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**Towards a Robust Rainwater Harvesting Site Selection:
Integrating Hydrological Dynamics into GIS-Based Decision Models**

Titolo della tesi

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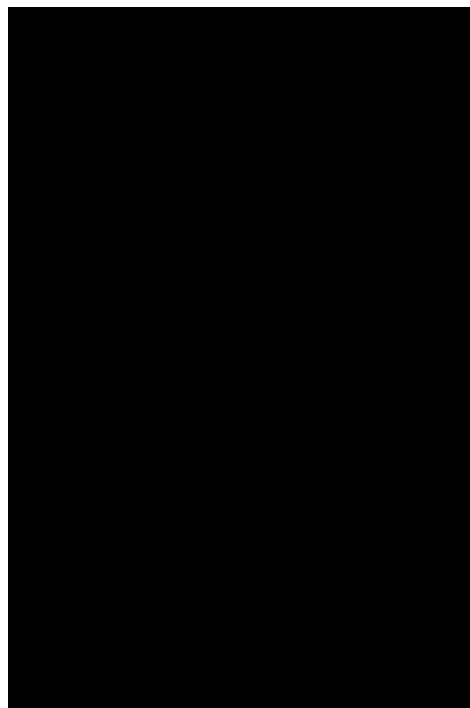
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"For nothing will be impossible with God"

Luke 1:37

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Sommario

Secondo la FAO (Organizzazione delle Nazioni Unite per l'alimentazione e l'agricoltura), la scarsità idrica rappresenta una delle criticità più rilevanti a livello globale, con particolare incidenza nei paesi caratterizzati da climi aridi e semi - aridi. In queste aree, la disponibilità di acqua é fortemente compromessa dagli effetti dei cambiamenti climatici e dalle ricorrenti condizioni di siccità. Negli ultimi vent'anni, infatti, si é registrata una riduzione significativa delle precipitazioni accompagnata da un incremento dei consumi idrici, mettendo ulteriormente sotto pressione una risorsa che rimane imprescindibile per la sopravvivenza e il benessere umano.

La progressiva riduzione della disponibilità idrica rende sempre più complesso il raggiungimento di uno degli obiettivi fondamentali delle Nazioni Unite per lo sviluppo sostenibile: garantire entro il 2030 l'accesso universale ad acqua potabile e a servizi igienico-sanitari adeguati. La comunità scientifica é chiamata ad uno sforzo in questa direzione sia per comprendere le cause, i processi e le trasformazioni che potrebbero condurre a tale scenario, sia individuando al contempo strategie di mitigazione della scarsità idrica. Tra queste, la raccolta dell'acqua piovana (Rainwater Harvesting, RWH) si é dimostrata una soluzione efficace in diversi contesti geografici.

La fattibilità dei sistemi di raccolta dell'acqua piovana (RWH) é strettamente legata a una serie di condizioni idrologiche e geomorfologiche che ne determinano l'efficacia. Ad esempio il regime delle precipitazioni, la morfologia del terreno e le potenzialità di deflusso influenzano in modo significativo la disponibilità della risorsa, mentre la pendenza dei versanti incide sulla velocità di scorrimento e sulla localizzazione delle aree di ricarica e sulle possibilità di raccolta. La scelta della tipologia di struttura da adottare deve essere coerente con le caratteristiche ambientali e definita sulla base di un'analisi approfondita del contesto. Solo una valutazione integrata di questi aspetti consente di stimare correttamente il potenziale della raccolta dell'acqua piovana e di progettare soluzioni adeguate.

Negli ultimi anni, l'evoluzione delle tecnologie di analisi spaziale ha fa-

vorito lo sviluppo di metodologie avanzate per la valutazione del potenziale di raccolta delle acque di ruscellamento. Tra queste, gli approcci Index and Overlay-Based, implementati mediante Sistemi Informativi Geografici (GIS), si sono affermati come strumenti efficaci per la pianificazione territoriale e quindi anche per l'individuazione dei siti ottimali per l'implementazione di strutture di *Rainwater harvesting*. Gli approcci Index-Based si fondano sulla definizione di un indice sintetico che integra variabili fisiche e climatiche cheiamate *criteri*, quali pendenza, densità di drenaggio, uso del suolo e coefficienti di deflusso, consentendo una classificazione del territorio in funzione della sua idoneità alla raccolta. Gli approcci Overlay-Based, invece, utilizzano tecniche di sovrapposizione di strati tematici, i *criteri*, per combinare parametri geomorfologici e idrologici, fornendo mappe di idoneità spaziale che supportano decisioni strategiche su scala locale e regionale. Queste metodologie, grazie alla loro flessibilità e alla capacità di operare su grandi dataset, costituiscono strumenti fondamentali per la progettazione di sistemi RWH resilienti e adattabili alle diverse condizioni ambientali e consentono di analizzare rapidamente ambiti territoriali anche molto estesi.

La presente tesi si propone di sviluppare e valutare un approccio innovativo per la stima del potenziale di raccolta dell'acqua piovana (Rainwater Harvesting, RWH), introducendo una modifica sostanziale rispetto alle metodologie tradizionali e affiancando a tale innovazione una procedura di analisi critica volta a verificarne la robustezza e l'affidabilità.

L'approccio proposto consiste nell'aggiunta di un nuovo criterio, denominato deflusso aggregato, all'interno dei metodi AHP/GIS per la valutazione del potenziale di raccolta delle acque piovane (RWH). Questo criterio è concepito per simulare in modo semplificato i processi di aggregazione del deflusso all'interno di un bacino idrografico, consentendo una stima più realistica del volume d'acqua effettivamente disponibile in una determinata cella del bacino. La metodologia si basa chiaramente su una caratterizzazione geomorfologica dettagliata del bacino. Per il nuovo criterio si propone un sistema di classificazione basato sui quantili, dimostratosi robusto e flessibile, che ne consente l'applicazione a bacini di scale differenti. La combinazione di questo indicatore con parametri geomorfologici chiave, come pendenza e densità di drenaggio, permette di definire un Indice di potenziale RWH. La seconda parte dello studio è dedicata alla valutazione della variabilità spaziale e temporale dell'indice, al fine di analizzare l'influenza della variabilità pluviometrica sui risultati e verificare la stabilità della distribuzione dei valori nelle classi di idoneità. Tale analisi consente di individuare i siti ottimali per l'implementazione di sistemi di raccolta delle acque piovane in contesti caratterizzati da elevata variabilità climatica. La metodologia pro-

posta si basa su un indice semplice, radicato in principi fisici e flessibile nell'applicazione a qualsiasi framework. L'indice é stato calcolato su una serie storica di 72 anni (1951–2022), garantendo un'analisi temporale estesa e robusta. Per assicurare ulteriormente la trasferibilit  dell'approccio, esso é stato applicato a un contesto climatico e geomorfologico differente. Nonostante l'elevata variabilit  delle precipitazioni a scala stagionale, i risultati mostrano una notevole stabilit  tra i diversi bacini analizzati.

Nel complesso, i framework GIS convenzionali per la selezione dei siti RWH si basano su indicatori locali come il coefficiente di deflusso (RC), che spesso trascurano i flussi orizzontali e la natura cumulativa dei processi di deflusso. L'elemento innovativo introdotto in questo lavoro é l'integrazione del deflusso aggregato (AR), che rappresenta i contributi idrici a monte, e l'adozione di un sistema di classificazione basato sui quantili, adattabile alla distribuzione spaziale dei valori di deflusso. L'analisi comparativa tra gli indici basati su AR e RC su una serie storica pluridecennale (1951–2022) dimostra che AR fornisce una valutazione pi  realistica e stabile della disponibilit  idrica, soprattutto in condizioni di variabilit  pluviometrica e siccit . Il framework proposto rimane scalabile e adattabile per la progettazione di sistemi RWH resilienti in contesti geografici e climatici eterogenei, contribuendo alla gestione sostenibile delle risorse idriche.

Abstract

According to the FAO (Food and Agriculture Organization of the United Nations), water scarcity is one of the critical global challenges, particularly affecting countries categorized as arid or semi-arid. In these areas, the availability of water is often compromised by the effects of climate change and the resulting drought conditions. Over the past two decades, there has been a significant reduction in rainfall, along with an increase in water consumption. This situation adds additional pressure to one of the most valuable resources for human life and well-being.

This progressive reduction in water availability makes it increasingly difficult to achieve one of the key goals of the United Nations Sustainable Development Goals, which is to ensure access to safe drinking water and sanitation for everyone in the world by 2030. The scientific community is urged to take the necessary actions towards this goal. They must understand the processes, causes, and changes that lead to such water scarce scenarios and find strategies to mitigate water scarcity. Among the methods identified to mitigate water scarcity, Rainwater Harvesting (RWH) has emerged as an effective solution in various geographical settings.

The application of Rainwater Harvesting systems is closely related to certain hydrological and geomorphological conditions that influence their effectiveness. For example, rainfall patterns, topography, and runoff potential mainly impact the availability of water as a resource. Factors such as slope can affect flow velocity, recharge conditions, and the potential of the harvested water. The selection of the type of structure for implementation must be consistent with environmental conditions and requires an in-depth analysis of the context. The precision of estimating the rainwater harvesting potential and designing suitable RWH systems can only be achieved through integrated assessments of such aspects.

In recent times, the advancement of spatial analysis tools has promoted the development of methodologies to assess the potential of rainwater harvesting. Among these, multi-criteria decision analysis (MCDA)-based meth-

ods, integrated with Geographical Information Systems (GIS), have become effective tools for planning and identifying potential rainwater harvesting sites for the implementation of RWH systems. Index-based approaches primarily rely on defining an index that integrates physical and climatic variables, referred to as criteria, such as slope, drainage density, land use, and runoff coefficients. This method enables the classification of the application area according to its potential for Rainwater Harvesting. Overlay-based methods, on the other hand, utilize thematic layer overlay techniques to integrate geomorphological and hydrological parameters. This process results in spatial suitability maps that serve as decision-support tools for planners at both local and regional scales. The flexibility and capability of these approaches to manage larger datasets make them essential tools for designing RWH systems that are adaptable to various environmental conditions and facilitate rapid analysis of extensive areas.

This dissertation aims to develop and evaluate an innovative approach to estimating the potential of rainwater harvesting (RWH) by introducing a substantial modification to traditional methodologies. It then supports this innovation with a critical analysis procedure to verify its robustness and reliability.

The proposed approach consists of adding a new criterion, called aggregated runoff, to the AHP/GIS-based methods to determine rainwater harvesting potential. This criterion is designed to simulate the watershed runoff aggregation process in a simplified manner. By simulating the runoff aggregation processes, the methodology introduces an effective means of estimating the actual water volume available at a given pixel within a basin. This method is clearly based on the detailed geomorphological features of the basin. A classification system based on quantiles is proposed for the new criterion. This system has proven to be robust and flexible, allowing for application to basins of different scales. A combination of this new indicator, along with key geomorphological parameters such as slope and drainage density, results in an RWH potential Index.

The second part of the study focuses on evaluating the spatial and temporal variability of the index to analyze the influence of rainfall variability on the results and to verify the stability of the value distribution across the suitability classes. This analysis raises the question of how to identify potential sites for implementing rainwater harvesting structures in the context of climate variability. The proposed methodology is based on a simple index that is rooted in the physical characteristics of the study area and provides the flexibility to be implemented in any application framework. The index was computed for a time period of 72 years, from 1951 to 2022, using a larger

database. This approach ensures a robust and extensive temporal analysis. To further ensure the transferability of the approach, it is applied to a new climatic and geomorphic setting. Despite the high rainfall variability across the seasonal scale, the application has shown consistent stability across the basins.

Overall, conventional GIS-based frameworks for RWH potential site selection procedures rely on local runoff indicators, such as the runoff coefficient(RC), which often overlook horizontal water fluxes and cumulative flow processes. The innovative aspect introduced in this work is the integration of Aggregated Runoff (AR), which represents upstream water contributions. This integration is combined with a quantile-based classification system that adapts to spatial runoff distribution. A comparative analysis of AR-based and RC-based indices over a multi-decadal record (1951â2022) demonstrates that AR provides a more realistic and stable assessment of water availability, especially under conditions of temporal rainfall variability and drought. The proposed framework remains scalable and adaptable for designing resilient RWH systems in diverse geographic and climatic contexts, thereby supporting sustainable water resource management.

Contents

1	Introduction	2
1.1	Problem statement	2
1.2	State of the art	6
1.2.1	GIS based Multi criteria decision making (MCDM) . .	8
1.2.2	Hydrological modeling and SCS-CN methods	10
1.2.3	Data driven and Machine learning approaches	11
1.2.4	Groundwater recharge and hybrid applications	12
1.2.5	Socio-Economic factors and practical applications in RWH planning	12
1.3	Research Gaps	13
1.4	Objectives	14
1.5	Outline of the Dissertation	15
2	Methodology	17
2.1	Introduction	17
2.2	Definition of Rainwater harvesting potential index or $\rho(x, y)$.	20
2.3	Standard Procedure	21
2.3.1	AHP framework and pairwise comparison matrix . .	22
2.3.2	Consistency Check	24
2.3.3	Reclassification and ranking	25
2.3.4	Computation of the RWH potential index using RC ρRC	25
2.4	The Aggregated Runoff Approach	25
2.4.1	Computation of Aggregated Runoff AR	26
2.4.2	Quantile based scoring system of AR	27
2.4.3	Scope and applicability of the proposed approach . . .	29
3	Application Example	31
3.1	Introduction	31
3.2	Tiber at Ponte Felcino	32

3.2.1	Geology and Geomorphology	33
3.2.2	Hydrology and Climate	34
3.2.3	Land Use and Environmental Features	34
3.3	Datasets	35
3.4	Slope map	37
3.5	Drainage Density map	38
3.6	Runoff coefficient	40
3.7	Aggregated Runoff	42
3.7.1	Qantiles based classification	45
3.8	Temporal variability	46
4	Discussion	48
4.1	Introduction	48
4.2	Advantages of the aggregated runoff criterion	50
4.2.1	Dry year scenario	52
4.2.2	Wet year scenario	52
4.2.3	Average scenario 1951-2022	54
4.2.4	Matched-classification comparison (ρ_{RC} vs ρ_{AR} under quantile based RC and AR)	55
4.3	Influence of Slope and Drainage Density on Index Behavior .	57
4.4	Effects of inter-annual rainfall variability on ρ	59
4.5	Effects of intra-annual rainfall variability on ρ	61
4.6	Uncertainty and Cumulative distribution function (annual and seasonal scale)	66
4.7	Assumptions and Limitations of the Proposed Framework . .	68
4.8	Transferability under Variable Conditions: Simeto Basin (Sicily)	69
4.8.1	Basin hydrology and geology	70
4.8.2	DEM, Slope and Drainage Density	70
4.8.3	Aggregated Runoff and Runoff coefficient	71
4.8.4	Evaluation results for Simeto basin in comparison with Ponte Felcino	72
5	Conclusions	76
5.0.1	Future Research Directions	78
5.0.2	Closing Remarks	79

List of Figures

1.1	Figure shows the number of water stress mitigation strategies applicable to major basins across the globe(higher counts indicate greater water stress)	4
2.1	Methodological flow chart representing the proposed framework and analysis; includes the data collection, pre-processing of data, reclassification with weights, RWHP index analysis in different time frames, uncertainty analysis and adaptive planning strategies	19
2.2	Flowchart illustrating the Analytical Hierarchy Process (AHP) steps for weight determination, including hierarchy construction, pairwise comparison, weight calculation, consistency check, and final assignment of normalized weights to evaluation criteria	23
2.3	Sketch of the domain with horizontal and vertical fluxes, $RF_{m,n}$ is the relative contribution of the (m,n) cell to the total runoff $AR_{m,n}$ which depends on the area drained by the $(m,n)th$ cell (Orange line). Arrows indicate the flow lines. . .	28
3.1	Digital Elevation Model (DEM) of Ponte Felcino basin	36
3.2	Figure shows selected components for the study from BIG-BANG dataset such as total precipitation (P) and surface runoff (R) to support runoff coefficient and aggregated runoff calculations for rainwater harvesting potential assessment along with other variables , evapotranspiration (E), aquifer recharge (G) and soil/snow water storage (ΔV)	36
3.3	Spatial distribution of slope percentage across the Ponte Felcino basin	39
3.4	Spatial distribution of drainage density across the Ponte Felcino basin	41

3.5	Spatial distribution of runoff coefficient (RC) averaged over the 72-year period (1951–2022) across the Ponte Felcino basin	43
3.6	Spatial distribution of aggregated runoff (AR) averaged over the 72-year period (1951–2022) across the Ponte Felcino basin	44
4.1	The panel (a) shows the reclassified RC for the dry year, 2017, (b) for the wet year 2010 and (c) the time averaged reclassified RC for the years 1951–2022. The panel (d) shows the RWHP index ρ calculated using RC for the dry year 2017, (e) wet year 2010 and (f) the time averaged RWH Potential index using RC for the years 1951–2022.	53
4.2	The panel (a) shows the reclassified AR calculated using for the dry year 2017 and (b) wet year 2010 and (c) the time averaged reclassified AR for the years 1951–2022, (d) shows the ρ_{AR} calculated using AR for the dry year 2017, (e) wet year 2010 and (f) the time averaged ρ_{AR} using AR for the years 1951–2022.	54
4.3	The panel (a) shows the quantile based ρ_{RC} for the dry year, 2017, (b) ρ_{RC} for the wet year 2010 and (c) ρ_{RC} for time averaged RC for the years 1951–2022. The panel (d) shows the quantile based, ρ_{AR} for the dry year 2017, (e) wet year 2010 and (f) for time averaged AR for the years 1951–2022 .	56
4.4	Detail of the ρ_{AR} and ρ_{RC} maps for two selected locations. The three series of figure refer to the dry year (2017), the wet year (2010) and the average year (1955–2022).	58
4.5	Annual based distribution of the catchment area within the 6 classes of the RWHP index by using the proposed aggregate runoff criterion (Panel a) and by using the standard runoff coefficient criterion (Panel b).	60
4.6	Annual based spatial statistics (Panel a average values, Panel b coefficient of variation) of the RWHP index ρ by using the proposed aggregate runoff criterion (blue line) and by using the standard runoff coefficient criterion (orange line).	61
4.7	Monthly based distribution of the catchment area within the 6 classes of the RWHP index ρ by using the proposed aggregate runoff criterion ρ_{AR} (Panel a) and by using the standard runoff coefficient criterion ρ_{RC} (Panel b).	63
4.8	Analysis of effect of temporal rainfall variability on the index in of two seasonal extreme years on the years 2010 and 2017 based on ρ_{AR} (panels a, b) and ρ_{RC} (panels c, d)	64

4.9	Seasonal variability of RWHP index ρ based on runoff coefficient ρ_{RC} and aggregated runoff ρ_{AR} for 2017 (dry) and 2010 (wet). Panels (a, c) shows ρ_{RC} ; panels (b, d) shows ρ_{AR} , from January to December.	65
4.10	Monthly based spatial statistics (Panel a average values, Panel b coefficient of variation) of the ρ by using the proposed aggregate runoff criterion (blue line) and by using the standard runoff coefficient criterion (orange line).	66
4.11	Distribution of RWHP index ρ values across non classified RWH potential ρ index maps (a) using RC and (b) AR in a inter-annual scale	67
4.12	Distribution of RWHP index ρ values across non classified RWH potential index ρ maps (a) using RC and (b) AR in a intra-annual scale	68
4.13	DEM of Simetto basin	71
4.14	a) Reclassified slope percentage map of Simetto basin and b) drainage density map of Simetto basin	72
4.15	a) shows the aggregated runoff AR b) shows the runoff coefficient for the Jan 1951 and c) and d) shows Spatial distribution of ρ_{AR} vs ρ_{RC} on Jan 1951	73
4.16	Panels shows Spatial distribution of ρ_{AR} vs ρ_{RC} across Jan 1951 to Dec 2022 (area fractions by class).	74
4.17	Distribution of RWHP index ρ values across non classified RWH potential index ρ maps (a) using RC and (b) AR in a intra-annual scale	74

List of Tables

2.1	AHP weights for criteria (adapted from <i>Jha et al.</i> [2014]) . . .	22
2.2	Pairwise comparison matrix and derived weights used by <i>Jha et al.</i> [2014]	23
2.3	Random Index (RI) values for different matrix sizes n , used in AHP to calculate the Consistency Ratio for assessing judgment consistency	24
3.1	Classified spatial distribution of percentage of slope with its criteria and feature class weights including the area fraction for each class	38
3.2	Classified spatial distribution of drainage density with its criteria and feature class weights including the area fraction for each class	40
3.3	Classified spatial distribution of variables runoff coefficient with its criteria and feature class weights for the mean RC 1951–2022 including the area fraction for each class	42
3.4	Classified spatial distribution of variables aggregated runoff(AR) with its criteria and feature class weights for the mean AR 1951–2022 including the area fraction for each class	46
4.1	Comparison of advantages and disadvantages of Aggregated Runoff (AR) and Runoff Coefficient (RC) for rainwater harvesting potential assessment.	49
4.2	Relative amount of the catchment area in each class as predicted by the two indices ρ_{RC} and ρ_{AR} for the three scenarios presented.	55

Chapter 1

Introduction

1.1 Problem statement

Water scarcity is considered one of the key problems faced by humanity in the 21st century *UN-Water* [2024]. It has become a global issue that mainly affects people living in arid and semi arid regions (*Ahmed et al.* [2023]). Recent statistics estimate that around half of the world population is experiencing severe water scarcity for at least part of the year *UN-Water* [2024]. Approximately a quarter of the world's population living in 25 countries faces extremely high levels of water stress; they consume almost 80% of their annual freshwater supply. In fact, we know that only 2.5% of freshwater is available worldwide, with 1% available for human use. Hence, there are dramatic changes in the planet's water resources.

Even today, due to accelerating climate change, population growth, intensive farming, industrialization, and water pollution, the aforementioned numbers change drastically in future climate scenarios *Adham et al.* [2022]. These factors also increase water demand around the world *UN-Water* [2024]. 70% of global water consumption is primarily used for agriculture, while industries use 20%, and domestic use represents 10%.

Climate change and global warming contribute to the uncertainty of water availability, particularly due to changing rainfall patterns, such as dry periods with reduced rainfall and wet periods of the year characterized by excessive rainfall. There is an increase in extreme rainfall events globally, accompanied by a rise in the duration and frequency of meteorological drought *UN-Water* [2024]. Water scarcity being caused by various factors that directly impact human health, food security, and livelihoods. Additionally, water scarcity leads to environmental consequences, including

the depletion of water levels in lakes. Groundwater resources are also impacted by the overexploitation of these reserves, resulting in the depletion of groundwater levels. These factors contribute to the intrusion of seawater into coastal cities worldwide. These cumulative effects highlight the urgent need for innovative and sustainable water management strategies that can function effectively, even under uncertain and variable climatic conditions.

Figure 1.1 represents a global map illustrating the regional feasibility of water stress mitigation strategies across major river basins worldwide. Each basin is color coded to indicate the number of strategies that could be applied to reduce water stress Wada *et al.* [2014]. Areas without water stress are depicted in a light beige color, while basins where all six strategies can be applied are colored red. Intermediate colors represent basins with fewer strategies; for example, orange indicates five strategies, yellow indicates four, green indicates three, blue indicates two, and purple indicates one strategy. The map thus reveals that basin level regions across the globe with severe water stress—such as North Africa, the Middle East, South Asia, the northern part of China, and the western part of North America are identified as areas that must adopt the maximum number of strategies, ranging from five to six. However, basins with one or two applicable strategies are dispersed across regions with distinct issues, indicating that there is limited flexibility. This image clearly emphasizes the importance of implementing sustainable water resource management strategies based on regional conditions while also illustrating the global distribution of water stress.

Water stress is widespread throughout the world and is particularly prominent in densely populated areas. Water stress leads to an increase in the depletion of water resources. This situation can negatively impact water reserves by contributing to the salinization of aquifers and adversely affecting water dependent ecosystems.

To address the challenges of water stress, several integrated mitigation strategies have been proposed. These strategies include improving agricultural water productivity, enhancing irrigation efficiency, increasing the intensity of domestic and industrial water use, limiting the rate of population growth, and increasing water storage in reservoirs and through seawater desalination Wada *et al.* [2014]. These strategies often consist of a combination of demand side measures, such as water conservation and improvements in efficiency, along with supply side interventions that include rainwater harvesting (RWH), groundwater recharge, and the reuse of wastewater. Recently developed frameworks emphasize the need for holistic approaches that can integrate projects at both the technical and institutional levels.

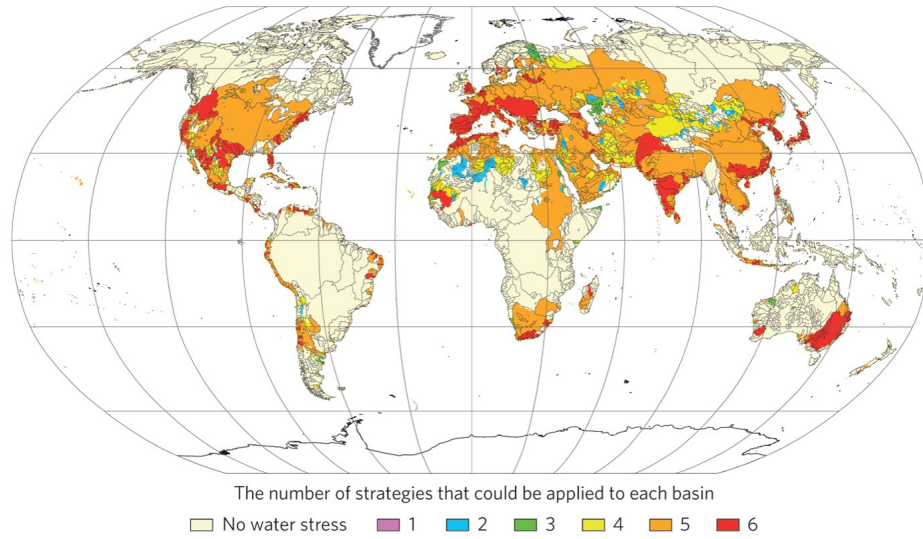


Figure 1.1: Figure shows the number of water stress mitigation strategies applicable to major basins across the globe(higher counts indicate greater water stress)

These approaches are supported by stakeholder engagement and adaptive governance to ensure resilience and sustainable water resource management.

The problem of water scarcity not only depends on absolute rainfall but is also primarily influenced by the spatial and temporal variability of rainfall, as well as the uneven distribution of freshwater reserves. Different regions may share the same annual average precipitation; however, they may experience varying levels of water stress due to the variability of rainfall intensity and seasonality *Cristiano et al.* [2017], *Atieh et al.* [2017]. High-intensity seasonal rainfall is often followed by prolonged dry periods. This situation presents a problem that necessitates robust storage and management systems to adequately address the gaps within the supply domain. Additionally, freshwater sources such as rivers, lakes, and aquifers are unevenly distributed throughout the world. Some of these sources are in critical stages due to the overextraction of water resources, while others are not utilized to their full potential due to infrastructure issues and constraints imposed by governmental bodies *Wolkeba et al.* [2023], *Aragón-Hernández et al.* [2024].

Based on this context, Rainwater Harvesting (RWH) structures have emerged as a solution to mitigate water stress *Ahmed et al.* [2023] by harvesting rainwater and storing it for domestic, agricultural, and industrial use. These RWH structures minimize the effects of water scarcity by improving groundwater recharge, thereby contributing to adaptation strategies for managing climate change. Not only does this method tackle water dis-

tribution, but the implementation of RWH can also mitigate uncertainty in water supplies that primarily arise from climate and socioeconomic changes. The RWH approach can help reduce the risks of flooding and drought, which are historically extreme climatic events, by enhancing the recharge of the aquifer and thus increasing the availability of agricultural and domestic water. The RWH strategy is particularly applied in arid and semi-arid regions, serving as an effective method for collecting water, primarily for non potable use. Furthermore, RWH is adaptive to climate change; if utilized properly, it can provide long term water security. At a small scale, such as in houses and community systems, RWH involves rooftop rainwater collection in storage tanks or cisterns for non potable domestic use, or, if treated, even for potable use. At a medium scale, typical applications include farm ponds, contour bunds, and small check dams that can intercept surface runoff for irrigation and groundwater recharge. These structures help stabilize agricultural productivity and reduce vulnerability to droughts. At a large scale, watershed interventions such as percolation tanks, recharge pits, and managed aquifer recharge systems are designed to store greater volumes of runoff; these systems can also be utilized to control floods and rejuvenate the groundwater system. This large scale application can also meet the needs at the industrial and municipal levels, thereby supporting socioeconomic resilience. Above all, all these applications align with the sustainability goals of SDG 6 (clean water and sanitation) and SDG 13 (climate action) by improving integrated water resource management and adaptation to climate change. Therefore, the flexibility of RWH methods is not only a technical solution to the problem of water scarcity but also a key tool to inform policies for sustainable development *UN-Water* [2024]. Figure 1.1 describes the baseline water stress around the world.

RWH structures encompass a wide range of configurations in different scales, including:

- Roof catchment systems equipped with storage tanks are utilized for the water supply of individual houses for domestic purposes;
- Infiltration basins and recharge pits are implemented to recharge the aquifers;
- Rain gardens and bio-retention systems in urban environments can enhance sustainable stormwater management
- Modular cisterns and underground reservoirs serve residential or industrial applications

Poor site selection can lead to reduced water supply, structural failures, and environmental degradation.

However, the success of RWH structures primarily depends on site selection, which determines their efficiency and reliability in water harvesting. Proper site selection ensures that sufficient runoff is collected, thereby reducing the risk of an inadequate water supply. *Kahinda et al.* [2008], *Singh et al.* [2017]. Successful selection of sites also reduces construction costs by avoiding areas with unsuitable slopes or unstable soil, which can lead to structural failure or erosion *Critchley et al.* [1991], *Patton* [1988]. In addition, selecting the right site helps integrate the system with local land use patterns, supports groundwater recharge, and prevents environmental issues such as sedimentation *Oweis and Hachum* [2006], *Adham et al.* [2016]. In short, accurate site selection is the foundation for achieving reliable performance, cost effectiveness, and long term sustainability of rainwater harvesting systems *Jha et al.* [2014], *Preeti et al.* [2022].

1.2 State of the art

Research on the selection of RWH sites has improved significantly, evolving from hydrological models based on physical principles to integrated multi-criteria analysis (MCA) decision frameworks that leverage large scale Geographic Information Systems (GIS) *Jha et al.* [2014]. This evolution allows for the integration and spatial analysis of various datasets across larger spatial areas. GIS based approaches enable planners to combine the effects of multiple physical and socio-economic criteria, such as rainfall, slope, drainage density, and soil type, depending on the planner's objectives. These approaches utilize composite suitability maps that serve as decision support tools. This capability is particularly valuable in large scale assessments where site evaluation is impractical *Singh et al.* [2017], *Kahinda et al.* [2008]. Among the GIS based techniques, Multi-criteria analysis (MCA) methods, primarily the Analytical Hierarchy process (AHP), are widely utilized. The Analytic Hierarchy Process (AHP) provides a structured methodological framework for assigning weights to criteria based on various factors, including expert judgment. In this process, a group of experts determines the weights based on the impact of the factors on the decision. Additionally, AHP utilizes benchmark weights that have been previously applied and analyzed in similar decision making applications. This application ensures transparency and consistency in the decision making process *Saaty* [1987], *Jha et al.* [2014].

Various studies have demonstrated the effectiveness of GIS based MCA in the RWH planning process. This includes applications in semi-arid regions, agricultural lands, and, in some cases, urban environments *Mbilinyi et al.* [2007], *Saleem et al.* [2018]. This method creates spatially analyzed data and utilizes available spatial datasets to provide a practically scalable solution for the preliminary filtering of suitable sites.

Recent studies in the field of Rainwater harvesting have shifted from observation based empirical sizing methods to process driven, physics-based models that can accurately simulate hydrological and hydraulic processes. These models provide detailed simulations of water related physical processes. These models aim to represent the processes of rainfall–runoff generation, infiltration, and storage dynamics using the principles of conservation laws rather than simple empirical coefficients. This approach enables the prediction of the performance of rainwater harvesting (RWH) systems under variable climatic conditions across both space and time.

Earlier, RWH design methods primarily relied on physically based hydrological models, such as zero dimensional (0-D) and one dimensional models. These models simplify the movement of water by focusing on the local water balance at a point that has no dimensions, hence the term 0-D. This approach generally considers processes such as rainfall, infiltration, evapotranspiration, and surface runoff within a confined area. Such models have been used for small scale applications, such as housing or farming level RWH systems. However, their scope is limited, because this approach cannot incorporate the interactions between adjacent areas or the cumulative nature of runoff across a catchment. Some studies have attempted to aggregate these models for small districts or urban areas. These models are generally constrained by data requirements and computational complexity, which makes these impractical for larger scale planning *Concha Larrauri et al.* [2020].

- SWMM (Storm Water Management Model *Khatooni et al.* [2025]) and HEC–HMS are widely used for urban stormwater and catchment-scale simulations, providing a detailed representation of runoff and storage processes *Ndeketeya and Dundu* [2021].
- MIKE SHE and HYDRUS are tools that provide integrated surface–subsurface modeling that is essential for the evaluation of infiltration-based RWH structures and groundwater recharge *Baek et al.* [2020].
- Advanced frameworks increasingly integrate these models with GIS-

based spatial analysis to optimize site selection and system design, considering terrain, soil properties, and land use *Kadam et al.* [2012].

Mechanistic models capture *nonlinear responses* to extreme rainfall events, allow for *scenario testing under climate change projections*, and support *multiobjective optimization* for water supply, flood mitigation, and aquifer recharge. They also enable integration with probabilistic and stochastic methods for analyzing tank size and reliability, thereby improving resilience and cost-effectiveness *Di Chiano et al.* [2025].

Despite these advances, limitations persist regarding *data availability*, *computational complexity*, and *model calibration*, particularly in regions with limited data monitoring infrastructures.

During the past decade, a significant number of studies have focused on developing frameworks for determining potential rainwater harvesting (RWH) sites through spatial analysis, hydrological modeling, and decision support systems. In such a tool, the Analytical Hierarchy Process (AHP) technique, which is commonly used in the decision making process, is applied. This process involves integrating layers such as rainfall, slope, soil type, and land use to create potentiality maps. More recent studies have applied machine learning algorithms, physically based hydrological models, and integrated socio-economic factors into the frameworks, enhancing the effectiveness of practical applications. Several studies have developed a hybrid framework that has been used to assess RWH. Despite the substantial volume of applications, most of these studies share certain limitations. This section of the state of the art discusses details of the different aspects of the existing literature, mainly focusing on their approaches and limitations, which highlight the need for modifications that can enhance current frameworks to identify potential rainwater harvesting sites.

1.2.1 GIS based Multi criteria decision making (MCDM)

Geographic information systems (GIS), in combination with Multi criteria decision Analysis (MCDA) methods such as the Analytical Hierarchy Process, have been widely adopted for rainwater harvesting (RWH) site selection application studies. These applications have involved the integration of various spatial factors or criteria to create suitability maps that serve as decision support systems for planners and stakeholders. For example, *Adham et al.* [2016] applied AHP within the GIS environment ArcGIS to combine layers such as rainfall, land use, slope percentage, soil texture, and curve number to prepare a suitability map in their study. The prepared maps assisted

in identifying suitable sites for implementing RWH structures such as farm ponds, check dams, contour ridges, cisterns, and runoff basins to mitigate the effects of water scarcity. The application developed by *Kahinda et al.* [2009], named RHADEES, is a GIS based decision making framework that uses $100m^2$ grid cells for the evaluation of potential RWH sites. This application was implemented in a semi arid region, and the results indicated that approximately 12% of the area is highly suitable, while 2% is of moderate suitability. In Tanzania, a GIS based decision support system is utilized in a study by *Mbilinyi et al.* [2007]. This study is conducted in the Makanya basin, utilizing proxies such as elevation, soil depth, soil texture, slope, land cover, and drainage density. Validation against existing RWH structures in the study area basin demonstrated that 40% of the area has very high suitability, while 41% falls under high suitability classes. Zhu and Dale *Zhu and Dale* [2001] introduced JAVA AHP, a web based decision support system that can leverage the use of layers such as slope, aspect, transportation, land use, and cost within this framework. These applications are primarily effective in preliminary screening, but they often depend on constant proxies; therefore, there is a lack of consideration regarding temporal variability. Consequently, this limitation affects robustness under changing climatic conditions.

The need for larger scale planning tools has grown mainly due to the increasing problem of water scarcity. Researchers and planners have started adopting Geographic Information systems to integrate a diverse set of data and decision oriented factors or criteria, *Jha et al.* [2014], *Sajil Kumar et al.* [2022]. The success of this approach in selecting the RWH site is primarily based on the ability to create spatial datasets and the availability of a comprehensive database of hydrological and other physical factors.

Integrating Multi criteria analysis (MCA/MCDM) with GIS is the key to RWH planning, which is an objective based decision making problem that relies on biophysical, socioeconomic, and environmental conditions *Singh et al.* [2017]. This integration has proven to be a powerful and effective method for managing complex real world problems in water resource management *Singh et al.* [2017], *Shadmehri Toosi et al.* [2020], *Jha et al.* [2014].

The analytical hierarchy process (AHP) is one of the most widely used methods for the selection processes of RWH sites *Ibrahim et al.* [2019], *Ibrahim et al.* [2019], *Husen et al.* [2019], *Mahmood et al.* [2020]. It systematically organizes and evaluates complex decisions using a structured framework based

on expert knowledge and a benchmark established in the literature. *Preeti et al.* [2022], *Darabi et al.* [2021]. The AHP approach uses a pairwise comparison matrix to assign weights to various criteria *Adham et al.* [2016], *Rajasekhar et al.* [2018], and *Sajil Kumar et al.* [2022]. Other decision making rules, such as the weighted linear combination, are also commonly used and are sometimes integrated with AHP *Mahmood et al.* [2020], *Preeti et al.* [2022], and *Sallwey et al.* [2018].

These frameworks have been used to generate suitability maps based on a combination of biophysical factors, such as slope, drainage density, runoff potential, land cover, rainfall, and primarily socioeconomic factors *Adham et al.* [2016], *Shadmehri Toosi et al.* [2020], *Preeti et al.* [2022], *Ziadat et al.* [2012], *Darabi et al.* [2021]. Very important biophysical criteria used in the RWH site selection process with this approach include:

- Rainfall *Ibrahim et al.* [2019], *Preeti et al.* [2022], *Adham et al.* [2016]
- Slope *Ibrahim et al.* [2019], *Preeti et al.* [2022], *Adham et al.* [2016], *Shadmehri Toosi et al.* [2020], *Ziadat et al.* [2012]
- Soil type/ soil texture and soil depth *Ibrahim et al.* [2019], *Adham et al.* [2016], *Shadmehri Toosi et al.* [2020], *Ziadat et al.* [2012]
- Land use/land cover (LULC) *Ibrahim et al.* [2019], *Adham et al.* [2016], *Shadmehri Toosi et al.* [2020], *Ziadat et al.* [2012]
- Drainage density and stream order *Ibrahim et al.* [2019], *Preeti et al.* [2022], *Mahmood et al.* [2020]

1.2.2 Hydrological modeling and SCS-CN methods

The soil conservation service number (SCS-CN) method is widely used as an empirical approach to estimate direct runoff from rainfall events. It assumes a lumped representation of a catchment and does not account for time variability, slope effects, or detailed infiltration processes. Instead, infiltration is indirectly represented through the curve number, which aggregates land

use, soil type, and hydrological conditions into a single parameter. Although this approach is simple and practical, it cannot capture spatial heterogeneity and cumulative runoff processes; therefore, it poses limitations on the applicability of the method in the design processes for rainwater harvesting (RWH) systems.

The hydrological modeling based approaches, particularly the one using the SCS-CN method, have often been integrated with GIS to estimate runoff potential, which could serve as a proxy for identifying potential rainwater harvesting (RWH) sites. *Kadam et al.* [2012] applied the SCS-CN method in the semi arid region of western India to identify potential rainwater harvesting sites. This application involved the use of land use data derived from Landsat imagery, USDA soil classification data, as well as geological and rainfall data to calculate the potential runoff. The validation of the results has been conducted through ground truthing; the error matrix indicated that the results are 89% accurate. A similar approach has been undertaken by *Napoli et al.* [2014], who integrated hydrological modeling using the SCS-CN method with GIS to identify priority zones for implementing RWH structures; this study has demonstrated the application of RWH in a European climate context in a region of Northern Italy. Although these studies indicate that physically based models can provide more realistic outcomes compared to proxy indicators, they often require more detailed input data and calibration, which can be challenging in large scale applications.

1.2.3 Data driven and Machine learning approaches

There is a recent advancement in RWH site selection applications that have employed machine learning and data driven techniques primarily. This effort was often made to reduce the subjectivity inherent in conventional AHP applications. *Darabi et al.* [2021] has compared three AI algorithms, namely Support Vector Machines (SVM), Maximum Entropy (MaxEt), and the genetic algorithm for Rule set Prediction (GARP), for land suitability assessment. The study utilized criteria layers that included rainfall, slope, temperature, elevation, and distance to streams and lakes. The study results indicated that an annual rainfall of 350–390 mm could be more suitable for RWH and pointed out that the suitability of RWH increases with the distance from streams and lakes. This study is noteworthy because it has highlighted the potential of AI driven models that can enhance predictability. It exhibits less dependence on expert judgment than is typically required when assigning priority weights in GIS based approaches. However, such frame-

works often require larger datasets and computational resources, which can pose an additional limitation when applied in data-scarce regions or basins.

1.2.4 Groundwater recharge and hybrid applications

Although the main focus of this thesis is on the potential for rainwater harvesting, it is worth mentioning that GIS based multicriteria frameworks have a very wide range of applications in the field of groundwater potential mapping and in identifying potential sites for artificial recharge. Studies such as *Anteneh et al.* [2022], *Goodarzi et al.* [2016], and *Xu et al.* [2021] demonstrate that these frameworks are not only flexible but can also integrate various field objectives and proxy indicators, such as lithology, geomorphology, soil properties, and hydrological conditions. This adaptability illustrates the flexibility of GIS based decision support systems. These approaches can primarily be utilized in integrated water management planning by combining surface water and groundwater recharge planning. Although groundwater studies fall outside the scope of this work, addressing them was essential within the framework of its basic principles to support MCDA applications aimed at solving water scarcity problems.

1.2.5 Socio-Economic factors and practical applications in RWH planning

Although irrelevant to this study, the use of socioeconomic factors in the search for potential RWH sites has been primarily considered over the past decade. This subsection briefly explores the perspectives of different socioeconomic factors and the practical considerations involved in choosing RWH sites. Socio-economic criteria are another key factor that enhances the effectiveness of the RWH planning process *Shadmehri Toosi et al.* [2020]. Some of the most commonly used factors include distance to roads, settlements, cities, the tenure period of land, and sometimes cost *Adham et al.* [2016], *Shadmehri Toosi et al.* [2020], *Preeti et al.* [2022], *Martínez-Acosta et al.* [2019]. These criteria are applied in a GIS environment in combination with other physical layers that can be used to optimize the study results based on economic conditions. Several practical applications regarding economic factors have been performed; for example, *Amos et al.* [2017] conducted an economic analysis comparing RWH systems in developed and developing countries using the ERain framework. This framework involves employing life cycle cost evaluation and benefit cost ratio analysis in the application of RWH systems. *De Melo Branco et al.* [2005] has examined projects based

on cisterns in a semi arid region of Brazil; the study addresses the need for government support, training local communities, and large scale implementation of strategies for RWH. *Shadeed et al.* [2019] has addressed domestic water poverty in the West Bank of Palestine, identifying suitable sites for RWH using GIS/AHP, and found that approximately 60% of the area was highly suitable for RWH implementations. *Lani et al.* [2018] has analyzed the performance of RWH systems in commercial buildings in Malaysia. This study focused on the optimal tank size and payback periods in different reliability scenarios.

1.3 Research Gaps

The review of existing frameworks highlights the remarkable evolution of RWH site selection techniques over the past decades. This evolution has transitioned from empirical sizing techniques to advanced GIS based multicriteria decision models and physically based hydrological models. The field has progressively utilized these tools, which can integrate spatial data, process based simulations, and decision supporting models. Recent developments, such as machine learning and hybrid applications, indicate a growing interest in the context of predictive accuracy based on climate change conditions.

Overall, both past and recent studies show that GIS based multicriteria frameworks integrate criteria from various factors, such as topography, hydrology, rainfall, slope, soil type, and drainage density, alongside socio-economic parameters, including distance to roads and streams. With certain weightings and combinations, these frameworks can generate explicit suitability maps. However, despite advancements in the diversity of approaches within GIS frameworks, there are a few common gaps found in the literature.

- there is no clear standard procedure for the RWH site selection process using AHP/GIS frameworks; this generally leads to methodological inconsistencies across various applications.
- Most of the current studies, with some exceptions, do not account for the water balance within the hydrological model. Instead, they attempt to estimate runoff potential indirectly through proxy indicators. *Jha et al.* [2014], *Singh et al.* [2017]. The runoff coefficient is one of those commonly used proxies *Singh et al.* [2017], or models based on

the Curve Number (CN) method that primarily rely on assumptions at local pixel scales *Mahmood et al. [2020]* *Napoli et al. [2014]*.

- This indirect assessment is typically applied at a pixel scale, often overlooking the movement of water between adjacent cells, which may lead to an underestimation of the actual runoff available for harvesting. For instance, two cells with identical characteristics, one located upstream and the other downstream in a sub basin, would possess the same suitability score. However, downstream cells may still have high potential due to flow accumulation.
- Another key limitation of these approaches is their neglect of the effects of temporal variability and the associated uncertainty concerning hydrological variables, resulting in a reliance on static classifications, such as time averaged annual or single event data. *Singh et al. [2017]*. Thus, dependency on a particular year or a limited number of observed yearly data may compromise the robustness of site selection outcomes.

1.4 Objectives

The scope of this study is to provide a solution to the aforementioned limitations by addressing the gap in methodologies that account for both cumulative runoff and the temporal variability of rainfall. This is achieved by proposing a novel enhancement to the AHP/GIS based approach through the integration of Aggregate Runoff (AR) as a main variable. AR represents the total upstream surface water collected at each pixel, which signifies the accumulation of water along the surface flow paths. This is crucial for hydrological analysis. This integration enables a more realistic and accurate assessment of the Rainwater Harvesting (RWH) potential compared to conventional approaches.

The Aggregated Runoff (AR) is evaluated using a simple hydrological model based on a standard geomorphological analysis that is generally applicable in GIS environments. This analysis considers the flow of water within the watershed basin. Thus, it represents the entire flow dynamics of the basin through flow accumulation. This new criterion supports a more accurate evaluation without increasing the complexity of calculations or data requirements. The proposed AR is independent of the specific methodology or the commonly adopted data layers, which enhances its flexibility for broader applications, and it can be easily integrated with existing GIS

frameworks.

The issue of temporal variability remains significant; the methodology proposes a quantile based classification scoring system. This classification scoring system facilitates the derivation of a stable RWH potential index. This improved robustness is particularly relevant in the context of climate change, where changes in the patterns of hydrological variables become highly unpredictable. The integration of Aggregated Runoff (AR) modifies the RWH potential maps, assigning higher values to the scores for the base of hill slopes while assigning lower values to the uphill areas based on their potential. This spatial pattern is often overlooked in conventional layers, such as the Runoff Coefficient (RC).

Furthermore, it is necessary to explicitly address the uncertainty surrounding rainfall variability when evaluating the potential of Rainwater Harvesting (RWH). This challenge is addressed by integrating larger hydrological datasets and statistical approaches that capture inter-annual and intra-annual fluctuations. These fluctuations are later tested for uncertainty using empirical frequency distribution curves in the pixel level.

The proposed approach can be applied in the context of Rainwater Harvesting (RWH) techniques, including farm ponds, small check dams, and small scale managed aquifer recharge systems. These interventions generally fall under the category of micro-catchment scale RWH interventions. The application is further elaborated upon in detail in the following chapter of the methodology.

1.5 Outline of the Dissertation

The chapters of the dissertation are described in detail. Each chapter corresponds exactly to a published article *Mathew Damascene et al.* [2025] and is organized as follows: Chapter (i) Introduction, which describes the background of the study, the problem statement, research gaps, and the scope of this study; Chapter (ii) Methodology, which provides a detailed description of the methodological framework and the integration of proposed Aggregated Runoff (AR) and classification scoring into AHP/GIS to determine the RWH potential index; Chapter (iii) Application example, which presents the case study of the upper Tiber river basin in Central Italy using the proposed AR; Chapter (iv) Discussion, which mainly discusses the results and compares them with existing methodologies using the runoff coefficient. It also

addresses the transferability and limitations of the approach; and finally, Chapter (v), Conclusion, outlines the performance implications and future research directions of the proposed methodological framework.

Chapter 2

Methodology

2.1 Introduction

This chapter begins by introducing the existing standard framework for computing the Rainwater Harvesting Potential Index (RWHPI), which will be referred to as ρ from this point onward. The ρ is a key factor in the potential site selection process. As described in the previous chapter, The objective is to propose an enhancement to the popular GIS/AHP based frameworks for computing the Rainwater Harvesting potential index using aggregated runoff as a new proxy. The main focus of this chapter is to address the structure and practical implementation of the proposed layer within the GIS framework, which includes the computational steps involved, the data used, and the integration of the processed data into a GIS based decision making environment.

Standard GIS/AHP procedures typically rely on local runoff proxies, such as the Runoff coefficient(RC), which is used by *Jha et al.* [2014] to compute the Rainwater harvesting Potential Index. In this approach, the Runoff coefficient (RC) plays a key role as the main hydrological criterion, alongside other physical factors such as slope and drainage density; these factors are reclassified into suitability classes and weighted through AHP pairwise comparisons. The final index is then calculated using a weighted Linear Combination(WLC) and is mapped into suitability zones, such as poor, moderate, and Good for RWH implementation. This runoff coefficient (RC) layer is typically derived from land use, soil type, and rainfall data. This approach assumes local runoff conditions. These proxy proxies neglect the cumulative nature of runoff along the flow paths. Hence, it fails to capture the movement of water within a watershed. As a result, the actual water availability for rainwater harvesting is primarily underestimated

downstream. To overcome this key limitation, the proposed study involves using an enhanced criterion called Aggregated Runoff(AR) which represents the runoff weighted over the flow accumulation computed by a physically consistent flow accumulation process. This layer of Aggregated Runoff (AR) is independent of any particular methodology and can be utilized in diverse basins and GIS frameworks. This makes the proposed approach improve hydrological realism without increasing data and computational complexity. Figure 2.1 shows the methodological framework adopted for this study in a flow chart.

Starting with the collection of data, preprocessing involves generating proxy layers such as slope and drainage density, as well as computing aggregated runoff and runoff coefficients. This is followed by an analysis of the RWH potential index. Inter-annual and intra-annual timescales involve analyzing seasonal extremes. Finally, the evaluation of uncertainty in both cases utilizes cumulative distribution functions for the temporal analysis, as shown in Figure 2.1.

This framework enables the evaluation of various criteria through spatial analysis, complemented by structured and classified weighting based on specified objectives. However, standard AHP/GIS based workflows for determining ρ at a given point rely on a local scale runoff coefficient (RC) and utilize a standard classification pattern. These conventional applications have exhibited two significant limitations.

- The key limitation is that standard applications neglect the cumulative runoff process along the flow paths, which generally leads to an underestimation of water availability in the downstream area of the watershed basin
- Another limitation of existing workflows is their reliance on static or short term variable data, particularly regarding rainfall or local runoff volume. This reliance does not capture the variability of both rainfall and runoff under changing climate

To overcome these limitations, the methodology introduces two key enhancements

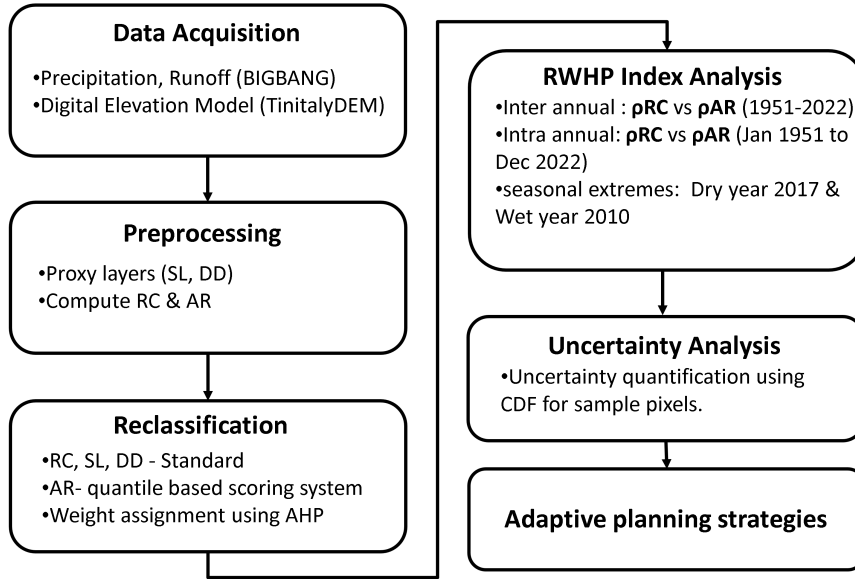


Figure 2.1: Methodological flow chart representing the proposed framework and analysis; includes the data collection, pre-processing of data, reclassification with weights, RWHP index analysis in different time frames, uncertainty analysis and adaptive planning strategies

- A more realistic hydrological criterion quantifies the total upstream surface water contributing to each cell
- A quantile based classification scoring system is designed to mitigate the effects of rainfall variability across inter-annual and intra-annual time scales, thereby ensuring the stability and robustness of suitability maps.

This chapter is organized as follows: Section 2.1 provides a clear definition of the Rainwater Harvesting Potential Index, and Section 2.2 explains the standard AHP/GIS procedure proposed by *Jha et al.* [2014], which serves as the key reference for the comparative analysis. Section 2.3 introduces the aggregated runoff approach, explaining its computation and its integration into the AHP/GIS structure, as well as its conceptual differences from traditional runoff proxies. Section 2.4 describes the quantile-based scoring system and its application to Aggregated Runoff (AR) to improve the stability of index calculations under temporal variability. Section 2.3 introduces the aggregated runoff approach, detailing its computation and how it is integrated into the AHP/GIS structure, along with its conceptual differences from tra-

ditional runoff proxies.

2.2 Definition of Rainwater harvesting potential index or $\rho(x, y)$

The suitability of a given point in space (x, y) for rainwater harvesting structures is assessed using the Rainwater Harvesting Index, denoted as $\rho(x, y)$, *Mathew Damascene et al.* [2025]. This index is commonly calculated using the Weighted Linear combination (WLC) method *Ibrahim et al.* [2019], *Singh et al.* [2017], *Jha et al.* [2014], which is one of the most widely applied methods for evaluating multiple criteria to determine ρ *Ibrahim et al.* [2019], *Xu et al.* [2021]. This method involves multiplying the weight of each factor by its corresponding score and then summing the results to derive a final suitability index map. *Ibrahim et al.* [2019].

Jha et al. [2014] has developed a GIS based framework to determine the rainwater harvesting potential using the AHP method. In this approach, a criterion is defined as a physical or hydrological factor that influences the Rainwater Harvesting potential, such as the runoff coefficient(RC), slope, and drainage density. Each criterion is represented as a spatial layer in GIS. To make these layers comparable, they are reclassified into suitability classes that *include very low, low, medium, high, and very high*. A score is then assigned to each class, reflecting its relative potential for RWH. For example, regarding the runoff coefficient, higher values indicate more runoff and, therefore, greater suitability. Consequently, classes with higher RC receive higher scores; for slope, gentler slopes are more suitable, so lower slope classes receive higher scores; for drainage density, higher values mean increased runoff, which also results in higher drainage density scores. The score generally ranges from 1, indicating the least suitability, to 9, indicating the highest suitability. These scores are combined with weights derived from AHP pairwise comparisons, which quantify the relative importance of each criterion. For instance, the runoff proxy is assigned the highest weight, and The final Index is computed by combining these criteria using a Weighted Linear Combination.

The calculation is formulated as follows.

$$\rho(x, y) = \sum_i^N w_i S(x, y)_i \quad (2.1)$$

- S_i is the score for the criterion i at a specific point (x, y) . The score is determined by reclassifying the data associated with the feature into suitability classes.
- w_i is the normalized weight of the criterion i , which is derived from the pairwise comparisons conducted through the Analytic Hierarchy Process (AHP). These weights are derived by calculating the eigenvector associated with the largest eigenvalue of the comparison matrix.
- N represents the number of criteria considered in the final calculation of the potentiality index $\rho(x, y)$

2.3 Standard Procedure

The standard procedure is adopted from the methodology proposed by *Jha et al.* [2014]. Like any other application, this is one of the foundational applications of the GIS/AHP framework for determining the rainwater harvesting potential index, particularly for large-scale assessments. *Jha et al.* [2014] in their standard procedure to determine the rainwater harvesting potential mainly relied on three commonly used physical factors: *the local* runoff coefficient, the percentage of slope, and the drainage density.

- Runoff coefficient (RC): this key parameter indicates the availability of water. RC is defined as the relative amount of surface runoff compared to the corresponding rainfall. RC is often derived from the types of soil layers, land use, slope, and rainfall *Te Chow et al.* [2010]. The widely used soil conservation service curve number method (SCS – CN) is also a common approach to estimating runoff for rainwater harvesting (RWH) studies. *Ibrahim et al.* [2019], *Mahmood et al.* [2020], *Jha et al.* [2014], *Napoli et al.* [2014].
- Slope percentage: Slope is considered a key topographic parameter for identifying potential rainwater harvesting sites *Ibrahim et al.* [2019], *Preeti et al.* [2022], *Mahmood et al.* [2020], *Jha et al.* [2014], *Singh et al.* [2017]. Gentler slopes are deemed more suitable for RWH because they can store runoff water and allow for greater infiltration. Lower slopes promote water residence time during movement; however, steep slopes

increase runoff and erosion *Ibrahim et al.* [2019], *Preeti et al.* [2022]. Thus, areas with higher slopes are generally considered unsuitable for rainwater harvesting structures.

- **Drainage Density** : The drainage density (DD) is commonly derived from the Digital Elevation Model and is used as a hydrological criterion in RWH Potential applications. A higher drainage density corresponds to a higher runoff rate and its proximity to movement towards RWH structures. This criterion is also important for micro-aqueduct systems and facilitates multiple localized studies.

2.3.1 AHP framework and pairwise comparison matrix

The AHP framework begins with the construction of a hierarchical structure, where all overall goals are positioned at the top level, followed by criteria and sub-criteria. The next step involves creating a pairwise judgment matrix in which each criterion is evaluated according to Saaty's 1-9 scale to demonstrate relative importance. In the standard AHP/GIS procedures for estimating the potential of rainwater harvesting, the process starts by defining the criteria M and constructing a pairwise comparison matrix of size $M * M$. Each criterion is compared with every other criterion using the Saaty scale *Saaty* [1987]. This scale ranges from 1 (indicating equal importance) to 9 (indicating extreme importance), with intermediate values representing varying degrees of preference. After completing the matrix, the relative weights (w_i) for each criterion are calculated by deriving the normalized eigenvector associated with the largest eigenvalue. Fig2.2 illustrates the Analytical Hierarchy Process workflow used to determine the criterion weights for the multi criteria decision making process.

Criterion	Weight (w_i)
Runoff Coefficient (w_{RC})	0.39
Slope (w_S)	0.35
Drainage Density (w_{DD})	0.26

Table 2.1: AHP weights for criteria (adapted from *Jha et al.* [2014])

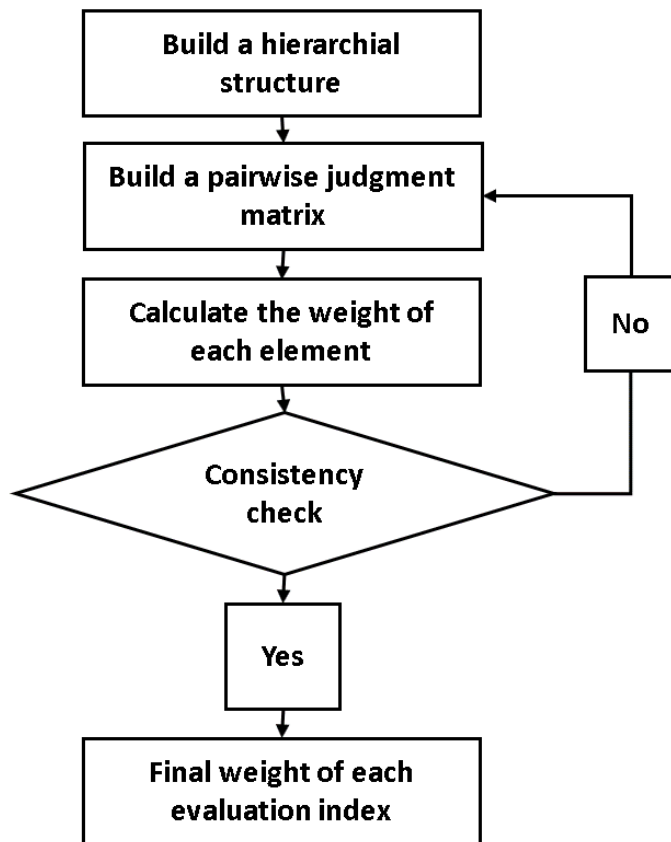


Figure 2.2: Flowchart illustrating the Analytical Hierarchy Process (AHP) steps for weight determination, including hierarchy construction, pairwise comparison, weight calculation, consistency check, and final assignment of normalized weights to evaluation criteria

Thematic Layers	Runoff Coefficient	Slope percentage	Drainage Density	Geometric Mean	Normalized Weights
Runoff coefficient	9/9	9/6	9/6	1.191	0.391
Slope	8/9	8/8	8/6	1.058	0.348
Drainage Density	6/9	6/8	6/6	0.794	0.261
Column Total				3.0432	1

Table 2.2: Pairwise comparison matrix and derived weights used by *Jha et al.* [2014]

2.3.2 Consistency Check

The subjected weights are validated by calculating the Consistency Ratio (CR). *Adham et al.* [2016]. The value of $CR < 0.1$ shows that the weights are consistent, but the value $CR > 0.1$ indicates an inconsistency that must be corrected. Pairwise comparisons in AHP are based on human judgment, which can be subjective and prone to inconsistency. To ensure logical consistency with the decision making process and improve the credibility of the outcome, it is very important to compute consistency using the consistency ratio. For each criterion i (with $i = 1, \dots, M$), the values associated with the feature classes are reclassified and given a score S_i that is related to each class in the reclassified criterion *Jha et al.* [2014], *Singh et al.* [2017], *Elewa et al.* [2021].

The Consistency Ratio evaluates the degree of consistency of the pairwise comparison matrix using the formulas 2.2 and 2.3 given in *Saaty* [1987]. Table 2.3 shows the value of the random index based on the number of criteria used in the AHP framework to compute the consistency of normalized weights across the selected parameters.

$$CR = \frac{CI}{RI} \quad (2.2)$$

Where:

$$CI \text{ (Consistency Index)} = \frac{\lambda_{\max} - n}{n - 1} \quad (2.3)$$

•

$\lambda_{\max}$ = largest eigenvalue of the comparison matrix

• n = number of criteria

• RI (Random Index) = average CI of randomly generated matrices of size n

n values are tabulated by *Saaty* [1987] given below

n	1	2	3	4	5	6	7	8	9	10
Random Index	0	0	0.52	0.90	1.11	1.25	1.35	1.40	1.45	1.49

Table 2.3: Random Index (RI) values for different matrix sizes n , used in AHP to calculate the Consistency Ratio for assessing judgment consistency

2.3.3 Reclassification and ranking

Due to the variety of measurements and scales for different criteria, each layer must be reclassified into suitability classes using a comparable scale *Adham et al.* [2016] and *Preeti et al.* [2022]. Higher ranking values are assigned to the feature classes that represent the most favorable conditions for rainwater harvesting *Adham et al.* [2016], *Ibrahim et al.* [2019]. For example, on a 5 point scale, 1 is considered very low, and 5 is considered highly suitable.

2.3.4 Computation of the RWH potential index using RC ρRC

The general ρ is calculated as the sum of the products of the weights of the criterion (w_i) and their respective suitability rank values. (S_i)

$$\rho(x, y) = w_R S_R + w_S S_S + w_{DD} S_{DD} \quad (2.4)$$

The resulting dimensionless RWHP Index values are classified into levels of suitability; for example, very poor, moderate, high, and very high suitability. In their study, *Jha et al.* [2014] classified the final RWHP index into 3 potential RWH zones: *good, moderate, and poor*.

2.4 The Aggregated Runoff Approach

The aggregated runoff is the innovative contribution proposed in this study. This proposal aims to enhance the current RWH potential mapping by integrating a more hydrologically accurate parameter while maintaining operational simplicity. The core idea of this approach is that the selection of potential RWH sites depends on the runoff generated upstream. The proposed Aggregated Runoff (AR) clearly considers the cumulative contribution of surface water from all upstream cells in the sub-aqueduct, thereby providing a more realistic representation of the hydrological conditions within that basin. As described above, this approach becomes innovative by replacing the conventional runoff coefficient criteria in the RWHP assessment, such as *Jha et al.* [2014], which overlook the exchange of water flow between cells.

2.4.1 Computation of Aggregated Runoff AR

The Aggregated Runoff (AR) is the total volume of cumulated runoff at a given point or location that results from both rainfall at that point and the surface flow adjacent to the cells. The AR of a specific cell is computed by summing the local runoff and contributions from upstream cells. The study area is discretized into a grid of N cells of uniform size, which allows for spatially explicit calculations. Figure 2.3 shown below depicts the general geomorphological framework of the cumulated runoff assessment. panel a) represents a vertical section along with vertical fluxes of both rainfall and infiltration, while panel b) shows the surface runoff cumulation. For each cell (m,n) , rainfall is partitioned into three key components. Infiltration ($I_{m,n}$), surface runoff ($RF_{m,n}$), and evapotranspiration ($Et_{m,n}$).

The generated surface runoff within a cell flows directly downslope through the steepest gradient, progressively accumulating over time with contributions from upstream cells until it reaches the stream network. The total amount of water available for rainwater harvesting (RWH), i.e, the aggregated runoff $AR_{m,n}$ within the sub-watershed of a given basin, is greater than the runoff generated by the cells $RF_{m,n}$. In practical terms, for example, for cells (2,3), the proposed aggregated runoff is calculated $AR_{2,3} = AR_{1,2} + AR_{2,2} + AR_{2,3}$. The fundamental reason for the proposed methodology lies in the effective evaluation of the total runoff that can be collected by the rainwater harvesting structure located in a cell. The above quantity can be first calculated by estimating the surface runoff $RF_{m,n}$ within every cell and then aggregating these values along the surface flow paths. The aggregated runoff $AR_{m,n}$ is obtained by calculating the flow directions and the accumulation of flow weighted by the local runoff. The process can be performed using standard geomorphological procedures *Formetta et al.* [2014]. All these steps can be easily executed by GIS platforms. Through these procedures, it becomes possible to introduce an effective runoff assessment as a criterion in the AHP assessment to select RWH sites.

The methodology described above offers two main advantages: i) it provides a reliable estimate of runoff that accounts for water transfer between cells within the basin; ii) it delivers an estimate that is within the limits of uncertainty regarding the potential of the site that can be harvested during the selected analysis period.

During the assessment of aggregated runoff, cells representing the stream network were systematically excluded. This approach ensures that the analysis focuses on the hillslope based RWH interventions; these interventions capture surface runoff before it reaches the river system. Although including the river network is technically possible, it would necessitate addressing other hydrological factors, such as subsurface flow, that contribute to the base flow. Moreover, the design and construction of in-channel RWH-structures require a more detailed and specialized analysis. To exclude stream networks, a flow accumulation threshold of 100,000 m^2 was applied to remove stream cells. In this way, the assessment in the hillslope areas is more focused, where surface runoff generation is most pronounced.

AR, combined with other criteria (e.g., slope, drainage density), can be used in AHP to classify N cells of the study area according to the index (ρ). This criterion can be easily integrated into a wide range of applications suggested in the literature for computing ρ . For example, *Jha et al.* [2014] and *Preeti et al.* [2022]. Although adopting Aggregated Runoff (AR) in place of local runoff represents an important conceptual change, it does not involve substantial modifications to the Analytic Hierarchy Process (AHP) structure; rather, it's a redefinition of the classification ranges. This adjustment is necessary due to the differences between AR and RF values, which are discussed in detail in the next chapter.

The process of calculating Aggregated Runoff (AR) begins with the evaluation of surface runoff $RF_{m,n}$ for each cell.

The evaluation of the surface flow directions is the initial step, which is determined using the D8 [*O'Callaghan and Mark, 1984*] algorithm in conjunction with GIS operations. This method ensures that Aggregated Runoff (AR) accurately represents the geomorphology and hydrological conditions of the basin. Aggregated Runoff (AR) can also be considered as the flow accumulation weighted by surface runoff.

2.4.2 Quantile based scoring system of AR

AR values exhibit higher spatial variability compared to the runoff coefficient, and the range of values is contingent upon the threshold that defines the separation between the hill slopes and the channel. Because maximum AR values are influenced by rainfall and basin dimensions, suitability classes cannot be defined using universally fixed values.

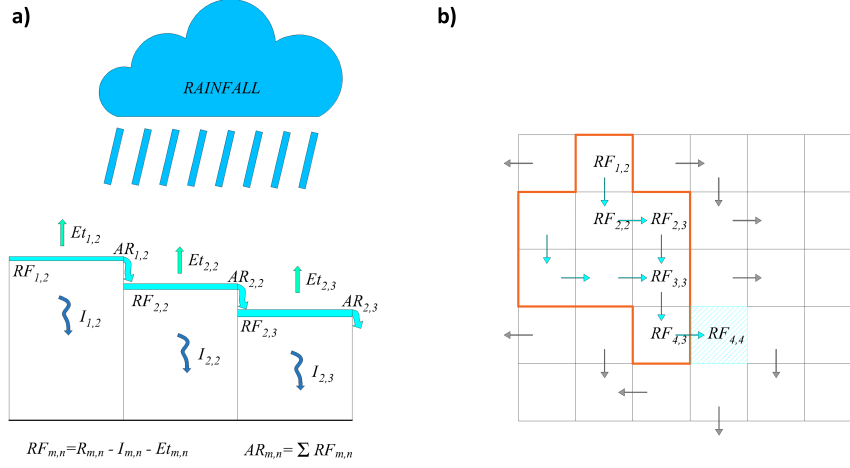


Figure 2.3: Sketch of the domain with horizontal and vertical fluxes, $RF_{m,n}$ is the relative contribution of the (m,n) cell to the total runoff $AR_{m,n}$ which depends on the area drained by the (m,n) th cell (Orange line). Arrows indicate the flow lines.

This study addresses the effect of the temporal variability of the index associated with hydrological variables by introducing a quantile based scoring system, particularly for aggregated runoff. This system classifies the Aggregated Runoff (AR) values by dividing the entire range of variability for each year into five quantile based classes.

For example, the mean Aggregated Runoff (AR) values for various years are divided into classes that range from 'very low' to 'very high,' with each class representing a specific range of quantiles. These classes are accompanied by suitability ranks, where higher quantiles are considered to possess greater harvesting potential. Hence, this is a data driven approach that defines the threshold based on the spatial distribution of the runoff values across the grid cells, thus ensuring it adapts to local conditions.

To ensure a fair comparison between the Aggregated Runoff (AR) and the conventional Runoff coefficient (RC), is classified using a quantile based scoring system. Unlike the standard classification thresholds, quantiles assign an equal area distribution for each class; this approach makes the results transferable across basins and years and minimizes sensitivity to rainfall variability. This step provides the rationale for the AR in our published article *Mathew Damascene et al. [2025]*. The AR magnitudes depend on catchment size and runoff, making quantiles an appropriate choice for robust basin scale filtering. The application of these quantiles on the RC eliminates classifi-

cation bias and highlights its true conceptual differences. AR integrates horizontal fluxes through routing, whereas RC, despite being classified by quantiles, remains a local proxy.

This approach of using a quantile-based classification scoring system offers substantial benefits for RWH planning, particularly in terms of transferability: the classification system is independent of the specific methodology, data layers, or combination of layers. This can be applied in any framework of GIS/AHP to find potential sites for rainwater harvesting, thus making this approach to AR easily transferable and applicable across other catchments globally without fixed limits.

The proposed approach provides highly stable baseline statistics and consistent suitability maps compared to conventional rainwater harvesting potential maps. In summary, the application of AR with the quantile based scoring methodology improves the accuracy and robustness of the resulting RWH potential maps ρ .

The robustness and transferability of the proposed quantile-based classification were further validated through an independent application to the semiarid Simeto Basin in Sicily. This analysis confirms that the methodology remains stable and reliable under substantially different rainfall regimes. A detailed discussion of the transferability of the methodology is provided in the Discussion section. The use of a quantile-based classification is essential because aggregated runoff scales with catchment area and avoids reliance on fixed threshold values, which are often not directly transferable between different basins.

2.4.3 Scope and applicability of the proposed approach

The proposed approach, based on aggregated runoff, is particularly suited for the identification and prioritization of rainwater harvesting (RWH) interventions at the micro-catchment scale. It is especially effective for small to medium scale interventions whose performance is primarily governed by local basin hydrology rather than by engineered storage capacity. Within a basin-scale planning framework, the methodology supports the selection and prioritization of RWH structures such as farm ponds, small check dams, percolation tanks, and managed aquifer recharge (MAR) systems. These interventions benefit the most from the proposed approach because their effectiveness is strongly influenced by the spatial and temporal variability of rainfall, runoff generation, slope, land use, and soil properties. By explicitly accounting for these hydrological controls, the approach enables informed

site selection and prioritization of decentralized RWH systems, ensuring that they are implemented where they can maximize runoff capture, enhance groundwater recharge, and improve local water availability. Furthermore, RWH systems serve distinct but complementary functions depending on their design and geomorphological context. Storage-oriented systems, such as farm ponds, primarily enhance seasonal surface water availability, whereas recharge-focused systems, including small check dams, percolation tanks, and MAR structures, contribute to groundwater replenishment and increased hydroclimatic resilience at the local scale. The proposed methodology effectively supports both categories by linking the suitability of the site to the underlying hydrological behavior of the microcatchment within the basin.

Chapter 3

Application Example

3.1 Introduction

This proposed enhanced approach has been applied to the upper basin of the Tiber River, which is closed at the hydrometric station of Ponte Felcino. The case study area is located in central Italy and extends into the regions of Tuscany, Umbria, and Emilia Romagna. The area is characterized by a complex geological and geomorphic setting.

This application primarily serves as an example to illustrate the method and to highlight the key advantages of using Aggregated Runoff (AR). The basic methodology and criteria proposed by *Jha et al.* [2014] were adopted as the reference framework, and suitable modifications were introduced to adapt the procedure to the new criteria proposed. This choice of reference study serves solely to illustrate the application of the proposed framework.

The complex geomorphological setup of this study area provides a detailed perspective on its application; it exhibits a Mediterranean climate characterized by moderate rainfall throughout the year. This methodology, similar to that used in the Ponte Felcino basin, has also been applied in the semi arid basin of Simetto in Sicily for a new geomorphological and climate setup. It has been demonstrated that the application is valid and yields stable outcomes despite high-intensity, short duration rainfalls and long term drought periods within a year. Alternative methodologies based on different criteria can also be applied. Furthermore, the selection of the M criteria is flexible and may depend on any factors that align with user objectives. The standard approach is utilized as the reference case to discuss the improvements associated with our proposed Aggregated Runoff (AR) criterion.

An additional innovative aspect of this work lies in the introduction of

a long historical time series for evaluating the RWHP. This feature is particularly relevant, as it enables the assessment of the temporal variability of the index. Hydrological variables, especially the runoff coefficient, exhibit a certain dependence on precipitation, which directly influences the RWH Potential. This dependence implies that wetter and drier years may exhibit different runoff capacities. Such variability may have implications, particularly at small spatial scales, and can be exploited for fine-tuning the selection of suitable RWH zones.

This chapter will describe the impact of aggregated runoff and the benefits of using a 72 year hydrological dataset. In their work *Jha et al.* [2014], the authors employed 3 criteria ($M = 3$) to define the Rainwater Harvesting Potential ρ : the runoff coefficient R , slope S , and drainage density (DD). The index ρ is obtained through the following linear combination.

$$\rho(x, y) = w_R S_R + w_S S_S + w_{DD} S_{DD} \quad (3.1)$$

With w_i , the weights of the i criteria and S_i determine the overall score. In the following sections, ρ_{RC} will be used to indicate the *RWH* potential index calculated using the local runoff coefficient (RC), while ρ_{AR} will denote the index calculated using the aggregated runoff (AR).

The classes with the given priority scores, except for the new aggregated runoff parameter and the criteria weights, are taken from the reference study and summarized in the table below, Table 2.1 ; The weights generally refer to the *Jha et al.* [2014]. in this chapter. The study area of the Ponte Felcino basin is discussed in detail, along with its physiological characteristic and the datasets utilized in the study.

3.2 Tiber at Ponte Felcino

The upper Tiber basin in central Italy, which is closed at the Ponte Felcino hydrometric station, represents one of the physiographically diverse and hydrologically important basins in the region. This sub basin is located in the Umbria region and partially extends into Tuscany and Emilia Romagna, covering an area of approximately 2073 km^2 ; the elevation ranges from 190 to 1453 meters above sea level, with the average altitude being close to 518

meters. The main river course in this section of the Tiber extends for approximately 113 km. This area is topographically dominated by the western Apennines, which feature steep slopes averaging about 29%; this remarkably influences runoff generation and sediment transport dynamics.

Although these studies consider a different stretch of the Upper Tiber basin, most areas fall within the study area and generally represent the current state of the basin, including its complex hydrology, climate, land use, and environmental features. The Ponte Felcino section serves as one of the main hydrometric points for flood forecasting and climate adaptation planning. The physiographic complexity, combined with marked hydrological variability, makes it an ideal study area for applying the proposed approach that utilizes Aggregated Runoff (AR) in the RWH site selection application based on GIS/AHP.

The methodology outlined in the previous chapter describes the definition of a rainwater harvesting potential index within a GIS /AHP framework and presents our proposed enhancement to the index by using aggregated runoff. The modified enhancement is then compared to the standard reference scenario, which employs the conventional runoff coefficient, along with other layers such as slope and drainage density, as proposed by *Jha et al.* [2014]. This comparison is discussed in detail in the following chapter. The classes and associated weights of the criteria are derived from the reference study as described by *Jha et al.* [2014].

3.2.1 Geology and Geomorphology

The basin displays a complex geological framework that is primarily composed of flysch terrigenous deposits in its upper region, derived from the Tuscan and Umbria Marche formations. In contrast, the carbonate Apennine ridge occupies the eastern and southern sectors. Downstream of the basin, the Tiber graben contains deposits that range from marine to continental facies. Meanwhile, the southwestern region, marked by potassic and ultrapotassic heterogeneity, reflects the tectonic evolution of the Tyrrhenian back-arc domain, influencing both infiltration processes and groundwater recharge potential. In contrast, the eastern and southern sectors are occupied by the carbonate Apennine ridge.

3.2.2 Hydrology and Climate

The upper Tiber basin experiences a Mediterranean climate characterized by relatively high but unevenly distributed rainfall, which ranges from 900mm to 1200mm annually. Rainfall is highest during autumn and winter, while summers are predominantly dry. Therefore, there is a seasonal contrast in runoff and soil moisture. The Long term hydroclimatic analysis conducted by *Dari et al.* [2023] indicates a progressive decrease in annual precipitation and an increase in mean air temperature over the last century. These results align with broader trends in Mediterranean climate change. These shifts have led to a reduction in surface water availability and groundwater recharge, exemplified by a 40% reduction in rainfall, particularly during summer, along with an increase in temperature of approximately 3 to 5 °C by the end of the century.

The basin is sustained hydrologically by a combination of surface and sub-surface flows. Studies using a physically based model (SWAT) indicate that base flow contributes 60% of runoff, primarily derived from the shallow aquifer in the basin. The runoff response of the catchments is highly sensitive to soil infiltration and topographical factors, characterized by steep slopes and dense drainage systems that combine to accelerate runoff. The drainage density varies significantly across the basin and influences local infiltration and the aggregation of runoff *Fiseha et al.* [2013].

3.2.3 Land Use and Environmental Features

The upper Tiber basin exhibits various land use patterns and environmental characteristics that primarily influence its hydrological behavior. The basin consists of extensive hills and valleys with heterogeneous lithology, which mainly comprises clay, flysch, and limestone, and these materials influence soil permeability and vegetation cover. The land use in the basin is a combination of agricultural areas, forests, and urban settlements that exist on the valley floors and along riverbanks. There has been a historical change in land use due to reforestation in the mid 20th century, and a recent increase in built-up areas has resulted in further modifications to the channel morphology, shifting from braided systems to single-tailed channels with low sinuosity. These changes have increased flood vulnerability in the downstream reaches, especially along the drainage network *Reichenbach et al.* [1998].

3.3 Datasets

The methodology utilizes two primary datasets, TINITALY DEM and the BIGBANG database, to determine the RWH potential by integrating the physiographic and long term hydrological data within an AHP framework. As discussed previously, the conventional AHP/GIS approach typically relies on three main physical criteria: the runoff coefficient, slope, and drainage density; however, the runoff coefficient (RC) is used for comparison by utilizing the extensive dataset from BIGBANG as a substitute.

The **TINITALY DEM** is a 10-meter resolution Digital Terrain Model (DTM) that covers the entirety of Italy and was developed by the Istituto Nazionale di Geofisica e Vulcanologia (INGV). Originally developed as a triangulated irregular network in 2007 *Tarquini et al.* [2023], it was updated in 2023 to version 1.1. This updated version integrates heterogeneous elevation sources—including regional topographic maps, LiDAR, GPS, and radar altimetry—processed using the DEST algorithm to enhance break-line fidelity. Digital Elevation Models are critical tools that provide fundamental information regarding the topographic characteristics of the basin, which are key for hydrological modeling. Figure 3.1 shows the DEM of the Ponte Felcino basin.

The **BIGBANG dataset** is one of the most comprehensive hydrological databases available for Italy, providing a robust foundation for large scale water resource assessments. This database was developed by the Institute of Environmental Protection and Research *ISPRA*. BIGBANG is a national scale hydrological balance framework designed to operate within a GIS environment. Its main objective is to quantify the key components of the hydrological cycle: precipitation, evapotranspiration, and surface runoff across the entire Italian territory using standardized procedures and spatial modeling techniques *Braca et al.* [2023]. Figure 3.2 shows the variables from the BIGBANG database that are used in the assessment of the potential rainwater harvesting for this study. BIGBANG offers exceptional spatial and temporal resolution, which is key for capturing the temporal variability of hydro-climatic conditions. The dataset spans 72 years (1951–2022), covering historical hydrological data. The data are provided on both monthly and annual scales, enabling detailed inter-annual and seasonal analyses. Spatially, BIGBANG employs a uniform resolution grid $1km^2$. This resolution ensures compatibility with high resolution DEMs and other geospatial layers used in GIS based modeling.

BIGBANG integrates rainfall and runoff estimation derived from a physically based water balance approach. It accounts for the spatial variability

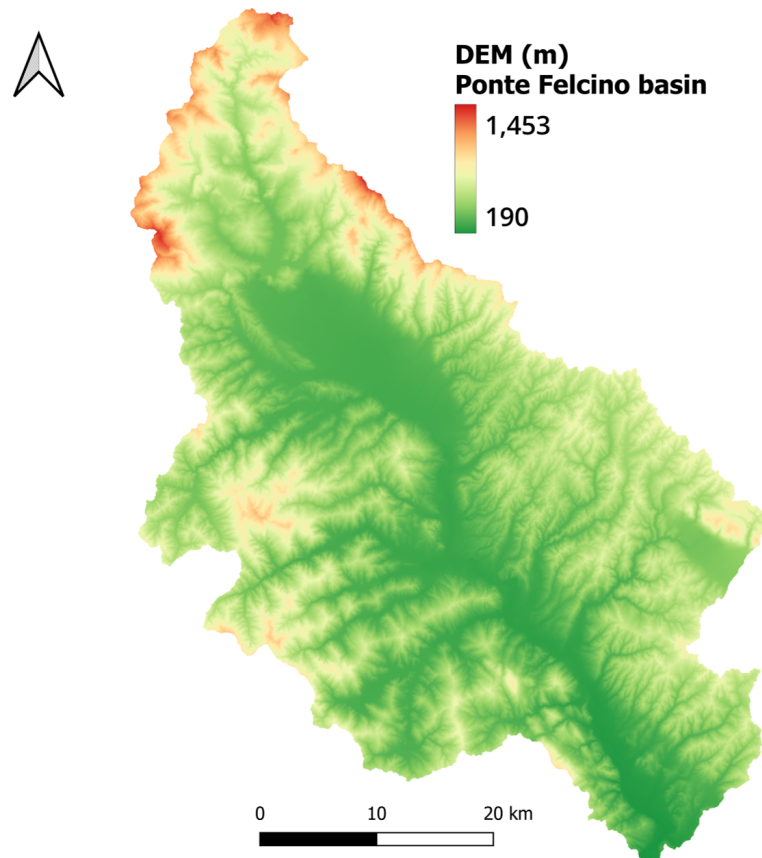


Figure 3.1: Digital Elevation Model (DEM) of Ponte Felcino basin



Figure 3.2: Figure shows selected components for the study from BIGBANG dataset such as total precipitation (P) and surface runoff (R) to support runoff coefficient and aggregated runoff calculations for rainwater harvesting potential assessment along with other variables, evapotranspiration (E), aquifer recharge (G) and soil/snow water storage (ΔV)

in rainfall distribution, soil characteristics, and land cover through standard tools and application algorithms to compute runoff generation and the

infiltration process. These results are considered very important in RWH studies, as they provide a direct estimate of surface runoff volumes.

3.4 Slope map

The slope is one of the key topographic factors that governs both runoff generation and the infiltration process within a basin. Steeper slopes increase surface flow velocity and reduce the time available for filtration. However, this rapid flow of water limits the potential for storage and sediment deposition, making steep slopes significantly less favorable for Rainwater Harvesting (RWH) structures, such as infiltration ponds or percolation tanks. In contrast, gentler slopes generally promote slower water movement, thereby enhancing infiltration and increasing water retention, which is beneficial for RWH interventions designed to augment soil moisture recharge *Critchley et al.* [1991]. Therefore, the slope possesses two main characteristics regarding runoff accumulation that limit storage possibilities, highlighting its crucial role in site selection for RWH structures. In this study, the slope was derived from the DEM using the GDAL slope algorithm implemented in QGIS *QGIS Development Team* [2022]. This tool computes the slope as the maximum change in elevation between each cell and its neighboring cell, expressed as a percentage. The Upper Tiber basin has slope values ranging from 0% to 175%, with most regions classified under medium to high slope values, reflecting the complex terrain conditions of the western Apennines. This variability introduces important spatial heterogeneity in hydrological behavior, influencing runoff generation.

Within the AHP framework, the slope was assigned the weight of the criterion $w_S = 0.35$, indicating its higher influence compared to other parameters such as drainage density and the runoff indicator. As shown in Figure 3.3, the slope percentage was classified into six suitability classes, each corresponding to its weight and normalized weight. The slope and its influence on the final RWHP score for site selection are nonlinear and inversely proportional; lower slopes correspond to higher suitability ranks due to their greater capacity to retain water flow, which facilitates the implementation of RWH structures; extremely steep slopes are assigned lower suitability ranks and normalized weights due to rapid runoff and the challenges associated with constructing RWH structures. Table 3.1 presents the class boundaries, suitability ranks, normalized weights, and the percentage of area falling within each classified class. Therefore, this classification ensures that the spatial variability of the slope is effectively incorporated into

the Rainwater Harvesting Potential Index (ρ).

The following table shows the normalized classes and relative weights (Table 3.1). The last column refers to the percentage of the catchment area that falls into the class. The slope map is shown in Figure 3.3.

Thematic Layer	Suitability Classes	Suitability Rank	Criteria Weight	Feature Class Weights	Normalized Weights	Area (%)
Slope percentage			8		0.35	
	0-1%	Very High		8	0.31	4.4
	1-3%	High		7	0.27	5.2
	3-5%	Medium		5	0.19	2.4
	5-10%	Low		3	0.12	4.8
	10-15%	Very Low		2	0.08	7.2
	>15%	Extremely Low		1	0.04	76.0

Table 3.1: Classified spatial distribution of percentage of slope with its criteria and feature class weights including the area fraction for each class

3.5 Drainage Density map

The drainage density (DD) is defined as the total length of the streams per unit area of a drainage basin. It is one of the most commonly used layers in determining the rainwater harvesting potential index. From a geomorphic perspective, a high drainage density is commonly associated with the intense dissection of the terrain, which is linked to lithological formations characterized by low permeability and a high potential for erosion. Such lithological features facilitate rapid runoff generation and the formation of additional stream channels, thereby underscoring the significance of the factor of drainage density. Denser drainage networks enable the establishment of multiple localized rainwater harvesting (RWH) structures throughout the basin, which facilitate micro-capture systems that are primarily effective in semi arid and arid environments, where rainfall is limited and spatially variable *Grigg et al.* [2023]. These systems predominantly leverage the natural efficiency of runoff routing in dissected landforms.

In this study, the DD map is derived from the stream network extracted from the DEM. The network delineation is based on the flow accumulation threshold and follows standard hydrological pre-processing steps, which mainly involve sink filling and determining flow direction. Specifically, the river network was defined by imposing a threshold of 4000 cells, corresponding to an area of approximately $0.4km^2$ on the flow accumulation raster.

Although different methods of stream generation exist in the literature, their influence is generally confined to the headwater cells and does not

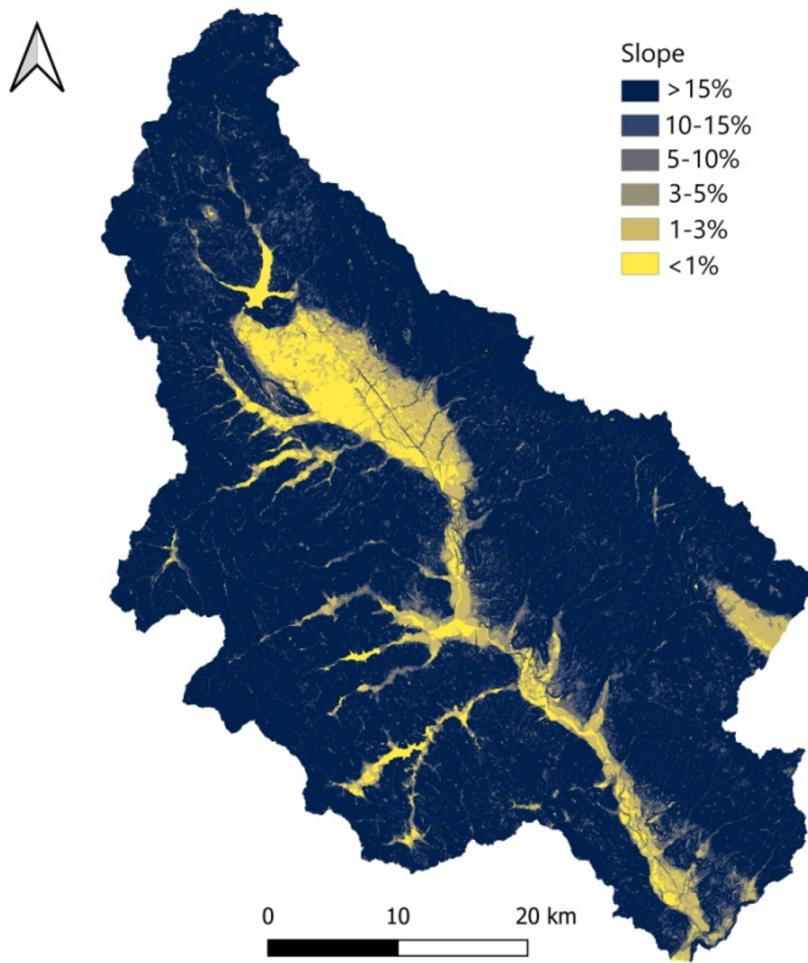


Figure 3.3: Spatial distribution of slope percentage across the Ponte Felcino basin

significantly affect basin scale drainage estimation. Given the relatively lesser weights assigned to the DD criterion in the AHP, a simplified approach was considered for operational purposes.

The drainage density is computed by sampling the stream network within circular subareas of 1 km radius, using the GDAL line density tool *Dragičević et al.* [2019]. This method provides a continuous spatial representation of the channel concentration expressed in units of km/km^2 . In the upper Tiber basin, the DD values range from 0 to $0.5 km/km^2$, with a higher number of intermediate values indicating the mixed lithological and topographical conditions of this basin. Areas with higher DD correspond to steep slopes and impermeable lithology, which are naturally predisposed to rapid runoff generation and therefore exhibit a greater potential for surface water har-

vesting

The weight associated with DD as a criterion is $DD = 0.26$, which is consistent with the relative influence of DD, along with other parameters such as slope and runoff indicators. Figure 3.4 represents the drainage density map, which is reclassified into 4 classes, with relative weights proportional to DD values. Areas with low drainage density were assigned lower suitability scores due to their limited runoff concentration. However, zones with high drainage density received the highest scores. This classification ensures that the spatial variability of the combined streams is well represented in the calculation of the final RWH Potential Index ρ . Table 3.2 shows the class boundaries and normalized weights, while the spatial distribution of DD in the Ponte Felcino basin is illustrated in Figure 3.4.

Thematic Layer	Suitability Classes	Suitability Rank	Criteria Weight	Feature Class Weights	Normalized Weights	Area (%)
Drainage Density			6		0.26	
	<0.75 km/km ²	Low		3	0.13	20
	0.75–1.5 km/km ²	Medium		5	0.22	47.9
	1.5–2.25 km/km ²	High		7	0.30	27.3
	>2.25 km/km ²	Very High		8	0.35	4.8

Table 3.2: Classified spatial distribution of drainage density with its criteria and feature class weights including the area fraction for each class

3.6 Runoff coefficient

The runoff coefficient is defined as the fraction of total precipitation that becomes surface runoff. This runoff coefficient is a critical parameter in RWH studies. This is because it directly influences the spatial representation of runoff and helps identify areas with greater potential for runoff accumulation that are suitable for RWH implementation. Traditional approaches to selecting potential sites for rainwater harvesting often use the runoff coefficient (RC) as a standard runoff indicator for the catchment. The RC can be calculated using hydrological analysis and physically based models, such as the SCS-CN method, the Green–Ampt method, or empirical correlations involving factors such as slope, soil type, and land use *Te Chow et al.* [2010].

These standard methodologies for generating RC maps mainly rely on the water balance equations applied to the 0–D scale, where runoff is estimated locally from precipitation without considering the horizontal water flux between cells *Jha et al.* [2014], *Singh et al.* [2017], *Adham et al.* [2016]. Although such application methodologies are computationally simple, they neglect the effects of runoff movement in the site selection process for rain-

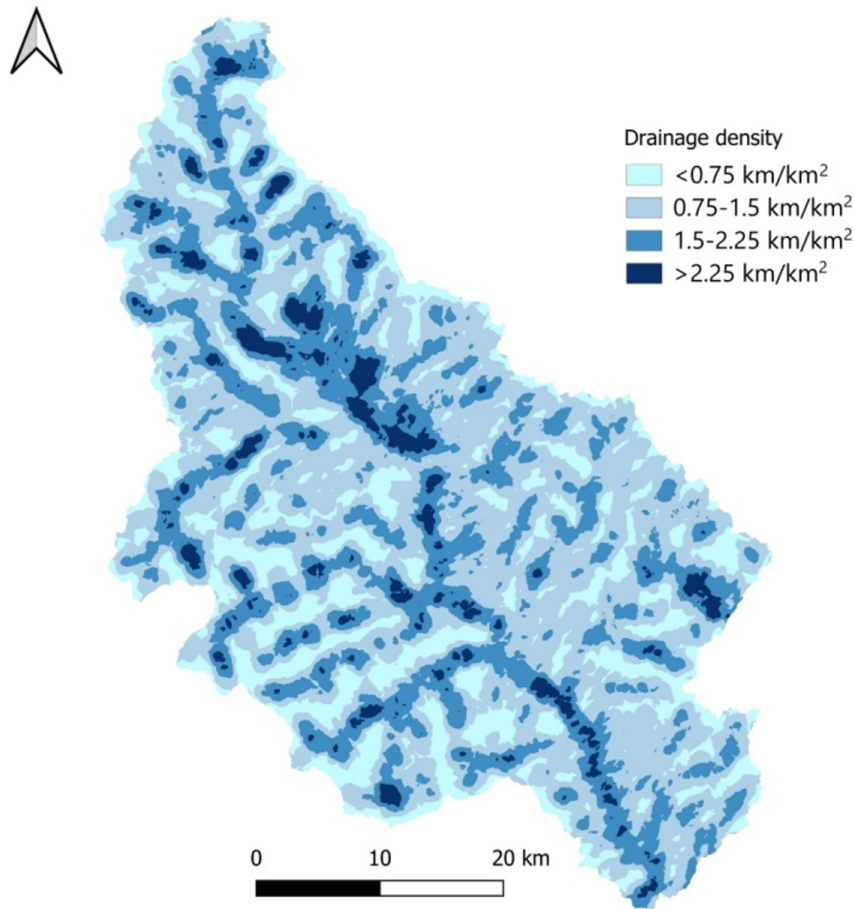


Figure 3.4: Spatial distribution of drainage density across the Ponte Felcino basin

water harvesting (RWH) structures.

Another matter of fact is that the Runoff Coefficient (RC) is inherently dynamic, reflecting a nonlinear relationship between rainfall intensity, infiltration capacity, soil moisture, and evapotranspiration. For example, wet years typically show higher RC values due to saturated soil conditions, whereas dry years exhibit reduced RC values, thereby emphasizing the strong temporal variability of this parameter.

Standard approaches often overlook the temporal variability of the runoff coefficient. They rely more on local runoff values from only a few years or on the average of those values over those years. This limitation becomes critical in the context of climate variability, as dependence on a single normal year can result in misclassifications of the resulting suitability zones.

To overcome these constraints, the proposed study utilizes the BIG-

BANG hydrological database *Braca et al.* [2023], which provides annual and monthly precipitation and runoff estimates for a uniform $1\text{km}/\text{km}^2$ grid across Italy for 72 years, from 1951 to 2022. This temporal coverage facilitates a robust analysis of the inter-annual variability and uncertainty of the runoff coefficient (RC). The runoff coefficient is computed at the pixel scale as the ratio of the runoff volume to the rainfall volume.

Within the AHP framework, the Runoff Coefficient (RC) was assigned the highest criterion weight of $w_R = 0.39$, which implies its dominant role relative to other factors, such as slope and drainage density. Figure 3.5 illustrates the map of runoff coefficients averaged over time for the years 1951–2022, which have been reclassified into 5 suitability classes. Higher weights signify higher runoff coefficients, indicating a greater potential for rainwater harvesting. The values of the runoff coefficient range from 0.1 to 0.5. Table 3.3 summarizes the class boundaries, suitability ranks, and the normalized weights of the classified runoff coefficients.

Thematic Layer	Suitability Classes	Suitability Rank	Criteria Weight	Feature Class Weights	Normalized Weights	Area (%)
RC mean			9		0.39	
	<0.1	Very Low		1	0.04	0.04
	0.1–0.2	Low		3	0.13	7.14
	0.2–0.3	Medium		5	0.22	70.88
	0.3–0.4	High		6	0.26	19.49
	>0.4	Very High		8	0.35	2.45

Table 3.3: Classified spatial distribution of variables runoff coefficient with its criteria and feature class weights for the mean RC 1951–2022 including the area fraction for each class

3.7 Aggregated Runoff

The aggregated runoff AR represents one of the main novelties of this study. Unlike traditional approaches that use the runoff coefficient (RC) as a proxy for runoff at the pixel scale with a zero dimensional approach, the AR integrated approach accounts for the cumulative effects of upstream contributions along flow paths, thus providing a physically consistent estimation of potential at any given location. This improvement is crucial because runoff does not behave as an isolated process; rather, it accumulates progressively as water moves downslope.

The conceptual framework

Aggregated runoff can be conceptualized as an extension of the flow accu-

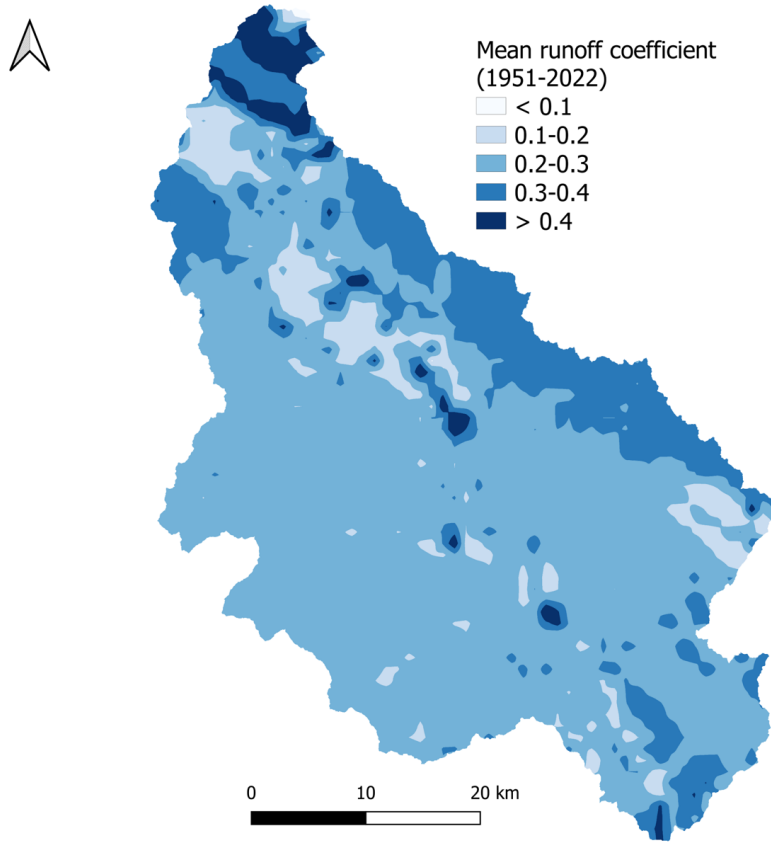


Figure 3.5: Spatial distribution of runoff coefficient (RC) averaged over the 72-year period (1951–2022) across the Ponte Felcino basin

mulation principle, which is commonly used in geomorphological analysis but weighted by runoff volumes rather than by the contributing area. In practical terms, Aggregated Runoff (AR) quantifies the total surface runoff generated within the sub-cavity that drains to a specific cell located downstream. Capturing the hydrological dynamics aligns with the movement of water across cells, which pixel based indicators often ignore. Therefore, this approach ensures that the site located downstream receives more water and is prioritized for Rainwater Harvesting (RWH) applications.

Computational procedures

The computation of the AR involves several steps:

- sink fillings were applied to remove the depressions in the DEM, thereby facilitating proper flow accumulation and streamflow.
- the flow direction in the study area domain is evaluated, this is per-

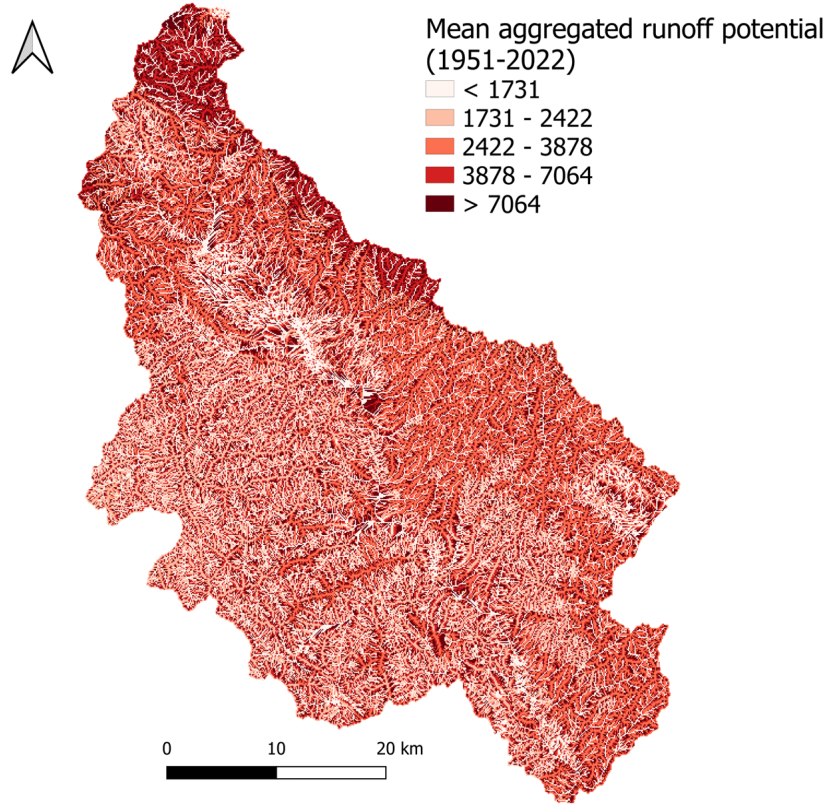


Figure 3.6: Spatial distribution of aggregated runoff (AR) averaged over the 72-year period (1951–2022) across the Ponte Felcino basin

formed using the D8 algorithm *O’Callaghan and Mark* [1984], which assigns each pixel a downslope neighbor among the eight adjacent cells based on the steepest descent criterion.

- the aggregated runoff for a given pixel K was calculated as :

$$AR(x_k, y_k) = \sum_j^{M_k} RF(x_j, y_j) \quad (3.2)$$

where $RF(x_j, y_j)$ denotes the local runoff generated in the cell j and M_k represents the set of all cells upstream that contribute to the closed sub basin at the pixel k . Generally, this procedure replicates flow accumulation but substitutes cell area with runoff volumes, using the monthly runoff estimates provided by the BIGBANG database *Braca et al.* [2023] Figure 2.3 illustrates the conceptual framework of this aggregation process.

Compared to RC, aggregated runoff shows significant spatial variability, mainly driven by the cumulative nature of flow routing and the geomorphological complexity of the watershed basin. The potential of the AR is mainly influenced by the threshold used to delineate hillslopes from channels, which defines the upper boundary of the aggregation domain. This variability precludes the use of standard class boundaries as adopted for RC.

3.7.1 Quantiles based classification

Beyond the reliance on mean values in standard applications, this study introduces the use of quantiles as a key and innovative change in the framework for the classification of aggregated runoff. Quantiles are statistical values that divide a probability distribution into equal intervals. Thus, they provide a comprehensive representation of the underlying variability and value distribution of hydrological variables. The use of averages usually tends to hide the impact of extreme values and simplify the temporal variations into a single average value. However, the use of quantiles makes it possible to clearly identify the different segments of the distribution, such as the median (50th percentile), lower quantiles (10th or 25th percentile), and upper quantiles (75th or 90th percentile). This method of classification is important and is often adopted in hydrological studies. In general, system performance, risk assessment, and optimization are often driven by extreme values. For example, lower quantiles highlight drought conditions or low runoff periods, while higher quantiles represent peak flows that can challenge storage capacity and infrastructure performance. By integrating quantile based analysis, the study moves beyond the conventional average based approaches and introduces a distribution-sensitive framework that accounts for both central tendencies and tail behaviors. The innovative contribution of this work lies in utilizing quantiles not only as descriptive statistics but also as operational tools for decision making and performance evaluation. This approach enables the development of criteria that can withstand variability and extreme events, resulting in a more robust framework for evaluating the Rainwater Harvesting Potential (RWHP) under diverse climate regimes.

Instead, a quantile based classification scoring system was used for classifying AR into 5 classes. Figure 3.6 represents the aggregated runoff map averaged over time for the years 1951–2022. This approach enhances the classification and statistical robustness of the runoff distribution. Hence, it reduces sensitivity to extreme values and ensures a possible comparison between the different hydrological effects of climate change.

The Aggregated Runoff (AR) was assigned the same weight as the Runoff Coefficient (RC) ($w_R = 0.39$), which highlights the dominant role of the Runoff Coefficient in comparison to slope and drainage density. Table 3.4 summarizes the class boundaries, suitability ranks, and normalized weights of the aggregated classified runoff.

Thematic Layer	Suitability Classes	Suitability Rank	Criteria Weight	Feature Class Weights	Normalized Weights	Area (%)
AR mean			9		0.39	
	<1731	Very Low		1	0.04	20
	1731–2422	Low		3	0.13	20
	2422–3878	Medium		5	0.22	20
	3878–7064	High		6	0.26	20
	>7064	Very High		8	0.35	20

Table 3.4: Classified spatial distribution of variables aggregated runoff(AR) with its criteria and feature class weights for the mean AR 1951–2022 including the area fraction for each class

In this study, the cells corresponding to the stream network were excluded from the computation of Aggregated Runoff (AR). This decision reflects a focus on hillslope based Rainwater Harvesting (RWH) structures that intercept surface runoff before it enters the main channel. Therefore, while integrating streamflow into the framework is technically possible, it would require modeling additional hydrological processes, such as subsurface flow and baseflow contributions, and even considering the dynamics of storage elements, which are beyond the scope of this preliminary screening methodology.

3.8 Temporal variability

The temporal variability of precipitation dependent hydrological variables leads to corresponding variations in runoff and aggregated runoff, which can be analyzed at different temporal scales. In this study, both annual and monthly aggregation scales are considered. Therefore, the values used for the calculation of the criteria are based on the monthly and annual averages. The availability of an extensive database with almost 72 years of spatial data provides the basis for a comprehensive assessment of temporal variability and its impacts on the resulting Rainwater Harvesting (RWH) potential value. To establish a reference scenario that represents the average year, the runoff coefficient (RC) and aggregated runoff (AR) data were averaged at the pixel scale over the entire time period, thereby producing an "average year" that reflects the local runoff conditions and serves as a reference dataset. A more

detailed analysis of temporal variability is described in the following chapter.

Chapter 4

Discussion

4.1 Introduction

This chapter of the discussion explains the methodological innovations and the empirical results presented in the work. This chapter highlights the implications for assessing the potential of RWH at the basin scale. The main objective of the study is to address two crucial limitations in conventional GIS based multicriteria approaches: 1) the negligence of the cumulative flow process in runoff estimation, and 2) the minimal representation of the temporal variability of hydrological variables. 3) the limited attention given to the uncertainty of seasonal variability in the existing RWH site selection frameworks.

This study has integrated aggregated runoff (AR) as a new criterion within the AHP framework. This approach further utilizes a 72 year hydrological dataset from the BIGBANG database. Thus, the study provides a physically consistent and temporally robust methodology for the preliminary screening of RWH sites. In this study, variable climatic conditions refer to the variability observed in historical rainfall patterns. This includes the inter-annual and intra-annual fluctuations captured over 72 years. It is important to note that no climate projections or future predictions were used in this study. The analysis is primarily based on the observed historical data. Thus, it is crucial to ensure that the RWH potential evaluation is based on actual past data rather than hypothetical future scenarios.

This section presents a comparative analysis of the Aggregated Runoff (AR) approach in relation to the traditional Runoff Coefficient (RC) method. It aims to interpret the spatial and temporal variability within the study area. Furthermore, the study explores the broader implications for water resource planning in the context of observed rainfall variability.

The analysis will proceed through a detailed comparative assessment of RWHP maps generated using traditional methods and those derived from the aggregated runoff approach. This evaluation will be conducted in an average year, which serves as the reference scenario, followed by an in-depth examination of a dry year and a wet year to capture the extremes of climatic variability.

Subsequently, the study will be extended to include the analysis of different local and basin-scale metrics, investigating their temporal evolution and implications for system performance and planning strategies. This multi-scale and multi-scenario approach provides a comprehensive framework for understanding how runoff potential responds to varying climatic conditions and methodological choices.

Before proceeding with the comparative analysis, it is appropriate to outline some general considerations regarding the methodological framework and the characteristics of the data set. These preliminary remarks will provide context for interpreting the results. The replacement of the runoff coefficient with aggregated runoff represents a fundamental conceptual shift in evaluating the RWH potential. This shift specifically utilizes the local runoff coefficient *Jha et al.* [2014] and *Singh et al.* [2017] as proxies for the runoff indicator. The table provided below shows a comparison of the advantages and disadvantages of Aggregated Runoff (AR) and Runoff Coefficient (RC) in the evaluation of RWH.

Aspect	Aggregated Runoff (AR)	Runoff Coefficient (RC)
Physical Reality	considers upstream runoff distribution along flow paths	considers only local runoff at pixel scale
Spatial truth	prioritizes downslope and valley bottoms where runoff gets concentrate	Wrongly classifies sites with similar properties but at different points along flow paths
Robustness	stable under rainfall variability and less sensitive to extremes climatic conditions	Highly sensitive to annual rainfall changes; value distribution across classes vary between dry and wet years
Data availability	Requires DEM for flow routing and runoff data (e.g., BIGBANG); uses standard GIS tools (D8 algorithm, flow accumulation)	need rainfall and runoff data; simpler to compute but less informative
Limitations	Needs careful threshold assignment for hillslope and stream separation; class boundaries depends on the dataset	Ignores cumulative nature of hillslopes; oversimplifies the hydrological changes with space and time

Table 4.1: Comparison of advantages and disadvantages of Aggregated Runoff (AR) and Runoff Coefficient (RC) for rainwater harvesting potential assessment.

To clarify the scope, assumptions, and transferability of the proposed framework, the following points are highlighted. The proposed framework relies on runoff inputs derived from the BIGBANG hydrological dataset, which provides a runoff dataset for the years 1951 to 2022 and offers spatially distributed runoff estimates based on a physically consistent water balance approach. In this framework, runoff represents the integrated effect of all contributions of liquid water, including rainfall and, where relevant, snowmelt. This enables applicability across different hydrological regimes without requiring explicit process level modeling. A key advantage of the methodology is its ability to capture geomorphology-driven flow accumulation through the Aggregated Runoff (AR) approach, which is combined with a larger dataset and quantile-based classification. This combination enhances its robustness to interannual and seasonal variability and supports transferability across basin scales.

However, the framework remains intentionally simplified and does not explicitly distinguish between runoff sources (e.g., rainfall versus snowmelt) nor does it resolve temporal dynamics such as snow storage and delayed melt processes. Consequently, while it provides a reliable spatial screening tool for identifying runoff concentration and rainwater harvesting potential, its application in strongly seasonal or snow-dominated systems should be interpreted in terms of runoff potential rather than a detailed representation of hydrological processes.

4.2 Advantages of the aggregated runoff criterion

This section provides a detailed explanation of the classification patterns of ρ , computed using both RC and AR , under three representative hydro-climatic conditions: a dry year (2017), a wet year (2010), and the average behavior obtained by averaging the Aggregated Runoff (AR) or Runoff Coefficient (RC) over the 72 years of data from 1951–2022. These scenarios are chosen to represent the influence of rainfall variability on rainwater harvesting (RWH) potential and to assess how each index responds to contrasting hydrological conditions. The comparison offers insights into the stability and distribution of suitability classes across different annual hydrological and temporal scales. This analysis provides practical implications for the planning of RWH structures based on hydrological extremes and average conditions.

Figure 4.1 provides a visual representation of the variability of the runoff coefficient (RC) and the corresponding Rainwater Harvesting Potential In-

dex (ρ_{RC}) under different rainfall conditions. The discussion begins with an analysis of the ρ , which was calculated using the runoff coefficient (RC). The adoption of the BIGBANG dataset allowed for a detailed examination of hydrological dynamics and the temporal variability of rainfall, which directly influences the variability of the runoff coefficient. This coefficient is not a constant value; rather, it varies according to rainfall patterns and soil characteristics, which are affected by processes such as evapotranspiration, infiltration, and storage. Soil properties determine the available runoff through typically non-linear relationships, resulting in significant differences in RC values from year to year.

Figure 4.1 illustrates this variability by comparing two different years: 2017, which was characterized by low rainfall, and 2010, a year marked by high precipitation. Panels (a) and (b) show the runoff coefficient (RC) maps for these years, while panel (c) represents a standard year obtained by averaging RC values during the period 1951–2022. The corresponding annual mean precipitation totals are 670 mm, 1347 mm, and 951 mm, respectively. Panels (dâf) display the predicted ρ_{RC} . In terms of spatial distribution, the dry year (panel a) exhibits pronounced heterogeneity in RC values, largely driven by variations in soil properties and saturation dynamics. In contrast, the wet year (panel b) exhibits a more uniform distribution of the runoff coefficient (RC), likely due to more consistent rainfall and soil moisture conditions. The strong spatial variability observed in 2017 also contributes to greater fluctuations in ρ_{RC} . Comparing these scenarios reveals substantial differences in the potential for rainwater harvesting (RWH), particularly in the western and central regions of the basin. These differences are crucial for identifying optimal sites for implementing rainwater harvesting structures, especially considering their strategic importance during periods of drought.

Regarding influencing factors, ρ_{RC} has reached the highest values near the stream channels due to the gentler slopes, reflecting a clear correlation between slope and ρ_{RC} . Although low slopes are generally more favorable for water retention, their effect can reduce runoff that rapidly returns to streams. Similarly, the drainage density peaks near the watercourses, which can primarily affect areas classified under moderate values of ρ_{RC} .

The aggregated runoff is integrated with the slope; the drainage density in the equation 3.1 is calculated. The results of the aggregated rainwater harvesting potential ρ_{AR} are shown in figure 4.2. The analysis depicts the same set of spatial maps as in the previous analysis described with reference to figure 4.1. The spatial pattern observed in ρ_{AR} exhibits a number of similarities when compared to ρ_{RC} , which was previously described. The zone in the southeastern part of the basin has been confirmed to be less suitable

for RWH harvesting; however, the zones near streams and floodplains are still considered appropriate. The difference between ρ_{AR} and ρ_{RC} is approximately 64% of the total area across all 3 cases. The significance of the results lies in the fact that ρ_{AR} and ρ_{RC} are prepared using the same slope and drainage density, which accounts for a similarity of 35% to the overall index value distribution in these 3 cases.

4.2.1 Dry year scenario

The dry year scenario refers to the year 2017, which had an annual rainfall of 674 mm. The spatial distribution value of the index derived from the Runoff Coefficient (RC) is shown in the 4.1 (panel d), indicating that a greater number of values correspond to the lower suitability classes. In particular, 41% of the basin area falls under the Poor class, while 17% falls under the Very Poor class. This indicates that the RC approach considers the majority of the basin to be unsuitable for rainwater harvesting (RWH). This conclusion arises because this index has a greater sensitivity to the runoff coefficient.

In contrast, (ρ_{AR}) as shown in Figure 4.2 (panel d) for the dry year 2017 illustrates that there is a similar spatial pattern to ρ_{RC} . However, there is a more balanced distribution of index classes. Table 4.2 represents the percentage of area distribution among the classes in the Index layers derived from both the proposed AR and conventional RC approaches. The results show that 31.7% of the area falls under the nearly moderate class and 21.8% under moderate, while the good and very good classes cover a smaller percentage of the area, as mentioned in Table 4.2. This shift in the Index value distribution compared to ρ_{RC} in 2017 demonstrates the capacity of ρ_{AR} to provide a more reliable representation of water availability, even under drought conditions. Down-slope areas continue to benefit from upstream contributions. Thus, they preserve their potential for RWH implementation. Figure 4.2 (panel d) shows that integrating aggregated runoff (AR) with GIS/AHP based applications reduces the higher spatial variability seen in ρ_{RC} .

4.2.2 Wet year scenario

The year 2010 is represented as a wet year. In this year, approximately 1347 mm of annual rainfall was observed. As shown in Figure 4.1 (panel e), the index distribution significantly shifts towards the higher suitability classes during this wet year. The ρ_{RC} results show that 61.9% of the area falls under the moderate classes, while 10.2% falls under the very good classes 4.2. This

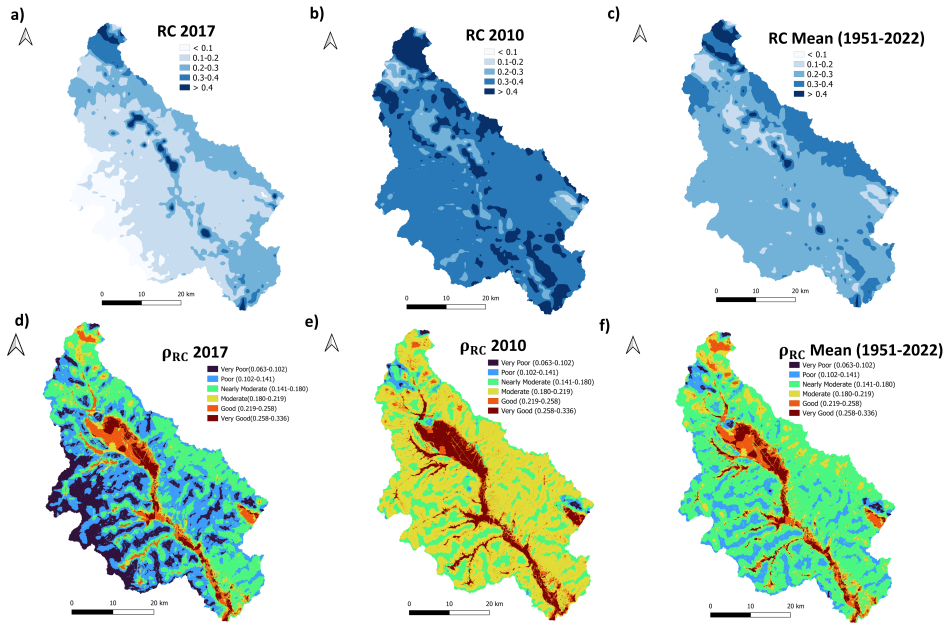


Figure 4.1: The panel (a) shows the reclassified RC for the dry year, 2017, (b) for the wet year 2010 and (c) the time averaged reclassified RC for the years 1951–2022. The panel (d) shows the RWHP index ρ calculated using RC for the dry year 2017, (e) wet year 2010 and (f) the time averaged RWH Potential index using RC for the years 1951–2022.

deviation in the value distribution, compared to the previous case, indicates the sensitivity of ρ_{RC} to temporal variability. Therefore, the index value distribution across the classes can be significantly altered by the rainfall extremes of a single year. For example, classes often shift from very poor to moderate or good during wet years. This adds to the uncertainty in decision making regarding the implementation of RWH systems.

However, Figure 4.2 (panel e) shows that ρ_{AR} maintains a stable distribution of index values between classes. Classes such as nearly moderate and moderate together make up approximately 55% of the total area, as mentioned in table 4.2, with only a small variation in the good and very good classes. This consistency across the value distribution reflects the robustness of the aggregated runoff approach. Therefore, it mitigates temporal fluctuations through flow accumulation and quantile-based classification. The figure clearly indicates that the proposed AR method is less sensitive to the variability of temporal rainfall.

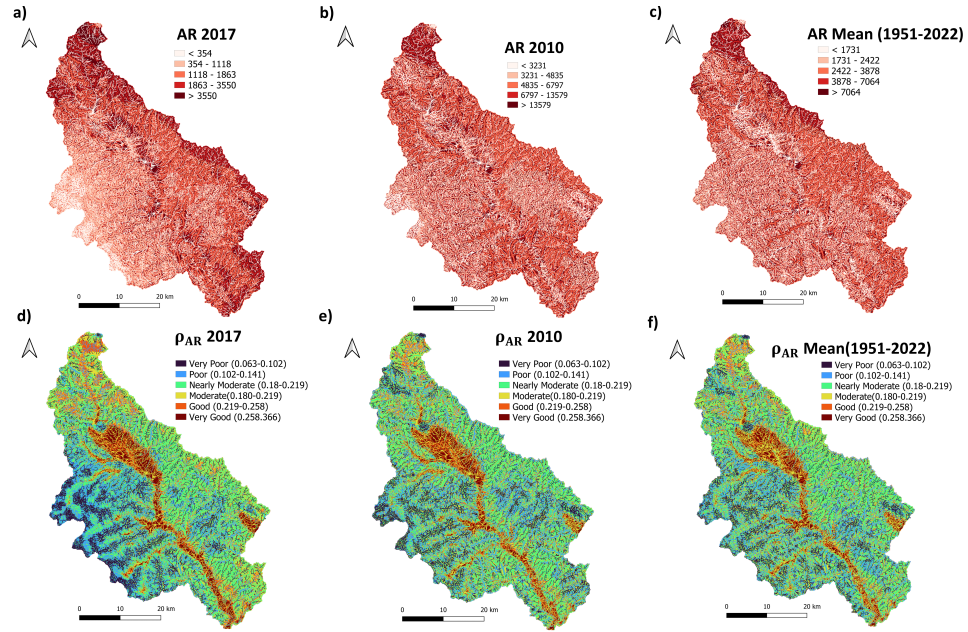


Figure 4.2: The panel (a) shows the reclassified AR calculated using for the dry year 2017 and (b) wet year 2010 and (c) the time averaged reclassified AR for the years 1951–2022, (d) shows the ρ_{AR} calculated using AR for the dry year 2017, (e) wet year 2010 and (f) the time averaged ρ_{AR} using AR for the years 1951–2022.

4.2.3 Average scenario 1951-2022

The index ρ was calculated using time-averaged RC and AR, and the resulting ρ_{RC} and ρ_{AR} are shown in panel (f) of figures 4.1 and 4.2. In this case, ρ_{RC} exhibits a strong concentration of values within the nearly moderate class (59%), with minimal representation in the classes of very good (1%) and very poor (0.6%) classes, as shown in Figure 4.1 (panel e). Although this distribution appears less extreme than those observed for individual years, time-averaged conditions do not necessarily reflect real world cases, particularly in the context where climate change alters rainfall patterns over time. This is critical because the implementation of RWH structures depends on these inter-annual variations.

In contrast, Figure 4.2 (panel e) shows that ρ_{AR} provides a more balanced distribution of index values throughout the study area. Approximately 32.5% of the area falls under the nearly moderate class, 23.8% under moderate, and 13.5% under very poor, with relatively stable representation in the good and very good classes. This pattern confirms that the aggre-

gated runoff approach effectively incorporates geomorphological controls on water availability, thereby reducing spatial variability over time. The table 4.2 below summarizes the three cases and their respective index value distributions as percentages of areas.

Table 4.2: Relative amount of the catchment area in each class as predicted by the two indices ρ_{RC} and ρ_{AR} for the three scenarios presented.

Class	ρ_{RC}			ρ_{AR}		
	2017	2010	Mean	2017	2010	Mean
Very poor	17.3	0.4	0.6	14.9	14.1	13.5
Poor	41.0	1.5	20.5	18.3	18.3	18.3
Nearly moderate	24.4	21.0	59.0	31.7	32.3	32.5
Moderate	7.3	61.9	13.3	21.8	22.9	23.8
Good	7.5	5.0	5.6	7.8	7.7	7.4
Very good	2.6	10.2	1.0	5.5	4.7	4.6

4.2.4 Matched-classification comparison (ρ_{RC} vs ρ_{AR} under quantile based RC and AR)

The figure 4.3 depicts the ρ_{RC} with quantiles (panels a,b,c) and ρ_{AR} with quantiles (panels d,e,f); the latter maps are the same as those in figure 4.2. When RC is classified using quantiles, the distribution of index values across classes becomes more stable across the three scenarios. However, two key differences remain.

First, while the spatial patterns of AR consistently emphasize downslope areas and near-channel hillslopes as higher suitability classes—reflecting the accumulation of upstream contributions through routing. RC classified by quantiles produces broader and less structured mid-range patches when calculating ρ_{RC} . Second, under wet conditions, both indices shift toward higher suitability classes; however, ρ_{AR} maintains a clear gradient from the headwaters to the valley bottoms, while ρ_{RC} exhibits a more homogeneous pattern. Under dry conditions, ρ_{AR} still identifies a limited set of reliable hillslopes, while ρ_{RC} tends to distribute values more uniformly across mid-range classes. These findings indicate that the stability introduced by quantile classification is not the sole factor driving the better performance of AR. Rather, the underlying routing processes embedded in AR generate spatially coherent and hydrologically realistic suitability patterns that

remain informative across varying scenarios.

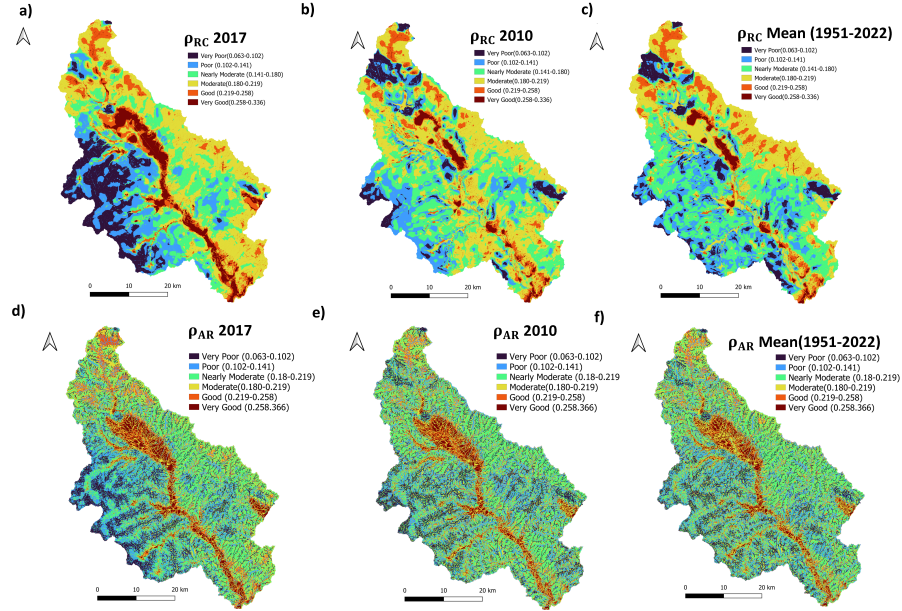


Figure 4.3: The panel (a) shows the quantile based ρ_{RC} for the dry year, 2017, (b) ρ_{RC} for the wet year 2010 and (c) ρ_{RC} for time averaged RC for the years 1951–2022. The panel (d) shows the quantile based, ρ_{AR} for the dry year 2017, (e) wet year 2010 and (f) for time averaged AR for the years 1951–2022

Figure 4.4 provides a close-up view of two representative areas within the basin, illustrating the spatial behavior of the Rainwater Harvesting Potential indices ρ_{AR} and ρ_{RC} under the three different scenarios introduced.

Even when the aggregated runoff maps provide a general understanding of the spatial variability, there is a need for localized analysis to identify the micro-scale variations that affect the practical application of the proposed AR.

To provide a clear illustration of this issue, in this study, three areas with different characteristics have been selected. Zone 1 is located on the midslope of the terrain with moderate drainage density, and zone 2 is situated near a valley bottom that receives cumulative upstream contributions. These differences in the selection of zones help us examine how each index responds to changes in rainfall and flow accumulation at different geomorphic setups. the Figure represents Zone 1 and zone 2 within the study area.

The mean scenario shows the baseline for the RWH planning. Here ρ_{RC} combines towards the mid range categories, which reduces the spatial contrast and potentially limits the accuracy of the potentiality. In contrast, ρ_{AR} maintains variability based on the geomorphic setup, consistently ranking the cells higher while keeping the mid-slope areas within the intermediate classes. For planners, these observations imply that areas with high suitability rankings across all scenarios, such as valley bottoms in Zone 2, should be prioritized for RWH planning, while sites with fluctuating classes could be considered for adaptive RWH applications or even as a supplementary measure to ensure performance under variable conditions.

In 2017 (the dry year), the spatial patterns differ markedly between the indices ρ_{AR} and ρ_{RC} . The ρ_{RC} maps are dominated by poor and nearly moderate classes, particularly in Zone 2, where most cells fall into the very poor category. In contrast, ρ_{AR} reveals scattered patches of higher suitability (Moderate, Good, and Very Good) along the flow paths and valley bottoms, even under drought conditions. This outcome is a direct consequence of the quantile-based classification, which adjusts class boundaries to the specific year. These findings indicate that the aggregated runoff approach captured by ρ_{AR} enables the identification of micro-level zones with rainwater harvesting potential during water-scarce periods. Moreover, dry-year scenarios appear to be better suited for RWH potential classification, as they highlight critical areas where interventions are most needed.

On the other hand, the wet-year scenario (2010) exhibits conditions that closely resemble those of the long-term average year, both in terms of overall suitability and spatial distribution patterns. Beyond the discussion presented and without withstanding the inherent limitations of the proposed framework, figure 4.1 clearly demonstrates that the *AR* methodology enables a significantly more accurate identification of areas most suitable for the implementation of rainwater harvesting structures. This enhanced capability comes from its ability to assess the potential of the available water more effectively than traditional approaches.

4.3 Influence of Slope and Drainage Density on Index Behavior

An important aspect of interpreting the differences between ρ_{AR} and ρ_{RC} is the role of the geomorphological parameters that are common to both

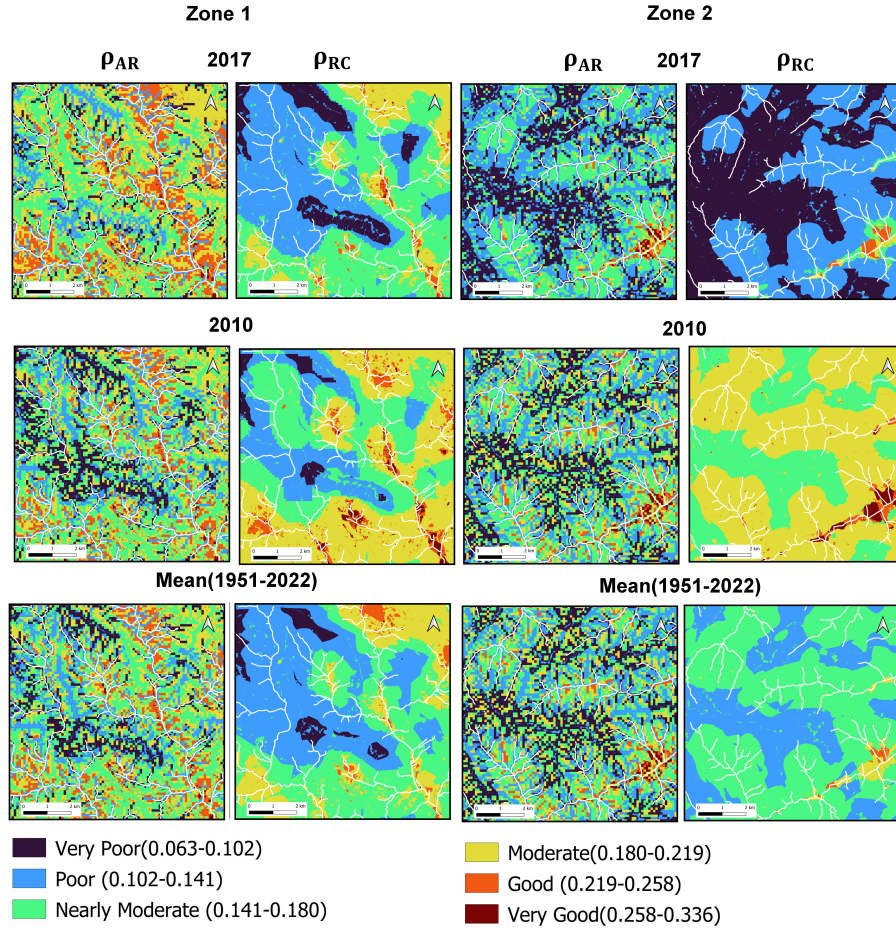


Figure 4.4: Detail of the ρ_{AR} and ρ_{RC} maps for two selected locations. The three series of figure refer to the dry year (2017), the wet year (2010) and the average year (1955–2022).

indices. Since slope and drainage density are employed as a common layer in the calculation of ρ_{AR} and ρ_{RC} , the similarity observed between the two indices is primarily influenced by these two layers.

The slope distribution of the basin, characterized by gentle gradients along valley bottoms and steeper slopes along the Apennine ridges, naturally drives both indices toward similar spatial patterns in these zones. Similarly, the drainage density is higher in the dissected uplands and lower in the alluvial plains, which adds a comparable influence on both ρ_{AR} and ρ_{RC} . Areas with high drainage density tend to accumulate a higher runoff potential in both approaches.

This geomorphological control explains why approximately 35% of the

index value distributions overlap across the three scenarios. This percentage represents the proportion of spatial variability that is not affected by the choice of runoff indicators, specifically Aggregated Runoff (AR) and Runoff Coefficient (RC)); rather, it reflects the underlying terrain structure. In other words, the combined contributions of slope and drainage density establish a stable baseline, upon which the differences introduced by AR become more evident.

By understanding this common geomorphological baseline, the added value of the aggregated runoff criterion becomes clearer. The deviations from this baseline highlight the areas where Aggregated Runoff (AR) captures hydrological processes, such as flow accumulation and the upstream contribution area. These factors cannot be represented by the standard runoff coefficient (RC).

4.4 Effects of inter-annual rainfall variability on ρ

Rainfall variability is a dominant factor that influences the potential for RWH applications; it is often overlooked by conventional GIS/AHP frameworks. Addressing inter-annual rainfall variability remains a critical challenge that standard and commonly adopted approaches often fail to adequately consider. In this study, the temporal behavior of the index over many years is introduced as a primary factor contributing to the complexity of RWH potential assessments. While the previous sections focused on three specific scenarios: dry, wet, and time average, this section broadens the analysis to encompass the entire 72-year observation period (1951–2022). The objective is to capture both the inter-annual and spatial variability of the index, thereby providing a more comprehensive understanding of long-term trends and fluctuations across the study area, while also assessing the implications of using a limited number of years in the analysis. Although rainfall is recognized as the primary climatic driver, its operational influence on ρ indices is mediated by runoff dynamics. Both indices ρ_{RC} and ρ_{AR} respond to fluctuations in rainfall, but in different ways. As defined, RC is computed as the ratio of runoff to rainfall, making it highly sensitive to annual rainfall anomalies. On the other hand, AR is integrated by considering the contribution of runoff to the flow paths.

Statistical parameters and temporal changes are summarized in Figure 4.5, which presents the proportion of catchment areas falling within each suitability class, ranging from very poor to very good, for the two indices ρ_{RC} (based on the runoff coefficient) and ρ_{AR} (based on aggregated runoff) across all years in the time series. Although the figure provides an ag-

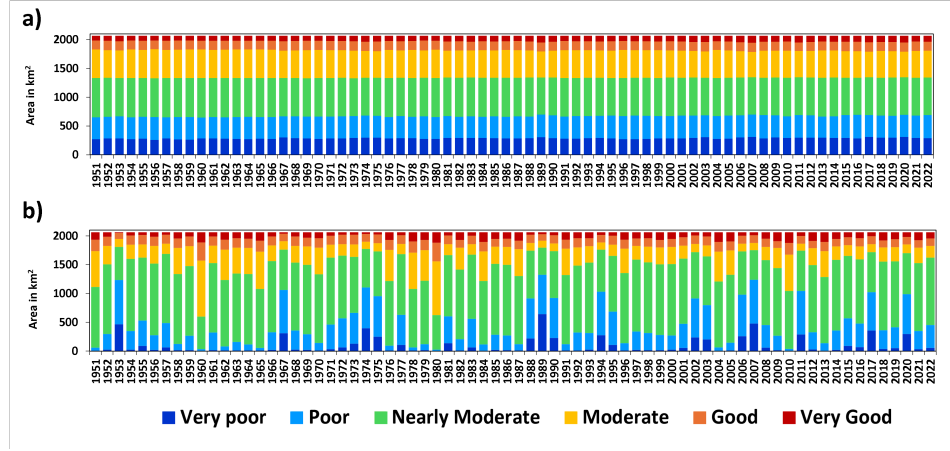


Figure 4.5: Annual based distribution of the catchment area within the 6 classes of the RWHP index by using the proposed aggregate runoff criterion (Panel a) and by using the standard runoff coefficient criterion (Panel b).

gregated representation of basin-wide behavior, previous analyzes suggest that high suitability values are consistently associated with the same spatial zones. The percentages associated with ρ_{RC} are characterized by high temporal variability, with values significantly dependent on the total amount of rainfall. Values may vary by up to tens of units in percentage, particularly for the Moderate class, while the percentage of the Very good class ranges from a minimum of 1% to a maximum of 10%. On the other hand, the area classification by ρ_{AR} shows very stable values, identifying 4% of the catchment area as Very good. The stability of the values indicates a reduction in uncertainty regarding the selection of areas for the implementation of RWH structures; this feature renders the new index particularly suitable as a tool for planning basin management policies and optimizing the allocation of economic resources.

In figure 4.6, an additional analysis of the time variability of ρ_{RC} (shown as the orange line) and ρ_{AR} (shown as the blue line) is presented. Panels (a) and (b) illustrate the spatial statistics of the RWHP index, including average values and the coefficient of variation of the indices. In processing the first two graphs, the index values have not been reclassified; they are those obtained from Equation (3.1). When examining the average values, the indices at the catchment scale are very similar (approximately 0.18), corresponding to a range from nearly moderate class to moderate range. Both indices evolve over time, reflecting the variability of annual rainfall, with a higher variation associated with ρ_{RC} ; the analysis of mean values is

of little significance and will not be discussed further. More interestingly, the temporal variability of the indices is demonstrated by the coefficient of variation in panel (b). In general, the spatial variability of ρ_{RC} is greater than that of the corresponding ρ_{AR} ; this result must be interpreted as indicating a higher resolution and sensitivity of ρ_{AR} , which incorporates more information than ρ_{RC} , rather than as a lack of robustness of the index. In fact, ρ_{AR} is characterized by a higher degree of robustness, as reflected in the greater stability of the observed coefficients of variation across different years.

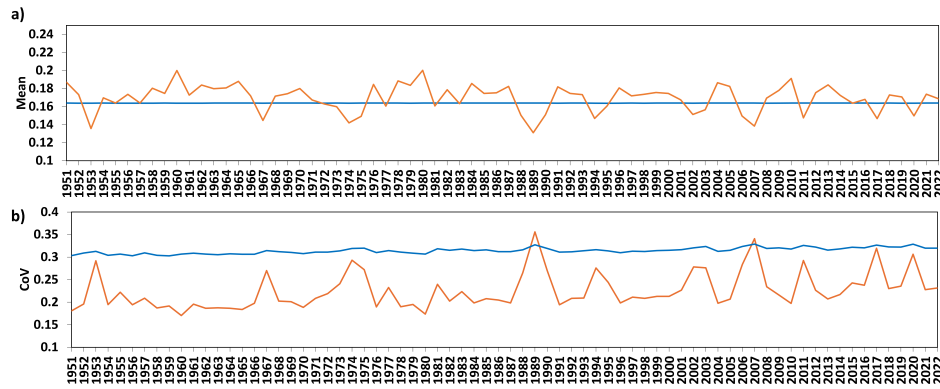


Figure 4.6: Annual based spatial statistics (Panel **a** average values, Panel **b** coefficient of variation) of the RWHP index ρ by using the proposed aggregate runoff criterion (blue line) and by using the standard runoff coefficient criterion (orange line).

4.5 Effects of intra-annual rainfall variability on ρ

The Inter-annual rainfall variability and its effect on the index, as discussed in the previous subsection, continue to challenge the idea that the variability in the annual time averaged case may not represent the real situation. Furthermore, rainfall variability occurs over much smaller time frames, such as months and even smaller scales like days. This challenge is addressed by extending the analysis from interannual to intraannual or seasonal rainfall variability. The Ponte Felcino basin exhibits a Mediterranean climate, with seasonal rainfall changes being highly uneven; winters are wet, whereas summers are very dry, leading to a sharp difference in water availability. This high variability poses a challenge to the robustness of the RWH potential indices because runoff generation varies significantly with rainfall volumes. On a monthly scale, there are clear transitions between high and low suit-

ability classes; therefore, the classes remain less stable over time compared to the inter-annual time scale.

In this study, the BIGBANG monthly dataset is utilized, consisting of 864 months of rainfall and runoff data. Therefore, the aggregated runoff and runoff coefficient are calculated for all monthly datasets. In addition to the slope and drainage density constants, the ρ is calculated for all years. Figures 4.7 and 4.8 illustrate the comparison of the intra-annual spatial variability of both indices: panel a ρ_{AR} and panel b ρ_{RC} , applying the same figure styles and methodological approaches previously used at the annual scale.

The runoff coefficient is characterized by seasonal variability. In the Mediterranean climate, the wetter winter months are associated with high runoff coefficients, resulting in elevated RC values. In contrast, the drier summer months are characterized by very low runoff coefficients. This periodicity is evident in the Rainwater Harvesting Index (ρ), which is calculated using the runoff coefficient (Panel b) and displays an oscillation with an annual cycle. Furthermore, since the RC value is highly sensitive to rainfall changes, panel b shows a greater variation in value distribution across suitability classes. During rainy months, the value of the index predominantly falls within the moderate, good, and very good classes, which significantly increases; however, the value distribution across the poor and very poor classes remains very low. In contrast, during the drier months, the index value distribution changes inversely, with the very poor class occupying most areas of the basin, while higher suitability classes, such as very good, nearly disappear. The oscillation of ρ_{RC} should not be interpreted as providing additional information about the months with higher productivity; this observation is quite evident and should ideally be filtered by runoff aggregation processes. Instead, it must be regarded as an indication of the extremely high sensitivity of the index to the chosen criterion. This disruptive change indicates that the index ρ_{RC} demonstrates the sensitivity of the index to rainfall variability and seasonal extremes, thereby reducing its reliability in planning for RWH.

In contrast, ρ_{AR} , shown in panel a, exhibits different behavior: the distribution of index values between classes remains nearly uniform throughout all 864 months. The nearly moderate and moderate classes consistently account for most of the basin area, while the very poor and very good classes are confined to specific zones throughout all years. This stability indicates that the AR-based index effectively mitigates the impact of short-term rainfall fluctuations while preserving its inherent characteristic of assigning higher suitability to valley bottoms for rainwater harvesting. This stability can

be attributed to both the underlying criterion of aggregated runoff and the quantile-based classification approach.

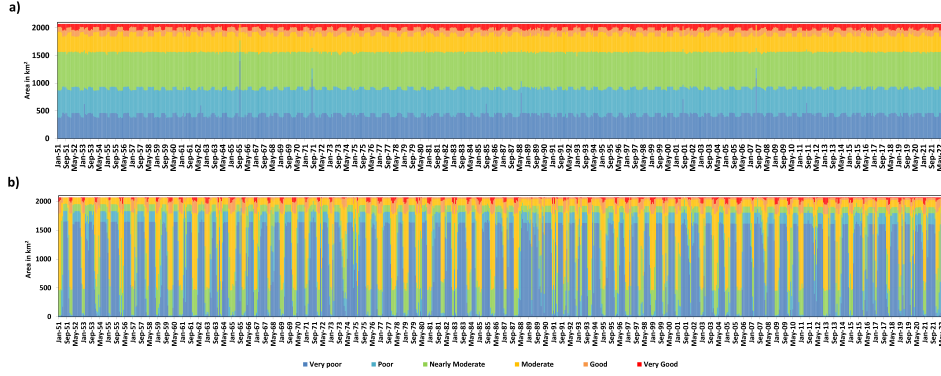


Figure 4.7: Monthly based distribution of the catchment area within the 6 classes of the RWH index ρ by using the proposed aggregate runoff criterion ρ_{AR} (Panel a) and by using the standard runoff coefficient criterion ρ_{RC} (Panel b).

Spatial variability analysis, conducted on a monthly scale, is comparatively performed for both ρ_{RC} and ρ_{AR} for the years 2010 and 2017, which represent two hydrological extremes: a dry year and a wet year, as shown in the previous section within an annual timeframe. In this subsection, the years 2010 and 2017, characterized as a dry year and a wet year, respectively, are examined in further detail at the monthly scale. The figure 4.8 illustrates that the distribution of index values for ρ_{RC} among the classes changes accordingly on a monthly basis. In 2010, the months of January and February demonstrate a balanced distribution of index values, with a significant area classified as moderate and good classes. However, as the year progresses into summer, particularly in June and August, the distribution of values changes abruptly, resulting in the dominance of the very poor and poor classes, indicating heightened sensitivity. This change is particularly evident in 2017. From March onward, the very poor classes occupy more than 60% of the basin, while in January, February, and December, there is negligible distribution of moderate and good classes. As expected, the index value distribution of ρ_{AR} remains stable across the classes in both 2010 and 2017.

Figure 4.9 illustrates the monthly spatial distribution of rainwater harvesting potential, calculated using the Runoff Coefficient (RC) and the aggregated runoff for the dry year 2017 and the wet year 2010. Panels a and c display ρ_{RC} , while the right panels, b and d, represent ρ_{AR} . Each panel

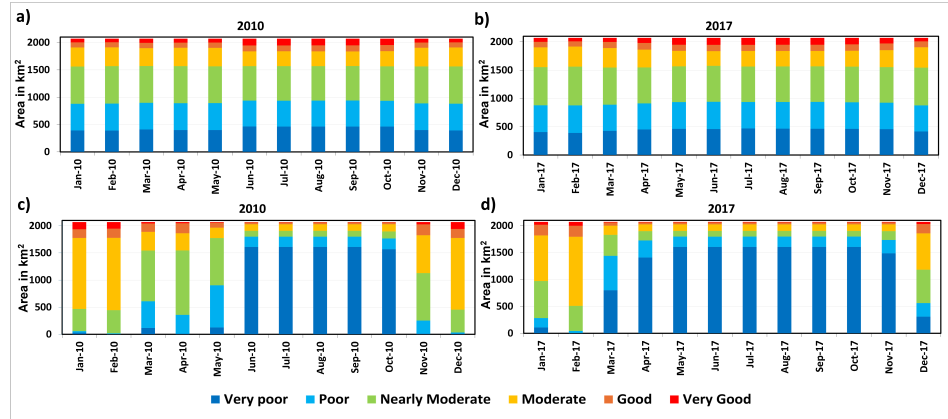


Figure 4.8: Analysis of effect of temporal rainfall variability on the index in of two seasonal extreme years on the years 2010 and 2017 based on ρ_{AR} (panels a, b) and ρ_{RC} (panels c, d)

features index maps showing data from January to December, facilitating a detailed comparison of seasonal variability.

In panels a and c, ρ_{RC} maps show a strong sensitivity to fluctuations in rainfall, demonstrating an increase in areas categorized as having very poor and poor suitability during the dry months. During the wet months, the value distribution shifts towards higher suitability classes, such as very good, good, and moderate. This finding indicates a high runoff, particularly noted during the wet year of 2010 (panel c). A sharp contrast is observed in the value distribution during the monthly extremes when comparing both years, 2010 and 2017.

On the other hand, panels b and d represent the spatial behavior of ρ_{AR} , which displays a smoother gradient along the flow paths; the monthly variability is evident in both cases. However, there is stability in the index along the hillslopes over the months.

This observation explains that when using the ρ_{RC} seasonal extremes, whether prolonged drought or intense rainfall, the index value can shift directly from poor to good or vice versa within a few months. This analysis reinforces the previously presented findings and once again confirms the consistency and validity of the new index.

The figure 4.10 shows the two statistical parameters: mean (a) and coefficient of variation (CoV) (b) for the indices ρ_{RC} (shown as an orange line) and ρ_{AR} (shown as a blue line). Panel a indicates that the mean values of the index ρ_{RC} fluctuate sharply between 0.10 and 0.23, forming a clear cyclical pattern that reflects seasonal rainfall variability. The peaks represent the

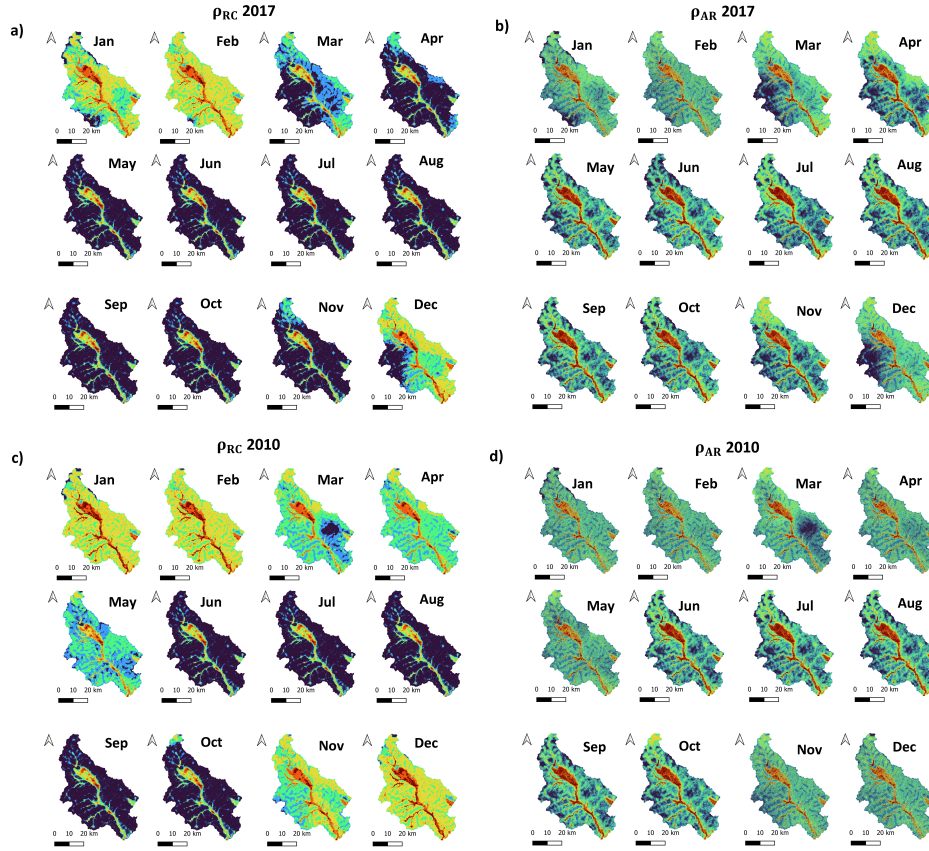


Figure 4.9: Seasonal variability of RWHP index ρ based on runoff coefficient ρ_{RC} and aggregated runoff ρ_{AR} for 2017 (dry) and 2010 (wet). Panels (a, c) shows ρ_{RC} ; panels (b, d) shows ρ_{AR} , from January to December.

rainy months, while the dips correspond to the drier months, demonstrating the index's sensitivity to rainfall variability. In contrast, the mean values of ρ_{AR} remain constant within the range of 0.15 to 0.18, further confirming the stability of the index.

Panel b) shows the coefficient of variation, which measures the relative variability of the index. The ρ_{RC} (orange line) indicates more frequent value spikes within the range of 0.10 to 0.5 or even higher; values increase more during the drier months and decrease during the rainy months. In contrast, the ρ_{AR} (blue line) index exhibits stable values around 0.35, with only minor fluctuations. Together, these statistical parameters illustrate the fundamental differences in the behavior of the index.

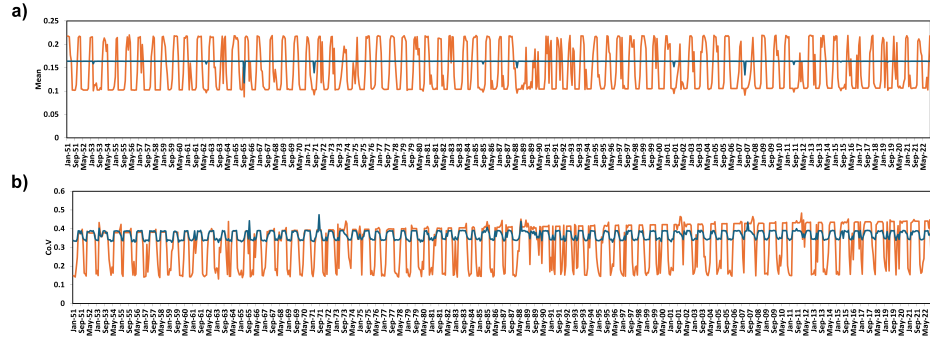


Figure 4.10: Monthly based spatial statistics (Panel **a** average values, Panel **b** coefficient of variation) of the ρ by using the proposed aggregate runoff criterion (blue line) and by using the standard runoff coefficient criterion (orange line).

4.6 Uncertainty and Cumulative distribution function (annual and seasonal scale)

In the evaluation of rainwater harvesting potential indices, uncertainty analysis plays a key role, primarily in determining the robustness of methodological improvements. This analysis is crucial because it quantifies the spatio-temporal variability of the indices. Both inter-annual and intra-annual analyses of the index reveal distinct modes of uncertainty. Variable climatic conditions affect the annual average values; however, seasonal fluctuations in index values introduce instability on shorter timescales. Empirical cumulative distribution functions (CDF's) were used to elucidate the varying conditions of the index at the pixel level. CDFs were computed for the selected pixels from each class based on the time averaged index ρ_{RC} from the 1951–2022 inter-annual scale, which provides the probability distribution of index values over this timeframe.

Uncertainty arises from the changes in rainfall and runoff patterns from year to year on an annual scale. Figure 4.11 shows the empirical frequency curves for 6 pixels associated with the sample of local values ρ_{RC} and ρ_{AR} , which were obtained over a period of 72 years, from 1951 to 2022. A pixel sample is randomly chosen from each class based on the average year. Empirical frequency analysis was then performed for the unclassified values, as indicated in Equations 2.1 and 3.1. The finite number of values that ρ_{RC} and ρ_{AR} can assume is reflected in the discrete distributions shown in Figure 4.11. Focusing on panel (a), It is observed that each pixel is characterized by a certain variability of ρ_{RC} , implying that the classification score of

the analyzed pixel is not unique but depends on the specific year. There is also an observation that the pixel classified as Moderate according to the potential ρ_{RC} changes its score to Very good when considering the new classification based on aggregated runoff. In contrast, the pixel classified as Good shifts to the moderate class. Variability is much less pronounced in the same analysis conducted for ρ_{AR} , as depicted in panel (b), where a very low level of variability is observed; this variability transforms into a deterministic value for sites with higher scores. In other words, the runoff coefficient (RC)-based index ρ_{RC} is characterized by a wider dispersion of value distribution on an annual scale, signifying that the index values shift across the classes depending on the year analyzed. This variability is further supported by the previously mentioned statistical parameter, the Coefficient of Variation (CoV), which often exceeds 0.5, indicating a high level of instability over time. The Aggregated Runoff (AR)-based ρ_{AR} shows narrower cumulative distribution function (CDF) curves and CoV values, suggesting that aggregated runoff controls abrupt deviations within the class distribution. Although both indices respond to rainfall variability, the degree of uncertainty differs markedly between them, with ρ_{AR} providing a more contained probability distribution.

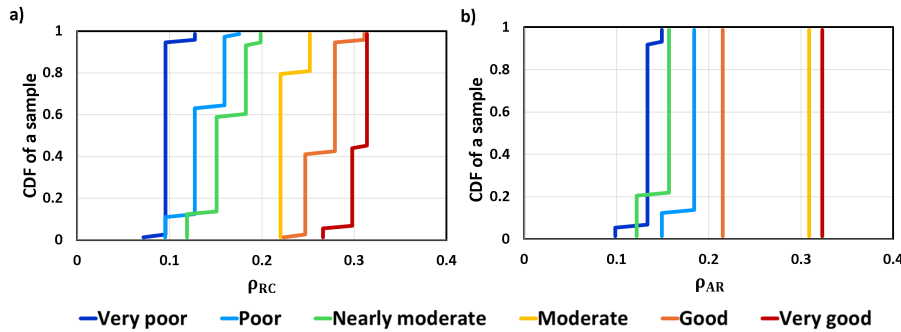


Figure 4.11: Distribution of RWHP index ρ values across non classified RWH potential ρ index maps (a) using RC and (b) AR in a inter-annual scale

The analysis was also extended to a monthly scale, as represented in Figure 4.12. Seasonal variability introduces an additional layer of complexity to the assessment of RWH potential indices. The cumulative distribution function (CDF) analysis conducted at a monthly resolution demonstrates that the runoff coefficient (RC)-based index, ρ_{RC} , is highly sensitive to short-term rainfall fluctuations. This sensitivity manifests as widely spaced

CDF curves that correspond to rapid shifts in suitability classes between wet and dry months.

For example, during the summer, the probability of a pixel being classified as *very poor* can increase to 0.6; whereas, in the winter, the same pixel demonstrates a high probability of being classified under *the moderate* or *good* categories. This pronounced deviation suggests that utilizing RC-based indices for selecting the RWH site could result in significant changes within a single year, thereby complicating the planning and prioritization processes.

In contrast, the AR-based index, ρ_{AR} , maintains relatively stable cumulative distribution functions (CDF's) throughout the months, particularly within high-suitability classes such as *very good*, *good*, and *moderate*.

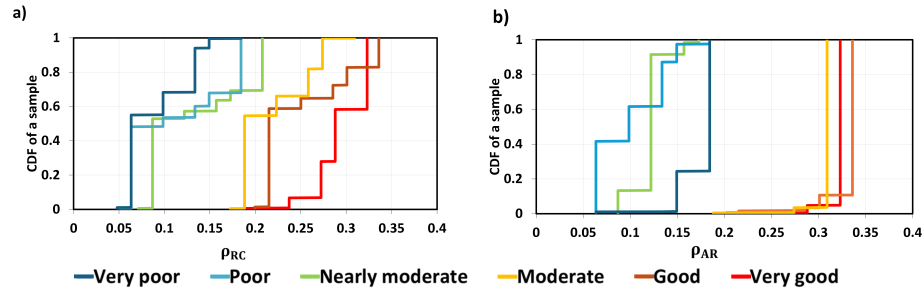


Figure 4.12: Distribution of RWH index ρ values across non classified RWH potential index ρ maps (a) using RC and (b) AR in a intra-annual scale

4.7 Assumptions and Limitations of the Proposed Framework

The proposed methodology is subject to several assumptions and limitations that are important for interpreting its applicability and guiding future developments.

First, the framework is based on a naturalized representation of runoff. This representation means that human interventions, such as reservoirs, abstractions, irrigation systems, and environmental flow requirements, are not explicitly considered. As a result, the derived rainwater harvesting (RWH) suitability maps should be interpreted as indicators of inherent hydrological

potential rather than as representations of actual water availability.

Second, the Aggregated Runoff (AR) criterion, derived from the flow routing of BIGBANG runoff, represents an integrated response of liquid water contributions, including rainfall and, where relevant, snowmelt. However, it does not explicitly distinguish between runoff sources or resolve processes such as snow accumulation, delayed melt, and temperature-dependent dynamics.

Furthermore, the transferability of the framework across spatial scales depends on the type of RWH intervention considered. AR-based suitability is most directly applicable to small-scale structures (e.g., check dams, farm ponds, and percolation tanks), where hydrological responses are governed by local hillslope connectivity and short-range upstream contributions.

In contrast, for large reservoirs or regulated basins, where storage dynamics and operational controls significantly modify flow regimes, this approach may not fully capture the system's behavior and should, therefore, be applied with caution.

Despite these limitations, the methodology remains a robust spatial screening tool and offers strong potential for replication due to its low data requirements and its physically consistent basis. Future developments could enhance its realism through the integration of water management data and operational rules; however, such extensions would require detailed information that is not currently included in this study.

4.8 Transferability under Variable Conditions: Simeto Basin (Sicily)

This section evaluates the transferability of the proposed RWH potential index using aggregated runoff. The same classification scheme used for the Ponte Felcino basin was applied to the Simeto basin to ensure methodological consistency. The objective of this section is not to rewrite the methodology but rather to evaluate its performance across various climatic and geographic settings. Although the Ponte Felcino Basin is characterized by a humid Mediterranean climate with a relatively even rainfall distribution, the Simeto Basin exhibits pronounced seasonal fluctuations, including frequent

droughts and short term heavy rainfall events that often lead to pluvial flooding. These characteristics make the Simeto Basin an appropriate case study for evaluating the robustness of the proposed approach. Accordingly, the evaluation is carried out at a monthly temporal resolution to explicitly capture seasonal variability and assess its influence on the stability and consistency of the index outcomes.

4.8.1 Basin hydrology and geology

The Simeto River Basin is the largest drainage system in Sicily. The river originates in the Nebrodi Mountains, flows along the western flank of Mount Etna, and crosses the Holocene Catania Plain before reaching the Ionian Sea, draining more than 4,000 km² of central-eastern Sicily *Di Stefano et al.* [2013]. Its catchment includes both the sedimentary units of the Sicilian–Maghrebian chain and, to a lesser extent, the volcanic rocks of Etna. Geologically, it forms part of the Gela–Catania foredeep, a tectonically controlled basin composed of Upper Pliocene–Quaternary marine sediments with volcanic intercalations. This basin is bordered to the north by Pleistocene terrigenous deposits from the Terreforti hills and is locally influenced by the volcanic basement of Mount Etna. This basin is also bordered to the north by Pleistocene terrigenous deposits of the Terreforti hills and is influenced locally by the volcanic basement of Mount Etna.

4.8.2 DEM, Slope and Drainage Density

Figure 4.13 presents the digital elevation model of the Simeto Basin, along with the extracted stream network derived from the MERIT DEM dataset *Yamazaki et al.* [2017]. This figure highlights the strong topographic gradient associated with Mount Etna, which reaches a maximum elevation of 3278 m in the northeastern part of the basin. Figure 4.14 shows the reclassified slope and drainage density layers derived from the same DEM, utilizing standard GIS tools. The slope percentage values range from 0 to 77%, while the drainage density varies between 0 and 4.1 km/km². As described in the chapter on application example of Ponte Felcino basin, the slope classes were categorized based on their potential to promote runoff retention, while the drainage density was classified according to its role in contributing to runoff concentration.

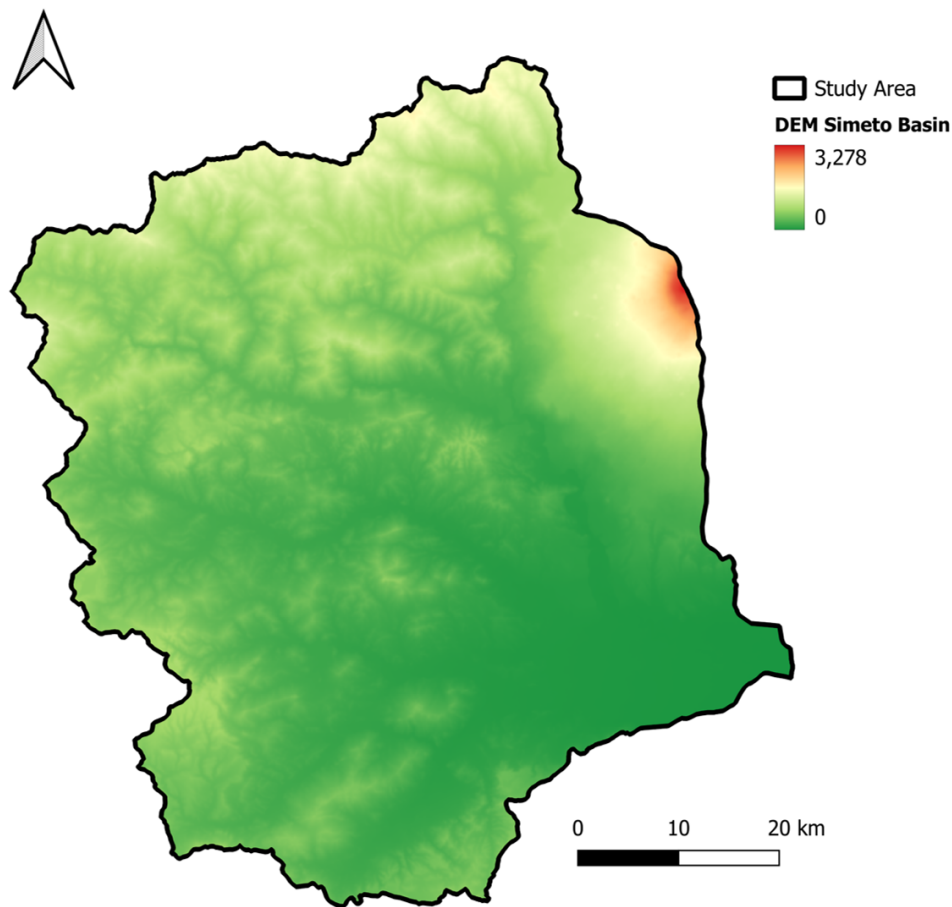


Figure 4.13: DEM of Simetto basin

4.8.3 Aggregated Runoff and Runoff coefficient

Figures 4.15 Panels a and b illustrate the aggregated runoff and the runoff coefficient utilized for the Rainwater Harvesting (RWH) potential index maps for the Simetto basin in Sicily during January 1951. The aggregated runoff is classified into quantiles to assess the temporal stability of the index, while the runoff coefficient is categorized according to the standard method of equal intervals. The resulting index maps are presented in panels c and d. the computation was conducted for the time period from 1951 to 2022, utilizing all rainfall runoff data from the BIGBANG database.

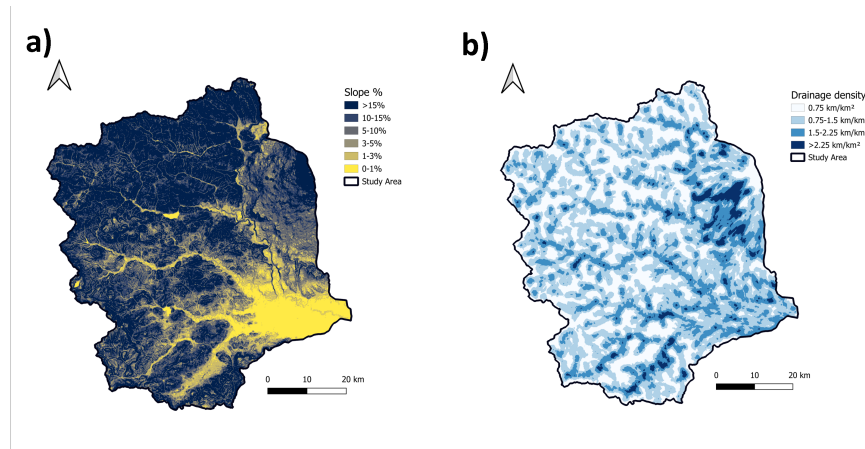


Figure 4.14: a) Reclassified slope percentage map of Simetto basin and b) drainage density map of Simetto basin

4.8.4 Evaluation results for Simeto basin in comparison with Ponte Felcino

The comparison between the Ponte Felcino and Simeto case studies provides important insights into the transferability of the proposed methodology. While both basins are predominantly rainfall-driven, the Simeto Basin exhibits more pronounced runoff variability due to its steeper terrain, volcanic lithology, and strong seasonal contrasts. These factors promote episodic and flashy hydrological responses. This observation is clearly reflected in the results, where a greater degree of variability is noted compared to the more stable behavior identified in the Ponte Felcino basin.

In particular, the influence of intermittent rainfall patterns and seasonal droughts introduces noticeable fluctuations in the suitability index within the Simeto Basin, as evidenced by the temporal analysis.

However, when compared to the conventional runoff coefficient-based index (ρ_{RC}), these variations remain significantly less pronounced. As illustrated in Figure 4.16, ρ_{RC} exhibits substantial instability between wet and dry periods, as it frequently reclassifies the same locations across suitability classes in response to short-term variations in rainfall and soil moisture conditions. In contrast, while ρ_{AR} is not entirely invariant, it maintains a more consistent spatial prioritization of hydrologically relevant areas, particularly along hillslopes and in valley bottoms.

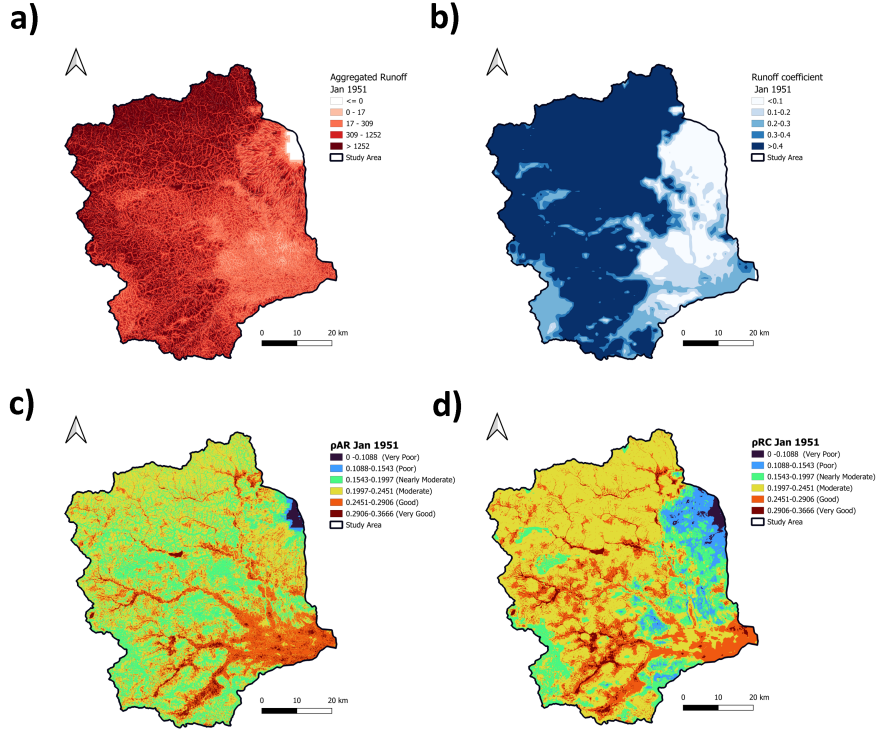


Figure 4.15: a) shows the aggregated runoff AR b) shows the runoff coefficient for the Jan 1951 and c) and d) shows Spatial distribution of ρ_{AR} vs ρ_{RC} on Jan 1951

Overall, these results suggest that, while the proposed framework demonstrates good transferability to basins characterized by high rainfall variability, its performance should not be interpreted as uniformly stable across all conditions. Instead, the methodology provides a comparatively more robust and physically consistent representation of runoff potential than traditional approaches, particularly under conditions of temporal variability and hydrological extremes. Extending the framework to snow-dominated or mixed-regime basins would, nevertheless, require additional considerations, including meltwater timing, temperature-driven processes, and delayed runoff dynamics, which are not explicitly represented in the current formulation.

The monthly CDF analysis for the Simeto Basin (Figure 4.17) further highlights the differences in temporal behavior between the two indices. At this finer temporal resolution, ρ_{RC} shows a strong sensitivity to short-term

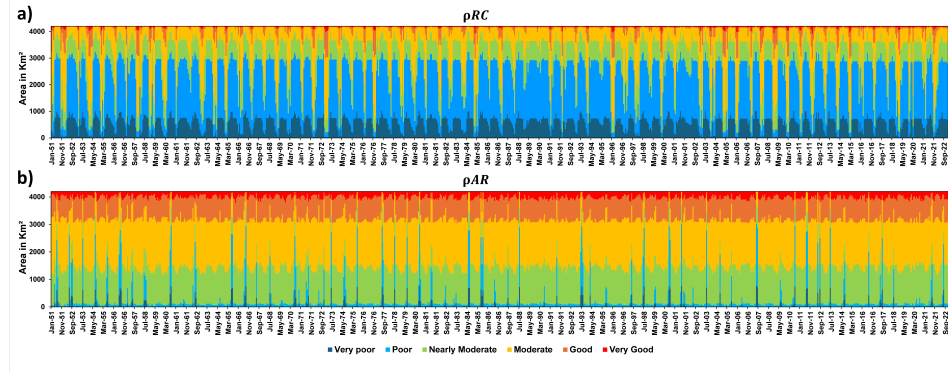


Figure 4.16: Panels shows Spatial distribution of ρ_{AR} vs ρ_{RC} across Jan 1951 to Dec 2022 (area fractions by class).

rainfall variability, with widely dispersed CDF curves and frequent shifts toward lower suitability classes. This behavior reflects a high degree of intra-annual instability at the pixel scale. In contrast, ρ_{AR} exhibits a comparatively lower degree of dispersion, with CDFs that remain more closely grouped over time. However, unlike in the Ponte Felcino basin, the CDFs in Simeto are not fully overlapping, indicating that some variability persists due to the highly episodic rainfall regime and seasonal drought conditions. These patterns suggest that, while aggregated runoff reduces short-term fluctuations, it does not entirely eliminate variability under more extreme hydro-climatic conditions.

The Aggregated Runoff (AR) criterion is particularly suitable for decen-

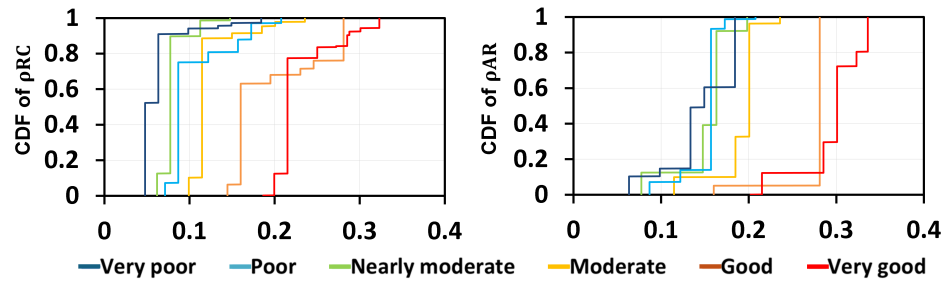


Figure 4.17: Distribution of RWH index ρ values across non classified RWH potential index ρ maps (a) using RC and (b) AR in a intra-annual scale

tralized, hillslope-scale Rainwater Harvesting (RWH) interventions. such interventions include farm ponds, check dams, percolation tanks, and infiltration structures, which are primarily governed by short-distance upslope

runoff contributions. In both case studies, AR consistently identifies these areas as suitable locations. However, for larger storage infrastructures, in which baseflow, groundwater contributions, and regulated releases play a more significant role, the simplified representation adopted in this framework may not fully capture the governing hydrological processes. In this context, the exclusion of stream channels, while appropriate for hillslope-focused applications, may require refinement when the objective is to assess in-channel storage or regulated systems.

The application of the framework to the Simeto Basin provides a valuable test of its transferability under high rainfall variability. While the methodology continues to perform consistently in identifying hydrologically relevant zones, a higher degree of temporal variability is observed compared to the Ponte Felcino basin. This indicates that the approach is adaptable across different settings; however, its performance is influenced by local hydro-climatic characteristics, particularly in basins affected by strong rainfall intermittency and drought cycles. Therefore, the transferability of the framework should be interpreted in a relative sense, acknowledging both its strengths and its sensitivity to basin-specific dynamics.

Despite the improved temporal consistency of the Aggregated Runoff (AR)-based index relative to conventional approaches, both basins exhibit deviations during periods of prolonged drought. These conditions reduce overall runoff generation and can temporarily limit the discriminatory capacity of the index across suitability classes. This highlights the importance of considering climate extremes, particularly drought stress, when applying AR-based suitability maps for planning purposes.

Overall, the results demonstrate that the proposed framework offers a more robust and physically consistent representation of runoff potential compared to traditional runoff coefficient-based methods, particularly under conditions of temporal variability. At the same time, the analysis clearly indicates the conditions under which its performance may be reduced, emphasizing the need for careful interpretation and, where necessary, the integration of additional hydrological or management factors in future applications.

Chapter 5

Conclusions

This dissertation advances the assessment of rainwater harvesting (RWH) potential by introducing the concept of *aggregated runoff* (AR) within AHP/GIS-based site selection frameworks. The central idea is that the water available at a potential site depends not only on local runoff but, more importantly, on the accumulated upstream contributions, which increase along flow paths as a function of basin geomorphology and flow connectivity.

The identification of optimal locations for RWH structures requires robust and integrated decision support tools capable of incorporating hydrological, technical, and socio-economic factors. Within this context, GIS-based Multi-Criteria Analysis (MCA) frameworks, particularly those based on the Analytic Hierarchy Process (AHP), have been widely adopted. However, conventional approaches exhibit two critical limitations: (i) the neglect of horizontal water fluxes and upstream runoff contributions, and (ii) the limited representation of temporal rainfall variability and its impact on suitability outcomes. As a result, these frameworks often rely on local indicators, such as the runoff coefficient (RC), which may not adequately capture the spatial dynamics of water availability.

To address these limitations, this study introduces Aggregated Runoff (AR) as a primary hydrological criterion, replacing the standard local runoff proxy. The Aggregated Runoff (AR) integrates key geomorphological factors, such as slope and drainage density, and is implemented using standard GIS-based flow routing procedures. This approach produces spatially explicit suitability maps that can be seamlessly incorporated into AHP/GIS frameworks, enabling basin-scale analysis without increasing computational complexity or adding data requirements. As a result, this methodology enhances both the physical realism and robustness of RWH potential assessments.

Another key innovation of this work is the adoption of a quantile-based classification system for Aggregated Runoff (AR), which significantly improves the stability of the Rainwater Harvesting Potential Index (ρ) by adapting class thresholds to the spatial distribution of runoff values. This approach reduces sensitivity to rainfall variability and ensures more consistent classification over time and across different basins.

The methodology was applied to the Ponte Felcino basin (Tiber River) and benchmarked against a conventional RC-based approach. Furthermore, to evaluate its applicability under contrasting hydro-climatic conditions, the framework was applied to the semi-arid Simeto Basin (Sicily), with analyzes conducted at a seasonal (monthly) resolution. This dual application enables both validation and assessment of transferability.

The main findings of this work can be summarized as follows:

(i) Spatial redistribution of Suitability : The integration of Aggregated Runoff (AR) significantly modifies the potential maps for Rainwater Harvesting (RWH). It increases suitability in downslope and valley-bottom areas while reducing suitability in ridge-top and locally confined zones. This redistribution reflects the processes of upstream runoff accumulation, which cannot be captured by local indicators.

(ii) Improved screening performance : The AR-based approach enhances the identification of hydrologically relevant areas for RWH implementation by aligning classification with effective catchment-scale water availability rather than relying on point-scale proxies.

(iii) Enhanced robustness through quantile classification : The use of quantile-based thresholds stabilizes suitability classes and reduces sensitivity to hydrological variability, thereby enabling consistent interpretation across years and basin types.

(iv) Increased temporal stability : The Aggregated Runoff (AR)-based index exhibits substantially lower temporal variability compared to the Runoff Coefficient (RC)-based maps, which demonstrate significant fluctuations under varying rainfall conditions.

(v) Reduced pixel-scale uncertainty : Cumulative distribution function (CDF) analyzes demonstrate that Aggregated Runoff (AR)-based indices exhibit reduced dispersion and more stable class assignments across both annual and seasonal time scales.

(vi) Transferability under hydro-climatic variability The application to the Simeto Basin confirms that the proposed framework remains effective under conditions of strong hydro-climatic variability. While increased temporal variability is observed compared to the Ponte Felcino basin, particularly due to seasonal droughts and episodic rainfall events, the AR-

based index maintains a more consistent spatial prioritization than conventional RC-based approaches. This demonstrates that the methodology is transferable in a relative sense, providing a robust and physically consistent representation of runoff potential across different climatic contexts, while remaining sensitive to local basin characteristics.

In summary, the proposed Aggregated Runoff (AR) framework represents a simple yet effective enhancement to AHP/GIS-based RWH site selection methods. It improves spatial targeting, strengthens temporal robustness, and enables a more accurate representation of hydrological processes without increasing methodological complexity. The integration of AR with quantile-based classification provides a scalable and adaptable approach that can be applied across basins of different sizes and climatic regimes.

Furthermore, the adoption of CDF-based analyzes provides a transparent framework for evaluating uncertainty, including class transitions and variability metrics across temporal scales. This is particularly relevant in the absence of standardized protocols for RWH site selection, as it offers a reproducible and data-driven basis for decision making.

Overall, this work contributes to the development of a transferable and robust framework for large-scale RWH planning that utilizes standard GIS datasets and tools. This framework supports policy formulation and sustainable water resource management, particularly under conditions of increasing climate variability.

5.0.1 Future Research Directions

Based on these findings, the following research directions are recommended:

- **Hybrid screening:** Combine Aggregated Runoff (AR) with local indicators, such as the Runoff Coefficient (RC), to support sensitivity analyzes and multi-scale prioritization.
- **Process integration:** Incorporate infiltration dynamics, soil water balance, and the storage behavior of Rainwater Harvesting (RWH) structures to enhance physical representation.
- **Decision support integration:** Embed AR-based indices into broader planning tools, including cost-benefit analysis and policy-driven prioritization.

5.0.2 Closing Remarks

Introducing Aggregated Runoff as a primary criterion represents a conceptually simple yet impactful advancement in RWH site selection. It enables a more realistic representation of effective water availability and improves the reliability of suitability assessments under variable climatic conditions. Although the framework is not universally invariant, its ability to maintain spatial coherence and reduced sensitivity to rainfall variability makes it a robust tool for long-term planning.

The application to the Simeto Basin highlights that, although variability increases under more extreme hydro-climatic conditions, the Aggregated Runoff (AR)-based approach consistently outperforms conventional methods in maintaining stable spatial prioritization. This confirms that the framework is adaptable across diverse geographic settings, provided that its outcomes are interpreted within the local hydrological context. Ultimately, the integration of AR within GIS/AHP frameworks supports the design of resilient Rainwater Harvesting (RWH) systems capable of addressing the challenges posed by climate variability and water scarcity.

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