Agricultural Water Management 333 (2026) 110577

Contents lists available at ScienceDirect

Agricultural Water Management

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

A statistical modelling approach to site suitability of small agricultural reservoirs

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ARTICLE INFO

Keywords:
Water harvesting
Small agricultural reservoirs
Suitability analysis
Multi-criteria decision analysis
Data-driven approach

ABSTRACT

Agricultural production increasingly relies on irrigation to withstand droughts, precipitation variability or support agricultural intensification. Small Agricultural Reservoirs (SmARs) can contribute to sustainable agricultural water management by providing additional water without increasing pressure on surface and groundwater resources. The construction of SmARs is usually subject to a phase of suitability analysis, which helps discern suitable places within a large area, before exploring the potential locations with major details. This task is traditionally performed using deductive approaches relying on multi-criteria decision analysis (MCDA), which are based on relevant macro criteria for the location of SmARs, often supported by hydrological modelling. In this work, we present a data-driven statistical modelling approach based on a large database of existing SmAR locations. Our empirical approach shows a better match with a validation sample, with about 71% of SmARs in very high suitability areas compared to about 5% for the MCDA for the Italian case study in Tuscany. Moreover, our approach provides suitability models for different SmAR sizes, aiding more detailed analysis.Our results can directly support high level suitability in Tuscany, while the proposed approach can be further extended and applied in different contexts, scales, and applications.

1. Introduction

Climate change is altering major hydrological variables, including precipitation amount and timing, challenging water availability (Koutroulis et al., 2019; Piemontese et al., 2019) and agricultural production in the near future (Calzadilla et al., 2013). To cope with potential water deficits during droughts or long-term water scarcity conditions, increasing water storage is a major adaptation strategy (Schmitt et al., 2022).

Small Agricultural Reservoirs (SmARs) are water harvesting infrastructure that allow the collection and storage of runoff generated in a small catchment for agricultural purposes (López-Felices et al., 2020). SmARs allow increasing water storage, thus providing additional irrigation water without further pressure on freshwater ecosystems (Wang et al., 2022; Wisser et al., 2010). The effectiveness of such structures in increasing water supply and supporting the resilience to drought was demonstrated for the South and the North shores of the Mediterranean (Albergel et al., 2004; Casas et al., 2011), in Africa (Owusu et al., 2022; Rockström and Falkenmark, 2015), Asia (Bastakoti et al., 2016; Forzini et al., 2022), and South America (Magliano et al., 2015; Niborski et al., 2023), covering multiple water needs for irrigation and livestock. For instance, Heinzel et al. (2022) showed how projected yield losses in Thuringia, could be reduced by supplemental irrigation from reactivated unused SmARs, leading to the complete mitigation of all the losses and, in some cases, to a 6.2–13.5% increase in production.

However, if not appropriately planned or managed, SmARs can generate uneven effects at the catchment scale, only partially alleviating impacts or even potentially exacerbating them (Dile et al., 2016; Wanders and Wada, 2015). For example, building SmARs in unsuitable locations can lead to a sudden siltation of the structure, thus causing reduced water storage, additional costs for SmAR restoration and impact on water supply for food production (Alahiane et al., 2016; Liu et al., 2014). These unexpected negative consequences of SmARs can generate social tensions (Studart et al., 2021) and jeopardise the spread and effectiveness of SmARs (Donchyts et al., 2022). The identification of suitable locations for the construction of new SmARs is therefore a

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https://doi.org/10.1016/j.agwat.2026.110577
Received 28 August 2025; Received in revised form 18 December 2025; Accepted 25 June 2026
Available online 29 June 2026

crucial step to ensure SmAR effectiveness and avoid negative impacts, especially for large-scale implementation plans.

Conventional approaches to site suitability of SmARs, as well as most water harvesting infrastructure, rely on common top-down analysis based on a variety of multi-criteria decision analysis (MCDA) methods (Liu et al., 2023; Luís and Cabral, 2021; Singh et al., 2009). MCDA is based on a selection, classification, and weight of relevant criteria, which are combined with spatial analysis tools to depict areas of higher or lower suitability based on a linear score (Hajkowicz and Collins, 2007).

Despite being of easy implementation and widely applied to assess SmAR and other water harvesting infrastructures, MCDA relies on subjective decision on most steps, including the selection of relevant criteria, their suitability classification ranges and weights (Masi et al., 2024). The substantial subjectivity of MCDA is the major source of uncertainty and limitation, making it suitable for a rapid preliminary assessment or exploratory screening phase, yet requiring further extensive field inspection and participatory approaches at a smaller scale (Forzini et al., 2022; Piemontese et al., 2023).

In recent years, machine learning and statistical methods have increasingly been adopted in site suitability studies for water harvesting and related infrastructures with the aim of reducing the space of subjectivity and uncertainty (e.g., Al-Ruzouq et al., 2019; Hasan et al., 2025). However, the majority of these applications do not rely on inventories of existing reservoirs as training data, but instead use expert-defined suitability classes or MCDA-derived maps as target variables (Al-Ruzouq et al., 2019; Desalegn and Sintayehu Angualie, 2025). As a result, many so-called data-driven approaches remain conceptually top-down, with machine learning primarily serving to optimise or reproduce expert-based decision rules rather than to infer suitability directly from observed infrastructure locations (Khuc et al., 2023; Vojtek et al., 2021). Truly bottom-up, occurrence-based statistical modelling approaches – where suitability is learned from the spatial characteristics of existing infrastructure – remain rare in the literature, particularly for small-scale water storage systems (Donchyts et al., 2022; Malerba et al., 2021).

The objective of this study is presenting a new occurrence-based approach to site suitability of water infrastructure, particularly SmAR, which is based on statistical data modelling of existing SmARs. We describe our approach in comparison with the conventional MCDA and highlight strengths, limitations, and potential further development.

We apply our approach to site suitability analysis of SmARs in Tuscany, an Italian region with large portions of hilly agricultural areas and conditions of climate change and drought vulnerability (Villani et al., 2022), which make it particularly beneficial for SmAR expansion. Finally, we discuss the potential applicability of our approach and its limitations, considering that local-scale suitability investigations have already started (Masi et al., 2024), since the expansion of water storage through SmAR is considered a key National strategy to increase water supply in the near future.

2. Materials and methods

2.1. Analytical framework

Our approach is based on the combination of two different methods providing complementary perspectives on SmAR suitability: a) MCDA, and b) data-driven statistical modelling based on inhomogeneous Poisson process. While MCDA is a deductive approach, which follows deductive reasoning and is based on expert decision in selecting relevant criteria, setting the suitability range of the criteria and attributing weights to the criteria based on their relative importance on the suitability conditions, the statistical modelling method is mostly an inductive method. Starting from the same criteria, the statistical method allows attributing weights and discerning the relevance of selecting suitability criteria (Fig. 1). The first approach assumes that suitable conditions are set based on the theoretical and experiential knowledge of researchers. On the other hand, the statistical approach assumes that existing SmARs are in suitable areas, therefore it extrapolates the suitability conditions (in terms of criteria scores and relative weights) of existing SmAR locations to similar areas in the region. The two methods, providing different results, are then compared to assess overlaps and differences, which provide a measure of uncertainty and increase the reliability of the results.

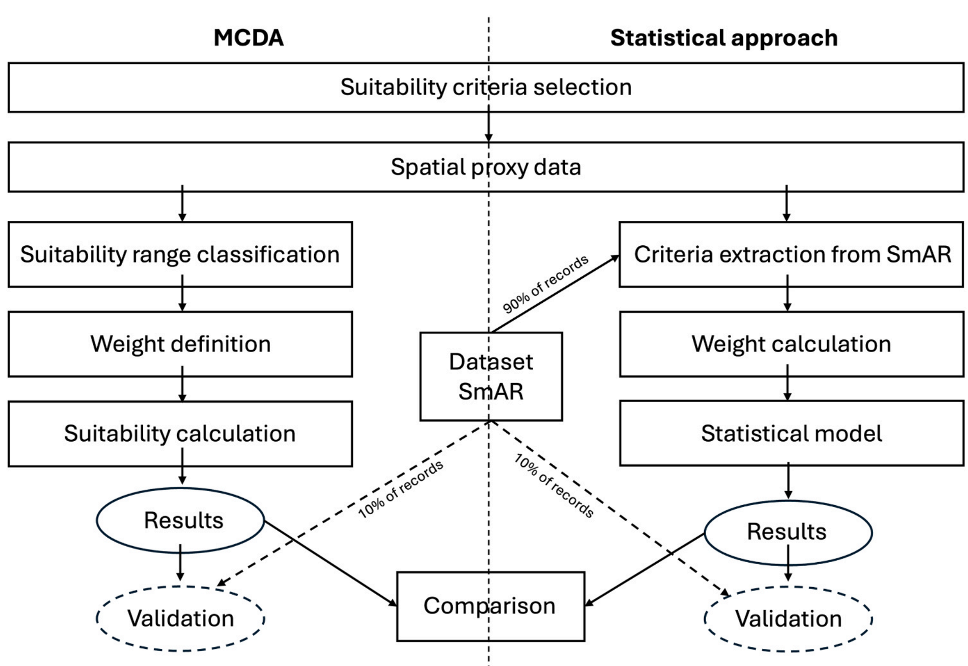

Fig. 1. Schematic representation of the analytical framework. Both methods are depicted in sequential steps, including the MCDA (left) and the data-driven statistical model (right). The flow chart shows the common steps (i.e the selection of suitability criteria and their proxy spatial data); the SmAR dataset is used in both methods, but with different purposes, while the two methods are validated with the same dataset subset and finally compared at the end.

For consistency and comparability, we use the same criteria and their proxy spatial data for both methods. Hereinafter we describe them before explaining both methods in detail.

2.2. Case study

The analysis was performed in Tuscany, a region of Central-Northern Italy with a Mediterranean climate. Tuscany's territory is mostly hilly, with altitudes ranging from the sea level in the western coastal area to about 2000 m in the Northern and Eastern Apennines (Fig. 2). Most areas, especially the internal ones, are characterized by forests and rainfed agriculture – mostly cereals and extensive rangeland (Orlandini et al., 2011). Other relevant cultivations include olive groves and vineyards, while irrigation is mainly practised in coastal plains, using water from coastal aquifers (Rossetto et al., 2013). Climate change is expected to increase drought impacts, especially in the Southern and coastal areas (Villani et al., 2022), making it a relevant case for testing SmAR siting and implementation.

2.2.1. SmAR database of Tuscany

SmARs are widespread in Italy. The Italian law 584/94 (Degli Innocenti et al., 2025) defines as "Large Dam of National Interest" all the reservoirs with a volume over 1 million m3 or with a height of the dam over 15 m, while smaller reservoirs are considered SmAR. The number of SmARs is difficult to estimate, given the scattered construction process that has taken place since the 1960s and 1970s, supported by government subsidies (Degli Innocenti et al., 2025). Only in Tuscany, nearly 16,000 have been mapped by the Lamma Consortium (Giambastiani et al., 2020). The SmAR database used in this study was developed through a hybrid and region-wide approach. First, existing regional datasets were collected and harmonised. Then SmARs were systematically checked one by one through expert photo-interpretation of 20 cm resolution imagery in Red-Green-Blue and Near-Infrared. This process supported the automated classification of SmARs on surface size, seasonality, and changes from older related datasets. Each reservoir was then individually checked and its planimetric boundary manually digitised from orthophotos, allowing the removal of false positives and the correction of geometries inherited from pre-existing datasets. A sample of 300 of them was also validated by site inspection.

Starting from the 1980s the development of the reservoirs suffered a marked slowdown towards a period of abandonment (Uzzani, 2012), when the maintenance problems of SmARs have become a critical issue for farmers and landowners, also due to the investment needed, especially for the silting process that require an expensive cost for the sludge disposal (Braga et al., 2019).

2.3. Criteria selection and proxy data

After reviewing the literature on best siting of SmAR and other generic water harvesting structure (Ettazarini, 2021; Forzini et al., 2022; Jamali et al., 2014; Luís and Cabral, 2021; Mahmoud and Alazba, 2015) we selected 6 criteria, including elevation., slope, land cover, catchment area and water availability. The criteria selection was intentionally kept parsimonious, since the main objective of this study is to compare the bottom-up, statistical approach with the MCDA one, rather than to provide an operational suitability analysis including all possible criteria. Limiting the number of predictors reduces model complexity and facilitates the interpretation of differences between the two approaches, while avoiding redundancy among correlated variables. To represent these criteria in our analysis we chose the proxy spatial data listed in

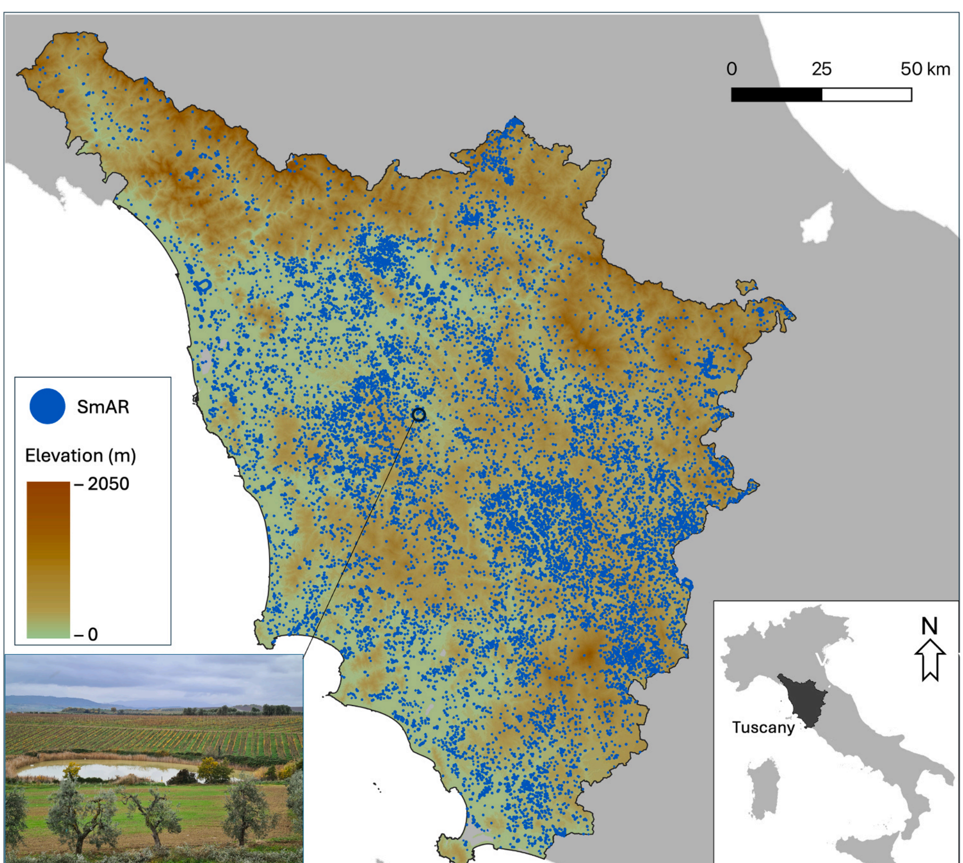

Fig. 2. Elevation (green to brown shades) and SmAR distribution (in blue) in the Italian region of Tuscany. A picture of a SmAR in a typical Tuscan landscape of vineyards and olive groves in Val D'Orcia is reported on the bottom left corner.

Table 1
List of suitability criteria, proxy data and their classification.

Criteria	Proxy data	Suitability levels				
		Highly unsuitable	Not suitable	Moderately suitable	Suitable	Highly suitable
Elevation	DTM (m)	1550–2050	1350–1550	900–1350	450–900	< 450
Slope	Slope (%)	> 15.1	10.1–15	7.1–10	3.6–7	0–3.5
Soil	Clay (%)	0–13	13–26	26–39	39–52	> 52
Land cover	Land cover 2019	Urban lands	Wetlands, Water bodies	Open forest, Other cultivated areas	Shrubland, Agroforestry	Arable land, Grassland
Catchment area	Upslope contributing area (km^2)	> 500	50–500	< 0.05	5–50	0.05 – 5
Water availability	Water balance (mm)	> 207	−60–207	−327– −60	−461– −327	< −595

Table 1. The same criteria and proxy data were used for both analyses, although with a fundamental difference. In fact, for the statistical analysis, the proxy data were used with their actual magnitude and unit of measurement, while for the MCDA, we had to classify the criteria according to their effect on SmAR suitability. The only classified criterion used for the statistical analysis is land cover, because it is a categorical value. Also, since the statistical approach aims at retrieving the suitability conditions under which the SmARs were constructed, the land cover used for the statistical analysis is that of 1978, because most of the SmARs in Tuscany were built between the 60 s and the 80 s. Once the suitability coefficients of the covariates were estimated, the final statistical suitability map was then produced using the recent land cover map, the one of 2019 – the same one used for the MCDA.

The unclassified proxy data are shown in Fig. 3, while the classification scores for the MCDA are described below and reported in Table 1, along with the open access data sources.

The DTM is a proxy for the elevation, which is a factor influencing the needs and presence of reservoirs. Generally, in Mediterranean contexts, reservoirs are most needed in lower altitudes, where agriculture is most often practised and at larger scales. The higher the altitude, the lower the potential runoff generation and gradually lower also the practice of agriculture (Luís and Cabral, 2021). However, this is not a mandatory criterion in many suitability analyses (Ammar et al., 2016).

Higher slopes have a higher risk of landslides and higher costs for dams; moreover, the lower the slope, the higher the potential storage volume (Ahmad and Verma, 2018; Critchley et al., 2013). According to the literature, the maximum suitability values are in the range of 0–3.5%, with high suitability up to 7% in slope (Al-Adamat, 2008).

Subsurface characteristics were represented through soil texture, which captures key hydrological controls relevant for small reservoirs at the regional scale. In fact, soils with a high sand content are too permeable and therefore unsuitable. Clay and clay-loam soils have the

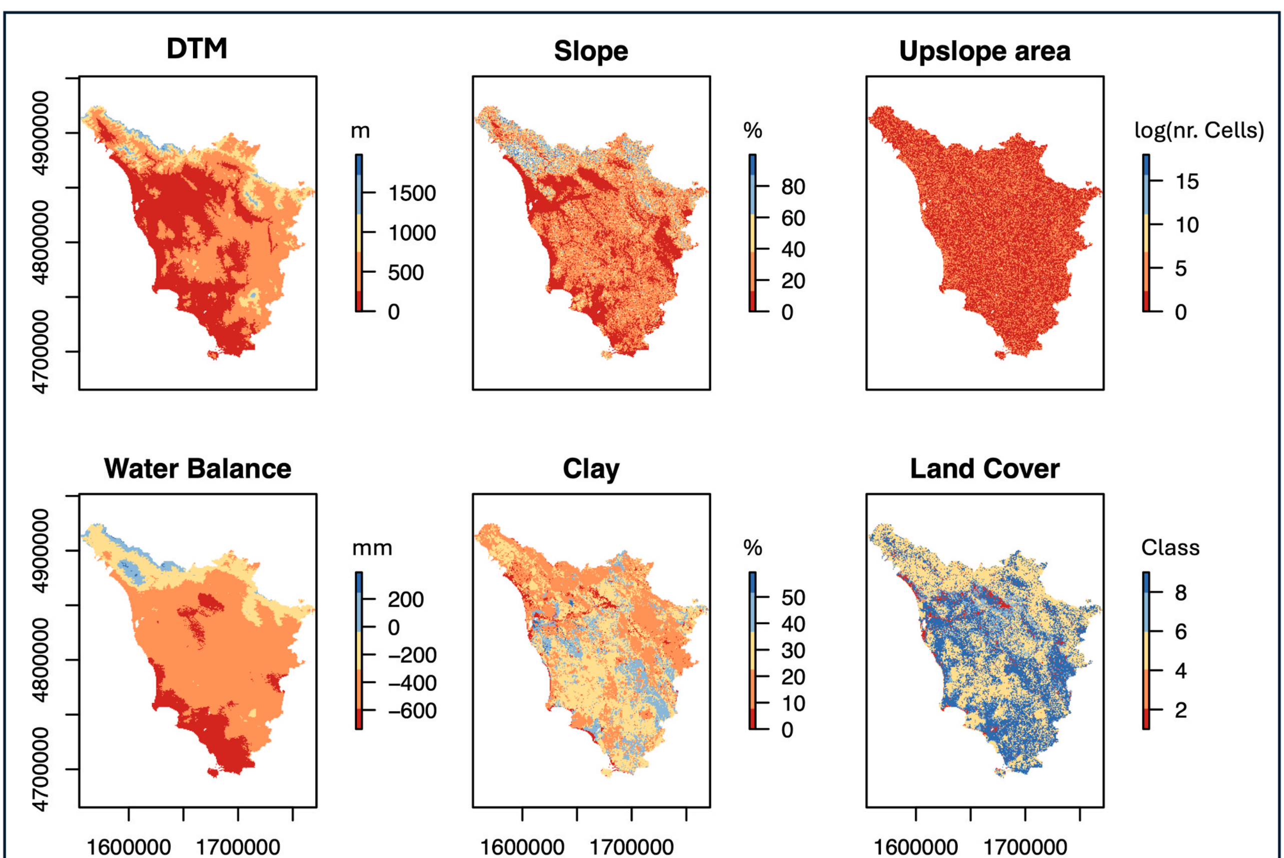

Fig. 3. Maps of the proxy data for the criteria used for both the MCDA and statistical analysis. Upslope area is shown in log values, because of its very skewed distribution, while land cover was reclassified because it was originally with categorical values.

highest suitability, with suitability decreasing as the percentage of clay in the soil decreases (Luís and Cabral, 2021). For this reason, we chose the percentage of clay content in the soil as a proxy of soil texture for assessing the permeability of the soil for SmAR suitability.

The most suitable land cover type for SmARs, considering their irrigation purpose, is agricultural areas, with due consideration on their cultivation – e.g. not replacing valuable crops or near urbanised areas (Dile et al., 2016). Maximum values were assigned to croplands and grasslands. Urbanised areas were excluded from the analysis, and existing water bodies were eliminated and recalculated as the average of suitability values in an area adjacent to the reservoirs within a 200 m radius.

The catchment area upstream of each location was represented by the upslope contributing area. This is fundamental to ensure a sufficient drainage area for a proper runoff generation, able to fill the storage volume of the reservoirs, but not too large to avoid flooding problems (Forzini et al., 2022). Through a statistical analysis of reservoirs in the Lamma database with an area between 9000 and 11000 m^2 (sample reservoir), maximum suitability values were assigned to sites with an upslope contributing area in the range of 0.05–5 km2. The final upslope contributing area map was produced through the watershed function of QGIS based on the DTM dataset.

The seasonal water balance is the average value of the difference between precipitation and potential evapotranspiration during the driest period (March-August) in the last 10 years. Areas with higher values are those that suffer less from drought. The lowest values have been assigned the highest suitability, as these are the areas most in need of irrigation. This criterion was preferred over the most common hydroclimatic criterion, which is precipitation, because it is more specific for the climate of Tuscany, where precipitation is not always the limiting factor for agriculture. Before excluding precipitation, however, we performed a spatial correlation with the water balance, which resulted to be very strong (92%), confirming that the two indicators are mutually exclusive.

2.4. MCDA

The reclassified criteria were used in MCDA. The MCDA approach allows the joint assessment of multiple effects (i.e. criteria) with different units of measurement. The methodological steps of MCDA are based on literature and expert opinion. They are summarised as follows (Grum et al., 2016):

1. Selection of relevant suitability criteria for achieving the objective, as explained in Section 2.3.
2. Establishment of suitability ranges for each criterion on a scale from 0 to 9. Suitability ranges were defined according to the expected effect of each variable on SmAR suitability. A linear formulation was adopted for most continuous criteria (slope, altitude, upslope contributing area, water balance, and soil texture), while land cover was classified using ad hoc ranges, given its categorical nature.
3. Assignment of a weight to each criterion. Equal weights were assigned to all criteria to minimise subjectivity and to ensure a transparent benchmark for comparison with the occurrence-based statistical approach, rather than to optimise MCDA performance.
4. Combination of suitability values of all weighted criteria to produce the final suitability map calculated by a weighted average of the criteria.

The final suitability score was computed with a simple weighted average – Eq.1:

$$\text{Suitability}_{\text{MCDA}} = (DTM+S+C+LC+UCA+WB)/6 \quad (1)$$

Where:

- DTM = Digital Terrain Model
- S = Slope
- C = Clay
- LC = Land cover
- UCA = Upslope Contributing Area
- WB = Seasonal water balance

2.5. Statistical approach

2.5.1. Inhomogeneous Poisson process

From a statistical perspective, SmARs are considered as events in space, with their locations identified as the points of maximum water accumulation. These locations are treated as a realisation of an *inhomogeneous* Poisson point process $Y(A)$, which is a stochastic mechanism that generates the locations of some events of interest (the SmARs in our case) within a delimited region A (Diggle, 2013).

Formally, we indicate with $N(A)$ the number of reservoirs located in a generic region A and we assume that the count $N(A)$ follows a Poisson distribution with mean $\lambda(A) = \int \lambda(\mathbf{s})d\mathbf{s}$, where λ is the process's intensity measure. The intensity $\lambda(\mathbf{s})$ varies with location $\mathbf{s}$ (thus the process is inhomogeneous), allowing for non-uniform distribution of the SmARs across the region; for example, there may be more reservoirs in rural areas compared to cities.

If we denote by $\mathbf{X}(\mathbf{s})$ a set of variables that vary across space – such as the criteria considered useful for identifying reservoir locations – we can directly model the intensity of the process, $\lambda(\mathbf{s})$, as a function of these variables:

$$\lambda(\mathbf{s}) = \exp(\alpha + \beta^{T} \mathbf{X}(\mathbf{s})) \quad (2)$$

where α is the intercept and $\boldsymbol{\beta}$ denotes the vector of coefficients associated with the explanatory variables. Estimation of Eq.2 is obtained by maximising the log-pseudolikelihood for $\lambda(\mathbf{s})$ as a function of the observed data, using the package "spatstat" in the R computing environment (Baddeley and Turner, 2005, 2000). To select between various potential specifications for the regression model, we can rely on the value of the likelihood ratio test and on the significance of each model coefficient (Davison, 2003).

Specifically, in our analysis, we modeled the intensity of SmAR locations as a function of the same variables used to define the criteria for the MCDA. Initially, we considered including some additional variables available in the data sources, such as the percentage of sand and silt, and the amount of rain precipitation. However, due to their strong correlations with other criteria, the coefficients for these additional variables were not significant, leading us to exclude them during the model specification phase. We use the land cover of 1978 for the estimation of the model coefficients since it is the closest to the construction period of most reservoirs. Most variables are included in the model as linear terms, except the DTM and the upslope contributing area (UCA), for which the relation with process intensity was better represented by nonlinear functions. Consequently, the DTM was included in the model as a quadratic term, while the UCA was transformed using a logarithmic scale.

Finally, the estimated model was used to produce a predicted value of intensity in 2019 the statistical suitability map for the entire Tuscany region. First, we obtained a predicted value of intensity in 2019, using land cover 2019 as in the MCDA. Then the suitability score is defined by dividing the predicted intensity into quintiles, assigning the lowest score to the first quintile of intensity and the highest score to the last quintile.

2.5.2. Marked inhomogeneous Poisson processes

When additional attributes are observed for each event, we can use some of these variables to characterize the point process under study into different types. These types are usually referred to as marks, and the resulting process is known as a marked point process (Diggle, 2013).

Since the SmARs database includes information about the surface dimensions of reservoirs, we decided to classify them by size. In particular, we create four size groups, defined by dividing the surface dimension distribution into quartiles: Mark 1 [1000–1599 m2], Mark 2 [1599–2865 m2], Mark 3 [2565–6288 m2], Mark 4 [6288–244670 m2].

In this case, the entire point process $Y(A)$ is divided into four sub-processes $Y_1(A)$, ..., $Y_4(A)$, one for each mark, each with a specific intensity $\lambda_m(s)$. The SmARs counts for the entire process $Y(A)$ are given by the (4×1) vector $\boldsymbol{N}(A) = [N_1(A),\ldots,N_4(A)]$, where the generic element $N_m(A)$ is the number of reservoirs with mark m generated by the sub-process $Y_m(A)$.

In analogy with model (1), we can specify a regression model for the intensity of each sub-process:

$$\lambda_m(s) = \exp(\alpha_m + \beta_m^{\mathrm{T}} \boldsymbol{X}(s)) \tag{3}$$

where $\alpha_1,\ldots,\alpha_4$ and $\boldsymbol{\beta}_1,\ldots,\boldsymbol{\beta}_4$ denote mark-specific intercepts and coefficients associated with the covariates, respectively. As for model (1), the estimation for model (2) is obtained by maximising the log-pseudolikelihood for $\lambda_m(s)$.

3. Results

3.1. Statistical suitability results

Following the approach described in Section 2.5.1, SmAR locations are modelled as an inhomogeneous Poisson point process with the intensity of the process assumed to be parametrically dependent (as in Eq.2) on the same variables used to define the criteria for the MCDA.

Table 2 reports the final model's estimated coefficients, with their corresponding standard errors (i.e. Coeff) and significance levels. All the coefficients are highly significant, and their values identify the contribution of each covariate to the point process intensity on the logarithmic scale: negative coefficients indicate a negative effect, whereas positive coefficients indicate a positive effect on the intensity of finding a reservoir.

The last column of Table 2 presents the exponential transformation of the coefficients, which quantify the magnitude of the effect of each criterion on the intensity and can be interpreted as their weight in explaining the location of existing reservoirs. To interpret the results correctly, it must be noted that the effect is multiplicative. For example, the variable "slope" is highly significant with a negative coefficient of −0.0885. This indicates that for every one-degree increase in slope, while keeping the other variables constant, the intensity of finding a reservoir is multiplied by exp(−0.0864) = 0.9172, resulting in an intensity reduction of 8.47%. Following the same reasoning, if the water balance increases by one millimetre, the expected intensity decreases by 0.13%, whereas if the clay increases by 1%, the intensity increases by 1.47%.

The land cover 1978 is a categorical variable, and a description of each category can be found in Table 1. The coefficient for each score should be interpreted as the effect on intensity compared to the baseline score, which is set to "urban land". Being in an area with a land cover score of 9 ("arable land, grassland") increases the intensity by 161.84% in comparison to being on urban land, whereas a score of 5 ("open forest, other cultivated areas") or 7 ("shrubland, agroforestry") has nearly the same effect, increasing the expected intensity by 110.76% and 108.38%, respectively, in comparison to being on urban land. The high coefficient of the score 3 ("wetlands, water bodies") has a specific reason: this category corresponds to those SmARs created before 1978, and therefore included in the land cover 1978 as water bodies. The high value of the coefficient indicates that, quite obviously, the presence of water bodies is a good predictor for those same water bodies.

Since the effects of DTM and UCA are nonlinear, their impact is not constant over their range of values, and their interpretation is less straightforward. The UCA has a positive but decreasing effect (the coefficient for log UCA is positive), whereas the effect of DTM follows a parabolic trajectory, positive for small altitude values but negative for larger values (the coefficient for DTM squared is negative).

Fig. 4 shows the average predicted intensity as function of each covariate. Predictions are computed over the range of values for a variable, with all other variables set at their average values.

Table 2
Estimated coefficients of the model, with the corresponding standard errors, Z-test values, significance levels, and exponential transformations.

Covariates	Coeff.	S.E.	Z value	Signif.	exp (Coeff.)
intercept	−17.7167	0.1555	−113.95	***	**0.0000**
slope	−0.0885	0.0022	−40.20	***	**0.9153**
DTM (Km)	3.1875	1.8904	16.86	***	**24.2289**
DTM^2 (Km^2)	−2.8066	2.6041	−10.78	***	**0.0604**
water balance	−0.0013	0.0002	−6.57	***	**0.9987**
upslope contrib area (in log)	0.3176	0.0035	90.97	***	**1.3738**
% clay	0.0146	0.0011	12.74	***	**1.0147**
Land cover 1978: (baseline is Score 1, urban land)					
Score 3 (wetlands, water bodies)	1.8814	0.1074	17.52	***	**6.5626**
Score 5 (open forest, other cultivated areas)	0.7455	0.1063	7.02	***	**2.1076**
Score 7 (shrubland, agroforestry)	0.7342	0.1158	6.34	***	**2.0838**
Score 9 (arable land, grassland)	0.9626	0.1019	9.45	***	**2.6184**

Note: Significance levels: *** prob < 0.001, ** prob < 0.01, * prob < 0.05.

3.2. Comparison between the methods

The suitability scores of the two methods, displayed in Figs. 5a and 5b, show a moderate degree of similarity; in fact, the correlation between them is 0.45. Despite showing a similar pattern, the main differences are mostly in the magnitude of the scores. For example, MCDA has very low values (dark red areas in Fig. 5b) in all mountain regions in the North and North-Eastern part of the region, while the statistical results show spots with low to high suitability. In general, the scores of MCDA seem more polarized compared to the ones of statistical analysis. The majority of SmARs from the validation sample are in high and very high suitability classes for both models, although the statistical results have as much as about 70% of them in the highest class (Fig. 5c), while MCDA has only about 5% (Fig. 5d). However, most of the SmARs in the MCDA validation fall within high suitability scores (about 67%), which validates the approach. It is important to notice that most SmARs were built between the 1960s and the 1980s, so the low suitability values of some SmARs could be due to a change in land cover over the last decades. For example, if a reservoir was built in a proper land cover area in the 1960s, for example agricultural land, that area might now have become urban, thus no longer suitable for the construction of new reservoirs.

For a further comparison, a bivariate map of SmAR suitability was produced based on the scores of the two approaches. The rationale behind this analysis is that where both indicators have similar suitability scores, there is less uncertainty on the potential suitability of the site. Fig. 6 shows the areas where both scores agree on a 3-grade score (the light grey to dark blue colors on the diagonal of the bivariate legend). These areas are indeed the light grey region in the Northern and North-Eastern side of Tuscany, the mountainous and forestry areas of the Apennines, with both models indicating low suitability. In this sub-region, however, we can also see areas of marked spatial divergence between the two suitability approaches, where the statistical model indicates high suitability while the MCDA assigns predominantly low suitability scores. This discrepancy is mainly driven by the treatment of topographic variables within the MCDA framework, which penalises areas above certain elevation and slope thresholds based on expert-defined suitability ranges. The presence of numerous SmAR in these

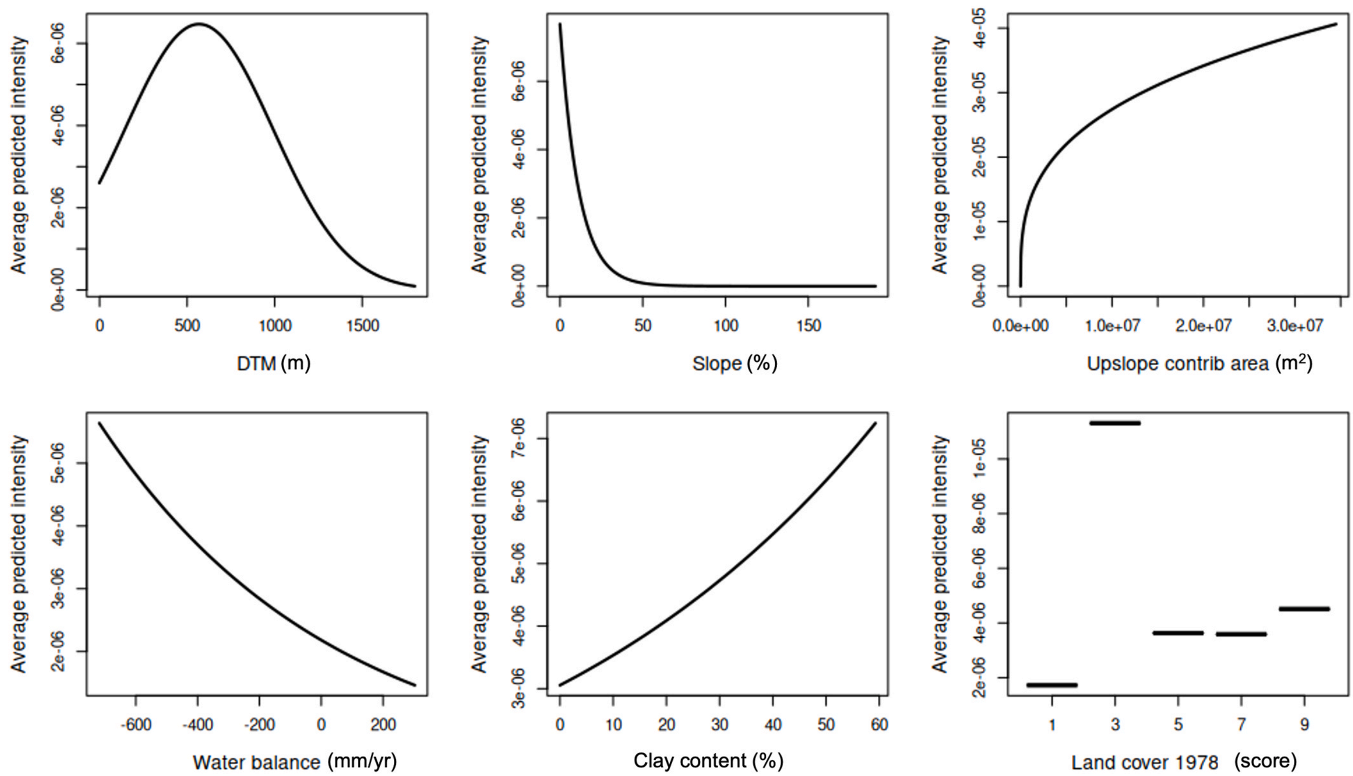

Fig. 4. Intensity predicted with the estimated coefficients of Table 2, as function of each covariate. Predictions are computed over the range of values for a covariate, with all other covariates set at their average values.

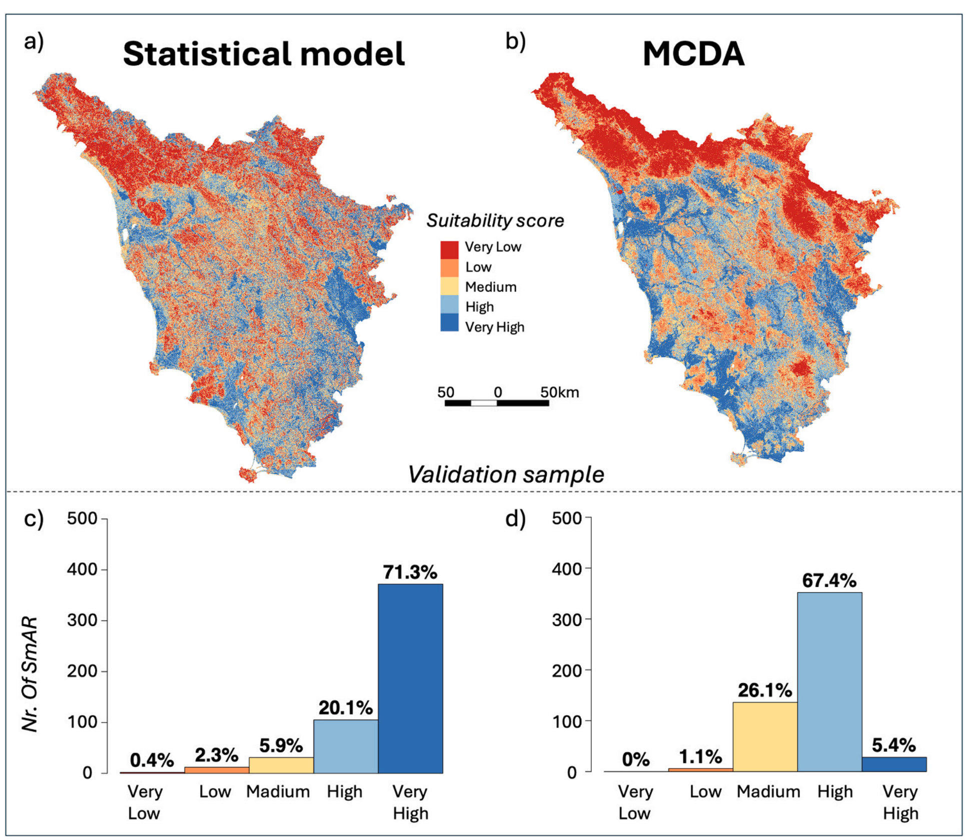

Fig. 5. Suitability map based on the MCDA method (a) and the statistical approach (b), and suitability values of the validation sample for the statistical model (c) and MCDA (d).

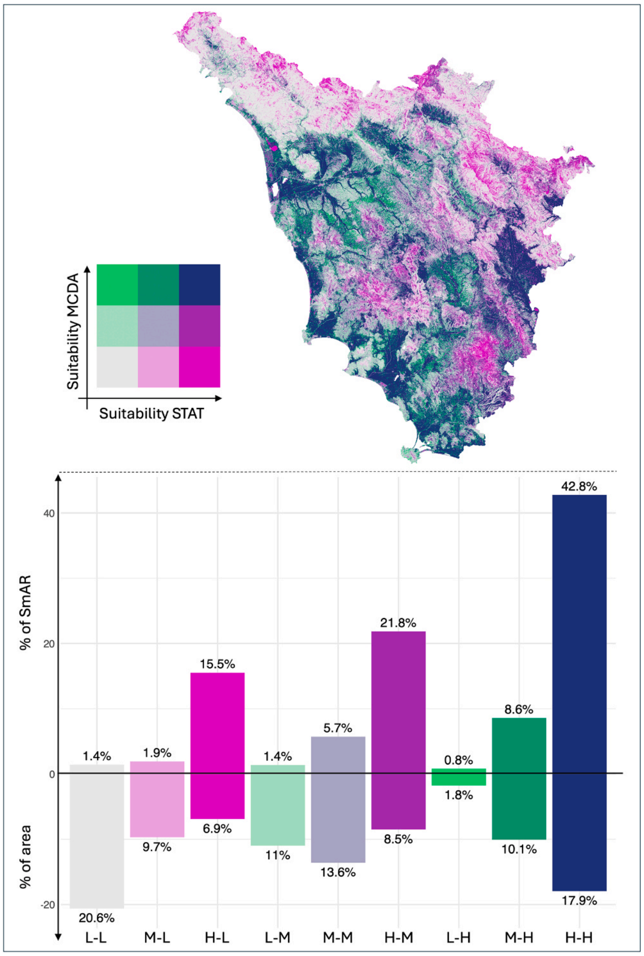

Fig. 6. Bivariate map (top) showing agreement between the two suitability methods divided in three scores. The colors represent different combinations of Low (L), Medium (M) and High (H) suitability for either method. For example, the light grey represents areas of low suitability for both methods (L-L), meaning high agreement between the methods, while the dark blue areas (H-H) are very highly suitable and with high agreement between the two methods. The double histogram (bottom graph) shows the % of SmARs from the validation sample in each bivariate category on the positive y axis, while the % of the total area of Tuscany is split into the 9 bivariate categories.

areas suggests that such top-down thresholds may not fully capture the local conditions that have historically enabled reservoir construction and operation. In contrast, the occurrence-based statistical model, while relying on the same set of input variables, learns suitability directly from observed reservoir locations and therefore identifies context-specific ranges that are consistent with the existing SmAR distribution in Tuscany. As a result, the statistical model may implicitly capture the influence of additional, unmodelled factors – such as local socio-economic conditions or historical land use – through their correlation with the observed spatial patterns. This highlights how bottom-up statistical modelling can partially compensate for missing or simplified criteria in conventional MCDA frameworks.

The darkest areas along the Arno River in the North-West and the coastal plains and gentle hills in the South-West show high agreement and high suitability for SmAR. In general, 17.9% of Tuscany territory falls into highly suitable areas with high agreement between the models, while about 20.6% of the territory is classified as low suitability (according to this 3-grade classification). It is interesting to notice that most of the existing SmARs fall within areas marked as highly suitable for the MCDA, although with increasing values for higher STAT scores. Overall, more than 42.8% of SmARs are in highly suitable areas, while only 1.4% in areas of low suitability by both methods.

3.3. Statistical suitability for different SmAR dimensions

Since the SmAR database contains information on the surface dimension of the reservoirs, we decided to divide them by size and treat their location as an inhomogeneous marked Poisson point process. We create four size groups, defined by dividing the surface dimension distribution into quartiles: Mark 1 [1000–1599 m^2], Mark 2 [1599–2865 m^2], Mark 3 [2565–6288 m^2], Mark 4 [6288–244670 m^2].

Then, we estimate the intensity of the marked point process as a parametric function of the same variables used to define the criteria for the MCDA. This analysis resembles what was presented in Section 3.1; however, in this case, the model for the intensity is defined as shown in Eq.3, which allows for mark-specific coefficients of the covariates.

The covariates of the regression model are the same variables discussed in Section 3.1: slope, water balance, and clay in linear terms; digital terrain model (DTM) in quadratic terms; upslope contribution area in logarithmic terms; and land cover from 1978 as a categorical variable. The final model specification incorporates all the variables with mark-specific coefficients, except for clay and land cover. For these two covariates, the mark-specific effects were not statistically different from each other, indicating that the percentage of clay and the land cover scores have the same effect (consistent with the estimates in Table 2), regardless of the size of the reservoir.

Table 3 reports the marked model's estimated coefficients, with their corresponding standard errors, significance levels and exponential transformation. Almost all the coefficients are highly significant, with signs analogous to what we observed in Table 2. However, the mark-specific coefficients indicate that the impact of the covariates differs depending on the size of the reservoir. The magnitude of the effect of all the covariates increases with the size: for mark 4 we have the larger negative impact of the slope, the larger positive effect of the upslope contribution area, the water balance is no longer significant, and both the DTM coefficients are the smallest, indicating that, on average, larger SmARs tend to exhibit greater intensity at lower altitudes. The contrary is observed for marks 1 and 2: slope and altitude have less negative influence on the expected intensity, the water balance has a significant negative impact, whereas the upslope contribution area still has a positive effect, but it is the smallest.

With the estimated covariate coefficients of Table 3, we can produce four suitability maps, one for each mark, for the entire Tuscany region (Fig. 7). First, we obtained a predicted value of intensity for each mark and for the entire region, and then the suitability score is defined by dividing the predicted intensity into quintiles. Although the suitability of different size SmARs show a similar pattern, the vary in intensity of suitability, particularly between small (Fig. 7b) and larger SmARs (Fig. 7d).

Summing up all the scores for the 4 marked suitability, most of the land (about 77%) is ranked with varying suitability scores depending on the size of the SmARs (the yellow bar in Fig. 8), while only 12,7% has minimum suitability across sizes and 10.2% has maximum suitability for all sizes. This highlights the strong size-dependence of suitability patterns and supports the use of size-specific suitability models, suggesting that using a single suitability analysis would likely render coarser outcomes.

4. Discussions

Our results suggest a very suitable area (the highest of five suitability scores) of about 18% of total land with the MCDA approach, which is comparable to other studies – for example 17% in Bangladesh (Hoque et al., 2022). Although other 5-suitability scores MCDA have found lower percentages, for example 7% of highly suitable areas in Mozambique (Luís and Cabral, 2021), common high scores are usually much lower. For example, studies in India and Burkina Faso (Stemn,

Table 3
Estimated coefficients of the marked model, with the corresponding standard errors, Z-test values, significance levels, and exponential transformations. Marks are defined by the SmAR surface dimension: Mark 1 [1000–1599 m^2], Mark 2 [1599–2865 m^2], Mark 3 [2565–6288 m^2], Mark 4 [6288–244670 m^2].

Covariates	Coeff.	S.E.	Signif.	Z value	exp (Coeff.)
Intercept					
Mark 1	−19.2627	0.2775	***	−69.42	**0.0000**
Mark 2	−19.3656	0.2830	***	−68.42	**0.0000**
Mark 3	−19.2541	0.2762	***	−69.70	**0.0000**
Mark 4	−18.5070	0.2522	***	−73.38	**0.0000**
slope					
Mark 1	−0.0781	0.0038	***	−20.71	**0.9249**
Mark 2	−0.0918	0.0042	***	−21.95	**0.9123**
Mark 3	−0.0874	0.0044	***	−20.06	**0.9163**
Mark 4	−0.1069	0.0053	***	−20.14	**0.8986**
DTM (in Km)					
Mark 1	3.8883	0.3631	***	10.71	**48.8293**
Mark 2	4.5143	0.3872	***	11.66	**91.3102**
Mark 3	3.4204	0.3982	***	8.59	**30.5806**
Mark 4	1.3807	0.3821	***	3.61	**3.9775**
DTM^2 (in Km^2)					
Mark 1	−2.9026	0.4579	***	−6.34	**0.0549**
Mark 2	−3.9271	0.5426	***	−7.24	**0.0197**
Mark 3	−3.5149	0.5970	***	−5.89	**0.0298**
Mark 4	−1.6892	0.5598	**	−3.02	**0.1847**
water balance					
Mark 1	−0.0016	0.0004	***	−4.03	**0.9984**
Mark 2	−0.0018	0.0004	***	−4.26	**0.9982**
Mark 3	−0.0015	0.0004	***	−3.74	**0.9985**
Mark 4	−0.0003	0.0004		−0.74	**0.9997**
upslope contrib area (in log)					
Mark 1	0.2738	0.0071	***	38.49	**1.3149**
Mark 2	0.2869	0.0069	***	41.88	**1.3323**
Mark 3	0.3241	0.0064	***	50.76	**1.3828**
Mark 4	0.3703	0.0059	***	62.68	**1.4482**
% clay	0.0149	0.0011	***	13.02	**1.0150**
Land cover 1978: (baseline is Score 1, urban land)					
Score 3 (wetlands, water bodies)	1.8711	0.1075	***	17.41	**6.4955**
Score 5 (open forest, other cultivated areas)	0.7432	0.1062	***	6.99	**2.1026**
Score 7 (shrubland, agroforestry)	0.7282	0.1158	***	6.29	**2.0713**
Score 9 (arable land, grassland)	0.9571	0.1019	***	9.39	**2.6041**

Note: Significance levels: *** prob < 0.001, ** prob < 0.01, * prob < 0.05.

2016) range from 0.5% to 3.7%. Although these countries have completely different hydroclimatic and socioeconomic characteristics, this suggests that depending on the criteria, weights and even number of suitability scores of the final indicators, the results can vary significantly.

The added value of our analysis is in fact to not rely on any quantitative top-down method for the identification of weights of the criteria. Criteria are often weighted using methods such as analytic hierarchy process (AHP), topis, best worst, vikor, etc (Aliani et al., 2021; Pourkhabbaz et al., 2014; Tercan, 2021; Yalew et al., 2016). In data-rich regions like Europe, where most data on SmAR locations are available for a relatively long period, using actual dam locations can help avoid top-down analysis based on subjective classification and rough weight estimation methods. This is the main motivation for our study, which compares the conventional MCDA with an inductive estimate of suitability areas based on existing SmARs. Although new, this approach is gaining traction in the field. In fact, a recent publication (Vergni et al., 2025), which was inspired by an earlier version of this study (Piemontese et al., 2024a), has adopted a similar philosophy in a different Italian Region (Umbria). Their approach uses data of SmAR location to calibrate weights for the MCDA, thus producing 2 MCDA models, a deductive one and an inductive, data-driven one. They found that both models show good suitability where SmARs are located, although the two models have generally low agreement. While our analysis shows a relatively better agreement between the statistical approach and MDCA, the result by Vergni et al. suggests that our assumption that SmARs are in suitable areas (which is also the assumption of our approach) is well-founded.

One of the most relevant advantages of our statistical approach is the marked analysis. which shows that suitability scores can vary significantly among SmARs of different dimensions (Fig. 8). This is a particularly relevant finding considering the wide range of needs and costs of reservoirs. For example, the negative coefficient of slope suggests that reservoirs were (thus should preferably be) built in gently sloped areas. This finding not only confirms the "expert opinion" documented in the literature (Forzini et al., 2022; Shadmehri Toosi et al., 2020) but also adds that, in the case of Tuscany, this proportional relationship has a precise magnitude, corresponding to an 8.3% decrease in suitability for each additional degree of slope. This is a very specific, as well as practical information for possible planning and design purposes in Tuscany.

Our data-driven approach can thus complement classic MCDA suitability evaluations for eventually providing a more targeted and robust decision-making support tool. However, it is important to note that our work does not consider the actual convenience or overall opportunity to expand water storage at the landscape level, which would require investigating additional issues. In fact, several problems can arise when water storage expansion happens without a systemic understanding of socio-hydrological dynamics. For example, a classic problem can be the increasing competition between upstream and downstream locations. In this sense, although increasing water storage can boost agricultural production, the whole hydrological balance needs to be carefully assessed to not affect water availability in downstream locations, especially in semi-arid areas (Ribeiro Neto et al., 2024). Another potentially negative consequence of water storage expansion is a paradoxical worsening of water scarcity conditions via the so-called "reservoir effect" – which depicts cases where increasing water storage triggers water consumption beyond the systemic capacity in the long term (Di Baldassarre et al., 2018; Piemontese et al., 2024b). It is also important to consider that SmARs tend to decrease their water storage capacity because of siltation, which occurs particularly rapidly in situations of massive land cover change, particularly deforestation (Degli Innocenti et al., 2025; Ogilvie et al., 2019). Finally, other potential threats to SmAR effectiveness are represented by climate change, which is expected to negatively impact water storage of SmAR, particularly inter-annual and intra-annual variability (Donchyts et al., 2022; Krol et al., 2011). This would require a complex and careful management strategy to compensate for water losses and avoid potential impact (Ribeiro Neto et al., 2024).

From a decision-making perspective, the results suggest that site suitability assessments should not rely on a single method. The moderate agreement between the statistical and MCDA approaches supports the use of both methods as complementary screening tools to identify priority areas while providing a measure of uncertainty. The statistical method also provides empirically grounded information on the relative importance of suitability criteria, which can support more transparent and evidence-based planning, particularly in the design of funding schemes, regulatory guidelines, and technical standards for SmAR construction. Finally, the marked analysis highlights that suitability conditions vary substantially with reservoir size, indicating that uniform planning criteria may be inadequate. Policymakers and technical agencies could therefore differentiate design guidelines and permitting procedures according to reservoir size and function. Such an integrated approach is essential to ensure that SmAR expansion enhances agricultural resilience and water security without generating unintended environmental or social impacts.

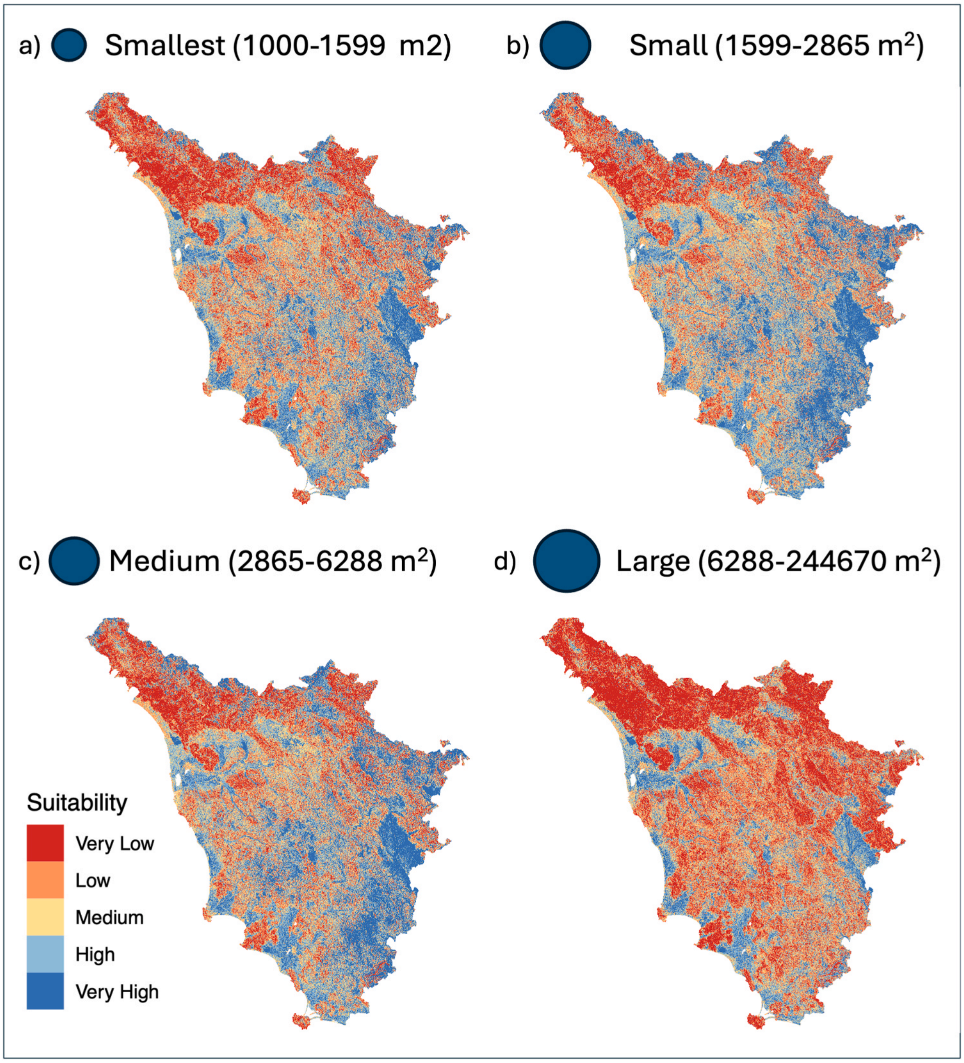

Fig. 7. Suitability maps of the 4 marked processes corresponding to different SmAR surface dimensions (a – Mark 1 [1000–1599 m^2], b – Mark 2 [1599–2865 m^2], c – Mark 3 [2565–6288 m^2] and c– Mark 4 [6288–244670 m^2]).

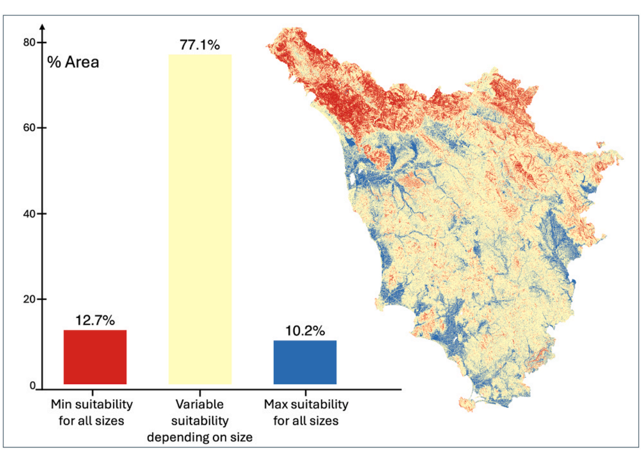

Fig. 8. Distribution of land area according to the consistency of suitability scores across SmAR size classes. Red and blue bars indicate areas that are consistently classified as low or high suitability for all SmAR sizes, respectively. The yellow bar represents locations where suitability varies depending on reservoir size.

4.1. Limitations, future research, and implications for decision-making

While the proposed statistical modelling framework provides a complementary, bottom-up perspective to conventional MCDA-based suitability analyses, several limitations should be acknowledged, which also indicate directions for future research. In this study, the MCDA implementation relies on expert-defined criteria and weights without further optimisation or calibration. This also implies that the comparison does not isolate the full potential performance of MCDA-based approaches. Optimised or data-informed weight-setting strategies – such as sensitivity analysis, participatory weighting, or calibration against observed infrastructure – are a common practice and usually lead to different suitability patterns (Ammar et al., 2016). However, the objective of the comparison was not to identify a "best-performing" algorithm, but to contrast two conceptually distinct paradigms: a top-down, expert-driven suitability framework and a bottom-up, occurrence-based statistical approach. In this sense, the absence of weight optimization in MCDA is a deliberate choice that allows highlighting the shift from subjective to empirically inferred criterion importance. This shift represents a key advantage of statistical modelling in terms of transparency and reproducibility, but it also introduces new assumptions, including the representativeness of existing infrastructure and the implicit treatment of past decisions as proxies for suitability. Future research should therefore explore hybrid frameworks in which occurrence-based statistical models inform or constrain MCDA weighting schemes, for example by using statistically inferred predictor importance as prior information for expert-based weighting. Systematic sensitivity analyses and cross-validation exercises could further clarify how different weighting strategies affect suitability outcomes and decision robustness.

Another key factor to consider is that the occurrence-based approach assumes that existing SmARs reflect suitable conditions at the time of construction. Although supported by the general alignment between observed SmAR locations and high suitability scores, this assumption may not always hold, as some reservoirs may result from historical practices, socio-economic constraints, or land-use conditions that have changed over time (Piemontese et al., 2020). Future work should explicitly address temporal dynamics in land use and climate, as well as potential biases in legacy infrastructure datasets. Also, the framework is constrained by data availability and does not explicitly account for reservoir performance, maintenance status, or sedimentation processes, which are critical for long-term functionality (Barbour et al., 2016; de Haas et al., 2018). Integrating monitoring data and process-based sediment or hydrological models would allow moving from construction suitability toward operational and sustainability-oriented assessments.

Finally, the analysis primarily considers biophysical and hydroclimatic factors, while socio-economic and institutional dimensions – such as land tenure, access to financial resources, water rights, and governance arrangements – are not explicitly included. These factors are known to strongly influence the success and equity of small water storage interventions (Rockström and Falkenmark, 2015). For large-scale analysis, we recommend expanding the set of criteria to include relevant socio-economic factors and test their relevance and opportunity – despite their difficult availability. For smaller-scale applications, hybrid approaches combining statistical modelling with participatory and stakeholder-driven assessments represent a key avenue for future integration and development of our approach.

5. Conclusions

This work presents a statistical modelling approach based on existing infrastructure to improve the estimation of SmAR suitability at the Regional scale. Going beyond conventional MCDA, this work shows that more sophisticated statistical models can provide more robust results, as demonstrated by the 95% of the SmAR validation sample in highly suitable areas. Although achieving a moderate correlation with the conventional MCDA results (45%), the statistical approach proves to be a versatile tool in assessing size-specific suitability and demonstrates the potential of this approach for refined applications. With empirical data becoming more available, our statistical approach can further develop to provide evidence-based suitability indications for guiding operational decisions on mainstreaming SmARs at the landscape level.

CRediT authorship contribution statement

Elisa Michelotti: Writing – review & editing, Formal analysis, Data curation. **Chiara Bocci:** Writing – original draft, Visualization, Methodology, Formal analysis, Data curation, Conceptualization. **Luigi Piemontese:** Writing – original draft, Visualization, Methodology, Formal analysis, Data curation, Conceptualization. **Elena Bresci:** Writing – review & editing, Supervision, Funding acquisition, Conceptualization. **Giulio Castelli:** Writing – review & editing, Conceptualization. **Tobia Papini:** Writing – review & editing, Formal analysis, Data curation. **Federico Preti:** Writing – review & editing, Supervision, Methodology, Data curation, Conceptualization.

Declaration of Competing Interest

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

Acknowledgements

This study was carried out within (i) the RETURN Extended Partnership and received funding from the European Union NextGenerationEU (National Recovery and Resilience Plan – NRRP, Mission 4, Component 345 2, Investment 1.3 – D.D. 1243 2/8/2022, PE0000005); (ii) "CASTLE - Creating Agricultural reSilience Through smaLl rEservoirs" funded by MUR within the project PRIN - PROGETTI DI RICERCA DI RILEVANTE INTERESSE NAZIONALE - 2022. CASTLE - COD. PROG. 2022XSERL4 and the (iii) Space It Up! Project (Contract n. 2024-5-E.O, CUP n. I53D24000060005) funded by the Italian Space Agency (ASI) and the Ministry of University and Research (MUR). The SmAR dataset of Tuscany is made available by the regional government and the Lamma Consortium.

Data Availability

The data that has been used is confidential.

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