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Climate change as main driver of centennial decline in river sediment transport across the Mediterranean region

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ABSTRACT

The analysis of suspended sediment transport and of its variations over time is crucial for understanding environmental evolution and it is the key to future challenges caused by current global warming. The Mediterranean area is a hot spot for global changes, and the variation of precipitation amount and intensity will modify the environment of this region.

In this work, we analyse the time series of suspended sediment transport of two rivers located in central Italy by using statistical and artificial intelligence techniques. Our study aims to re-analyze time series of suspended sediment transport, in order to demonstrate that climate change is responsible for the substantial decrease in the amount of sediment over the past century, in relation to the atmospheric teleconnections of the North Atlantic. Anthropic pressures like reforestation, land use change, and dam building have influenced the sediment transport capacity of rivers, causing a reduction of sediment concentration in water.

These results are key factors to determine the future management of the Mediterranean areas, where the future scenarios predict a greater drop in yearly precipitation, and therefore a possible further decrease in the sediment transport capacity of the rivers, with major consequences for coastal and fluvial environments.

1. Introduction

Suspended sediment transport plays a fundamental role in geomorphological and hydrological processes in the fluvial environments and affects the coastal sediment budget. The complex interplay between sediment transport and other important factors, both climatic and anthropogenic, significantly impacts sediment balance and morphology of watercourses (Asselman, 1995; Gurnell et al., 2002; Hooke, 2006; Naik and Jay, 2011). This interdependence between sediment transport, climatic conditions, and human activities constitutes a crucial field of study to understand the underlying mechanisms of these events and to formulate suitable strategies for land management. The impact of these factors can vary considerably according to the specific characteristics of each watershed. While climatic fluctuations such as precipitation and temperature can influence sediment mobilization, anthropogenic activities like deforestation, urbanization, and water resource management can introduce significant alterations to the solid transport regime (Asselman, 1995; Favaro and Lamoureux, 2015; Naik and Jay, 2011; Rodríguez-Blanco et al., 2016; Surian and Rinaldi, 2004; Thodsen et al., 2008).

However, a comprehensive understanding of human-climate interaction is often hindered by the lack of measured data and challenges in analysing existing historical records. This lack of accurate data restricts our ability to quantify the specific contribution of each factor to overall sediment transport and to predict how potential changes might affect the sediment balance of watercourses.

The significance of suspended sediment transport extends beyond its impact on river basins; it also plays a pivotal role in shaping coastal environments. The intricate interplay between sediment transport, both in suspension and along the bed, and various factors including climatic and anthropogenic influences, deeply affect the morphology and evolution of the coastlines. Indeed, the sediment discharged from rivers into coastal waters contributes to the formation of deltaic landforms, beach replenishment, and overall equilibrium of coastal ecosystems (Leatherman et al., 2000; Zhang et al., 2004).

In this context, the Mediterranean region emerges as an optimal area to undertake studies aimed at exploring temporal variations in suspended sediment transport linked to anthropogenic pressures associated

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with high population density (El Mahrad et al., 2020; Newton et al., 2014), and to its status as climate change hotspot (Cos et al., 2022; Giorgi, 2006). A thorough study of the data and regions within the Mediterranean holds significant importance, as it poses a pivotal challenge for accurate future spatial planning of these fragile areas.

The application of machine learning (ML) techniques in climate research has aroused considerable interest (Reichstein et al., 2019). Such methods have proven useful in various tasks including downscaling, data mining analyses, and prediction of climate variable time series such as temperature, humidity, and runoff (Almikaeel et al., 2022; Chattopadhyay et al., 2020; Lupi et al., 2023; Luppichini et al., 2022a; Ng et al., 2023). Previous studies have shown that climatic time series contain valuable information about the temporal dynamics of complex systems, including essential properties like chaos (Livieris et al., 2020; Patil et al., 2001). Consequently, there is growing concern about the capability of machine learning algorithms to accurately capture and reconstruct these temporal dynamics (Carroll, 2018; Du et al., 2017; Pathak et al., 2017; Watson, 2019). Machine learning has shown great promise in reconstructing the chaotic attractors of systems like the Lorenz and Rossler models (Carroll, 2018; Pathak et al., 2017). These findings are crucial for a deeper understanding of the potential applications of machines in climate research. Machine learning models are used to predict and reconstruct suspended sediment load in different types of rivers (e.g., Alp and Cigizoglu, 2007; Buyukyildiz and Kumcu, 2017; Melesse et al., 2011; Salih et al., 2020; Samantaray et al., 2020).

In this study, we focus on the Ombrone and Arno rivers located in central Italy, where the catchment experienced the climatic condition and the anthropogenic impact typical of many Mediterranean areas –, including a general reduction in river discharge as a result of diminished atmospheric precipitation (Baronetti et al., 2022; Blöschl et al., 2020, 2019; Deitch et al., 2017; Fratianni and Acquaotta, 2017; Gentilucci et al., 2019; Longobardi and Villani, 2010; Lopez-Bustins et al., 2008; Merz et al., 2014), and of marked anthropogenic pressure followed by the abandonment of reforestation in the last decades (Hooke, 2006; Sorriso-Valvo et al., 1995; Surian and Rinaldi, 2004). In this work, we have used the repository of the best historical data series of the last century made available by the Italian territorial authorities. We intend to define a possible methodology based on a statistical and mathematical approach for the study of the Mediterranean areas. In particular, the methodology is based on the statistical analysis of the trends of precipitation, flow rate, and suspended sediment transport, and their relationship with the North Atlantic Oscillation Index (*NAOI*), which is the main atmospheric driver of the Northern Hemisphere (Deser et al., 2017; Hurrell, 1995; Hurrell et al., 2019, 2003; Hurrell and Kushnir, 2003; Visbeck et al., 2001). We intend to re-examine the dynamics of suspended sediment transport by using machine learning models for a more detailed analysis of the past trend of the time series, in order to hypothesize and predict future scenarios. Finally, this work is designed to investigate the relation between sediment concentration and flow rate. Any variations in this ratio indicate changes in sediment availability within the watershed, while climatic variations help to understand whether there have been any changes in transport capacity. This study will enable us to contribute by pinpointing a technique capable of ensuring the continuity of solid transport time series, thereby addressing the data gap in this crucial subject. Possessing continuous and extensive historical series over time will empower us to refine numerous studies and fully comprehend the morphological dynamics of many environments associated with river regimes and how they will be affected by the

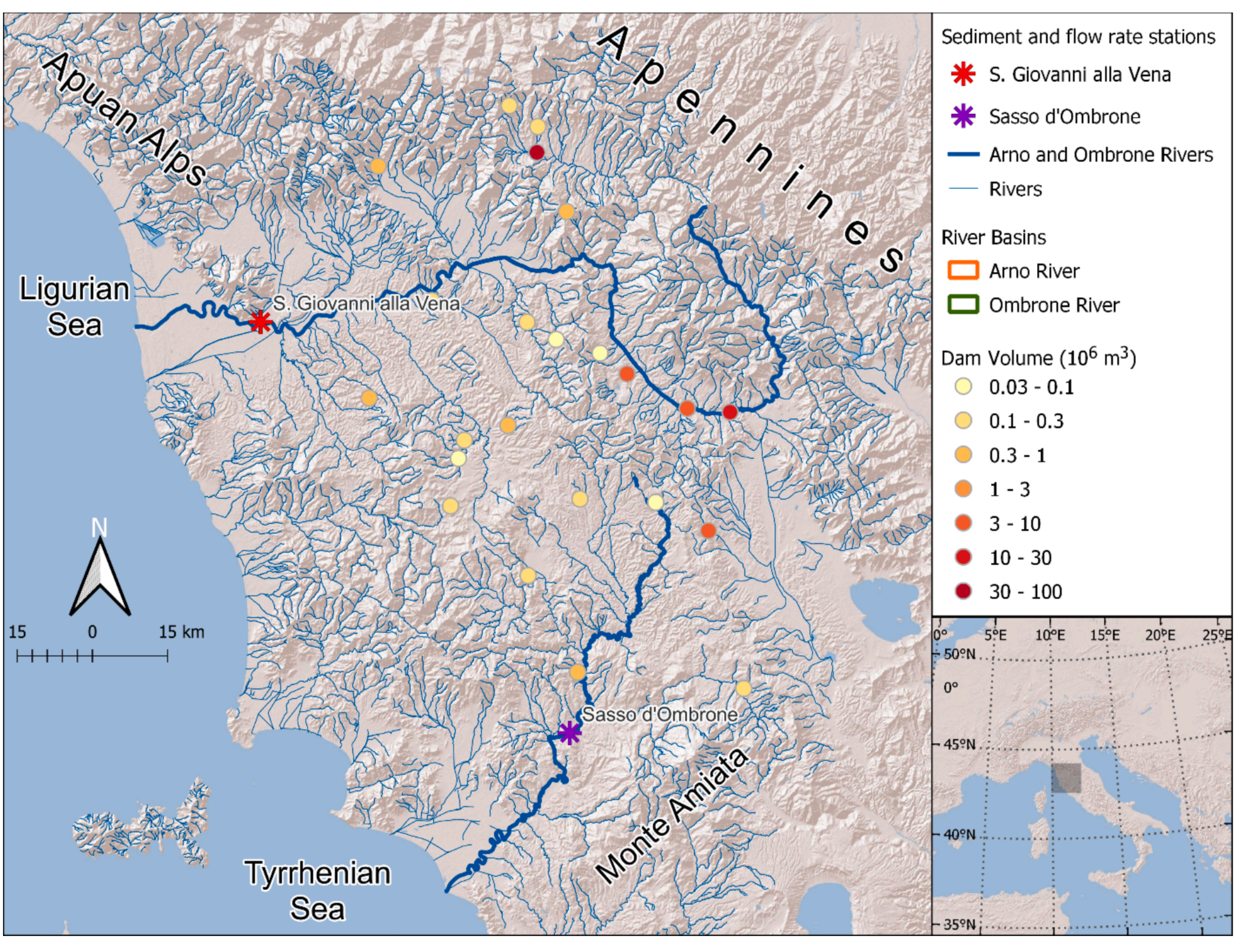

Fig. 1. Study area.

current global warming.

2. Study area

This study is focused on the Arno and Ombrone Rivers, located in central Italy (Fig. 1). Both rivers have a watershed area of about 8500 km^2 and 3550 km^2, respectively. The Arno River Basin (ARB) is bordered by the Apennine chain from north to east, while the Ombrone River Basin (ORB) is flanked by Monte Amiata. Since 1930, several dams have been constructed in the two basins, 18 dams in the ARB, and 5 dams in the ORB (Fig. 1). The Arno and Ombrone Rivers are characterized by a great variability between the dry and the overflow phases. The Arno River has a mean flow rate of about 85 m^3/s and the 99th percentile is about 740 m^3/s. The Ombrone River is characterized by a mean flow rate of 32 m^3/s and a 99th percentile of about 310 m^3/s.

Starting from the beginning of the last century the coastal areas bordering the two river deltas have been marked by erosion processes (Anfuso et al., 2011; Besset et al., 2019, 2017; Bini et al., 2021, 2008; Cipriani et al., 2013, 2001; Pratellesi et al., 2018). Despite the absence of precise direct measurements, several authors have identified a decrease in sediment load transportation as the main cause of coastal erosion in this area (e.g., Bini et al., 2021; Pratellesi et al., 2018).

The basins of the Arno and Ombrone rivers have been characterized by an increase of the woodlands in the last century, while the areas along the two rivers have been home to several dams since 1930. The changes in the woodland area and the cumulative volume of dams in the ARB and ORB are shown in Fig. 2. The forest area coverage is derived from a database of the territorial authorities and from the Copernicus database (https://land.copernicus.eu/pan-european/corine-land-cover), while the dam dataset has been provided by the *Ministero delle Infrastrutture e dei Trasporti* of the Italian Government (https://dgdighe.mit.gov.it/categoria/articolo/_cartografie_e_dati/_cartografie/cartografia_dighe).

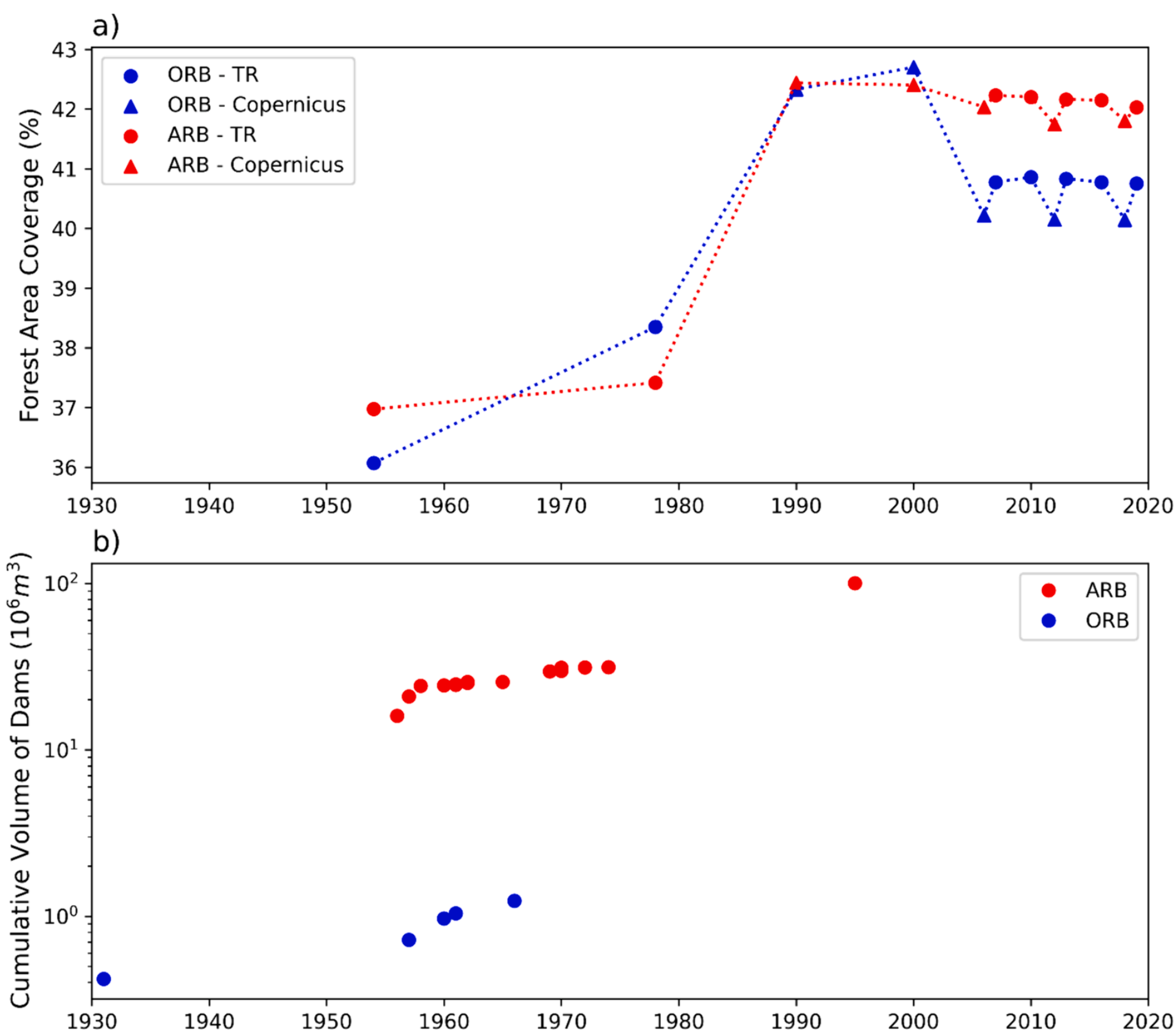

Fig. 2. Changes in soil use over time for the Arno River Basin (ARB) and for the Ombrone River Basin (ORB). a) Changes in forest area coverage: the data represented by the dots derive from the Tuscany Region database, while the data represented by the triangles derive from the Copernicus database (https://land.copernicus.eu/pan-european/corine-land-cover); b) Cumulative volume of dams built in the Arno River Basin (ARB; red dots) and Ombrone River Basin (ORB; blue dots): the data are extracted from the dataset of the "Ministero delle Infrastrutture e dei Trasporti" of the Italian Government (https://dgdighe.mit.gov.it/categoria/articolo/_cartografie_e_dati/_cartografie/cartografia_dighe). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

3. Methods

3.1. Precipitation and temperature data

In this study, the suspended sediment and river flow rate time series are compared to the precipitation and temperature data, in an attempt to understand the presence of any relations between these climate variables. The precipitation and temperature times series are provided by the Regional Hydrological Service of the Tuscany Region (http://www.sir.toscana.it/). The precipitation time series are located in Florence, Pisa, and San Miniato for the ARB and in Grosseto for the ORB (Fig. 1). The temperature time series are referred to the stations of Florence and Pisa for the ARB, and to the stations of Grosseto for the ORB. These time series are the longest and most complete for the two study areas since before the 1950′s.

3.2. Suspended sediment and river flow rate data

The "Italian Hydrographic and Mareographic Service" has manually collected suspended sediment samples from the Arno and Ombrone rivers. The main stations for the Arno and the Ombrone are located at S. Giovanni alla Vena and at Sasso d'Ombrone, respectively (Fig. 1). The measurements of the suspended sediment were acquired at S. Giovanni alla Vena in the period 1936–1985, and at Sasso d'Ombrone in the period 1953–1991. The Hydrologic Annals yield the maximum (C_M), minimum (C_m), and mean monthly suspended solid concentrations ($C_A; kg/m^3$), the maximum (Qs_M), minimum (Qs_m), and mean monthly solid discharges (Qs_A), where:

$$Qs = C\hat{A}\cdot Qw(kg/s) \quad (1)$$

and Qw is the river flow rate.

The *Italian Hydrographic and Mareographic Service* also collected the daily Qw data, which were digitalized by the Regional Hydrological Service of the Tuscany Region (http://www.sir.toscana.it/). The Qw time series of S. Giovanni alla Vena and of Sasso d'Ombrone are the longest and most complete for both the Arno and the Ombrone Rivers starting, respectively, in 1924 and in 1942, and they are still active. In this study, we chose to use the time series of S. Giovanni alla Vena and of Sasso d'Ombrone for their temporal length and associated suspended sediment transportation data, and also because these stations are the closest to the river mouths. This position makes it possible to study the total transportation of sediment before the rivers flow into the sea, thus allowing for an estimation of the total amount of sediment reaching the coast.

3.3. North Atlantic oscillation index and statistical correlations

The *Climate Analysis Section of the US National Center for Atmospheric Research* (NCAR) provided the NAOI dataset, which derives from the principal component (PC)-based index of the NAO. This dataset includes the time series of the leading Empirical Orthogonal Function (EOF) of sea-level pressure (SLP) anomalies over the Atlantic sector, spanning from 20°N to 80°N and from 90°W to 40°E. The NAOI dataset, based on the PC analysis, serves as a measure of the annual NAOI, by tracking the seasonal movements of the Icelandic Low and of the Azores High. The dataset covers the period from January 1889 to 2023, with a monthly frequency. The employment of PC-based indices enables more optimal representations of the complete spatial patterns of NAOI (Climate Analysis Section, 2003).

For the study area, Luppichini et al., (2021,2022) showed that the rainfall amount is correlated with the negative phase of NAOI ($NAOI^-$). This suggests that even Qw can be correlated with $NAOI^-$, also considering the dependence between the winter precipitation and discharges with NAOI highlighted for the Po River (Zanchettin et al., 2008).

To quantify the statistical correlations, we used Spearman's correlation coefficient (SCC; Spearman, 1904), in agreement with previous studies that investigated the correlation with the atmospheric teleconnections in the study area or in the nearby areas (Caloiero et al., 2011; Luppichini et al., 2022b, 2021; Vergni et al., 2016). The statistical correlation is conducted between precipitation, flow rates, and $NAOI^-$ time series using a 10-year mobile average. In this study, the precipitation and river flow rates are expressed as percentage anomalies, while the temperature time series are expressed as a simple anomalies, and both the time series of anomalies are compared to the climatology of the 1961–1990 period In the case of precipitation and rainfall, the anomalies are normalized on the mean values of 1961–1990.

3.4. Re-analysis of suspended sediment transportation

Machine learning techniques can be used to reconstruct the Qs_A time series. We chose to use five different types of ML models: Decision Tree Regressor (DTR), k-Nearest Neighbors (kNN), Random Forest (RF), Stochastic Gradient Descent (SGD), and Support Vector Regressor (SVR). The different models used in these works allowed us to investigate the capacity of various algorithms in order to predict Qs_A starting from Qwvalues.

DTR is a non-parametric algorithm that constructs a tree-like model for regression tasks by partitioning the feature space into segments and predicting values based on the majority target values in each segment (Torgo, 2017). kNN is an instance-based learning method that predicts outcomes by finding the k-training instances closest to the input data point and by averaging their target values (Kramer, 2011). RF is an ensemble technique that combines multiple decision trees to improve predictive performance and to reduce overfitting, by averaging their individual predictions (Breiman, 2001). SGD is an optimization algorithm commonly used to train linear models. It updates the model's parameters iteratively by using subsets of the training data, which make the model computationally efficient for large datasets (Tsuruoka, 2009). SVR is a regression model aimed at finding a hyperplane that best fits the training data, and allowing tolerance for errors. The model focuses on the data points (known as support vectors) that are closest to the regression line, so as to determine the optimal fit (Awad and Khanna, 2015). Each of these models has its own strengths and weaknesses, making them suitable for different types of data and problems.

The models are developed using the Python language and, more specifically, the Scikit-learn library (Pedregosa et al., 2011). The models use the Qw data as input, making it possible to predict the monthly Qs_A. The daily Qw data are prepared to ensure the extraction of statistic monthly values. We designed two different types of input matrix: the former ($M0$) is composed of year, month, median Qw, Qwsum, minimum Qw, maximum Qw, mean Qw, and standard deviation of Qw; the latter ($M1$) is similar to $M0$, but it also contains the same statistics of the previous month. The input matrix is randomly divided into two parts, with a repartition of 70 % for the training dataset and 30 % for the test dataset. The training dataset is used during the learning phase, while the test dataset is used to evaluate the quality of the model following the learning processes (Aichouri et al., 2015; Dibike and Solomatine, 2001; Hu et al., 2020; Huang et al., 2020). The randomly created division of the input dataset was repeated 30 times for each type of model by creating 150 different models. In this way, we were able to test the uncertainty of the models by estimating the variability introduced by the input dataset (Hassangavyar et al., 2022; Michelucci and Venturini, 2021; Saraiva et al., 2021). The models were evaluated using the Nash-Sutcliffe model efficiency coefficients (NSE;Nash & Sutcliffe, 1970) and the Root Mean Square Error, calculated as follows:

$$NSE = 1 - \frac{\sum_{t=1}^{T}\left(Q_o^t - Q_m^t\right)^2}{\sum_{t=1}^{T}\left(Q_o^t - \overline{Q}_o\right)^2} \quad (2)$$

$$RMSE = \left(\frac{1}{T}\sum_{t=1}^{T}\left(Q_o^t - Q_m^t\right)^2\right)^{0.5} \tag{3}$$

where $\overline{Q_o}$ is the mean of observed Qs; Q_m is the modeled Qs; and Q_o^t is the observed Qs at time t.

3.5. Sediment concentration and flow rate over time

The ratio between C and Qw (RCQ) is analyzed in the work for both rivers, for C_M and C_A with Qw_M and Qw_A, respectively. We also wish to understand whether there is a variation of the ratio between sediment concentration and river discharge. A change in this ratio would indicate a variation in the hydrographic basin, with a decrease or increase of the sediment available and transportable by the rivers. This important information is linked with territory management and would be a proxy of anthropic activities. The trend of RCQ is examined for some quantiles of the river flow rate. The focus of the investigation is also to understand the variation of the RCQ for different river regimes, so as to exclude the lowest flow rate when the concentration of solid particle sediments is influenced by several factors such as vegetation, local discharge, etc. The percentage variation of RCQ is quantified by calculating the difference between mean value of the period 1950–1969 and mean value of the period 1971–1990, normalizing on the first period, as follows:

$$\mathrm{RCQ}_{f,q} = \frac{1}{20}\sum_{y=1950}^{1969}\frac{C_A^y Qw > Qw_q}{Qw^y_{Qw>Qw_q}} \tag{4}$$

$$\mathrm{RCQ}_{l,q} = \frac{1}{20}\sum_{y=1971}^{1990}\frac{C_A^y Qw > Qw_q}{Qw^y_{Qw>Qw_q}} \tag{5}$$

$$\Delta RCQ_q = \frac{RCQ_{l,q} - RCQ_{f,q}}{RCQ_{f,q}} \times 100 \tag{6}$$

where q is the quantile between 0 and 0.95.

3.6. Climate component on the quantification of sediment concentration

The C values are the result of a complex function based on several factors such as flow rate, geological and geomorphological characteristics of watershed, land use, and human activities (Crawford, 1991; Syvitski et al., 2000). We can assume that the factors influencing sediment concentration can be divided into two main categories: climate factors and territorial factors. We can represent C as follows:

$$C = C_{Qw} + C_{R,} \tag{7}$$

where C_{Qw} is the sediment concentration component that depends on river flow rate , while C_R is the component that depends on territorial factors, C_R is an estimation of the other contributions (land use, anthropic activities, etc.) to sediment concentration. Modelling is very difficult and complex due to the natural system and to the lack of high-resolution data that would otherwise provide a more accurate estimation of each component. We can quantify C_{Qw} with a fitting of logarithmic regression (using the scikit-learn library), and then we can derive the residual values (C_R). In this way, from an analysis of the time series of the river flow rates and of sediment concentration, we can quantify the role of the river discharge on the quantification of sediment concentration.

4. Results

Sediment concentrations and solid transport present strong correlations with the river flow rate of the studied rivers (Figs. 3 and 4). In more detail, C_A is correlated with Qw_A, with SCC values of 0.69 for the Arno river, and 0.65 for the Ombrone river (with p-values < 0.001), while the relation between Qs_A and Qw_A is quantified by SCC values of 0.91 and 0.88 respectively (with p-values of 8.80E-128 and 3.95E-75). Qs is

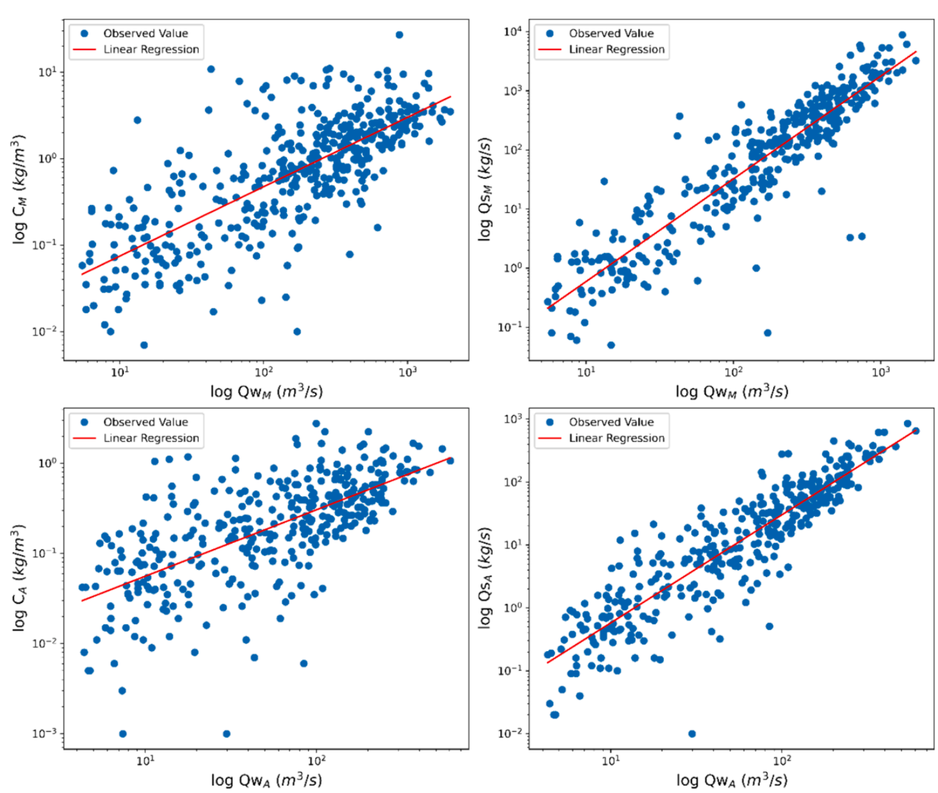

Fig. 3. Relation between monthly flow rate (Qw), average (A), and maximum (M), with monthly sediment suspended concentration (C) and sediment suspended flow rate (Qs) for the S. Giovanni alla Vena station.

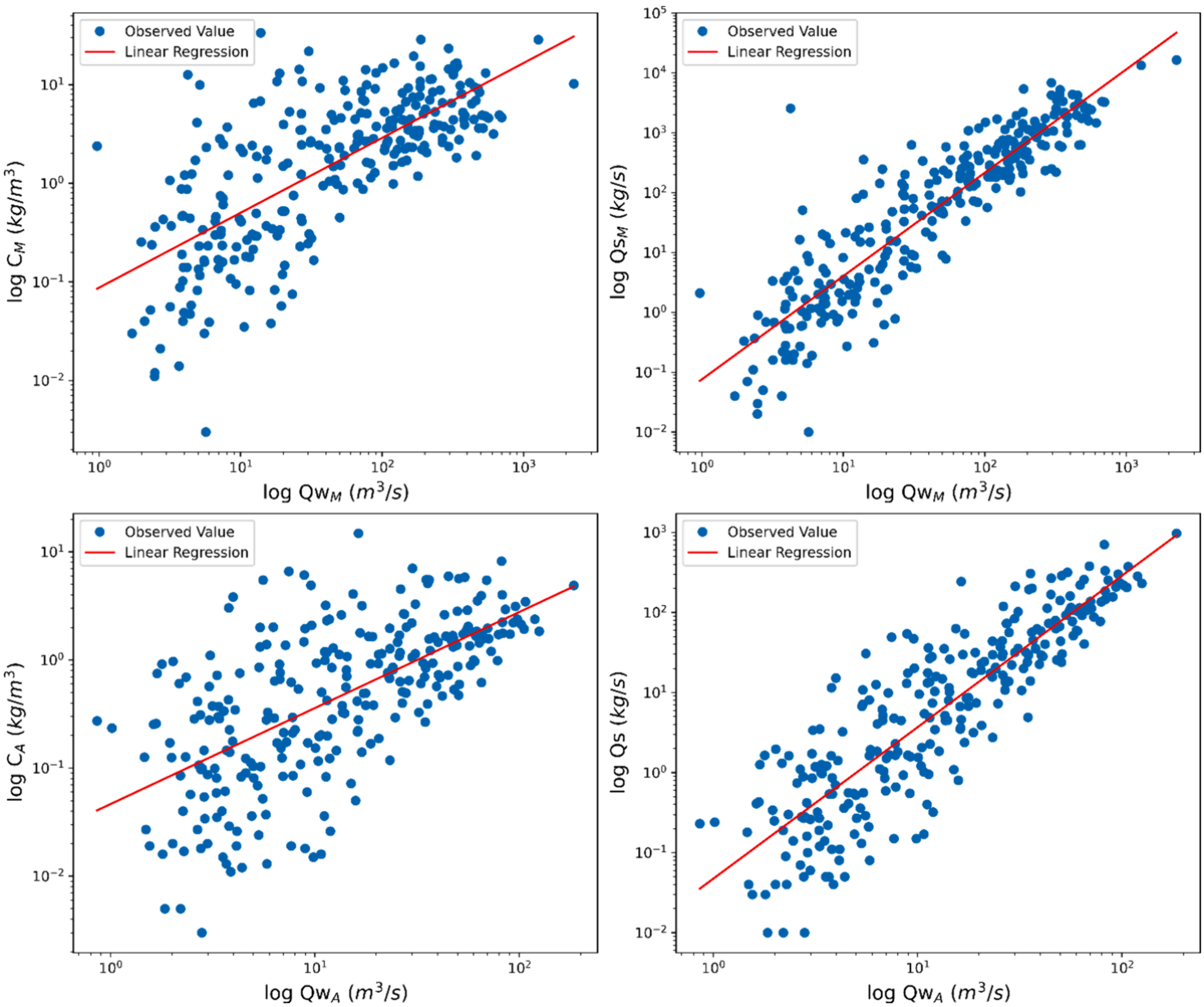

Fig. 4. Relation between monthly flow rate (*Qw*), average (*A*), and maximum (*M*), with monthly sediment suspended concentration (*C*) and sediment suspended flow rate (*Qs*) for the Sasso d'Ombrone station.

statistically correlated with *Qw* and is stronger than *C*, showing that sediment concentration is more influenced by the availability of sediment in the watershed than *Q*, which is influenced almost exclusively by the capacity of the rivers to transport sediment (quantifiable by *Qw*).

4.1. Statistical correlation between climatic variables

The temperature time series for ARB show a clear trend to increase until reaching a temperature anomaly of more than 1.5 °C (referred to the mean of 1961–1990) in the last years. The temperature time series for ORB also indicates an increase in temperature anomalies starting from 1980.

In the period 1950–2023 the river flow rates of the Arno and Ombrone rivers are characterized by three peaks around 1970, 1990 and 2010, corresponding to as many negative peaks of $NAOI^-$ (Fig. 5). However, the three river flow rate peaks show a progressive decrease of intensity, where the first peak is the highest and the last one is the lowest (Fig. 5e,f). For the Arno River, these trends are valid also considering the peak of the period around 1945, where the river flow rate was about 45 % higher than the mean of the period 1961–1990 (Fig. 5e). After 1960, a progressive decrease in the river flow rate (Fig. 5e,f) characterizes the oscillation of both rivers, but the Ombrone River actually has a lower river flow rate (about −20 %) compared to the mean of 1961–1990 (Fig. 5f).

This described trend for the river flow rates is also observed for the precipitations characterized in the last 70 years by an oscillation between wetter and drier periods, but with a general reduction of the precipitations (Fig. 5c,d).

In ARB, the statistical correlation between precipitation and flow rate is 0.69 (p-value < 0.001); the statistical correlation between precipitation and $NAOI^-$ is −0.15 (p-value 0.15); the statistical correlation between flow rate and $NAOI^-$ is −0.28 (p-value < 0.007; Fig. 5). However, considering only the data after World War II, the statistical correlations between $NAOI^-$ on the one hand and flow rate and precipitation on the other are, respectively, −0.74 (p-value < 0.001) and −0.49 (p-value < 0.001), indicating an increase in the statistical correlation between this climate index and the climate variables in ARB after 1950.

The river flow rate and precipitation time series in ORB are statistically correlated with a Spearman coefficient of 0.65 (p-value < 0.001). Precipitation and river flow rate are statistically correlated to $NAOI^-$ with, respectively, a coefficient of −0.50 (p-value < 0.001) and of −0.83 (p-value < 0.001), showing a very strong correlation between the two variables (Fig. 5).

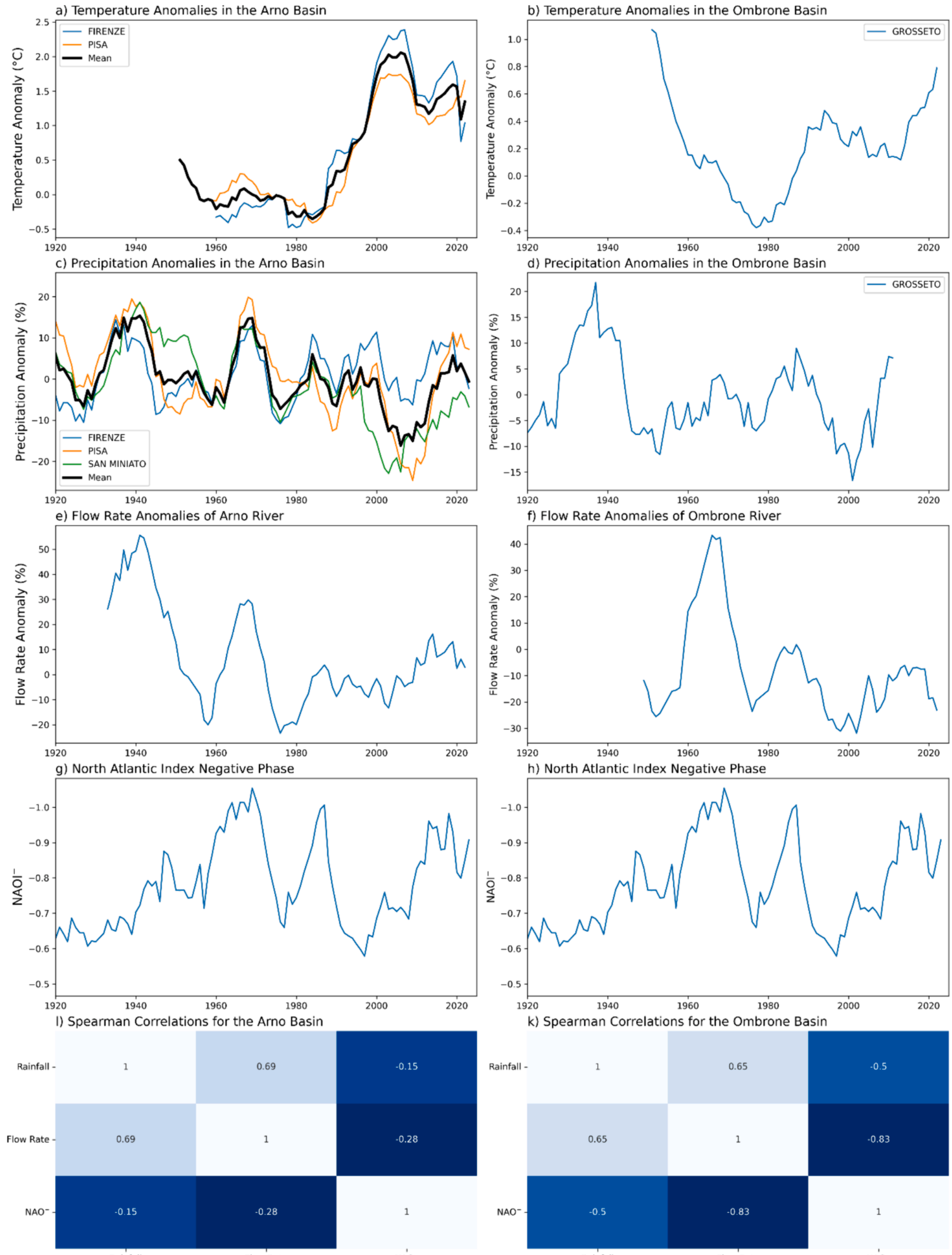

Fig. 5. Trends and correlation of the climate variables in the study area: a,b) indicate the 10-year mobile window of the temperature anomalies in the Arno and Ombrone basins; c), d) indicate the 10-year mobile window of the precipitation anomalies in the Arno and Ombrone basins; e), f) indicate the river flow rate anomalies using a 10-year mobile window of the Arno and Ombrone rivers; g), h) indicate the Negative Phase of the North Atlantic Oscillation (NAO⁻) using a 10-year mobile window; i), k) indicate the Spearman correlations between the 10-year mobile window of the climate variables. The anomalies are calculated using the reference period 1961–1990.

The flow rates of the Arno and the Ombrone rivers are strongly correlated with the precipitation amount linked to the main atmospheric teleconnection of the northern hemisphere, showing a close bond between these climatic variables.

4.2. Re-analysis of the suspended sediment transportation time series

The accuracy evaluation of the ML models used to predict Qs_A is reported in Fig. 6. The two types of input matrix (M0 and M1) provided similar results, so that it is very difficult to understand which one is better than the other. Moreover, it is not easy to highlight the best model kind. The models present similar errors, with some exceptions (such as M1-DTR at Sasso d'Ombrone, see Fig. 6d). The predictions of the models deviate substantially one from the other, as shown in Fig. 7, which reports the projections grouped in a 10-year mobile window. Despite this great variability, the models enable the creation of continuous time series with a similar trend, and could therefore be applied to the two rivers, which have a similar behaviour. The period around 1940 was characterized by the greatest Qs_A (Fig. 7a and b); Qs_A then decreased with a minimum around 1960. Another peak was present around 1970, while a decrease with a minimum peak was observed around 1980. Instead, in the last ten years the Arno and the Ombrone have shown a different trend. In these years, in the Arno river the models showed an increase of Qs_A, which is not observed in the Ombrone river, where there has also been a decrease of Qs_A in the last years.

4.3. Sediment concentration and flow rate over time

The ΔRCQ values calculated for different groups of Qw based on quantile distribution, as explained by equation n. 6, show a general decrease for the two time series over the period investigated (Figs. 8 and 9). The RCQ values are characterized by a 50–70 % drop, with Sasso d'Ombrone recording the highest reduction. In other words, the results demonstrate that a hypothetic flow rate event is characterized by a significantly different sediment concentration in the 1950–1969 period and in the 1971–1990 period.

4.4. Climate component on the quantification of sediment concentration

Sediment concentration is the result of a complex function influenced by several factors. We tried to estimate the ratio between the C component derived from the w (C_{Qw}) and the C component derived from other factors (C_R). For the maximum and average concentration and flow rate and for the two stations, this ratio indicates that C_{Qw} is about 1.5 times higher than C_R. In more detail, for S. Giovanni alla Vena, the average ratios are 1.58 and 1.80 calculated using maximum and average concentrations and flow rates, respectively. For Sasso d'Ombrone the average ratios are 1.46 and 1.39. This indicates that the flow rate plays the main role, and that the other factors have an incidence which is approximately the half on the quantification of sediment concentration.

5. Discussion

The climate analysis conducted in this study underlines the effects of

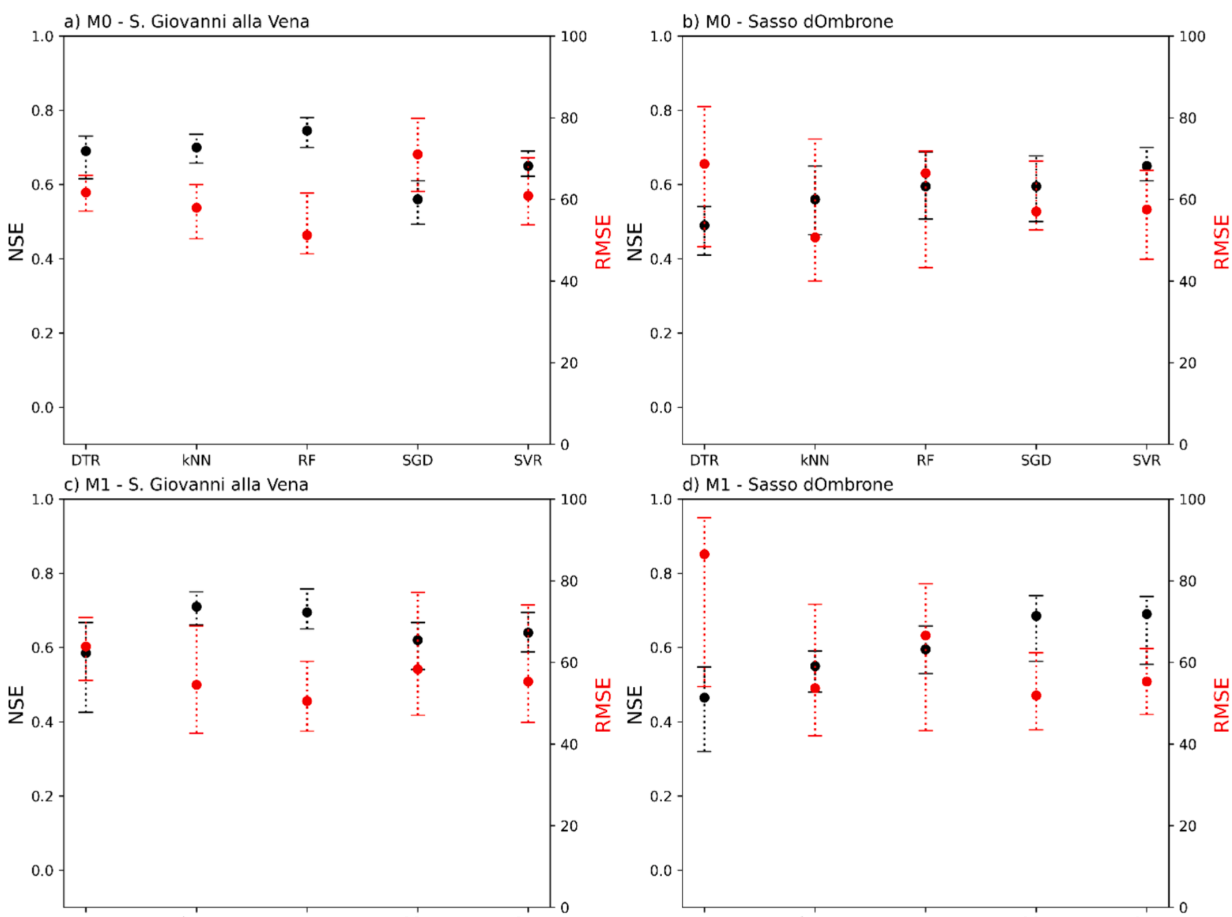

Fig. 6. Nash-Sutcliffe model efficiency coefficients (NSE; black dots and black bands) and Root Mean square Errors (RMSE; red dots and red bands). The dots represent the mean value and the bar represents 50% of the confidential interval. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

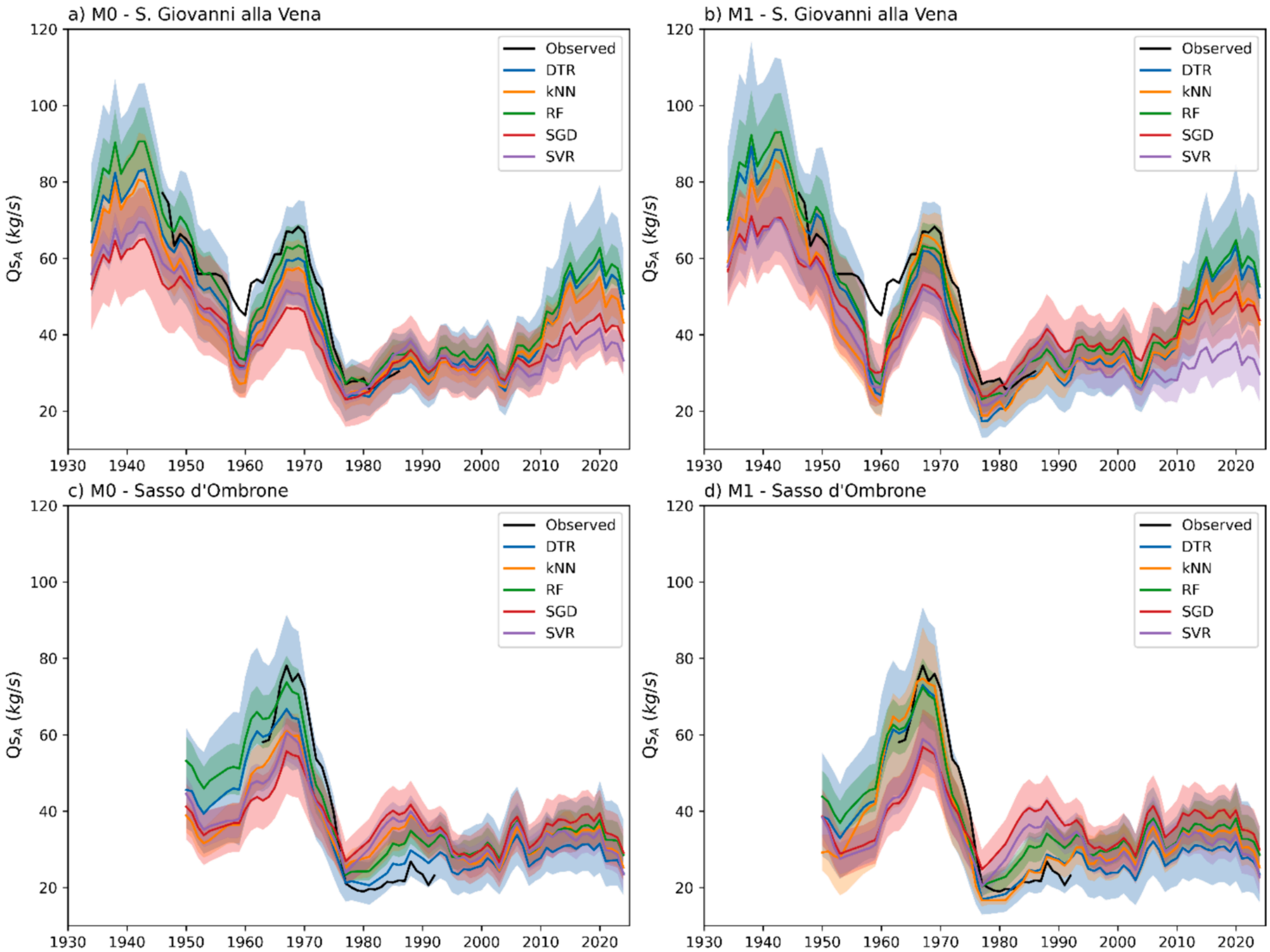

Fig. 7. Predictions of the machine learning models with a mobile average of 10 years at S. Giovanni alla Vena (a and b) and Sasso d'Ombrone (c and d). The solid line represents the median, while the bands represent the 50 % confidence intervals.

rising temperatures and declining precipitations in the study area over the past 70 years. Recent temperature anomalies (based on the 1961–1990 reference period: see Fig. 5) suggest that increases in projected temperatures under the RCP 2.6 scenario (Calvin et al., 2023) – estimated at around 1.6 °C (with a range of 0.9 °C to 2.3 °C) by 2081–2100 compared to the pre-industrial era (averaged between 1850–1900) – have already been surpassed in this region. This study area notably highlights the Mediterranean as a hot-spot of climate change (Giorgi, 2006).

The last century has been characterized by a drastic reduction in precipitation and river discharge in the Mediterranean, linked to current global warming (An et al., 2023; Bertola et al., 2019; Blöschl et al., 2019, 2020; Deitch et al., 2017; Hall et al., 2014). This tendency characterizes also the Arno and Ombrone Rivers, where there is a strong correlation between rainfalls and flow rates: owing to a general decrease in the rainfall occurrence, the flow rates of the investigated rivers have diminished. The decrease of the rainfall amount in the Mediterranean area is due to the increase in air and sea temperatures, which induces a shift of the cyclonic areas of the North Atlantic and of the Mediterranean (Börgel et al., 2020), leading to the establishment of high-pressure systems at the studied latitudes and consequently to a reduction in flow rates (Billi and Fazzini, 2017; Blöschl et al., 2019) and in solid discharge. The strong correlations identified between rainfall and flow rate time series with NAO^{-} agree with several studies (Ferrari et al., 2013; Luppichini et al., 2022b, 2021; Vergni et al., 2016; Vergni and Chiaudani, 2015), thus confirming an influence of the North Atlantic atmospheric circulation on the climatology of the study area.

In agreement with the evolution of the climatology of the study area, the amount of sediment transported by rivers has decreased over the past 70 years, as confirmed by the indirect observations obtained through various methodologies (Anfuso et al., 2011; Bini et al., 2021; Cipriani et al., 2013; Pratellesi et al., 2018; Surian and Rinaldi, 2004). The reduction in suspended sediment transport was reconstructed using artificial intelligence models (Fig. 8), which appear to have been the best representations achievable with available data over the last century. Machine learning models for predicting suspended sediment transport have been employed in several studies, and the results obtained in this work are comparable to those of others (Abda et al., 2021; Dibike et al., 2001; Francke et al., 2008; Lafdani et al., 2013; Lin et al., 2006; Nhu et al., 2020). In particular, the findings of this study can be juxtaposed with those of Nhu et al. (2020), whose models achieved NSE scores ranging from 0.68 to 0.83. This range closely aligns with the results presented in Fig. 6. In this work, although the differences are not thoroughly addressed, we can assume that the best results are obtained by using RF (for S. Giovanni alla Vena) and SVM (for Sasso d'Ombrone). These models have performed successfully in suspended sediment transport prediction in previous studies (Francke et al., 2008; Lafdani et al., 2013).

The results obtained from studying the role of different contributes to the quantification of sediment concentration have shown that river flow rate is the most important (see paragraph 4.4). The outcomes clearly indicate a predominant role of the flow rate, which is about 1.5 times

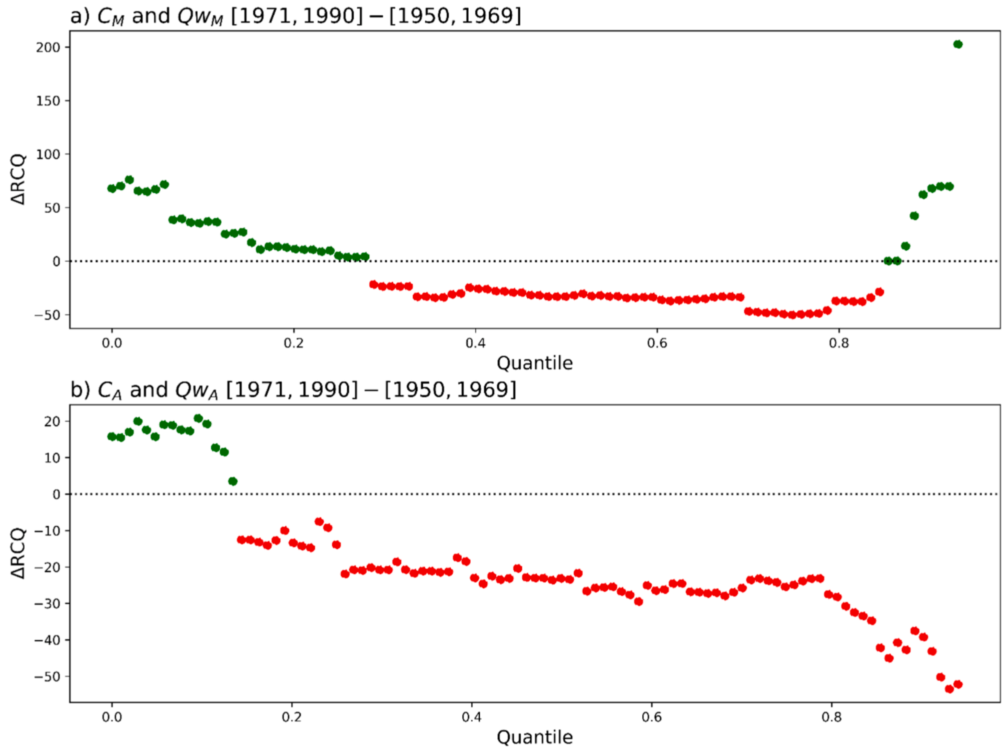

Fig. 8. Variation of ratio between sediment concentration and river flow rate at S. Giovanni alla Vena: a) maximum sediment concentration (C_M) on the maximum monthly river flow rate (Qw_M); b) average sediment concentration (C_A) on the average monthly river flow rate (Qw_A). The red dots are the negative values and the green dots are the positive values. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

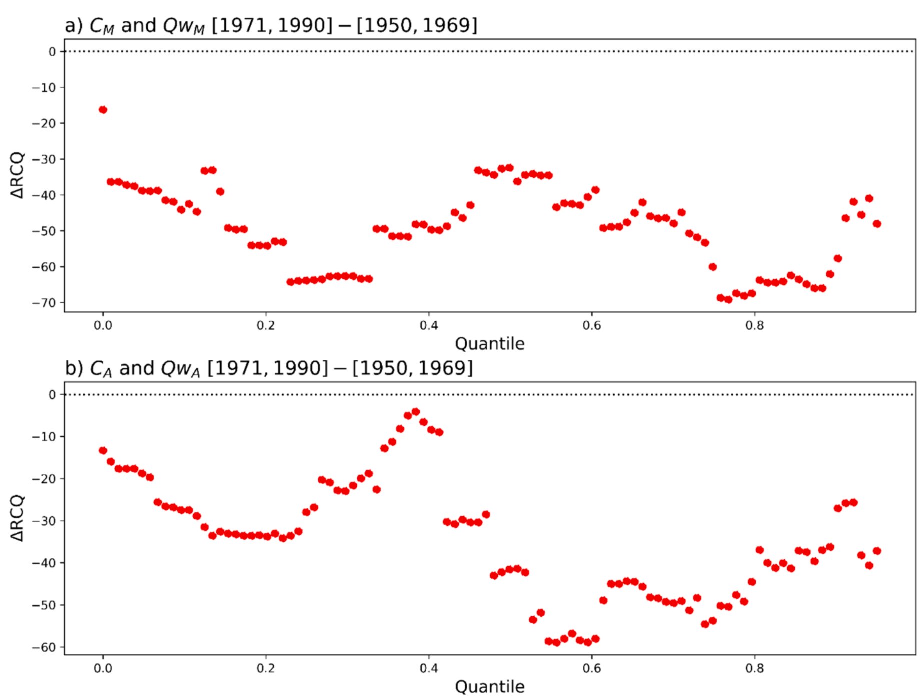

Fig. 9. Variation of ratio between sediment concentration and river flow rate at Sasso d'Ombrone: a) maximum sediment concentration (C_M) on the maximum monthly river flow rate (Qw_M); b) average sediment concentration (C_A) on the average monthly river flow rate (Qw_A). The red dots are the negative values. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

higher than the other factors, demonstrating that climatic factors are predominant in the regulation of the solid transport of these rivers. The other factors (represented by parameter C_R in Eq. (7) influencing sediment concentration are to be connected to human activities. Human activities such as reforestation, river regime regulation, and dam construction can induce a change in the amount of sediments available. The study area has been characterized by a change of land use and cover, with an increase of the forests over the last century (Hooke, 2006;

Sorriso-Valvo et al., 1995; Surian and Rinaldi, 2004) and the construction of dams along the main rivers (Fig. 2). As a matter of fact, analysis of the variation of RCQ values indicates a decrease in sediment concentration with the same river flow (Figs. 8 and 9). In other words, statistically speaking, an event occurred in the period 1950–1969 transported more sediment than the same event occurred in the period 1971–1990 (Figs. 8 and 9). The lack of data (characteristic of the study area, but not only) concerning the quantity of solid transport and reliable values associated with human activities (high-resolution reforestation rates, sediment quarrying from riverbeds, etc.) has led to difficulties in quantifying the relations between environmental changes, solid transport, and anthropogenic pressures. However, this decrease of the ratio between sediment concentration and river flow rate may depend on forest cover area change and on the presence of the dams that clearly characterized the study area (Billi and Rinaldi, 1997; Rinaldi, 2003; Surian et al., 2009; Surian and Rinaldi, 2004).

In the rivers of central and northern Italy, geomorphological changes in watercourses (e.g, Billi & Rinaldi, 1997; Dufour et al., 2015; Rinaldi, 2003; Rinaldi et al., 2015; Surian et al., 2009; Surian & Rinaldi, 2004) and river deltas (e.g., Besset et al., 2019; Pratellesi et al., 2018) have been observed since the beginning of the last century. This phenomenon has been attributed to an intensification of human activities especially in the period from 1950 to 1990, which corresponds to the period of maximum industrial activity for several Italian plains (Felice et al., 2013). However, the studies in this field have not taken into account the issue of climate change, assumed to be a constant over time; instead, this specific period was also marked by a significant reduction in precipitations and river flow rates on account of increased temperatures and changes in North Atlantic atmospheric circulation, These factors should be considered the primary drivers of decreased solid transport capacity and, therefore, of environmental changes.

The machine learning models developed in this study present the solid flow rate as a function of the liquid flow rate. This premise helps us to say that, if we want to provide future projections of the solid flow rate, we will also need to know the liquid flow rate in the future. There are several methods that allow to obtain a future projection of the river flow rate, from those based on the analysis of time series to those based on climate models (Bürger et al., 2011; Shepherd et al., 2010). We believe that to provide future projections of climate variables, the best current approach is that of the climate models which, at least in principle, can integrate the observed data with the future trend of human activities (Centre et al., 2013). We would like to emphasize that this kind of studies the Mediterranean area and the central Italy are poorly supported by observed data. Such characteristic regards many European climate studies, where the work of groups involved in research projects of this kind is based on large amounts of data for central and northern Europe, whereas the Mediterranean area is investigated with smaller amounts of data. For more accurate results for the Mediterranean, the reanalysis and bias correction of these great databases should be based on the use of the observed data also for this area where several datasets are available. For this reason, currently, these datasets present great uncertainties and an improvement of the future projections is required to have acceptable results. This important improvement of the future projections of the flow rate of the rivers of the Mediterranean will allow us to apply methodologies as described in this work to project the suspended sediment load time series considering the different future scenarios.

6. Conclusions

This work has demonstrated the crucial role of climate change in the decrease of suspended sediment transport in an area of the Mediterranean over the last century. Despite the active human role in reducing solid transport, it is however important to study this aspect without considering climate as a constant. Climate change seems to be a key and preponderant factor in reducing solid load, and its combination with anthropic effects can lead to alarming future scenarios for the consequent alteration of coastal and river environments.

This work has used one of the few time series of suspended sediment transport for the Mediterranean to re-analyze the time series, making it possible to reconstruct the past trend over the last century. In the future, it will be possible to exploit this new dataset (available in "Supplementary Material") in different applications for a more detailed study of the evolution of environments like coastal erosion; in support of other data and proxies; and for territorial management.

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CRediT authorship contribution statement

Marco Luppichini: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Marco Lazzarotti:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Monica Bini:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Resources, Project administration, Methodology, Funding acquisition, 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.

Data availability

The data used in the work are uploaded with the manuscript

References

Abda, Z., Zerouali, B., Alqurashi, M., Chettih, M., Santos, C.A.G., Hussein, E.E., 2021. Suspended sediment load simulation during flood events using intelligent systems: a case study on semiarid regions of mediterranean basin. Water (basel) 13. https://doi.org/10.3390/w13243539.

Aichouri, I., Hani, A., Bougherira, N., Djabri, L., Chaffai, H., Lallahem, S., 2015. River flow model using artificial neural networks. Energy Procedia 74, 1007–1014. https://doi.org/10.1016/j.egypro.2015.07.832.

Almikaeel, W., Čubanová, L., Šoltész, A., 2022. Hydrological drought forecasting using machine learning—gidra river case study. Water (switzerland) 14. https://doi.org/10.3390/w14030387.

Alp, M., Cigizoglu, H.K., 2007. Suspended sediment load simulation by two artificial neural network methods using hydrometeorological data. Environ. Model. Softw. 22, 2–13. https://doi.org/10.1016/j.envsoft.2005.09.009.

Anfuso, G., Pranzini, E., Vitale, G., 2011. An integrated approach to coastal erosion problems in northern Tuscany (Italy): Littoral morphological evolution and cell distribution. Geomorphology 129, 204–214. https://doi.org/10.1016/j.geomorph.2011.01.023.

Asselman, N.E.M., 1995. The impact of climate change on suspended sediment transport in the river Rhine. In: Zwerver, S., van Rompaey, R.S.A.R., Kok, M.T.J., Berk, M.M. (Eds.), Studies in Environmental Science. Elsevier, pp. 937–942 https://doi.org/https://doi.org/10.1016/S0166-1116(06)80119-6.

Awad, M., Khanna, R., 2015. Support Vector Regression. In: Awad, M., Khanna, R. (Eds.), Efficient Learning Machines: Theories, Concepts, and Applications for Engineers and System Designers. Apress, Berkeley, CA, pp. 67–80. https://doi.org/10.1007/978-1-4302-5990-9_4.

Baronetti, A., Dubreuil, V., Provenzale, A., Fratianni, S., 2022. Future droughts in northern Italy: high-resolution projections using EURO-CORDEX and MED-CORDEX ensembles. Clim Change 172, 22. https://doi.org/10.1007/s10584-022-03370-7.

Besset, M., Anthony, E.J., Sabatier, F., 2017. River delta shoreline reworking and erosion in the Mediterranean and Black Seas: the potential roles of fluvial sediment starvation and other factors. Elem. Sci. Anth. 5 https://doi.org/10.1525/elementa.139.

Besset, M., Anthony, E.J., Bouchette, F., 2019. Multi-decadal variations in delta shorelines and their relationship to river sediment supply: an assessment and review. Earth Sci Rev 193, 199–219. https://doi.org/10.1016/j.earscirev.2019.04.018.

Billi, P., Fazzini, M., 2017. Global change and river flow in Italy. Glob Planet Change 155, 234–246. https://doi.org/10.1016/j.gloplacha.2017.07.008.

Billi, P., Rinaldi, M., 1997. Human impact on sediment yield and channel dynamics in the Arno River. IAHS-AISH Publication, (central Italy), p. 245.

Bini, M., Casarosa, N., Ribolini, A., 2008. L'evoluzione diacronica della linea di riva del litorale Pisano (1938–2004) sulla base del confront di immagini aeree georeferenziate. Atti Della Societa Toscana Di Scienze Naturali, Memorie Serie A 113, 1–12.

Bini, M., Casarosa, N., Luppichini, M., 2021. Exploring the relationship between river discharge and coastal erosion: An integrated approach applied to the pisa coastal plain (italy). Remote Sens (basel) 13. https://doi.org/10.3390/rs13020226.

Blöschl, G., Hall, J., Viglione, A., Perdigão, R.A.P., Parajka, J., Merz, B., Lun, D., Arheimer, B., Aronica, G.T., Bilibashi, A., Boháč, M., Bonacci, O., Borga, M., Čanjevac, I., Castellarin, A., Chirico, G.B., Claps, P., Frolova, N., Ganora, D., Gorbachova, L., Gül, A., Hannaford, J., Harrigan, S., Kireeva, M., Kiss, A., Kjeldsen, T.R., Kohnová, S., Koskela, J.J., Ledvinka, O., Macdonald, N., Mavrova-Guirguinova, M., Mediero, L., Merz, R., Molnar, P., Montanari, A., Murphy, C., Osuch, M., Ovcharuk, V., Radevski, I., Salinas, J.L., Sauquet, E., Šraj, M., Szolgay, J., Volpi, E., Wilson, D., Zaimi, K., Živković, N., 2019. Changing climate both increases and decreases European river floods. Nature 573, 108–111. https://doi.org/10.1038/s41586-019-1495-6.

Blöschl, G., Kiss, A., Viglione, A., Barriendos, M., Böhm, O., Brázdil, R., Coeur, D., Demarée, G., Llasat, M.C., Macdonald, N., Retsö, D., Roald, L., Schmocker-Fackel, P., Amorim, I., Bělínová, M., Benito, G., Bertolin, C., Camuffo, D., Cornel, D., Doktor, R., Elleder, L., Enzi, S., Garcia, J.C., Glaser, R., Hall, J., Haslinger, K., Hofstätter, M., Komma, J., Limanówka, D., Lun, D., Panin, A., Parajka, J., Petrić, H., Rodrigo, F.S., Rohr, C., Schönbein, J., Schulte, L., Silva, L.P., Toonen, W.H.J., Valent, P., Waser, J., Wetter, O., 2020. Current European flood-rich period exceptional compared with past 500 years. Nature 583, 560–566. https://doi.org/10.1038/s41586-020-2478-3.

Börgel, F., Frauen, C., Neumann, T., Meier, H.E.M., 2020. The Atlantic Multidecadal Oscillation controls the impact of the North Atlantic Oscillation on North European climate. Environ. Res. Lett. 15.

Breiman, L., 2001. Random Forests. Mach Learn 45, 5–32. https://doi.org/10.1023/A:1010933404324.

Bürger, G., Schulla, J., Werner, A.T., 2011. Estimates of future flow, including extremes, of the Columbia River headwaters. Water Resour Res 47. https://doi.org/10.1029/2010WR009716.

Buyukyildiz, M., Kumcu, S.Y., 2017. An estimation of the suspended sediment load using adaptive network based fuzzy inference system, support vector machine and artificial neural network models. Water Resour. Manag. 31, 1343–1359. https://doi.org/10.1007/s11269-017-1581-1.

Caloiero, T., Coscarelli, R., Ferrari, E., Mancini, M., 2011. Precipitation change in Southern Italy linked to global scale oscillation indexes. Nat. Hazards Earth Syst. Sci. 11, 1683–1694. https://doi.org/10.5194/nhess-11-1683-2011.

Calvin, K., Dasgupta, D., Krinner, G., Mukherji, A., Thorne, P.W., Trisos, C., Romero, J., Aldunce, P., Barrett, K., Blanco, G., Cheung, W.W.L., Connors, S., Denton, F., Diongue-Niang, A., Dodman, D., Garschagen, M., Geden, O., Hayward, B., Jones, C., Jotzo, F., Krug, T., Lasco, R., Lee, Y.-Y., Masson-Delmotte, V., Meinshausen, M., Mintenbeck, K., Mokssit, A., Otto, F.E.L., Pathak, M., Pirani, A., Poloczanska, E., Pörtner, H.-O., Revi, A., Roberts, D.C., Roy, J., Ruane, A.C., Skea, J., Shukla, P.R., Slade, R., Slangen, A., Sokona, Y., Sörensson, A.A., Tignor, M., van Vuuren, D., Wei, Y.-M., Winkler, H., Zhai, P., Zommers, Z., Hourcade, J.-C., Johnson, F.X., Pachauri, S., Simpson, N.P., Singh, C., Thomas, A., Totin, E., Alegría, A., Armour, K., Bednar-Friedl, B., Blok, K., Cissé, G., Dentener, F., Eriksen, S., Fischer, E., Garner, G., Guivarch, C., Haasnoot, M., Hansen, G., Hauser, M., Hawkins, E., Hermans, T., Kopp, R., Leprince-Ringuet, N., Lewis, J., Ley, D., Ludden, C., Niamir, L., Nicholls, Z., Some, S., Szopa, S., Trewin, B., van der Wijst, K.-I., Winter, G., Witting, M., Birt, A., Ha, M., 2023. IPCC, 2023: Climate Change 2023: Synthesis Report. Contribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [Core Writing Team, H. Lee and J. Romero (eds.)]. IPCC, Geneva, Switzerland. https://doi.org/10.59327/IPCC/AR6-9789291691647.

Carroll, T.L., 2018. Using reservoir computers to distinguish chaotic signals. Phys Rev E 98, 52209. https://doi.org/10.1103/PhysRevE.98.052209.

Centre, J.R., Sustainability, I. for E. and, Thielen, J., Gomes, G., Sint, H., Lorini, V., Zambrano-Bigiarini, M., Ntegeka, V., Salamon, P., 2013. EFAS-Meteo – A European daily high-resolution gridded meteorological data set for 1990-2011. Publications Office. https://doi.org/doi/10.2788/51262.

Chattopadhyay, A., Nabizadeh, E., Hassanzadeh, P., 2020. Analog forecasting of extreme-causing weather patterns using deep learning. e2019MS001958-e2019MS001958 J Adv Model Earth Syst 12. https://doi.org/10.1029/2019MS001958.

Cipriani, L.E., Ferri, S., Iannotta, P., Paolieri, F., Pranzini, E., 2001. Morfologia e dinamica dei sedimenti del litorale della Toscana settentrionale. Studi Costieri 119–156.

Cipriani, L.E., Pranzini, E., Vitale, G., Wetzel, L., 2013. Adaptation to beach erosion at Maremma regional park (Tuscany, Italy). Geoecomarina 19, 65–76.

Climate Analysis Section, 2003. NAO Index Data provided [WWW Document]. https://climatedataguide.ucar.edu/climate-data/hurrell-north-atlantic-oscillation-nao-index-pc-based.

Cos, J., Doblas-Reyes, F., Jury, M., Marcos, R., Bretonnière, P.-A., Samsó, M., 2022. The Mediterranean climate change hotspot in the CMIP5 and CMIP6 projections. Earth Syst. Dyn. 13, 321–340. https://doi.org/10.5194/esd-13-321-2022.

Crawford, C.G., 1991. Estimation of suspended-sediment rating curves and mean suspended-sediment loads. J Hydrol (amst) 129, 331–348.

Deitch, M.J., Sapundjieff, M.J., Feirer, S.T., 2017. Characterizing precipitation variability and trends in the world's mediterranean-climate areas. Water (basel) 9. https://doi.org/10.3390/w9040259.

Deser, C., Hurrell, J.W., Phillips, A.S., 2017. The role of the North Atlantic Oscillation in European climate projections. Clim Dyn 49, 3141–3157. https://doi.org/10.1007/s00382-016-3502-z.

Dibike, Y.B., Solomatine, D.P., 2001. River flow forecasting using artificial neural networks. Phys. Chem. Earth Part B 26, 1–7. https://doi.org/10.1016/S1464-1909(01)85005-X.

Dibike, Y.B., Velickov, S., Solomatine, D., Abbott, M.B., 2001. Model induction with support vector machines: introduction and applications. J. Comput. Civ. Eng. 15, 208–216.

Du, C., Cai, F., Zidan, M.A., Ma, W., Lee, S.H., Lu, W.D., 2017. Reservoir computing using dynamic memristors for temporal information processing. Nat Commun 8, 2204. https://doi.org/10.1038/s41467-017-02337-y.

Dufour, S., Rinaldi, M., Piégay, H., Michalon, A., 2015. How do river dynamics and human influences affect the landscape pattern of fluvial corridors? Lessons from the Magra River, Central-Northern Italy. Landsc Urban Plan 134, 107–118. https://doi.org/10.1016/j.landurbplan.2014.10.007.

El Mahrad, B., Abalansa, S., Newton, A., Icely, J.D., Snoussi, M., Kacimi, I., 2020. Social-environmental analysis for the management of coastal lagoons in north africa. Front Environ. Sci. 8.

Favaro, E.A., Lamoureux, S.F., 2015. Downstream patterns of suspended sediment transport in a High Arctic river influenced by permafrost disturbance and recent climate change. Geomorphology 246, 359–369. https://doi.org/10.1016/j.geomorph.2015.06.038.

Felice, E., Vecchi, G., Università, V., di Roma, G., Vergata, T., 2013. Italy's Growth and Decline. 1861–2011 Italy's Growth and Decline.

Ferrari, E., Caloiero, T., Coscarelli, R., 2013. Influence of the North Atlantic Oscillation on winter rainfall in Calabria (southern Italy). Theor Appl Climatol 114, 479–494. https://doi.org/10.1007/s00704-013-0856-6.

Francke, T., López-Tarazón, J.A., Schröder, B., 2008. Estimation of suspended sediment concentration and yield using linear models, random forests and quantile regression forests. Hydrological Processes: an International Journal 22, 4892–4904.

Fratianni, S., Acquaotta, F., 2017. The Climate of Italy, in: Soldati, M., Marchetti, M. (Eds.), Landscapes and Landforms of Italy. Springer International Publishing, Cham, pp. 29–38. https://doi.org/10.1007/978-3-319-26194-2_4.

Gentilucci, M., Barbieri, M., Lee, H.S., Zardi, D., 2019. Analysis of rainfall trends and extreme precipitation in the middle adriatic side, Marche Region (Central Italy). Water (switzerland) 11. https://doi.org/10.3390/w11091948.

Giorgi, F., 2006. Climate change hot-spots. Geophys Res Lett 33. https://doi.org/10.1029/2006GL025734.

Gurnell, A.M., Piegay, H., Swanson, F.J., Gregory, S.V., 2002. Large wood and fluvial processes. Freshw Biol 47, 601–619. https://doi.org/10.1046/j.1365-2427.2002.00916.x.

Hassangavyar, M.B., Damaneh, H.E., Pham, Q.B., Linh, N.T.T., Tiefenbacher, J., Bach, Q.-V., 2022. Evaluation of re-sampling methods on performance of machine learning models to predict landslide susceptibility. Geocarto Int 37, 2772–2794. https://doi.org/10.1080/10106049.2020.1837257.

Hooke, J.M., 2006. Human impacts on fluvial systems in the Mediterranean region. Geomorphology 79, 311–335. https://doi.org/10.1016/j.geomorph.2006.06.036.

Hu, Y., Yan, L., Hang, T., Feng, J., 2020. Stream-Flow Forecasting of Small Rivers Based on LSTM.

Huang, C., Zhang, J., Cao, L., Wang, L., Luo, X., Wang, J.-H., Bensoussan, A., 2020. Robust forecasting of river-flow based on convolutional neural network. IEEE Trans. Sustainable Comput. 5, 594–600. https://doi.org/10.1109/TSUSC.2020.2983097.

J.W. Hurrell Y. Kushnir, G.O.M.V. (Eds.), 2003. The North Atlantic Oscillation: Climatic Significance and Environmental Impact. Geophysical Monograph Series 84, 73. https://doi.org/10.1029/2003eo080005.

Hurrell, J.W., Deser, C., Phillips, A.S., 2019. North atlantic oscillation (NAO), in: Encyclopedia of Ocean Sciences. Elsevier, pp. 447–454. https://doi.org/10.1016/B978-0-12-409548-9.11621-5.

Hurrell, J.W., Kushnir, Y., Ottersen, G., Visbeck, M., 2003. An Overview of the North Atlantic Oscillation. Climatic Significance and Environmental Impact, The North Atlantic Oscillation https://doi.org/doi:10.1029/134GM01.

Hurrell, J.W., 1995. Decadal Trends in the North Atlantic Oscillation: Regional Temperatures and Precipitation. Science (1979) 269, 676 LP – 679–676 LP – 679. https://doi.org/10.1126/science.269.5224.676.

Kramer, O., 2011. Unsupervised K-nearest neighbor regression. arXiv preprint arXiv:1107.3600.

Lafdani, E.K., Nia, A.M., Ahmadi, A., 2013. Daily suspended sediment load prediction using artificial neural networks and support vector machines. J Hydrol (amst) 478, 50–62.

Leatherman, S.P., Zhang, K., Douglas, B.C., 2000. Sea level rise shown to drive coastal erosion. Eos Trans. AGU 81, 55–57. https://doi.org/10.1029/00EO00034.

Lin, J.-Y., Cheng, C.-T., Chau, K.-W., 2006. Using support vector machines for long-term discharge prediction. Hydrol. Sci. J. 51, 599–612.

Livieris, I.E., Pintelas, E., Pintelas, P., 2020. A CNN–LSTM model for gold price time-series forecasting. Neural Comput Appl 32, 17351–17360. https://doi.org/10.1007/s00521-020-04867-x.

Longobardi, A., Villani, P., 2010. Trend analysis of annual and seasonal rainfall time series in the Mediterranean area. Int. J. Climatol. 30, 1538–1546. https://doi.org/10.1002/joc.2001.

Lopez-Bustins, J.-A., Martin-Vide, J., Sanchez-Lorenzo, A., 2008. Iberia winter rainfall trends based upon changes in teleconnection and circulation patterns. Glob Planet Change 63, 171–176. https://doi.org/10.1016/j.gloplacha.2007.09.002.

Lupi, A., Luppichini, M., Barsanti, M., Bini, M., Giannecchini, R., 2023. Machine learning models to complete rainfall time series databases affected by missing or anomalous data. Earth Sci Inform 16, 3717–3728. https://doi.org/10.1007/s12145-023-01122-4.

Luppichini, M., Barsanti, M., Giannecchini, R., Bini, M., 2021. Statistical relationships between large-scale circulation patterns and local-scale effects: NAO and rainfall regime in a key area of the Mediterranean basin. Atmos Res 248, 105270.

Luppichini, M., Barsanti, M., Giannecchini, R., Bini, M., 2022a. Deep learning models to predict flood events in fast-flowing watersheds. Sci. Total Environ. 813, 151885 https://doi.org/10.1016/j.scitotenv.2021.151885.

Luppichini, M., Bini, M., Barsanti, M., Giannecchini, R., Zanchetta, G., 2022b. Seasonal rainfall trends of a key Mediterranean area in relation to large-scale atmospheric circulation: how does current global change affect the rainfall regime? J Hydrol (amst) 612, 128233. https://doi.org/10.1016/j.jhydrol.2022.128233.

Melesse, A.M., Ahmad, S., McClain, M.E., Wang, X., Lim, Y.H., 2011. Suspended sediment load prediction of river systems: An artificial neural network approach. Agric Water Manag 98, 855–866. https://doi.org/10.1016/j.agwat.2010.12.012.

Merz, B., Aerts, J., Arnbjerg-Nielsen, K., Baldi, M., Becker, A., Bichet, A., Blöschl, G., Bouwer, L.M., Brauer, A., Cioffi, F., Delgado, J.M., Gocht, M., Guzzetti, F., Harrigan, S., Hirschboeck, K., Kilsby, C., Kron, W., Kwon, H.H., Lall, U., Merz, R., Nissen, K., Salvatti, P., Swierczynski, T., Ulbrich, U., Viglione, A., Ward, P.J., Weiler, M., Wilhelm, B., Nied, M., 2014. Floods and climate: emerging perspectives for flood risk assessment and management. Nat. Hazards Earth Syst. Sci. 14, 1921–1942. https://doi.org/10.5194/nhess-14-1921-2014.

Michelucci, U., Venturini, F., 2021. Estimating neural network's performance with bootstrap: a tutorial. Mach Learn Knowl Extr 3, 357–373. https://doi.org/10.3390/make3020018.

Naik, P.K., Jay, D.A., 2011. Distinguishing human and climate influences on the Columbia River: Changes in mean flow and sediment transport. J Hydrol (amst) 404, 259–277. https://doi.org/10.1016/j.jhydrol.2011.04.035.

Nash, J.E., Sutcliffe, J.V., 1970. River flow forecasting through conceptual models part I—A discussion of principles. J Hydrol (amst) 10, 282–290.

Newton, A., Icely, J., Cristina, S., Brito, A., Cardoso, A.C., Colijn, F., Riva, S.D., Gertz, F., Hansen, J.W., Holmer, M., Ivanova, K., Leppäkoski, E., Canu, D.M., Mocenni, C., Mudge, S., Murray, N., Pejrup, M., Razinkovas, A., Reizopoulou, S., Pérez-Ruzafa, A., Schernewski, G., Schubert, H., Carr, L., Solidoro, C., PierluigiViaroli, Zaldivar, J.-m., 2014. An overview of ecological status, vulnerability and future perspectives of European large shallow, semi-enclosed coastal systems, lagoons and transitional waters. Estuar Coast Shelf Sci 140, 95–122. https://doi.org/10.1016/j.ecss.2013.05.023.

Ng, K.W., Huang, Y.F., Koo, C.H., Chong, K.L., El-Shafie, A., Najah Ahmed, A., 2023. A review of hybrid deep learning applications for streamflow forecasting. J Hydrol (amst) 625, 130141. https://doi.org/10.1016/j.jhydrol.2023.130141.

Nhu, V.-H., Khosravi, K., Cooper, J.R., Karimi, M., Kisi, O., Pham, B.T., Lyu, Z., 2020. Monthly suspended sediment load prediction using artificial intelligence: testing of a new random subspace method. Hydrol. Sci. J. 65, 2116–2127. https://doi.org/10.1080/02626667.2020.1754419.

Pathak, J., Lu, Z., Hunt, B.R., Girvan, M., Ott, E., 2017. Using machine learning to replicate chaotic attractors and calculate Lyapunov exponents from data. Chaos: an interdisciplinary. J. Nonlinear Sci. 27, 121102 https://doi.org/10.1063/1.5010300.

Patil, D.J., Hunt, B.R., Kalnay, E., Yorke, J.A., Ott, E., 2001. Local low dimensionality of atmospheric dynamics. Phys Rev Lett 86, 5878–5881. https://doi.org/10.1103/PhysRevLett.86.5878.

Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., Dubourg, V., Vanderplas, J., Passos, A., Cournapeau, D., Brucher, M., Perrot, M., Duchesnay, É., 2011. Scikit-learn: machine learning in python. J. Mach. Learn. Res. 12, 2825–2830.

Pratellesi, M., Ciavola, P., Ivaldi, R., Anthony, E.J., Armaroli, C., 2018. River-mouth geomorphological changes over 130 years (1882–2014) in a small Mediterranean delta: Is the Magra delta reverting to an estuary? Mar Geol 403, 215–224. https://doi.org/10.1016/j.margeo.2018.06.003.

Reichstein, M., Camps-Valls, G., Stevens, B., Jung, M., Denzler, J., Carvalhais, N., Prabhat, 2019. Deep learning and process understanding for data-driven Earth system science. Nature 566, 195–204. https://doi.org/10.1038/s41586-019-0912-1.

Rinaldi, M., 2003. Recent channel adjustments in alluvial rivers of Tuscany, Central Italy. Earth Surf Process Landf 28, 587–608. https://doi.org/10.1002/esp.464.

Rinaldi, M., Teruggi, L.B., Colombo, F., Groppelli, B., 2015. Trajectories of channel adjustments of the toce river (Northern italy), in: Engineering Geology for Society and Territory - Volume 3: River Basins, Reservoir Sedimentation and Water Resources. pp. 309–311. https://doi.org/10.1007/978-3-319-09054-2_64.

Rodríguez-Blanco, M.L., Arias, R., Taboada-Castro, M.M., Nunes, J.P., Keizer, J.J., Taboada-Castro, M.T., 2016. Potential impact of climate change on suspended sediment yield in NW Spain: a case study on the corbeira catchment. Water (switzerland) 8. https://doi.org/10.3390/w8100444.

Salih, S.Q., Sharafati, A., Khosravi, K., Faris, H., Kisi, O., Tao, H., Ali, M., Yaseen, Z.M., 2020. River suspended sediment load prediction based on river discharge information: application of newly developed data mining models. Hydrol. Sci. J. 65, 624–637. https://doi.org/10.1080/02626667.2019.1703186.

Samantaray, S., Sahoo, A., Ghose, D.K., 2020. Assessment of sediment load concentration using svm, svm-ffa and psr-svm-ffa in arid watershed, india: a case study. KSCE J. Civ. Eng. 24, 1944–1957. https://doi.org/10.1007/s12205-020-1889-x.

Saraiva, S.V., Carvalho, F. de O., Santos, C.A.G., Barreto, L.C., Freire, P.K. de M.M., 2021. Daily streamflow forecasting in Sobradinho Reservoir using machine learning models coupled with wavelet transform and bootstrapping. Appl Soft Comput 102, 107081. https://doi.org/10.1016/j.asoc.2021.107081.

Shepherd, A., Gill, K.M., Rood, S.B., 2010. Climate change and future flows of Rocky Mountain rivers: converging forecasts from empirical trend projection and down-scaled global circulation modelling. Hydrol Process 24, 3864–3877. https://doi.org/10.1002/hyp.7818.

Sorriso-Valvo, M., Bryan, R.B., Yair, A., Iovino, F., Antronico, L., 1995. Impact of afforestation on hydrological response and sediment production in a small Calabrian catchment. Catena (amst) 25, 89–104.

Spearman, C., 1904. The proof and measurement of association between two things. Am J Psychol 15, 72–101. https://doi.org/10.2307/1412159.

Surian, N., Rinaldi, M., 2004. Channel adjustments in response to human alteration of sediment fluxes: examples from Italian rivers. IAHS Publ. 288, 276–282.

Surian, N., Rinaldi, M., Pellegrini, L., Audisio, C., Maraga, F., Teruggi, L., Turitto, O., Ziliani, L., 2009. Channel adjustments in northern and central Italy over the last 200 years. Special Paper Geol. Soc. Am. 451, 83–95. https://doi.org/10.1130/2009.2451(05).

Syvitski, J.P., Morehead, M.D., Bahr, D.B., Mulder, T., 2000. Estimating fluvial sediment transport: the rating parameters. Water Resour Res 36, 2747–2760.

Thodsen, H., Hasholt, B., Kjærsgaard, J.H., 2008. The influence of climate change on suspended sediment transport in Danish rivers. Hydrol Process 22, 764–774. https://doi.org/10.1002/hyp.6652.

Torgo, L., 2017. Regression Trees. In: Sammut, C., Webb, G.I. (Eds.), Encyclopedia of Machine Learning and Data Mining. Springer, US, Boston, MA, pp. 1080–1083. https://doi.org/10.1007/978-1-4899-7687-1_717.

Tsuruoka, Y., Jun'ichi Tsujii, ‡, Ananiadou, S., 2009. Stochastic Gradient Descent Training for L1-regularized Log-linear Models with Cumulative Penalty, ACL and AFNLP.

Vergni, L., Chiaudani, A., 2015. Relationship between the NAO index and some indices of extreme precipitation in the Abruzzo Region.

Vergni, L., Di Lena, B., Chiaudani, A., 2016. Statistical characterisation of winter precipitation in the Abruzzo region (Italy) in relation to the North Atlantic Oscillation (NAO). Atmos Res 178–179, 279–290. https://doi.org/10.1016/j.atmosres.2016.03.028.

Visbeck, M.H., Hurrell, J.W., Polvani, L., Cullen, H.M., 2001. The North Atlantic Oscillation: Past, present, and future. Proceedings of the National Academy of Sciences 98, 12876. https://doi.org/10.1073/pnas.231391598.

Watson, P.A.G., 2019. Applying machine learning to improve simulations of a chaotic dynamical system using empirical error correction. J Adv Model Earth Syst 11, 1402–1417. https://doi.org/10.1029/2018MS001597.

Zanchettin, D., Traverso, P., Tomasino, M., 2008. Po River discharges: a preliminary analysis of a 200-year time series. Clim Change 89, 411–433. https://doi.org/10.1007/s10584-008-9395-z.

Zhang, K., Douglas, B.C., Leatherman, S.P., 2004. GLOBAL WARMING AND COASTAL EROSION.