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Correlation between small earthquakes and CO₂ anomalies in spring waters: a statistical experiment on the probability of seismic occurrence

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We correlated carbon dioxide (CO₂) time series detected at the Galliciano site in Tuscany, Italy, with low-magnitude earthquakes occurred in the surrounding area between 2017 and 2021. The CO₂ irregular component distribution was analyzed by a Pearson type VII fit, and its cumulate probability by the Gauss's hypergeometric function, to statistically evidence anomalous fluctuations. We calculated the Matthews correlation between gas concentrations and low-magnitude earthquakes by defining a binary occurrence of CO₂ anomalies and seismic events. A positive correlation was highlighted by a time lag between the digital series, which resulted in CO₂ anomaly detections ahead of the earthquake time of two days. The correlated earthquakes were mainshocks of local magnitude 1.2 to 3.6, with epicenters within 40 km from the Galliciano site. Correlations among rainfalls, CO₂ concentrations and earthquakes were also considered, showing that only few rainfall events were followed by a CO₂ anomaly, mostly a day late.

KEYWORDS

statistical correlations, conditional probability, small earthquakes, hydrogeochemical continuous monitoring, CO₂ time series

1 Introduction

The circulation of crustal fluids affects not only the transport of heat and chemical constituents, but also the mechanical processes that control rock deformation, and possibly generate earthquakes. Abnormal pressures in tectonically active areas were first reported by Anderson (1927), and overpressurized fluids were later identified as a primary agent of tectonic deformation by Hubbert and Rubey (1959). The observation of anomalous soil CO₂ concentrations in correspondence with major faults/fractured areas (Caucasus region; Ntreba et al., 1971), and of CO₂ degassing episodes after major seismic events (Gold, 1979; Gold and Soter, 1979; Gold and Soter, 1981) dates back to early 1970s'. Based on a worldwide compilation of data, it has been later established that crustal CO₂ predominantly discharges in tectonically active regions, and along major seismic zones (Barnes et al., 1978; Irwin and Barnes, 1980; Gold and Soter, 1985; Gold, 1999). The occurrence of CO₂ emissions in correspondence with principal zones of seismicity was recently observed whether during the preparation stages of major earthquakes (e.g., among many others, Kingsley, 2001; Bräuer et al., 2003), or during aftershock evolutions (Ventura et al., 2007; Massin et al., 2013; Miller, 2013; Fischer et al., 2017; Yoshida and Hasegawa, 2018; Chiodini et al., 2020), or in

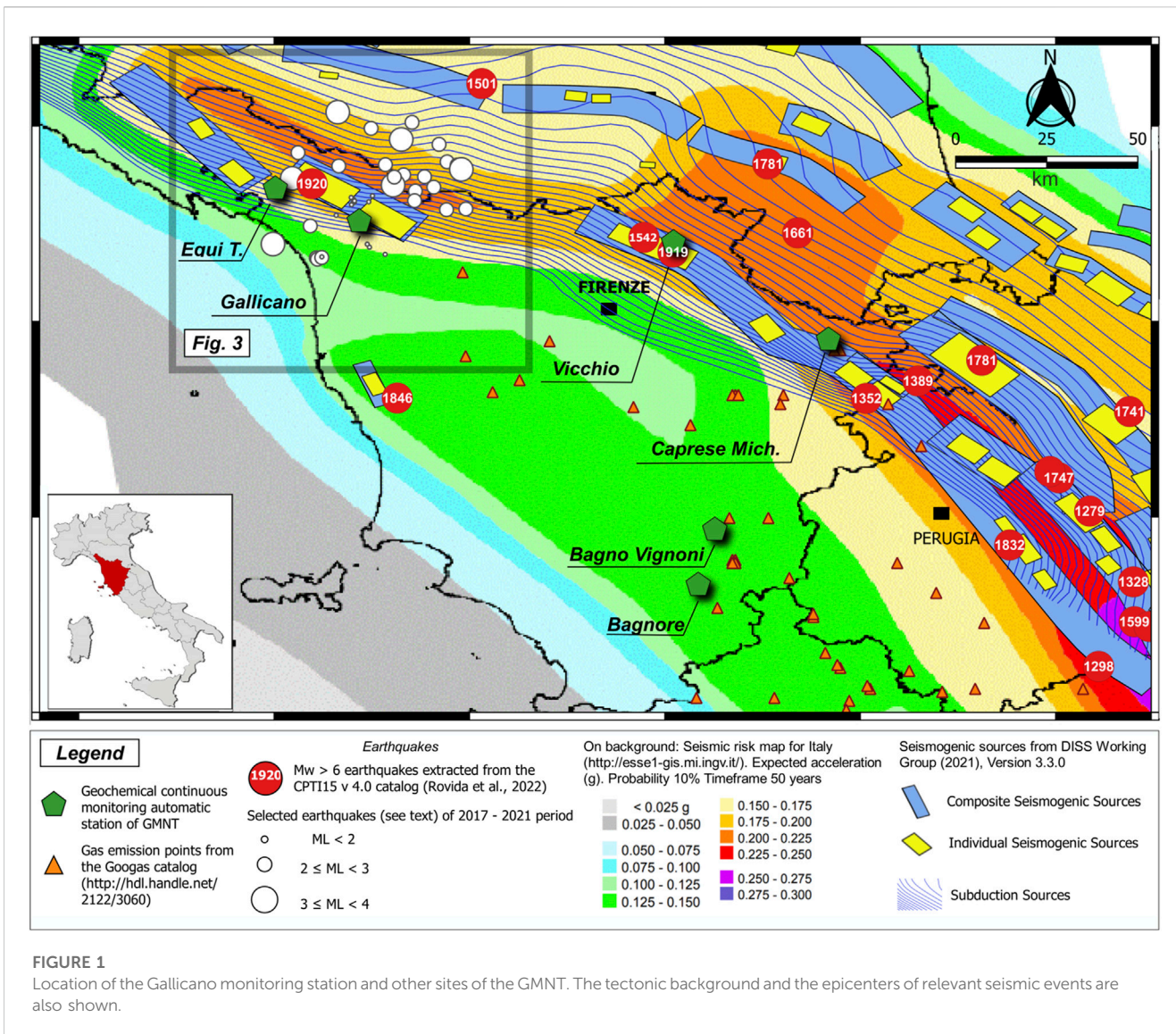


FIGURE 1 Location of the Gallicano monitoring station and other sites of the GMNT. The tectonic background and the epicenters of relevant seismic events are also shown.

concomitance with small seismic events (Heinicke et al., 1995). CO₂ excesses are predominantly observed in extensional domains (Tamburello et al., 2018), whereas compressional tectonic structures are suspected to create geological traps where crustal CO₂ may accumulate, possibly creating overpressurized reservoirs that may have the potential to trigger earthquakes (Chiodini et al., 2004). Overall, a strong connection between CO₂ discharge, seismic activity, and the existence of major faults has been identified in a number of different geodynamic contexts (Lee et al., 2016; Hunt et al., 2017).

In Central Italy, due to intense crustal deformation processes driven by the relative motion of the African and the Eurasian plates, two major areas affected by different tectonic and CO₂ degassing regimes have been identified (Chiodini et al., 2004): 1) the Tyrrhenian hinterland, characterized by extensional tectonic, crustal thinning, high heat flux and active volcanism near the Tyrrhenian Sea, where CO₂ is directly released into the atmosphere by the Tuscan-Roman and Campanian degassing structures; 2) the Adriatic foreland, characterized by

compressional tectonics, where CO₂ is predominantly dissolved into groundwaters circulating through major carbonate aquifers hosted along the Apennine fold-and-thrust belt.

The central-southern part of Apennines is a highly active seismic area, and some authors (e.g., Chiodini et al., 2004; 2020) have speculated that the existence of high-pressure, CO₂-rich fluid pockets at depth may play a major role in the generation of Apennine earthquakes.

Since early 1990s, a large amount of information on the possible correlation between CO₂ degassing and seismic activity has been obtained in Italy using manual samplings techniques (Dall'Aglio et al., 1990; Di Bello et al., 1998; Italiano et al., 2001; Italiano et al., 2004; Cardellini et al., 2017; Giudicepietro et al., 2019; Chiodini et al., 2020; Martinelli et al., 2020). The collection of continuous time series by means of automatic ground-based stations has started more recently (Cioni et al., 2007; Heinicke et al., 2012; Di Martino et al., 2013; Pering et al., 2014; Pierotti et al., 2015; Camarda et al., 2016; Camarda et al., 2018; Pierotti et al., 2017; Gherardi and Pierotti, 2018), and since early 2003 a network of six automatic monitoring

stations is operating in Tuscany, Central Italy (Geochemical Monitoring Network of Tuscany, GMNT; Figure 1).

Here we report on CO_2 time series collected during the 2017–2021 period from one of the stations of the GMNT (Gallicano station, NW Tuscany), advancing a new statistical interpretative approach borrowed from satellite data processing procedures (Fidani, 2021). So far, in fact, Gallicano time series have been processed with the aim to identify possible anomalies merely related to most energetic seismic events ($M_w > 4$; e.g., Pierotti et al., 2015). Now, instead, the focus is on the possible correlation between low to moderate seismic events, which are inherently more numerous, and geochemical anomalies identified in the residuals of the CO_2 continually recorded signal. The proposed statistical approach allows for identifying CO_2 anomalies by cumulative probability, and for correlating them with earthquakes, without explicitly addressing the cause-effect mechanisms between the two classes of observable events. Finally, a conditional probability of earthquake occurrence is defined for possible short-term forecasting. At this stage, for ease of interpretation of the correlations, we focused solely on the geochemical signal of the Gallicano monitoring station, which has proven to be sensitive to crustal deformations (Pierotti et al., 2015). Future work will improve on this by extending the approach to the analysis of multiple geochemical time series collected from different monitoring stations, insofar as they are geologically linked to the same seismogenic structures.

2 Description of the study area

2.1 The Gallicano site

By discharging high-salinity Na-Ca-Cl waters (2.4 to 4.2 g/L), with a temperature of 23.4°C–25.2°C, and an average flow rate of about 1.5 L/s, the Gallicano thermomineral spring (209 m a.s.l., Garfagnana Valley, northern Tuscany, Italy), is considered a suitable site to investigate possible correlations between seismic events and anomalies in CO_2 dissolved concentrations (Cioni et al., 2007; Pierotti et al., 2015). Garfagnana Valley is one of the areas with the highest seismic risks in Tuscany. The region was struck by a M_w 6.5 earthquake in 1920 (Garfagnana earthquake; Rovida et al., 2022), and is characterized by an expected horizontal peak ground acceleration (PGA) higher than 0.175 g, with a 10% probability of exceedance in 50 years (national reference seismic hazard model; Stucchi et al., 2011). The Gallicano thermomineral spring is fed by a major, fractured carbonate aquifer. After long underground circulation paths, thermal waters emerge in correspondence with neotectonic structures (Molli et al., 2021) belonging to one of the seismogenic boxes identified by the DISS Working group (2021). Chemical and isotopic data indicate that during their underground circulation path, Gallicano waters interact with evaporitic rocks of Triassic age, and experience the inflow of deep-seated CO_2 (Pierotti et al., 2015). These conditions reflect the essential criteria required for the successful monitoring of preseismic gas-geochemical signals (Martinelli and Albarello, 1997; King et al., 2006; Weinlich et al., 2006; Martinelli and Daddomo, 2017). Since April 2003, the spring is continuously monitored for a number of parameters, which include water temperature, pH, electrical conductivity, redox potential, and

dissolved concentration of CO_2 and CH_4 . Full details on the setup, operating mode, sensor technology, and performance of the automatic station are given by Pierotti et al. (2015).

2.2 Meteorological data

Operative since 2000, the automatic meteorological station of Gallicano (179 m.a.s.l., 44.064° Latitude North, and 10.443° Longitude East) is part of a regional network of about 440 manual and 133 automatic stations (Agro-Meteorological Network) managed by the Regional Hydrological Service (SIR) of Tuscany. The station is located in the municipality of Gallicano, some 800 m ENE of the monitored spring, and acquires meteorological data every 5 min. Rainfall data for the period April 2017 to March 2021 are characterized by an average annual value of 1732 mm/yr, consistent with the average annual value of about 1880 mm/yr estimated for the preceding period without data loss 2011–2016 (<https://www.sir.toscana.it/pluviometria-pub>). The two most abundant events recorded during the period of interest occurred on 2 February 2019 (134.8 mm) and 23 January 2021 (106.6 mm).

3 Methods

3.1 CO_2 monitoring

CO_2 concentrations are measured with a specifically designed cell built in the Pisa laboratories of CNR-IGG (Cioni et al., 2007). The apparatus relies on the measurement of variations in P_{CO_2} within the cell, with P_{CO_2} values expressed as percent of the total pressure. The measure is done with an IR spectrophotometer operating over the analytical range 0%–10%, with an accuracy better than $\pm 2\%$ of the range. Chemical speciation calculations and salting out corrections are used to periodically verify the response of the apparatus, by exploiting Henry's law to relate carbon dioxide partial pressure (P_{CO_2}) values measured in the cell to aqueous concentration ($\text{CO}_{2(aq)}$) measured in water samples. In this contribution, we focus on CO_2 time series acquired during the 2017–2021 period. We processed raw data with appropriate moving median smoothing procedures (Box and Jenkins, 1976; Velleman and Hoaglin, 1981) to filter out a number of outliers recorded during monthly maintenance operations. The moving-median smoothing approach was preferred to the moving-average smoothing because of its superior ability to reduce the impact of the outliers present in the smoothing window. Our protocol considers a standard maintenance activity that includes monthly inspection of the whole apparatus, with an interruption of about one hour of the spring water supply to the measurement equipment. Therefore, in order to eliminate the outliers due to maintenance operations without affecting the signal, we applied a moving median smoothing window of $2N + 1 = 25$ points. Following Pierotti et al. (2015), CO_2 time series have been decomposed according to Census I method (Makridakis et al., 1998) to detrend the CO_2 signal for external influences. In particular, according to Census technique, we polished the original time series for seasonal and cyclical components (combined with the additive

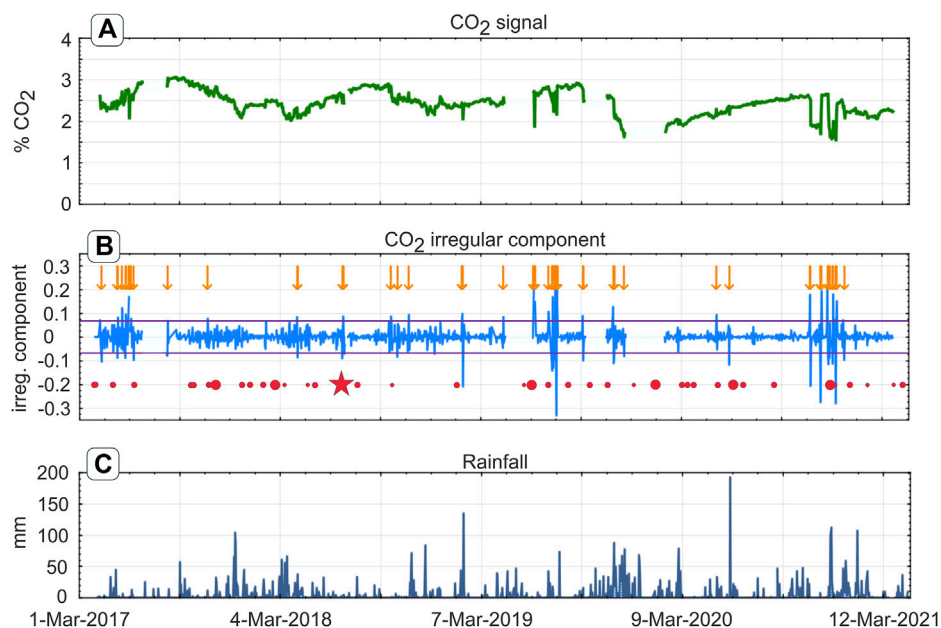


FIGURE 2

(A) CO_2 signal in vol.% of the headspace of the measurement cell; Cioni et al., 2007; Pierotti et al., 2015) acquired during the period April 2017–March 2021. (B) Irregular component of CO_2 time series, obtained by application of the Census I method. Purple lines represent the threshold for anomalous values (values outside this range have 99% probability of not belonging to a Pearson distribution). Orange arrows and red dots mark sixty-one (61) selected CO_2 anomalies and forty-two (42) selected seismic events (see text), respectively. Dots dimensions progressively increase with local magnitude (M_L). Seismic events are ranked into three classes of magnitude: low- ($M_L < 2$), intermediate- ($2 \leq M_L < 3$), and high-energy events ($M_L \geq 3$). The most energetic event of 7 January 2018 (M_L 3.6) is indicated by a red star. (C) rainfall at the Gallicano pluviometric station (data from <https://www.sir.toscana.it/pluviometria-pub>).

model) to separate a residual component called “irregular component” (Figure 2). The decomposition was performed following a step-by-step procedure that considered a reference frame of 12 months (Makridakis et al., 1998). By definition, the irregular component of the CO_2 time series is the residual CO_2 time series resulting from non-systematic, short-term fluctuations, and corresponds to the high-frequency fluctuations of the series.

3.2 Earthquake declustering

We downloaded earthquake data from the catalog of the ISIDE Working Group (Italian Seismological Instrumental and parametric database; <http://iside.rm.ingv.it>) to obtain a subset of “significant events” with magnitude greater or equal to 1.0. The set was declustered using the Reasenberg (1985); Gardner and Knopoff (1974) methods, as implemented in the zmap suite of Matlab tools (Wiemer, 2001). The focus was on the low seismicity period between 19 March 2017, to 18 April 2021. During this period, we identified 785 seismic events within a radius of 50 km from the Gallicano site, and a maximum hypocentral depth of 50 km. The estimated magnitude of completeness was 1.4 (Figures 3A, B), and the greatest observed local magnitude $M_L = 3.6$ (1 July 2018; epicenter near Pievpelego, about 700 m elevation, Modena Province). The areal distribution of seismicity is shown in Figure 3A, along with the traces of the main faults around the Gallicano site, whereas the distribution of hypocentral depths is shown in Figure 3C. Meteorological data were retrieved from the

web archive of the Gallicano pluviometric station (<https://www.sir.toscana.it/pluviometria-pub>).

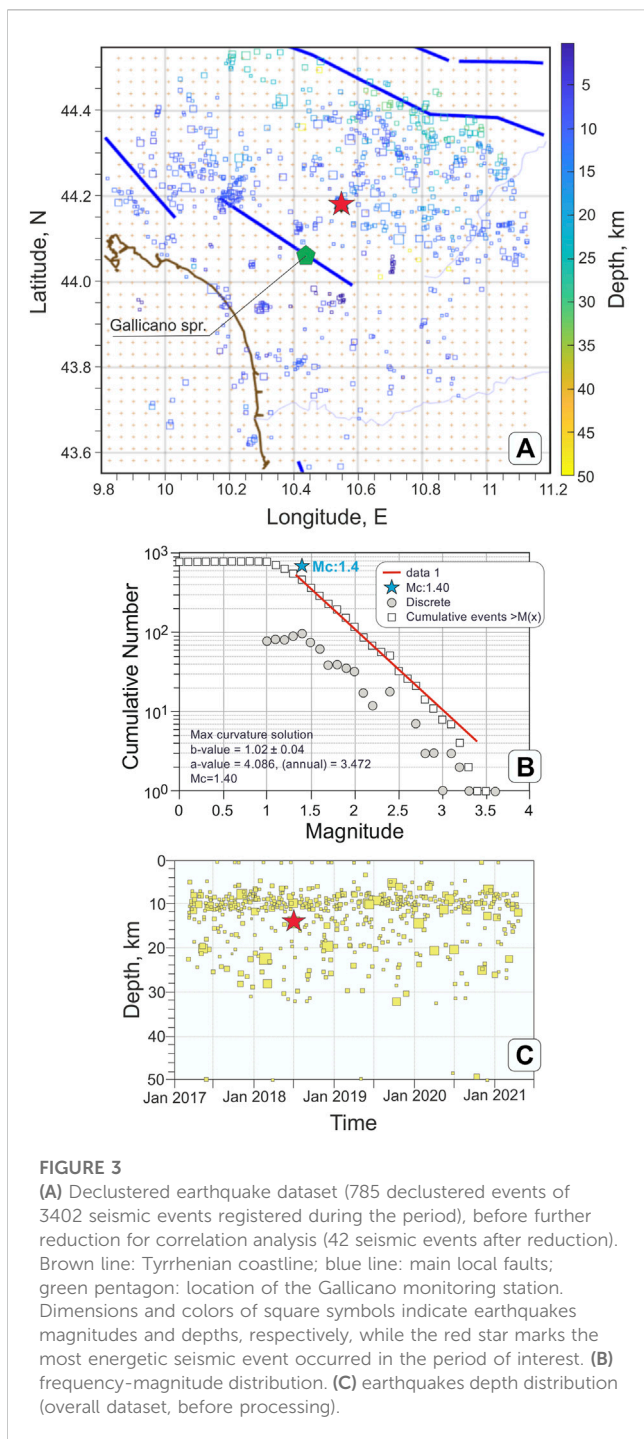
3.3 Statistical treatment

The identification of CO_2 anomalies from the irregular dataset was realized with a standard step-by-step method. First, we fitted the CO_2 irregular component to the shape of the input dataset. Then, we calculated the probability density value from any given test input, to evaluate the probability of each of these test input to be an anomaly. The lower the probability, the higher the likelihood of being an anomaly. Therefore, the challenge to identify anomalies was converted into the problem of setting an anomaly threshold. We considered as anomaly “1” any datum beyond this threshold, and the remaining data as anomalies “0”. This approach transformed the data series into binary series, given a certain time step, where the probability of the anomaly was given by the anomaly frequency

$$P = \frac{N(1)}{N_{tot}}, \quad (1)$$

with N_{tot} being the total number of steps for any chosen time interval.

We calculated the Pearson cross-correlation coefficient R to compare pairs of data series. The Pearson correlation measures the strength of the linear relationship between two variables. It may take values between -1 and 1 , with a $R = -1$ meaning total negative linear correlation, $R = 0$ no correlation, and $R = +1$ total positive



correlation. In this study, we considered three time series, and we compared them two-by-two: CO₂ anomalies, earthquakes in the surroundings of the Gallicano site, and rainfall amounts registered at the Gallicano pluviometric station. Three Pearson correlation coefficients were then calculated, one for each of the three possible pairs. After having defined a threshold for both CO₂ anomalies and “significant earthquakes”, each of these series was transformed into a binary series of events, separated by the same time step of the others series: variations in CO₂ concentration = (EC), earthquake occurrences = (EQ). The correlation coefficient

between binary series is the Matthews correlation (Matthews, 1975), and possesses specific properties (Fidani, 2020):

$$corr(EQ; EC) = \frac{(\sum EQ \times EC) / N_{tot} - P(EQ)P(EC)}{\sqrt{P(EQ)[1 - P(EQ)]P(EC)[1 - P(EC)]}} \quad (2)$$

where $\sum EQ \times EC$ is the number of coincidences between the two types of events that runs over the same time steps, and both $P(EQ)$ and $P(EC)$ were defined by (1). By introducing a time shift Δt , the possible time lag between the different type of events taken into consideration was evaluated by creating a correlation histogram for each pair of time series

$$corr(EQ; EC(\Delta t)) = \frac{(\sum EQ \times EC(\Delta t)) / N_{tot} - P(EQ)P(EC)}{\sqrt{P(EQ)[1 - P(EQ)]P(EC)[1 - P(EC)]}} \quad (3)$$

In Eq. 3, the presence of Δt indicates that the time step of the considered EC event is given by the sum $t_{EQ} + \Delta t$, where t_{EQ} is the time step of the event EQ. $P(EC)$ is defined by the EC frequency and not depends on Δt , $P(EC) = N(EC = 1) / N_{tot}$, where $N(EC)$ is the number of $EC = 1$, that is the number of CO₂ anomalies.

It was demonstrated (Fidani, 2018) that the conditional probability between two sets of digital events can be defined starting from the Matthews correlation. For negative values of the time shift ($\Delta t < 0$), the conditional probability becomes a forecasting probability. Given two EC and EQ events, with EC occurred earlier by a time $|\Delta t|$, the conditional probability of the EQ event is given by

$$P(EQ|EC(\Delta t)) = P(EQ) + corr(EQ, EC(\Delta t)) \sqrt{P(EQ)[1 - P(EQ)][1/P(EC) - 1]} \quad (4)$$

The forecasting relation (4) means that if a correlation exists between EQ and EC values, and a CO₂ anomaly is observed, then an EQ of magnitude above the threshold is expected to occur with a probability increased by a term proportional to the correlation at a time following the CO₂ anomaly observation by $|\Delta t|$. The ratio $P(EQ|EC(\Delta t)) / P(EQ)$ defines the increase in earthquake probability due to the CO₂ anomaly observation, and is called probability gain $G(\Delta t)$.

4 Results and discussion

4.1 CO₂ anomalies

The CO₂ irregular component obtained by application of the Census method was distributed on 29 amplitude intervals, and analyzed. The irregular component showed a very peaked, although symmetric distribution. We obtained adequate confidence levels of the fit distribution by means of a type VII Pearson distribution (Pearson, 1916). The four-parameter function was:

$$P(x) = \frac{A \Gamma[m]}{\Gamma[m - 1/2]} [\pi (2m - 1)]^{-1/2} \left\{ 1 + \frac{(x - \mu)^2}{\sigma^2 (2m - 1)} \right\}^{-m} \quad (5)$$

where Γ is the Gamma function, μ the average, σ^2 the variance, and A a generic fitting parameter. After having selected appropriate m values to get a well-defined variance (e.g., $m = 1.51 > 3/2$), we got the

following best fitting values: $\mu = 4.8 \times 10^{-4}$, $\sigma^2 = 1.6 \times 10^{-3}$, $A = 37.246$. Due to the combination of 29 intervals and 4 parameters, the statistical system had 25 degrees of freedom. The Chi-square test gave a χ^2 value of 9.1, equivalent to a goodness of approximation >99%.

CO₂ anomalies were statistically defined by comparison with a reference threshold. Fluctuations of the CO₂ irregular component above this threshold had a 99% of probability of not occurring by chance. The cumulative probability of every fluctuation was calculated by the cumulate of the relation (5), which was demonstrated to correspond to the Gauss's hypergeometric function (Johnson et al., 1995):

$$\Pr(x) = 1/2 + \frac{(x - \mu)}{\sigma[\pi(2m - 1)]^{1/2}} \frac{\Gamma[m]}{\Gamma[m - 1/2]} {}_2F_1 \left[m; 1/2; 3/2; -\frac{(x - \mu)^2}{\sigma^2(2m - 1)} \right]. \quad (6)$$

Given the symmetry around the averages, positive and negative thresholds were defined as $x_+ = 0.07243$, $x_- = -0.07147$. Finally, sixty-one (61) CO₂ anomalies were selected from the CO₂ irregular component over the 1,458 days-long time interval between April 2017 and April 2021, and tagged with the number "1" in the series of daily anomalies. This analysis revealed that a CO₂ anomaly preceded by 3 days the most energetic event (M_L 3.6) of the period. Further inspection of our time series also allowed excluding any hypothetical correlation between CO₂ anomalies and major earthquakes occurred worldwide during the same period (passage of Rayleigh seismic waves; e.g., Manga and Wang, 2015), as observed elsewhere for groundwater level variations (e.g., Cooper et al., 1965; Brodsky et al., 2003; Sil and Freymueller, 2006; Shi and Wang, 2014; Zhang et al., 2015; Barberio et al., 2020; He and Singh, 2020). This assessment was based on the lack of correlation with Italian, Mediterranean, and global earthquakes with magnitude greater than or equal to 4.5, 5.5, and 6.5, respectively (see Supplementary Material S1).

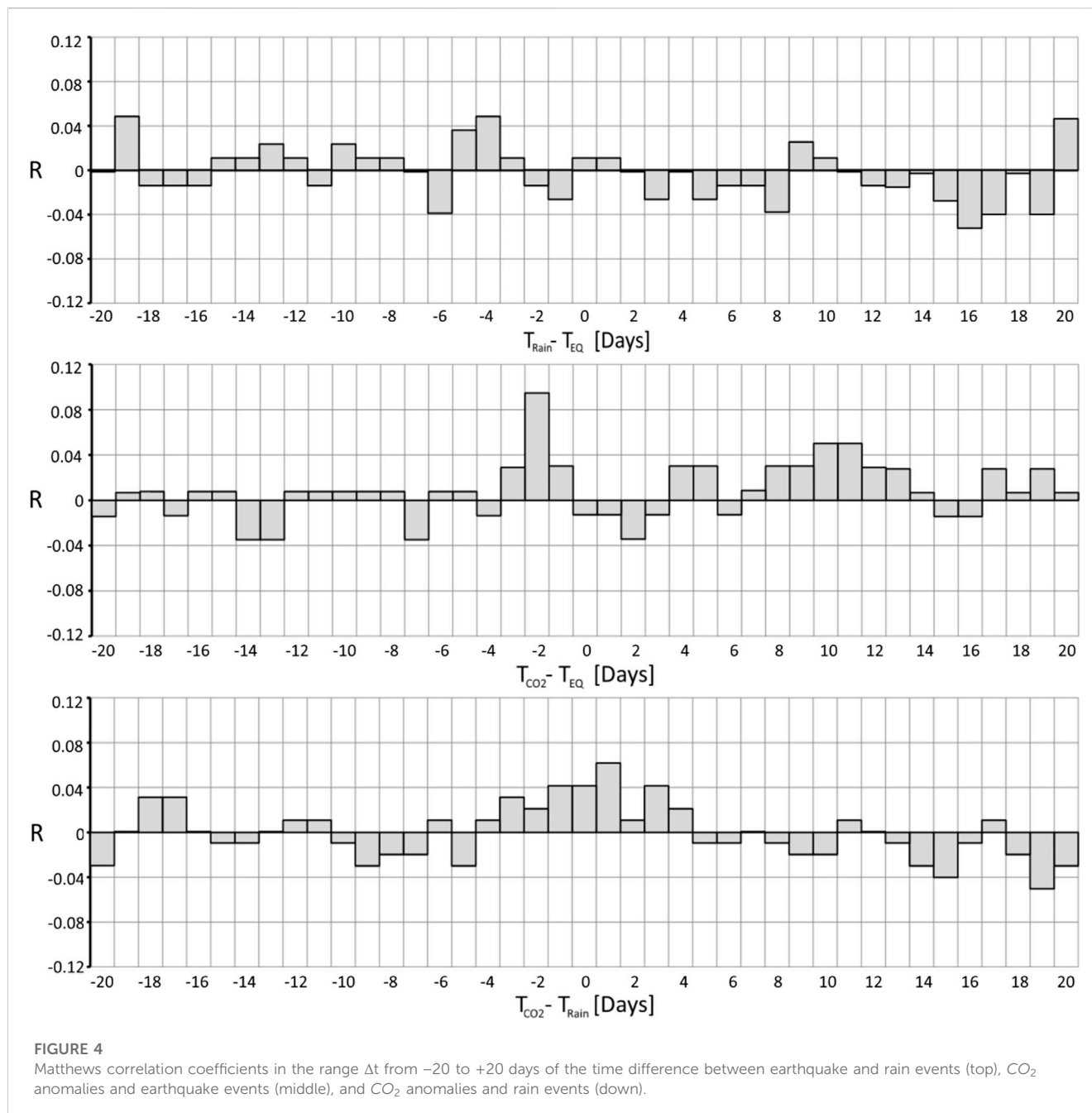
4.2 Correlations

The purpose of the statistical treatment presented in this work was to explore possible correlations between declustered small earthquakes and CO₂ anomalies obtained by a Pearson type VII fit. The applicability of this approach strictly relies on the availability of a large number of data. Accordingly, we have leveraged a long-term record of CO₂ data to evaluate the characteristics of the geochemical signal, along with a relatively large number of seismic events occurred within a hypocentral radius of 50 km from the Gallicano station. The distance between the hypocenters of relevant earthquakes to the Gallicano spring was the basis for estimating the statistical significance of the correlations. Different theoretical and empirical models exist in the literature to correlate epicentral distance and magnitude of seismic events (e.g., Dobrovolsky et al., 1979; Ohnaka, 1992; Rikitake, 1994; Bowman et al., 1998), but their applicability is still under debate (e.g., Rebetsky and Lermontova, 2018; Woith et al., 2018), in particular for low magnitude phenomena. We considered all these models, along with an empirical correlation recently proposed for Italy (e.g., Martinelli et al., 2021, and references therein), to approximate the largest

region where a physical connection could be expected between earthquake occurrences and variations in CO₂ concentration. None of these models resulted in a database of seismic events sufficiently large to be considered statistically relevant for our application (three events at most, selected over the period of interest). We thus iteratively enlarged the area of physical connection until obtaining a comparable number of selected seismic events per number of selected geochemical anomalies. This allowed to identify a maximum radius of about 47 km, equivalent to considering seismic events with hypocenter distances below three (3) Dobrovolsky radii (<3D) from Gallicano station. Under these conditions, forty-two (42) earthquakes of M_L 1.2 to 3.6, with epicentral distances <40 km, were tagged as relevant (EQ = 1). This was equivalent to assuming a physical link between CO₂ anomalies and seismic events around the magnitude of completeness in the epicentral region, and in a larger area, likely beyond the borders of Tuscany region, for seismic events of moderate magnitude.

The time lag correlation was obtained by filling a histogram with each CO₂ anomaly, $\sum_{\{EQ;EC\}} (EQ \times EC)$, occurred within a temporal interval (Δt lag) of ± 20 days, with respect to the date of occurrence of each selected seismic event. Moreover, a correlation histogram was also created between rain events (ER) and CO₂ anomalies, to assess any possible influence of rainfall amounts on CO₂ concentrations in spring waters. Rain events were considered to be significant (ER = 1) above the arbitrary rainfall threshold of 10 mm/day. So, another histogram based on the coincidence of one rainfall significant event with one CO₂ anomaly, $\sum_{\{ER;EC\}} (ER \times EC)$, was filled. Finally, for sake of completeness, an additional correlation histogram between rain events and seismic events was created, $\sum_{\{ER;EQ\}} (ER \times EQ)$, to possibly exclude any direct link between rainfalls and seismicity. A time difference Δt of 1 day was used for all correlation diagrams of Figure 4.

The correlation plots were drawn for time differences Δt of ± 20 days (i.e., $\Delta t = +20$ days and $\Delta t = -20$ days indicate an advance and a delay of 20 days, respectively, of the first type of event with respect to the second one). The correlation between rain and earthquake events is shown in Figure 4 (top diagram). We did not observe any significant correlation between meteorological and seismic phenomena. The middle plot of Figure 4 reports a significant peak of correlation between seismic and CO₂ events associated with a time difference Δt of -2 days. Being Δt the time difference $T_{CO_2} - T_{EQ}$, this is equivalent to say that on a statistical basis CO₂ anomalies tend to anticipate seismic events by 2 days. The cross-correlation peak corresponding to -2 days is 0.0947. We evaluated the uncertainty of the procedure by repeating the correlation calculus for 100 additional randomly generated earthquakes datasets. By obtaining correlation histograms with correlation peaks greater than 0.1 in only three cases (equivalent to 3%), we can discard the hypothesis that the correlation peak is due to chance. In an entirely equivalent way, by applying the Statistica® software (Statsoft Inc., 2013), we also obtained a p -value <5%, which further confirms that the null hypothesis can be discarded. Noteworthy, the statistical procedure has highlighted the same cross-correlation peak corresponding to -2 days also when we considered a larger temporal interval (Δt lag) of ± 30 days, or a smaller earthquake dataset devoid of



$M_L < 2$ seismic events, as shown in the [Supplementary Material S1](#).

Based on Eq. 4, the correlation peak defines the conditional probability that a seismic event may occur 2 days after a CO_2 anomaly $P(EQ|EC)$. This probability can be significantly greater than the normal frequency of earthquakes $P(EQ) = 0.0277$ of a given magnitude, within a distance of $3D$ from the Gallicano station. It was calculated that $P(EQ|EC) = 3.63 P(EQ)$, which corresponds to a probability gain of $G \approx 3.6$. The plot at the bottom of Figure 4 represents the correlation between rainfalls and CO_2 anomalies. Here, a mild correlation aroused for a time difference $\Delta t = T_{CO_2} - T_{Rain} = +1 \text{ day}$, indicating that rainfalls tend to anticipate CO_2 anomalies by 1 day.

5 Conclusion

We propose a first comprehensive statistical analysis of CO_2 time series registered at the Gallicano test site, Italy, where a continuous automatic station is operating since 2003 to investigate the geochemical response to local seismic activity of a deep aquifer feeding a thermomineral spring. The availability of continuous time series emerged as an essential prerequisite to evolve towards the calculus of the conditional property of the seismic events. The focus is on CO_2 concentration values measured in spring water during the period April 2017 to April 2021. We modeled the irregular component of the CO_2 time series by a suitable fit based on the Pearson type VII distribution, and we used the Gauss's

hypergeometric function to retrieve the cumulative probability. Based on this value, we defined the threshold for 99% probability of fluctuations not occurring by chance. We calculated the cross-correlation between the binary series of CO_2 anomalies and low to moderate magnitude seismic events, disclosing a positive correlation for CO_2 anomalies occurring 2 days before the earthquakes. We extended the procedure to rainfalls vs. earthquakes, and CO_2 vs. rainfalls time series. In both cases, we estimated negligible correlations, compared to the CO_2 vs. earthquakes case. In particular, rainfall and earthquakes appeared completely uncorrelated, and just a mild correlation was observed for rains occurring 1 day before CO_2 anomalies.

A key aspect of this analysis is that the observed positive correlation between CO_2 anomalies and seismic events concerned small earthquakes with hypocenters within relevant distances from the Gallicano spring, and that this assessment is independent from the mechanisms possibly suggested to explain the cause-effect relationship between CO_2 anomalies and small seismic events. This allows us to advance the hypothesis that CO_2 variations registered in Gallicano spring water can be considered a “short-term candidate precursor” (Molchanov and Hayakawa, 2008) for low seismic activity, regardless of whether the natural mechanisms behind this correlation inherently remain poorly constrained. From this perspective, we calculated a conditional probability based on the observation of a CO_2 anomaly, which resulted in 3.6 times the unconditioned earthquake probability. The knowledge of the conditional probability of the seismic events is, in perspective, a fundamental step to switch from the mere recognition of anomalous signals to the possible forecasting of seismic events. Future work will focus on the analysis of longer time series that also includes moderate to strong seismic activity, to augment the applicability of the method in terms of seismic hazard mitigation. Moreover, it is expected that the statistical analysis of the correlation between CO_2 anomalies and seismic events can be further refined through a more in-depth examination of the possible relations between CO_2 anomalies and rainfalls.

Data availability statement

The raw data supporting the conclusion of this article will be made available by the authors, without undue reservation.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Supplementary material

The Supplementary Material for this article can be found online at: <https://www.frontiersin.org/articles/10.3389/feart.2023.1128949/full#supplementary-material>

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