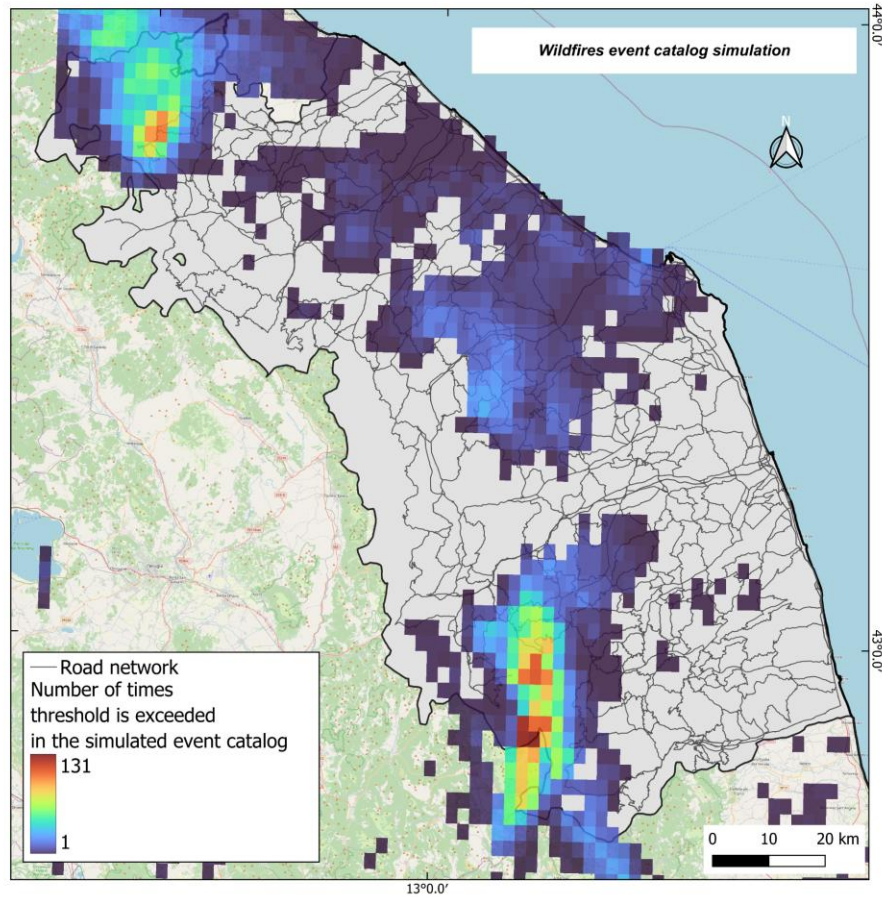


Figure 31. Counting of number of events with meteorological conditions favourable for fire occurrence.

Finally, the PML curves were calculated to relate the percentage of total shortest paths affected to the return period in years. Each curve in Figure 32 corresponds to a selected origin node (isolated location) in the Marche region and illustrates how the isolation index, the proportion of connectivity loss to any service center, changes with increasing return periods. All curves begin to rise at the 25-years return period, confirming the results expressed in terms of the annual average, where impacts are dominated by frequent but minor events (close to zero in this analysis).

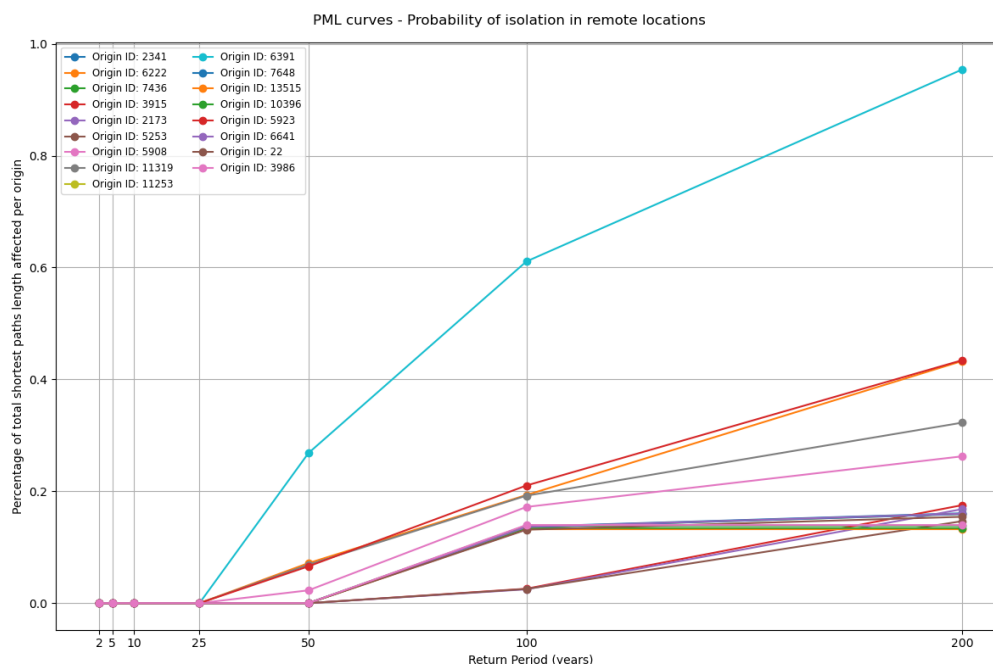


Figure 32. PML curves for the origin locations analyzed.

This pattern is likely linked to the fact that areas with meteorological conditions favorable to forest fires are localized in specific parts of the region, particularly to the south (Figure 31), leaving portions of the road network largely unaffected. Additionally, roads are typically located along valleys near rivers, making them more prone to flooding, whereas these same areas generally have low wildfire intensity classifications. Consequently, only at higher return periods, likely corresponding to more widespread events, the isolation index begins to increase, particularly for origins locations in the southern part of the region.

3.3.c.2 New method for wildfire hazard mapping and consequent hydrological risk management

3.3.c.2.1 Remote sensing and falling-head infiltration test results

The primary aim of the study was to assess whether the infiltration capacity of the affected soils had returned to pre-fire conditions and to understand how meteorological factors influenced this recovery process.

In this deliverable, post-wildfire terrain modifications are investigated from different perspectives: at a broader scale through remote sensing techniques, and at a smaller scale through field infiltration tests, laboratory rainfall simulations, permeameter measurements, and thermal tests carried out directly on soil samples. The selected case study is the Sorico wildfire, located in northern Italy, occurred in January 2019.

Post-fire field monitoring started in October 2019, ten months after the wildfire event. The monitoring activities were carried out in three sub-areas (Figure 12 of DV 6.3.3 – 1 – Methodology Report): the first within the area of highest fire severity characterised by coniferous woodland, the second in a grassland area mildly affected by the fire, and the third, in a coniferous area outside the burnt perimeter, served as a control site.

Over the six-year monitoring period, the burnt woodland area showed signs of vegetation recovery, which had originally been characterised by almost bare soil and a few burnt pine trees. The remote sensing analysis considered the temporal variation of the Normalized Burn Ratio (NBR) and the Normalized Difference Vegetation Index (NDVI), computed from Copernicus Sentinel-2 raw bands as follows:

$$NBR = \frac{B8 - B12}{B8 + B12} \quad (3.3.5)$$

$$NDVI = \frac{B8 - B4}{B8 + B4} \quad (3.3.6)$$

where B8 corresponds to the Near Infrared (NIR, 842 nm), B12 to the Short-Wave Infrared (SWIR, 2190 nm), and B4 to the Red band (665 nm). Vegetation-sensitive bands (Red, NIR, SWIR) were used to detect wildfire effects, with NIR and SWIR showing the largest pre- to post-fire changes. Only Sentinel-2 images with <30% cloud cover and no snow were used.

A preliminary analysis published in Corti et al. (2022) suggested a complete recovery of the site around July 2025, almost seven years after the wildfire event, following a logarithmic recovery trend as described in Ryu et al. (2018). The updated analysis is shown in Figure 33 and Figure 34, in terms of NBR and NDVI, together with a photographic comparison. Both indices indicate that before the wildfire the burnt area and the unburnt conifer woodland displayed similar values, but over time the burnt area has evolved following the same pattern as the grassland. These two vegetation types show different temporal behaviours: conifers maintain almost constant values through time, whereas grassland exhibits clear seasonality with higher values in summer and lower values in winter.

This pattern reflects typical vegetation recolonisation dynamics following a disturbance event, where the first species to establish are pioneer plants such as ferns and grasses (already present in October 2019, ten months after the fire), followed by shrubs such as broom (November 2020, two years after the fire), and lastly the first new pine trees (May 2021, two and a half years after the fire). This natural evolution was altered by artificial reforestation carried out in 2025, probably around March, as suggested by the marked decrease in NBR. This intervention consisted of the removal of burnt trees and the planting of broadleaf species. At present the area is fenced and covered by grass vegetation. Overall, the remote sensing analysis shows an evolution that is consistent with field observations. Given the alteration of the natural succession trajectory, a return to the original pre-fire conditions is not expected. Nevertheless, seven years after the event the site can be considered largely stabilised. The removal of the burnt trees was appropriately carried out to prevent potential hazards related to their fall along the road below.

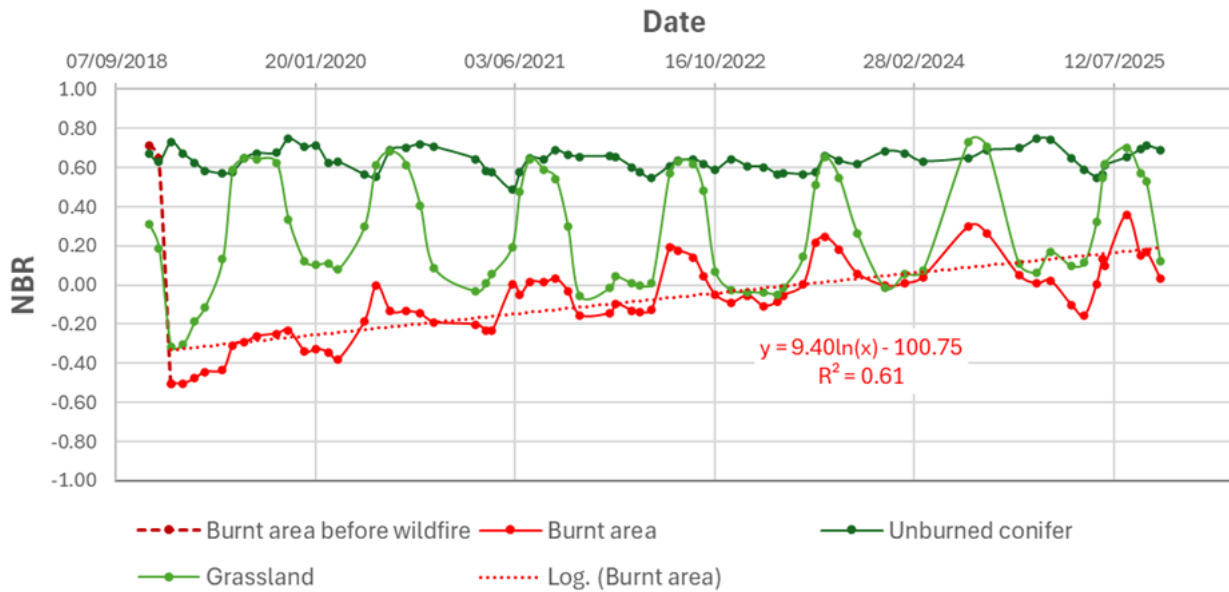


Figure 33. Recovery trend derived by NBR index analysis. The blue circle highlights the low peak likely corresponding to the reforestation work.

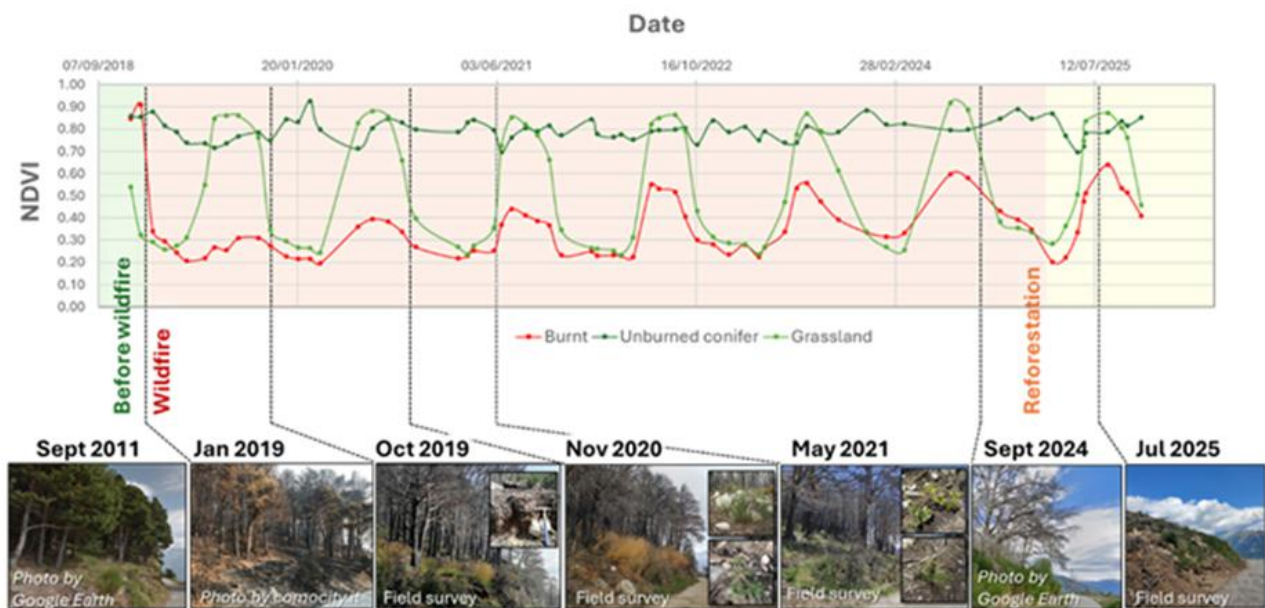


Figure 34. NDVI evolution analysis compared with selected photographs from the site.

Since satellites can only partially infer the restoration of hydrological conditions, field measurements were carried out to validate the remotely sensed trends. Periodic falling-head infiltration tests were performed to assess post-fire infiltration capacity of Sorico soils, using both single-ring and double-ring infiltrometers. The test procedure consisted of pouring water into the infiltrometer and measuring the variation of the hydraulic head over time, as discussed in the DV 6.3.3 – 1 – Methodology Report. The resulting infiltration data were analysed using Horton's exponential model, which allowed the estimation of key parameters such as field capacity (the asymptotic infiltration rate) and two curve-fitting coefficients (a and b) describing the initial infiltration rate and its decay over time. These parameters were then examined to identify trends in soil recovery and their relationship with environmental conditions.

The results of the statistical analysis indicate that, three years after the wildfire, the burnt area still exhibits a markedly different hydrological behavior compared to the unburnt reference area. Overall, infiltration

parameters appear to remain almost constant through time in both the burnt woodland and the grassland. Field capacity in the burnt zone remains relatively stable and does not display a clear trend toward recovery, suggesting that the soil water absorption has not returned to pre-fire conditions. In contrast, the unburnt area presents greater variability in infiltration parameters, likely driven by short term meteorological fluctuations, while the grassland has intermediate characteristics, with partial recovery but still influenced by external factors.

Two-way ANOVA approach confirmed significant differences in field capacity among the three sub-areas, although no consistent time-related trend was detected. The coefficients a and b exhibited greater variability, particularly in the unburnt zone, indicating that infiltration dynamics in this area are more sensitive to changing conditions. Multiple regression models revealed that meteorological variables such as relative humidity and cumulative rainfall preceding the tests were significant predictors of infiltration in the unburnt and grassland areas. For example, in the unburnt woods, field capacity was strongly influenced by relative humidity and rainfall over the previous ten days, while in the grassland it was affected by rainfall over twenty days and time since fire. Conversely, no significant predictors were identified for the burnt woodland, reinforcing the conclusion that its hydrological behavior remains largely insensitive to short-term weather fluctuations.

A new measurement campaign was carried out in July 2025. However, as highlighted in the previous paragraph, the site conditions had changed substantially: the grassland area where previous tests had been conducted is no longer accessible, as is now fenced. In addition, the removal of the dead trees has transformed the entire area into grassland, and their hydrological behaviour can be assumed to be similar (Figure 35).

In conclusion, this study indicates that hydrological recovery in burnt soils is a slow process and can persist for years after fire. In the case of the Sorico wildfire, this period was estimated at least five years. While unburnt and grassland areas respond dynamically to meteorological factors, burnt soils remain altered and relatively insensitive to short-term environmental changes. These results highlight the need for long-term monitoring and more comprehensive datasets to better understand post-fire soil dynamics and to inform land management strategies aimed at mitigating the hydrological impacts of wildfires.



Figure 35. Comparison between (a) the wildfire area at the beginning (2019) and (b) at the end of the monitoring period (2025).

3.3.c.2.3 Experimental analysis: landslide simulator test results

To better understand the influence of burnt and unburnt soils on the development of slope instabilities, experiments conducted using the landslide simulator (discussed in DV 6.3.3 – 1 – Methodology Report) compared tests with burnt and unburnt soils, collected in the Sorico wildfire area, against reference tests carried out with homogeneous sand. These experiments were conducted by varying not only the type and layering of material but also the slope angle, which ranged from 25° to 35° , and the rainfall intensity, which ranged from 41 mm/h to 59 mm/h. Table 5 shows the characteristics of the considered material. All details

of the experiments performed with the simulator, together with the complete dataset, are provided in Longoni et al. (2025).

Table 5. Characteristics of the material used in the experiments: n is the porosity, k_s is the hydraulic conductivity, and D_{10} , D_{50} and D_{90} are the grain-size parameters.

Material	n [-]	k_s [m/s]	D_{10} [mm]	D_{50} [mm]	D_{90} [mm]
Sand	0.48	$5.60 \cdot 10^{-4}$	0.3	0.54	0.8
Burned soil	0.51	$7.52 \cdot 10^{-4}$	0.023	0.43	4.0
Natural soil	0.55	$5.29 \cdot 10^{-6}$	0.013	0.4	1.6

As in previous works (Ivanov et al., 2020; Panzeri et al., 2022; Longoni et al., 2022; Ivanov et al., 2021), the landslide bodies were prepared with homogeneous medium sand ($d_{50} = 0.54$ mm, uniformity coefficient $C_u = 2$, internal friction $\phi = 34^\circ$). The material was placed and compacted in three layers for a total thickness of 15 cm. Only the uppermost layer differed between tests, being composed of burnt soil, unburnt soil or sand depending on the specific configuration, while the lower two layers were always sand. During the experiments, the volumetric water content (VWC) was monitored on the surface using a time-domain reflectometer (TDR), while suction was assessed using two tensiometers positioned at the upper and lower parts of the slope between the second and third soil layer. This monitoring system was completed by two optical cameras. After the strata layers and the monitoring system were settled, the upper platform was lifted and rainfall was initiated. Data was continuously recorded by the sensors, and the runoff was collected and measured at different time intervals. The tests were organised into three groups, each including one experiment with homogeneous sand, one with burnt soil and one with unburnt (natural) soil. The three groups were defined as follows:

1. rainfall intensity of 47 mm/h and slope angle of 25° ,
2. rainfall intensity of 41 mm/h and slope angle of 35° ,
3. rainfall intensity of 59 mm/h and slope angle of 35° .

After rainfall activation, progressive wetting front propagation induced slope failure, typically in about 15-20 minutes in all three tests groups, with only one exception, as summarized in Figure 36. The failure initiated through the formation and subsequent opening of cracks from the surface, a phenomenon similarly observed as in previous other experiments executed using the same equipment, as fully described in (Longoni et al., 2025). In general, the first fracture developed in the middle section of the slope or at the toe and then spread retrogressively towards the top of the flume). On the contrary, almost no activity was observed in the upper slope, consistent with water movement along to slope. In terms of depth, failure generally occurred near the boundary of the first and second soil layers (approximately 5 cm depth) and never at the sand-flume interface, suggesting that soil layering was the preferred weak surface.

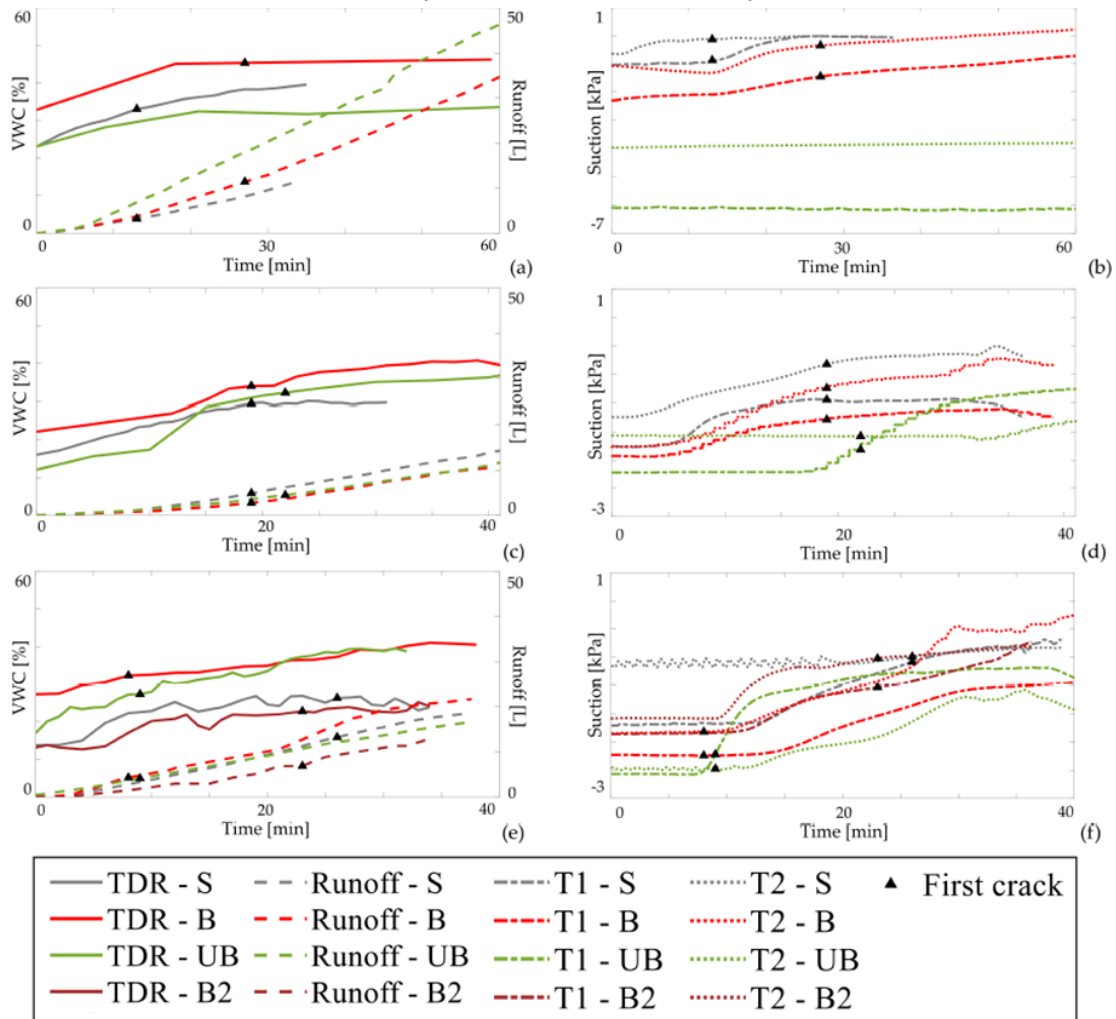


Figure 36. Summary of test results: a–b corresponds to group 1, c–d to group 2, and e–f to group 3. S indicates sand, B burnt soil, and UB unburnt soil. The time of the first crack is highlighted.

Not every experiment resulted in a full collapse. The unburnt soil of group 1 did not develop any fractures, whereas crack formation occurred in the same experiment with burnt soil, even though a full collapse was not achieved (Figure 37). This group is particularly interesting because the slope angles correspond approximately to those observed in the Sorico wildfire area, showing that a landslide could indeed develop following an intense rainfall event. However, in the absence of root cohesion, which was of course absent in these tests, the natural soil would be less prone to failure. This behaviour is evident in the summary graphs: in tests with unburnt soil, the wetting front advances much more slowly than in burnt soil, which saturates rapidly and collapses. This effect is likely due to the presence of soil water repellency typical of coniferous forest soils, which is largely absent in the burnt soil as it is destroyed by the high temperatures reached during the fire.

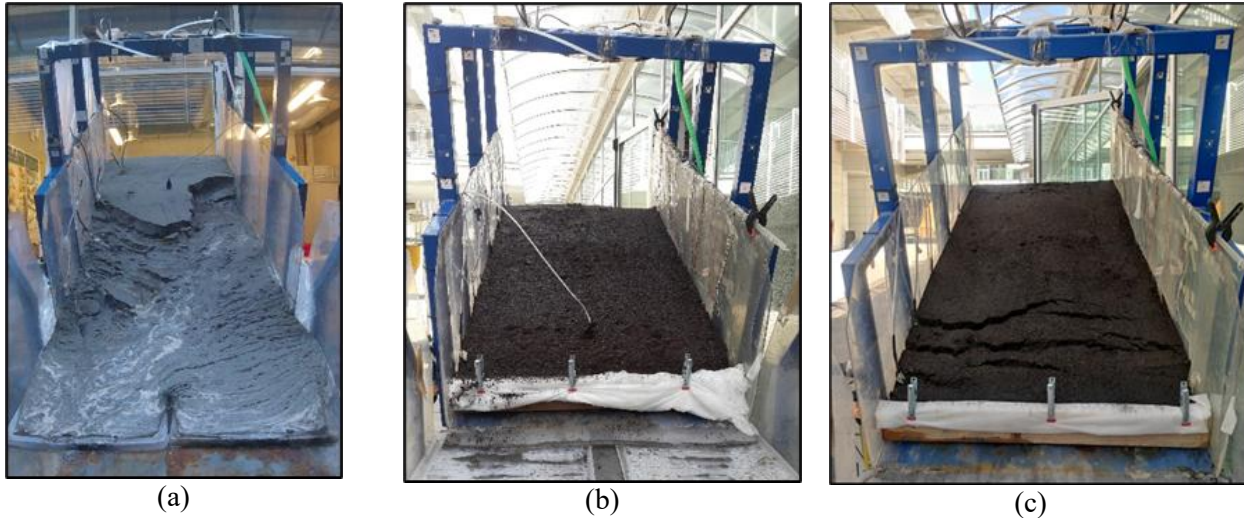


Figure 37. Group 1 landslide bodies at the end of the experiments: (a) sand, (b) unburnt soil and (c) burnt soil.

Subsequent tests, conducted with the same materials but at higher slopes and under more intense rainfall, showed that even the unburnt soil could fail. It was also observed that the initially slow advance of the wetting front gradually disappears in repeated tests, probably due to the progressive washing out of fine particles.

3.3.c.2.3 Experimental analysis: shock-tube test results

As discussed in the previous paragraphs, wildfires induce profound and long-lasting alterations in soil properties, hydrological processes, and slope stability. These changes can persist for years, influencing runoff generation, erosion rates, and the overall equilibrium of drainage basins, which makes understanding these dynamics essential for developing effective risk mitigation strategies and improving predictive models for post-fire landscape evolution. Several authors have reported that, among the fire-induced alterations coupled with slope failure predisposition, the development of soil water repellency plays a crucial role in controlling post-fire infiltration dynamics and runoff generation. However, depending on vegetation coverage and organic matter content, soil water repellency may already characterize slopes prior to wildfires, as in the Sorico case study. Laboratory studies have shown that the onset of soil water repellency is strongly influenced by temperature, soil composition and organic matter content, whereas its breakdown occurs at higher temperatures. Yet the direct contribution of temperature-induced changes in soil water repellency to slope failure processes remains unclear.

The present study investigates temperature development and breakdown of soil water repellency, and how this property influences soil infiltration capacity. Laboratory experiments were conducted on both homogeneous and heterogeneous soil samples subjected to controlled thermal treatments within temperature ranges recognised as representative of soil water repellency initiation and degradation under wildfire conditions. The tested materials included commercial quartzose sand (non-repellent), natural soil collected in Sorico, and their mixtures. After heating, the hydrophobic behaviour was assessed through water drop penetration time (WDPT) tests, while the hydraulic conductivity was evaluated using a permeameter. Unheated samples were used as reference to quantify the temperature-induced variation.

The tests were conducted using two devices: a shock tube device (all details in Colombo et al., 2011) and a cylindrical oven, shown in Figure 38 and in Figure 39. Temperature was monitored over the tests using four thermocouples (Figure 40).



(a)



(b)

Figure 38. Experimental setups: (a) the shock tube facility and the cylindrical sample of Sorico soil (50 cm height), and (b) the cylindrical oven. Both the samples were rotated to perform the tests: test a was horizontal, while test b were vertical.



(a)



(b)



(c)

Figure 39. Shock tube test: (a) evidence of thermal propagation (3.5 cm in the soil sample), (b) areas with different water repellency (darker colours still water repellent, the area marked by 2 is wettable) and (c) soil sample with evidency of water repellence.

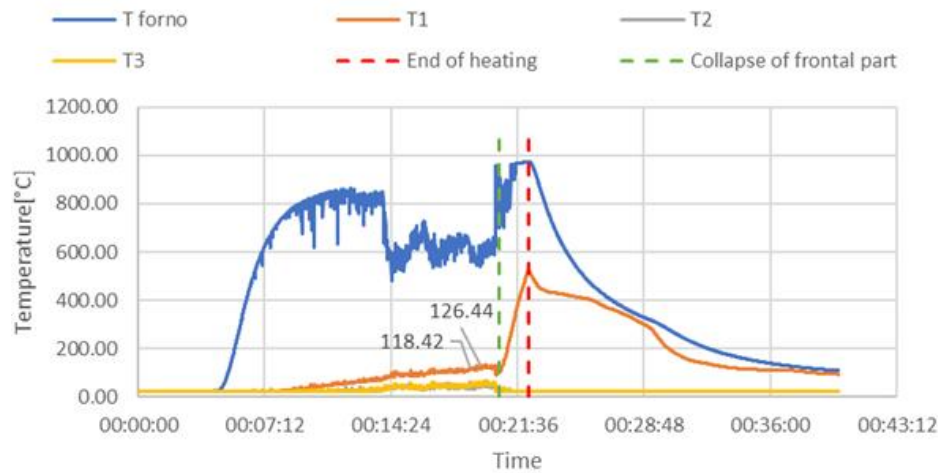


Figure 40. Temperatures recorded by thermocouples during the shock tube test: T1 is the closest to the fire source (5 cm).

The shock tube test was performed using a cylindrical sample with a height of 39 cm and a diameter of 50 cm, leaving 11 cm between the top of the sample and the flame. The material used was entirely Sorico soil. Four thermocouples were placed at 5, 10 and 15 cm from the top of the sample. The results showed that, despite the flame temperature exceeding 800°C for a prolonged period, the sample itself never reached such high temperatures due to the low thermal conductivity of the material (Figure 40). This is also evident from the colour change of the sample holder (Figure 39). Only the superficial layer, closest to the flame, reached approximately 400°C, as part of the material collapsed after around 20 minutes, bringing the thermocouple closer to the heat source. In terms of water repellency, this resulted in a non-uniform destruction of the property. The wettable portion of the soil was found to be concentrated only near the surface.

Similar results were obtained from the oven tests. In this case, tests were conducted on Sorico soil, on a sample of pure sand as a control, and on a mixed sample consisting of 97% quartz sand and 3% Sorico organic material. Water repellency did not develop in the pure sand, highlighting the importance of organic content for the development of this property. It was observed in the mixed sample, where it was initially absent, and was partially destroyed in the pure Sorico soil sample, in a heterogeneous manner similar to the shock tube test.

3.3.c.2.4 Discussion

Overall, the integrated approach demonstrates that soil permeability can return to pre-fire levels within a few years even in Alpine environments. Water repellency dynamics depend strongly on vegetation type and thermal processes, and vegetation recovery follows a two-phase trajectory characterized by rapid initial regrowth and slower forest establishment influenced by ecological and climatic factors. These findings underscore the importance of combining field measurements, laboratory validation, and remote sensing for a comprehensive understanding of post-fire landscape evolution and highlight the need for long-term monitoring to capture the full recovery cycle and inform land management strategies.

Results reveal a temperature-dependent response only in samples containing organic matter: moderate heating promotes the development of soil water repellency, while higher temperatures lead to its degradation through the thermal breakdown of organic compounds responsible for hydrophobicity. Moreover, differences in thermal conductivity among the tested materials produced heterogeneous responses to heating, suggesting a non-uniform reduction of repellency even after prolonged exposure to elevated temperatures.

These findings indicate that temperature exerts a complex control on soil wettability and, consequently, on post-fire infiltration behaviour.

3.3.d Enhanced methodology for deriving drought effects on the water supply system

3.3.d.1 Drought water service interruptions - Water supply management (reservoir management and integration of different sources) under drought conditions, including analysis of future scenarios of water availability and user demand

This section presents the results obtained by applying the methodological framework, developed for the optimal management of multi-source water supply systems, to the test-case study in the Romagna region. Specifically, the framework was used to derive and evaluate optimal withdrawal rule curves for the Ridracoli reservoir and to simulate historical and future patterns of withdrawal and deficit volumes under various climate scenarios. The findings detailed herein aim to assess the resilience of the system to future stress conditions, providing the water managers with insights for improving short- and long-term planning.

The work summarised here was presented at the XIII World Congress of the European Water Resource Association (Neri and Toth, 2025a), published in a national journal (Neri and Toth, 2025b), and is currently under review for an international peer-reviewed journal.

3.3.d.1.1 Test-case study and data

The Ridracoli Reservoir and the Water Supply System of the Romagna Region

The study area is the Romagna region, in Northern Italy, which is one of the most economically developed areas in Europe and characterized by an extremely profitable seaside tourist industry. RomagnaAcque – Società delle Fonti is the regional drinking water supplier and it provides wholesale water to more than one million permanent residents and millions of tourists. The water supply network is served by multiple water sources: the Ridracoli reservoir in the Apennines, which represents the focus of the study, wellfields all across the lowlands and lowland surface water (which requires intensive treatment processes).

The Ridracoli reservoir is indeed the more environmentally-sustainable and less energy-demanding water source in the system. In fact, maximizing the use of the high-quality and gravity-fed water from the reservoir allows not only economic advantages, but also to mitigate the groundwater overexploitation, which, particularly in coastal regions, can cause subsidence, saline intrusion, and irreparable harm to the fragile coastal ecosystem. The reservoir meets alone half of the demand of the users in the three provinces, providing on average 54 millions of m³ per year, and may be delivered to almost the entire water distribution network of the Romagna region. Conversely, the other sources provide water “locally”, i.e. to limited portions of the region. For this reason, in this work we will refer to such alternative sources with the term “Local Sources”.

The reservoir system is quite complex since the lake is fed not only by the “direct” catchment closed at the dam, but also by four additional nearby catchments in the North-West connected to the reservoir with a system of intakes and tunnel pipes (Figure 41).

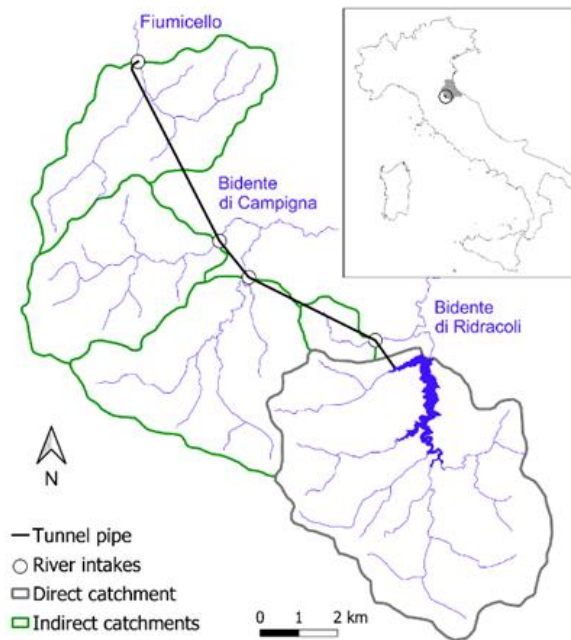


Figure 41. Catchments feeding the Ridracoli reservoir: the upstream basin closed at the dam (grey contour) and the four indirect catchments (green contours) connected to the lake with a system of intakes and tunnel pipes.

Data collection

It was possible to retrieve all the data needed for the implementation of the approach and described in Section 3.3.d.1.3 of the methodological deliverable (and not repeated here for the sake of brevity).

For what concerns climate data, the E-OBS dataset (Cornes et al., 2018) is used for estimating past meteorological forcings, whose accuracy in representing precipitation and temperature spatial field is not uniform across Europe. However, for the study region the companion study conducted by Sarigil et al. (2024), in cooperation with Spoke DS, demonstrated the reliability of E-OBS, proving its ability to well reproduce the observed streamflow series when used to force a rainfall-runoff model.

For the simulation of the future climatic forcings, an ensemble of ten CMIP5 climate simulation chains, belonging to the EURO-CORDEX products, is exploited. In particular, the ensemble is composed by the ten GCM-RCM modelling chains driven by the emission scenario RCP 8.5 and bias-corrected by Dosio (2016) across the entire Europe, by means of the technique developed by Piani et al. (2010), using E-OBS as reference datasets, which further supports the choice of using such data for representing the historical climate.

Performance of the bias-corrected GCM-RCMs over the control period and expected future climatic changes

In a preliminary phase, the selected bias-corrected climate modelling chains are validated in order to verify their ability to adequately reproduce historical climate, comparing daily precipitation and maximum and minimum temperatures against observations (E-OBS). Following such verification (whose results are omitted here for brevity), the future pattern of seasonal precipitation and temperature are evaluated. Figure 42a illustrates the expected changes in monthly mean areal precipitation simulated by the GCM-RCM ensemble across the three future time horizons. These changes are expressed as the ratio between future and historical simulations (control period), shown for both the raw and bias-corrected climate model outputs. On average, precipitation during the months of March to October is projected to progressively decrease, reaching up to 30% reduction in the summer months by the end of the century. Conversely, winter precipitation is expected to show a slight increase (approximately 5–10%). Figure 42b illustrates the same results for the mean daily minimum temperature: the GCM-RCMs project a growing trend over the course of the century, rising by more than 4°C in summer for the long-term future horizon. Similar results are obtained for the mean daily maximum temperature, which are not shown here for brevity.

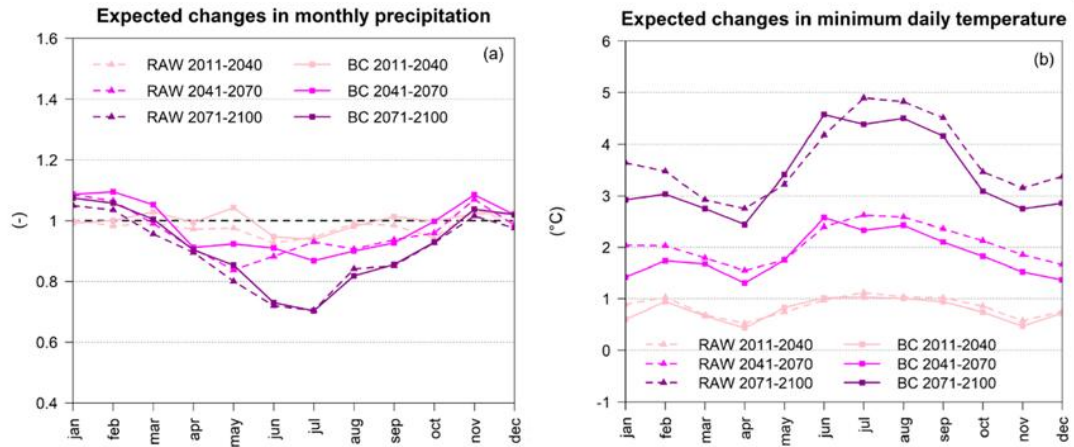


Figure 42. Future changes simulated by the GCM-RCM ensemble. Left: Expected changes in the ensemble's monthly areal mean precipitation for different future time horizons, expressed as a ratio to the historical period. Right: Expected changes in the mean daily minimum temperature relative to the historical period.

3.3.d.1.2 Assessment of minimum demand from the reservoir

As described in the methodology, the minimum withdrawal volume (here named mQ) represents the portion of the regional water demand which cannot be provided by the Local Sources at any given time t . Considering that, while the Ridracoli reservoir is serving the entire water distribution network, Local Sources can provide water only to limited portions of the region, the approach is based on three main steps: i) the subdivision of the water supply network into seven sub-networks (each one connected to a different set of Local Sources); ii) the analysis of the historical water consumption of each sub-network, in order to define a monthly demand assuming the most critical conditions, that is by adopting, for each month of the year, the maximum consumption registered in such month during the entire observation period; iii) the computation of the minimum monthly volume which must necessarily be provided from the Ridracoli reservoir to each subnetwork, obtained as the difference between the subnetwork water demand and the capacity of the Local Sources for that month. Summing up the requirements from each subnetwork, the methodology leads to the definition of the overall minimum flow that must be withdrawn from the Ridracoli reservoir, mQ_j , for any given month of the year j in order to satisfy the demand that can not fulfilled by the Local Sources. Possible future changes in the urban water demand in the region and in the future capacity of the alternative regional sources are not considered here, thus focusing on the impact of the change in climatic forcings and water availability. Further research studies may address the use of regional water demand models (see Toth et al., 2018) to predict the future demand that, when combined with the simulation framework developed herein, would allow a more thorough analysis of the synergistic impact of future availability and demand on the system.

Figure 43 shows the estimated minimum demand mQ_j , where the colored bands represent the contributions needed from the different sub-networks (left), along with the location of the corresponding sub-network supply areas (right). It is evident a strong seasonality in the demand, which confirms the need to define different monthly operating rules. Secondly, it is evident that the seasonal peaks are due to the demand in coastal areas, while the hinterlands (yellow, light blue and orange areas), that are less affected by summer tourism, are characterized by a nearly constant demand throughout the year (and the grey S3 area instead may rely, when needed, exclusively on its Local Sources).

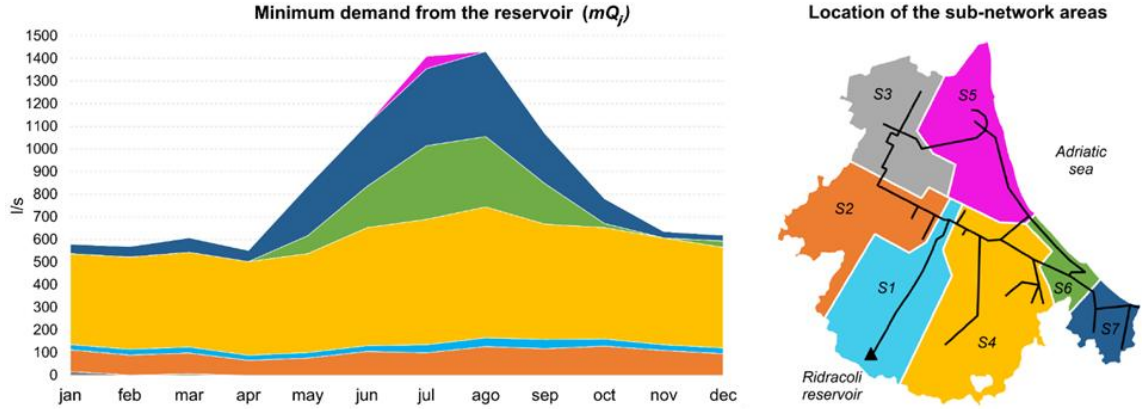


Figure 43. Minimum demand from the seven sub-networks (left) and corresponding rough location across the region and the entire water supply network (right).

3.3.d.1.3 Simulation-optimization framework: implementation details

This section details the specific configuration and parameterization used to adapt the general methodological framework to the Romagna region's water supply system.

Rainfall-runoff modelling

The TUV model, a version of the HBV model (Bergström, 1976; Lindström et al., 1997) developed by Viglione and Parajka (2018), is here implemented over each one of the river basins. Details about model inputs, routines and parameters can be found in Neri et al. (2020). The parameterization of the model is performed by forcing it with E-OBS observed meteorological fields and minimizing the differences between the simulated outputs and the observed records of hourly discharges, available at the basin outlets starting from 1996. To ensure consistency in the results over past and future years, hydrological simulations are also used for the historical period, even though flow observations are available.

Reservoir system model

The model is based on the water balance equation at the dam:

$$V_{t+1} = V_t + ID_t + II_t - E_t - S_t - R_t - Q_t \quad (3.3.7)$$

where V_t and V_{t+1} are the stored volumes at the beginning and at the end of time step t , respectively; ID_t is the inflow generated over the direct basin and II_t is the inflow transferred from the indirect catchments (intercepted at river intakes and delivered to the reservoir through the tunnel pipe); E_t is the evaporation from the reservoir obtained as product of the water surface area and the evaporation rate; S_t is the spillway outflow depending exclusively on the storage level (since it is not gated); R_t is the outflow downstream released from the dam bottom outlets and Q_t is the withdrawal outflow, which is then treated at the downhill plant and fed into the water supply network. All the quantities of the equation above are expressed as volumes (m³).

An in-depth analysis of the historical records of reservoir operations, in collaboration with the utility managers, allowed to model all the operational maneuvers concerning intakes (and thus II_t) and releases based solely on the state of the system at time t , that is the reservoir volume (V_t) and its rate of increase ($V_t - V_{t-1}$). For the sake of brevity, the flowchart model of the system which regulates operations on II_t and R_t is not reported here. Finally, withdrawal outflow Q_t , is treated separately in the next sections, being the variable to be optimized.

Formulation of withdrawal operating rules

The withdrawal operating rules that prescribe the flow to be withdrawn at time t , Q_t , are expressed as function of only the stored volume V_t , but adopting different rules for the different months of the year j , to account for the seasonality of the inflows and of the demand. Following a comprehensive consultation process with

RomagnaAcque engineers and several experimental trials, it was decided to adopt as rule form the piecewise linear function presented in Figure 44, which shows in the left panel the relationship between Q_t and the stored volume V_t in the j -th month of the year (black line) and its admissible domain (green polygon), while the right panel reports the pattern of the deficit DF_t , defined as the volume of resource that, although requested by the downstream network, it is not possible to withdraw and deliver to the users (i.e. it quantifies the system failure) when the storage is below the minimum drawdown level value LV . They are defined by the following systems of equations:

$$Q_t = \begin{cases} 0, & V_t < LV \\ mQ_j, & LV \leq V_t < x_j \\ \min(mQ_j + a(V_t - x_j), MQ), & x_j \leq V_t < V_c \end{cases} \quad (3.3.8)$$

$$DF_t = \begin{cases} mQ_j, & V_t < LV \\ 0, & otherwise \end{cases} \quad (3.3.9)$$

where, while LV and a are fixed a priori for the already mentioned technical constraints of the system, x_j with $j=1,12$ are the 12 decision variables (one for each month of the year j) to be optimized, thus allowing to define 12 different monthly rules. Of course, lower x_j corresponds to a less conservative rule form (i.e. withdrawal starts increasing above mQ_j for lower storages). Parameters x_j are allowed to assume values between LV and an upper limit UV_j , which is derived, based on the geometrical formulation of the curve, as function of the minimum demand mQ_j and the fixed slope a . In particular, such upper limit establishes the most conservative curve, thus allowing for maximum withdrawal MQ only when the stored volume reaches the maximum reservoir capacity V_c .

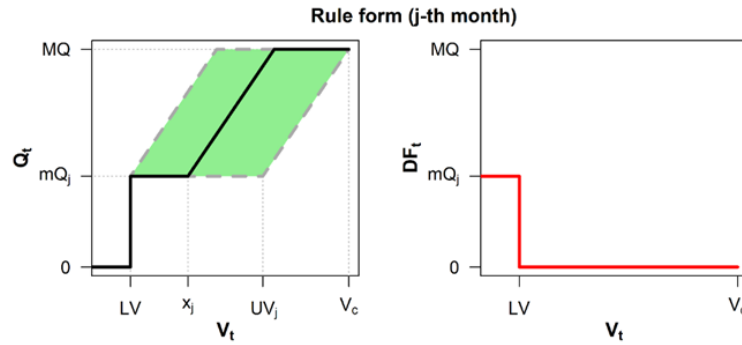


Figure 44. Graphical representation of the rule form. Left: the black line refers to the piecewise linear function which expresses the withdrawal Q_t as function of the stored volume V_t , while the green polygon represents the feasible rule domain. Right: the red line expresses the deficit volume DF_t as function of V_t .

Simulation-optimization scenarios

The parametrization of the monthly withdrawal rules, that is the optimization of the 12 x_j parameters, is conducted by means of the multi-objective optimization algorithm NSGA-II (Deb et al., 2002), with the twofold aim of i) maximizing the withdrawal volumes over the entire simulation period and, at the same time, ii) minimizing overall water deficit volumes. Therefore, two objective functions are implemented: i) the average annual withdrawal volume and the ii) the average annual deficit volume, respectively to be maximized and minimized.

The described simulation-optimization approach is applied multiple times by providing different meteorological forcings as input to the rainfall-runoff model, for optimizing the withdrawal operating policies under different historical or future climate scenarios.

Before using the outcome of the GCM-RCM modelling chains for predicting the future scenarios, the same models are first tested over the historical control period 1981-2010 (used here as reference for the current climatic conditions) and compared with the results obtained when feeding the system with the observed meteorological data over the same control period. For the future instead, even if the ten GCM-RCM meteorological time series cover all years following the control period, up to 2100, the optimization of the

rules refers only to the furthest future horizon, that is considering the conditions of the three-decades period 2071-2100. In particular, twenty-one simulation-optimization scenarios have been carried out:

- one observed-historical (OH) scenario: the operating rules are optimized for the historical control period 1982-2010 by forcing the model with observational E-OBS meteorological fields;
- ten CORDEX-historical (CH_{1-10}) scenarios: the operating rules are optimized for the historical control period 1982-2010 by forcing the model with each of the ten bias-corrected GCM-RCM meteorological fields for such period;
- ten CORDEX-far-future (CF_{1-10}) scenarios: the operating rules are optimized for the long-time horizon 2071-2100 by forcing the model with each of the ten bias-corrected GCM-RCM meteorological fields expected for the furthest future.

For each of the above twenty-one scenarios, a different set of withdrawal operating rules is obtained repeating the simulation-optimization procedure.

The rules are optimized only twice for each GCM-RCM chain: once over the control period (1982-2010, CH_{1-10}) and once over the furthest future (2071-2100, CF_{1-10}). However, for each of the optimized set of rules, the model is successively run across the entire 119-years period 1982-2100, allowing to evaluate how the use of rules that have been designed respectively under either present or far future conditions affects the pattern of model outputs (e.g. withdrawal and deficit volumes) across all the four three-decades intervals: control period (1981-2010), near future (2011-2040), medium-range future (2041-2070) and long-time horizon (2071-2100).

3.3.d.1.4 Optimal reservoir management rules

For each of the simulation-optimization scenarios, the NSGA-II algorithm produces a Pareto frontier of non-dominated and equally-eligible solutions. Figure 45 reports the results for the eleven historical simulation-optimization scenarios, where x-axis refers to the first objective function OF_1 (i.e. average annual withdrawal volume, to maximize), while y-axis to OF_2 (i.e. average annual deficit volumes, to minimize): the blue frontier refers to the non-dominated solutions obtained for the observed historical scenario (OH), the red Pareto frontiers are the solutions of the ten CORDEX simulation-optimization scenarios on the same historical control period (CH_{1-10}), while the orange Pareto frontiers are the solutions of the ten simulation-optimizations conducted on the long-time horizon 2071-2100 (CF_{1-10}).

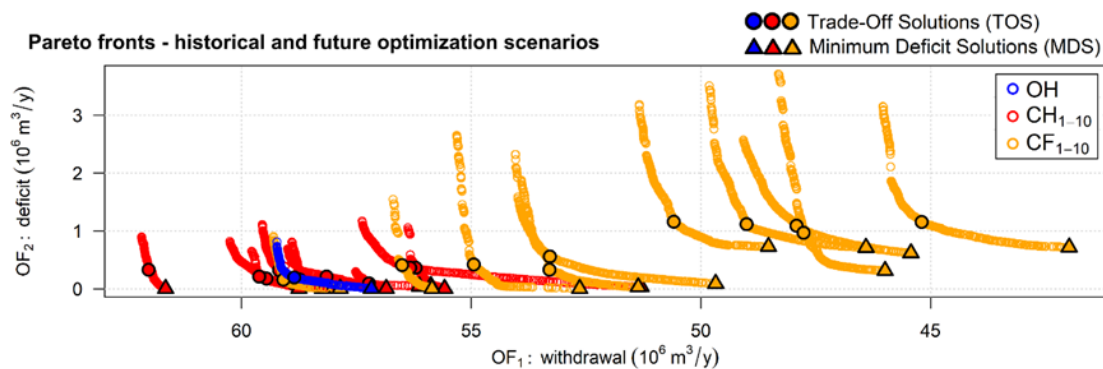


Figure 45. Pareto solutions for each of the simulation-optimization scenarios: observed-historical (OH, blue dots), ten CORDEX-historical (CH_{1-10} , red dots) and ten CORDEX-far-future (CF_{1-10} , orange dots). Trade-Off (TOS) and Minimum Deficit Solutions (MDS) are highlighted with bold dots and triangles respectively.

Firstly, the representativeness of the GCM-RCM ensemble for simulating the water availability during the historical reservoir management period was verified. As expected, ranges and forms of the frontiers are strongly related to the available water budget and thus to the temporal dynamics of precipitation during the simulation period. In fact, CH_{1-10} runs (red frontiers) differ substantially from one another, despite their good agreement with the reference observed precipitation (E-OBS). This is primarily due to the fact that even slight differences in the simulated occurrence of daily precipitation amount and timing can have a

significant impact on the water balance of the system. Despite such variability of the curves, the CH₁₋₁₀ runs (red fronts) are consistently distributed symmetrically and uniformly around the observed-historical optimization (blue front, OH), which suggests that the overall GCM-RCM ensemble can well represent the historical water availability and management in the system. By comparing the outcomes of the simulation framework obtained in the historical period for OH and for the ten CH₁₋₁₀ optimization scenarios, it was possible to further verify the representativeness of the ensemble of GCM-RCM scenarios for simulating historical water availability and reservoir management. Such analysis is not reported here for the sake of brevity.

The Pareto front resulting from the multi-objective optimization procedure represents a multitude of non-dominated alternative operation rules (each one corresponding to a set of monthly withdrawal rules). In practice, the choice of the optimal operating rule depends on the management policies that the resource manager chooses to adopt, keeping in consideration a wider framework of information including the environmental and socio-political consequences of each solution. In order to analyze and comparing the impact of the different rules on the two contrasting objectives and on the resulting reservoir behavior, two specific solutions for each Pareto front are here selected as possible reference among the possible optimal alternatives:

- the equal Trade-Off Solution (TOS), also known as 'knee' point and defined as the point which has the shortest Euclidian distance from the ideal solution of each Pareto front, i.e. the point of coordinates $[\max_{f_0}(OF_1); \min_{f_0}(OF_2)]$ in the present case, highlighted with bold dots in Figure 45. Although both objectives are expressed in water volumes, we calculate the Euclidean distance in a standardized space for each Pareto front. This standardization, achieved by scaling each axis to the maximum and minimum values of the objective functions, accounts for the differing operational meaning and impact of the quantities. Such a solution is commonly used to evaluate optimization results (Dumedah et al., 2010) and represents an equally balanced optimum solution.
- the Minimum Deficit Solution (MDS), which represents the solution corresponding to the lowest cumulated deficit volume during the entire simulation period (highlighted in Figure 45 with bold triangles). This is the most conservative solution, assuming the lowest level of risk of failure to supply the system and it is an important benchmark for the utility, even if it does not take into account the disadvantages deriving from an overexploitation of the alternative sources.

By comparing the form (i.e. the parameter x_j) of the withdrawal operating rules corresponding to MDS or TOS solutions on the Pareto fronts obtained when optimizing during historical CH₁₋₁₀ or future periods CF₁₋₁₀, we are able to quantify to what extent the withdrawal operating rules should change in order to adapt the system management policies to future climatic forcings. Such results are omitted here for brevity, but the full comprehensive findings and detailed discussion will be made available upon publication of the associated manuscript, which is currently undergoing international peer review.

3.3.d.1.5 Impact of the optimized rules on the water supply system: historical and future pattern of withdrawals and deficit volumes

Finally, the pattern of withdrawals and deficit volumes resulting when simulating the reservoir management adopting the different set of operating rules are compared.

In order to understand what would happen using a fixed set of rules (designed respectively over the historical or future scenarios) over all the decades, the modelling framework is run over the entire period 1982-2100 twice (by adopting the operating withdrawal rules corresponding respectively to the TOS and MDS solutions) for each of the ten CH₁₋₁₀ and of the ten CF₁₋₁₀ simulation-optimization scenarios (for a total of 40 model runs: two Pareto front points for each of the ten GCM-RCMs, following either the rule optimized under current and future climate). Therefore, the operating rules optimized for historical climatic conditions are used to run the simulation framework not only on the same control period, but also over all the future decades. Analogously, the operating rules optimized under the climatic conditions expected for the farthest time horizon (2071-2100) are used to simulate the reservoir management over the entire 1982-2100 period.

The impact of different management policies on the reservoir behavior and the corresponding effect of adapting rules to future climate is evaluated by focusing on the resulting pattern of the overall annual outputs of the described 40 simulations. Figure 46 shows the average annual withdrawals (left panels) and deficit volumes

(right panels) in the four three-decades periods (historical, 2011-2040, 2041-2070 and 2071-2100), when considering the set of operating rules optimized for historical (red dots, CH_{1-10}) or far-future (orange dots, CF_{1-10}) climatic conditions.

Consistent with the findings on future precipitation projections, the total withdrawn water volumes decrease, and the magnitude of deficit volumes (right panels, b and d) increases over the course of the century. Deficit conditions worsen particularly severely for the less conservative Trade-Off Solution (TOS) designed on the historical period (red squares in panel b). Conversely, the Trade-Off rules, when recalibrated for the future scenarios, allow for the mitigation of the deficit conditions that would result from optimizing them on the historical period (panel b, yellow squares). At the same time, this recalibration limits the steep reduction in potable volumes (panel a) that is projected if the more conservative Minimum Deficit Strategies (MDS) rules are maintained (panel c).

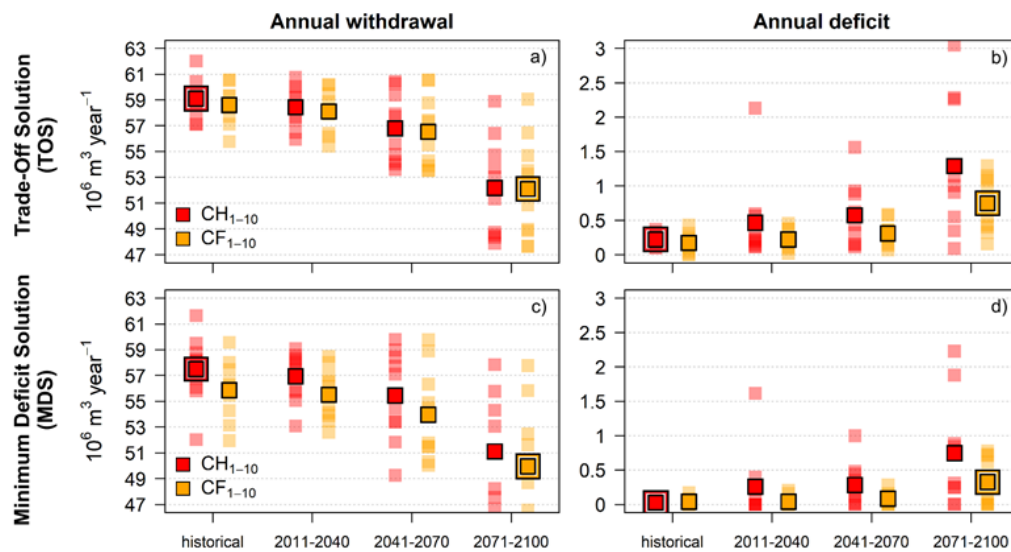


Figure 46. Average annual withdrawal (left) and average annual deficit (right) volumes simulated during the historical control period and the future time horizons by adopting the operating withdrawal rules optimized for the TOS (top) and MDS (bottom) solutions of the CORDEX-historical (red, CH_{1-10}) and CORDEX-far-future (orange, CF_{1-10}) optimizations. Shaded dots refer to the individual GCM-RCM scenarios while bold dots to the ensemble average.

3.3.d.1.6 Assessment of the results under an alternative forcing climate scenario provided by Spoke DS

The entire methodology is separately repeated by adopting as meteorological forcings the outputs of a high-resolution downscaling of CMIP6 global climate projections, driven by the MPI-ESM1-2-HR model under three different emission scenarios (SSP1-2.6, SSP2-4.5, SSP5-8.5) and produced by ENEA in Spoke DS (Struglia et al., 2025). The limitation of this supplementary experiment is the reliance on a single climate model instead of an ensemble. While all the steps described for the main experiment are repeated, here a very short summary of the results is reported for the sake of brevity.

First, the seasonal pattern of precipitation and temperature values simulated by the climate model during the historical and future periods are analysed: overall, future expected changes in monthly precipitation and temperatures for the less optimistic scenario SSP5-8.5 are similar to those predicted by CMIP5 models under RCP8.5.

Then, the framework for the optimization of the withdrawal rules is replicated for four simulation-optimization scenarios: one ENEA-historical (EH) scenario, where the operating rules are optimized for the historical control period 1982-2010 by forcing the model with the historical simulation of the climate chain, and three ENEA-far-future scenarios (EF_{SSP126} , EF_{SSP245} , EF_{SSP585}), where the rules are optimized during the end-of-century decades 2071-2100 by forcing the model with each of the three future climate simulation corresponding to the three emission scenarios.

As an example of the results, Figure 47 shows the future pattern of withdrawal and deficit volumes obtained for the EH scenario and for the worst future scenario EF_{SSP585} (which is the equivalent of RCP8.5, considered in the main experiment) by adopting the best Trade-Off solution (TOS). The effect of the management strategy on the pattern of the results is generally in line with what observed in the main experiment (adapting the rules to the future scenario, brown markers, allows to mitigate the deficits, but decreasing the overall production), even if the interpretation of the results is limited by the use of a single climatic chain.

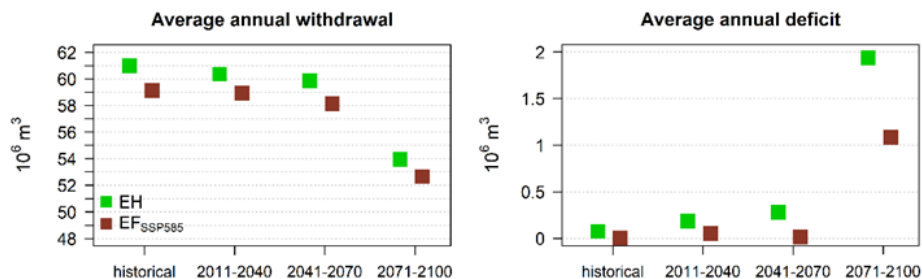


Figure 47. Average annual withdrawal (left) and average annual deficit (right) volumes simulated during the historical control period and the future time horizons by adopting the operating withdrawal rules optimized for the TOS solution of the ENEA-historical (green, EH) and ENEA-far-future for the SSP5-8.5 emission scenario (dark brown, EF_{SSP585}) optimizations.

3.3.d.1.7 Value and Applicability of Results

The study modelled the behavior of the multi-basin water supply system and the management of the Ridracoli reservoir, optimizing its operational withdrawal rules under both historical and future meteorological forcings, aiming at reducing system failure (reservoir deficit conditions occurring during hydrological droughts), while maximizing the overall water volumes supplied from the reservoir (thus reducing stress on other, less sustainable, and more energy-demanding regional sources). In particular, it was possible to estimate the corresponding expected future patterns of withdrawal volumes and water deficit volumes, i.e., the total volumes of user demand that will not be met by the reservoir system and would have to be supplied by other sources (unless water shortages occur).

The findings enable the estimation of expected changes in the reservoir behavior for future time-horizons: in general, the pattern of overall withdrawals and water deficit volumes obtained when applying optimized rules show how the adoption of highly risk-averse management policies aiming at zero-deficit conditions (MDS) would imply a substantial reduction in the total volumes supplied from the reservoir along the years, at the expense of an increased exploitation of the alternative (and less sustainable) sources in the region. Conversely, management policies that involve a slightly greater risk of incurring sometimes in deficit conditions (TOS) allow to partly counterbalance the expected future decrease of water availability, thus mitigating the water stress on the alternative sources.

Overall, the approach proposed for optimizing the operating rules in relation to both present and future climate might be replicated in other study regions, provided that reservoir and demand data are available. Such outcomes may be beneficial to decision-makers for evaluating future water shortage risk and for informing long-term water resource management planning, in order to mitigate the water stress on less sustainable water sources.

3.3.d.2 Water supply service interruptions: reservoir management under drought conditions, including analysis of future scenarios of water supply and user demand

This section presents the results of applying the methodological framework developed to integrate climate model outputs and hydrological analyses for assessing the impacts of climate change on the management of multipurpose reservoir systems. In such systems, water allocation is often influenced by competing demands - including hydropower production, agricultural irrigation, and urban supply - which are increasingly affected by hydroclimatic variability. Here, the focus is placed on the hydropower use of the reservoir, examining how changes in precipitation, temperature, and runoff regimes may alter water availability and energy generation in a basin where water and energy systems are strongly interlinked under changing climate conditions.

3.3.d.2.1 Reservoir management for Hydropower Production under Climate Change

3.3.d.2.1.1 The test case reservoir system

The test case study focuses on a large multipurpose reservoir system, located in a semi-arid basin characterized by pronounced hydroclimatic variability and strong interconnections between water and energy systems. The basin's hydrology is primarily snowmelt-driven, exhibiting marked seasonality that directly influences both water availability and hydropower generation. Wet winters and dry summers exacerbate the challenges of water storage and allocation among competing sectors such as agriculture, energy production, and urban supply. In this context, shifts in precipitation patterns, snow accumulation, and runoff timing pose major challenges for sustainable water and energy management. Process-based studies consistently show that rising temperatures reduce runoff efficiency through enhanced evapotranspiration and snow-albedo feedback, resulting in substantial streamflow declines per degree of warming.

The analysis integrates both observed and model-based datasets. Reference precipitation and temperature data are derived from a 4-km gridded climatological dataset spanning from 1981 to the near present. Climate projections are obtained from the Coupled Model Intercomparison Project Phase 6 (CMIP6; Eyring et al., 2016), including daily outputs from 21 Global Climate Models (GCMs) - namely ACCESS-CM2, ACCESS-ESM1-5, CanESM5, CESM2-WACCM, CMCC-CM2-SR5, CMCC-ESM2, EC-Earth3, EC-Earth3-Veg, EC-Earth3-Veg-LR, FGOALS-g3, GFDL-ESM4, INM-CM4-8, INM-CM5-0, IPSL-CM6A-LR, MIROC6, MPI-ESM1-2-HR, MPI-ESM1-2-LR, MRI-ESM2-0, NorESM2-LM, NorESM2-MM, and TaiESM - with spatial resolutions ranging from approximately 25 km to 200 km. Historical simulations cover the period 1981–2014, while precipitation projections under four Shared Socioeconomic Pathway (SSP) scenarios - SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5 - extend from 2015 to 2100.

Observed hydrological data include daily inflow and reservoir elevation records from 1963 to 2024, together with monthly hydropower production data (in MWh) covering the 2005–2024 period.

3.3.d.2.1.2 Results

Before constructing models to examine the relationship between basin-averaged precipitation and hydropower production, we first seek to explore the underlying causal mechanisms that could explain why these two variables are potentially connected. To understand the underlying physical processes influencing hydropower production, we explore the relationships between paired variables: precipitation and inflow, inflow and elevation, and elevation and hydropower production based on historical observations for the 2005–2022 period. Analysing the relationships among the three pairs of variables (i.e., precipitation and inflow, inflow and elevation, and elevation and hydropower), we find that the maximum correlation coefficient shows significant values (Figure 48).

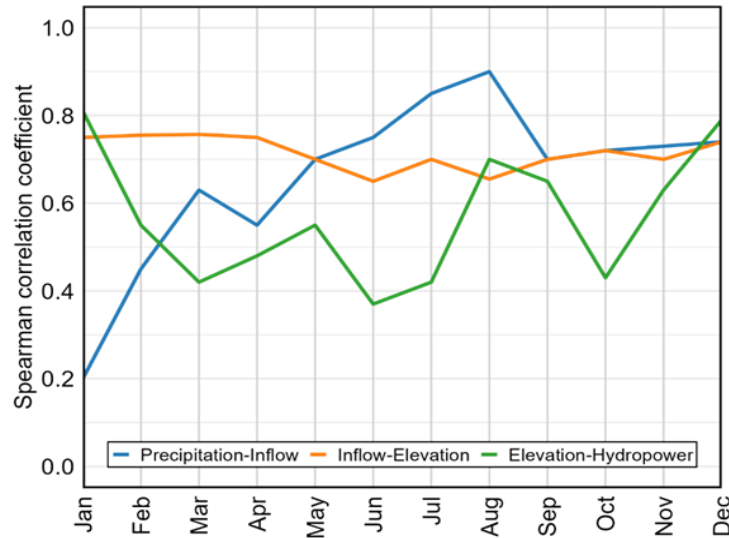


Figure 48. The monthly maximum Spearman correlation coefficient (ρ) between paired variables: precipitation and inflow, inflow and elevation, and elevation and hydropower production for the period 2005-2022.

For precipitation-inflow, the correlation ranges from 0.2 to 0.9, for inflow-elevation, it spans from 0.7 to 0.8, and for elevation-hydropower, it is between 0.4 and 0.8. These significant correlations indicate a physical link through three stages, supporting an investigation of the direct relationship between the initial and final stages in this sequence (i.e., precipitation and hydropower production). We assess the temporal aggregation scale that maximizes the Spearman correlation coefficient (ρ) between monthly hydropower production and antecedent basin-averaged precipitation over 2005–2022 (Figure 49).

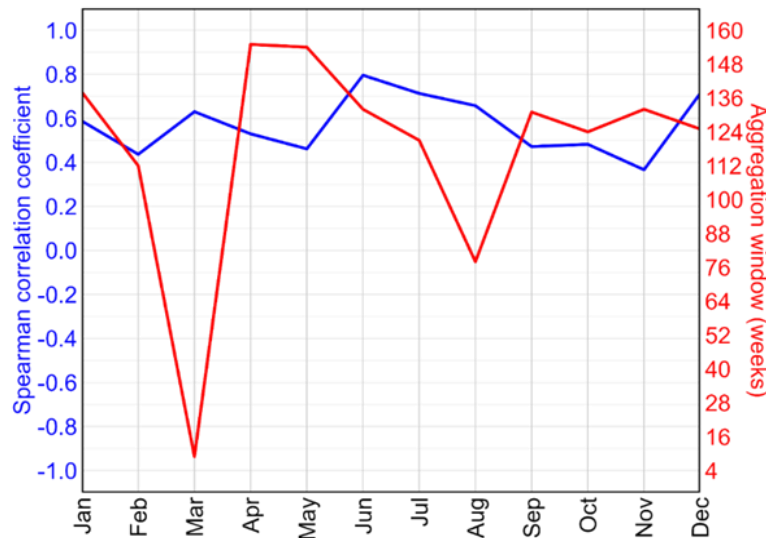


Figure 49. The aggregation window (in weeks) that maximizes the Spearman correlation coefficient (ρ) between monthly hydropower production and the antecedent basin-averaged precipitation (2005-2022).

The values of ρ range from 0.4 to 0.8, depending on the month. On average, the optimal aggregation window is approximately 2.5 years, except for March (which is excluded from further analyses). Notably, for March, the peak correlation occurs for a 9-week window, likely due to snowmelt influences during this period. The ~2.5-year optimal aggregation window indicates a long memory effect consistent with the hydrologic behaviour of the basin. Multiyear snow accumulation, groundwater contributions, and the large storage capacity result in delayed hydrologic responses, whereby precipitation anomalies can affect inflows and hydropower production several years later. In terms of modelling, we provide results regarding the selected

distributions, parameter configurations, and model choices based on Schwarz Bayesian Criterion (SBC, Schwarz 1978) and Standardized Mean Squared Error (SSMSE, Hashino et al., 2007) criteria (Table 6).

Table 6. Selected distributions and model configurations based on SBC and SSMSE.

Month	Probability Distribution	Parameter Configuration	Model
January	Inverse gamma	$\mu \sim P, \sigma \text{ const}$	$\log(x)-y$
February	Inverse gamma	$\mu \sim P, \sigma \text{ const}$	$\log(x)-\log(y)$
March			
April	Inverse gamma	$\mu \sim P, \sigma \text{ const}$	$\log(x)-y$
May	Inverse gamma	$\mu \sim P, \sigma \text{ const}$	$\log(x)-y$
June	Generalized gamma	$\mu \sim P, \sigma \sim P$	$\log(x)-y$
July	Inverse gamma	$\mu \sim P, \sigma \text{ const}$	$x-\log(y)$
August	Inverse gamma	$\mu \sim P, \sigma \sim P$	$x-\log(y)$
September	Inverse Gaussian	$\mu \sim P, \sigma \sim P$	$x-\log(y)$
October	Inverse gamma	$\mu \sim P, \sigma \text{ const}$	$\log(x)-\log(y)$
November	Inverse gamma	$\mu \sim P, \sigma \text{ const}$	$\log(x)-\log(y)$
December	Inverse gamma	$\mu \sim P, \sigma \text{ const}$	$\log(x)-y$

The inverse gamma distribution is identified as the best fit for January, February, April, May, July, August, October, November, and December, covering the majority of months; the three-parameter generalized gamma distribution with a constant v parameter for June; and the inverse Gaussian distribution for September. For March, however, model convergence is not achieved. This is likely due to the distinct hydroclimatic regime during the transition from winter to spring, when snowmelt processes dominate and the relationship between precipitation and hydropower production becomes nonlinear and weakly correlated. During this month, inflows are primarily driven by accumulated snowpack rather than concurrent precipitation, which reduces the explanatory power of precipitation-based predictors and leads to unstable parameter estimation in the statistical model. The shorter optimal aggregation window (9 weeks) identified for March supports this interpretation, indicating a faster hydrologic response associated with snowmelt rather than long-term precipitation accumulation. The parameter μ consistently depends on precipitation, while σ remains independent of precipitation for most months, with the exception of June, August, and September, where it also varies with precipitation. The SSMSE, indicating model performance across months, ranges from 0.1 to 0.4, showing moderate agreement (Figure 50).

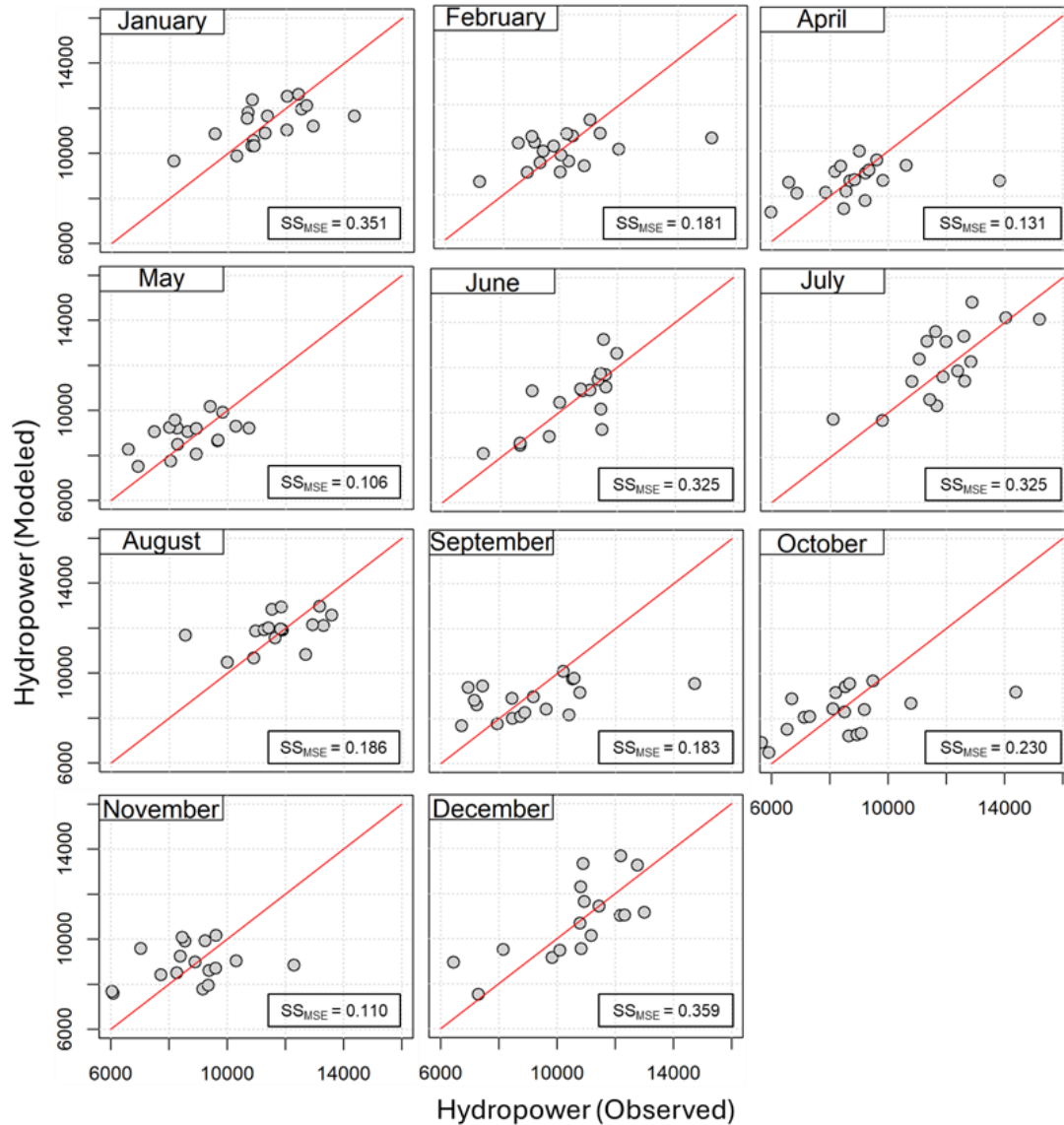


Figure 50. Scatterplots illustrating the relationship between observed and modelled monthly hydropower production for each month. The values in the bottom-right corner refer to the skill score used to quantify the model's performance. Values closer to 1 indicate a stronger agreement between the reference data and the model output.

The plots in Figure 50 highlight the agreement between observed and modelled values from the Generalized Additive Models for Location, Scale and Shape (GAMLSS, Rigby and Stasinopoulos 2005), confirming precipitation as a valuable driver of hydropower production across the 2005–2022 period. When assessing the suitability of the different GCMs, we find that 76% of the models (16 out of 21) models perform well across all 11 months (Figure 51), and, therefore, we use these 16 GCMs to calculate the ensemble mean and the envelope.

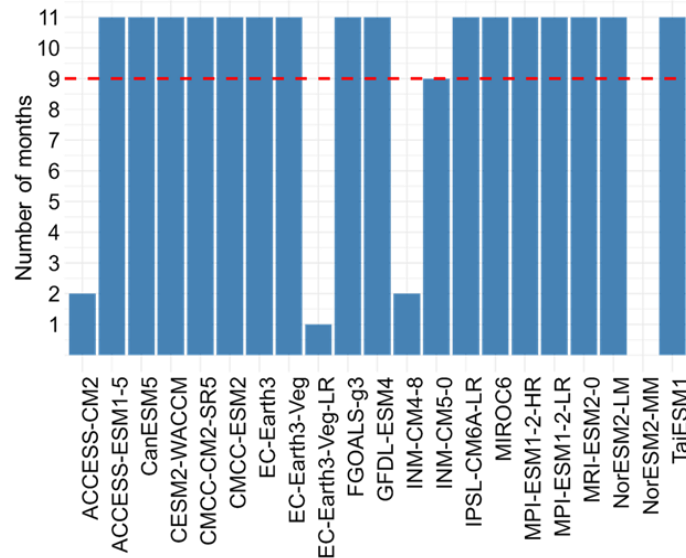


Figure 51. Historical screening of GCMs based on Kendall's τ for 2015–2022 (taken from the initial SSP2-4.5 years). The red dashed line marks the selection threshold: bars above the line indicate models that match the significance (5% level) and, when significant, the sign of the observed trend across all months. Retained models ($n = 16$) are used for both the ensemble mean and envelope; excluded models are not used further.

We then calibrate the statistical models linking basin-averaged precipitation to monthly hydropower production over the 2005–2022 period, comparing observed hydropower series with the envelope and the ensemble mean of hydropower outputs generated by bias-corrected and downscaled GCM precipitation data for each SSP scenario. While perfect year-to-year correspondence is not expected because we are using the coupled GCMs and the historical simulations, the observed series generally falls within the model envelope. An exception is the peak observed in 2011, which exceeds the envelope, and a decline in 2021–2022, largely unrepresented in most models. The projections of monthly hydropower production, in terms of ensemble mean and envelope across the four SSP scenarios over the period 2015–2100 are shown in Figure 52.

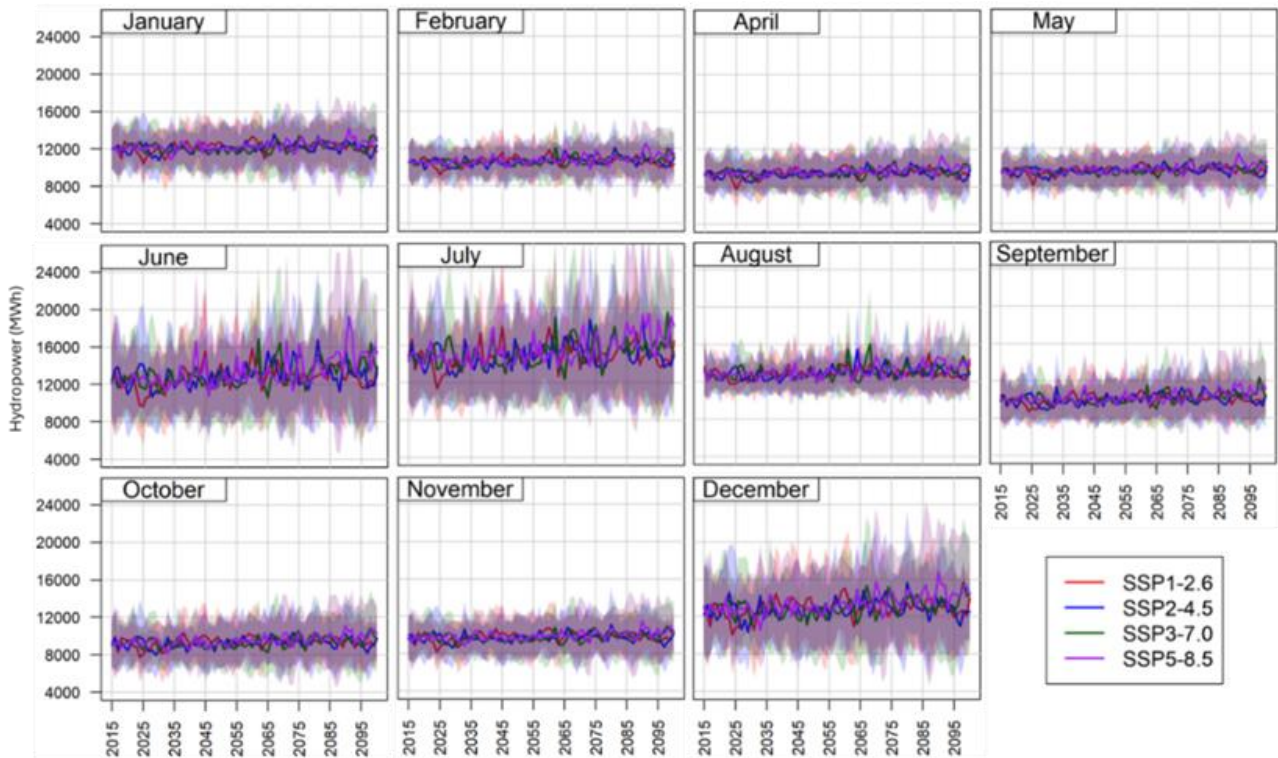


Figure 52. Monthly envelopes and ensemble means of hydropower projections from the 16 selected GCMs for four SSP scenarios (SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5) over the period 2015–2100.

Finally, we assess trends in the ensemble mean and in the number of models showing significant positive or negative trends over time windows of at least 10 years, from 2005 to 2100. Some differences emerge across scenarios and months, pointing to the influence of emissions on hydropower production trends and the seasonal variability inherent in the system. In higher emission scenarios (SSP3-7.0 and SSP5-8.5), positive trends in hydropower production become more consistent, especially in the second half of the century. This is most evident in warmer months (e.g., May–August), where stronger trends are driven by increased water availability from snowmelt. Conversely, lower emission scenarios (SSP1-2.6) exhibit subdued trends and reduced variability. A seasonal pattern emerges: warmer months display robust positive trends, while cooler months, like January and February, remain more stable with less sensitivity to emission scenarios. Across models, higher emission scenarios show stronger agreement on positive trends, particularly in spring and summer, suggesting amplified responses to warming. In contrast, lower-emission scenarios reveal a balanced distribution of positive and negative trends, indicating greater variability and weaker climate impacts.

These results highlight the seasonal and emissions-driven dynamics of hydropower production, with higher emissions leading to more robust increases and lower emissions presenting a wider range of potential outcomes. Motivated by process studies documenting warming-induced declines in runoff efficiency, we extended the precipitation-only GAMLSS framework to a two-covariate statistical model with precipitation and temperature. Incorporating temperature allows us to partially capture snowmelt timing and evapotranspiration effects, improving monthly skill, especially from late spring through summer, when temperature-driven processes dominate. For each month, we evaluated multiple combinations of aggregation windows and temporal lags for both precipitation (P) and temperature (T), identifying the optimal configuration that maximized model performance according to the Schwarz Bayesian Criterion (SBC) and the Mean Squared Error Skill Score (SSMSE). The selected configuration for each month is reported in Table 7, where P_feat and T_feat represent the aggregation and lag parameters used in the final model. For each target month, basin-averaged precipitation and temperature were aggregated using a moving window of varying length (e.g., 1, 3, 6, 12, or 24 months). The aggregation window defines the number of months included in the moving sum or mean preceding the target month. Different temporal lags (in months) were tested to capture the delayed response of hydropower production to climatic forcing. Specifically:

- A lag of 0 indicates that the window ends in the target month (t);
- A lag of 1 means that the window ends in the previous month (t-1);
- In general, for a given window length and lag, the aggregation covers months from t-1-k+1 to t-1 (both included).

Table 7. The aggregation window (in months) and lags (in months) for the best configuration for each month.

Month	P_feat	T_feat
January	Pcp 24m lag3	Temp 6m lag2
February	Pcp 3m lag2	Temp 24m lag1
March	Pcp 24m lag0	Temp 1m lag3
April	Pcp 24m lag1	Temp 1m lag2
May	Pcp 2m lag2	Temp 24m lag0
June	Pcp 1m lag2	Temp 2m lag1
July	Pcp 2m lag2	Temp 24m lag2
August	Pcp 1m lag1	Temp 2m lag3
September	Pcp 24m lag0	Temp 6m lag2
October	Pcp 12m lag3	Temp 24m lag3
November	Pcp 12m lag1	Temp 24m lag2
December	Pcp 24m lag3	Temp 24m lag1

Table 8 summarizes the selected distributions and model configurations for the two-covariate formulation, whereas Figure 53 shows the observed versus modelled hydropower production, respectively, for each month. Model performance, as quantified by the SSMSE, showed a slight improvement compared to the precipitation-only model, with values ranging between 0.5 and 0.8. The largest improvements were observed from May through September, consistent with the stronger influence of temperature on snowmelt and inflow generation during this period.

Table 8. Selected distributions and model configurations based on SBC and SSMSE.

Month	Probability Distribution	Parameter Configuration	Model
January	Gamma	$\mu \sim P+T, \sigma \sim T$	$\log(P)+T - y$
February	Inverse gamma	$\mu \sim P+T, \sigma \sim P+T$	$P+T - y$
March	Gamma	$\mu \sim P+T, \sigma \sim P$	$\log(P)+T - \log(y)$
April	Gamma	$\mu \sim P+T, \sigma \sim P$	$\log(P)+\log(T) - y$
May	Inverse gamma	$\mu \sim P+T, \sigma \sim P+T$	$\log(P)+\log(T) - y$
June	Inverse gamma	$\mu \sim P+T, \sigma \sim P+T$	$\log(P)+T - y$
July	Inverse gamma	$\mu \sim P+T, \sigma \sim P$	$P+\log(T) - \log(y)$
August	Inverse gamma	$\mu \sim P+T, \sigma \sim P+T$	$\log(P)+\log(T) - y$
September	Inverse gamma	$\mu \sim P+T, \sigma \sim P+T$	$P+\log(T) - y$
October	Inverse gamma	$\mu \sim P+T, \sigma \sim P+T$	$\log(P)+\log(T) - y$
November	Inverse gamma	$\mu \sim P+T, \sigma \sim T$	$P+\log(T) - y$
December	Inverse gamma	$\mu \sim P+T, \sigma \sim P+T$	$P+\log(T) - y$

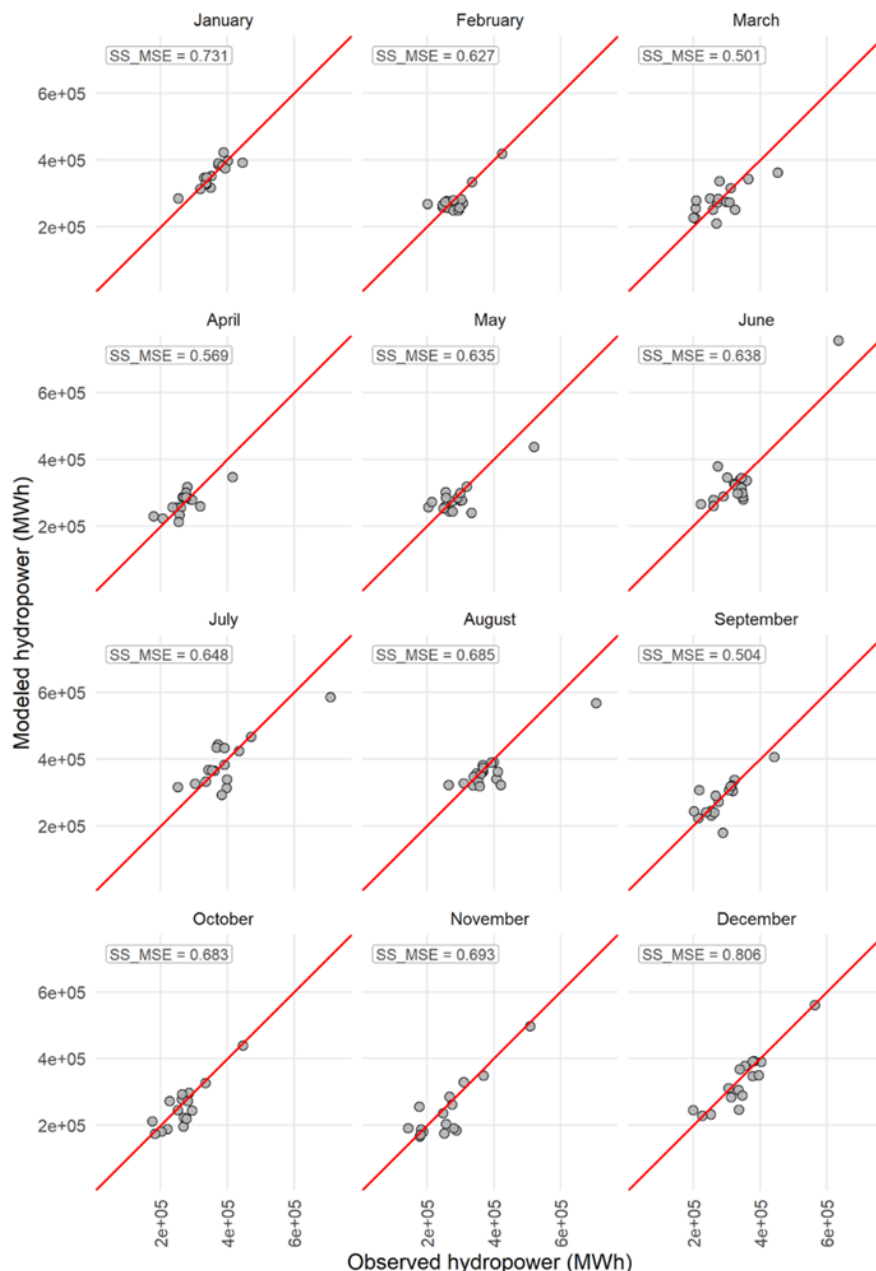


Figure 53. Scatterplots illustrating the relationship between observed and modelled monthly hydropower production for each month for the two-covariate model (precipitation and temperature). The values in the top-left corner refer to the skill score used to quantify the model's performance. Values closer to 1 indicate a stronger agreement between the reference data and the model output.

3.3.d.2.1.3 Value and applicability of results

This study highlights significant relationships among precipitation, inflow, reservoir elevation, and hydropower production, revealing key aspects of the basin's hydrological and operational dynamics. The correlation between monthly hydropower generation and antecedent basin-averaged precipitation suggests a memory effect, with an optimal aggregation period of approximately 2.5 years. Statistical modelling using GAMLSS confirms that precipitation consistently influences hydropower production, although the strength of this relationship varies seasonally and monthly. Projections based on selected GCMs indicate that different emission scenarios lead to varying hydropower responses, emphasizing the sensitivity of the system to future climatic conditions. Under future climate scenarios, the results obtained with the single-covariate model - where precipitation is used as the sole climatic predictor - show that higher-emission pathways (SSP3-7.0 and SSP5-8.5) yield stronger positive trends in projected hydropower production,

particularly during spring and summer, suggesting amplified system responses to warming. Conversely, lower-emission scenarios (SSP1-2.6) display weaker trends and lower variability. These findings highlight the influence of emission trajectories on hydropower outcomes and reinforce the importance of integrating climate-driven variability into long-term planning.

Since the inclusion of temperature as a second covariate has proven to improve the model's performance and its ability to reproduce hydropower variability, future work will extend this framework to a two-covariate formulation jointly incorporating precipitation and temperature as predictors. This enhancement will enable a more realistic representation of the physical processes influencing runoff and hydropower generation, and a more comprehensive assessment of how combined hydroclimatic drivers may affect future water and energy system resilience.

While the results provide valuable insights, some limitations must be acknowledged. The analysis relies on statistical models that, despite aligning well with observations, cannot fully reproduce certain events and interannual fluctuations. Future work could benefit from comparisons with physically based models, which explicitly simulate hydrological processes and reservoir operations. Incorporating additional variables such as snow water equivalent (SWE), soil moisture, or evaporation could further refine the model's ability to capture the mechanisms driving inflows and energy generation.

The methodological framework developed in this study can be extended to basins with similar hydroclimatic conditions, allowing for cross-basin comparisons and assessing how local characteristics influence hydropower responses to changing climate drivers. Adapting the model to regions with different precipitation regimes, storage capacities, or management constraints would help evaluate its robustness and transferability.

Overall, the results contribute to a broader understanding of how climate variability and change affect coupled water-energy systems. They provide useful guidance for reservoir management, power system planning, and climate adaptation policies. The approach supports risk assessment and long-term hydropower planning, promoting more resilient water and energy management strategies under future climate conditions.

3.3.d.3 Water shortage hazard on urban water distribution users, under current and future climate scenarios

3.3.d.3.1 Introduction

In many water-scarce regions, climate variability and infrastructure constraints force utilities to implement intermittent water supply regimes, where water is delivered only during limited hours. This practice is increasingly common in Mediterranean urban areas such as Palermo (Sicily), as a means to cope with resource limitations and reduce leakage. However, intermittent supply is a major concern for water utilities because it can undermine service reliability and equity. When continuous 24/7 delivery is not possible, customers resort to private roof tanks and booster pumps to store water during supply hours. For example, in Palermo's network users have installed tanks of about 200–250 liters per capita and pump systems to collect as much water as possible whenever the system is pressurized. The utility has also deliberately lowered the network pressure to curb losses from aging pipes, which further necessitates these user-level storage and pumping solutions. While such measures help communities get through supply interruptions, they introduce complex dynamics into the distribution system and raise fairness issues: some users may secure more water (by quickly filling large tanks) while others, especially at network extremities or higher elevations, receive less than their fair share.

To analyze these scenarios, the study employs a **head-driven hydraulic modeling approach** tailored for intermittent supply networks. Traditional demand-driven analysis assumes each node's full demand is met and then computes pressures, an approach that fails under intermittent conditions – it can predict node pressures below the minimum service level or even negative values when the network cannot meet all demands. In reality, under low-pressure intermittent service, not all demand is satisfied and the design delivery rates cannot be maintained. Therefore, a pressure-dependent simulation is necessary, wherein **node outflows are treated as functions of available pressure (head)** rather than fixed demands. This head-driven approach reflects the fact that actual consumption drops when pressure is insufficient, instead of forcing unrealistic zero-pressure solutions. Researchers since the 1980s have developed various formulations for such pressure–outflow relationships. In this study, we adopt and extend the method of Reddy and Elango (1989), which was originally developed for networks operating intermittently with all users equipped with private reservoirs. In such a system, each node draws the maximum flow the network can provide based on the current head, and outflow at a node stops only when the user's local reservoir is full. We modified this formulation to account for extremely low-pressure conditions (i.e. when node head falls below the normal minimum required for service) by calibrating a pressure–consumption function that still allows some draw even when standard service pressure is not met. This modification acknowledges the effect of household booster pumps: even if pressure at a node is below the usual requirement to push water into a building, users can still siphon water up into their tanks with pumps. By incorporating this extended head-driven model, we capture the reality of intermittent networks where consumption is **pressure-dependent** throughout the supply cycle.

The enhanced model was implemented in an enhanced version of EPANET 2, augmented with the ability of simulating emptying and filling of pipes and with a representation of **user-level storage and pumping**. Specifically, a small virtual reservoir (rooftop tank) and a pump were associated with each demand node, providing a detailed model of the pervasive private tank systems in intermittent supply areas. Each tank is sized to the nodal daily demand, and each pump is specified to fill its tank in roughly 4–5 hours. The pump operation follows realistic household behavior: it switches on when the local tank is empty and switches off when the tank is full or if the network pressure falls to zero. This configuration reproduces the surge of consumption when supply begins (as many empty customer tanks start filling simultaneously) and the subsequent tapering of flow as tanks fill up. Incorporating distributed storage and pumping in the model is crucial for **Mediterranean cities like Palermo**, because it captures how individual user actions (e.g. quickly pumping water into private tanks) collectively affect network pressures and flows. The result is a more faithful simulation of intermittent distribution performance, including the competition among users for water and the delays some areas experience before receiving supply.

To evaluate system performance under these constrained conditions, the study introduces two **equity indices**, **EQ1** and **EQ2**, which quantify how fairly water is distributed among users during intermittent service. **EQ1** is defined as the ratio of the water volume actually supplied to a given user in one complete service cycle

(for example, over two days if water is delivered every other day) to that user's nominal water demand for the same period. An EQ1 value below 1 indicates a user receiving less water than required, whereas a value above 1 indicates a user receiving more than their nominal demand (e.g. by capturing extra water in storage). This index thus gauges **overall sufficiency and fairness** of supply on a per-user basis over the long run. However, even if total volumes are balanced over a day or cycle, the timing of delivery can vary widely across the network. The second index, **EQ2**, addresses this by comparing the flow rate to a user during intermittent supply to the flow they would get under ideal continuous supply conditions at that same time. In effect, EQ2 measures **momentary or short-term equity**: at a given hour, a high EQ2 (>100%) for a user means they are receiving water at a rate higher than their normal demand (often because they are quickly filling an empty tank), while an EQ2 near 0% means the user is receiving little or no water at that time. By examining EQ2 over the course of a supply day, one can identify periods when certain users or areas are "ahead" or "behind" in terms of water access. These indices are important because they shed light on both cumulative performance and distributional fairness. For instance, a network might achieve nearly equal EQ1 for all users by the end of the day (meaning everyone eventually received most of their required volume), yet still exhibit large discrepancies in EQ2 during the day – indicating that some users had water early and others had to wait much longer. Such temporal inequities can heavily influence user experience and **perceptions of service reliability**. Therefore, by using EQ1 and EQ2 alongside traditional metrics (like pressure and total delivered volume), the methodology provides a comprehensive assessment of an intermittent supply network's performance and fairness. In summary, the **Palermo case study** will apply this head-driven modeling approach with integrated user tanks/pumps and the EQ1/EQ2 indices to examine how climate-related water shortages impact an urban distribution system, and to identify strategies to improve equity and performance under intermittent supply conditions.

3.3.d.3.2 The case study

The proposed model was applied to one of 17 supply networks of Palermo, Italy (Figure 54).

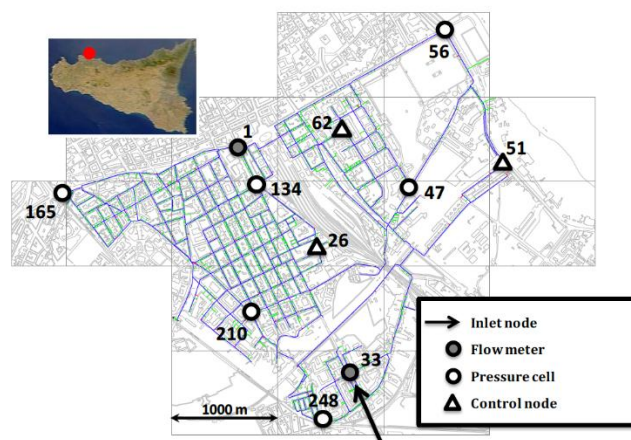


Figure 54. A schematic of the network.

All the geometric characteristics of the network as well as the number and the distribution of user connections, the water volumes supplied and measured, and the pressure and flow values in a few important nodes are precisely known. The network was, in fact, totally rebuilt in 2002 even if the old cast-iron feeding pipes still remain in service. These pipes connect the network with two reservoirs at different levels that can store up to 40,000 m³ per day and supply the 8,700 user connections of the network (nearly 35,000 inhabitants).

The entire network is made of polyethylene and it is about 40 km long. The pipes have diameters ranging between 110 and 225 mm, the network node (street level user connections) elevation spans from 3 to 47 m above sea level, while building height ranges from 5 to 50 m. The network was designed to supply about 400 l/capita/d, but actual average consumption is about 260 l/capita/d. As consequence, the network was characterised by low water velocities and correspondently high pressures, which resulted in substantial leakage in the past. Intermittent distribution on a daily basis was introduced as a common practice over the last five years (at least during summer period), leading users to acquire local private tanks, with specific volume equal to 200-250 l/capita. Furthermore, the water utility decided to reduce the pressure level on the network because of the significant water loss that occurs in the feeding pipe. This encouraged users to

maintain their own tanks and to adopt a local pumping system to feed the tanks even if the network pressure is not adequate.

The network is monitored by six pressure cells and two electromagnetic flow meters (Figure 55) that have provided data on hourly basis almost continuously since 2001. The calibration of the network hydraulic model is constantly updated when new data become available (Fontanazza et al., 2007; Fontanazza et al., 2008). In this paper, the pressure data used to represent the filling and the emptying processes have a time resolution of five minutes and refer to the period between June and October 2002, during which the network was managed by intermittent supply on a daily basis. For the same period, flow data entering the network were available with the same temporal resolution. During the monitoring period, per-capita water supply was not reduced and intermittent supply was mainly adopted for reducing network leakages.

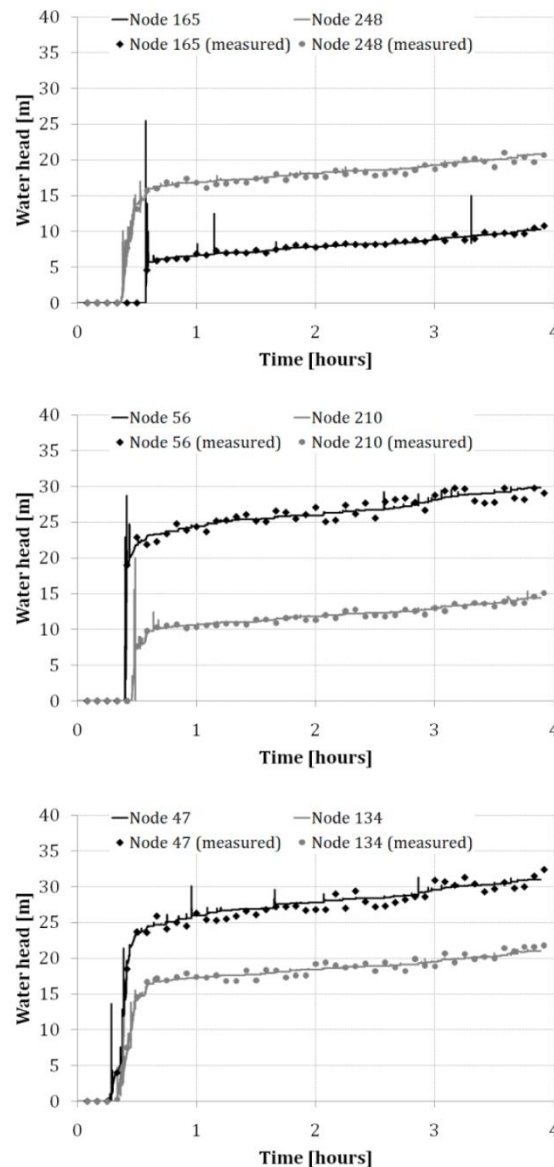


Figure 55. Comparison between simulated and measured pressures in the pressure gauge nodes (24/06/2022).

The node head-discharge model parameters were set to the averages obtained in a field campaign conducted in the same network in 2007 and 2008 (Criminisi et al., 2009): is set equal to 0.57, and to 2.8 cm². For the sake of simplification in the following model application, the average network pressure profile and inflow patterns are computed for the 78 daily time series for which both hourly pressures and discharges were available.

3.3.d.3.3 Results analysis

The model was initially calibrated according to the pressure profiles available during the monitoring period in the six pressure cells installed in the network (Figure 54). Figure 55 shows the agreement between the simulated and measured pressure time series. The peaks in simulated pressures result from small water hammer events due to the opening and closing of the ball valves supplying the private tanks near the pressure gauges, demonstrating the sensitivity of the proposed modelling approach.

After calibration, three hypothetical scenarios were simulated by progressively reducing network water supply from 100% to 90%, 70% and 50% of users water demand. In this way, the model was applied for evaluating the inequalities among users that may rise in water scarcity conditions managed by intermittent supply.

In each scenario, the filling process is adequately simulated by the model: initially, each monitored node receives water depending on its distance from the inlet node; the pressure rises rapidly until private tanks start to be supplied depending on their height above ground (usually between 5 and 50 m). Then, pressure rises gradually as private tanks become full. The results of the filling process analysis of network show the high inequality in supplying users even in the condition when 100% of water demand is delivered.

Figure 57 shows the dynamics of pipe filling and clearly indicates the location of the disadvantaged users in the left corner of the network. Network mains start filling very soon after the water network is supplied. After 600 seconds, only a few secondary pipes near the inlet node are filled, while the upper part of the network is still empty after 1800 seconds. The network is entirely full about one hour after water supply begins, but the pressure levels for several users are still inadequate to allow for private tank supply. The high consumption of the advantaged users due to the filling of their private tanks at the beginning of service protracts the time needed to fill the network completely and generates high head losses in pipes, conveying discharges higher than the design node demand.

The likelihood of private tanks being filled depends on the water head of building roof tanks, so all of the advantaged users are not necessarily in the topographically lower part of the network due to the combination of average building height and pressure level. Only a few users can be supplied by the network after the filling process finishes (after 3950 sec) because pressure levels on the network are not sufficient to supply the private tanks.

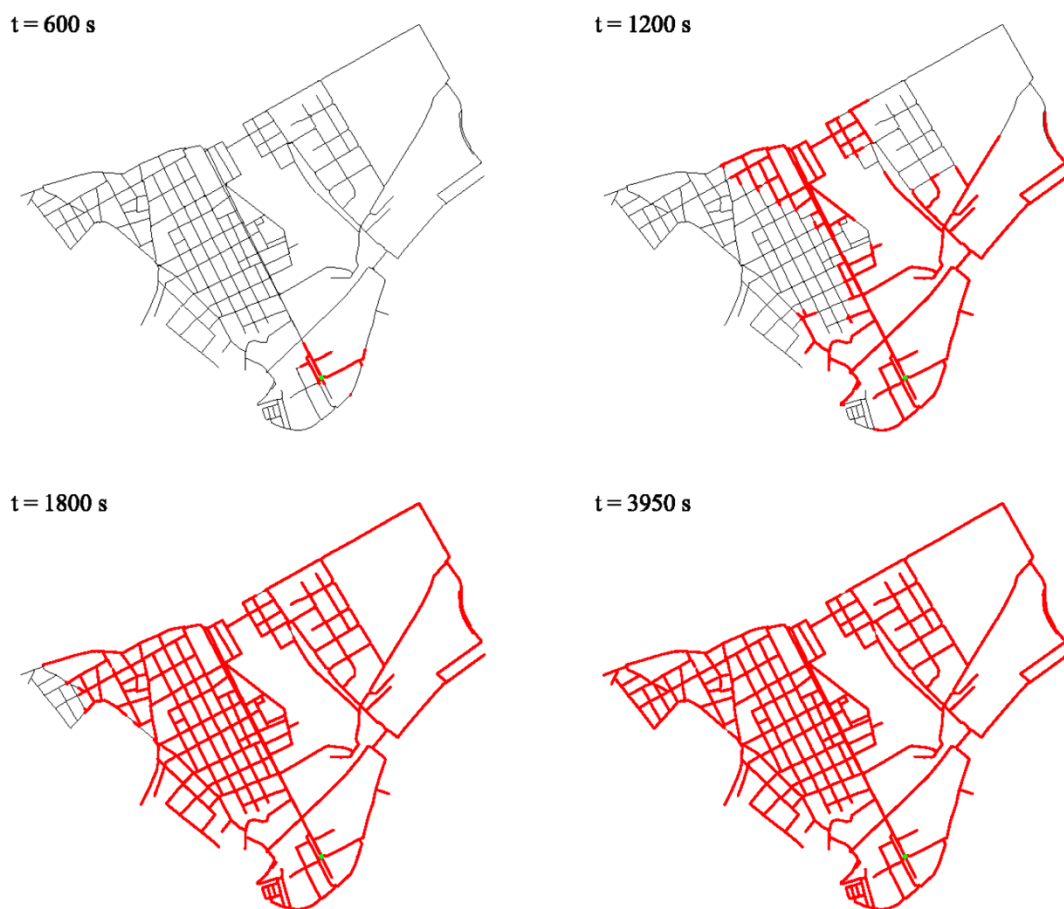


Figure 56. Average dynamics of pipe filling in time and space.



Figure 57. Distribution of EQ1 values over the network.

The network was analysed by the mean of a long-term simulation, with a time step equal to one hour, involving a whole service cycle in intermittent distribution condition. In this simulation, water resources availability is considered equal to the demand (intermittent distribution is adopted only for leakages reduction) so the iniquitous water supply is due to wrong distribution of resources among users. Index EQ1 was computed

for the whole period and for each network node. The index EQ2 was computer for each node and each analysis time step. The analysis of equity index EQ1 shows that in intermittent conditions the inequity in water volumes distributed to users are limited within 15% (Figure 57). This number can be considered acceptable because it does not generate a great compression of user water consumption, but it has to be stressed that this value has been generated in a condition where water supply would be able to fully satisfy users demand.

The analysis of index EQ2, on the contrary, demonstrated that, in the first part of the service day (just after the restart of the water service), the lower nodes drain the most part of the available resources for filling their local reservoirs showing values of EQ2 near to 250%; in the meantime, at higher elevated nodes, water is still not available and EQ2 values are near to zero (Figure 58a). When lower reservoirs are filled (Figure 58b), water resources are available for elevated nodes that show high values of EQ2, while lower nodes (where reservoirs are filled) show low EQ2 values. EQ2 is highly variable and it demonstrates that the network subjected to intermittent distribution will work in conditions that are quite far from the design ones and also from the operating conditions that take part in continuous distribution.

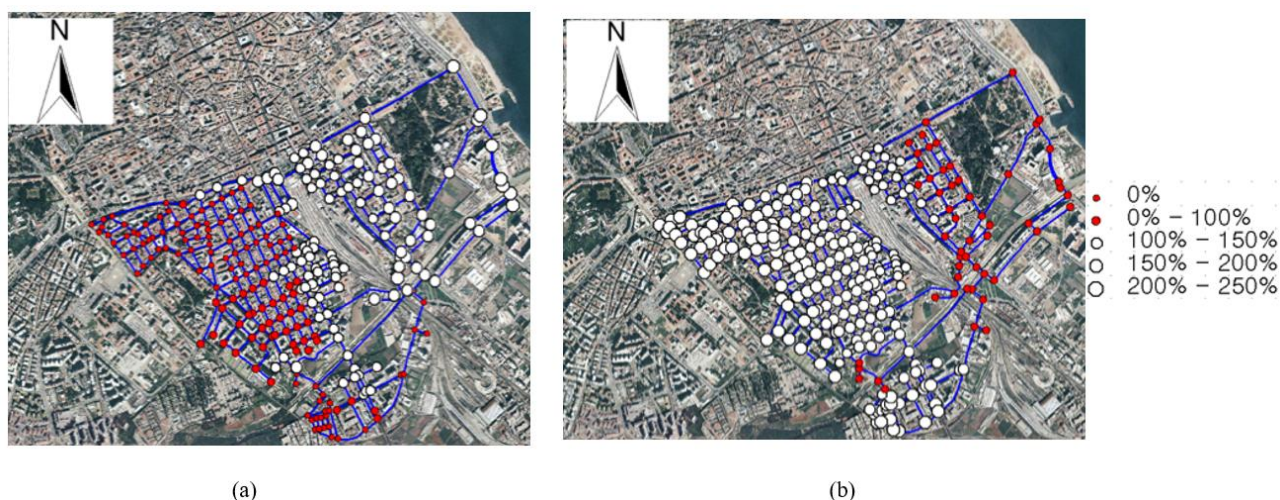


Figure 58. EQ2 values at the beginning (a) and at the end (b) of the service period.

3.3.d.3.4 Conclusions

The application of this advanced modeling approach to Palermo's water distribution network yielded key findings about system behavior and equity under intermittent supply. First, the model's performance was validated against real network data, giving confidence in its predictions. Calibration results showed that simulated pressures closely match measured pressure time series at multiple monitoring points in the network. The model accurately reproduced observed phenomena such as the minor pressure transients caused by household tank valves opening and closing, demonstrating high fidelity to the actual system dynamics. This successful validation indicates that the head-driven simulation, augmented with private tank and pump representation, can reliably capture the complex hydraulics of intermittent service. It set a sound basis for exploring hypothetical scenarios of reduced supply in the Palermo case.

Using the calibrated model, three reduced supply scenarios were analyzed, delivering only 90%, 70%, and 50% of the typical water demand, respectively. These simulations mimic increasing levels of water scarcity (for example, due to drought or emergency rationing) and allowed assessment of network performance as available supply dwindles. The results highlight that significant inequalities in water delivery emerge even when total supply is sufficient to meet demand. In fact, the model revealed high disparity among users even in the 100% supply case (normal demand fully met), purely due to the uneven way water flows when the network is turned on intermittently. At the start of a supply period, water rushes into the empty pipes and begins filling user tanks. The simulation showed that certain "advantaged" users – often those near the supply inlet or at lower elevations – are able to begin filling their reservoirs almost immediately, drawing large amounts of water and causing strong head losses that slow down the propagation of pressure to more distant points. For example, after the first few minutes of reopening the supply, only the primary mains and a few secondary pipes close to the inlet had been recharged, while peripheral reaches of the network

remained empty even 30 minutes into the cycle. It took on the order of an hour for the entire network to become filled and pressurized; even then, the pressure at several user connections was still too low to initiate flow into their rooftop tanks. In the model, some users at higher elevations or at the far end of the service zone had to wait until nearly the end of the supply window (over an hour) before any water reached their taps, and a few never attained sufficient pressure to fill their tanks at all in the most extreme scenario. As expected, these disparities worsened as the total available water was reduced – under the 50% supply scenario, many peripheral or high-elevation customers would only receive a fraction of their needed volume, if any, within the limited supply hours (whereas others closer to the source fully satisfied their demand). This demonstrates how supply cuts disproportionately affect different parts of the network, creating a form of “water stress inequality” under intermittent operation.

The spatial and temporal patterns of inequality observed are instructive. Spatially, the model identified specific zones (e.g. a branch in the leftmost corner of the Palermo network) where users were consistently disadvantaged, receiving water much later and at lower rates than elsewhere. These disadvantaged areas were not always the highest in elevation; rather, they resulted from a combination of factors including distance from the source, local topography, and the distribution of tank elevations (building heights). This means that purely topographic fixes (like boosting pressure based on elevation alone) may not fully resolve the issue – one must also consider network layout and where initial flows are going. Temporally, there was a pronounced imbalance right after each supply resumption. In the early hours of an intermittent supply cycle, a subset of users essentially monopolized the available flow to refill their empty tanks, while others received almost nothing. Quantitatively, the equity index EQ2 captured this stark contrast: at the beginning of the service period, some lower-lying nodes showed EQ2 values approaching 250% (meaning they were receiving 2.5 times their nominal continuous flow rate as they hurriedly filled storage), whereas many higher or distant nodes had EQ2 near 0% (virtually no water). Only after the “advantaged” users’ tanks became full did the situation improve for the rest: later in the cycle, water could finally reach the elevated and remote nodes, causing their EQ2 values to rise while the initially advantaged nodes’ flow rates dropped off. This temporal progression was clearly reflected in the model results, and it underscores that the network under intermittent supply operates in a highly non-uniform, transient regime quite unlike the steady conditions of continuous supply. In essence, intermittent operation creates a moving wave of water availability that does not reach all customers equally or at the same time.

The use of the equity indices provides a succinct way to interpret these findings from a performance and fairness standpoint. Over a full service cycle, the EQ1 index showed relatively modest inequality in total volumes delivered: in the base (100% supply) scenario, all users received between roughly 85% and 100% of their required volume, i.e. volumetric inequity was limited to about a 15% shortfall at worst. This level of aggregate inequity might be deemed acceptable in an emergency supply situation, since nearly everyone eventually gets most of their needed water. However, EQ1 alone does not reveal the serious short-term inequities experienced during the cycle. The EQ2 index exposed those, quantifying the extreme differences in timing and flow rates. At the start of supply, EQ2 values spanned from near 0% for some users to about 250% for others, a range that indicates a dramatic imbalance in service provision. Such a range confirms that the network, when run intermittently, deviates significantly from the design intent of providing uniform service pressure and delivery. From a user perspective, this means that some households perceive the water service as very unreliable (waiting hours for water, or perhaps not receiving any in a given cycle) even though on paper the utility delivered the required volume by the end of the day. This mismatch between technical metrics and customer experience is critical. It implies that water managers must look beyond total supply delivered, and also consider when and how that water is distributed. A user who technically receives 90% of their daily requirement, but only at the very end of the day after repeated delays, will understandably view the service as deficient. As noted in the analysis, such disparities can erode the perceived reliability of the water supply.

The Palermo case study offers practical takeaways for utilities in similar urban contexts with intermittent delivery. It demonstrates the value of advanced hydraulic modeling for diagnosing problem areas: by using a pressure-driven model with realistic user tank behavior, managers can pinpoint which neighborhoods or elevations are at risk of not getting water during each supply window. The introduction of equity indices (EQ1 and EQ2) provides decision-makers with quantifiable measures of fairness, enabling a more informed evaluation of operational strategies. For instance, if simulation shows certain users consistently have very low EQ2 in the early hours, the utility might implement remedial measures – such as staggering the opening

of valves, installing flow restrictors for fast-filling areas, or providing mobile water tankers to high-need zones – to improve equity. The insights also suggest that infrastructure design and planning should account for intermittent operation: networks originally designed for continuous supply may require modifications (e.g. additional sectionalizing valves, booster pumping stations, or enlarged local storage in critical areas) to function acceptably under intermittent regimes. Moreover, communication with customers and managing their expectations becomes easier when the utility can demonstrate that it is monitoring equity: for example, using EQ1/EQ2 metrics to ensure no district is systematically favored or disadvantaged. Ultimately, the model's results underscore that while intermittent supply can be a necessary adaptation to water scarcity (including climate-related droughts), it must be managed carefully to avoid hidden service inequalities. By rigorously quantifying performance and fairness – as done in this study – water managers can devise strategies to maintain an acceptable level of service for all users. This approach strengthens climate resilience for water infrastructure by ensuring that limited water resources are distributed as equitably and efficiently as possible, preserving both technical functionality and public trust in the water supply system.

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