Science of the Total Environment 957 (2024) 177498

Contents lists available at ScienceDirect

Science of the Total Environment

journal homepage: www.elsevier.com/locate/scitotenv

# Assessing the long-term trend of spring discharge in a climate change hotspot area

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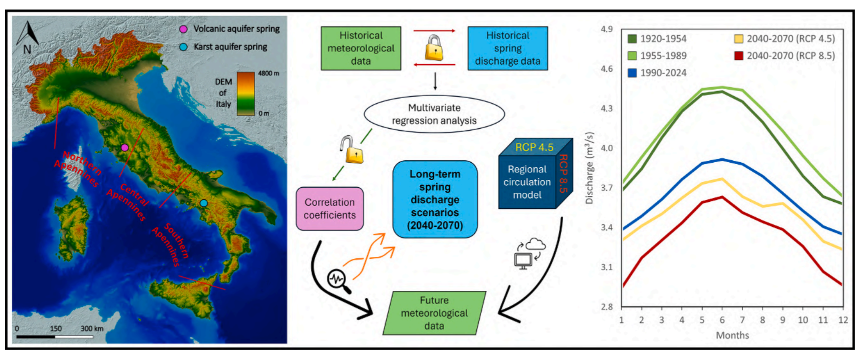
## HIGHLIGHTS

- Long-term effects of climate change on spring discharge under a Mediterranean climate
- Statistical correlation analyses between spring discharge and recharge-related data
- Application of correlation factors to RCPs 4.5 and 8.5 future weather scenarios
- Estimation of long-term spring discharge scenarios for the 2040–2070 period
- A projected 9–11 % decrease in flow rate is expected to affect the studied springs.

## GRAPHICAL ABSTRACT




ARTICLE INFO

Editor: Dan Lapworth

*Keywords:*
Spring discharge
Mediterranean region
Climate change
Multivariate statistics
Regional circulation model
Long-term discharge projections

## ABSTRACT

Global warming affects atmospheric and oceanic energy budgets, modifying the Earth's water cycle. The Mediterranean region is a critical zone for climate change due to a decrease in recharge and an increase in the frequency and severity of droughts over recent decades. While the impacts of possible emissions scenarios on surface water have been extensively studied, the effects on groundwater discharge remain uncertain at both global and local scales. The primary objective of this study is to predict the long-term effects of climate change on the discharge of two springs with extensive discharge records, located in distinctly different hydrogeological settings within the Mediterranean climate zone. Through multivariate statistical analyses on secular time-series, correlation factors were identified between the springs' historical discharge and recharge-related parameters representative of their catchment. Future climate projections from a Regional Circulation Model were used to estimate long-term discharge trends of the springs for the 2040–2070 period. The results indicate that the discharge of both springs, on a multi-decadal trend scale, could decrease by 9 % to 11 % by 2040-2070 compared to that of the past few decades. The consistent negative trends observed across the two different hydrogeological settings suggest that the multi-decadal decline in spring discharge is more influenced by climatic factors than by specific hydrogeological features. This leads to the speculation that similar trends could be expected in other springs within Mediterranean-type climates worldwide. Future water shortages will significantly impact the hydrogeological contexts within these climates. Therefore, the long-term outcomes of this study are crucial for

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https://doi.org/10.1016/j.scitotenv.2024.177498
Received 27 August 2024; Received in revised form 5 November 2024; Accepted 8 November 2024
Available online 19 November 2024

assisting water utility agencies in the sustainable management of groundwater resources, providing them with adequate time to plan and implement large-scale infrastructure projects over the coming decades.

## 1. Introduction

Global climate change is expected to have a significant impact on the water cycle. Extensive studies have been performed on the impact on atmospheric and surface branches of the cycle (Pekel et al., 2016; Trenberth et al., 2003), but comparatively less attention has been provided on the groundwater component. Comprehensive assessments of climate change effects on groundwater resources, particularly in regions encountering increasing qualitative and quantitative impacts on surface water (Secci et al., 2023), are needed given the crucial role of groundwater in providing key ecosystemic services. Climate change affects the recharge of groundwater and in turn the long-term average renewable groundwater resource. This impact arises from rising mean air temperature, shifts in mean precipitation, and modifications in precipitation typology and regime, with extreme regional variability of the effects (Caloiero et al., 2018; Kundzewicz and Döll, 2009). Mediterranean-type climates according to the Köppen-Geiger classification (Kottek et al., 2006) are among the areas of the planet most exposed to droughts, as demonstrated by various researchers (Alilou et al., 2022; Blake et al., 2010; Fiorillo and Guadagno, 2012; Garreaud et al., 2017; Scanlon et al., 2012; Van Loon et al., 2014). In particular, the Mediterranean region stands out as one of the hotspots for climate change, experiencing a rate of global warming that overcomes the global mean trend (Giorgi, 2006; Sivelle et al., 2021; Todaro et al., 2022). These critical factors are expected to have a major impact on groundwater recharge and its future availability.

Among other impacts, the declining discharge of springs has becoming more pronounced in recent decades, as a consequence of recurring droughts (Jeelani, 2008) and the associated shortage of recharge. This alarming trend emphasizes the vulnerability of groundwater to climate-induced alterations of the hydrologic cycle (Hao et al., 2006; Portoghese et al., 2013). In addition to the quantitative aspect, another significant threat to springs, particularly in karst settings (Kalhor et al., 2019), is aquifer pollution resulting from human activities associated with societal development and expansion in the context of a changing climate (García-Ruiz et al., 2011). The infiltration of chemicals and various types of waste into the subsurface degrades groundwater quality and poses risks to both human and ecological health (Balaram et al., 2023). The exploitation of groundwater through the uptake of natural springs discharge is widely common (Simsek et al., 2008) as springs typically provide high-quality water (Nicholson et al., 2018). In the Mediterranean region, especially along the Apennine chain in Italy, spring water frequently serves as the primary source of potable water. Prominent urban centers, such as Rome and Naples, rely on springs to meet the demands of public aqueducts (Kresic and Stevanovic, 2009). Across the Italian peninsula, the effects of climate change on both the quantity and quality of spring discharge have been extensively studied in the southern (Allocca et al., 2014; Fiorillo et al., 2015b; Fiorillo and Guadagno, 2012; Leone et al., 2021; Polemio and Casarano, 2008) and central Apennines (Barbieri et al., 2023; Petitta et al., 2022; Sappa et al., 2018; Sappa et al., 2019). In recent years, these impacts have also been documented in the northern part of the mountain range (Filippini et al., 2024; Rotiroti et al., 2023; Secci et al., 2021).

The connection between recharge and spring discharge in the Mediterranean region, in relation to climate drivers, has been studied through various quantitative approaches, primarily to understand the impacts of climate change on spring flow and, in some cases, to estimate future discharge scenarios as well. These methods include the application of various types of models, such as rainfall-runoff hydrologic models (Cervi et al., 2018; Joigneaux et al., 2011), karst reservoir models (Cinkus et al., 2023; Fan et al., 2023), and multiple hydrogeological numerical models (Doummar et al., 2018; Gattinoni and Francani, 2010; Kovačič et al., 2020; Kovács and Stevanović, 2023). Other estimates of the recharge-discharge connection have been achieved with long-term time series statistical and correlation analyses on data extending back decades or centuries, such as the extensive discharge time series of Sanità Spring (Southern Italy) starting in 1883 (Diodato et al., 2017), the flow monitoring dataset of Fontaine de Vaucluse Spring (South-Eastern France) monitored since 1878 (Bonacci, 2007), or the discharge time series of Serino Spring group (Southern Italy) dating back to 1887 (Fiorillo et al., 2007). Alternative statistical methods were employed by Zhu et al. (2020), who studied the relationship between climatic variables and groundwater discharge using regression coefficients derived from multivariate regression analyses; and by Fiorillo et al. (2015b), who used the Rescaled Adjusted Partial Sums (RAPS) technique to examine the influence of a cyclic atmospheric circulation pattern, the North Atlantic Oscillation (NAO), on spring discharge. Furthermore, Artificial Intelligence (AI) techniques, such as those based on Artificial Neural Networks (ANN) (Smiatek et al., 2013; Wunsch et al., 2022), have been employed to investigate trends and fluctuations in recharge-discharge datasets, also in relation to climate change effects (Secci et al., 2023). Additional ANN studies (Di Nunno et al., 2021; Lambrakis et al., 2000) and studies based on multiple machine learning models (Granata et al., 2018) have focused on the potential for short and medium-term forecasting of spring discharge. Lastly, other researchers have combined multiple methods to simulate spring discharge, such as ANN models with multilinear regression analyses (Gholami and Khaleghi, 2019), or random forest techniques with hydrogeological numerical models (Bouhafa et al., 2024). Although these studies are based on various types of analyses and different initial datasets – most of which do not extend further back than the 1990s – they share a common objective: analyzing the relationship between spring discharge and meteorological variables and/or recurring climate phenomena. Some studies pursue this aim solely to quantify the effects of climate change on the qualitative and quantitative status of groundwater, while others also seek to estimate short-term future discharge trends, sometimes using meteorological scenarios derived from General Circulation Models (GCMs).

To the best of our knowledge, none of the previous studies focus on long-term future discharge estimation, which is essential for allowing water utility agencies sufficient time to plan and implement large-scale infrastructure projects. By establishing long-term discharge relationships with recharge-related meteorological parameters based on extensive historical records (>80 yr; Chen et al., 2004; Leone et al., 2021), there is a potential to project these relationships into the future, leveraging climate scenario data (i.e., General Circulation Models; Klaas et al., 2019; Shepherd et al., 2010) over similar multi-decadal spans. Moreover, all the previous studies considered the dynamics of single springs, missing a broader eye on the global effects of recharge reductions induced by climate change. The discharge dynamics of each spring are undeniably shaped by the features of its basin (Tóth et al., 2022). This complexity poses a challenge in gauging the impact of climate change beyond the boundaries of individual spring watersheds, e.g., extending to broader climatic zones. However, long-term spring discharge dynamics, spanning decades, are typically less tethered to the unique attributes of specific basins and more reflective of climate shifts within a given area (Hartmann et al., 2014; Zhong et al., 2016). Thus, assuming a broader applicability of future multi-decadal discharge trends, these could also aid in managing springs throughout a climatic zone lacking sufficiently extensive hydrogeological data for detailed analysis.

The present research focuses on the application of multivariate statistical analysis to extensive historical discharge records of two springs of the Apennine Mountain chain in Italy. ANN and hydrogeological modeling methods have had various successes in simulating/predicting discharge on relatively short time scales, but it is unclear if they represent a clear advantage for long-term projections based on climate scenarios spanning several decades. Therefore, in this first exploratory paper, we focus on well-tested multivariate regression techniques to assess the potential predictability of spring discharge. The Apennine Mountains are a highly representative example of a Mediterranean setting rich in groundwater discharge through springs, particularly in its southern and central sectors. Most groundwater in this region is stored in karst aquifers (De Vita et al., 2012; Petitta and Tallini, 2002; Sappa et al., 2019). Nonetheless, aquifers with a significant yield are also found in other geological settings, related to volcanic and arenitic formations (Doveri et al., 2012; Filippini et al., 2024). The two investigated springs, namely Sanità (Cervialto Massif, Southern Apennines) and Ermicciolo (Amiata Volcano, Northern Apennines), are associated to watersheds that are affected by similar climatic variability typical of the Mediterranean-type climates, however situated in two very different hydrogeological settings, i.e., a carbonatic karstified massif and a fractured volcanic structure, respectively. For both springs, continuous discharge monitoring is available with at least monthly measurements, from the beginning of the 20th century and extending to the present day. The aim of the study is to identify the historical connection between spring discharge and recharge-related meteorological parameters from a multi-decadal perspective, to utilize this relationship in conjunction with future meteorological variables projected by GCMs to assess the multi-decadal discharge availability for the period 2040–2070.

## 2. Geological and hydrogeological settings

The Apennine Mountain chain is the backbone of the Italian peninsula and extends for about 1200 km in a NW-SE alignment, between Ligurian-Tyrrhenian Seas to the West, and Adriatic-Ionian Seas to the East. The chain is subdivided into Northern, Central and Southern Apennines (Fig. 1a). From a geological standpoint, Apennines are a Neogene accretionary fold-thrust belt that formed from the subduction between the African Plate below Eurasia within the Alpine System (Patacca et al., 1993). The structure of the chain presents a series of tectonic units thrusted over each other, subjected after the

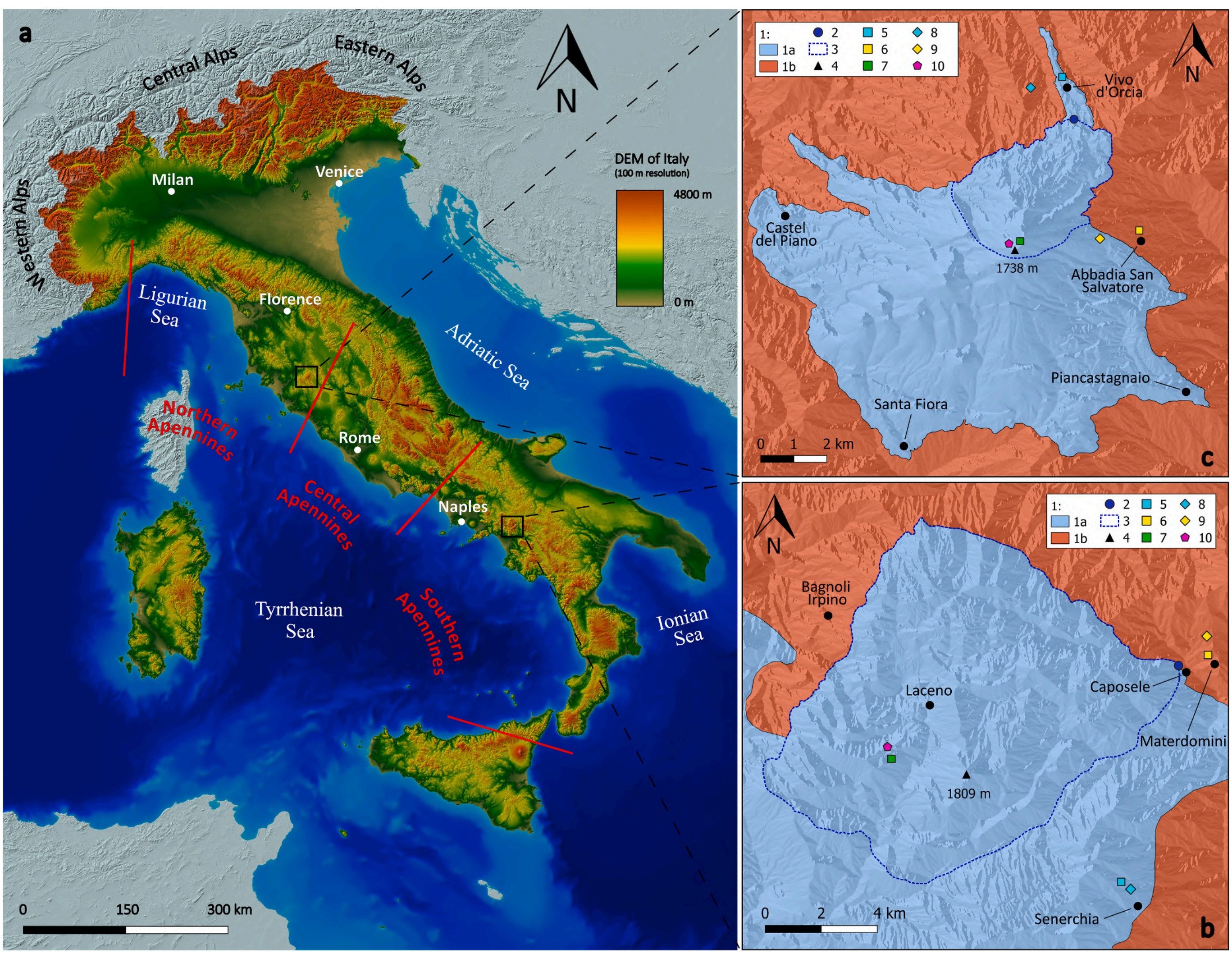


**Fig. 1.** Location of the two study areas in the Apennines Mountain chain: (a) 100 m resolution Digital Elevation Model (DEM) of Italy realized by the National Institute of Geophysics and Volcanology (INGV) (Tarquini et al., 2023), with indication of the Apennines subdivision into Northern, Central and Southern sectors; (b) 1. Geological formations; 1a. Karst aquifer; 1b. Aquitard units; 2. Sanità Spring; 3. Sanità Spring catchment; 4. Cervialto Massif peak; 5. "Senerchia" rain gauge; 6. "Materdomini" temperature gauge; 7. "Rifugio Laceno" snow gauge; 8. CMCC-CLM TLP chosen grid point; 9. CMCC-CLM 2 m °C chosen grid point; 10. ERA5 (HSR) snowfall chosen grid point; (c) 1. Geological formations; 1a. Volcanic aquifer; 1b. Aquitard units; 2. Ermicciolo Spring; 3. Ermicciolo Spring catchment; 4. Mount Amiata peak; 5. "Vivo d'Orcia" rain gauge; 6. "Abbadia San Salvatore" temperature gauge; 7. "Monte Amiata" snow gauge; 8. CMCC-CLM TLP chosen grid point; 9. CMCC-CLM 2 m °C chosen grid point; 10. ERA5 (HSR) snowfall chosen grid point.

compressional phase to an extensional one with volcanic activity in the Tyrrhenian side (Carminati et al., 2010; Carminati et al., 2012).

The first of the two investigated springs, Sanità Spring, is situated nearby the village of Caposele in Campania Region (Southern Apennines) at an elevation of 417 m above sea level (asl) (40° 48′ 58.8″ N, 15° 13′ 13.9″ E) (Fig. 1b). Sanità Spring, with a mean annual discharge of 4.0 $m^3$/s, is considered the most significant spring draining the Cervialto Massif (peak elevation of 1809 m asl), one of the main Meso-Cenozoic carbonate platforms of the Central-Southern Apennines, acting as key groundwater reservoir (Allocca et al., 2014; Fiorillo et al., 2015b). The Cervialto Massif is composed of a series of limestone and limestone-dolomite (Late Triassic-Miocene) with a thickness ranging between 2500 and 3000 m (Fiorillo et al., 2021). Karst processes have transformed the morphology of the massif creating endorheic areas known as 'polje', surrounded by steep slopes of 35°–45° controlled by fault scarps, where recharge is concentrated, constituting almost the entire contribution area of Sanità Spring (Fiorillo et al., 2015a). The spring is of strategic significance to Southern Italy, particularly for the Puglia Region, which represents one of the areas with the lowest precipitation in the central Mediterranean region, receiving approximately 600 mm of annual precipitation. The water from Sanità Spring is conveyed through a 450 km long gravity-driven series of tunnels and bridges from the Campania Region to the southernmost part of Puglia since the 1930s (Fiorillo, 2009). The climate in Sanità Spring catchment area is Mediterranean and falls within the "Csa" category according to the Köppen-Geiger classification (Kottek et al., 2006). The average annual precipitation and temperature at the mean elevation of the spring catchment are approximately 1500 mm and 12.1 °C (www.centrofunzionale.regione.campania.it).

The second spring of interest, Ermicciolo Spring, is situated along the northern slope of Mount Amiata, in the southern part of the Tuscany Region at an elevation of 1020 m asl (42° 55′ 25.8″ N; 11° 38′ 29.5″ E), approximately 100 km to the south-west of the Northern Apennines main divide (Fig. 1c). Ermicciolo Spring is one of the major springs in the Tuscany region, with a mean annual discharge of about 0.15 $m^3$/s and a maximum recorded flow rate of nearly 0.4 $m^3$/s. Mount Amiata (peak elevation of 1738 m asl), an extinct volcano, represents the youngest Quaternary volcanic edifice of the Tuscan Roman Magmatic Province (Frondini et al., 2009) and covers an outcropping surface of about 80 $km^2$. The evolution of the volcano is associated to the most recent Apenninic post-orogenic extensional phase that occurred between 300 ky and 190 ky, when several dacitic, rhyodacitic and olivine-latitic eruptions gave rise to the volcanic edifice (Bortolotti and Passerini, 1970). From a hydrogeological perspective, the volcanic structure is a fractured aquifer that can be broadly divided into two distinct groundwater flow systems separated by a dynamic groundwater divide located near the peak of the mountain (Fig. 1c; Doveri et al., 2012), with Ermicciolo Spring being fed by the northernmost system. Amiata aquifer stands as one of the crucial groundwater reservoirs for Southern Tuscany as it feeds major springs utilized by the local water company, providing

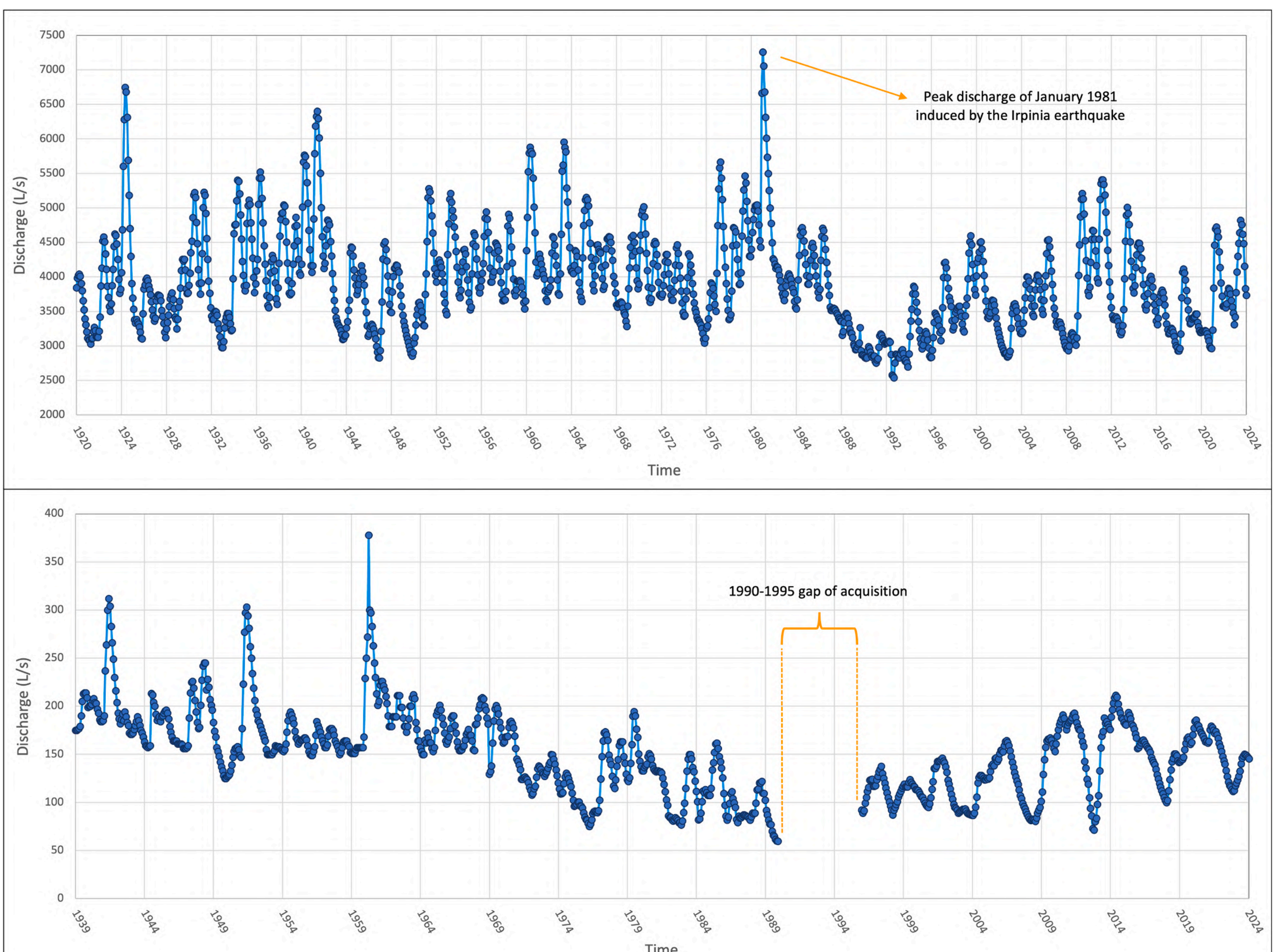


**Fig. 2.** Mean monthly discharge of Sanità (top) and Ermicciolo (bottom) Springs. The labels on the x-axis indicate January of each respective year.

drinkable water to the surrounding lowlands and coastal areas, which are characterized by lower precipitation, aquifer overdrafting, and groundwater salinization issues. The climate in the spring catchment is Mediterranean and categorized as "Csb" (Beck et al., 2023), with average annual precipitation and temperature of about 1200 mm and 10.6 °C (www.sir.toscana.it).

## 3. Materials and methods

### 3.1. Discharge monitoring

Measurements of the total discharge at Sanità Spring started in January 1920 (Fig. 2) when the Italian National Hydrographic Institute established a systematic monitoring. The spring is uptaken by the water company Acquedotto Pugliese S.p.A. (AQP) since the beginning of twentieth century (Fiorillo and Guadagno, 2012) with an artificial draining tunnel, characterized by several niches, along the discharge front at the base of the mountain slope. A portion of the spring discharge is released as overflow, providing ecological services to a local river. Originally, the discharge was quantified through a hydrometric reel along the main channel, with a monitoring frequency of two times per month (on the 2nd and 16th day of each month). Since their introduction in 1927, Venturi tubes have allowed for more frequent discharge measurements (Fiorillo et al., 2021). The monitoring system was further improved in 1980, when data acquisition became daily.

Ermicciolo Spring is uptaken through a draining tunnel constructed between 1908 and 1914 (Parco Vivo, 2019 - https://www.parcovivo.it/sorgenti-del-monte-amiata/) on the north side of Mount Amiata aquifer complex. The tunnel is lined with concrete and connects three niches in the walls, enabling direct gravity drainage of groundwater from the aquifer's primary transmissive fractures. A portion of the spring discharge is withdrawn by the local water utility, Acquedotto del Fiora S.p.A. (AdF) (Doveri et al., 2012), while the excess overflows from the tunnel into a nearby stream. Total flow rate data are available from 1939 to nowadays, with a gap of acquisition from 1990 to 1995 inclusive (Fig. 2). Initially, flow rate monitoring was performed manually using stage measurements with a thin-wall weir, at a variable frequency of 2–3 times per month. Since the 1990s, an automatic contactless hydrometer has been installed, with a measurement frequency of four and a half hours (approximately 5 measurements per day).

The hydrographs in Fig. 2 represent monthly values, each averaged from all available single-shot measurements corresponding to that month.

### 3.2. Thermo-pluviometric and snowfall data

Monthly average air temperature and monthly cumulative precipitation data for the catchment area of the two investigated springs were obtained from local meteorological stations managed by regional authorities (Fig. 1), within the same time intervals covered by spring discharge monitoring. The stations used for Sanità Spring watershed are the "Senerchia" station for precipitation (approximately 600 m asl), and the "Materdomini" station for air temperature (550 m asl) (www.centrofunzionale.regione.campania.it). For Ermicciolo Spring catchment the "Vivo d'Orcia" station was considered for precipitation (about 842 m asl), while air temperature was acquired from the "Abbadia San Salvatore" station (855 m asl) (www.sir.toscana.it).

Precipitation time series at the selected stations were collected through non-heating rain gauges. Thus, their capacity to record snowfall precipitation is poor. Snowfall is a fundamental parameter for groundwater recharge in mountainous regions in terms either of snow depth or of permanence of snow to the ground (Halloran et al., 2023), as also put in evidence in the investigated sites (Doveri et al., 2012; Petitta et al., 2022). To avoid the risk of underestimating total precipitation in the springs' catchment area, it was decided to add the snowfall precipitation, as measured by local specific snow gauges, to the liquid precipitation recorded by conventional rain gauges. This approach has been recently adopted by other authors for hydrogeological budgeting of an Alpine area in Northern Italy (Stevenazzi et al., 2023). However, time series of direct measurements of snowfall in the investigated areas are available only for the most recent 30–40 yr, and can be found on the MeteoMont website (meteomont.carabinieri.it), a service for avalanche prevention and forecasting. Specifically, the available data include the number of days with snow-covered ground and the total snowfall within 24 h; for our study, only the daily snowfall data were collected and then aggregated into monthly cumulative totals. The snowfall stations "Rifugio Laceno" (1460 m asl) and "Monte Amiata" (1700 m asl) were selected as representative of Sanità and Ermicciolo Springs catchment, respectively (Fig. 1). In the former case, data are available from 1996 to the present, while in the latter from 1982.

Snowfall data from earlier decades were estimated by reconstructing them using the fifth version of ECMWF ReAnalysis (ERA5) data. Reanalyses combine historical observations with models to generate consistent time series of various atmospheric and ground variables at numerous grid points, with precise coordinates, centered and pertaining to a specific area (Tarek et al., 2020). Developed by the European Centre for Medium-Range Weather Forecasts (ECMWF), ERA5 provides hourly data, spanning from 1940 to 2023, for atmospheric, land-surface, and sea-state parameters, with a $\simeq$31 km horizontal resolution (Hersbach et al., 2020). For both case studies, monthly cumulative snowfall data were selected from the nearest ERA5 node to the local MeteoMont snow gauge. To achieve even better spatial resolution, the new dataset created by Raffa et al. (2021) was also utilized, albeit covering only the period 1981–2023. This dataset is based on a dynamically downscaling over Italy of the ERA5 reanalysis, improving the horizontal resolution to approximately 2.2 km. Monthly cumulative snowfall data were picked from two nodes of the ERA5 dataset with High Spatial Resolution (HSR) (Fig. 1), chosen based on their distance to the two snow gauges pertaining to MeteoMont.

#### 3.2.1. Past snowfall data reconstruction

In the time frame where ERA5 and ERA5 HSR datasets overlap (1981–2023), a linear regression analysis was performed to determine the coefficients linking the datasets. Through these coefficients, the ERA5 HSR time series was extended back to 1940. The same procedure was then applied between the extended ERA5 HSR and the local snow gauge time series to similarly reconstruct the MeteoMont snowfall data back to 1940. These steps were undertaken for both Sanità and Ermicciolo Springs catchment to obtain snowfall data with the highest possible spatial resolution and the longest possible temporal coverage. Once the snowfall data was reconstructed (Fig. 3) it was converted into Snow Water Equivalent (SWE). Given that the initial data of the three datasets are provided on an hourly or, at most, daily basis, it can be assumed that the recorded snowfall data represent recently fallen and uncompacted snow. Consequently, a density of 100 kg/m$^3$ was used in converting snowfall precipitation to SWE (Mekis and Brown, 2010). Assuming a density of rainwater of 1000 kg/m$^3$, the data conversion was performed by a simple division by 10. The resulting data were added to the rainfall data. This process yielded a combined precipitation measure, referred to as the Total Liquid Precipitation (TLP), which represents the aggregate contribution of both liquid and solid forms of precipitation, with the latter contributing to a lesser extent.

### 3.3. Combined statistical analysis of spring discharge and meteorological variables

To unravel the relationship between meteorological parameters and spring discharge, univariate and multivariate linear regression analyses (Gholami and Khaleghi, 2019; Zhou and Zhang, 2023) were conducted on historical meteorological data (cumulative TLP and average monthly air temperature) as independent variables, and on monthly discharge data as the dependent variable.

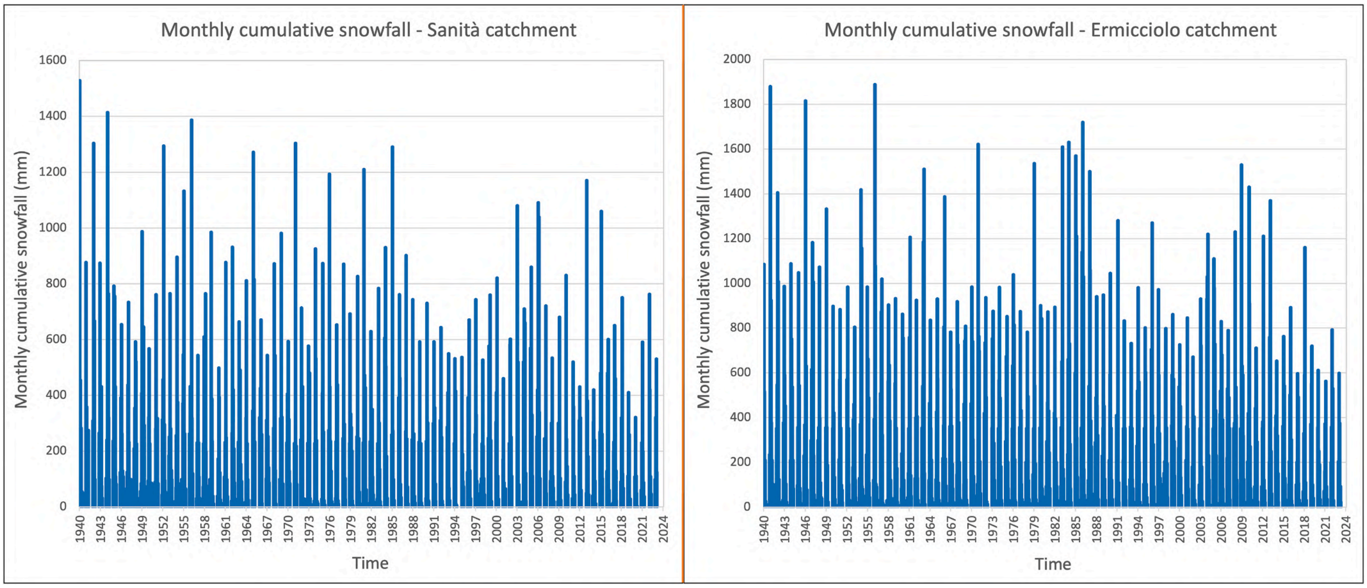


**Fig. 3.** MeteoMont monthly cumulative snowfall (1940–2023), partially reconstructed (1940–1996 for Sanità Spring and 1940–1982 for Ermicciolo Spring) using ERA reanalyses, pertaining to the contribution area of Sanità (left) and Ermicciolo (right) Springs.

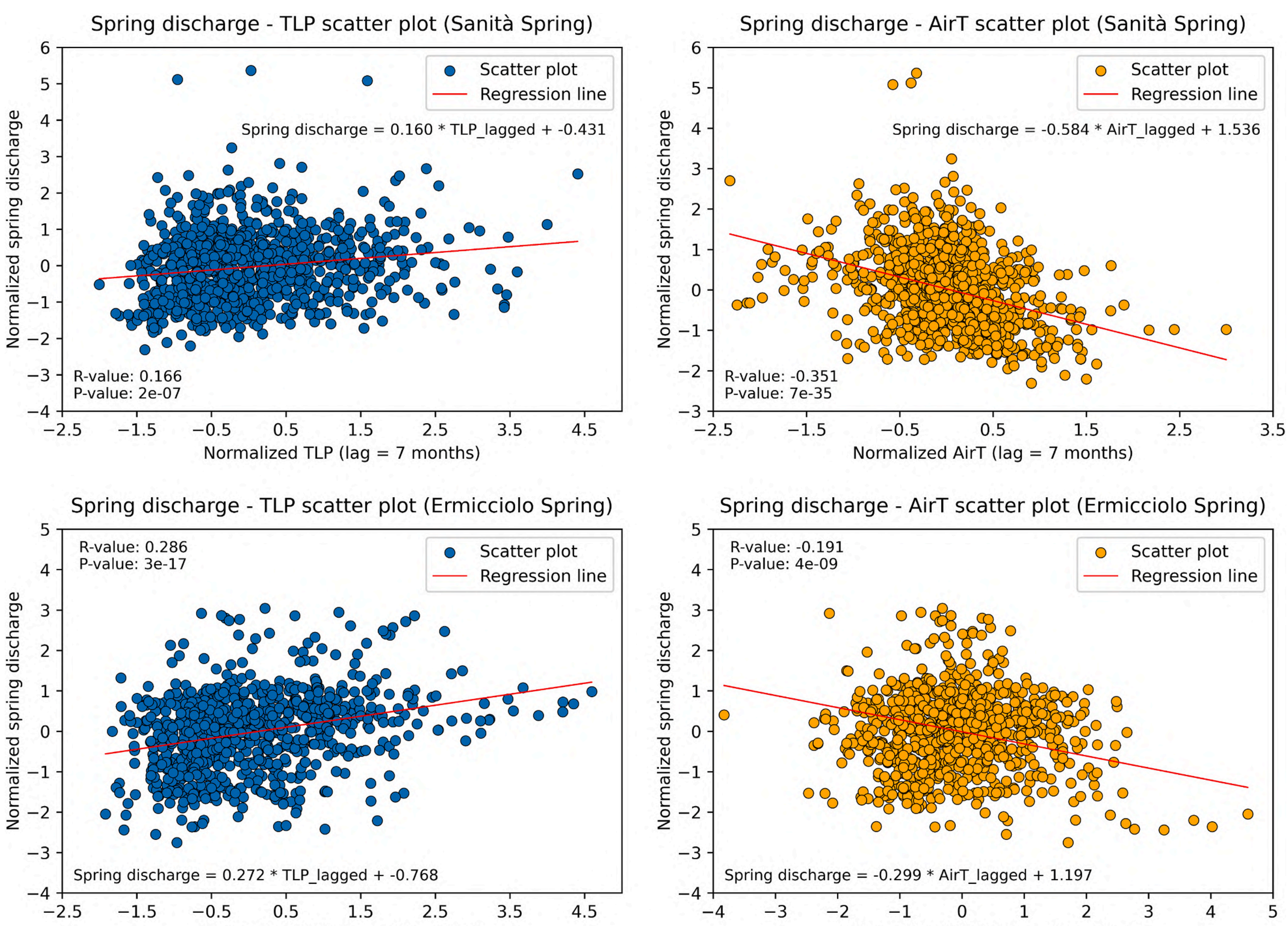


**Fig. 4.** Scatter plots resulting from the univariate linear regressions performed between the dependent variable (spring discharge) and the independent variables (TLP and AirT). For both case studies, the lag time that yields the best correlation (i.e., the highest R-value) with spring discharge is 7 months for both meteorological variables. The relatively modest R-values are due to noise in the data.

Prior to regression analyses, all datasets underwent normalization using monthly mean and standard deviation values calculated from the whole dataset (1940–2023), a process commonly referred to as anomaly normalization (Brockwell and Davis, 2016). Specifically, each value in the dataset was transformed by subtracting the mean of the corresponding month and then dividing by the standard deviation calculated across the entire data population for that same month. Data normalization plays a crucial role in the analysis of time series with disparate units of measurement and numerical scales, ensuring fair comparisons among parameters (Montgomery et al., 2008).

As a first step, separate linear regressions were performed between the dependent variable (discharge) and each independent variable, TLP or air temperature (AirT), to analyze the individual relationships between these parameters and to identify possible variable-specific time lags to be considered in the subsequent multivariate analyses. Once the correlations among the individual variables were established, twelve different monthly lags, ranging from 1 to 12 months, were implemented in the linear regression. The time lag that yielded the highest R-value, indicating a stronger relationship between the parameters, was selected (Fig. 4).

The multivariate statistical analysis was performed using the Ordinary Least Squares (OLS) model from the Python statsmodels library (Seabold and Perktold, 2010). The OLS model is a commonly utilized linear regression technique that evaluates, through the estimation of Correlation Factors (CF), the relationship between a dependent variable and one or more independent variables by minimizing the sum of the squares of the differences between the observed and predicted values (Farahani et al., 2010; Hayes and Matthes, 2009). Additionally, the OLS model determines the uncertainty associated with the regression coefficients by estimating confidence intervals for these factors. The *p*-value, used to assess the significance of the relationship between variables, and the R-squared, which represents the proportion of variance in the dependent variable explained by the independent variables (Kutner et al., 2005; James et al., 2013), were also evaluated.

### 3.4. Estimation of future spring discharge

#### 3.4.1. RCPs 4.5 and 8.5 climate projections

The Representative Concentration Pathways (RCPs), provided by the Intergovernmental Panel on Climate Change (IPCC, 2014), are climate scenarios, expressed in terms of greenhouse gas concentrations (Van Vuuren et al., 2011), that estimate emissions of greenhouse gasses (GHG) and air pollutants levels of 8.5, 6.0, 4.5 and 2.6 $W/m^2$, by the end of the century. These RCPs were estimated depending on both socio-economic development scenarios and the associated climate policies that will be implemented to reduce the production of GHG. For example, the RCP 4.5 scenario anticipates that emissions will be halved by 2080, while the RCP 8.5 scenario represents an estimate of emissions that will be reached by the end of the century if no additional efforts are made to constrain the generation of greenhouse gasses.

General Circulation Models (GCMs) using multiple emission scenarios (Klaas et al., 2019; Shepherd et al., 2010) represent the most advanced instruments for simulating the response of the global ocean-atmosphere system to climate changes (Shahgedanova et al., 2020). The RCPs are indeed employed in GCMs to estimate future meteorological variables. General Circulation Models require a downscaling process to represent the hydrogeological watershed-scale dynamics, which involves obtaining more detailed and localized information (Gudmundsson et al., 2012; Haylock et al., 2006). Ban et al. (2021) enhanced the downscaling capabilities of GCMs by providing climate data with a spatial resolution ranging from 1 to 3 km and an hourly temporal resolution. These improvements reduce associated errors and add value to the estimation of atmospheric variables at the local scale.

Each of the RCPs covers the 1850–2100 period and is reported at a $0.5 \times 0.5^\circ$ spatial resolution (approximately 40–55 km) (Van Vuuren et al., 2011). To achieve a better spatial resolution of the future climate scenarios, projections derived from the Euro-Mediterranean Center on Climate Change Foundation — Climate Model (CMCC-CM), elaborated with the RCPs 4.5 and 8.5, were utilized (Raffa et al., 2023). These estimates, which are available from January 2006 up to December 2070, were generated at approximately 2.2 km resolution through a dynamical downscaling process using the regional climate model "COSMO-CLM" (Consortium for Small-scale Modeling - Climate Limited-area Model) over Italy, allowing for the generation of highly detailed and comprehensive datasets of projected climatological data (Raffa et al., 2023). Just as for the ERA5 reanalyses data, these future projections over Italy were computed at numerous grid points, pertaining to a specific area. For this study, monthly data were selected for the variables "Total precipitation" and "2 m temperature", covering each of the Sanità and Ermicciolo Springs catchments. The variables were acquired from grid nodes based on their proximity to meteorological stations (Fig. 1), ensuring relevance to the collected historical thermo-pluviometric data. Furthermore, data were acquired for both RCPs 4.5 and 8.5, providing insights into both moderate and more extreme climate futures. Before using these meteorological projections, quality control was performed on the data. Considering the period spanning from January 2006 to December 2023, during which both the climate projections and the historical data from weather stations are available, a comparison was made to detect and correct any constant deviations of the scenarios from the actual historical data. The historical and forecasted meteorological time series were compared by means of simple subtractions. This process facilitated the verification of the presence of any deltas between each meteorological parameter.

#### 3.4.2. Application of CF to weather scenarios

The regression equations and corresponding correlation factors obtained from the OLS models were applied to the two selected meteorological data outputs of the 4.5 and 8.5 future projections (2040–2070), previously normalized using the same approach described in Section 3.3 for past time series. The normalized future discharge dataset for Sanità and Ermicciolo Springs were then determined between January 2040 and December 2070, for both RCP 4.5 and RCP 8.5 scenarios. Subsequently, the projected discharges were denormalized by applying the reverse process described for normalization, using the same monthly means and standard deviations, in order to obtain the estimated spring discharge values for the period 2040–2070.

### 3.5. Multi-decadal hydrographs

With the aim of analyzing the long-term trend of spring discharge, a multi-decadal cycle approach was used. Considering that at least 30 yr of data are required to appreciate climate trend (Livezey et al., 2007), the historical flow rate dataset of Sanità Spring was divided into three 35-yr subsets: 1920 to 1954, 1955 to 1989, and 1990 to 2024. As for Ermicciolo Spring, the historical discharge data were divided into three multi-decadal groups, with the oldest one spanning only 16 yr: 1939 to 1954, 1955 to 1989, and 1990 to 2024. The two most recent periods are consistent with that of Sanità Spring, thereby enabling a comparison between the multi-decadal discharge values of the two springs. In both cases, the historical discharge subsets were plotted along with standard deviation uncertainty bands around the mean, defined by adding/subtracting the standard deviation of the monthly spring discharge values for each multi-decadal group to the mean of those values. The projected discharge data of Sanità and Ermicciolo Springs were graphed alongside the historical data by creating two 30-yr groups for each spring, spanning from 2040 to 2070, respectively in relation to RCPs 4.5 and 8.5 scenarios. For the future discharge estimates, the uncertainty bands around the mean were derived from the flow rate values obtained through the lower and upper bounds of the coefficients' confidence intervals determined by the multivariate OLS models.

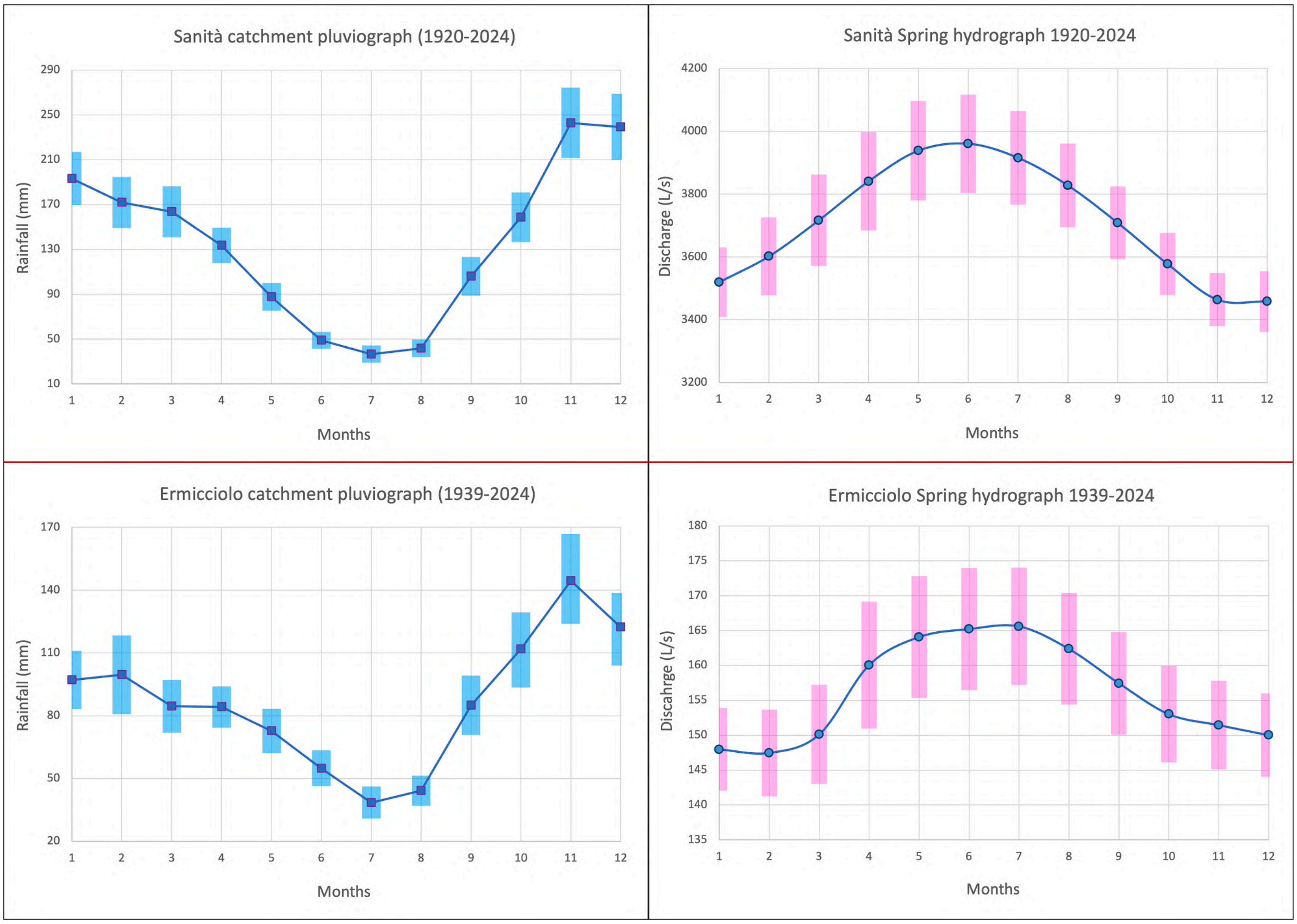


**Fig. 5.** Monthly mean rainfall of Sanità and Ermicciolo Springs reference rain gauges (on the left); monthly mean discharge of Sanità and Ermicciolo Springs (on the right). For each monthly mean value, the error bar represents the 95 % confidence interval.

## 4. Results

### 4.1. Discharge time series

Sanità and Ermicciolo Springs have century-long continuous discharge monitoring dating back to January 1920 and 1939, respectively, and extending to the present. In Fig. 2, the last data point represented is that of January 2024 and the data are presented as monthly averages in accordance with the temporal scale used in the statistical analyses of the present study. Sanità Spring hydrograph since 1920 (Fig. 2) exhibits an annual cyclic variation in relation to recharge, with the yearly peak discharge occurring between May and July, and the low flow period between November and December (Fig. 5). The average hydrological year for this spring, throughout the entire monitoring period, exhibits a discharge ranging from approximately 3.3 $m^3$/s to 5.4 $m^3$/s (Fig. 2), placing it within the second (II) class of Meinzer's (1923) spring discharge classification. Ermicciolo Spring hydrograph since 1939 (Fig. 2) shows a peak discharge during the same months as Sanità, while the low flow occurs slightly later, between January and February of the following year (Fig. 5). The average spring discharge of Ermicciolo fluctuates from roughly 90 L/s to 210 L/s (Fig. 2), placing it between the III and IV classes of Meinzer's classification. Notably, a decreasing trend in Ermicciolo Spring Meinzer's class is apparent when comparing the periods before and after the mid-1970s.

The secular discharge data of Sanità and Ermicciolo Springs have the potential to provide valuable insights into changes in water resource availability due to climate change effects, given (i) the length of the series, (ii) the systematic quality of the records and (iii) the absence of human-made alteration of the natural conditions of the aquifers, for the almost absence of pumping wells or groundwater draining facilities (Doveri and Menichini, 2017; Leone et al., 2021). The only significant effect not attributed to natural recharge variations is linked to the major earthquake of November 23rd, 1980 (Surface wave Magnitude – Ms – 6.9, the Irpinia earthquake). With its epicenter located approximately 10 km southeast of Sanità Spring, the earthquake impacted the spring's discharge, leading to an extraordinary anomalous value of 7.32 $m^3$/s recorded on January 19th, 1981 (Fiorillo and Guadagno, 2012) (Fig. 2).

### 4.2. Regression analysis

Before conducting the linear regression analyses, we applied multiple tests to explore potential non-linear or threshold relationships between the variables. The results did not provide any significant evidence of these patterns (high *p*-value) in each of the four univariate cases, suggesting that the linear form of the model is appropriate for our datasets. The univariate linear regressions (Fig. 4) showed that, for Sanità and Ermicciolo Springs, discharge has the strongest negative correlation with the average AirT (R-value: −0.351 and −0.191, respectively) and the strongest positive correlation with cumulative TLP (R-value: 0.166 and 0.286, respectively) with a time lag of 7 months (Fig. 4), which is consistent from a physical standpoint as peak liquid precipitation (representing the majority of TLP) occurs in November, while peak discharge is observed in summer (Fig. 5). It is also logical that air temperature is more strongly correlated with spring discharge at the same lag time as TLP, since higher air temperatures increase evapotranspiration, thereby reducing the effectiveness of precipitation in recharging aquifers (Cardell et al., 2020). Thus, a time lag of 7 months was used in the subsequent multivariate analysis for AirT and TLP. The two variables registered 7 months in advance compared to discharge will be called "$AirT_{Lag7}$" and "$TLP_{Lag7}$" hereafter.

For both Sanità and Ermicciolo Springs, the multivariate analysis confirms a positive correlation between $TLP_{Lag7}$ and discharge (Q), and a negative correlation between $AirT_{Lag7}$ and discharge. Specifically, for the Sanità Spring, the OLS model produced the following equation (Eq. 1):

$$Q_{San} = +0.143 + 0.183*TLP_{Lag7} - 0.544*AirT_{Lag7} + \varepsilon \quad (1)$$

where "$Q_{San}$" represents the dependent variable, which in this case is the predicted flow rate of Sanità Spring, the error term "ε" represents the difference between the observed value of the dependent variable and the value predicted by the linear regression model, and "$TLP_{Lag7}$" and "$AirT_{Lag7}$" are the independent variables.

The confidence intervals provided for the coefficients are calculated at the 95 % confidence level. Specifically, for the $TLP_{Lag7}$ variable, the confidence interval bounds of the relative Correlation Factor (CF) are [+0.253, +0.113], resulting in an uncertainty margin of ±0.07; for $AirT_{Lag7}$, the CF confidence interval bounds are [−0.414, −0.674], indicating a margin of error of ±0.13; for the intercept term the confidence interval bounds are [+0.213, +0.073], resulting in an uncertainty margin of ±0.07.

Similarly, for Ermicciolo Spring, the regression equation (Eq. 2) is as follows:

$$Q_{Erm} = -0.032 + 0.278*TLP_{Lag7} - 0.289*AirT_{Lag7} + \varepsilon \quad (2)$$

where "$Q_{Erm}$" represents the predicted discharge of Ermicciolo Spring, "ε" is the error term, and "$TLP_{Lag7}$" and "$AirT_{Lag7}$" are the recharge-related independent variables.

The confidence intervals for the coefficients calculated at the 95 % confidence level are the following: for $TLP_{Lag7}$, the confidence interval bounds of its regression coefficient with the discharge are [+0.338, +0.218], resulting in an uncertainty margin of ±0.06; for the $AirT_{Lag7}$ variable, the CF confidence interval bounds are [−0.089, −0.489], indicating a margin of error of ±0.20; for the intercept term, finally, the confidence interval bounds are [+0.038, −0.102], resulting in an uncertainty margin of ±0.07.

Both models exhibit statistically significant results, as evidenced by the consistently low p-value, remaining below $1 \times 10^{-4}$ in both case studies, indicating a high level of confidence in the observed relationships.

### *4.3. Future recharge-related meteorological parameters*

Thanks to the comparison of climate projections with historical meteorological data for the 2006–2023 period, it was found that in both case studies, the historical precipitation aligns closely with both projections of the RCPs 4.5 and 8.5 scenarios, with a maximum monthly deviation of 15 %. However, a systematic bias was found for the 2 m temperature leading to a deviation from historical data of 2 °C in the case of Sanità Spring catchment and 3 °C in the case of the Ermicciolo's one. These constant deviations were then used to adjust the entire historical series of future temperature projections.

Considering the adjusted RCPs 4.5 and 8.5 future data (2024–2070) and the historical values (1940–2023), it is evident that air temperature will experience a significant increase in the future, whereas total precipitation, which has shown a relatively increasing trend from the 1990s to the present, is projected to undergo a considerable decrease (Fig. 6).

### *4.4. Multi-decadal spring discharge analysis*

The multi-decadal analysis of Sanità Spring discharge data displays an average flow rate ranging from approximately 3580 to 4430 L/s during the oldest 1920–1954 historical band (Fig. 7), with a standard deviation uncertainty band that varies from 70 to 180 L/s both below and above the average value. The intermediate historical band (1955–1989) is characterized by the highest discharge and partially overlaps with the first band. It covers a range between 3820 and 4630 L/s, with an uncertainty band oscillating from 80 to 150 L/s indicating lower variability compared to the preceding period. The most recent historical band (1990–2024) shows an average discharge ranging from 3360 to 3920 L/s, with a standard deviation uncertainty band that fluctuates around the mean of 70–130 L/s, suggesting less variability in the data. The uncertainty bands for the two future discharge scenarios (2040–2070) exhibit even lower variability, ranging from 60 to 120 L/s on both sides of the average value, giving them a narrower appearance. In the RCP 4.5 scenario an average discharge from 3220 to 3830 L/s is observed, with the band slightly intersecting that of the most recent 35-yr historical period. In the more severe RCP 8.5 scenario, the average discharge varies from 2970 to 3630 L/s, showing a partial overlap with the values of the other future scenario.

Concerning Ermicciolo Spring, the three historical bands show a progressively lower average discharge moving from the two older periods to the most recent, with the following discharge ranges: 172–201 L/s (1939–1954), 135–157 L/s (1955–1989), and 131–147 L/s (1990–2024) (Fig. 8). The standard deviation uncertainty bands vary from 5 to 11 L/s in the first two cases and from 8 to 11 L/s in the third, suggesting an overall lower variability in the data population compared to Sanità Spring. Regarding the bands of the two future discharge scenarios (2040–2070), the average discharge ranges from 131 to 146 L/s in the RCP 4.5 scenario and from 116 to 131 L/s in the 8.5 scenario. In both cases, the data variability is very low, with bands oscillating of only 2–5 L/s around the mean. Additionally, a partial overlap exists among the two most recent historical bands and the future one related to the RCP 4.5 scenario.

## 5. Discussion

The hydrographs of the investigated springs (Fig. 2) provide insights into both the specific features of the hydrogeological setting, and the broader effects of climate change over the Apennines Mountain chain.

The flow rate of Sanità Spring indeed shows greater variability compared to that of Ermicciolo Spring. This difference is linked to the typical dynamics of a karst environment. Ermicciolo Spring, on the other hand, reflects the dynamics of a less heterogeneous fractured context (i.e. a volcanic aquifer) than the former, resulting in less discharge variability. However, univariate regression at both springs reveals a robust, inverse statistical correlation between AirT and monthly discharge, with a lag of 7 months. In contrast, the cumulative monthly TLP exhibits a statistically significant positive correlation with the discharge over the same time lag (Fig. 4). Surprisingly, the same time lag between the historical independent variables and historical spring discharge was found to characterize two rather different hydrogeological watersheds. Sanità Spring is fed by a karst system that is expected to show quicker discharge responses to precipitation compared to the lower permeability fractured volcanic aquifer feeding Ermicciolo Spring. Nonetheless, it appears that the extensive catchment associated to Sanità Spring can considerably delay the effects of direct recharge. The contribution area of the spring is 110 $km^2$ (Fiorillo and Doglioni, 2010), whereas Ermicciolo Spring catchment is one tenth the area, at around 13 $km^2$ (Doveri and Raco, 2021). For this reason, the similar TLP lag identified for the two watersheds is considered reasonable.

Regarding the effects of global warming on spring discharge along the Apennines, Fig. 2 indicates that climate change in the Mediterranean region has negatively affected the discharge availability of Sanità and

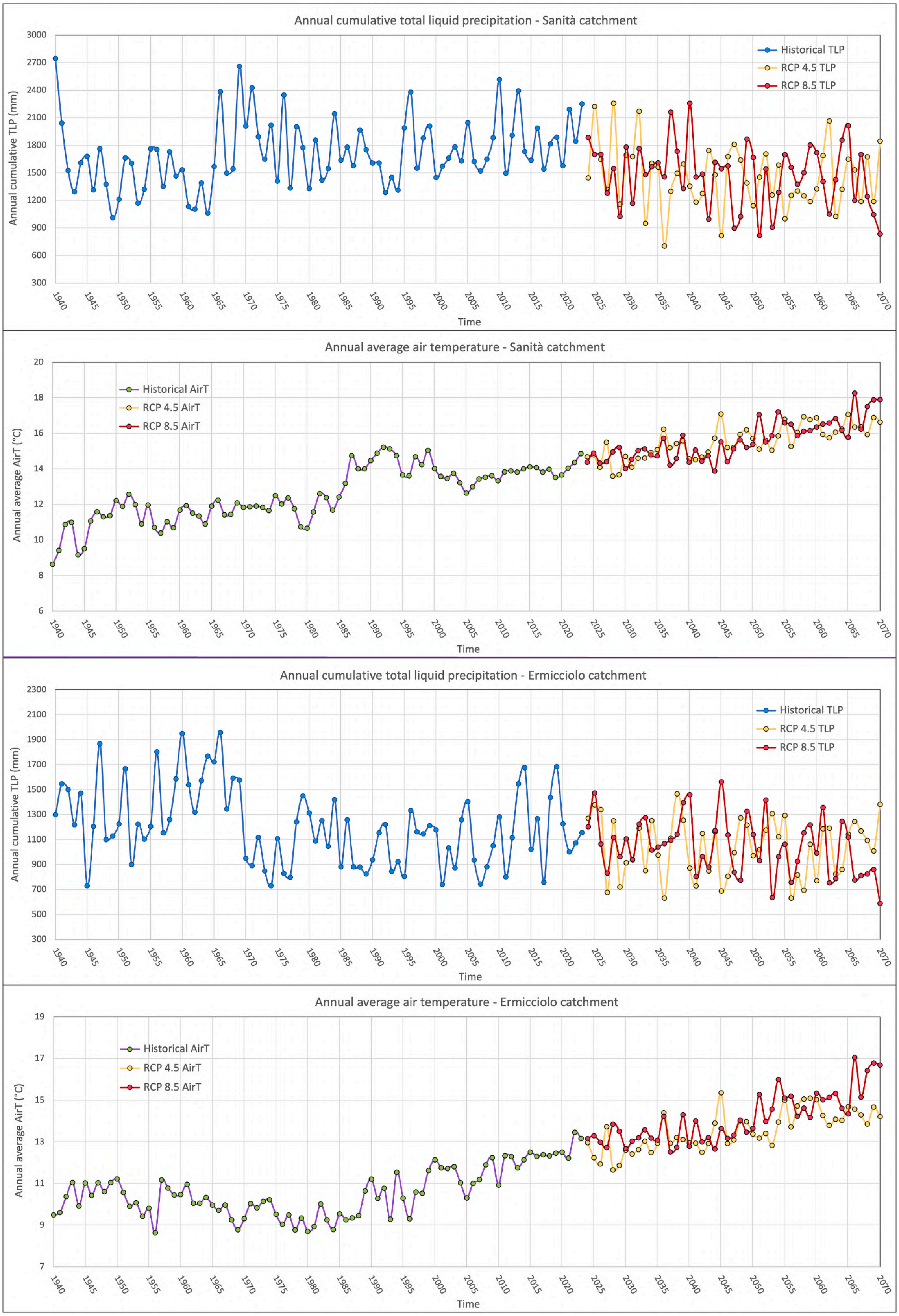


**Fig. 6.** Plots of annual cumulative TLP and mean annual AirT for the contribution area of Sanità (top) and Ermicciolo (bottom) Springs. Both historical data (1940–2023) and future projections of the RCPs 4.5 and 8.5 scenarios (2024–2070) are plotted on all graphs.

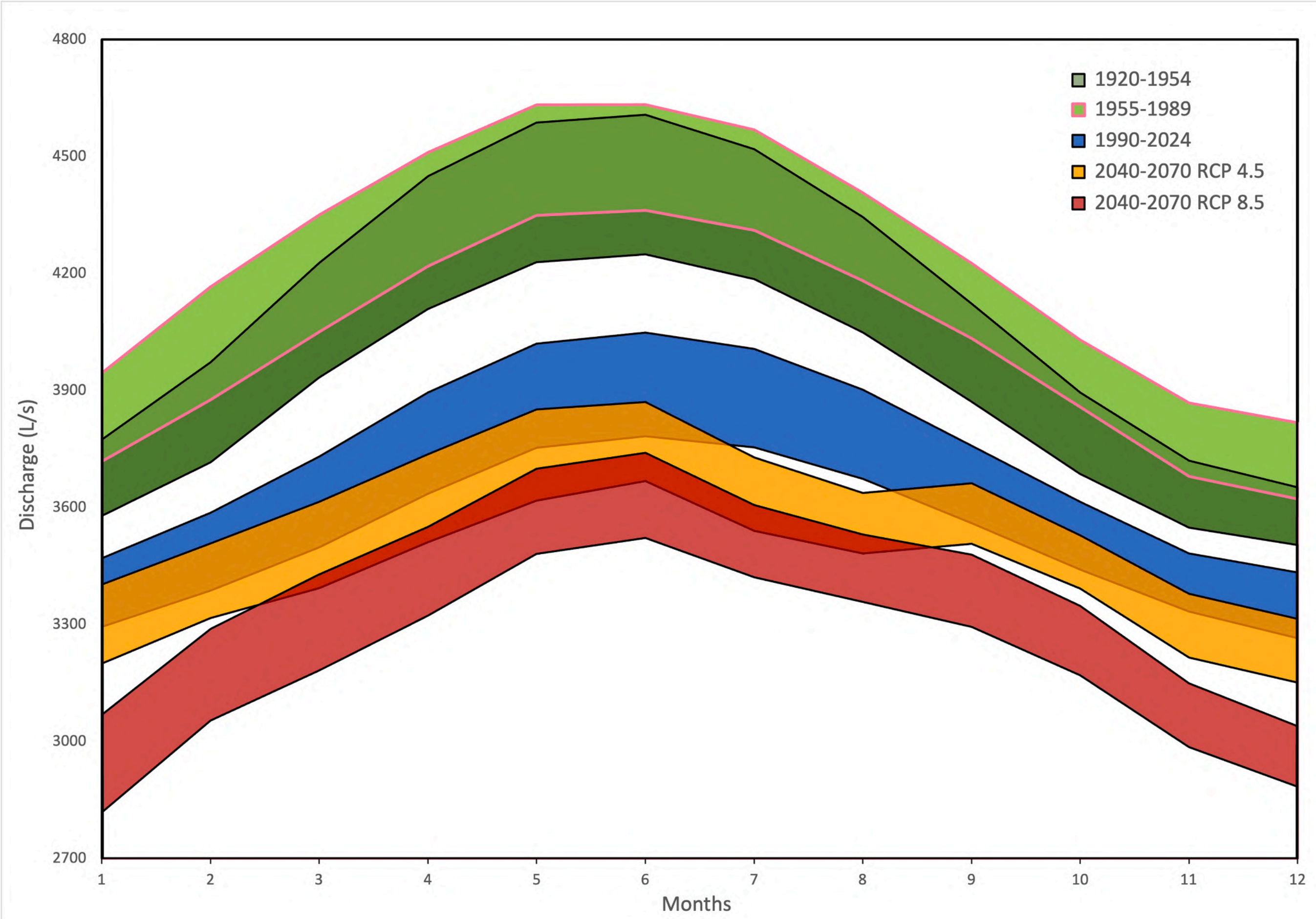


**Fig. 7.** Hydrographs of Sanità Spring based on the mean multi-decadal approach with uncertainty bands. Three bands are constructed using historical data, while the remaining two are built using the future discharge projections resulting from the multivariate statistical analysis performed on the Sanità dataset.

Ermicciolo Springs over the past 3–4 decades. At the multi-decadal scale, negative consistent historical trends are indeed observed between the two springs, with the last 35-yr period exhibiting a decrease in discharge and reduced data variability in both case studies compared to the previous period (Fig. 7, Fig. 8). At Sanità Spring, the percentage discharge decreases between the most recent period, 1990–2024, and the intermediate period, 1955–1989, was a significant 12.5 %. In contrast, at Ermicciolo Spring, the reduction over the same periods was only 3.7 %. The greater reduction in discharge at Sanità compared to Ermicciolo can likely be attributed to the Irpinia earthquake, which temporarily caused a substantial increase in discharge that partially depleted the aquifer in the following 3–4 yr. Moreover, previous research (Fiorillo and Guadagno, 2012) shows a discharge drop after 1986 in many springs in Southern Italy, plausibly related to climate change, which is consistent with the trend observed in Sanità Spring.

The expected rise in air temperatures in the Mediterranean region will result in increased evapotranspiration and consequent reduction of liquid precipitation recharging the aquifers (Cardell et al., 2020; Rosenberg et al., 1999; Yusoff et al., 2002). Moreover, there will be adverse effects on solid precipitation, as already observed in Italy in recent decades (Diodato et al., 2019; Diodato et al., 2022), with a shorter duration of snow permanence to the ground and a significant reduction in total snowfall (also confirmed in the two study areas, Fig. 3), further amplifying the groundwater recharge reduction. Additional critical factors that impair recharge must be considered, including the projected decrease in total precipitation associated with the RCPs 4.5 and 8.5 scenarios (Fig. 6), as well as the increased frequency of extreme precipitation events, which is expected to reduce the infiltration rate relative to the surface runoff rate.

Given the concerning future outlook for groundwater in the Mediterranean region, a multivariate OLS model was employed in both case studies to estimate future spring discharge. With this model, we sought to identify the regression coefficients linking recharge-related variables to spring discharge using nearly century-long historical datasets (1940–2023). Although climatic conditions are changing with increasing rates and variability in recent decades (Caloiero et al., 2018), the assumption underlying our study is that the processes by which meteorological factors affect spring discharge remain consistent when looking at a long-term trend. For this reason, using only the past decade or the past two to three decades (during which climate change has accelerated) for the multivariate analyses was not considered ideal for identifying the best long-term recharge-discharge relationships. As evidence of this, during the validation process of both the multiregression models, we tested the use of only these recent decades; however, the results showed lower statistical significance and much weaker correlations between the variables compared to those of the 1940–2023 data models, potentially leading to unreliable predictions.

Thanks to the correlation factors derived from the OLS 1940–2023 data models (Eq. 1, Eq. 2), it was possible to estimate the future discharge scenarios of Sanità and Ermicciolo Springs within the 2040–2070 period. The reconstructed discharge clearly exhibits a further decreasing trend compared to the historical dataset of both springs, with some differences in relation to the chosen RCP scenario. Under the RCP 4.5 scenario, the future discharge projections appear to

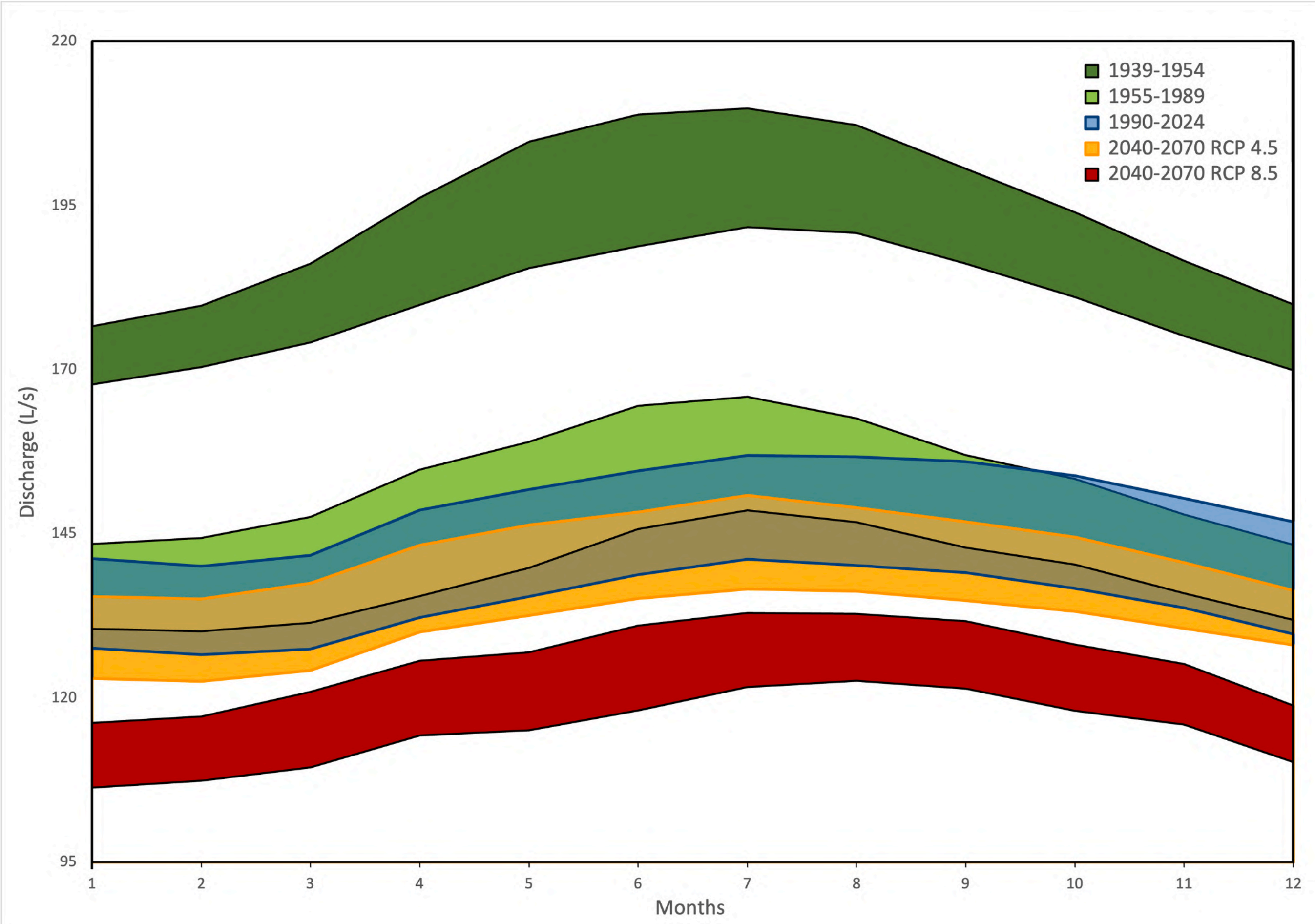


**Fig. 8.** Hydrographs of Ermicciolo Spring based on the mean multi-decadal approach with uncertainty bands. The division of discharge bands is the same as in Fig. 7.

show no excessive impairment in flow rate output compared to the most recent historical period (Fig. 7, Fig. 8). Indeed, the estimated decrease in discharge is only 3.0 % for Sanità Spring and 0.1 % for Ermicciolo Spring. Conversely, under the more severe RCP 8.5 scenario, characterized by higher greenhouse gas emissions, a further decrease in spring discharge is evident in the 2040–2070 time frame, with a percentage decrease of 8.6 % relative to the 1990–2024 interval (19.9 % when compared to the 1955–1989 period, characterized by the highest groundwater yield), at Sanità Spring, and a similar percentage decrease of 10.8 % relative to the most recent 35-yr period (or even 33.3 % when compared to the 1939–1954 time frame) at Ermicciolo Spring.

The results in terms of percentage associated with the RCP 8.5 scenario indicate that Sanità Spring could lose, over the 2040–2070 period, an average of 9.8 million $m^3$ of water/yr, when compared to the annual average discharge of the last 35 yr. Regarding Ermicciolo Spring, the future estimated discharge loss respect to the 1990–2024 interval amounts to almost 0.5 million $m^3$/yr, considering the same scenario. Analyzing these losses in spring discharge and considering a daily water consumption per person of 220 L (Eurispes, 2023 - https://eurispes.eu/en/news/a-system-that-treads-water-the-condition-of-water-in-italy/), the average annual decrease in discharge at Sanità equates to the annual demand of a city with 122,000 inhabitants. Applying the same calculation to the results obtained for Ermicciolo Spring, the decrease in discharge would be sufficient to meet the water needs of a town of over 6000 inhabitants.

Given that long-term spring discharge dynamics, which span decades, tend to be less influenced by the specific characteristics of individual basins and more indicative of broader climate shifts within a region (Hartmann et al., 2014; Zhong et al., 2016), the similar multi-decadal downtrend in spring discharge forecasted through future climate factors for both Sanità and Ermicciolo Springs for the 2040–2070 period is likely extendable to other settings within Mediterranean-type climates.

The approach presented here offers new insights into the ability to estimate future trends in groundwater discharge. Recent studies in the literature have employed machine learning methods, particularly Artificial Neural Networks, as well as hydrogeological numerical models, to achieve the same objective of estimating future spring discharge. These studies have demonstrated the capability to accurately forecast spring discharge from weeks up to three months ahead (Granata et al., 2018) or even up to 12 months (Di Nunno et al., 2021). Some researchers have also managed to estimate annual peak and minimum spring discharge values up to the end of the current century using these methods (e.g., Doummar et al., 2018; Fan et al., 2023). However, both approaches present certain limitations. As highlighted by Cinkus et al. (2023) and Di Nunno et al. (2021), these methods require high temporal resolution data, ideally daily or at least bi-weekly measurements. Moreover, they struggle to reproduce long-term discharge values and extreme events, and are often time-consuming to run. The multivariate statistical analysis approach, although it may provide less accurate short-term forecasts compared to ANN-based systems (Gholami and Khaleghi, 2019), offers the advantage of making long-term discharge projections using only monthly resolution data, provided the analysis is applied to century-long datasets, as in the present research. This method allows for the estimation of expected long-term annual peak and minimum discharges for springs, as well as the generation of springs' hydrographs over a multi-decadal time span, depicting monthly discharge fluctuations in the mid-to-late 21st century (2040–2070).

## 6. Conclusions

Two strategic aqueduct springs, Sanità and Ermicciolo, located along the Apennines Mountain chain (Italy) in two distinct hydrogeological settings but under a similar Mediterranean-type climate, have been the focus of this work due to their rare, century-long historical record of discharge data. The study approach was based on the multivariate statistical correlation between spring discharge and recharge-related data (air temperature and total precipitation), representative of the springs' catchment area. The regression coefficients derived from the statistical analyses were then applied to projected meteorological data from the RCPs 4.5 and 8.5 future climate scenarios to estimate the long-term discharge trend for both Sanità and Ermicciolo Springs. Under the most severe emission scenario, a significant decrease in discharge is observed for both springs during the 2040–2070 period compared to the most recent historical one (1990–2024). The estimated percentage decrease in flow rate between these two periods is 8.6 % at Sanità Spring and 10.8 % at Ermicciolo Spring, corresponding to a reduction in discharge of 310 L/s and 15 L/s, respectively. It is important to note that these decreases will affect two springs that, due to climate change, are already experiencing a decline in discharge compared to previous decades. Past and future multi-decadal discharge reductions are consistent across two different hydrogeological settings, suggesting a greater influence from climatic drivers (common to both sites) as opposed to the specific hydrogeological features of the individual catchments. This allows us to speculate that the observed negative trends may also be valid in other springs within similar climatic contexts. There is a strong and widespread perception that water scarcity in the future will profoundly impact the Apennines, already facing water crises (Fiorillo et al., 2015b; Fiorillo and Guadagno, 2012). This has been confirmed in the northern part of the chain as well (Filippini et al., 2024), and most likely these negative effects will be extended to many major springs within similar Mediterranean-type climates. Therefore, for local public water supply companies, the results obtained in this work hold significant importance as they allow for proactive measures in addressing forthcoming water crises within their respective management areas, and possibly beyond. The methods applied in this study hold potential for application in other hydrogeological settings, contingent upon the availability of continuous secular datasets for both spring discharge and meteorological parameters.

## CRediT authorship contribution statement

**T. Casati:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **A. Navarra:** Writing – review & editing, Validation, Methodology, Conceptualization. **M. Filippini:** Writing – review & editing, Writing – original draft, Investigation, Conceptualization. **A. Gargini:** Writing – review & editing, Writing – original draft, Validation, Supervision, Project administration, Investigation, Conceptualization.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Acknowledgements

The authors wish to express their gratitude to the public water supply companies Acquedotto Pugliese S.p.A. and Acquedotto del Fiora S.p.A., for granting access to the springs discharge data. Special thanks are directed to Gerardo Ventafridda and Massimo Bellatalla, who served as vital points of communication with the respective entities. Additional appreciation is extended to Acquedotto Pugliese S.p.A. for supporting this research as part of the first author's doctoral program, which included an internship period at the company's headquarters in Bari, Puglia Region. The authors also acknowledge Paola Mercogliano from CMCC for facilitating access to the future climate scenarios. This research was supported by the Fondo Sociale Europeo (FSE) with resources from the Recovery Assistance for Cohesion and the Territories of Europe (REACT-EU) program, through the Programma Operativo Nazionale (PON) of the Ministero dell'Istruzione, dell'Università e della Ricerca (MIUR) for doctoral reasearch in innovation and green topics, 37$^{th}$ PhD cycle.

## Data availability

Thermo-Pluviometric data are available on the website of the Centro Funzionale Multirischi della Protezione Civile Regione Campania (www.centrofunzionale.regione.campania.it), pertaining to the Sanità Spring catchment, and on the web page of the Centro Funzionale della Regione Toscana (www.sir.toscana.it), relating to the Ermicciolo Spring catchment; snowfall data for both case studies can be downloaded from the website of the Servizio MeteoMont del Comando Carabinieri per la tutela Forestale (meteomont.carabinieri.it); ERA5 and ERA5 HSR snowfall data are available respectively on the web pages of the Copernicus Climate Data Store (cds.climate.copernicus.eu), operated by the European Centre for Medium-Range Weather Forecasts, and the CMCC Data Delivery System (dds.cmcc.it), developed by the Euro-Mediterranean Center on Climate Change Foundation; future climate projections under the RCPs 4.5 and 8.5 scenarios can also be accessed on the CMCC Data Delivery System; discharge data have been provided by Acquedotto Pugliese S.p.A., Bari, Italy, and by Acquedotto del Fiora S.p.A., Grosseto, Italy.

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