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Methodological advancements in soil erosion: a meta-analysis of organic matter content and erosion in the Mediterranean region

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A R T I C L E I N F O

Dataset link: data for meta-analysis from publications (Reference data)

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A B S T R A C T

Topsoil organic matter content (OMC), particularly within the upper 30 cm, is critical for soil fertility, ecosystem functioning, and resilience. In Mediterranean environments, OMC is highly vulnerable to soil water erosion (SWE), a process intensified by increasingly frequent and intense rainfall. While SWE research has largely focused on mineral soil loss, its effects on OMC, especially the balance between depletion in source areas and accumulation in depositional zones, remain poorly quantified at regional scales. This study applies advanced analytical approaches, including multilevel meta-analytic models, to examine the spatial dynamics of OMC redistribution under SWE and to evaluate how scale and methodology influence reported outcomes. A meta-analysis was conducted using data from 71 studies across Mediterranean landscapes. Due to the limited availability of land-use-specific studies, the analysis adopts a broad regional perspective rather than stratification by management type. Results reveal extremely high heterogeneity, driven primarily by methodological differences, spatial scale, and timing. Mean effects varied by study type: field experiments showed a weakly negative association between SWE and OMC ($\beta = -0.0421$, $k = 68$), rainfall-based studies showed a positive relationship ($\beta = 0.7209$, $k = 66$), and simulation studies indicated a mild positive trend ($\beta = 0.0835$, $k = 14$), all with high heterogeneity ($I^2 > 90$ %). Overall, the findings demonstrate that SWE does not uniformly result in OMC loss but often reflects spatial translocation. These results highlight the need for improved methodological consistency and ecologically grounded frameworks to interpret OMC dynamics in Mediterranean erosion-prone landscapes.

1. Introduction

Poor soil health and erosion are considered among the main causes of the demise of the major ancient Mediterranean civilisations (Kraamwinkel et al., 2021), as early as the Sumerians in Mesopotamia (2300 BCE). Today, soil erosion is still a major threat to the Mediterranean ecosystem as it depletes the already meagre organic matter of the topsoil. This fraction plays a major role in soil fertility and soil health. Therefore, its exhaustion undermines the restoration capacity of degraded Mediterranean land and interventions towards Land Degradation Neutrality (SDG 15.3) through scientific (e.g. REACT4MED, SUPERB, MERLIN, REST-COAST) and applied projects (Eu commission) (e.g., Trillion Trees, Plant-for-the-Planet, EU planting 3 billion additional trees by 2030). It is backed by policy (e.g., Biodiversity Strategy for 2030, Green Deal), global initiatives (UN Environment program, 2025) (e.g. United Nations Decade on Ecosystem Restoration), and European funding instruments (e.g. the Common Agricultural Policy) (EU Agriculture Policy, 2025). These initiatives illustrate the broader context in which SWE and OMC interactions occur, underscoring the urgency of region-specific syntheses that connect biophysical processes to actionable restoration strategies.

Due to this significant risk, the erosion process and its impacts have been rigorously studied, focusing on aspects such as crop types (Roy et al., 2018), cropping systems and agricultural management practices (García-Orenes et al., 2009a, 2009b), use of fertilisers (Baldantoni et al., 2019), nutrients in the soil (Durán Zuazo et al., 2004), soil type (Roose and Barthès, 2005), minerals, edaphic and lithologic properties, topography, etc. In (Prosdocimi et al., 2016a, 2016b), the authors aim to

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compile a comprehensive database on splash, sheet, and rill erosion rates in Mediterranean vineyards. By focusing on the Mediterranean region, known for significant soil losses (SL) due to its unique topography, soil conditions, and climate, the study highlights the urgent need for sustainable viticulture practices. European studies have estimated soil organic carbon stocks and erosion rates (Panagos et al., 2015; Yigini and Panagos, 2016). The SOC stocks in the European Mediterranean region range from 48.7 to 94.9 t ha^{-1} (Yigini and Panagos, 2016), while erosion rates vary from 2.05 to 8.46 t ha^{-1} yr^{-1} (Panagos et al., 2015). Meta-analyses have evaluated the effectiveness of various soil and water conservation practices (Rajbanshi et al., 2023). The effects of long-term agricultural management and erosion on mineral-associated soil organic matter have been investigated (Wang et al., 2019). Biochar application has been found to reduce soil erosion and runoff (Gholamahmadi et al., 2023). Organic amendments have been shown to reduce element losses during soil erosion, but their effectiveness varies depending on the element (Shi and Schulin, 2018). A global meta-analysis approach was studied, incorporating organic amendments can enhance soil health and OMC reduce the risk of SWE (Bai et al., 2023; Ma et al., 2024). However, beyond the technical strength of the methodologies used, understanding how land use practices such as crop rotation, grazing intensity, and reforestation directly influence OMC dynamics is crucial. Land use is not merely a contextual backdrop but an active driver that mediates the extent and pattern of erosion-induced organic matter redistribution across Mediterranean landscapes.

Various studies have explored soil erosion and its impacts. Dendrochronological methods have been used to infer past environmental conditions and date geomorphic events (Smith, 2007). Root anatomy has been applied to quantify soil erosion rates (Gärtner, 2007). Vineyard studies have assessed long-term erosion patterns using graft calluses (Casalí et al., 2009). The Revised Universal Soil Loss Equation (RUSLE) model has been used for predicting SL (Kenneth et al., 1997). The Soil and Water Assessment tool (SWAT) model has been evaluated for its effectiveness in various settings (Douglas-Mankin et al., n.d.). Soil organic carbon and carbon isotope signatures have been used to detect early-stage soil erosion (Schaub and Alewell, 2009). Cover crops have been shown to reduce soil organic matter loss in vineyards (López-Vicente et al., 2020a, b, c). Different management strategies have been compared for their impact on SL and runoff in apricot orchards (Keesstra et al., 2016a, 2016b).

(Ferreira et al., 2022) reviews the literature on soil degradation processes in the European Mediterranean region, with a focus on physical, chemical, and biological degradation. Saying the Mediterranean region is highly susceptible to soil degradation due to unsustainable management practices and climate change, highlighting the lack of consistent and comprehensive soil monitoring data across the region. Soil erosion is a major issue, but other degradation processes, such as loss of biodiversity loss, are poorly documented. Soil compaction is a concern, particularly in agricultural and forest areas, but studies are limited in time and scope. SOM and SOC have been investigated to agricultural practices and post-fire management. Soil salinization is increasing due to irrigation practices and sea-level rise. The importance of soil biodiversity is emphasized for ecosystem services, crop production, and carbon sequestration, also advocating for a harmonized soil monitoring system to track spatial and temporal changes in soil degradation.

(Cilek, 2017), focused on soil organic carbon (SOC) losses due to water erosion in a Mediterranean watershed, building upon previous research estimating SOC stocks in various regions. It includes a reference to the use of the CORINE land cover database in France for soil analysis. The study uses a wide variety of research to discuss carbon dynamics in soil, with reference to organic carbon in sediments and soil erosion risk. Referring to the European Soil Bureau for information on soil erosion risk. It includes a discussion of how soil organic carbon can be modelled using a multiple regression approach.

The above studies provide valuable insights into the relationship between soil water erosion (SWE) and organic matter content (OMC) in the Mediterranean region through different analytical methods. However, they often suffer from limitations that hinder the generalization of their findings. These limitations include varying experimental settings, diverse sampling techniques, data intriguing and the use of different scales of analysis. More research is needed to better understand how Soil Loss (SL), Soil Water Erosion (SWE), and Organic Matter Content (OMC) interact across Mediterranean landscapes (Bai et al., 2023; Tanner et al., 2023; Ma et al., 2024). One challenge is that findings are often aggregated from studies operating at very different scales, which can blur or even reverse patterns. Typically, it's assumed that higher OMC in soils helps reduce erosion – resulting in a negative correlation between OMC and SL (Hancock and Wells, 2021; Monreal et al., 1997; Prosdocimi et al., 2016b). But this isn't always the case. Some studies report a positive correlation (Márquez-García et al., 2013; Starr et al., 2008; Starr et al., 2000), where areas with higher OMC also experience greater soil loss. This raises a bit of a paradox: perhaps OMC is being preferentially detached and carried away with the sediment, rather than staying in place (García-Ruiz et al., 2010; Pachepsky and Hill, 2017; Van Oost and Six, 2023; Wei et al., 2012; Yair and Raz-Yassif, 2004). In light of this, there's a real need for future research to apply more standardized methods and to look beyond simple cause-effect models – especially if we want to truly capture the range of factors shaping the SWE-OMC relationship across Mediterranean settings.

Deeper scientific knowledge and better environmental monitoring allow scientists to improve their assessments of the status of, drivers of and trends in (Perevolotsky and Sheffer, 2011) land degradation and desertification, and to propose innovative sustainable soil and water management. Nevertheless, to sustainably restore degraded land and soil and to eventually achieve Land Degradation Neutrality (SDG 15.3), the key is to assess both soil loss and organic matter losses from an environmental point of view. Remaining knowledge gaps hinder affected communities in adopting and stakeholders from investing in good land management and restoration practices (Cerdà et al., 2018a, 2018b) that will allow local ecosystems to continue supporting their livelihoods. Restoration actions (e.g. REACTMED) aim to enhance and support increased agropastoral productivity, accelerate technological innovation and dissemination, reverse soil degradation and improve the livelihoods. Since soil degradation (decline in soil quality) is measured, among various parameters, by the loss of organic matter, decline in soil fertility, and erosion (mainly affecting the structural condition), it is crucial to assess soil and organic matter losses. Such assessment is essential not only for quantifying degradation, but for tracing cause-effect relationships that underpin land restoration strategies. By understanding what is lost, where, and under which conditions – whether through depletion or redistribution of organic matter – we can better evaluate how specific land use actions contribute to degradation, and design targeted interventions to reverse it.

To address this issue and better understand the erosional dynamics involved, both in terms of detaching and transporting soil particles and the fate of organic matter, we conducted a systematic meta-analysis of experimental studies focused on the Mediterranean region. Our analysis examined the combined effect magnitudes of the relationship between SWE and OMC across a wide set of studies. The literature thus presents an 'OMC-Erosion Paradox', where contrasting findings of positive and negative correlations are abundant. We posit that the massive statistical heterogeneity observed is a robust indicator current studies failure to standardize protocols that consistently separate and quantify the erosion-induced loss mechanism (source) from the deposition-driven accumulation mechanism (sink). Specifically, we aimed to: (a) explore the mutual interactions feedbacks between SWE processes and organic matter dynamics; (b) evaluate how the relationship between SL and OMC varies across different spatial and methodological scales; (c) assess how variations in research design influence the patterns observed. The structure of this paper is as follows: Section 2 presents the systematic review process, based on PRISMA guidelines, and outlines the data extraction and model estimation procedures. Section 3 reports the main findings, including the distribution of effect sizes across experimental, rainfed, and computational studies. Sections 4 and 5 discuss these results in light of methodological heterogeneity and the complex nature of erosion dynamics. Section 6 concludes with implications and recommendations for improving future research through more standardized approaches.

2. Methodology

2.1. Literature search strategy (data extraction)

The search strategy followed was based upon the steps proposed by the PRISMA (Preferred Reporting Items from Systematic Reviews and Meta-Analysis) guidelines (Moher, 2009), which ensure a rigorous and transparent approach to identifying, selecting, and evaluating research studies. The data collection for the meta-analysis was performed by combining two search strategies. The first strategy used the EBSCO provider that includes exclusively scholarly (peer-reviewed) academic journals in the English language published between 1984 and 2023. A second search strategy used Google Scholar for peer-reviewed publications in English, French, and Spanish within the same period. For both search strategies, four-term categories were defined by combining keywords using search engine-specific logical operators. The term categories were: “soil erosion”, “organic content”, “Mediterranean region”, and “agriculture”, codified for the search as S1, S2, S3, and S4, respectively (Supplementary 1).

The study included in the meta-analysis is about reports on SL and OMC, or provides sufficient data for these variables. The studies are experimental, involving controlled conditions that allow for assessing the relationship between SL and OMC.

The study employed a systematic approach to identify relevant research articles by searching according to four main thematic categories: (1) soil erosion, (2) organic matter content, (3) the Mediterranean region, and (4) agriculture. We combined these categories using logical operators to filter studies that met our focus.

The initial search in EBSCO yielded 953 records, which after duplicate removal were reduced to 823 unique articles. An additional search in Google Scholar identified 52 records, with no duplicates. Together, this resulted in 875 records for screening. We then applied eligibility criteria: (a) studies must report soil loss (SL), (b) provide organic matter content (OMC) measures or at least a correlation (r or R^2) between SL and OMC, (c) report more than two paired values of SL and OMC, and (d) specify the number of samples collected. After exclusions, 71 studies remained, from which 148 effect sizes were derived (49 from the EBSCO set and 22 from the Google Scholar set). Only peer-reviewed journal articles in English, French, or Spanish were included; no gray literature was considered.

In the first step, we searched for terms related to soil water erosion (SWE), including “soil erosion,” “sediment yield,” and various models and units describing soil loss (SL). Next, we added terms referring to organic matter in soil, such as “organic carbon,” “soil organic matter (SOM),” and “total organic carbon (TOC).” Combining these two categories yielded a subset of studies relevant to both erosion and organic matter. We then narrowed the search further by focusing on studies carried out in Mediterranean countries and those specifically dealing with agricultural settings, using keywords related to crops, vineyards, and specific types of land use. This step-by-step filtering helped us arrive at a focused group of studies most relevant to our objectives.

For both search strategies, the eligibility criteria were applied to exclude studies that did not meet the requirements such as: (a) studies that did not report measures of SL; (b) studies that did not provide OMC measures or at least a correlation coefficient (r or R^2) between SL and OMC; (c) studies reporting fewer than two values for SWE and OMC, and (d) studies that did not specify the number of samples collected.

After screening, the relevant data were manually extracted into an Excel sheet. The extracted variables included: (a) first author; (b) year of publication; (c) number of samples; (d) reported SL/SWE rate (e.g., Mg ha^{-1} y^{-1}); (e) forms of OMC reported (e.g., SOM, SOC, TOC, particulate organic carbon), along with their units, and (f) the method used in the study. No duplicate records were found between the EBSCO and Google Scholar searches.

Further details about this strategy are described in Section 1 of Supplementary Material 1.

2.2. Data organization

This study distinguishes between two conceptual scenarios: **Case 1** reflects situations where erosion results in a net *loss* of organic matter from the topsoil, producing a **negative correlation** between soil loss (SL) and organic matter content (OMC); **Case 2**, in contrast, describes cases where eroded sediments are *enriched* in organic matter, leading to a **positive correlation** between SL and OMC. This dual pattern illustrates the complexity of SWE-OMC interactions across different contexts. It also highlights a major challenge: many erosion studies use diverse experimental designs, often reporting data at different spatial or temporal scales, or failing to measure both SL and OMC concurrently. To account for these discrepancies, we applied a multilevel meta-analytic model specifically suited to the nonlinear and nested structure of environmental data (Hancock and Wells, 2021; Monreal et al., 1997; Prosdocimi et al., 2016b).

Conceptually, the study distinguishes between local, site-specific processes (Fig. 1, Case 1) and broader, spatial processes (Fig. 1, Case 2), emphasizing that while these processes are different, they may interact.

SWE involves two distinct, hierarchically structured processes: soil mass removal (Fig. 1, Case 1) and SL (Fig. 1, Case 2). While both processes contribute to SWE, their interactions and scales differ. Soil mass removal, a local-level phenomenon, occurs at specific sites within a spatial unit due to factors like topography, climate, soil texture, and lithology. SL, a global-level process, represents the total solid material removed from the entire spatial unit and is influenced by factors like vegetation cover, OMC, and soil permeability.

To measure soil mass removal, we monitored changes in OMC at specific locations within the spatial unit. This approach is site-dependent and provides local-level insights. In contrast, measuring SL involves assessing the amount of solid material carried away by runoff at the boundaries of the spatial unit. This method is less site-dependent and provides a global-level perspective.

Despite their differences, soil mass removal and SL are interconnected. SL, occurring at a larger scale, sets the overall environmental context for local-level soil mass removal events. Conversely, local-level processes can influence SL by contributing to the overall material removed from the system. This complex interplay highlights the hierarchical nature of SWE, where both top-down and bottom-up forces are at work. The premise is that massive and effective land restoration actions are more robust and have a lasting impact when the top-down approach (introduces broad-scale) is aligned and integrated with the bottom-up approach.

In Fig. 1, Case 1 depicts an inverse relationship between OMC at original soils (OMC_{origin}) and total SL (SL_{tot}) – OMC measures from the soil before experimenting – represented using a negative correlation (*r*). An increase in the SL_{tot} will imply a decrease in the OMC_{origin}. Case 2 describes a direct relation between OMC in sediments (OMC_{sed}) and SL_{tot} – OMC measures from the soil after experimenting, represented using a positive correlation (*r*), measuring the increase in SL_{tot} followed by an increase in OMC_{sed}.

2.3. Analysis at the macroscopic and microscopic levels

A meta-regression model was applied using a multilevel framework with moderators to better understand how the relationship between

SWE and OMC varies across different study designs and contexts. We used Fisher's Z correlation coefficients to standardize the results from multiple studies and to allow comparisons of both the direction (whether the correlation is positive or negative) and the strength (how strong the relationship is). This approach was chosen because it helps distinguish between opposing findings, for example, when one method reports a strong positive correlation, and another shows a negative one. It also allows us to account for differences between research methods and experimental designs. This analysis focused on two key aspects:

(1) variation between groups of studies using different methodological approaches, and (2) variation within each group, based on whether they showed positive or negative correlations.

We aimed to evaluate how much of the variability in the SWE-OMC relationship could be explained by methodological differences, by analyzing the overall mean effect of Fisher's Z values across these groups. Furthermore, we analyzed the combined average effective magnitudes of correlation within each method, paying special attention to whether correlations were positive or negative. This allowed us to identify patterns based on the direction of the relationship. The methods used in the studies were treated as categorical variables and examined using a meta-regression based on the multilevel (hierarchical) random-effects model, which is particularly useful in environmental research where data often come from nested or clustered study designs.

2.4. Meta-analytic models' estimation

To achieve this, we applied two meta-analytic models: (1) a simple multilevel random-effects model to estimate the overall effect across all studies, and (2) a meta-regression model that incorporates study methods as moderators to account for variation across approaches. The dataset included three types of research methods – experimental, rainfed, and computational – which served as categorical moderators in the analysis. These models helped uncover how the relationship between SL and OMC differs across methodological contexts and provided a clearer picture of the variability in effect sizes among study types. In the random-effects model, we consider (i = 1, 2, 3, …., k), each providing independent effect size estimates. The goal is to estimate the true overall effect size using the following expression is provided in Eq. (1).

$$z_j = \beta_0 + u_j + m_j \tag{1}$$

where z_j is the observed effect size from the j^{th} study, β_0 is the overall mean (unknown), u_j is the true effect for the j-th study (assumed to follow a normal distribution $N(0,\tau^2)$ with between-study variance τ^2, and m_j is the sampling error associated with the j^{th} study (assumed to follow a normal distribution $N(0, v_j)$ where v_j is the estimated sampling variance).

The true effects are assumed to be normally distributed with mean β_0 and variance τ^2. The primary objective is to estimate β_0 (the average true effect) and τ^2 (the heterogeneity among the true effects). The main effect $\widehat{\beta_0}$ is estimated using the weighted mean provided in Eq. (2).

$$\widehat{\beta_0} = \sum_{j=1}^{k} \frac{w_i}{w} z_j \tag{2}$$

where with study weights now defined as and $w_j = \left(\widehat{v}_i + \widehat{\tau}^2\right)^{-1}$ and $w = \sum_{j=1}^{k} w_j$.

However, the random-effects model assumes that the number of effective magnitudes equals the number of studies and that these magnitudes are independent. These assumptions are often not appropriate for environmental science data, which are typically characterized by complex non-independence and scale dependencies. Environmental studies, those in soil science and agriculture, involve heterogeneous data with varying research designs, methods, locations, and influential variables like topography, climate, soil types, and crop types. Consequently, the true effects may differ across studies, generating dependencies between effective magnitudes and relationships between SWE and OMC.

One significant limitation of the random-effects model in environmental science is its inability to account for the hierarchical structure of the data, where variances can be divided between-study variance (third level), within-study variance (second level), and sampling variance (first level). To address this, a multilevel/hierarchical random-effects model is more suitable, especially in environmental science contexts. Methodologically, we proceeded to collect data on SL and OMC, then estimated Pearson's product-moment correlation coefficient (r) for each dataset, followed by converting (r) to Fisher's Z-transformed correlation coefficient as provided by Eq. (3).

$$Z = \frac{1}{2} ln\left(\frac{1+r_1}{1-r_i}\right) = artanh\,(r_i) \quad i = \{1,2,3,\ldots,n_i\} \tag{3}$$

where $v = \frac{1}{n_i - 3\}}$ is the sampling variance, and n_i is the sample size for each r_i in the corpus studies. (when r gets closer to 1 the value of Z is higher, while r gets closer to -1 the value of Z is lower).

The Fisher's Z transformation helps in bias correction and facilitates the normality assumption in meta-analytic models. We then fitted two multilevel/hierarchical random-effects models using the restricted maximum-likelihood (REML) estimator. The first model, without moderators, estimates the overall mean of the collected data provided by Eq. (4).

$$z_i = \beta_0 + u_{j[i]} + e_i + m_i \tag{4}$$

where $u_{j[i]}$ is the between-study effect corresponding to the j^{th} study and i^{th} effect size, with $u_{j[i]} \sim N(0,\tau^2)$; e_i is the within-study effect corresponding to the i^{th} effect size, with $e_i \sim N(0,\sigma^2)$; and v_i is the sampling error related to the i^{th} sampling variance, v_i.

To further analyze the heterogeneity, we extended the model to a meta-regression model provided in the Eq. (5).

$$z_i = \beta_0 + \beta_1 x_{1j[i]} + u_{j[i]} + e_i + m_i \tag{5}$$

where β_1 represents the slope of the moderator x_1, accounting for the linear (additive) effects due to x_1 and $x_{1j[i]}$ denotes the value of x_1 corresponding to the j^{th} study and the i^{th} effect size.

The meta-regression model allows for subgroup meta-analysis by employing different categorical subdivisions across the dataset. This moderator varies at the between-studies level, explaining the variance component τ^2, which is further referred to I^2_{study}. Meanwhile, $x_{1\mathrm{i}}$ represents the moderator varying at the within-study level (Effective magnitudes of relationship level), explaining the variance component τ^2, which is further referred to as I^2_{effect}.

Meta-regression models allow us to conduct meta-analyses across different categorical subdivisions within the dataset, enabling "subgroup meta-analysis" or, in this case, meta-analysis of grouped data. We employed two meta-regression models which utilize the methods applied by the studies as the moderator (corresponding to the second level in our tree structure, see the Discussion section). Then use the sign of Fisher's Z correlation coefficient as the moderator (third level in our tree structure, see the Discussion section). These models enable evaluation of not only the strength (correlation value) but also the direction (correlation sign) of the relationship. The Q-test for moderators (denoted as QM) indicates the significance of the moderators for each model run. The variance explained by the moderators in each model was estimated using marginal R^2, defined as in Eq. (6).

$$R^2 = \frac{f^2}{f^2 + \tau^2 + \sigma^2} \tag{6}$$

where f^2 is the explained variance due to the moderator, defined as in Eq. (7).

$$f^2 = f^2_{study} + f^2_{effect} \tag{7}$$

with f^2_{study} corresponding to the explained variance at the study level and f^2_{effect} the explained variance at the effect size level.

The goodness-of-fit tests for both models indicated that the restricted REML estimator was superior, with higher log-likelihood (logLik) values and lower information criteria, i.e. Akaike's Information Criterion (AIC) and Bayesian Information Criterion (BIC), compared to the maximum likelihood (ML) estimator, making REML the preferred choice. In environmental studies, each study has its specific mean and the "true" effective magnitudes, which may differ, yet it is crucial to account for inconsistencies or consistencies (heterogeneity) in the data. A realistic modelling approach, particularly suited for environmental science, is the multilevel/hierarchical random-effects model. To evaluate potential publication bias, we additionally conducted funnel-plot diagnostics, Begg and Mazumdar's rank correlation test, Egger's regression, fail-safe N, and trim-and-fill estimation.

All models were fitted using the metafor package in R (function rma.mv with method = 'REML') and visualized using the orchaRd package. For transparency, we report QM statistics, marginal R^2, and level-specific I^2 (with 95 % CIs) for both the intercept-only and moderator models.

2.5. Heterogeneity estimation

Heterogeneity indicators can be written following the expressions provided in Eqs. (8)–(10).

$$I^2_{total} = \frac{\tau^2 + \sigma^2}{\tau^2 + \sigma^2 + \overline{v}} \tag{8}$$

$$I^2_{study} = \frac{\tau^2}{\tau^2 + \sigma^2 + \overline{v}} \tag{9}$$

$$I^2_{effect} = \frac{\sigma^2}{\tau^2 + \sigma^2 + \overline{v}} \tag{10}$$

where τ^2 is the between-study variance; σ^2 the study variance, and $\overline{v}$ the sampling variance. For the estimation of the two types of multilevel/hierarchical random-effect models and plotting the results, the R package "metafor" (Viechtbauer, 2010) was used together with the "orchaRd" (Nakagawa et al., 2023a) package.

Cochrane's test of heterogeneity Q contributes to general information on the level of heterogeneity. This approach provides a tight association with the p-value. Therefore, it is recommended, especially for environmental science (Nakagawa et al., 2023b; Nakagawa and Santos, 2012), to estimate heterogeneity from the meta-analytic model variables.

For the multi-level/hierarchical model the estimation of heterogeneity based on the model's parameters can be described in three levels, with a range from 0 to 100 %: total heterogeneity of the overall input data to the model (I^2_{total}) comprising the total heterogeneity for both between and with study variance; the heterogeneity derived from between-study variance or at study level (I^2_{study}) and the heterogeneity derived from within-study variance or at effect level (I^2_{effect}).

2.6. Burr type XII distribution

The Burr Type XII distribution emerged as the best fit for the data, as confirmed by numerical and statistical tests. This three-parameter distribution is an extension of the original two-parameter model developed by Burr in 1942. It includes a scale parameter (α) and two shape parameters (c) and (k), making it a right-skewed distribution on the positive real line. The shape parameters (c) and (k) determine the distribution's skewness and kurtosis, respectively, while the scale parameter (α) indicates where the data is most concentrated. The cumulative distribution function (CDF) are expressed as Eq. (11).

$$F\left(x|\ \alpha, c, k\right) = 1 - \frac{1}{\left(1 + \left(\frac{x}{\alpha}\right)^c\right)^k}, \quad x > 0, \alpha > 0, c > 0, k > 0 \tag{11}$$

The probability density function of the distribution is described by the Eq. (12).

$$f(x|\alpha, c, k) = \frac{\frac{kc}{\alpha}\left(\frac{x}{\alpha}\right)^{c-1}}{\left(1 + \left(\frac{x}{\alpha}\right)^c\right)^{k+1}}, \quad x > 0, \alpha > 0, c > 0, k > 0 \tag{12}$$

The Burr Type XII distribution is highly flexible, effectively modelling long upper tails with significant skewness and kurtosis, making it ideal for data with such characteristics. It is also known for its computational tractability and reliability, particularly in modelling rare events compared to distributions with exponential tails. To evaluate the fit of our empirical data to various heavy-tailed distributions, we used the R packages "fitdistrplus", "actuar" and "moments". The Burr Type XII distribution's versatility has led to its application in numerous fields, including soil temperature and moisture dynamics, travel time reliability, unemployment patterns, optical speckle analysis, geological exploration, hydrology, forestry, meteorology, and crop price modelling.

Beyond descriptive fit, the Burr distribution allows us to model extreme erosion-OMC interactions and identify thresholds of soil loss where disproportionate changes in OMC occur, providing insight for soil conservation and management.

2.7. Estimation of Tsallis and Shannon entropies

Tsallis q-statistics and nonadditive entropy conceptualization have been growingly applied to analyze a variety of complex dynamical systems (Picoli Jr. et al., 2009; Robledo and Velarde, 2022). For the sake of comparison between Tsallis q-index which denotes degrees of complexity, and the traditional conceptualization of Shannon entropy, we applied a generalized expression as a gain function, we used Shannon entropy to describe how variable soil erosion is across different areas. When the entropy is high, it means the erosion patterns change a lot from place to place, which can point to regions with higher risk. This helps us see how different land uses or practices affect erosion and organic matter loss. Yet, this method works best when the system behaves in a stable and predictable way. In our case, the data showed irregular patterns and jumps that didn't always follow a smooth trend. That is why we also used Tsallis entropy. It's better suited for systems that are less predictable, where sudden changes can happen, and the parts of the system don't add up in a simple way. Tsallis entropy helped us detect unusual behavior and long-distance effects that standard entropy might miss. It gave us a clearer view of the complexity in how erosion and organic matter interact over space and time. We also explored whether q values varied across study types (experimental, rainfed, computational). Differences in q reflect heterogeneity and scale-dependence in the data, consistent with the variability identified in our multilevel models.

In this context, heavy-tailed behavior is not merely a statistical artefact but reflects ecological threshold behavior in erosion-OMC dynamics, where extreme events disproportionately drive system responses.

For entropy estimation, we considered both Tsallis' nonadditive entropy (S_q) and Shannon entropy (H_s). Tsallis' entropy is defined as in Eq. (13).

$$S_q = \frac{k}{q-1}\sum_{i=1}^{W} p_i\left(1 - p_i^{q-1}\right) \tag{13}$$

where k is a conventional positive constant pi is the probability associated with an event and q is any real number, a parameter of relative to the subject matter in question. For the sake of comparison between different values of Tsallis q-index denoting degrees of complexity with the traditional conceptualization of Shannon entropy, we applied a generalized expression as power function or gain function of the form (Singh et al., 2017) is given in Eq. (14).

$$\Delta I\,(x_i) = \frac{1}{q-1}\,\left(1 - {p_i}^{q-1}\right), \qquad \sum_{i=1}^{N} p_i = 1 \tag{14}$$

where the gain function $\Delta I(x_i)$ corresponds to the gain information from event i, while N is the total number of events, that is size effects considered in our data set. Whereas Shannon entropy was estimated as in Eq. (15).

$$H_s = -k\sum_{i=1}^{N} p_i log(\,p_i) \tag{15}$$

where k is typically set to 1. Tsallis' q-statistics and nonadditive entropy have been increasingly applied to analyze complex dynamical systems, such as earthquake properties, network complexity, geographically growing networks, EEG inter-occurrence times, and cell motion.

3. Results

Fig. 2 demonstrates the flowchart of the applied literature search strategy. (See Fig. 1.) (See Fig. 3.) (See Fig. 9.)

From the initial pool of 953 articles, studies were screened, and those meeting the inclusion criteria were selected, resulting in a final dataset of 148 effective magnitudes of relationship derived from 71 studies. The studies were conducted across eight Mediterranean countries, ensuring a broad geographical representation that captures the diversity of Mediterranean ecosystems. The key data extracted from each study included measures of SL, OMC, and other relevant variables that could influence their relationship.

This first search strategy resulted in a total of articles (n) = 953. After checking for duplicates, the first strategy yielded 823 unique articles. The second search strategy used similar combinations but targeted different aspects. This strategy also resulted in a significant number of articles, n = 52; however, the second strategy did not have any duplicates.

Ultimately, the analysis included 148 effective magnitudes derived from 71 studies (just 8 % of the initial articles) across eight Mediterranean countries: Spain, France, Italy, Croatia, Greece, Syria, Tunisia, and Algeria, where SL and OMC values were reported together (Fig.). The largest effective magnitudes came from natural rainfed-based studies (66) and experimental-based studies (68). The rainfed studies were mostly positive (36), while the experimental studies were predominantly negative (47). Computational simulation-based studies contributed 14 effective magnitudes, with the majority being negative (12).

Initially, a general model – without moderators – was employed to estimate the overall mean from the entire dataset (Fig. 3). Subsequently, a meta-regression model, which extends the general model by incorporating moderators, was used to better understand and explain the observed variation through heterogeneity measures. The goodness-of-fit for both the general model (first level in the tree graph, see 3) and the meta-regression model (second level in the tree graph, see 3) was assessed, with the results summarized in Tables 1 and 2. Table 1 represents the goodness-of-fit for the general simple model estimator. ML and REML were tested. Results indicated higher logLik with lower AIC and BIC, favouring the selection of the REML estimator. Table 2 represents the goodness-of-fit for the meta-regression model estimator. ML and REML were tested. logLik with lower AIC and BIC for REML, favouring the selection of the REML estimator.

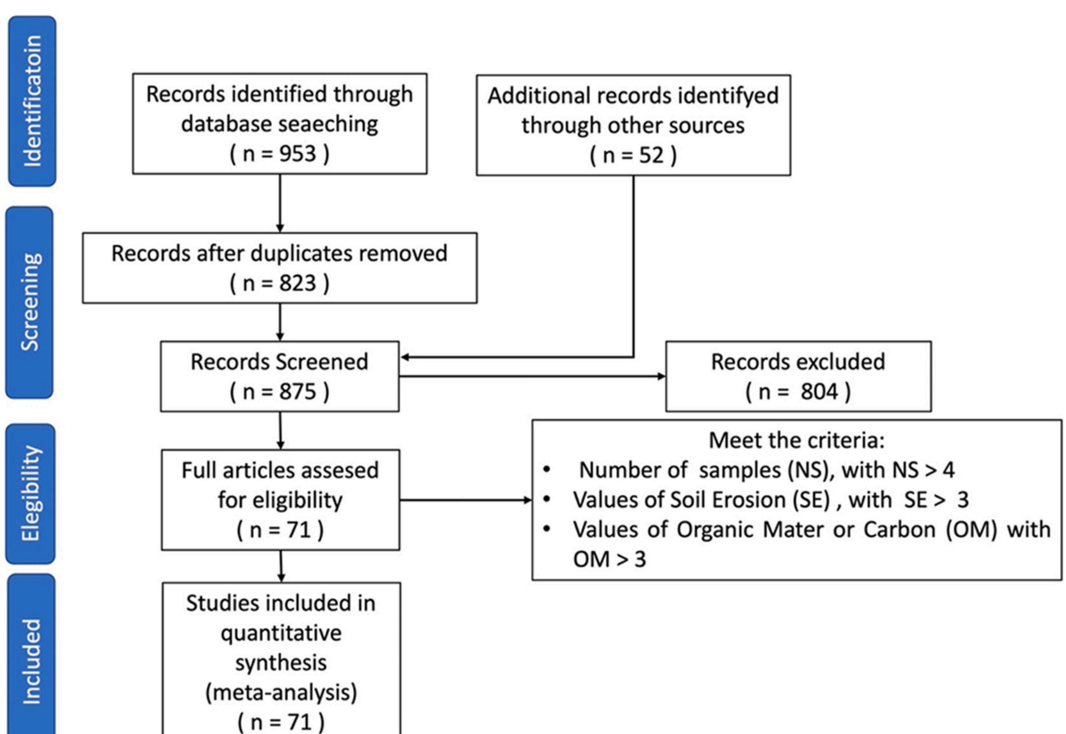

Fig. 2. PRISMA Flowchart for the Study. The flowchart with two search outputs ($n = 953$) and ($n = 52$) were initially retrieved. The exclusion criteria were applied after removing duplicates: $n = 823$ from EBSCO + n = 52 from Google Scholar = 875 totaL. Only those records with a total number of samples larger than 4 (NS > 4) values are included. Among all included studies (considered as the input set of studies, $n = 71$ for this meta-analysis).

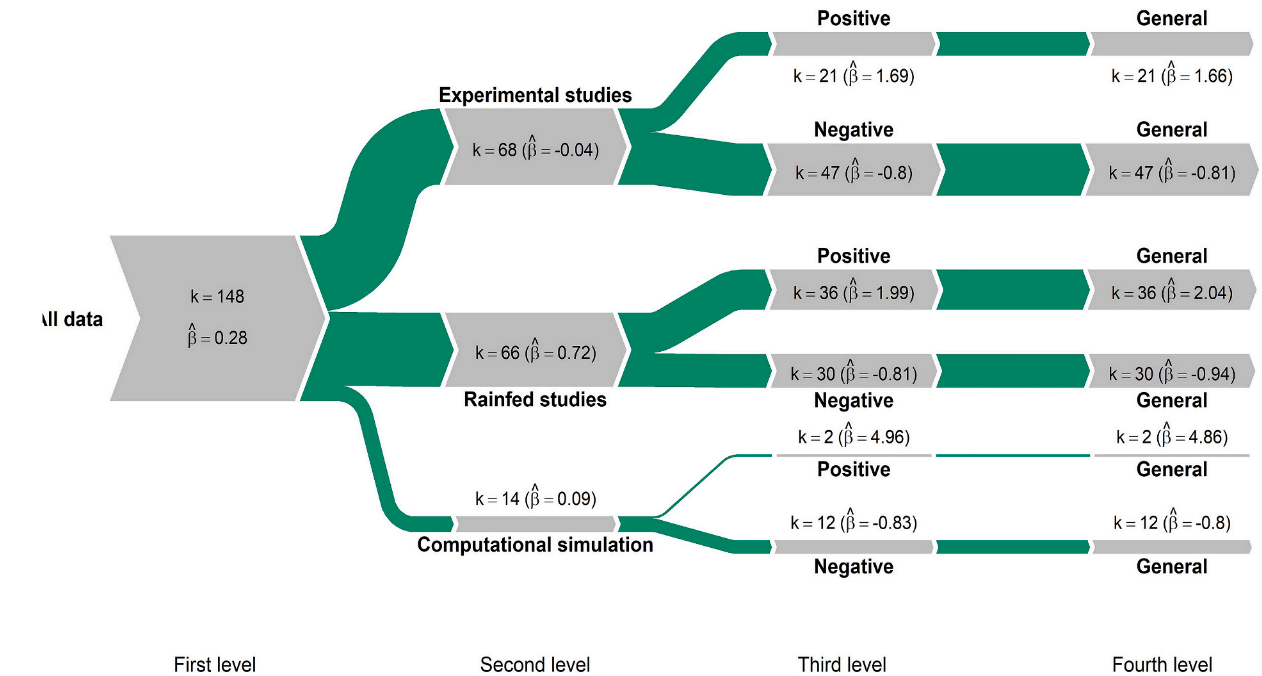

Fig. 4|. Multilevel hierarchical tree structure of effective magnitudes obtained from the meta-analysis. The analysis was structured as a four-level hierarchical model to examine how methodological differences and correlation directions influence the relationship between SWE and OMC. Two types of meta-analytic models were used: a simple multilevel model for broader trends, and a meta-regression model to account for subgroup differences.

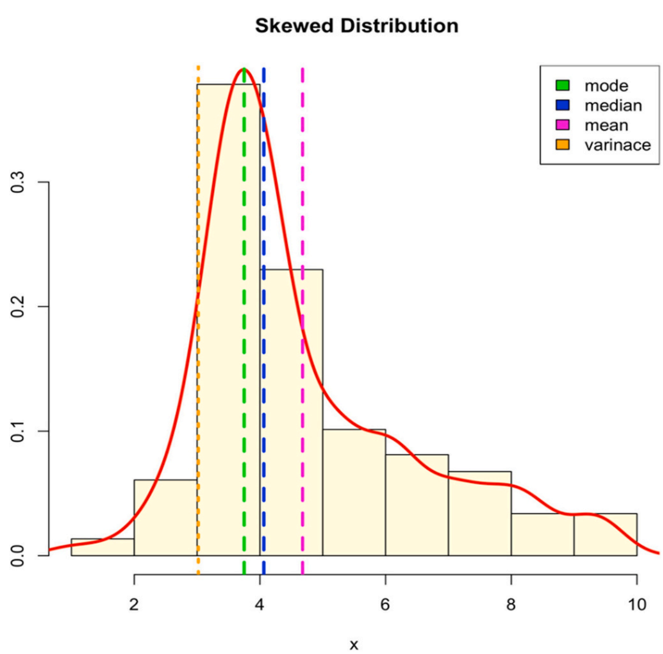

Fig. 5. Histogram and density plot of the complete dataset of effective magnitudes. Demonstrating right-skewed distribution can be observed through the histogram and density plot. The dashed lines show the expected relationship for skewed distributions where *mode > median > mean*. The x-axis corresponds to Fisher's *Z*-transformed effective magnitudes, and the y-axis to the density function.

In experiential Methods (k = 68), a weak negative overall mean estimate (β = −0.0421) was found, with most studies (69 %) showing negative outcomes (Fig. 4). In rainfed Methods (k = 66), a positive overall mean estimate (β = 0.7209) was observed, with 54.5 % of studies showing positive outcomes. In computational Simulation Methods (k = 14), a low positive overall mean estimate (β = 0.0835) was found, with 85.7 % of studies showing positive outcomes. The detailed analysis is provided in Section 2 of Supporting Material 1.

3.1. Details of the tree graph

The first level represents the overall average effect size across all studies, regardless of method or correlation sign. This gives a general sense of how SWE and OMC are related in the full dataset. A low positive effect size (0.28) was observed at this level. At the second level, studies were grouped by the research method used: experimental, rainfed, or computational simulations. This allowed us to compare how different methodological approaches influence the observed correlation. Here, experimental methods showed a negligible negative effect (−0.04), rainfed methods a moderate positive effect (0.72), and computational methods a slight positive effect (0.09), though the latter had limited sample size.

The third level dives deeper by splitting each method group into studies with positive vs. negative correlations. This level examines whether the direction of the correlation (positive or negative) plays a role within each methodological group. For example, within experimental methods, studies showing positive correlations had a strong average effect (1.69), while those showing negative correlations had a moderate effect in the opposite direction (−0.80). Similar patterns were found for rainfed and computational methods.

The fourth level aggregates the correlation direction (positive vs. negative) across all methods, allowing us to see if the direction of correlation itself has consistent effects regardless of methodology. This level helps determine whether positive or negative findings dominate in the literature. Results were consistent with those observed at the third level, confirming strong positive effects for positive studies and moderate negative effects for negative ones across all method types.

The low overall effect size at the first level can be attributed to the dominance of experimental and rainfed methods, which together account for the majority of studies (136 out of 148). While these methods exhibit relatively small effects, their combined influence outweighs the negligible impact of computational simulations, which are limited in both sample size and effect size. The negative effect size observed for

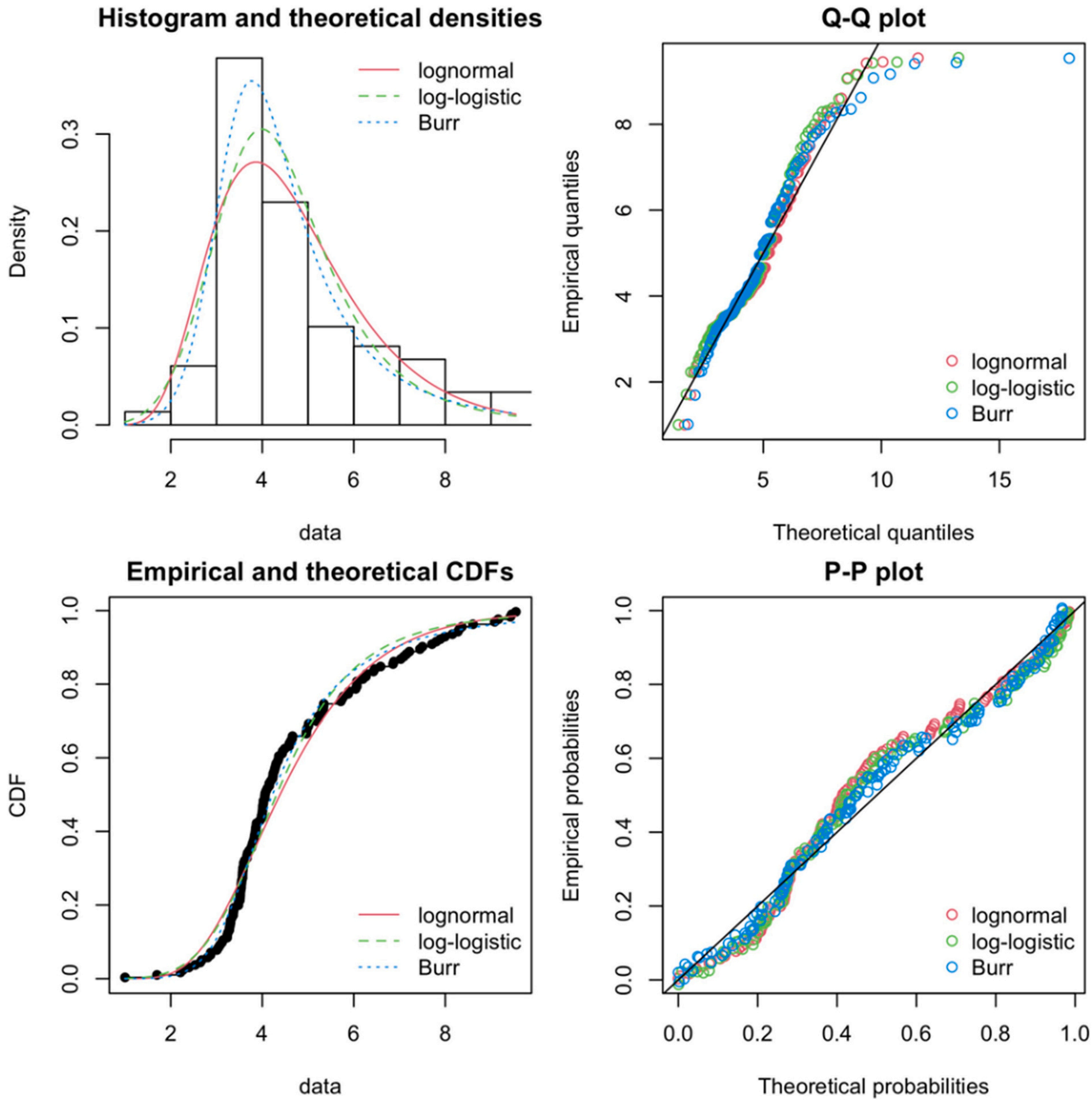

Fig. 6. Comparison of fit between heavy-tailed distributions and effective magnitudes (k = 148). The histogram of the effective magnitudes with density function, plot comparing between the theoretical and empirical quantiles (Q-Q plot or quantile-quantile), fit of the CDFs and that of effective magnitudes, plot comparing between empirical and theoretical probabilities (P-P plot or probability-probability plot).

experimental methods (−0.04) is likely due to the presence of a substantial number of negative studies (47 out of 68) within this group. Conversely, the moderate positive effect for rainfed methods (0.80) can be explained by the preponderance of positive studies (36 out of 66) and their associated larger effective magnitudes. The slight positive effect for computational simulations (0.09) is primarily driven by the few positive studies within this group, which exhibit exceptionally high effective magnitudes.

The similarity between the results at the third and fourth levels is a consequence of the simple hierarchical model used in both analyses. This model maintains the same parameters without differentiating between subgroups or moderators, thereby preserving the relationships observed at the third level.

3.2. Fitting Burr type XII distribution

The distribution of effect sizes appeared to be right-skewed and deviated from a normal (Gaussian) shape, with some values showing large magnitudes on either end. This prompted us to explore whether a heavy-tailed distribution would better capture the underlying structure of the data. The Burr Type XII distribution, a flexible probability distribution, was selected due to its suitability for modelling data with skewness or heavy tails. We began by performing a graphical test of skewness, comparing the mode, median, and mean of the dataset to assess asymmetry (see Fig. 4). We analyzed the distribution of the effective magnitudes to identify an appropriate statistical model that could provide a good empirical fit. Understanding the distribution helps reveal the dynamics of the erosion-organic matter relationship across studies. A comparison of the mode, median (η), and mean (μ) indicated a positively skewed distribution, following the relation mode < median < mean, with values of 3.748561, 4.061263, and 4.678312, respectively (Fig. 5). Skewness and kurtosis were estimated as $\gamma = 1.032055$ and $\beta_2 = 3.481985$, supporting the presence of long right tails. Based on this, we assumed that right-skewed, heavy-tailed distributions might provide a

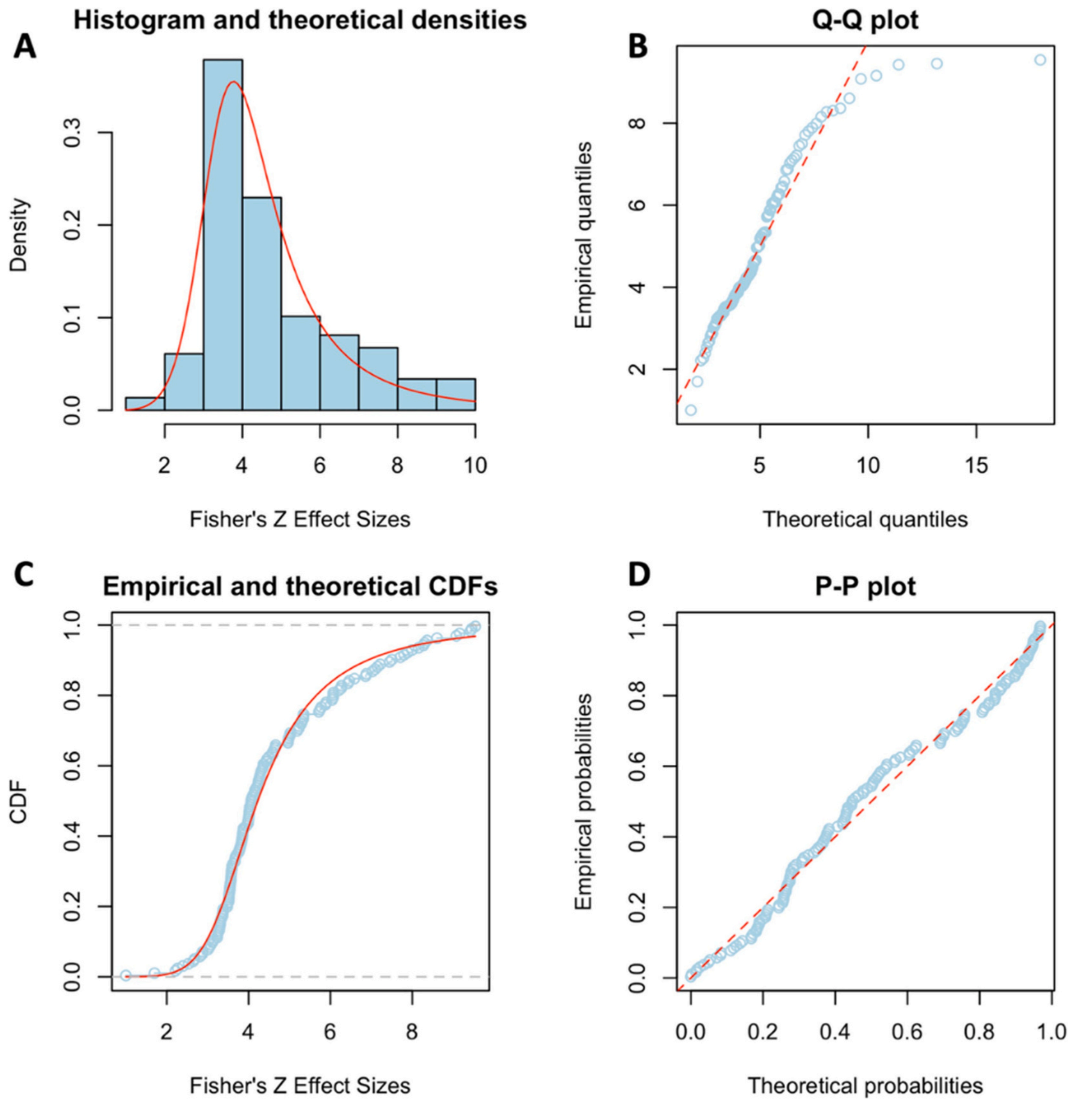

Fig. 7. Burr Type XII distribution fit to empirical data of effective magnitudes (k = 148). the effective magnitudes with regards to the Burr density distribution function, plot comparing between the theoretical and empirical quantiles (Q-Q plot or quantile-quantile), fit of the Burr distribution CDF and effective magnitudes, plot comparing between empirical and theoretical probabilities (P-P plot or probability-probability plot).

better fit for the data. We tested the fit of several heavy-tailed distributions – lognormal, log-logistic, and Burr Type XII – and found that the Burr Type XII distribution offered the best visual and statistical fit (Fig. 6). A full graphical analysis of the Burr fit to the empirical data is shown in Fig. 7. To prepare the data for this fit, we applied a transformation to the Fisher's Z values, shifting all values to be positive using the formula $Y = (Y + 1 - min(Y))$, which corresponded to an x-axis translation of +4.36077.

We further applied the maximum likelihood estimation (MLE) method to estimate the best fit among several skewed distributions. We estimated the Kolmogorov-Smirnov (KS), Cramer-von Mises (CvM), Anderson-Darling (AD) goodness of fit test together with AIC and BIC. Both graphical analysis (Fig. 8) and numerical analysis (Table 3) have shown that the three-parameter Burr type XII distribution fit outperformed other heavy-tailed distributions tested. Further, employing MLE we approximate the values for Burr type XII parameters (c, k, α) (Table 4). Table 3 explains goodness of fit statistics for KS, CvM, and AD test as well as Goodness of fit information criteria (AIC and BIC) show for all cases of heavy-tailed distributions the lowest value for the Burr Type XII distribution indicating it's numerical superior fitting. Table 4 explains fitted values through MLE for the three parameters c, k, and α, together with corresponding standard errors.

To perform the testing of several heavy-tailed distributions on the effective magnitudes data set (k = 148), we first sorted the Fisher's Z correlation coefficients dataset in decreasing order and converted them to positive values. Observational analysis of the histogram with a density plot of the distribution of the complete dataset of effective magnitudes indicates a right-skewed distribution.

We further analyzed the distribution of the effective magnitudes to select an appropriate statistical model that accurately fits the dataset using AIC and BIC. Both graphical and numerical analyses showed that the three-parameter Burr type XII distribution fit outperformed other heavy-tailed distributions tested (Table 3). Further, employing MLE we approximated the values for Burr type XII parameters (Table 4).

3.3. Datasets of effective magnitudes

The distribution of effective magnitudes was analyzed using a caterpillar plot, revealing a skewed distribution fitting the Burr type XII distribution (Tadikamalla, 1980), though no clear pattern was associated with the country of origin. Despite most effective magnitudes being negative, the distribution displayed an almost symmetrical S-shape

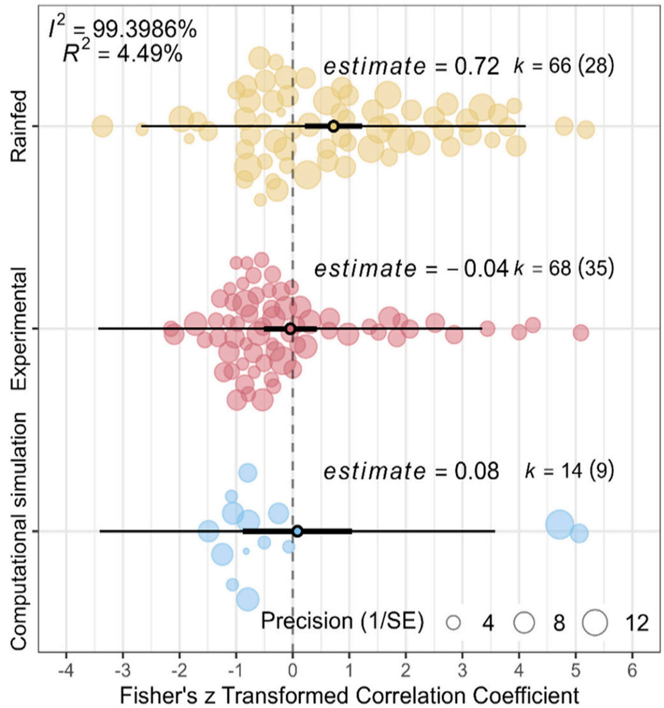

Fig. 8. Orchard plot for the estimated output of the multivariate multi-level random effect model. Fig. 8 represents the moderators used to group the data in agreement with the methods employed by the studies included in the data set (y-axis, categorical). The magnitude of effective magnitudes corresponding to the studies is represented in the x-axis. Each point corresponds to an individual effect size. The size of each point represents its precision, a measure of its uncertainty, as the inverse of the standard error (1/SE).

around the reference line at x = 0. The overall effect size of each group is also calculated according to the country and experiment type and represented as a forest map in Supplementary Materials 2 and 3.

3.4. The statistical results for the two types of models applied

Green rows correspond to the results of the multilevel hierarchical random effect model (MHREM) with moderators (Table 5) and the orange rows to those of applying MHRE without moderators (Table 6). Categories indicate study division (OV: overall mean estimate, ES: experimental studies, RS: rainfed studies, CS: computational studies), Group overall dataset (A) or subset according to the moderators (M: methods, P: positive correlation sign, N: negative correlation sign), Level the position in the hierarchical structure for each of the categories, k the number of studies, k (%) the percentage of studies according to different categories, $\widehat{\beta}$ the overall estimated mean, 95 % CI the 95 % confidence

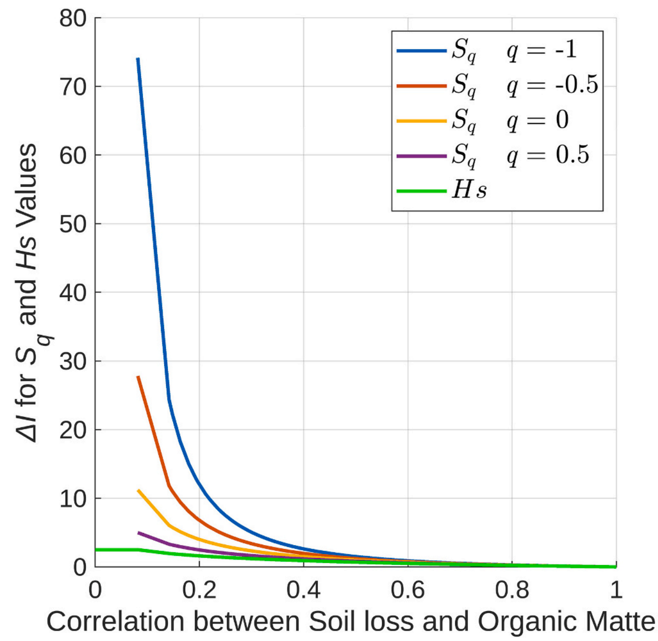

Fig. 11. Computation of the comparison between Tsallis (S_q) and Shannon (H_s) entropies. Different values for Tsallis entropy index q are compared with Shannon entropy using a generalized power function (ΔI). Tsallis entropy index tested for q = −1, −0.5, 0, 0.5 denotes an exponential increase indicating the presence of nonlinear system while when applying Shannon's entropy function the distribution is close to zero showing nearly a linear system.

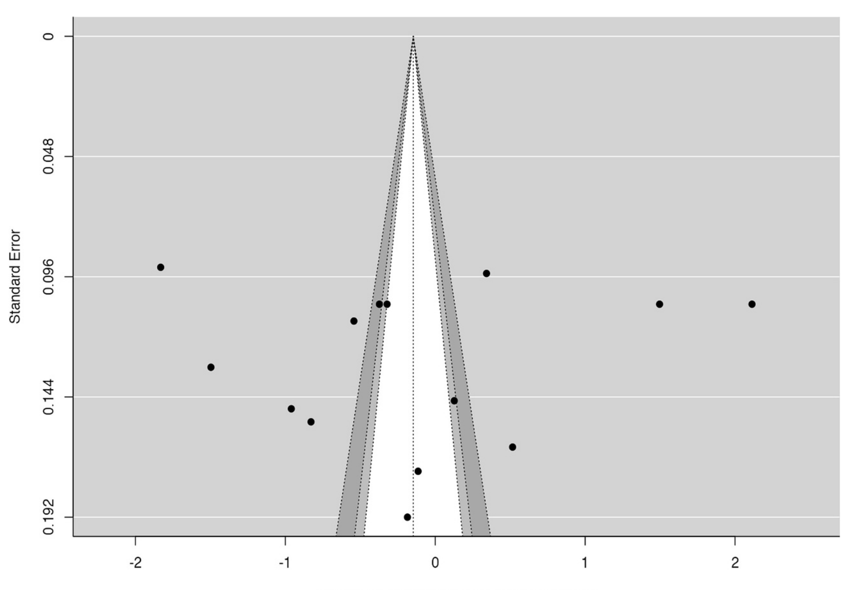

Fig. 10. Funnel plot of Fisher's *Z*-transformed effect sizes showing assessment of publication bias. The distribution of effect sizes is plotted against their standard errors. The approximate visual symmetry around the pooled effect suggests no substantial small-study effects or selective reporting bia.

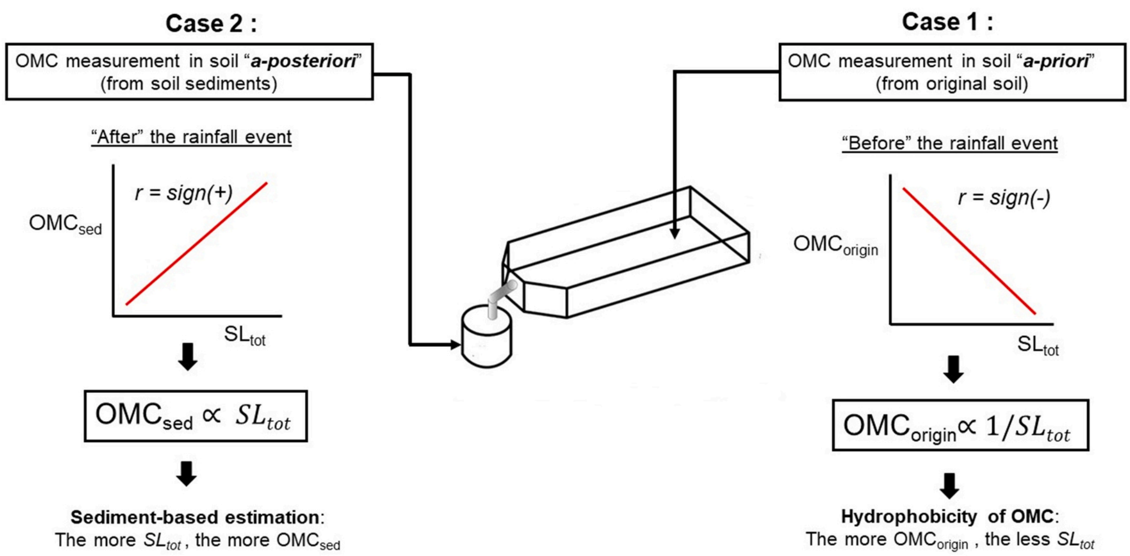

Fig. 1. Representation of case 1 and case 2. Case 1 depicts an inverse relationship between OMC at original soils (OMC_{origin}) and total SL (SL_{tot}), then OMC measures from soil before performing the experiment, which is represented utilizing a negative correlation (r). An increase in the SL_{tot} will imply a decrease in the OMC_{origin}. While case 2 describes a direct relation between OMC in sediments (OMC_{sed}) and SL_{tot}, OMC measures from soil after experimentation are represented using a positive correlation (r). Measured Increase in SL_{tot} is followed by an increase in OC_{origin}.

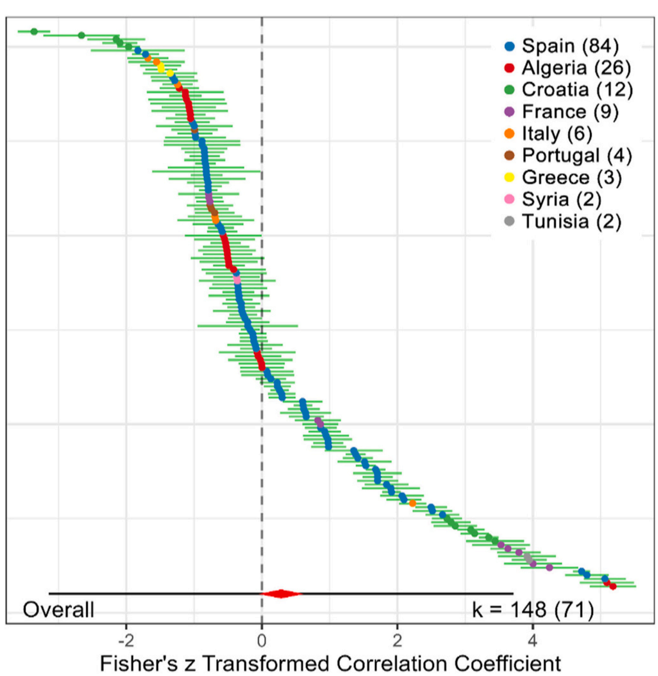

Fig. 3. Caterpillar plot of the complete dataset of Effective magnitudes (k = 148). A nearly symmetric S-shaped distribution of effective magnitudes with respect to the reference line (at x = 0) is observable. This S-shape suggests that the distribution of correlations includes a balanced mix of positive and negative values, with most falling close to zero and fewer showing very strong effects. It reflects a typical heavy-tailed structure, where extreme values are rare, and most studies report moderate effects. Dots correspond to the individual effective magnitudes, colored by the country of origin, and green lines represent their confidence intervals. The red diamond corresponds to the overall mean effect (148 correlations obtained from 71 studies); its height indicates the average value, and its length reflects the 95 % confidence interval. The x-axis corresponds to Fisher's Z correlation coefficients, while the y-axis shows the rank-ordered effect sizes (i.e., sorted from largest to smallest, k = 148).

interval, z the z-test statistics, SE the standard error, Q the Cochran's Q-test of heterogeneity, QM the Omnibus test for moderators, R^2 the R^2 marginal in percentage, I^2 the Higgins & Thompson heterogeneity test (Higgins, 2003; Higgins and Thompson, 2002), for which I^2 (L2) the within-study heterogeneity, I^2 (L3) the between-study heterogeneity and I^2 (L0) the heterogeneity derived from the sampling variance.

3.5. Overall association between SL and OMC

Initially, a general model without a moderator was employed to determine the combined mean effect size for the entire dataset of Fisher's *Z*-transformed correlations (k = 148). The Fisher's Z correlation coefficients ranged from −3.3608 to 5.1818, resulting in a weak yet positive overall mean estimate ($\widehat{\beta}$) = 0.2846 (95 % CI: −0.0498 to 0.6191), with z = 1.6679, Standard Error (SE) = 0.1707, and a *p*-value of 0.0953.

The heterogeneity test indicated substantial statistical heterogeneity, with Q (df = 147) = 24,876.2778 and a *p*-value < .0001. This heterogeneity was further quantified using Higgins & Thompson's I^2 statistic, which was found to be 99.42 % (Chen and Peace, 2021; Higgins, 2003; Higgins and Thompson, 2002; Egger et al., 2001; Hedges and Vevea, 1998). This reflects the complexity and diversity of the research on the relationship between SL and OMC, depending on the study methods used. The between-study heterogeneity estimate was I^2 = 28.59 % (Level 3), while the within-study heterogeneity estimate was I^2 = 70.83 % (Level 2).

3.5.1. Experiential methods

For studies utilizing experiential methods (k = 68), the overall mean estimate was weakly negative, $\widehat{\beta}$ = −0.0421 (95 % CI: −0.5083 to 0.4242), with z = −0.1768, SE = 0.2379, and a *p*-value of 0.8597. Most of the studies (69 %) reported negative outcomes, while 38.8 % reported positive outcomes. The test for residual heterogeneity (QE (df = 145) = 23,113.2669, p-value < .0001) confirmed high heterogeneity, with an estimated I^2 = 99.4 %.

3.5.2. Experimental methods general model

A general meta-analytic model was applied to studies following the experiential method, separately assessing those with positive and negative correlations. Studies with positive correlations (k = 21) yielded an overall mean estimate of $\widehat{\beta}$ = 1.66 (95 % CI: 0.9848 to 2.3317), with z = 4.8260, SWE = 0.3436, and a *p*-value < .0001. For negative

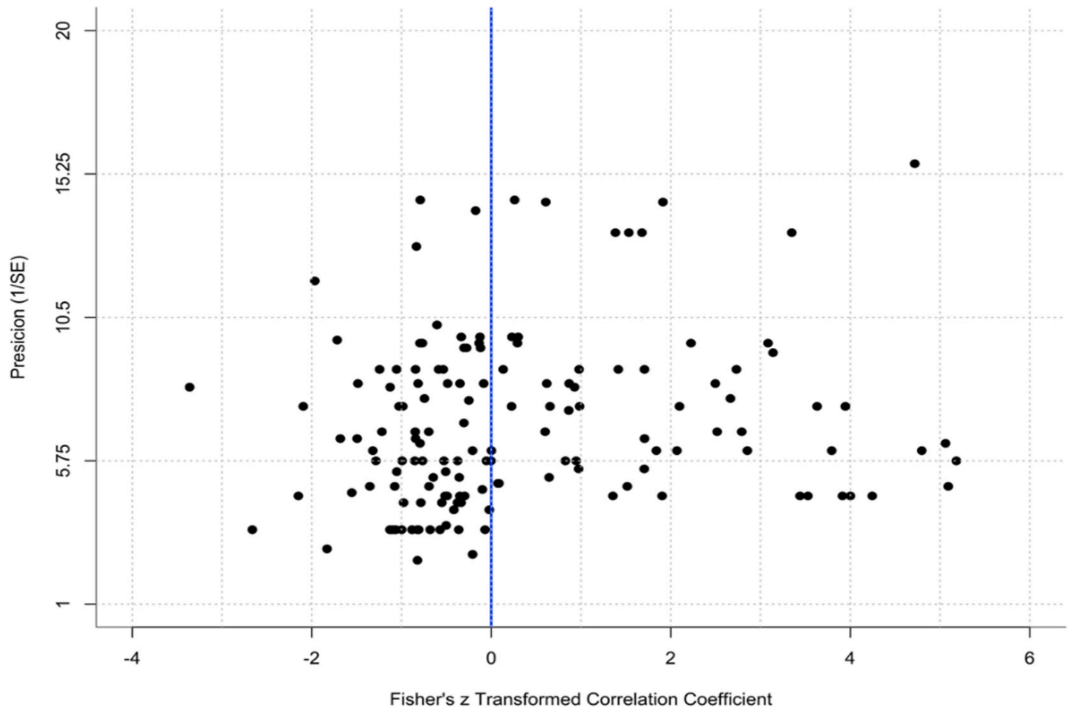

Fig. 9. Scatterplot of effective magnitudes and Standard Error (SE). The effective magnitudes (x-axis) as Fisher's Z correlation coefficients are plotted against precision defined as 1/SE (y-axis). The scatterplot shows the relation between the effective magnitudes and a measure of their uncertainty (i.e., 1/SE). The scattering of points does not show any clear identifiable pattern. The blue vertical line is the reference line dividing positive from negative effective magnitudes.

Table 1
Model fit statics and information criteria.

Model	logLik	Deviance	AIC	BIC	AICc
ML	−287.8699	854.8702	581.7398	590.7315	581.9065
REML	−286.2244	572.4489	578.4489	587.4202	578.6167

Table 2
| Model with moderators Fit Statistics- Information criteria.

Model	logLik	Deviance	AIC	BIC	AICc
ML	−285.4204	849.9712	580.8409	595.8269	581.2634
REML	−280.6739	561.3477	571.3477	586.3477	571.7794

Table 3
Goodness-of-fit statistics and criteria.

The goodness of fit statistics				
Statistics	Log-normal	Log-logistic	Pareto	Burr
Kolmogorov-Smirnov (KS)	0.114883	0.09405392	0.3998191	0.06518612
Cramer-von Mises (CvM)	0.4223419	0.34073989	6.2850392	0.1675498
Anderson-Darling (AD)	2.3103055	2.13346092	30.4798379	1.09644237
The goodness of fit criteria				
Akaike's Information (AIC)	557.1667	553.5676	756.7095	550.0146
Bayesian information (BIC)	563.1611	559.562	762.7039	559.0063

Table 4
Burr type XII Parameter Estimation. (Maximum Likelihood Estimation fit).

Co-efficient	Parameters	Estimate	Std. error
c	Shape1	0.4933939	0.12491412
k	Shape 2	7.192251	1.12165392
α	Scale	0.276848	0.01535073

correlations ($k = 47$), the overall mean estimate was $\widehat{\beta} = -0.81$ (95 % CI: -0.9710 to -0.6453), with $z = -9.7251$, $SE = 0.0831$, and a p-value $<$ .0001. Both groups exhibited significant heterogeneity, with I^2 estimates of 98.96 % for positive correlations and 90.05 % for negative correlations.

3.5.3. *Rainfed method*

The total number of studies in each group is represented with the letter k with several studies providing only one effect size per group, described in brackets (Fig. 4). Predicted average values (estimated) are presented as a circle with the thicker lines parallel to x-axis being its 95 % confidence intervals (CIs) while the thinner (longer) lines correspond to the 95 % prediction interval (Riley et al., 2011) for each method category.

For studies employing the rainfed method ($k = 66$), a higher positive overall mean estimate was observed, $\widehat{\beta} = 0.7209$ (95 % CI: 0.2165 to 1.2253), with $z = 2.8011$, $SE = 0.2574$, and a *p*-value of 0.0051. Most of these studies (54.5 %) reported positive outcomes, while 45.4 % reported negative outcomes. Again, high heterogeneity was evident (QE ($df = 64$) = 5009.7311, p-value $<$ .0001), with an I^2 estimate of 98.90 %.

3.5.4. *Rainfed method general model*

For studies using the rainfed method, a general model was also applied separately to those with positive and negative correlations. Positive correlation studies ($k = 36$) had an overall mean estimate of $\widehat{\beta} = 2.04$ (95 % CI: 1.6035 to 2.4859), with $z = 9.0827$, $SE = 0.2251$, and a p-value $<$ .0001. Negative correlation studies ($k = 30$) had an overall mean estimate of $\widehat{\beta} = -0.94$ (95 % CI: -1.3561 to -0.5292), with $z = -4.4689$, $SE = 0.2109$, and a p-value $<$ .0001. High heterogeneity was observed in both cases, with I^2 estimates of 99.31 % for positive correlations and 97.66 % for negative correlations.

Table 5
The multilevel hierarchical random effect model (MHREM) with moderators.

Category	RS	CS	ES		RS		CS	
Group	M	M	P	N	P	N	P	N
Level	2	2	3	3	3	3	3	3
k	66	14	21	47	36	30	2	12
k (%)	44.59	9.45	30.88	69.11	54.54	45.45	14.28	85.71
$\widehat{\beta}$	0.7209	0.09	1.69	−0.8	1.9918	−0.81	4.96	−0.83
95 % CI	(0.2165, 1.2253)	(−0.8823, 1.0493)	(1.2890, 2.0820)	(−1.0680, −0.5350)	(1.5806, 2.4030)	(−1.2562, −0.3617)	(4.5355, 5.3845)	(−1.1269, −0.5424)
z	2.8011	0.1695	8.3325	−5.8949	9.4928	−3.5449	22.901	−5.5969
SE	0.257	0.493	0.202	0.136	0.21	0.228	0.217	0.149
p	0.0051	0.8654	<0.0001	<0.0001	<0.0001	0.0004	<0.0001	<0.0001
(Q)			1990.4		5009.7		77.9	
p			<0.0001		<0.0001		<0.0001	
(QM)			104.181		116.826		866.113	
p-value			<0.0001		<0.0001		<0.0001	
R^2			61.8		60.5		96.4	
I^2			97.2		98.9		90.2	
I^2 (L3)			97.2		20		90.3	
I^2(L3)			0		78.9		0	
I^2 (L0)			2.81				9.75	

Table 6
The multilevel hierarchical random effect model (MHREM) without moderators.

Category	OV	ES		RS		CS	
Group	A	P	N	P	N	P	N
Level	1	4	4	4	4	4	4
k	148	21	47	36	30	2	12
k (%)	100	30.88	69.11	54.54	45.45	14.28	85.71
$\widehat{\beta}$	0.2846	1.66	−0.81	2.04	−0.94	4.86	−0.8
95 % CI	(−0.0498, 0.6191)	(0.9848, 2.3317)	(−0.9710, −0.6453)	(1.6035, 2.4859)	(−1.3561, −0.5292)	(4.5280, 5.1915)	(−1.1193, −0.4865)
z	1.6679	4.826	−9.7251	9.0827	−4.4689	28.708	−4.9731
SE	0.171	0.344	0.083	0.225	0.211	0.169	0.161
p	0.0953	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001
(Q)	24,876.3	1479.7	510.8	4041.3	968.4	4.1	73.9
p	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	0.0438	<0.0001
(QM)							
p-value							
R^2							
I^2	99.4	99	90.1	99.3	97.7	75.4	89
I^2(L2)	28.6	14.8	34.8	0	91.6	37.7	89
I^2(L3)	70.8	84.2	55.2	99.3	6.04	37.7	0
I^2 (L0)			0.69			11	

3.5.5. Computational simulation methods

For studies employing computational simulation methods (k = 14), a low positive overall mean estimate was observed, $\widehat{\beta} = 0.0835$ (95 % CI: −0.8823 to 1.0493), with z = 0.1695, SE = 0.4928, and a p-value of 0.8654. Most studies (85.7 %) in this group reported positive outcomes. Despite the small sample size, significant heterogeneity was present (QE (df = 12) = 77.9272, p-value < .0001), with an overall heterogeneity estimate of $I^2 = 90.24$ %.

3.5.6. Computational simulation methods general model

For studies using computational simulation methods, the general model was applied to both positive and negative correlation groups. The positive correlation group (k = 2) had an overall mean estimate of $\widehat{\beta} = 4.86$ (95 % CI: 4.5280 to 5.1915), with z = 28.7083, SE = 0.1693, and a p-value < .0001. The negative correlation group (k = 12) had an overall mean estimate of $\widehat{\beta} = -0.80$ (95 % CI: −1.1193 to −0.4865), with z = −4.9731, SE = 0.1614, and a p-value < .0001. Both groups exhibited high heterogeneity, with I^2 estimates of 75.39 % for positive correlations and 89.01 % for negative correlations.

3.6. Hierarchical tree structure

The overall positive effect size at the first macroscopic level (0.28) can be attributed to the influence of the experimental and rainfed methods, which comprise most of the data (136 out of 148 effective magnitudes). The rainfed method had a moderate positive effect size (0.72), while the experimental method had a very low negative effect size (−0.04). The computational simulation method had a negligible impact due to its small sample size (14 effective magnitudes) and very low positive effect size (0.09).

At the microscopic level, the experimental method showed a high positive effect size (1.69) for positive correlations and a moderate negative effect size (−0.80) for negative correlations. The rainfed method showed a high positive effect size (2.04) and a moderate negative effect size (−0.94). The computational simulation method showed a high positive effect size (4.96) and a moderate negative effect size (−0.83). A detailed study of each model is provided in Section 2 of (SM 1).

Additionally, studies have explored the relationship between soil porosity, the microbiome, and organic carbon. When a scatterplot was applied for comparing the effective magnitudes against a measure of uncertainty, such as precision, defined by 1/SE, an apparent disordered pattern or chaos seemingly emerges. Such a lack of an observable trend indicates the absence of a coherent and consistent pattern in the effective magnitudes (Fig. 9). This outcome was further reflected in the high degree of heterogeneity measured. The scatterplot (Fig. 9) shows the relation between the effective magnitudes and a measure of their uncertainty (i.e., 1/SE).

The funnel plot (Fig. 10) shows a generally symmetric distribution of Fisher's Z-transformed effect sizes around the pooled mean, suggesting no meaningful asymmetry or small-study effects. This visual impression is supported by the formal publication bias diagnostics summarized in Table 7. Both Begg and Mazumdar's rank correlation test ($\tau = -0.034$, $p = .868$) and Egger's regression intercept (-0.290, $p = .772$) were statistically non-significant, indicating no detectable directional bias. The Rosenthal fail-safe N was 64 ($p < .001$), meaning that 64 additional unpublished null-effect studies would be required to negate the observed overall trend, which suggests robustness of the pooled estimate. The trim-and-fill method estimated that only three studies may be missing, and these would not materially change the effect size. Taken together, the visual (Fig. 10) and statistical evidence (Table 7) indicate that there is no substantive publication bias affecting the results of this meta-analysis.

The hierarchical analysis revealed an overall mean positive outcome ($\hat{\beta} = 0.2846$), despite most individual study outcomes being negative (60 %). This phenomenon, known as Simpson's paradox, occurs when aggregated data show a trend opposite to that of the individual groups. This paradox has been observed in various fields such as ecology (Allison and Goldberg, 2002; Qian et al., 2019; Scheiner et al., 2000), biology (Chuang et al., 2009), epidemiology (von Kugelgen et al., 2021), and spatial data analysis (Sachdeva and Fotheringham, 2023; Wilson, 2013). The positive and negative phenomenon of the average effective magnitudes are obtained in Fig. . However, none of the method-specific groups exhibited this association reversal phenomenon.

To make the conditioning explicit, Table X compares the overall pooled mean with subgroup-specific means. This shows that while the pooled mean is weakly positive, most subgroup estimates are negative, a reversal consistent with Simpson's paradox.

To make the conditioning explicit, Table 8 compares the overall pooled mean with subgroup-specific means. This shows that while the pooled mean is weakly positive, most subgroup estimates are negative, a reversal consistent with Simpson's paradox. Although the overall mean was slightly positive, subgroup-specific analyses (Table 8) revealed predominantly negative outcomes, especially in experimental studies. This conditioning illustrates Simpson's paradox explicitly: an aggregated trend opposite to the subgroup patterns.

Our data reveal a departure from linear behavior, with an exponential increase observed when the Tsallis q-exponential distribution was applied at q values of −1, −0.5, 0, and 0.5 (Nadarajah and Kotz, 2007; Nadarajah and Kotz, 2006). Conversely, when compared with Shannon entropy, our data show a nearly linear distribution function with values close to zero (Fig. 11) (Brouers et al., 2004; Tsallis, 2009; Tsallis, 1988). This explains the use of Tsallis non-extensive statistical mechanics to analyze complex dynamical systems. The Tsallis q-index is used to measure the degree of nonlinearity in these systems. Burr Type distributions, a particular case of q-exponential distributions, are found to be related to the statistical properties of complex dynamical systems.

4. Discussions

Our findings revealed that the overall mean effect size demonstrated an association reversal phenomenon, consistent with the Yule-Simpson paradox (Samuels, 1993; Simpson, 1951; Tu et al., 2008) and the Burr Type XII distribution. This result illustrates how aggregated data may present a misleading trend that contradicts the patterns observed within individual subgroups. Moreover, this pattern aligns with the complex dynamics of systems described by Tsallis's q-statistics formalism (Nadarajah and Kotz, 2007, 2006), which accounts for non-linear behavior and interdependence across multiple scales. The substantial heterogeneity observed in the mean effective magnitudes can be attributed to two main factors. First, there is a lack of coherence and consistency among the studies, ranging from differences in research design and experimental settings to sampling methods, measurement units, and spatial/temporal scales. Second, heterogeneity arises from the aggregation of effect sizes derived from events occurring at vastly different scales, whether global (macroscopic) or local (microscopic). As a result, these discrepancies limit the ability to compare findings across studies in a meaningful way and highlight the need for a paradigm shift in how research on SL and OMC is designed and interpreted.

To address the high heterogeneity observed across studies, the model accounted for three levels of variance: Level 1: Within-study sampling error. Level 2: Variance within studies due to methodology or other study-specific factors. Level 3: Between-study variance reflecting broader contextual differences (e.g., geography, scale). We used Moderator Included, such as study methodology (experimental, rainfed, computational) and other covariates (e.g., study scale, climate). Weights were assigned based on study sample size and precision to reduce the impact of smaller or less reliable studies. REML estimation was used to ensure robust parameter estimation and improve the accuracy of variance decomposition. The goodness-of-fit tests (e.g., AIC, BIC) confirmed the model's adequacy in addressing the high heterogeneity. While our analytical framework is deliberately detailed to reflect the complexity of cross-study variability, future syntheses may benefit from streamlined protocols that improve accessibility without sacrificing methodological clarity. Although the findings do not point to a universal directionality in the SWE-OMC relationship, they highlight the absence of predictable patterns across methods and landscapes. This inconsistency is, in itself, a valuable conclusion: it suggests that erosion-related OMC loss or accumulation is highly context-dependent, shaped by both land use and landscape configuration.

The complexity of soil structure and function arises from the interplay between natural soil-forming processes and human impact (Lin, 2003). To better understand this complexity, we identify two scales – local and global – based on the cases described in Fig. . Soil structure and function can thus be viewed as structurally organized systems with a

Table 7
Formal publication bias diagnostics based on meta-analytic tests.

Test Name	Value	p
Fail-Safe N	64.000	< 0.001
Begg and Mazumdar Rank Correlation	−0.034	0.868
Egger's Regression	−0.290	0.772
Trim and Fill Number of Studies	3.000	

Table 8
Overall vs. subgroup mean effect sizes (Fisher's Z) illustrating Simpson's paradox.

Group / Subgroup	k (effect sizes)	Mean effect size (Fisher's Z)	95 % CI	Direction
Overall pooled (all studies)	148	**0.28**	−0.05 to 0.62	Positive
Experimental methods	68	−0.04	−0.50 to 0.42	Negative
• Positive correlations	21	1.66	0.98 to 2.33	Positive
• Negative correlations	47	−0.81	−0.97 to −0.64	Negative
Rainfed methods	66	0.72	0.21 to 1.22	Positive
• Positive correlations	36	2.04	1.60 to 2.48	Positive
• Negative correlations	30	−0.94	−1.35 to −0.52	Negative
Computational methods	14	0.09	−0.88 to 1.05	Positive (weak)
• Positive correlations	2	4.86	4.52 to 5.19	Positive
• Negative correlations	12	−0.80	−1.11 to −0.48	Negative

multilevel hierarchy (Wu, 1999) composed of multiple levels or scales (Wei et al., 2012; Yair and Raz-Yassif, 2004), fractal properties (Burrough, 1983a,b; Monreal et al., 2013) and power law behavior (Starr et al., 2008; Starr et al., 2000). This hierarchy comprises various levels or scales and exhibits fractal properties and power-law behavior. In soil science and pedology, a hierarchical approach has been widely used to analyze the fractal properties of soils. Research has focused on porous media, describing their physical properties, modelling their physical processes, and quantifying their spatial variability (Bartoli et al., 1995; Li et al., 2018; Perfect, 1995; Perrier et al., 2000; Rieu and Sposito, 1991; Zhou et al., 2019).

Efforts have also been made to apply this hierarchical approach to the analysis of different aspects of the SWE process, such as the relationship between kinetic energy and rainfall intensity (Gonzalez-Hidalgo et al., 2012; Shin et al., 2016), the kinetics of soil disaggregation in water, sediment transport and discharge, daily extreme events and soil erosion, and the relationship between rainfall-runoff and soil erosion (Boardman and Favis-Mortlock, 1999; Wu et al., 2021). Furthermore, research has examined how soil erosion relates to vegetation cover (Fornis et al., 2005; Goulet et al., 2004; Kirkby, 2010; Kirkby et al., 2008; Xu et al., 2019). However, despite some exceptions, a well-established paradigm for understanding the SWE process's impact on topsoil's organic and inorganic composition, such as OMC, soil nutrients (N, P, K), and soil minerals, remains elusive (Starr et al., 2008, Starr et al., 2000).

The primary interest in using a multilevel hierarchy approach is to organize the heterogeneous and diverse knowledge in the research field of the SWE process's impact on topsoil properties, beyond the current phenomenological level of individual studies. Understanding the SWE process as a complex dynamic system offers a reliable method for achieving a more universal approach.

In this context, heavy-tailed distributions have been linked to complex system dynamics (Burton, 2012; Limpert et al., 2001). We demonstrate the heavy-tailed properties of the effect size distributions studied here, showing a high goodness of fit to the Burr Type XII distribution. Although the distribution of effective magnitudes reveals a high degree of heterogeneity, it appears to exhibit an apparent chaotic or disordered pattern due to the absence of a clear trend. This can also be seen as a characteristic of the dataset's complexity. We suggest that the lack of coherence and consistency arises from trying to explain two separate spatiotemporal dynamical mechanisms simultaneously. Averaging local information does not reveal global patterns. Similarly, from a macroscopic level (e.g., a storm), it is impossible to determine the state of specific local sites. Such reductionism or oversimplification of a multilevel hierarchical organization underestimates the complexity of the SWE process. Mixing both states leads to inconsistent and misleading results because aggregating or linearly approximating each local event does not allow for the direct identification, prediction, or deduction of general properties and patterns occurring at a global level, and vice versa.

Beyond heavy-tailed distributions, other common characteristics of complex dynamical systems have been described using the concept of nonadditive entropy and the generalized non-extensive statistical mechanics developed by Tsallis. This distribution explains the statistical properties of complex spatiotemporal dynamical systems at micro-, meso-, and macroscopic levels. The Tsallis q-index denotes the degree of nonlinearity in these systems. The reason is to confirm the dynamic and intricate nature of soil erosion processes according to Tsallis's q-statistics. Despite the inherently different nature of both processes, potential mutual dependencies might exist between them. If taken as two separate dynamical processes, at each level (Case 1 and Case 2 in Fig. S6), they portray two different unconnected hypotheses. However, Case 2 functions at the macroscopic level, providing a set of general constraints and an overall environmental frame of boundary conditions (or top-down constraints) where each site-specific microscopic event can initiate local-level processes (or bottom-up forces). Whereas at the same level, phenomena tend to be symmetrical, connected, and interacting in both directions. This reflects a set of intertwined hierarchic sequences rather than a strict hierarchic structure without interconnections. Future research should prioritize the development of standardized protocols to ensure consistency and reliability in this field. This integration of Burr-tail modelling and Tsallis entropy links statistical description to ecological meaning, highlighting how extremes and nonlinearities in erosion–OMC relationships translate into management-relevant thresholds.

5. Conclusion

Consistent with our initial objectives, the analysis not only quantified the SWE-OMC relationship across methodologies but also emphasized its dependency on contextual land use practices, reinforcing the need to integrate ecological and management factors into future erosion assessments. This meta-analysis shows that the relationship between soil water erosion (SWE) and organic matter content (OMC) is far more complex and inconsistent than commonly assumed, particularly in Mediterranean environments where conditions vary significantly. While it is often expected that erosion simply reduces OMC, our findings reveal that this relationship can reverse depending on context, method, and scale. The results point to high heterogeneity across studies, largely due to differences in methodology, experimental scale, and data quality. To address these complexities, we applied advanced statistical tools such as multilevel meta-analysis and Tsallis's q-statistics. These tools helped us uncover the non-linear and scale-dependent nature of the SWE-OMC relationship, reinforcing the importance of using more consistent and standardized approaches in future research.

A notable limitation of this meta-analysis is the broad generalization of land use types, specifically the difficulty in consistently distinguishing between detailed farmland and forestland categories across all analyzed studies. While this limitation stems from the lack of standardized reporting in the primary literature, we acknowledge that land use is a critical process moderator. We suggest that a significant portion of the remaining unexplained heterogeneity is likely attributable to these differences. Therefore, we strongly recommend that future reporting protocols mandate the explicit documentation of this data as an essential moderator variable to allow for a complete mechanistic understanding of OMC dynamics in erosion-affected areas.

A full summary of the methods, their effects, model performance, and fitted distributions is provided in Section 3 of Supplementary Material 1. The future studies include:

Standardized Methodologies: Develop uniform protocols for data collection and analysis to reduce heterogeneity and enable cross-study comparisons, particularly in SWE and OMC studies.

Integration of Models and Field Data: Combine computational simulations with experimental and rainfed studies to better predict erosion dynamics under varying climatic and land-use scenarios.

Exploration of Vegetation and Microbiome Interactions: Investigate the role of vegetation cover, root systems, and soil microbiomes in mitigating SWE and enhancing OMC retention.

Temporal and Spatial Dynamics: Conduct long-term studies to examine the temporal variability of SWE and OMC relationships across different Mediterranean subregions and topographies.

Climate Change Impacts: Evaluate the effects of extreme weather events and shifting rainfall patterns on soil erosion processes and their implications for sustainable land management.

Policy Integration: Translate findings into actionable strategies for soil conservation policies, emphasizing the importance of maintaining OMC levels to achieve LDN.

These directions aim to deepen the understanding of SWE and OMC dynamics while addressing the challenges posed by methodological inconsistencies and environmental changes.

List of studies analyzed

Results from the two-search strategy are presented below. The bibliography list corresponding to the 71 studies from where the 148 correlations extracted is divided into a first search resulting in 49 studies from EBSCO (Almagro et al., 2016; Álvarez et al., 2007; Ben Slimane et al., 2016; Blavet et al., 2009; Bogunovic et al., 2020a, 2020b, 2022; Boix-Fayos et al., 2017; Bombino et al., 2021; Cerdà et al., 2017, 2018, 2019; Cerdà and Jurgensen, 2008; García-Orenes et al., 2009b, 2012; Gaspar et al., 2020; Gómez et al., 2011; González-Rosado et al., 2021; Igor et al., 2020; Lizaga et al., 2018; Lozano-García et al., 2011; Marques et al., 2010; Martínez-Hernández et al., 2017; Martinez-Mena et al., 2008; Martínez-Mena et al., 2012, 2020; Mohammed et al., 2021b; Moreno-de las Heras, 2009; Novara et al., 2016; Nunes et al., 2010; Oeurng et al., 2011b; Ollobarren Del Barrio et al., 2018; Pardini et al., 2003, 2004, 2017; Pardini and Gispert, 2012; Parras-Alcántara et al., 2016; Repullo-Ruibérriz de Torres et al., 2018; Rodríguez Sousa et al., 2021; Rosskopf et al., 2020; Ruiz-Colmenero et al., 2013; Sousa et al., 2019; Spanos et al., 2005; Tejada and Gonzalez, 2007; Telak et al., 2021b, 2021a, 2021c; Zuazo et al., 2011, 2020) and a second search from Google Scholar resulting in 22 studies(Arabi and Roose, 1993; Barthès et al., 1998; Cerdà, 2011; Cerdà et al., 2021; Cerdà and Rodrigo-Comino, 2021; Keesstra et al., 2016b, 2019; Khorchani et al., 2023; López-Vicente et al., 2020b, 2020c; Martínez-Mena et al., 1999; Martínez-Zavala and Jordán, 2008; Masri et al., 2005a, 2005b; Morsli et al., 2005, 2004; Nadeu et al., 2015, 2014; Oeurng et al., 2011a; Rodrigo Comino et al., 2016; Roose and Barthès, 2005; Stanchi et al., 2015).

CRediT authorship contribution statement

Tom Avikasis Cohen: Writing – original draft, Visualization, Validation, Formal analysis. **Gabriel Cotlier:** Writing – original draft, Methodology, Funding acquisition, Formal analysis, Data curation. **Ioannis Daliakopoulos:** Writing – review & editing, Validation, Supervision, Project administration, Investigation, Formal analysis, Conceptualization. **Pandi Zdruli:** Writing – review & editing, Validation, Supervision. **Shahar Baram:** Writing – review & editing, Validation, Investigation, Conceptualization. **Anna Brook:** Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

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Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Corresponding authors, on behalf of all the authors of a submission, must disclose any financial and personal relationships with other people or organizations that could inappropriately influence (bias) their work. Examples of potential conflicts of interest include employment, consultancies, stock ownership, honoraria, paid expert testimony, patent applications/registrations, and grants or other funding. All authors, including those without competing interests to declare, should provide the relevant information to the corresponding author (which, where relevant, may specify they have nothing to declare). Corresponding authors should then use this tool to create a shared statement and upload to the submission system at the Attach Files step. Please do not convert the .docx template to another file type. Author signatures are not required.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.catena.2026.109793.

Data availability

data for meta-analysis from publications (Reference data) (cloud drive)

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