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1. Technical references

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2. ABSTRACT

Understanding and quantifying potential drought adaptation and mitigation strategies is fundamental for planning a resilient society against climate change. This work reports the recent advancements in modelling adaptation and mitigation strategies to drought. The activities cover the major aspects of i) cross-sectoral evaluation of drought impacts (section 4) and ii) strategies to mitigate impacts of droughts and conflicts related to water shortage (section 5). The case studies cover a diverse set of scales, hydroclimatic and socio-economic conditions from the North to the South of Italy, including the Po and Arno basins, and the peri-urban area of Palermo. Specifically:

- 4.1 develops a hydrologically-sound method to estimate the impact of water scarcity on intersectoral competition for water, with focus on food and energy sectors.
- 5.1 presents a comprehensive conceptual framework to guide knowledge co-creation for dought impact assessment and adaptation scenarios
- 5.2 develops a combined approach for assessing the site suitability to water storage expansion through small agricultural reservoirs in Tuscany
- 5.3 tests a range of in-situ agricultural drought management solutions in the peri-urban areas of Palermo
- 5.4 presents a quantification of the potential of Stormwater for non-potable use to reduce drought impact at the urban scale in the city of Palermo

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4 Cross-sectorial evaluations of drought impacts

4.1 Analysis of the impact of water scarcity on intersectoral competition for water, with focus on food and energy sectors

Water scarcity increases in drought conditions due to changes in both demand and availability, for both the food and energy sectors. For the food sector, evapotranspirative demand in agriculture increases due e.g. to increased temperature, while water availability for irrigation decreases. For the energy sector, the availability of water is shared with the food sector, and so it decreases as well, and the demand increases e.g. due to increased energy demands for domestic and industrial cooling. Furthermore, water extraction itself may become more energy intensive in water scarcity conditions and water scarcity for each sector may increase due to the increased demand of the other sector reducing water availability. More in general, the characteristics of freshwater as a common good (shared but subtractable) and its dynamic nature as a flowing resource create intersectoral competitions among users that exacerbate when the imbalance between demand and availability increases.

Blue water scarcity is a good representation of such imbalance because it holistically compares demands from different sectors with sustainable water availability, in a dynamic and spatially distributed way, but as a synthesis multisectoral indicator it is not able to disentangle the level of water stress of specific users. To understand how a single water user impacts on the water scarcity level of other users, blue water scarcity can be assessed in a leave-one-out way, analyzing variations of water scarcity in response to an additional water demand (Galli et al., 2023). Yet, while such an approach is able to highlight exacerbations of water scarcity also downstream of a variation in water demand, if this variation is not punctual but diffused it is not able to trace back a specific downstream variation in water scarcity to a specific variation in water demand. E.g., if the aim is to understand the specific impact of agriculture on blue water scarcity for other sectors, looking at blue water scarcity variations only is not sufficient to connect specific downstream water scarcity exacerbations to specific upstream agricultural areas. To fill this research gap, we have developed a methodology that essentially reverts the blue water scarcity algorithm. The methodology consists in iteratively decreasing a given water demand and assessing the response in terms of water scarcity until no water scarcity variations are observed anymore (Figure 1). The fraction of water demand that has not been cleared during the process is hydrologically sustainable in the sense that it is not creating additional competition for water, neither where it is located, nor downstream. This methodology has been published using pre-existing datasets, in particular with an application on the hydrologically sustainable expansion of irrigated agriculture in Kenya (Galli et al., 2023). Clearly, we plan to apply it using data produced within RETURN and possibly to refine it to include non-natural connections between water users and water sources.

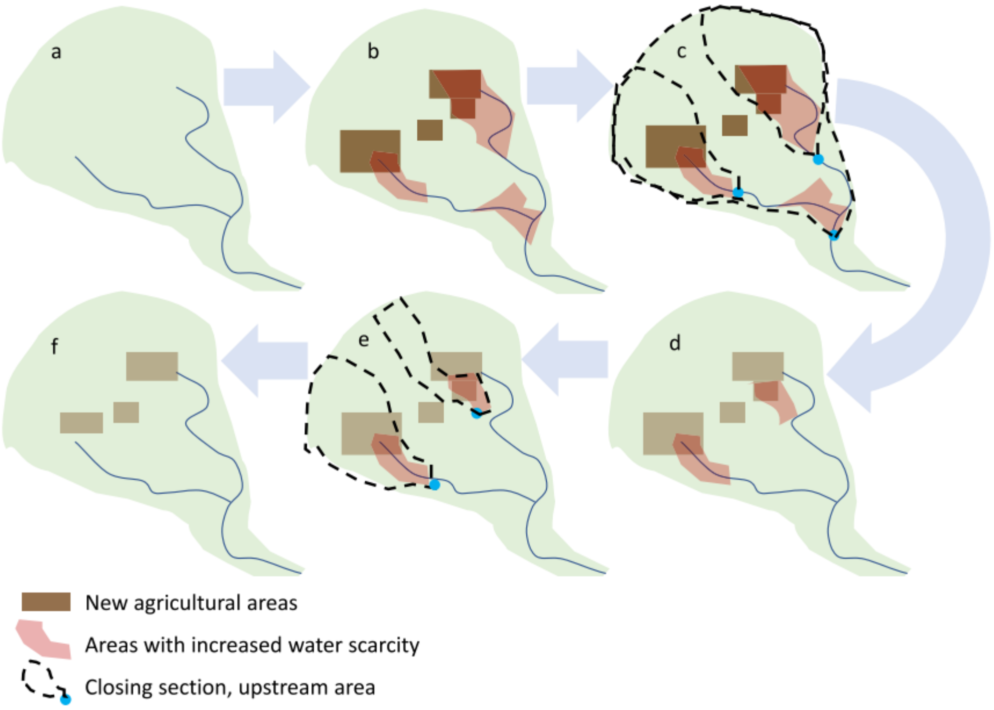


Figure 1. Scheme for the reverse blue water scarcity method for identifying hydrologically sustainable water demands and linking water scarcity variations to water demands variations. From Galli et al. (2023)

A further development that is in progress is the use of data-driven techniques to better understand the sensitivity of water scarcity as a synthesis multisectoral indicator to the single-sector demands that compose it.

5 Strategies for mitigating water use conflicts and improving governance policies

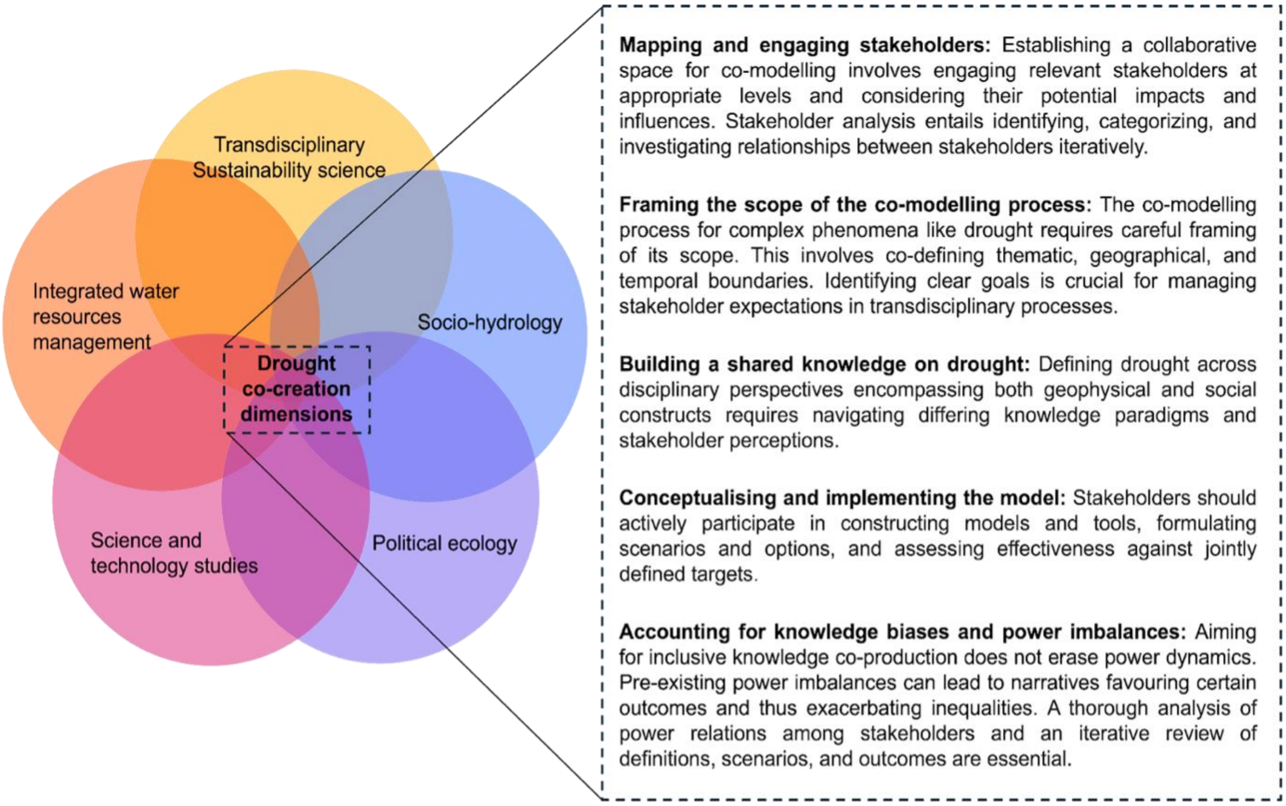
5.1 Integrated drought impact assessment (An interdisciplinary framework to guiding knowledge co-creation in drought impact and adaptation assessments)

Objectives

This action contributes to the drought impact task by proposing a framework to knowledge co-creation in drought impact assessment and adaptation. The framework can help design a comprehensive co-creation process and expand the application of transdisciplinary approaches to drought impact assessments.

Methods

We performed a critical literature review to inform the development of a conceptual framework. The framework provides a comprehensive analytical lens to examine multiple dimensions for co-creating knowledge in drought impact assessment and adaptation. It draws from a diverse body of literature on participatory modeling and transdisciplinary research in sustainability science, integrated water resources management, socio-hydrology, science and technology studies, and political ecology research fields. The framework is graphically depicted in Fig. 2 and outlines the five key dimensions of participatory drought impact knowledge co-creation.



Mapping and engaging stakeholders: Establishing a collaborative space for co-modelling involves engaging relevant stakeholders at appropriate levels and considering their potential impacts and influences. Stakeholder analysis entails identifying, categorizing, and investigating relationships between stakeholders iteratively.

Framing the scope of the co-modelling process: The co-modelling process for complex phenomena like drought requires careful framing of its scope. This involves co-defining thematic, geographical, and temporal boundaries. Identifying clear goals is crucial for managing stakeholder expectations in transdisciplinary processes.

Building a shared knowledge on drought: Defining drought across disciplinary perspectives encompassing both geophysical and social constructs requires navigating differing knowledge paradigms and stakeholder perceptions.

Conceptualising and implementing the model: Stakeholders should actively participate in constructing models and tools, formulating scenarios and options, and assessing effectiveness against jointly defined targets.

Accounting for knowledge biases and power imbalances: Aiming for inclusive knowledge co-production does not erase power dynamics. Pre-existing power imbalances can lead to narratives favouring certain outcomes and thus exacerbating inequalities. A thorough analysis of power relations among stakeholders and an iterative review of definitions, scenarios, and outcomes are essential.

Figure 2. Conceptual framework: graphical representation of the theoretical background (on the left); the five key dimensions of knowledge co-creation for socio-hydrological drought impact assessment and adaptation (on the right).

How the framework can help advance drought research

In introducing this framework, we have synthesized key concepts from a diverse body of literature to guide the co-creation of knowledge related to drought. While the conceptual framework is valuable to everyone involved in assessing drought impacts, it is specifically designed to support ‘positivist’ hydrologists who may find it challenging to navigate the extensive transdisciplinary literature. The proposed framework provides a foundational approach to help hydrologists, and others, effectively utilize transdisciplinary methods in the socio-hydrology of drought in a thorough and informed manner.

Table 13. Core actions that define each of the five key dimensions of knowledge co-creation for socio-hydrological drought impact assessment and adaptation.

Dimension	**Core actions**
Mapping and engaging stakeholders	· Implementation of a formal stakeholder analysis · Definition of different levels of engagement for each stakeholder group · Definition of clear strategies for stakeholder engagement
Framing the scope of the co-modelling process	· Co-setting of study boundaries (thematic, geographic, temporal) · Co-identification of key problems or criticalities · Co-definition of study goals
Building a shared knowledge of drought	· Co-definition of ‘drought’ or 'water scarcity' concepts · Co-definition of ‘impact’ concept · Consideration and integration of different knowledge paradigms
Conceptualising and implementing the model	· Co-identification of the modelling processes · Co-selection and/or co-development of tools and methods
Accounting for knowledge biases and power imbalances	· Explicit consideration of power dynamics among stakeholders · Discussion and agreement upon modelling outcomes · Measure in place to avoid power imbalances or biases among stakeholders

The framework outlines crucial core actions across five key dimensions (Table 13), providing a foundation for translating these actions into practical protocols or guidelines for transdisciplinary studies focused on drought impact assessment and adaptation.

Moreover, adopting the framework can support the advancement of impact-based drought forecasting by fostering standardised and scientifically sound collaboration with local communities. Incorporating indigenous knowledge addresses a current limitation in understanding exposure, vulnerability, and local coping strategies. This integration is crucial for identifying effective early actions and enhancing the overall response to drought impacts. Nevertheless, operationalizing this framework may introduce additional challenges related to the practical application of transdisciplinary approaches, necessitating compromises and potentially suboptimal decisions.

5.2 Water storage expansion through small agricultural reservoir – Identification of best locations

Objectives

This action contributes to the drought impact task by proposing an innovative approach for the identification of best locations for the construction of Small Agricultural Water Reservoir (SmAR).

Methods

Our approach is based on the combination of two different methods providing complementary perspectives on SmAR suitability: a) Multi Criteria Decision Analysis (MCDA), and data-driven statistical modelling. While MCDA is a top-down approach, which follows a deductive reasoning and is based on expert decision in selecting relevant criteria, setting suitability range of the criteria and attributing weights to the criteria based on their relative importance on the suitability conditions (Forzini et al. 2022), 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 (Figure 3). The first approach assumes that there exist suitable conditions set by theoretical and experiential knowledge. On the other hand, the statistical approach assumes that existing SmAR are located in suitable areas, therefore extrapolates the suitability conditions (in terms of criteria scores and relative weights) of existing SmAR location 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 final results.

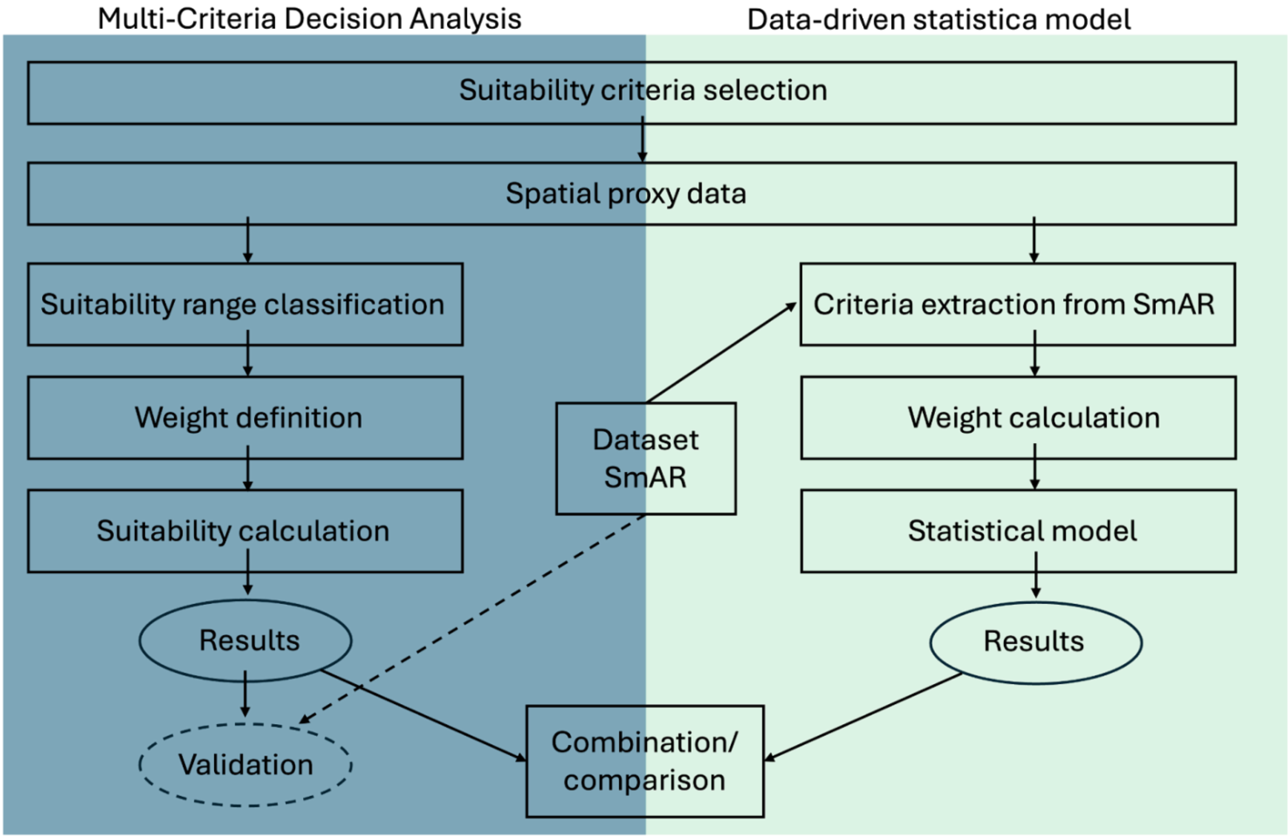


Figure 3. Schematic representation of the analytical framework. Both methods are depicted in sequential steps, including the MCDA (in blue) and the data-driven statistical model (in green). The flow chart shows the common steps (i.e the selection of suitability criteria and the proxy spatial data); the SmAR dataset is used in both methods, but with different purposes, while the two methods are finally combined and compared at the end.

Criteria selection and proxy data

Table 14. List of suitability criteria and their classification

Criteria	Suitability level				
	Highly unsuitable	Not suitable	Moderately suitable	Suitable	Highly suitable
Slope	> 15.1 %	10.1 – 15 %	7.1 – 10 %	3.6 – 7 %	0 – 3.5 %
Landcover	Urban lands	Wetlands, Water bodies	Open forest, Other cultivated areas	Shrubland, Agroforestry	Arable land, Grassland
Upslope contributing area	>500 km^2		50-500 km^2, <0.05 km^2	5 -50 km^2	0.05 – 5 km^2
Seasonal simplified water balance	>207	-60 ÷ 207	--327 ÷ -60	-461 ÷ -327	< -595

The criteria used were selected by reviewing the relevant literature and selecting the criteria that were considered most appropriate for the study area (Figure 4). Higher slopes have a higher risk of landslides and higher costs for dams; moreover, the lower the slope, the higher the potential storage volume. According to the literature, the maximum suitability value is in the range of 0% to 3.5%, high suitability up to 7% (4th) slope (Forzini et al., 2022). Soil texture is a key element; soils with a high sand content are too permeable and therefore unsuitable. Clay and clay-loam soils have the highest suitability, with suitability decreasing as the percentage of clay in the soil decreases. For reservoirs for irrigation purposes, the most suitable land cover was found to be close to agricultural areas, but not replacing valuable crops or urbanized areas. Maximum values were assigned to cropland and grassland. Urbanized 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 upslope contributing area should be sufficient to ensure that the reservoir is filled, but not too large to avoid uncontrolled flooding problems. Through a statistical analysis of reservoirs in the LaMMA database with an area between 9000 and 11000 m2 (sample reservoir), maximum suitability values were assigned to sites with an upslope contributing area in the range of 0.05 to 5 km2.

The seasonal simplified water balance is the average value of the difference between precipitation and potential evapotranspiration during the driest period of the year; 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.

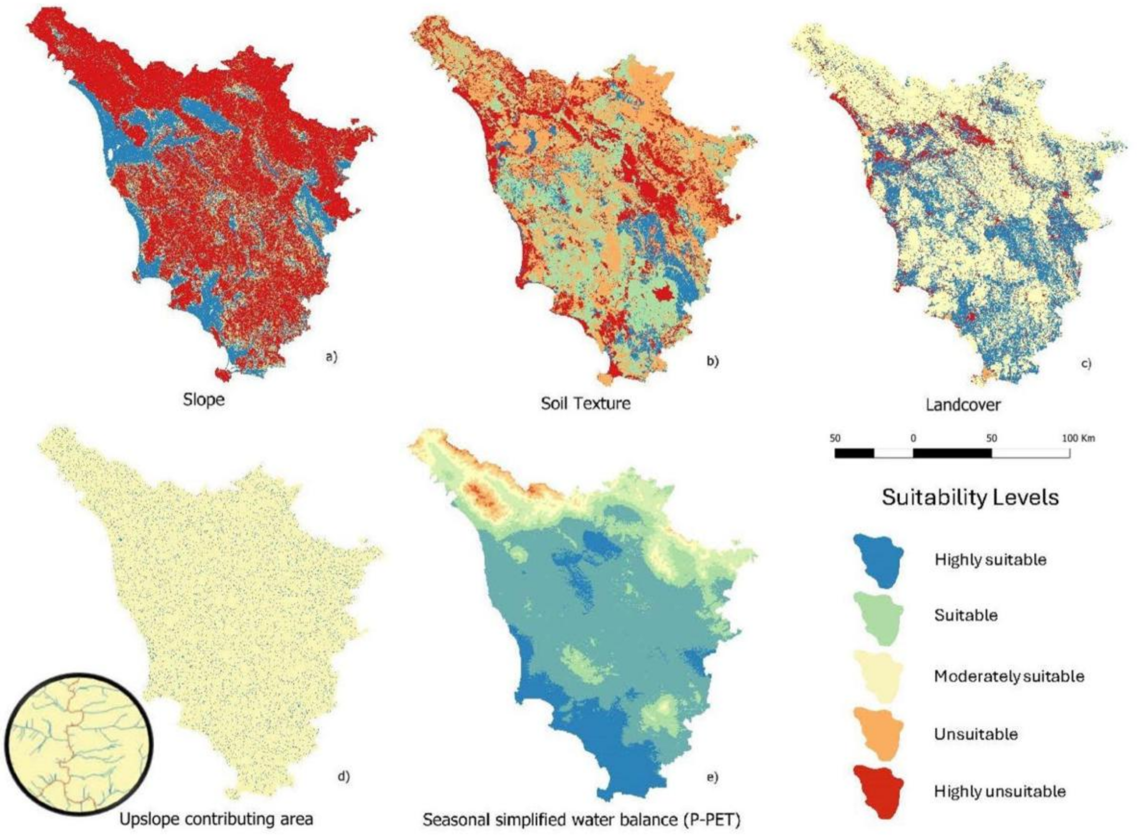


Figure 4. Reclassified criteria maps from 0 to 9 for suitable sites for reservoirs, used for the MCDA.

Results - MCDA

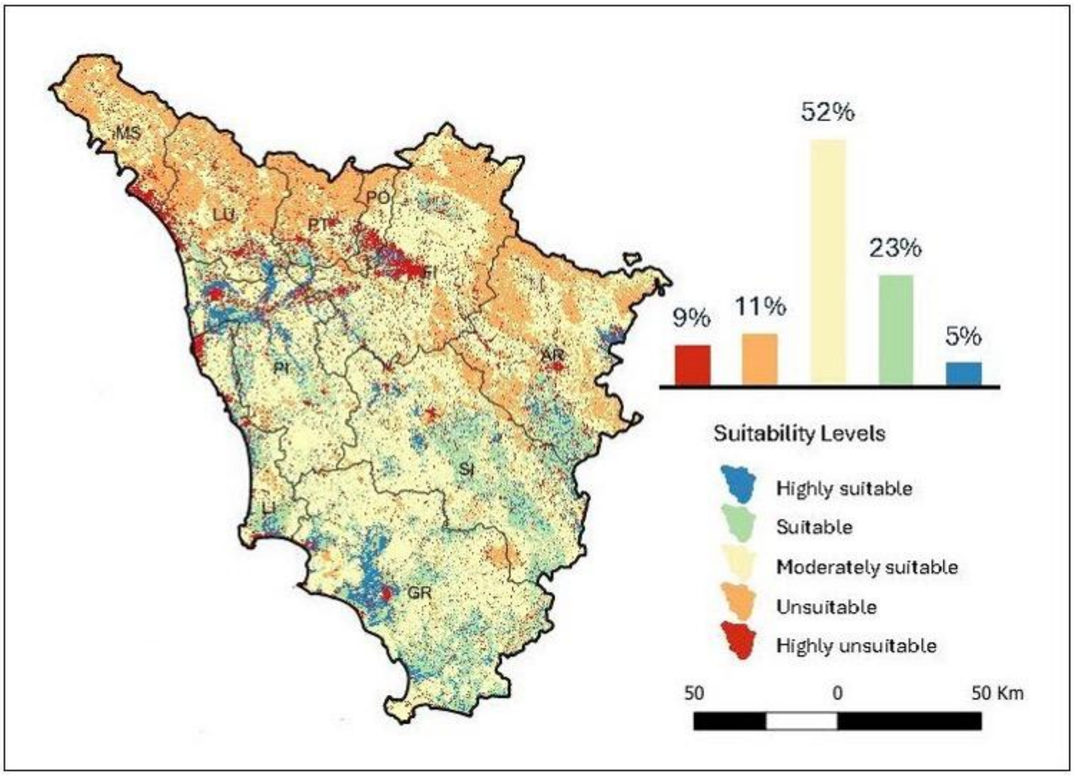


Figure 5. Suitability map and histogram of the percentage of area occupied by each suitability class.

A reservoir suitability map was produced with a histogram showing the area and percentage for the different suitability categories (Figure 5). Highly suitable is the 5% of the study area, but the total suitable areas are the 28% of Tuscany. Most of the study area was occupied by "moderately suitable" (52%), unsuitable areas are predominant on the mountain chains, while the urbanized areas coincide with the lowest suitability.

Future development

Next steps of the analysis will focus on including the results of the statistical approach, which will show areas with similar conditions as the ones with existing SmARs. The statistical results will also be produced for slices of the database including SmARs with different areas, to capture potential differences in predictors of locations for SmAR with different sizes.

5.3 Testing in-situ agricultural drought management solutions

Point source irrigation contributes to reduce evaporation losses by reducing the wetted surface. If well designed, the system can achieve values of water use efficiency well above 90 %. An accurate design of the point surface irrigation system requires knowledge of the soil hydrodynamic parameters. Philip (1984) proposed an analytical model for determining the horizontal and vertical dimensions of the wetting bulb from both surface and buried point source that requires the knowledge of soil hydrodynamic parameters governing water infiltration.

The citrus orchard at the experimental site of Villabate near Palermo (38°04'53.1" N, 13°25'08.4" E) is equipped with a subsurface drip irrigation system and capacitive soil probes that allow monitoring of soil water content close to the emitters. With the aim to validate the Philip model for the design of the subsurface irrigation system, a field and laboratory investigation was undertaken to test different infiltration techniques for estimating the soil hydrodynamic parameters.

Materials and Methods

The focus of the study was on the estimation of the soil hydraulic conductivity under saturated, Ks, and near-saturated, K, conditions. Three different infiltration methods were considered: i) the BEST (Beerkan Estimation of Soil Transfer parameters) method (Lassabatère et al., 2006); the Mini Disk Infiltrometer (MDI) (METER Group, 2021); the constant-head permeameter (CHP) method (Reynolds and Elrick, 2002). With BEST, a 3D field infiltration run under a nearly null ponded depth of water yields an estimate of Ks and the relationship between K and the water pressure head, h, in the form of the Brooks and Corey (1964) relationship. The MDI is typically used in the field to establish a 3D infiltration process to estimate the near saturated K values according to procedures proposed by Zhang (1997) and Dohnal et al. (2010). However, the MDI has also been used in the laboratory on soil columns to establish 1D estimates of K (Bagarello et al., 2007). The CHP represents the standard laboratory method for determining Ks by direct application of the Darcy’s law (Reynolds et al., 2000).

The three methods were applied in the experimental site of Villabate near Palermo (38°04'53.1" N, 13°25'08.4" E) with the specific aims to compare:

1) the K(h) values obtained with field and laboratory application of the MDI;
2) the K(h) relationship obtained with BEST with that determined by using 1D MDI and CHP methods.

The soil is a typic Rhodoxeralf with a moderate gravel content. According to the USDA classification, the soil texture is sandy-loam (clay, cl = 16.6%, silt, si = 20.2% and sand, sa = 63.2%).

Beerkan and MDI infiltration runs were conducted at 15 randomly selected sites. The BEST-steady algorithm (Bagarello et al., 2014) was applied to estimate the K(h) relationship. The K(h) value corresponding the established pressure heads at the MDI disk (h = -6, -3 and -1 cm) were calculated according to Zhang (1997) and Dohnal et al. (2010). Undisturbed soil cores (5-cm-diameter by 10-cm-high) collected at 15 randomly chosen points were used for MDI and CHP experiments in laboratory. The unit hydraulic gradient method was applied to estimate the K values corresponding to fixed h values from the steady state infiltration rate measured during MDI experiments.

Results

The 1D MDI experiment yielded higher *K* values than the 3D one by 22% for h_0 = -1 cm, 35% for h_0 = -3 cm and 77% for h_0 = -6 cm (Table 1). Given differences from a reference value by nearly 60% (Yilmaz et al., 2023) or by a factor of two or three (Elrick and Reynolds, 1992) could be considered negligible for some practical purposes, it could be suggested that the 1D and 3D MDI experiments overall yielded similar results, particularly close to saturation.

Table 15 - Summary statistics of the soil hydraulic conductivity values at saturation (Ks) and at pressure heads of -1 cm (K-1), -3 cm (K-3) and -6 cm (K-6) obtained with BEST-steady algorithms (BEST), the constant-head permeameter (CHP) method, one-dimensional mini-disk infiltrometer runs in the laboratory (1D MDI) and three-dimensional mini-disk infiltrometer runs in the field (3D MDI)

Variable	Statistic	BEST	CHP	1D MDI	3D MDI
K_s (mm/h)	Min	14.3	167.9	-	-
	Max	124.1	686.2	-	-
	Mean	73.1 (a)(b)	406.1 (b)	-	-
	CV (%)	47.9	41.8	-	-
K_{-1} (mm/h)	Min	14.3	-	31.5	43.0
	Max	123.9	-	267.1	172.0
	Mean	72.8 (a)(b)	-	122.6 (b)c	100.8 c
	CV (%)	47.9	-	62.1	35.0
K_{-3} (mm/h)	Min	13.9	-	9.6	4.5
	Max	121.8	-	36.7	23.4
	Mean	70.1 (a)(b)	-	20.5 (b)(c)	15.2 (c)
	CV (%)	48.5	-	31.7	37.3
K_{-6} (mm/h)	Min	12.6	-	3.1	0.08
	Max	112.5	-	12.5	10.0
	Mean	59.6 (a)(b)	-	7.3 (b)(c)	4.1 (c)
	CV (%)	51.3	-	33.1	59.2

Regardless of the considered variable (K_s, K_{-1}, K_{-3}, K_{-6}), the differences between the field (BEST) and the laboratory (CHP and 1D MDI) estimates of *K* were statistically significant (Table 1). The laboratory prediction of Ks was 5.6 times larger than the field one. For unsaturated soil conditions, the K estimates were nearly independent of h with BEST but they decreased appreciably according to the MDI data (Figure 6). Consequently, the two approaches yielded relatively similar results for h = -1 cm (difference by 1.7 times) but BEST predicted appreciably higher K values than the MDI in more unsaturated conditions (by 3.4 and 8.1 times for h = -3 and -6 cm, respectively).

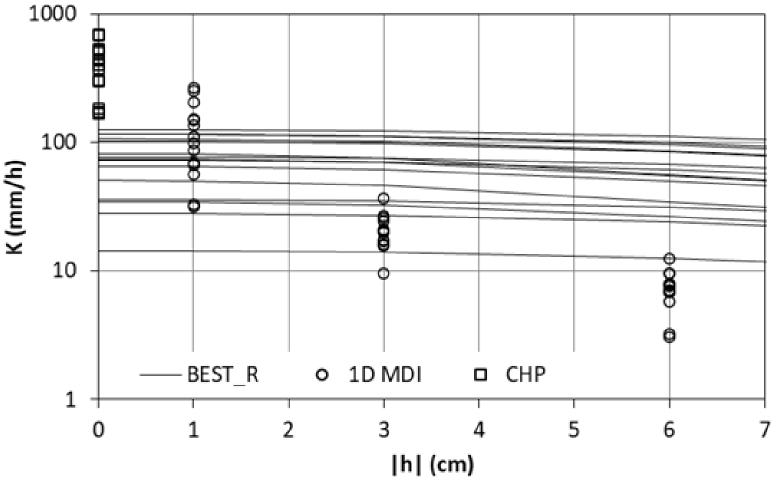


Figure 6. Soil hydraulic conductivity curves, K(h), estimated by BEST, saturated soil hydraulic conductivity, Ks, obtained with the constant-head permeameter (CHP) method, and K values for the -6, -3 and -1 cm pressure head, h, values obtained with the 1D MDI runs.

Future activities

In February an intensive field campaign was conducted at the experimental site of Villabate that included the study of three soil profile and the collection of several undisturbed soil samples at three soil horizons (0-20 cm, 20-60 cm and > 60 cm). The samples were used to determine the soil water retention curve by the tension hanging water column apparatus for pressure head values ranging from -0.01 to -1 m, and the

pressure plate extractors - for h values ranging from -1 to -150 m. Experimental data were fitted by the van Genuchten model that allowed to estimate the plant available water capacity (PAWC) and other soil physical quality indicators.

A further field distributed sampling is planned with the aim to spatialize the PAWC at the entire citrus orchard. Comparison of the estimated PAWC map with other maps derived from synthetic soil moisture or plant status indicators will allow to optimize irrigation use efficiency.

5.4 Stormwater for non-potable use to reduce drought impact at the urban scale

Context and Objectives

This research introduces a new version of the analytical-probabilistic approach to assess the probability of stormwater reuse for toilet flushing. Droughts can critically impact urban water supply, and they are becoming more and more frequent due to climate change and urbanization. The possibility of having an alternative water supply to be stored during rainiest periods and to be used during drier ones for non-drinking uses, such as toilet flushing, is essential. The model proposed here treats water demand as a random variable and simplifies previous rainfall contributions. It was validated in Palermo, Italy, using real water demand data from residential toilet flushing. Actually, Palermo, and more in general the Mediterranean area, is frequently affected by droughts. The main objective of this research is to provide a simple and supporting tool in both design and performance verification of Rainwater Harvesting Systems, contributing to the sustainable management of water resources.

Methods

A residential area of Palermo has been considered as a case study for the application of the method (Figure 7). Within the area there are 408 single-family homes, with the number of inhabitants ranging from 2 to 5 people.

For each individual house, it was assumed that there was a tank with a volume of 5 m^3, which collects rainwater coming from the roof, whose drainage surface varies between 40 and 700 m^2. The monitoring campaign, performed to collect real data of water consumptions for toilet flushing, and the subsequent analysis of collected data, allowed to obtain daily consumptions for each house, from 2002 to 2008.

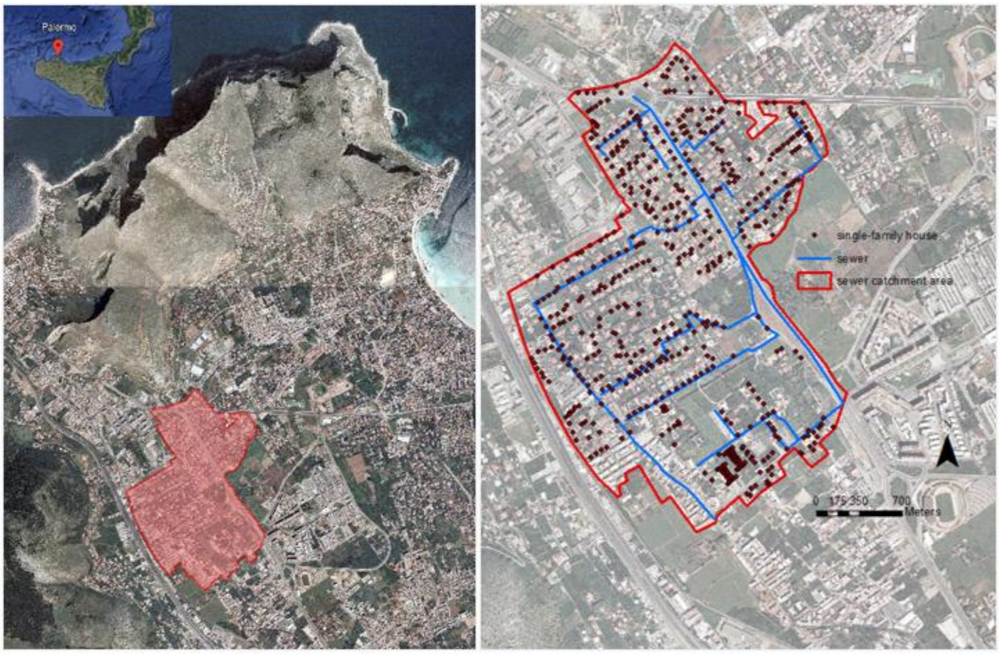


Figure 7: Overview of the residential area of Palermo and location of single-family houses.

In this new version of the probabilistic approach, rainfall variable is considered distributed as an exponential probability density function, while the water demand for toilet flushing was not treated as a fixed value, but rather as a random variable, distributed as a Weibull probability density function. The probability of reuse (P_R) of stormwater collected in the tank is defined as the probability that the reuse volume (i.e., the volume collected in the tank after a rainfall event) meets or exceeds the water demand. This reuse probability was evaluated using two different equations, both assuming that the reuse volume neither reaches nor exceeds the tank's maximum capacity (i.e., overflow does not occur). The first equation (1) incorporates the probability density function (PdF) of water demand, while the second equation (2) offers a simplified approach that substitutes the PdF with the average water demand, still assuming a Weibull distribution for water demand using the Gamma function.

Results

Figures 8 and 9 show the values obtained in the rainiest and driest year of the data set, 2005 and 2008, respectively.

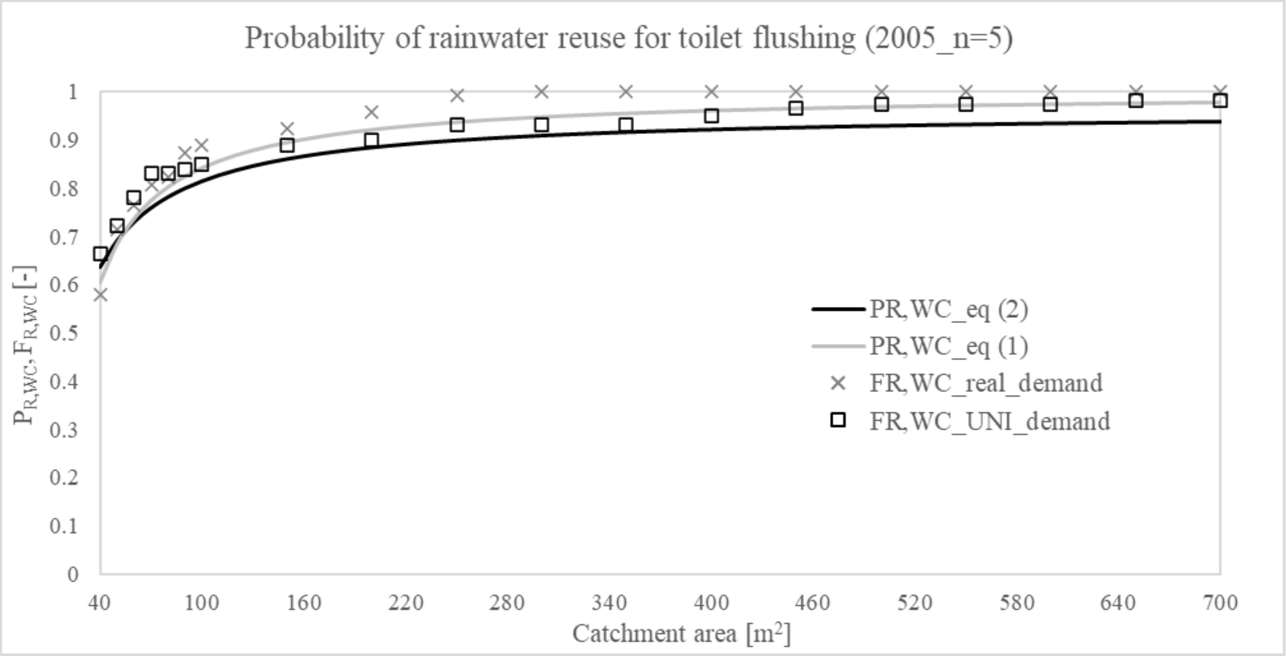


Figure 8: Comparison between probability (PR,WC) and frequency (FR,WC) of rainwater reuse for n=5, year 2005.

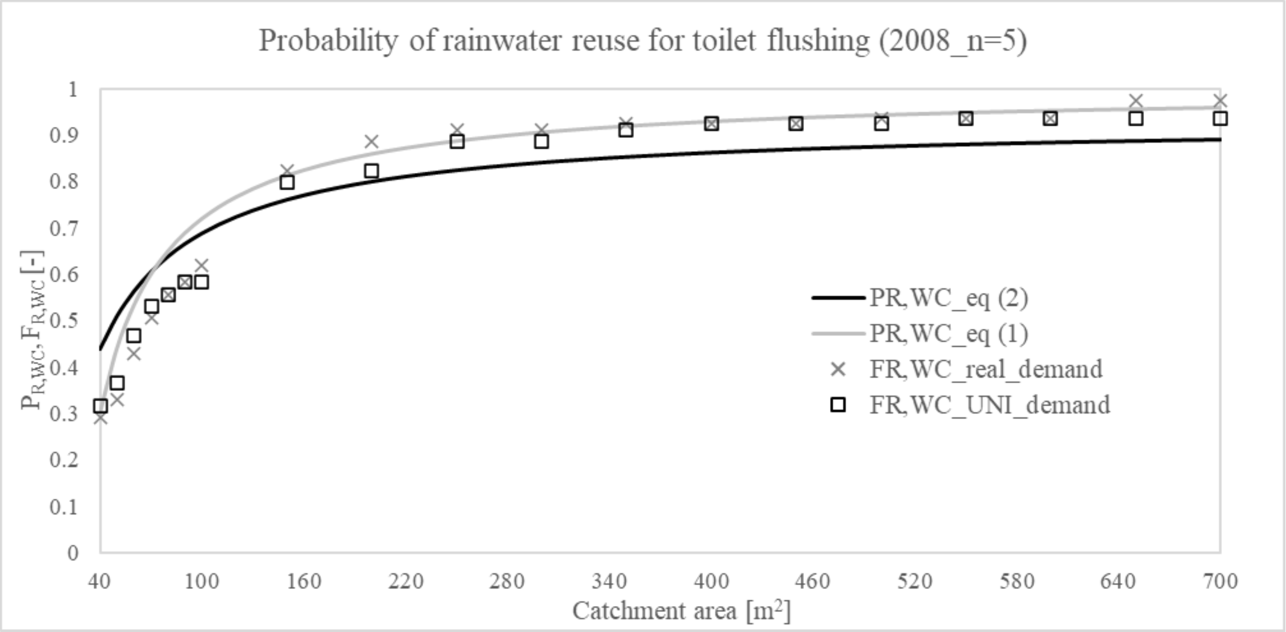


Figure 9: Comparison between probability (PR,WC) and frequency (FR,WC) of rainwater reuse for n=5, year 2008.

To validate the model, we compared the results of the probabilistic approach (equations 1 and 2) and continuous simulation, both considering the standard water demand for WC flushing, suggested by UNI/TS 11445, corresponding to 40 Liters per person per day, and the effective demand measured in the field campaign. Both equations (1) and (2) yield reliable results, as confirmed by the comparison with the continuous simulations.

Further research

Considering rainwater demand as a statistical variable implies knowledge of the actual distribution of consumption to calculate the parameters of the Weibull PdF. To apply this new formulation of the probabilistic method to different case studies, average values of them were calculated, based on the real values obtained in each year, for each number of people in the Palermo case study. This makes it possible to extend the application of the method to other contexts as well. Since they were calculated just based on real values of the city of Palermo, further research is needed to verify their goodness, involving real consumptions of other cities.

Furthermore, since rainfall data used here are quite old, another objective is to assess how more recent climatic data influence the reuse probability.

Finally, since the current formulas do not account for pre-fill volume, a further objective is to refine them to incorporate this aspect as well.

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